

Learning Plan Networks in Conversational Video Games

by

Jeffrey David Orkin

B.S., Tufts University (1995)

M.S., University of Washington (2003)

Submitted to the Program in Media Arts and Sciences
in partial fulfillment of the requirements for the degree of

Master of Science

at the

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Author
Program in Media Arts and Sciences
August 13, 2007

Certified by
Deb Roy
Associate Professor
Thesis Supervisor

Accepted by
Deb Roy
Chairperson, Departmental Committee on Graduate Students

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Abstract

We look forward to a future where robots collaborate with humans in the home and workplace, and virtual agents collaborate with humans in games and training simulations. A representation of common ground for everyday scenarios is essential for these agents if they are to be effective collaborators and communicators. Effective collaborators can infer a partner's goals and predict future actions. Effective communicators can infer the meaning of utterances based on semantic context. This thesis introduces a computational cognitive model of common ground called a Plan Network. A Plan Network is a statistical model that provides representations of social roles, object affordances, and expected patterns of behavior and language. I describe a methodology for unsupervised learning of a Plan Network using a multiplayer video game, visualization of this network, and evaluation of the learned model with respect to human judgment of typical behavior. Specifically, I describe learning the Restaurant Plan Network from data collected from over 5,000 players of an online game called *The Restaurant Game*.

Thesis Supervisor: Deb Roy
Title: Associate Professor

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Thesis Reader

Cynthia Breazeal
Associate Professor of Media Arts and Sciences
MIT Media Lab

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Thesis Reader

Henry Lieberman
Research Scientist
MIT Media Lab

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Thesis Reader

Will Wright
Chief Game Designer
Maxis, Electronic Arts

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Chapter 1

Introduction

Conversation is a collaboration. The sequence of utterances, “How are you today?” “Table for one please,” only makes sense because we understand the social and cultural context. This verbal exchange conjures images of a greeting between a customer and an employee of a restaurant. Taken out of context, these words appear to be a non sequitur, yet we understand them in the context of the “script” that we’ve all learned through myriad trips to a restaurant. These scripts serve as the common ground for the collaborative activity of dialogue, which allows the two actors in the script to move jointly towards common sub-goals, which may ultimately contribute to different role-dependent goals. In this case, the goal for the customer is to have a nice a meal at the restaurant, while the waitresses’ goal is to sell a meal at good price.

We look forward to a future where robots collaborate with humans in the home and workplace, and virtual agents collaborate with humans in games and training simulations. A representation of common ground for everyday scenarios is essential for these agents if they are to be effective collaborators and communicators. Effective collaborators can infer a partner’s goals and predict future actions. Effective communicators can infer the meaning of utterances based on semantic context. This thesis introduces a computational cognitive model of common ground called a Plan Network. A Plan Network is a statistical model that provides representations of social roles, object affordances, and expected patterns of behavior and language. I describe a methodology for unsupervised learning of a Plan Network using a multiplayer video game, visualization of this network, and evaluation of the learned model with respect to human judgment of typical behavior. Specifically, I describe learning the Restaurant Plan Network from data collected from over 5,000 players of an online game called *The Restaurant Game*.



Figure 1-1: *The Restaurant Game* was developed with the *Torque* game engine, and content from *The Sims 2*.

1.1 Motivation

Schank and Abelson (1977) were the first to recognize that providing machines with representations of common ground is essential for their understanding of everyday scenarios, but in 1977 they were ahead of their time. With the technological limits of the 1970's, they could only provide common ground in the form of hand crafted scripts. It would be a simple enough task to handcraft a restaurant script where a customer sits down and says “Bring me a steak”, a waitress brings a steak, and the customer pays the bill. In reality, however, there is an infinite variety of action and dialogue sequences that take place in this scenario. There are limits to the range of behavior that human scripters can possibly anticipate. Hand crafted scripts are brittle in the face of unanticipated behavior, and are unlikely to cover appropriate responses for the wide range of behaviors exhibited when players are given minimal instructions to play roles in an open ended environment. Furthermore, scripted characters have no means of detecting unusual behavior. Today we can do much better.

Today, there are millions of people playing video games together online. Von Ahn recognized this potential, which he leveraged with *The ESP Game* (2004) to collect a large image labeling corpus. With *The Restaurant Game*, I have harnessed the power of the internet to quickly capture an identical scenario played by thousands of pairs of people. In four months, *The Restaurant Game* has generated a corpus of over 5,000 examples of dramatic role-play in a

restaurant environment. Each gameplay session takes an average of 10 minutes, and consists of about 85 physical actions and 40 lines of dialogue produced through the interaction of two human players. It's safe to assume that any English speaking on-line game player is familiar with the social conventions followed in a restaurant, and subconsciously maintains a script for expected behavior in such an establishment. Over many games, we see that a Plan Network emerges, consisting of a common collection of goals, and a variety of utterances contributing to jointly satisfying these goals.

1.2 Learning Plan Networks

A plan refers to a sequence of actions taken to satisfy some goal. In the classical description of logical planning found in Artificial Intelligence text books like Russell and Norvig (1995), a goal is defined as some state of the world that an agent is trying to reach, and an action is an operation that changes the state of the world. The restaurant scenario consists of two agents (a customer and waitress) reaching a series of goal states. Social conventions require collaboration between the agents to reach many of these states. The first goal state is satisfied when a customer is sitting in a chair holding a menu. Social conventions require the waitress to show the customer to a table, and hand him a menu. Following goal states include the customer having eaten one or more dishes, the waitress collecting a paid bill, and the customer exiting the restaurant. A collaborative plan is formulated by the agents to accomplish each goal, and the restaurant scenario as a whole is accomplished through an ordered sequence of plans. The ordering of plans is not governed by physical dependencies -- a customer could choose to pay his bill before eating anything, however social conventions say that the waitress brings the bill after the customer has consumed his meal.

Each play session of *The Restaurant Game* produces a log file containing a trace of plan execution for the sequence of plans carried out by one pair of players. The trace provides a perfect record of actions taken by each player, and resulting changes to the state of the world. Since the initial state of the restaurant is the same for every game, and all state changes during gameplay are recorded, it is possible to learn the preconditions and effects of actions from the execution traces. Merging the execution traces from multiple gameplay sessions produces a graph-like network of actions, linked to one another by preconditions and effects. An agent who wishes to play one of the roles in the restaurant scenario can follow one of the paths in this network to guide his or her actions.

From a traditional A.I. planning perspective, what is learned from the execution traces is really an action network, because there is no explicit representation of the goals that the actors are trying to achieve. In this work, I am making the assumption that all behavior is intentional, and all state changes lead to a world state that is a goal or a sub-goal for the actors. In an unsupervised system that learns solely by observing physical behavior it is not possible to capture an actor's intentions, but by computing the frequencies of action sequences, the system can filter out many of the world states that are unlikely to be goals of the actors. Given this assumption of intentional behavior, what was once an execution trace for a human player now becomes a plan to be followed by an agent. From an agent's perspective, the network of actions is a network of potential plans, hence the name Plan Network. Merging the execution traces into

a graph of shared nodes provides agents with better coverage of the possibility space than could be achieved by selecting any single execution trace to follow.

Each node of the learned Plan Network is a physical action taken by either the waitress or the customer. By computing the statistics of actions taken by actors, the system learns social roles. For example, it learns that waitresses carry food from the kitchen to tables, and customers eat food while sitting at tables. Similarly, computing statistic of actions taken on objects allows learning role-specific affordances of objects. Chairs and stools are for customers to sit on. Steak and salad are carried by waitresses to tables, where they are eaten by customers. Automatically clustering objects by affordances into concepts like *food* and *dirty dishes* allows merging of action nodes that refer to these objects, producing a more generalized Plan Network.

Between each pair of action nodes in the Plan Network, there is a directed edge. An edge indicates that the system has observed one action following another. There is a probability associated with each edge, and a probability distribution at each node over all outgoing edges. Moving along an edge implies the passage of some amount of time, during which it is possible that the actors engaged in dialogue. The Plan Network stores all dialogue sequences observed between two actions with the associated edge. In effect, these dialogue sequences are clustered and *grounded* by the semantic context provided by the surrounding physical actions. The Plan Network provides a model of context that can encode different meanings of the same behavior given the physical positions of actors, the role of the agent, and the interaction history. For example, a waitress picking up a half-eaten steak from the table after the customer has eaten dessert, stood up, and paid the check is different from a waitress picking up the steak while the customer is still sitting and has just taken his first bite of steak. In the first case, the waitress is cleaning up a dirty table after the customer finished his meal. In the second, the waitress is probably bringing the steak back to kitchen because it was not cooked to the customer's liking.

1.3 Evaluating Plan Networks

Learning a Plan Network from data is only a worthwhile pursuit if the learned model is of high quality. Quality is measured by how well the model's assessment of likelihood for observed behavior and language correlates with human judgment of typicality, and how well the Plan Network covers the possibility space of what people will do in the restaurant environment. Graph visualizations of physical behavior and an interactive conversation browser alleviate the difficult problem of qualitatively evaluating such a large corpus. Quality can be measured quantitatively by borrowing modeling techniques from the field of Natural Language Processing. Chapter 5 demonstrates that the learned Plan Network does correlate well with human judgment of typical restaurant behavior by applying n-gram modeling techniques to estimate the likelihood of sequences of actions and words, and comparing these estimates to human ratings of 300 log files.

1.4 Outline of the Thesis

Chapter 2 reviews related work in the fields of cognitive science, chat bots, video games, and natural language processing. Chapter 3 describes data collection with *The Restaurant Game*, including details on the design and development of the game. Chapter 4 describes how Plan Networks are built and visualized from the raw game log data. Chapter 5 describes the evaluation methodology, and presents the results of the evaluation. Chapter 6 concludes with contributions of the thesis and a plan for future work.

Chapter 2

Related Work

This thesis draws from a range of influences, beginning with early work in cognitive psychology and chatbots, continuing through the latest innovations in computer games, language understanding, and learning plans.

2.1 Cognitive Psychology

Schank and Abelson (1977) introduced the idea that the human ability to understand stories and infer the missing details relies on the *scripts* that we've learned from childhood. Scripts consist of roles for people and objects in the story, entry conditions, and a sequence of *scenes* that capture a chain of dependent events at an abstract level. When we read that “John went to a restaurant. He ordered chicken. He left a large tip”, we can infer that he also sat down, looked at a menu, ate his chicken, and was pleased with it. These ideas were implemented in computer programs that relied on hand written scripts, and thus could only make inferences for questions predetermined by their programmers. Current computer game technology allows us to simulate a restaurant at a high level-of-detail, and exploit the gameplay experiences of thousands of players to capture a wider coverage of knowledge than could be hand crafted by a team of researchers decades ago.

Clark (1996) has theorized that language is a form of joint action. The actors in a dialogue can infer each other's meaning because they are taking part in a *joint project* with a common goal, and shared common ground. Shank's scripts are one example of common ground; knowledge of the situation that we can assume everyone shares. Within the script for dining in a restaurant, there are a number of joint projects, such as seating customers, taking orders for food, and paying the check. These joint projects are collaborative activities that require participation and communication from both the customer(s) and the waiter.

Clark views conversations as sequences of paired actions. Garrod and Pickering (2004) discuss a similar mechanism, and they argue that the existence of these paired actions reflects the fact that humans are designed for dialogue, rather than monologue. The conversation browser described in Chapter 4 demonstrates how the Plan Network captures and clusters paired actions, including speech acts in response to physical actions, and speech acts in response to other speech acts.

Bruner (1977) describes how two years olds acquire language through participating in social interaction language games. Through repeated interaction, an infant learns the social situation, which acts as scaffolding for language. Initially the language is redundant with the physical interaction. Over time, the child learns to predict actions, and is able to swap roles with the caregiver, and eventually substitute the redundant language for physical action. In a similar spirit, *The Restaurant Game* provides many examples of repeated interactions in the same social

scenario. These interactions provide scaffolding for the language that players use between actions, and allow the Plan Network to learn the semantic context of utterances. Chapter 4 demonstrates how this scaffolding can be leveraged for interactive browsing of learned conversations.

2.2 Chatbots and Video Games

The first chatbot was a virtual therapist named ELIZA (1966). While ELIZA's memoryless, purely associative, bag-of-words conversational system was able to fool people in the 1960s, today's audience is more sophisticated and demands more than templated, formulaic, canned responses.

Recently, an experimental game *Façade* (2005) has revisited the natural language problem, and has cast it within the context of a strong narrative. The human in *Façade* plays the role of a guest invited to a couple's apartment for cocktails, and witnesses the breakup of their marriage. The player can interact with the environment and freely type conversational text. It took two researchers five years to handcraft scripts for *Façade*, and the game takes about 15 minutes to complete. In Schank's work, hand crafted scripts lead to brittleness in handling unanticipated events. Hand crafted scripts in *Façade* force the narrative down one of the preconceived paths. In either case, the experience of a user interacting with the system will be limited by the range of user behaviors that the human script authors anticipated. This thesis takes first step towards automatically authoring a similar experience in dramatically less time by capturing human input and responses. Capturing what players actually choose to do in the environment, rather than what designers expect them to do, will provide responses to a wider range of player behaviors than a small number of script authors could anticipate.

The Sims (2000) designer Will Wright has coined the term *massively single player game* to describe his upcoming creation *Spore* (2008). As opposed to a *massively multiplayer game*, like *World of Warcraft* (2004), where thousands of humans play on-line together, in a *massively single player game*, each person plays the game alone, but benefits from the participation of potentially millions of other players on the internet. As players of *Spore* create unique creatures and environments, everything they create will be automatically uploaded to centralized servers, and shared with all other players. In this way, the game is constantly evolving on the player's desktop.

Wright's approach bears parallels to the Web2.0 movement, where users of MySpace.com and Flickr.com are empowered with tools to create shared content that benefit all other users. Luis von Ahn's *ESPGame* (2004) is another multiplayer game that entices people to do *Human Computation*, where people do work that is difficult for machines but easy for humans, such as labeling images. Similarly, here we are trying to harness the power of the internet to attack the difficult problem of natural language. Like *Spore*, a game powered by a learned Plan Network would evolve and improve as people provided new conversational content by playing the game.

Orkin (2004, 2005, 2006) introduced the application of logical planning systems to video games to give agents adaptive reasoning capabilities in combat scenarios. In this planning system, plan operators were hand coded by an engineer, and communication and collaboration of agents was

implemented in an ad hoc layer above the planning system. This approach to planning for characters with a handful of goal, actions, and utterances worked well for a first person shooter genred game, but would be impractical for modeling the behavior and dialogue of multiple actors in a social situation. Chapter 4 provides data documenting the enormous potential plan space of the restaurant scenario that dwarfs any plan space found in a current generation shooter.

Many of the points raised by Barbara Grosz (1994) about collaborative systems are still yet to be addressed in computer games. Grosz describes how agents in collaborative systems need to plan jointly with a commitment to mutually supporting one another. The collaborative plan is not the sum of the individual plans. Agents need to assume an attitude of *intending-that* in respect to a coloration partner, in addition to the attitude of *intending-to* do things itself. A customer *intends-to* eat food, which is accomplished by *intending-that* the waitress will bring the meal that he ordered. Neither actor can complete the goals that make up the restaurant scenario on their own; at least not without breaking accepted social conventions. The role-specific visualizations in Chapter 4 illustrate how Plan Networks can equip agents with models of other minds. These models provide perspectives into the interleaved collaborative plan, guiding decisions of action selection that will lead to mutual support.

2.3 Language Understanding

Gorin, Riccardi & Wright (1997) demonstrated unsupervised language acquisition for the AT&T *How May I Help You* call routing system. Their system generated a database of utterances from 10,000 spoken transactions, and computed mutual information to extract salient phrases with high likelihoods of indicating a particular type of call; for example, distinguishing between customers with billing questions, and those wanting directory assistance.

Gorniak and Roy (2005) used *Neverwinter Nights* (2002) to demonstrate the effect of plan recognition on understanding language in the context of a physical situation. This study collected language from pairs of humans solving a puzzle involving movement between rooms, and unlocking doors. Gorniak and Roy demonstrated that a probabilistic plan grammar can be used to recognize affordances and predict the next human action. Their system could successfully handle underspecified, ambiguous language such as “Do it now!”

The Open Mind Common Sense (2003) project uses the internet to collect common sense facts expressed in plain English from a large number of people. GloBuddy (2004) is one OMCS application, where the user describes a situation in text, and the system offers potentially relevant phrases in a foreign language. This thesis combines these ideas, learning a Plan Network that combines action and language in a statistical model of common ground that associates relevant utterances with semantic context.

2.4 Learning Plans

There has been previous work on learning plans. Nilsson (1998) describes how Minton’s Explanation-Based Generalization (EBG) (1989) can be used to learn new STRIPS rules based

on previously existing STRIPS rules. EBG is a technique for generating new rules by composing existing rules with known facts about the world, and generalizing these rules for maximum utility. A number of researchers including Shen (1994), Gil (1992), Wang (1995), and Benson (1997) have explored learning *action models* for agents that have a large number of available actions, but do not know their preconditions and effects a priori. The process of building a Plan Network involves learning the action lexicon itself in an unsupervised, bottom-up manner directly from data. Zettlemyer, Pasula, and Kaelbling (2005) learn STRIPS rules from training data in a stochastic 3D simulated blocks world with realistic physics. *The Restaurant Game* is not a stochastic environment. Effects of actions are deterministic, however the language used in dialogue between actors affects the probabilities of next actions. Furthermore, what separates this thesis from previous work on learning plans is that a Plan Network goes beyond learning planning rules by also learning socially acceptable sequences of plans.

Chapter 3

Data Collection with The Restaurant Game

The Restaurant Game launched online on February 21, 2007. 3,355 unique players have completed 5,200 games between February 21 and June 25, 2007. A game is considered *complete* if two players joined, both players typed chat text, and at least one player filled out the after-game survey. This chapter describes *The Restaurant Game* as a data collection device, and details the flow and sources of the data.

3.1 What is The Restaurant Game?

The Restaurant Game is a 3D simulation which anonymously pairs players online to play the roles of a customer and a waitress in a virtual restaurant. Each player is given a vague objective; the waitress tries to earn money, while the customer has dinner to satisfy his hunger. Players control characters from a first person perspective, and can manipulate objects in the environment, and type open-ended chat text to one another.

The Restaurant Game

OBJECTIVE:

YOU ARE A WAITRESS AT A RESTAURANT. YOUR OBJECTIVE IS TO WAIT FOR THE NEXT CUSTOMER TO ARRIVE, AND THEN EARN AS MUCH MONEY AS YOU CAN. WHEN YOU DEPOSIT A CHECK IN THE REGISTER, YOU WILL EARN 50% OF THE PRE-TAX TOTAL PLUS THE TIP.

 WHEN YOU HAVE COMPLETED YOUR OBJECTIVE, EXIT THE RESTAURANT, AND WALK TO THE 'OBJECTIVE COMPLETE' SQUARE ON THE SIDEWALK.

AFTER FILLING OUT A BRIEF SURVEY AT THE END OF THE SESSION, YOU WILL BE PRESENTED WITH A PERSONALITY PROFILE BASED ON HOW YOU CHOSE TO PLAY THE GAME.

BE YOURSELF, AND HAVE FUN !!

[CLICK HERE TO START THE GAME](#)



Figure 3-1: Vague objectives for the waitress.



Figure 3-2: Vague objectives for the customer.

The Restaurant Game affords players an unusual amount of freedom, compared to other games. While many players do what would be expected of people in a restaurant, players are free to take the story in any direction they choose, including stealing the cash register, eating the flowers, biting other players, and spinning around on the counter while holding the microwave. In spite of this apparent freedom, this thesis relies on shared assumptions of what one does in a restaurant to limit freedom in natural ways.

Within approximately 10 minutes, a pair of players play through a typical (or atypical) restaurant experience, including reading a menu, ordering food and drinks, eating, and paying the bill. All physical actions and chat text is logged on centralized game servers. The game concludes with a brief survey that asks players to describe the customer or waitress, and to speculate on the personality of the real person playing the opposite role.

3.2 Development of The Restaurant Game

I developed *The Restaurant Game* over the course of about five months. The game is built on top of the *Torque* game engine from Garage Games (2005, 2006). *Torque* was chosen for its cross platform support, networking capabilities, active online community, and its inexpensive licensing fee. The game runs on Windows and Mac OSX.

Most of the content (3D models, textures, and audio) in the game was exported from EA's *The Sims 2* (2004) with the help of a modding tool called *SimPE* (2004). I used Chumbalum Soft's *Milkshape3D* (1996) to animate *Sims* models and to export models in *Torque*'s DTS format, and the *QuArK* (*Quake Army Knife*) (2001) level editor to construct the shell of the restaurant.

Multiple dedicated server processes are running on multiple machines. A dedicated server is a lightweight non-graphical application that hosts two players in a stand-alone instance of the restaurant. 10 or 20 of these server processes run on each machine. Over the course of the project a total of between 30 and 80 server processes have been running on between three and six machines; mostly Windows boxes with one Mac G5. With 80 servers running at the height of the project, 160 players could be accommodated in 80 simultaneous games. In reality, the traffic peaked at 16 simultaneous games, but running an array of servers provided redundancy in the event of server failure, and helped balance the load. Garage Games runs a Master Server that allows *Torque* client applications to find *Torque* servers over the internet.

3.3 Design Considerations for The Restaurant Game

The desire to capture an accurate model of conversational behavior in the restaurant scenario dictated a number of design requirements. The game needed to be accessible to a wide audience, encourage natural conversation, provide freedom for dramatic role-playing, and hold players interest long enough to complete one or more games. Following are the considerations taken into account to meet each of these requirements.

3.3.1 Accessibility to a Wide Audience

The game needed to be simple to play for people with any level of gaming experience in order to maximize the number of potential players, and to ensure capturing data from a large cross-section of the population. All interaction is mouse-driven with a point-and-click interface, and a pop-up interaction menu. The left mouse button selects objects to interact with, and the right mouse button moves the character. (Players with one-button mice can use the arrow keys to move). Moving the mouse controls the viewpoint of the player. Prior to joining a multiplayer game, a 5-10 minute tutorial walks the player through instructions on how to interact with the world, without assuming any particular role (waitress or customer). Players learn to pick up, sit on, eat, inspect, and touch things, and to create bills, chat, and order food.



Figure 3-3: Interface for interacting with objects with icons inspired by The Elephant's Memory visual language (1994).

3.3.2 Player Retention

Once a player with capable hardware has been enticed to install the game and complete the tutorial, there are a number of measures in place to encourage this player to complete a game online one or more times. Players are informed that will be credited as Game Designers on a future game generated with the data collected from completed online games. The open-ended nature of the game keeps the experience fresh. The post game survey also acts as a motivator to play multiple times. The survey asks players to speculate on the personality of the real person playing the other role, rating their intelligence, sense of humor, honesty, consideration, eloquence, and patience, and to guess their occupation, geographic location, gender, age, and what they eat for breakfast. Results of the survey are presented to the other player, accumulated and averaged over all games played. Players are motivated to see their cumulative survey evolve over several games; people love to hear about themselves. Finally, the amount of virtual money in each player's account persists. Players start with \$50, and usually spend this money as a customer and earn money as a waitress. The intent is to encourage playing multiple times in different roles, under different financial constraints.

POST-GAME SURVEY

USE THREE WORDS TO DESCRIBE THE BEHAVIOR OF THE WAITRESS:
(e.g. POLITE, VEGETARIAN, CHEAPSKATE, CRAZY, ETC . . .)

Lively Attentive Sociable

CHECK HERE TO REPORT INAPPROPRIATE WAITRESS BEHAVIOR.

NOW DESCRIBE WHO YOU THINK THE REAL PERSON CONTROLLING THE WAITRESS IS:

GENDER: FEMALE AGE:

WHERE IS HE / SHE FROM?

WHAT IS HIS / HER OCCUPATION?

WHAT DOES HE / SHE EAT FOR BREAKFAST?

WHAT IS YOUR IMPRESSION OF THE REAL PERSON'S PERSONALITY ON A SCALE FROM 0 TO 10 (10 BEING THE BEST):

INTELLIGENT:

FUNNY:

CONSIDERATE:

HONEST:

WELL SPOKEN:

PATIENT:

PLEASE REPORT ANY PROBLEMS YOU ENCOUNTERED WHILE PLAYING THE GAME:

SURVEY COMPLETE

Figure 3-4: Post-game survey.

3.3.3 Natural Conversation

It is important to ensure there are no interface obstacles to players conversing, in alignment with the goal of capturing conversation in context. Any keyboard input is treated as chat text, allowing players to freely type open-ended text to each other at any time, without having to press any buttons first. The first-person perspective was a deliberate design decision to encourage natural situated and embodied dialogue, with players facing each other. Players can only hear one another when the speaker is facing the listener. Otherwise, the listener receives a message that the other player is speaking with his or her back turned, or is speaking to the staff. The scripted chef and bartender will only acknowledge orders for food and drinks if the speaker is facing the staff member, and within a reasonable proximity.

3.3.4 Freedom for Dramatic Role-Playing

The premise of this thesis is that modeling behavior by observing thousands of players will capture behavior that human scripters would have never anticipated. To demonstrate that this is the case, players are given the freedom to play through the scenario any way they choose. Video games typically offer players context-sensitive interactions with objects, and many objects in the world are purely decorative and non-interactive. *The Restaurant Game* does not presuppose desired interactions, and instead allows the player to interact in a consistent way with every object in the game world. Players get satisfying responses from every object when they try to pickup, inspect, touch, eat, or sit on them. The effect of these actions on the world varies depending on the type of action. For example, food visually diminishes when eaten, while eating a chair produces a chomping sound with no visual change. Touching (or operating) the cash register produces a bill, touching the microwave results in beeping sounds, touching a plate of food rotates it on the table. The other player receives narration to clarify events that do not visually change the world (e.g. “Waitress bit the chair”).

The open-ended design of *The Restaurant Game* subscribes to Will Wright’s definition of “good game aesthetics.” As Wright describes in Feldman’s Gamespot interview (2003) about designing *The Sims 2*:

Players obviously enjoy being subversive to some degree. And so we want to provide that and let them know that we’re on their side in that way [...]. It’s just another form of a player taking control. I think for most people, their kind of general aesthetic with games is that the more I control this experience, the better the game is [...] in terms of [finding that] I can choose to go off into an interesting path, and the game will support that path. This animal we’re calling subversion is really just empowering the players to not hit walls as often [...]. At a fundamental level it’s kind of convergent with what I would call “good game aesthetics.”

Players have, in fact, surprised me with unanticipated behavior, such as making a margarita by carrying the fruit bowl from the kitchen to the bar and using the blender. More than a few players have chosen to dramatize what happens when the customer steals the cash register. In *The Restaurant Game*, the social scenario is known a priori, but this will not always be the case. As user-created content in virtual worlds like *Second Life* (2003) become more prevalent, agents in the future will require the ability to learn expected social behavior in novel situations.

Other than their outfits, the game does not enforce any assumptions about social roles. The waitress does wear a uniform, but either player can eat food, request menu items from the staff, and operate the cash register to create or deposit bills.

The open-ended nature of the game provides a challenge in knowing when to consider a game complete, as opposed to prematurely aborted, intentionally or unintentionally. For instance, relying on detecting that the customer has eaten some food and paid a bill presupposes assumptions about this scenario. Initiation of the post game survey provides a good indicator that at least one player feels that the scenario has concluded. The survey also helps screen out

data from troublemakers who are not interested in contributing to research, because these abusive players often choose not to fill out the survey.

3.4 Where Does Data Come From?

This project began with many concerns. Will anyone actually play this game? Will people be willing to install a unique stand-alone application? Will people manage to find partners online at the same time? I originally aimed to collect 1,000 completed games. To my surprise, this goal was achieved in under two weeks, and the project continued on to collect over 5,000 games. The servers are still up, and over 100 games continue to trickle in every week. Who are these people, and how did they find out about *The Restaurant Game*?

3.4.1 Rallying the Masses

On February 21, I started the servers and posted the project web page, <http://theRestaurantGame.net>, consisting of a brief description of the project and downloadable installers for Windows and OSX. The page encourages people to participate with the following enticement:

Contribute to the first collaboratively authored computer game and earn Game Designer credit!

The Restaurant Game is a research project at the MIT Media Lab that will algorithmically combine the gameplay experiences of thousands of players to create a new game. In a few months, we will apply machine learning algorithms to data collected through the multiplayer *Restaurant Game*, and produce a new single-player game that we will enter into the 2008 Independent Games Festival. Everyone who plays *The Restaurant Game* will be credited as a Game Designer.

I announced the project quietly on Game/AI, a blog shared by game industry AI developers with a small readership (bloglines.com reports 67 subscribers). Within the week, several other gaming-related blogs posted about the project, including Grand Text Auto and TerraNova. This provided a good crop of players for beta testing and tweaking/bug fixing before announcing the project to wider audience a week later.

Once all major issues were resolved, word went out via email to six game industry websites, five Mac websites, and acquaintances at 24 software companies and 12 universities with game development programs. In addition, I listed the game on two shareware download sites, and two friends distributed fliers at conferences (the Game Developers Conference, and Human Robot Interaction). The flier at HRI caught the eye of a reporter from *New Scientist* magazine who wrote a short article in March (2007). Digg.com and Del.icio.us icons on the project webpage also helped spread the word through social bookmarking. More recently, a PCWorld.com review of the game was highlighted on MSN.com, drawing another wave of players.

Table 3-1 details various gameplay statistics. A total of 5,602 players logged into the game, but many failed to find a partner online at the same time, and never tried again. The first player to join a server is always the waitress, who must wait for a customer to show up.

Total Players Logged In	5,602		
Players Who Completed Games	3,355		
	Mean	Median	Max
Game Duration	11.18 min	9.82 min	94.2 min
Waitress Wait Time	2.41 min	1.12 min	78.31 min
Games Played Per Person	3	2	77
Games Over 20 min	427		
Waitress Wait Times Over 20 min	31		

Table 3-1: Gameplay statistics from 5,200 games.

Below is a graph of the number of games completed per week. The peaks correspond to weeks when *The Restaurant Game* was featured on popular video game news sites, or on MSN. The March 24th *New Scientist* article was one of the biggest draws of players, but does not correspond to a peak on this graph; rather it lead to a longer lasting steady stream of new players.

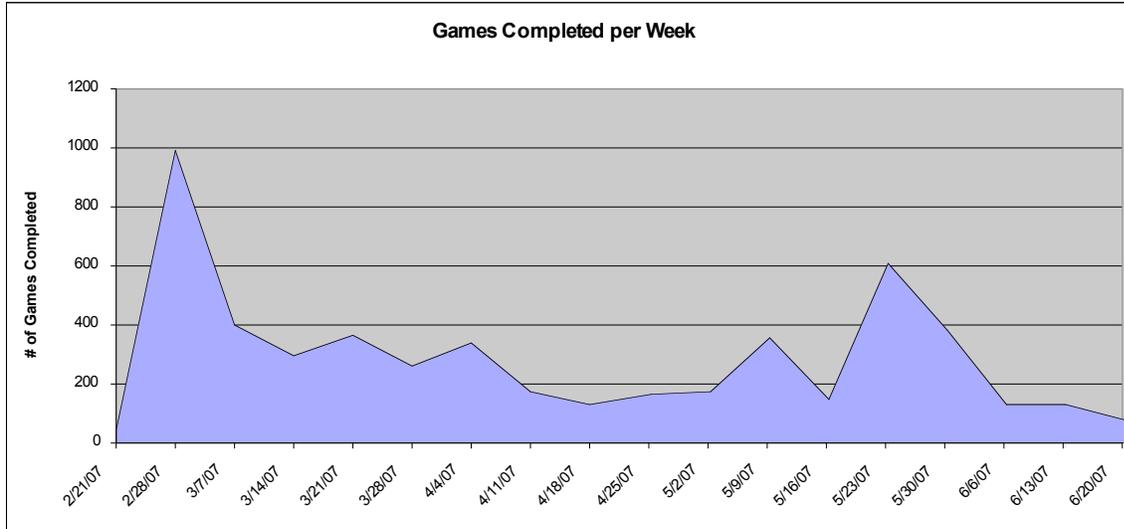


Figure 3-5: Games completed per week.

The next graph illustrates the number of page hits to the project webpage per week, as reported by Google Analytics. Between February 21 and June 25, Google reports that the page has been hit a total of 49,343 times by 42,358 unique visitors.

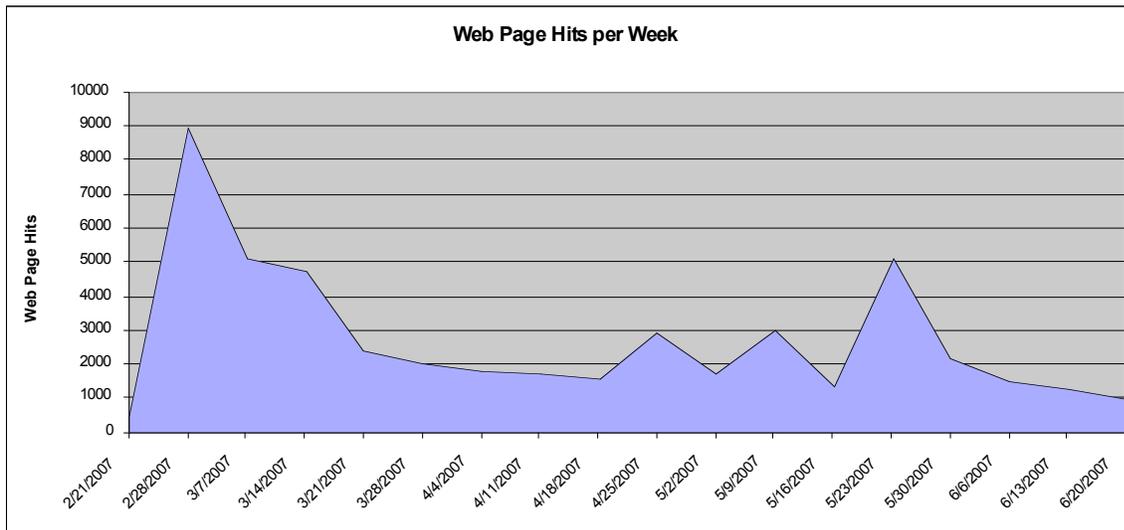


Figure 3-6: Project web page hits per week.

In addition, 7,501 people have downloaded the game from shareware download websites. So, in total the project attracted an audience of $42,358 + 7,501 = 49,859$ people (who either read about and/or played the game). Dividing the 5,602 unique players who logged in by the audience of

49,859 people yields that about 11% of the audience actually played the game. The 3,355 players who completed games account for about 60% of those who logged in, and about 7% of the total audience.

3.4.2 Player Demographics

Other than confirming that they are over 18, the game does not request any personal information from players. A bit of information about players can be gleaned through volunteered information, Google Analytics, and automatic platform detection.

The game’s login process allows players to voluntarily self-report where they heard about the game. 87% of the players who completed games reported, and the results of the survey are below. “Game Industry Sites” encompasses 22 different game industry news and blog sites. “Word of Mouth” covers everyone who reported hearing about the game through friends, family, instructors, or colleagues. “Other” combines counts from 353 unique responses that did not fit any other category.

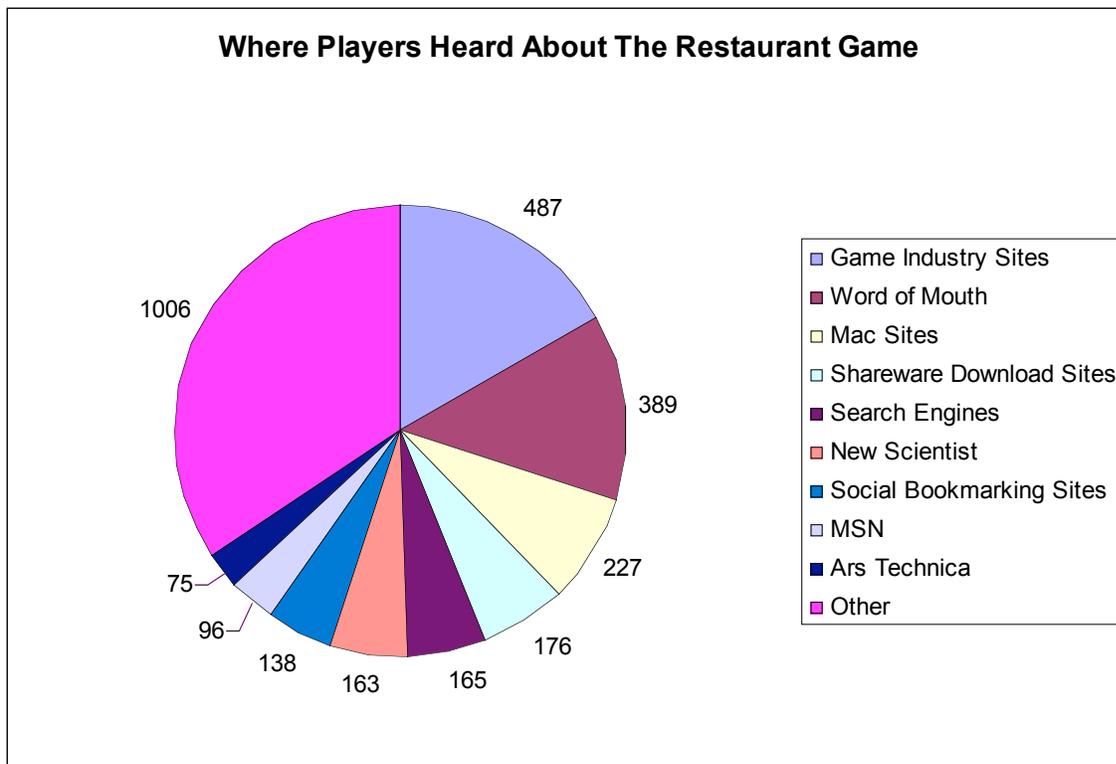


Figure 3-7: Where players heard about *The Restaurant Game*.

The client application detects the hardware and OS it is running on, and reports this to the server. The pie chart below details the number of games completed on each platform. Note that each game is played on two clients at once, so the total is 10,400 for the 5,200 completed games.

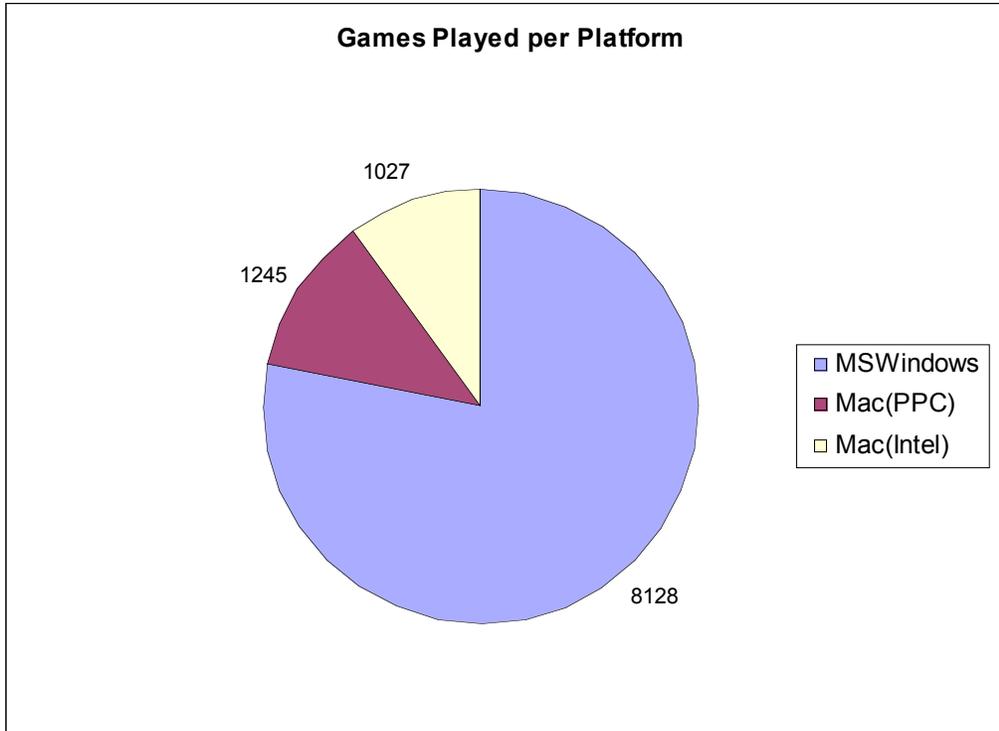
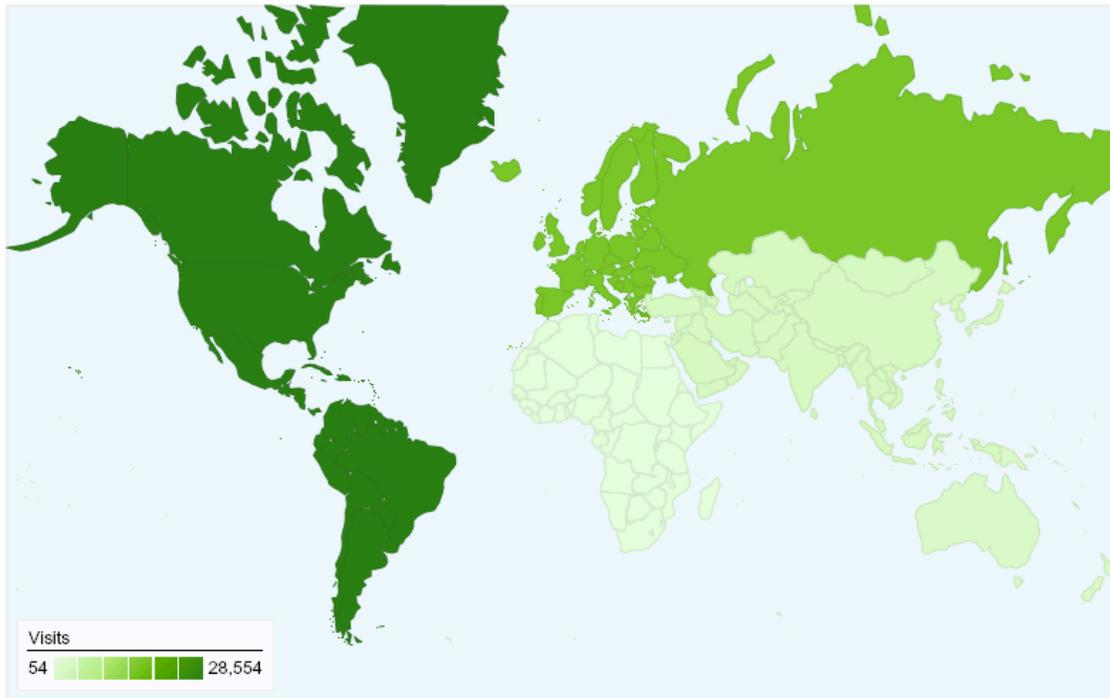


Figure 3-8: Games played per platform.

Google Analytics provides the geographic breakdown of where viewers of the project web page are located in the world. A significant number of players come from non-English speaking countries. The account creation process requires players to report their level of English proficiency, so that non-native speakers can be screened out if desired. The experiments in this thesis do not screen out anyone, but the results in Chapter 5 demonstrate that the statistical models are able to identify gameplay sessions containing foreign languages or broken English.



49,343 visits came from 6 continents

Site Usage						
Visits 49,343 % of Site Total: 100.00%	Pages/Visit 1.22 Site Avg: 1.22 (0.00%)	Avg. Time on Site 00:00:37 Site Avg: 00:00:37 (0.00%)	% New Visits 85.72% Site Avg: 85.74% (-0.02%)	Bounce Rate 83.63% Site Avg: 83.63% (0.00%)		
Continent	Visits	Pages/Visit	Avg. Time on Site	% New Visits	Bounce Rate	
Americas	28,554	1.24	00:00:42	84.40%	82.12%	
Europe	16,103	1.20	00:00:30	87.28%	85.65%	
Asia	2,676	1.21	00:00:33	89.65%	85.39%	
Oceania	1,732	1.19	00:00:34	85.39%	86.55%	
Africa	224	1.14	00:00:24	94.20%	86.61%	
(not set)	54	1.13	00:00:20	92.59%	87.04%	

Figure 3-9: Geographic distribution of players as reported by Google Analytics.

3.5 Lessons Learned About Game-Based Data Collection

There are many factors to consider when designing an online game for collecting data *in the wild* of the internet, and it is unlikely that the first iteration of the system will be perfect. This section describes lessons learned from the experience of launching *The Restaurant Game*; the first iteration of a data collection platform.

The design considerations detailed in section 3.3 contributed to the success of the data collection effort. The simple installation and user interface were amenable to a wide audience of thousands of players. Players seemed to enjoy open ended dramatic role playing and learning about others' impressions of themselves through post-game survey. It is difficult to tell how much impact the enticement of Game Designer credentials on a future game had on players, but this gimmick certainly helped attract attention from blogs and news web sites. However, the first lesson learned was the danger of promising the public a deliverable based on novel research by a specific date. The project web page promises Game Designer credit on a new game that will be entered into the 2008 Independent Games Festival (IGF 2008). The goal of automating characters with the learned Plan Network remains, but this will not be achieved in time for the IGF 2008 deadline.

3.5.1 Lessons Learned About Publicity

Regardless of the outcome, the promise of entry into the IGF proved newsworthy. New versions of *The Restaurant Game* and support for additional platforms also provided newsworthy information to report, and re-generate excitement and awareness of the project. Updated versions were necessary to fix minor bugs and expand supported platforms, but were equally useful in generating press. Blogs and web sites only re-post about a project if there is something new to report. While the great majority of players were Windows-based, supporting multiple platforms was worthwhile for broadening press coverage. The Mac community greets cross-platform supported software with enthusiasm, and there are a variety of Mac web sites that reach a heterogeneous cross-section of the public.

The Mac web sites reached audiences for *The Restaurant Game* that I did not realize existed, like the food service and hospitality industries. The project attracted interest from producers of a BBC production about restaurant management, a blog devoted to hotel technology, and the National Restaurant Association. How the word of a project like this spreads is unpredictable. I learned two lessons from missed publicity opportunities.

Word of the project reached a journalist writing an article about AI in games for *The Boston Globe*. The article ran in June, and mentioned *The Restaurant Game*, but neglected to print the URL. It is best to explicitly ask that press coverage includes information necessary for readers who wish to participate in the research.

The second missed opportunity was related to the social bookmarking sites Digg.com and Del.icio.us. Unfortunately, the biggest spike in activity came early in the project when two video game news sites posted about it, before I had added the Digg and Del.icio.us badges to the project web page. Visitors who click these badges increment the count of the number of people bookmarking the page. Prominent link placement on the main Digg and Del.icio.us pages depends on the rate of increase of people clicking these badges. Had I added the badges from the start of the project, these social bookmarking sites may have helped the project reach a much wider audience.

3.5.2 Lessons Learned About Third Party Technology

When activity does spike, it is useful to know the source of the spike. I relied on Google Analytics to find referring sources of web traffic. This information is not only useful for planning where to advertise in the future, but also for observing what information players are sharing with one another, some of which may be malicious. I learned of a number of issues by reading forum posts to video game news sites that reported on the project.

Players were teaching each other to exploit a bug that allowed waitresses and customers to literally fly through the roof by picking up the object that the player was sitting on. Players familiar with the *Torque* game engine were able to open the console and type commands such as *suicide*, to kill and re-spawn a player, wreaking havoc on the scenario. Most alarming, some of these players were aware that the same *Torque* executable is used for the client and server, and were attempting to run their own servers. This would have been a disaster, as I would never have access to the data collected by these rogue servers. Fortunately, these deviants never figured out all of the command-line parameters required to start a server, and gave up. The lesson learned is that extra precautions need to be taken when using third party technologies. *The Restaurant Game* should have been released with the command console disabled, and server functionality removed.

3.5.3 Old Habits Die Hard

The video game press attracts many capable players with an interest in novel games, however these players bring habits learned from previous gaming experiences. The data reveals a number of prevalent habits such as trying to move the character with the AWS keys (the standard control scheme for first person shooters), and beginning each line of chat text with the word *text*, as some online games require. These patterns are easy to detect and screen out of the dialogue data. Other habits highlight missing features that multiplayer gamers expect, and may be desirable in future data collection games. Players often try to augment the limited set of animations by typing *World of Warcraft*-style *emotes*, such as */wave*, */weep*, */kiss*, */burp*, or */applaud*. These emotes do not currently result in any animations, but adding some of these animations might enhance the interaction, and allow the system to learn gestures and body language as well as spoken language. Additional interface problems were related to foreign keyboards, and one-button mice.

Chapter 4

Building and Visualizing Plan Networks

The Restaurant Game has captured a large quantity of data, but in its raw form, it's not of much use to a human and much less to an agent. Following is an excerpt from a log file exported from one gameplay session.

```

[COGLOG] 6061977 EVENT CUSTOMER(Player) ENTERED doorTrigger(RegionTrigger)
[COGLOG] 6062055 STATECHANGE CUSTOMER(Player) ATPOS="(321.146 358.792 240.541)"
[COGLOG] 6063446 EVENT WAITRESS(Player) FACING CUSTOMER(Player)
[COGLOG] 6063446 STATECHANGE WAITRESS(Player) FORWARDDIR="(0.989292 -0.145949 0)"
[COGLOG] 6063446 STATECHANGE WAITRESS(Player) ATPOS="(314.443 359.182 240.54)"
[COGLOG] 6063446 SPEECHACT WAITRESS(Player) "welcome"
[COGLOG] 6066368 EVENT CUSTOMER(Player) FACING WAITRESS(Player)
[COGLOG] 6066368 STATECHANGE CUSTOMER(Player) FORWARDDIR="(-0.990476 0.137684 0)"
[COGLOG] 6066368 STATECHANGE CUSTOMER(Player) ATPOS="(320.765 358.845 240.541)"
[COGLOG] 6066368 SPEECHACT CUSTOMER(Player) "hi"
[COGLOG] 6069039 EVENT WAITRESS(Player) FACING CUSTOMER(Player)
[COGLOG] 6069039 STATECHANGE WAITRESS(Player) FORWARDDIR="(0.989292 -0.145949 0)"
[COGLOG] 6069039 STATECHANGE WAITRESS(Player) ATPOS="(314.443 359.182 240.54)"
[COGLOG] 6069039 SPEECHACT WAITRESS(Player) "please have a seat"
[COGLOG] 6074211 EVENT CUSTOMER(Player) FACING WAITRESS(Player)
[COGLOG] 6074211 STATECHANGE CUSTOMER(Player) FORWARDDIR="(-0.894119 0.440718 -0.0794913)"
[COGLOG] 6074211 STATECHANGE CUSTOMER(Player) ATPOS="(320.765 358.845 240.541)"
[COGLOG] 6074211 SPEECHACT CUSTOMER(Player) "where?"
[COGLOG] 6077489 STATECHANGE CUSTOMER(Player) ATPOS="(319.976 359.222 240.542)"
[COGLOG] 6077493 EVENT CUSTOMER(Player) EXITED doorTrigger(RegionTrigger)
[COGLOG] 6083586 EVENT WAITRESS(Player) FACING CUSTOMER(Player)
[COGLOG] 6083586 STATECHANGE WAITRESS(Player) FORWARDDIR="(0.989292 -0.145949 0)"
[COGLOG] 6083586 STATECHANGE WAITRESS(Player) ATPOS="(314.443 359.182 240.54)"
[COGLOG] 6083586 SPEECHACT WAITRESS(Player) "customers choice"
[COGLOG] 6102211 EVENT WAITRESS(Player) FACING CUSTOMER(Player)
[COGLOG] 6102211 STATECHANGE WAITRESS(Player) FORWARDDIR="(0.989292 -0.145949 0)"
[COGLOG] 6102211 STATECHANGE WAITRESS(Player) ATPOS="(314.443 359.182 240.54)"
[COGLOG] 6102211 SPEECHACT WAITRESS(Player) "you choose where you want to sit"
[COGLOG] 6108927 STATECHANGE CUSTOMER(Player) ATPOS="(318.712 359.725 240.542)"
[COGLOG] 6108946 EVENT CUSTOMER(Player) ENTERED podiumTrigger(RegionTrigger)
. . .
[COGLOG] 6132664 STATECHANGE CUSTOMER(Player) FORWARDDIR="(0.345101 0.930914 0.119601)"
[COGLOG] 6132664 STATECHANGE CUSTOMER(Player) ATPOS="(314.176 362.945 240.543)"
[COGLOG] 6132664 SPEECHACT CUSTOMER(Player) "ummmm let's see"
[COGLOG] 6135196 STATECHANGE CUSTOMER(Player) ATPOS="(314.176 362.945 240.543)"
[COGLOG] 6135296 STATECHANGE CUSTOMER(Player) ATPOS="(313.693 362.944 240.544)"
[COGLOG] 6135352 EVENT CUSTOMER(Player) ENTERED table3Trigger(RegionTrigger)
. . .
[COGLOG] 6139930 STATECHANGE CUSTOMER(Player) ATPOS="(307.938 362.384 240.546)"
[COGLOG] 6139930 ACTION CUSTOMER(Player) SITON chair6(DBChair)
[COGLOG] 6139930 STATECHANGE CUSTOMER(Player) SITTINGON="chair6(DBChair)"
[COGLOG] 6142821 STATECHANGE WAITRESS(Player) ATPOS="(314.443 359.182 240.54)"
[COGLOG] 6142821 STATECHANGE WAITRESS(Player) DEST="(309.925 360.189 240.632)"
[COGLOG] 6142821 ACTION WAITRESS(Player) GOTO table3(DBTable)
[COGLOG] 6142993 EVENT WAITRESS(Player) ENTERED table3Trigger(RegionTrigger)
[COGLOG] 6143039 STATECHANGE WAITRESS(Player) ATPOS="(313.318 359.394 240.541)"
[COGLOG] 6143039 ACTION WAITRESS(Player) PUTDOWN dynamic2753(DBMenu)
[COGLOG] 6143039 STATECHANGE dynamic2753(DBMenu) ATTACHEDTO="NULL"
[COGLOG] 6143039 STATECHANGE dynamic2753(DBMenu) ON="table3(DBTable)"
[COGLOG] 6143039 STATECHANGE dynamic2753(DBMenu) ATPOS="(311.177 360.455 242.635)"
[COGLOG] 6145123 STATECHANGE CUSTOMER(Player) ATPOS="(309.952 361.922 240.773)"
[COGLOG] 6145123 ACTION CUSTOMER(Player) PICKUP dynamic2753(DBMenu)
[COGLOG] 6145123 STATECHANGE dynamic2753(DBMenu) ON="NULL"
[COGLOG] 6145123 STATECHANGE dynamic2753(DBMenu) ATTACHEDTO="CUSTOMER(Player)"
[COGLOG] 6147118 ACTION CUSTOMER(Player) LOOKAT dynamic2753(DBMenu)
[COGLOG] 6147571 EVENT WAITRESS(Player) FACING CUSTOMER(Player)
[COGLOG] 6147571 STATECHANGE WAITRESS(Player) FORWARDDIR="(-0.89335 0.291024 -0.342391)"
[COGLOG] 6147571 STATECHANGE WAITRESS(Player) ATPOS="(312.704 359.534 240.541)"
[COGLOG] 6147571 SPEECHACT WAITRESS(Player) "here's a menu. Take your time"

```

Figure 4-1: A raw log file from a gameplay session.

These raw log files are difficult to interpret. It is straight forward to write a program that distills the logs into something that is more human-readable. Figure 4-2 shows the log file for the same game distilled into a script, which reads more like a theatrical script to a film or a play.

```

6044508      WAITRESS WALKS TO podium
6044993      WAITRESS PICKSUP Menu
6058118      CUSTOMER WALKS TO door

6063446 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
6063446 WAITRESS: "welcome"
6066368 CUSTOMER: "hi"
6069039 WAITRESS: "please have a seat"
6074211 CUSTOMER: "where?"
6083586 WAITRESS: "customers choice"
6102211 WAITRESS: "you choose where you want to sit"

6108727      CUSTOMER WALKS TO podium

6132664 [CONVERSATION BETWEEN CUSTOMER AND WAITRESS]
6132664 CUSTOMER: "ummmm let's see"

6135196      CUSTOMER WALKS TO table3
6139930      CUSTOMER SITSON chair6
6142821      WAITRESS WALKS TO table3
6143039      WAITRESS PUTSDOWN Menu ON table3
6144661      CUSTOMER PICKSUP Menu
6147118      CUSTOMER LOOKSAT Menu

6147571 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
6147571 WAITRESS: "here's a menu. Take your time"
6150633 CUSTOMER: "I'll have vegetable soup and the nectarine tart"

6200711      WAITRESS WALKS TO counter

6216133 [CONVERSATION BETWEEN WAITRESS AND CHEF]
6216133 WAITRESS: "one soup please"

6217133      Soup APPEARS ON Counter
6221461      WAITRESS PICKSUP Soup
6222149      WAITRESS WALKS TO table3
6225368      WAITRESS PUTSDOWN Soup ON table3
6225430      WAITRESS PICKSUP Menu
6226196      WAITRESS WALKS BETWEEN counter AND table2
6228086      CUSTOMER EATS Soup
6242774      WAITRESS PUTSDOWN Menu ON MenuBox
6242774      Menu DISAPPEARS
6245743      WAITRESS WALKS TO table3

6301211 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
6301211 WAITRESS: "anything for drink"
6309711 CUSTOMER: "water"
6315243 WAITRESS: "coming right up"

6316743      WAITRESS WALKS TO bar

6320508 [CONVERSATION BETWEEN WAITRESS AND BARTENDER]
6320508 WAITRESS: "one water"

6321508      Water APPEARS ON Bar
6324633      WAITRESS PICKSUP Water
6325649      WAITRESS WALKS TO table3
6328743      WAITRESS PUTSDOWN Water ON table3

```

Figure 4-2: A filtered script, generated from a raw log file.

A human can read through an entire game in a few minutes. These scripts are useful for spot checking the data, but are not a practical solution to understanding our corpus as a whole. Reading 5,000 games would take over ten days, but more importantly, merely reading the scripts is not equivalent to understanding their commonalities and differences. A Plan Network provides a generalized representation that incorporates everything observed in all gameplay sessions. This representation gives humans the gist of the behavior in the restaurant scenario, and provides a means of predicting future actions and recognizing when things are going off-script. The next section looks at ways to visualize a Plan Network, before delving into the details of how to build such a model in section 4.2.

4.1 Visualizing Plan Networks

Each gameplay session is composed of interleaved sequences of physical actions and speech acts performed by multiple characters in various social roles. Pulling apart the data based on these categories will provide perspectives into the data that are easier for humans to comprehend, and more powerful for planning and recognition by an agent.

4.1.1 Graphing Physical Actions

Figure 4-3 re-renders the log file seen previously in Figure 4-1 as a directed graph of physical actions. For the most part, the graph follows a linear path from START to END, with just a few loops for repeated behavior such as the customer eating multiple bites of an entrée. I created this graph automatically by exporting actions as nodes, and edges representing observed sequences of actions. In section 4.2, I will describe the process of creating a lexicon of actions, and clustering similar actions (e.g. eating salmon and eating pie are clustered as eating *food*).

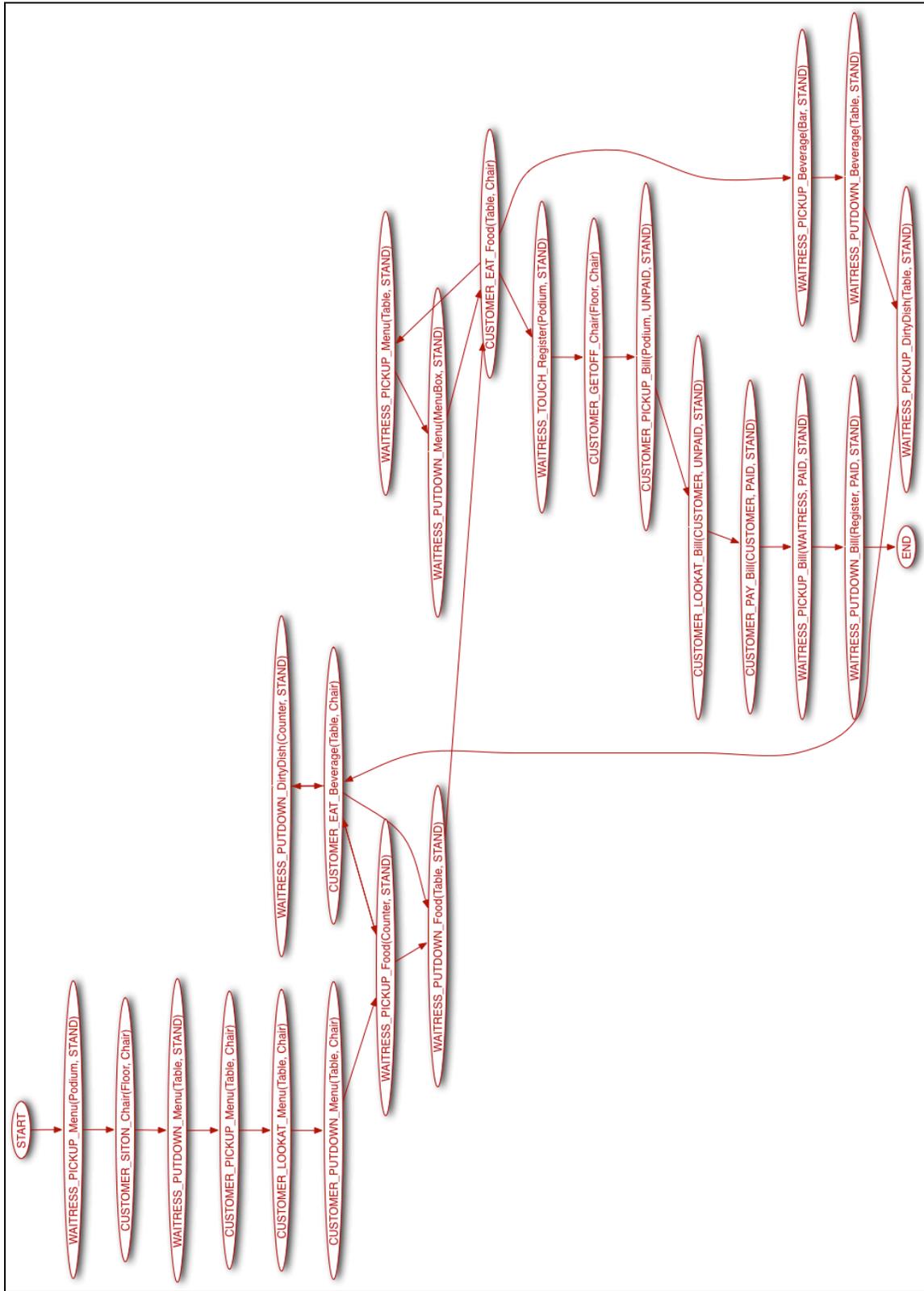


Figure 4-3: Graph visualization of one game.

Figure 4-4 depicts another gameplay session. The behavior in this session is similar to that in Figure 4-3, with a few minor variations. In the second game, the waitress gives the menu to the customer, rather than placing it on the table. The customer stands up before paying the bill in the first game, and pays while sitting at the table in the second.

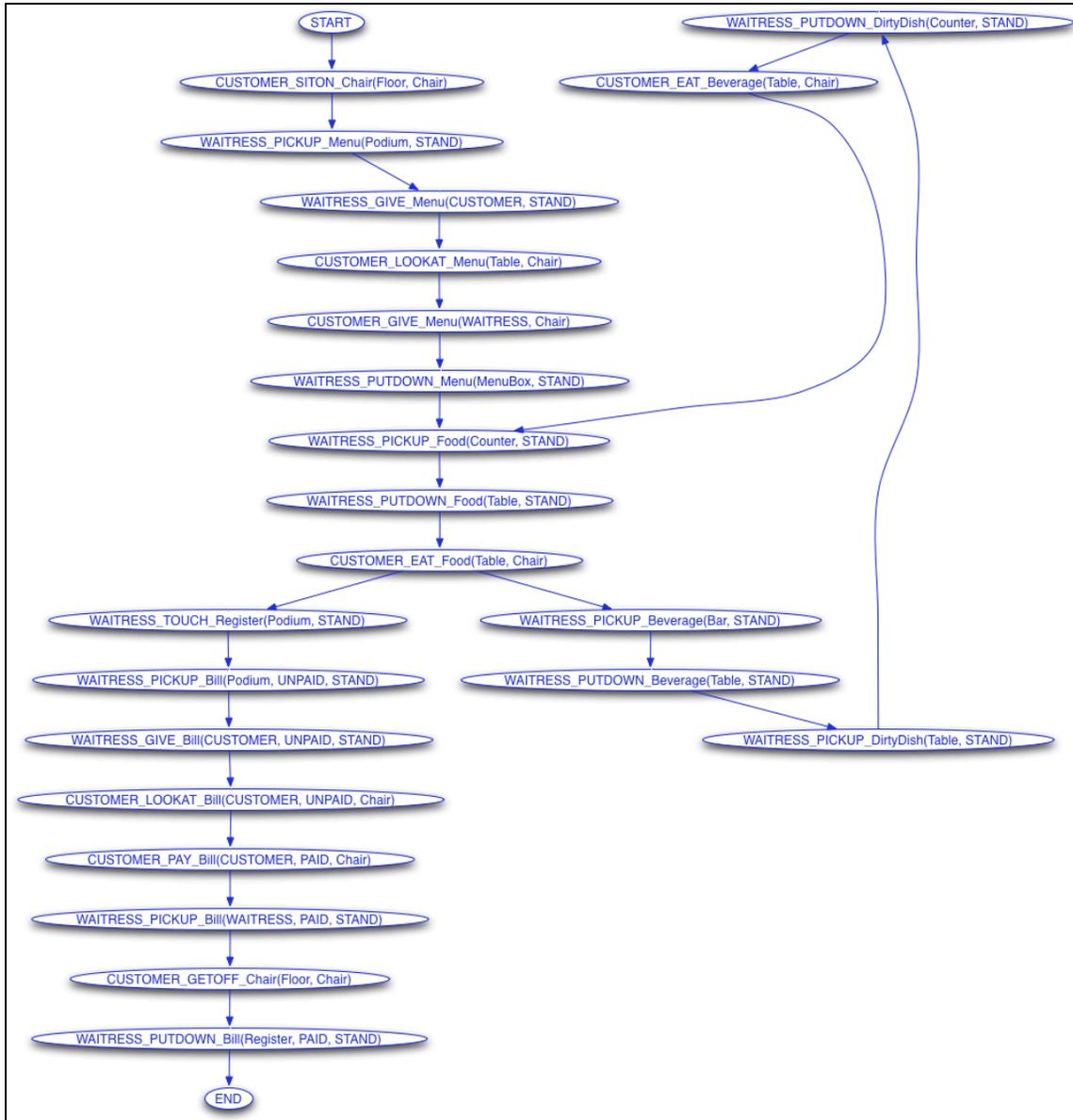


Figure 4-4: Graph visualization of a second game.

Multiple logs can be combined into the same graph, where the paths for each log share nodes for actions that occur in both gameplay sessions. Below are the results of incorporating a second log's sequence into the original graph from Figure 4-3. Nodes and edges are colored red or blue depending on whether they came from the first or second gameplay session. Nodes and edges appearing in both sessions are purple.

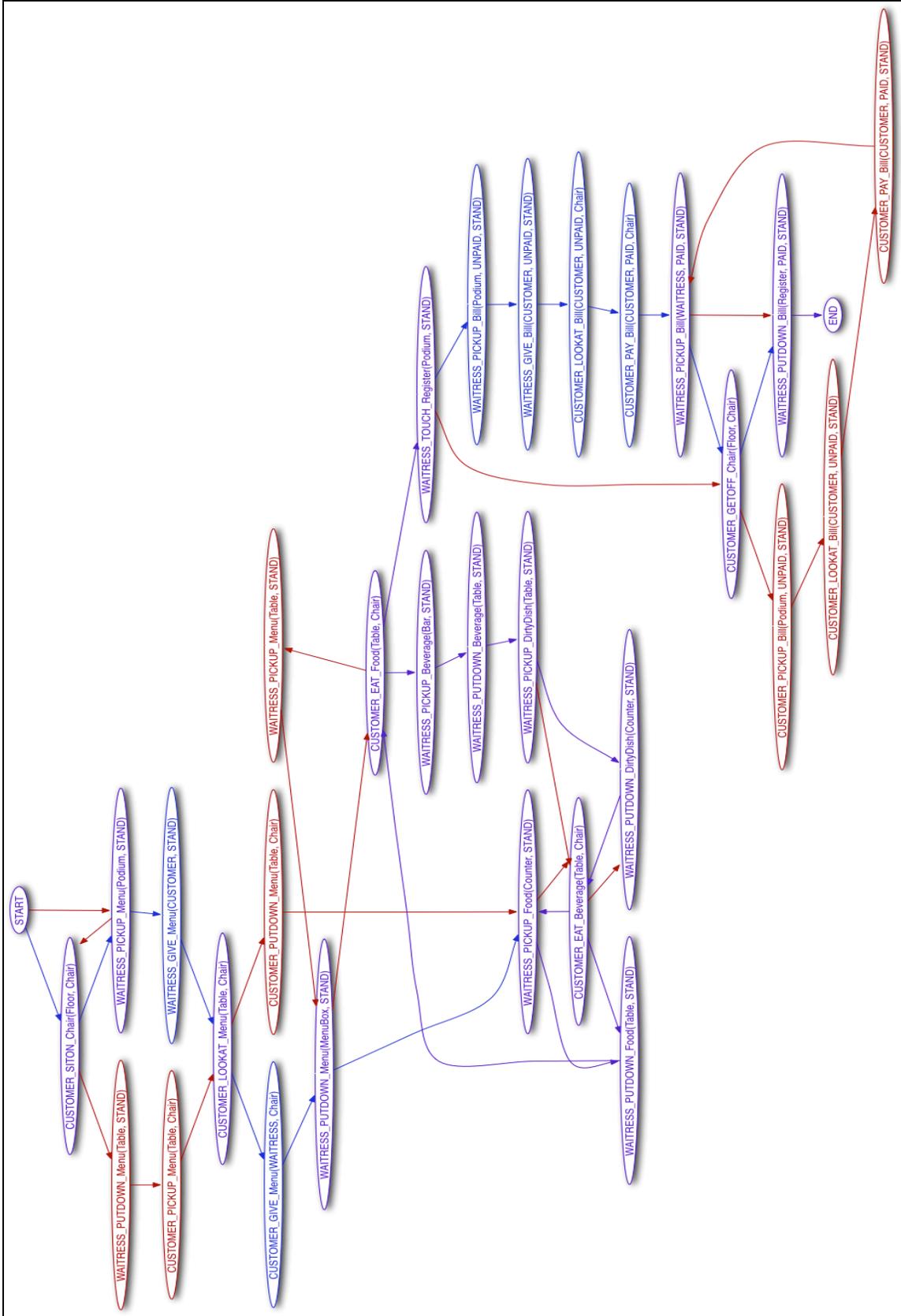


Figure 4-5: Graph visualization merging two games.

This process can be repeated for every gameplay session observed to generate a comprehensive graph of the action possibility space for the restaurant scenario. The portion of the graph in the red box will be expanded in Figure 4-7.

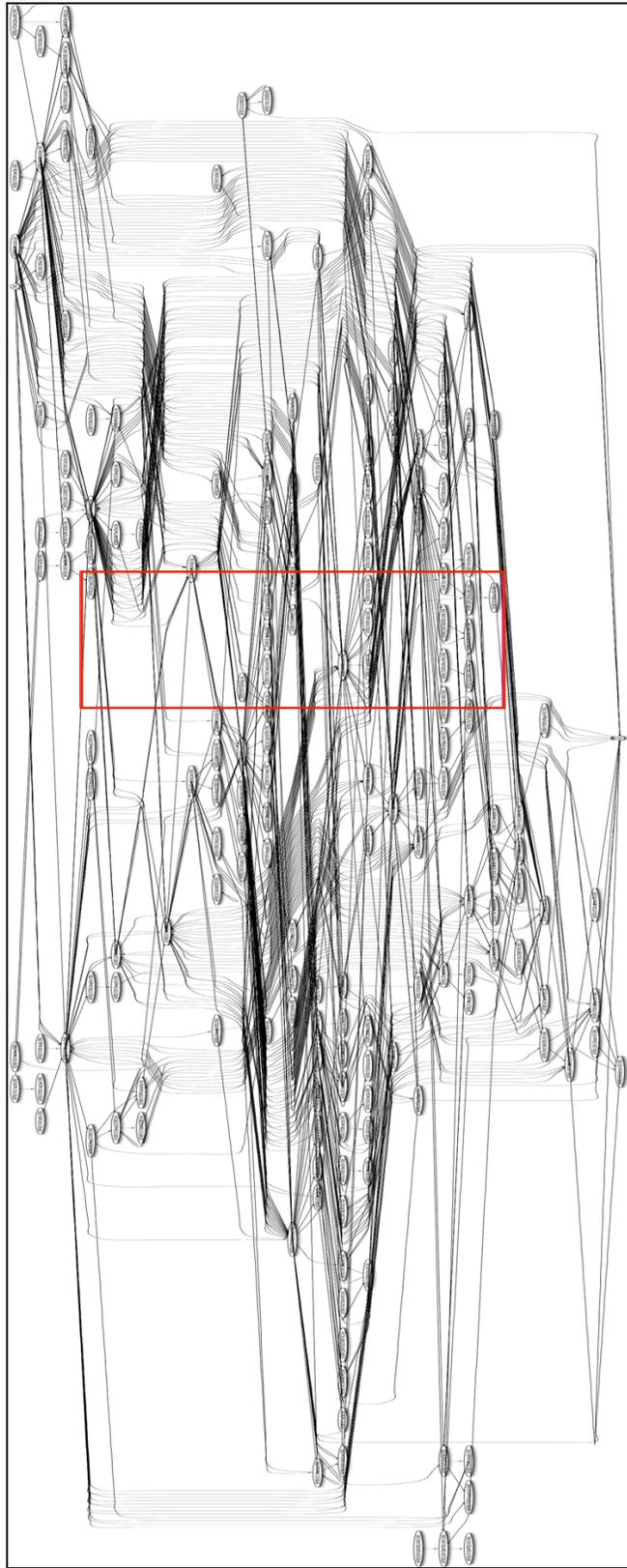


Figure 4-6: Graph visualization merging 5,000 games.

Figure 4-7 zooms in for closer inspection of a portion of the complete graph from Figure 4-6. The graph includes expected restaurant behavior such as waitresses giving drinks to the customers, and depositing bills in the cash registers, and atypical behavior like customers sitting on tables and picking up flower vases. The variety in ordering of actions results in a dense mesh of edges between nodes.

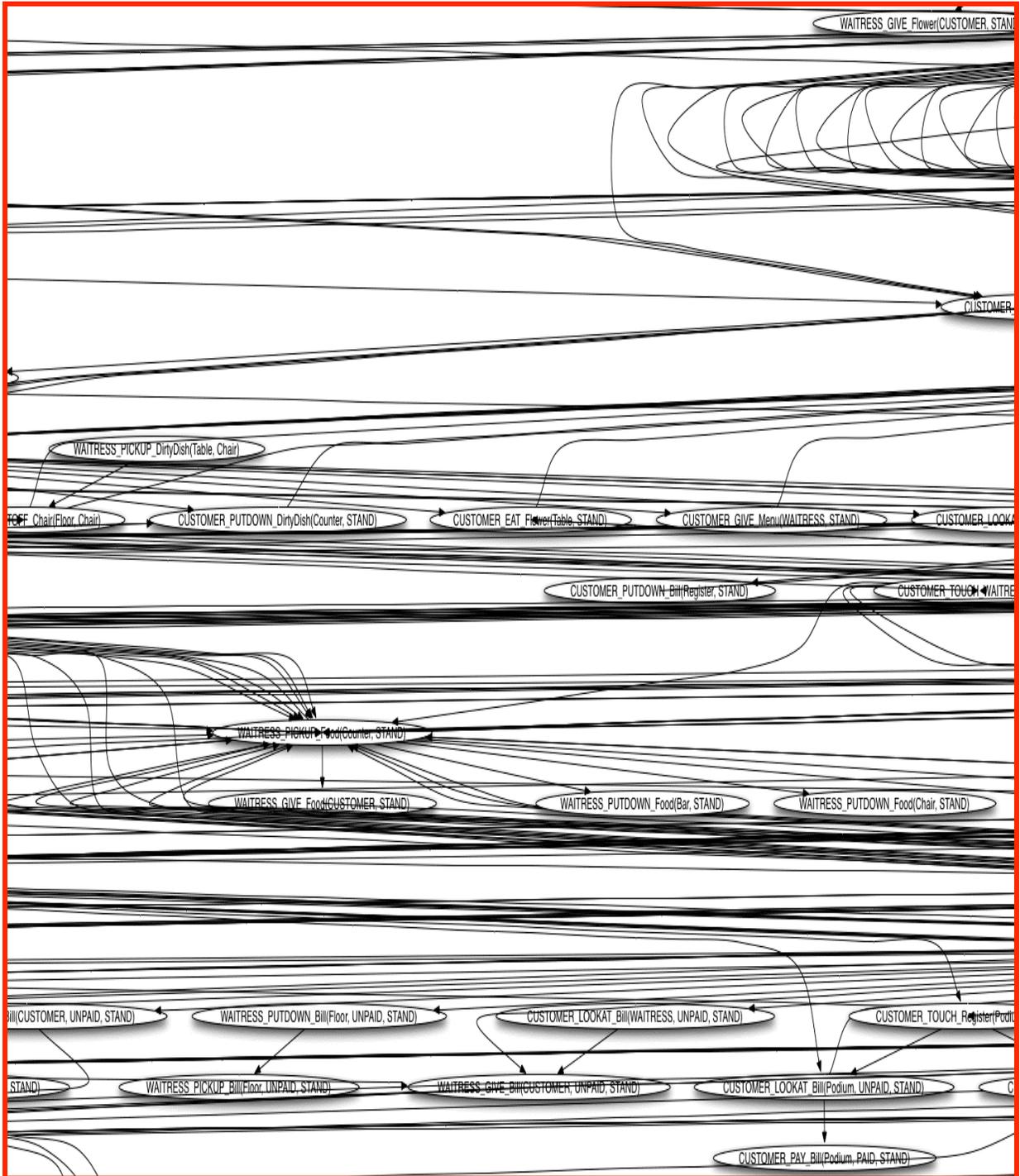


Figure 4-7: Zoomed-in portion of graph visualization merging 5,000 games.

This graph is quite complex, illustrating the huge amount of variation in the way pairs of people choose to play the game. The graph is so complex, in fact, that it is difficult to assess whether it is an accurate depiction of what people normally do in a restaurant. Leveraging the Plan Network's learned statistical models and understanding of social roles can greatly improve these visualizations.

The likelihood of any action can be computed by counting the frequency with which it occurs across all gameplay sessions. Setting a threshold on the likelihood allows filtering out of unlikely nodes and branches in the graph. Chapter 5 describes estimating likelihoods of entire gameplay sessions, which is useful for filtering atypical sessions out of the graph entirely.

Interleaving the actions of the two actors produces a lot of noise, due to the fact that much of the time these two are acting in parallel, and one's next action does not depend on the other. Below is a graph of behavior for a single social role, the waitress, with statistically unlikely actions filtered out.

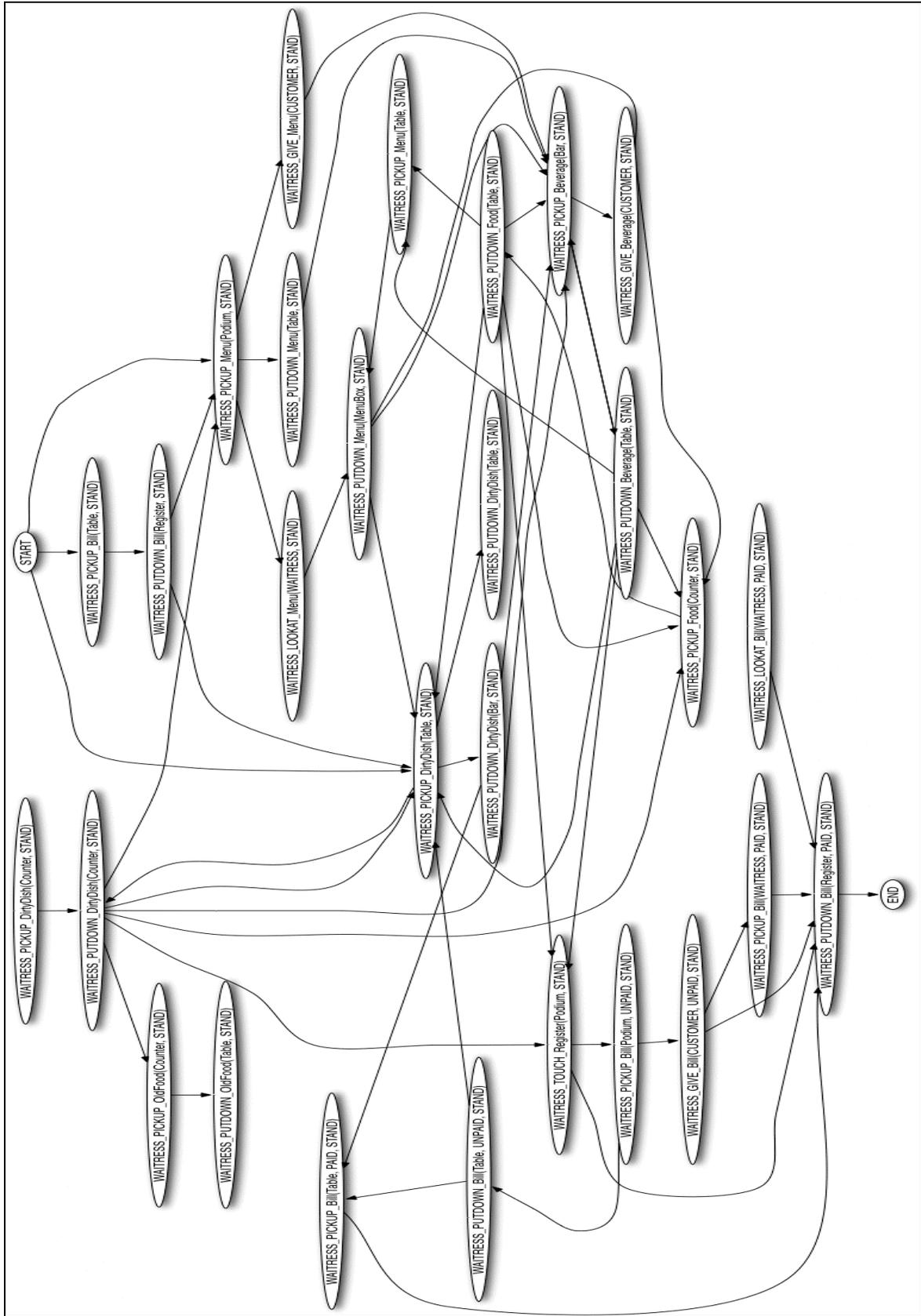


Figure 4-8: Filtered graph of only waitress behavior from 5,000 games.

This graph of filtered waitress behavior is much simpler than the previous graph, yet still gives the gist of behavior learned from 5,000 games. Beyond visualization, filtering gives the system a sense of typical behavior, and equipping an agent with separate models of social roles provides a mental model of others, useful for inferring goals of a collaboration partner. Zooming in on a few portions of the graph allows verification that the learned behavior is what one would expect from a waitress in a restaurant.

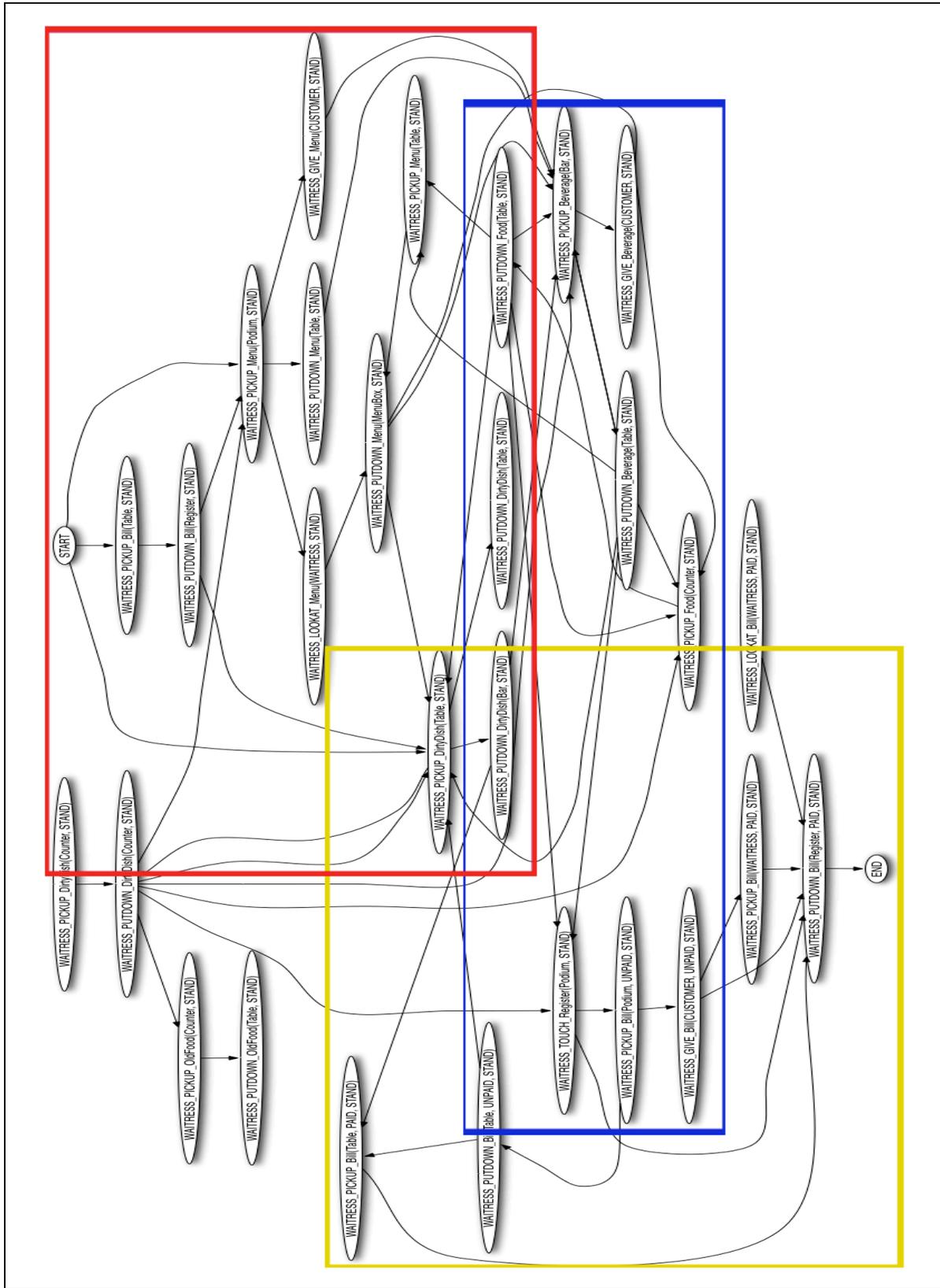


Figure 4-9: Filtered graph of only waitress behavior from 5,000 games, with color-coded portions that will be expanded in the following figures.

After serving a customer, the waitress might serve him more food, or create a bill at the cash register (by touching the register).

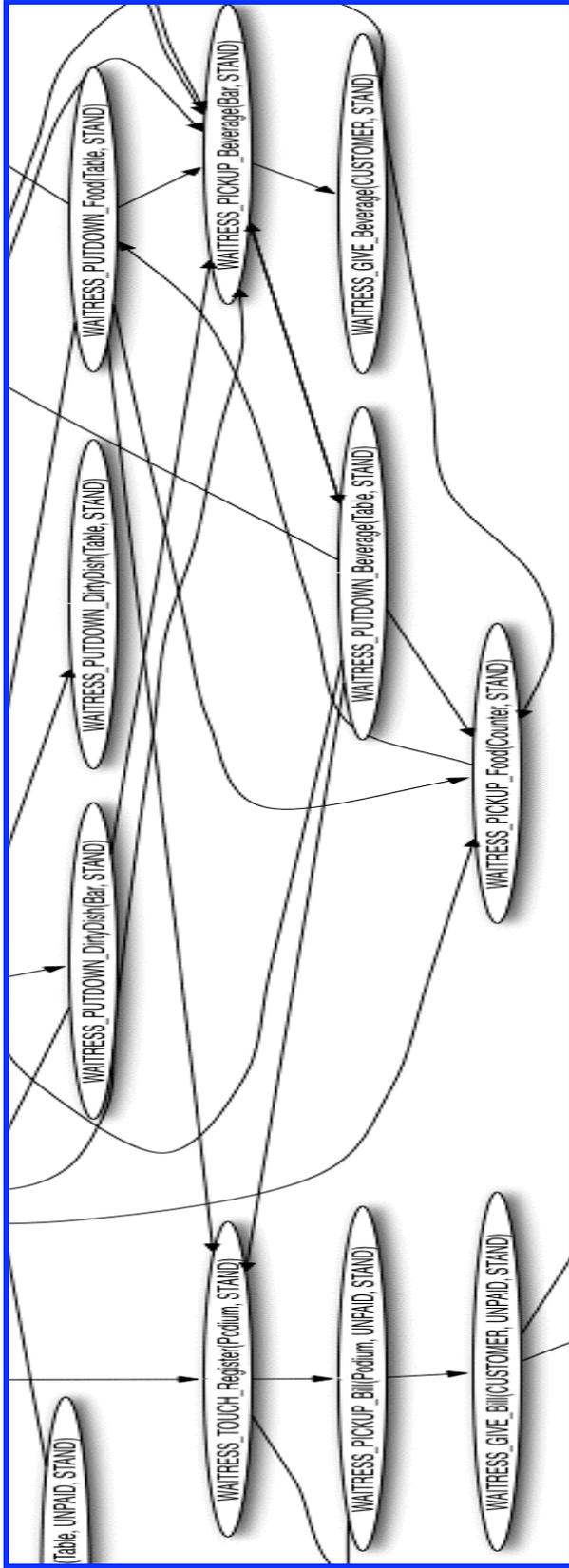


Figure 4-11: Decision point for waitress, as learned from 5,000 games.

Finally, after creating the bill, the waitress puts the bill on the table for the customer and picks it up for deposit once it's been paid. The edge in Figure 4-12 from touching the register to putting the bill down on the register is actually capturing a common point of interface confusion. Touching the register creates a new bill, but many players try this first accidentally before realizing that depositing a bill is accomplished by putting it down on the register.

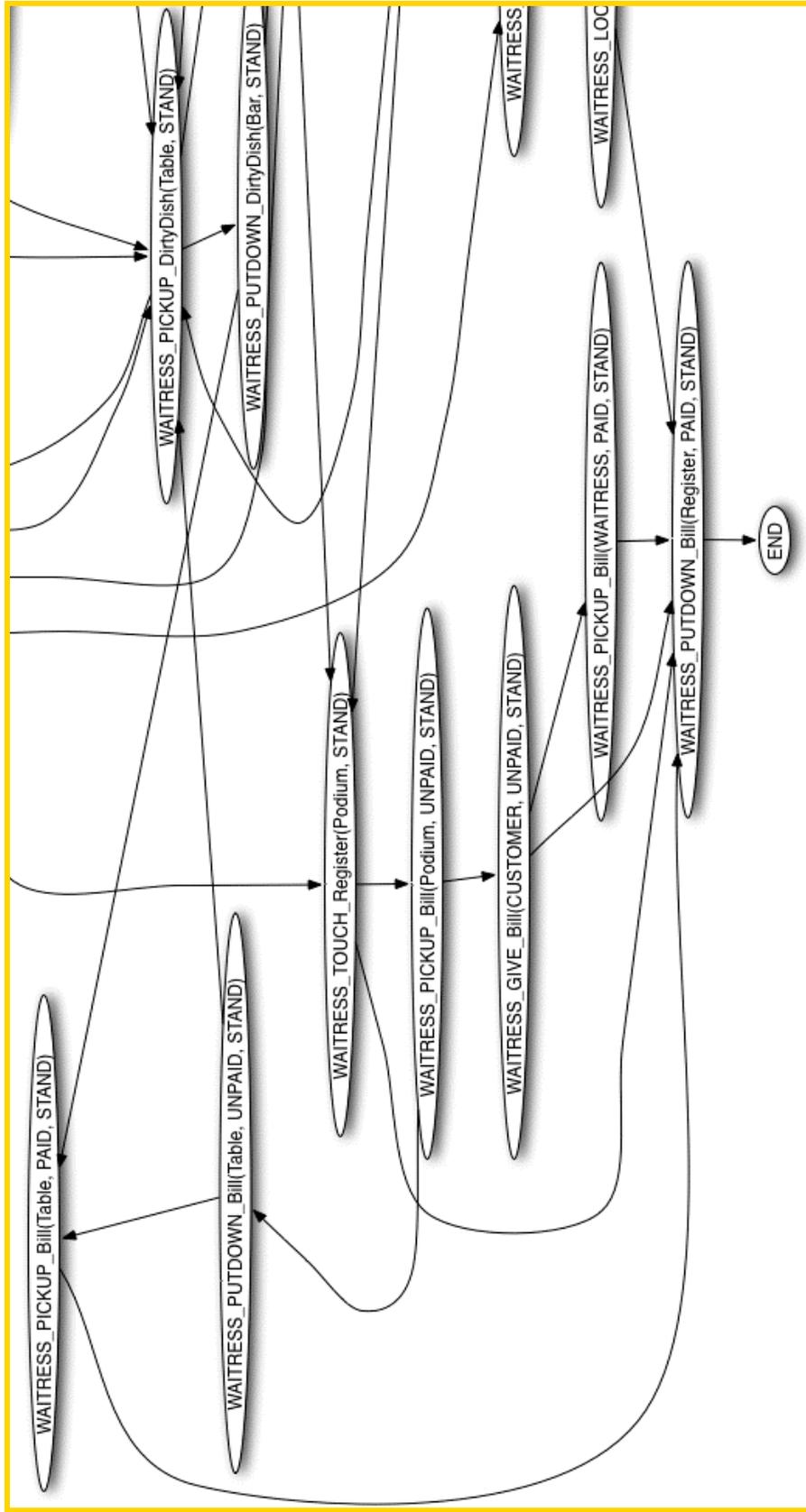


Figure 4-12: End of game for waitress, as learned from 5,000 games.

This section has shown that the learned statistics and social roles benefit visualization for humans. The evaluation in Chapter 5 demonstrates that these techniques are also beneficial in building a cognitive model that correlates well with human conceptualization of typical restaurant behavior.

4.1.2 Browsing Conversations

Graphing models of physical behavior give humans the gist of the behavior captured in our data. This section explores how to get a similar view of linguistic data. Taking inspiration from Bruner’s theory, the graphical model of physical behavior can provide the scaffolding that lends meaning to utterances. Between any two physical action nodes, all conversations uttered between players can be clustered. Following is a screenshot of the conversation browser application that runs alongside *The Restaurant Game*. The browser is networked with the game, tracking events through messages sent via TCP/IP. Each time either player takes a physical action, the browser updates a display of the likelihood of the current action, and a sorted list of the most likely next actions. If the user clicks on any of the potential next actions, the browser displays a list of all conversations observed in between these two actions in the 5,000 captured games. Each speech act within a conversation is automatically labeled with a speech act classifier.¹

In the first example, a waitress picks up some filet mignon from the counter. The interface reports that picking up filet mignon is not highly likely on its own, due to the variety of foods waitresses may pick up, but when clustered with all other food this action is recognized as highly likely. There is a long list of potential next actions, but the system has a strong preference for one action – the waitress putting the food down on a table. Clicking on the most likely action generates a list of 1,593 unique examples of conversations that the system has observed between the time a waitress picks up a dish and puts it down on a table.

¹ Prior to the online study, I conducted an in-lab pilot study with 50 pairs of people. Data from the pilot study was used to train an HMM-based speech act classifier, implemented using Joachim’s SVMlight HMM package (2004). HMMs have been shown to be effective speech act classifiers previously in Jurafsky (2003). Classification performance on the online corpus has not been formally evaluated.

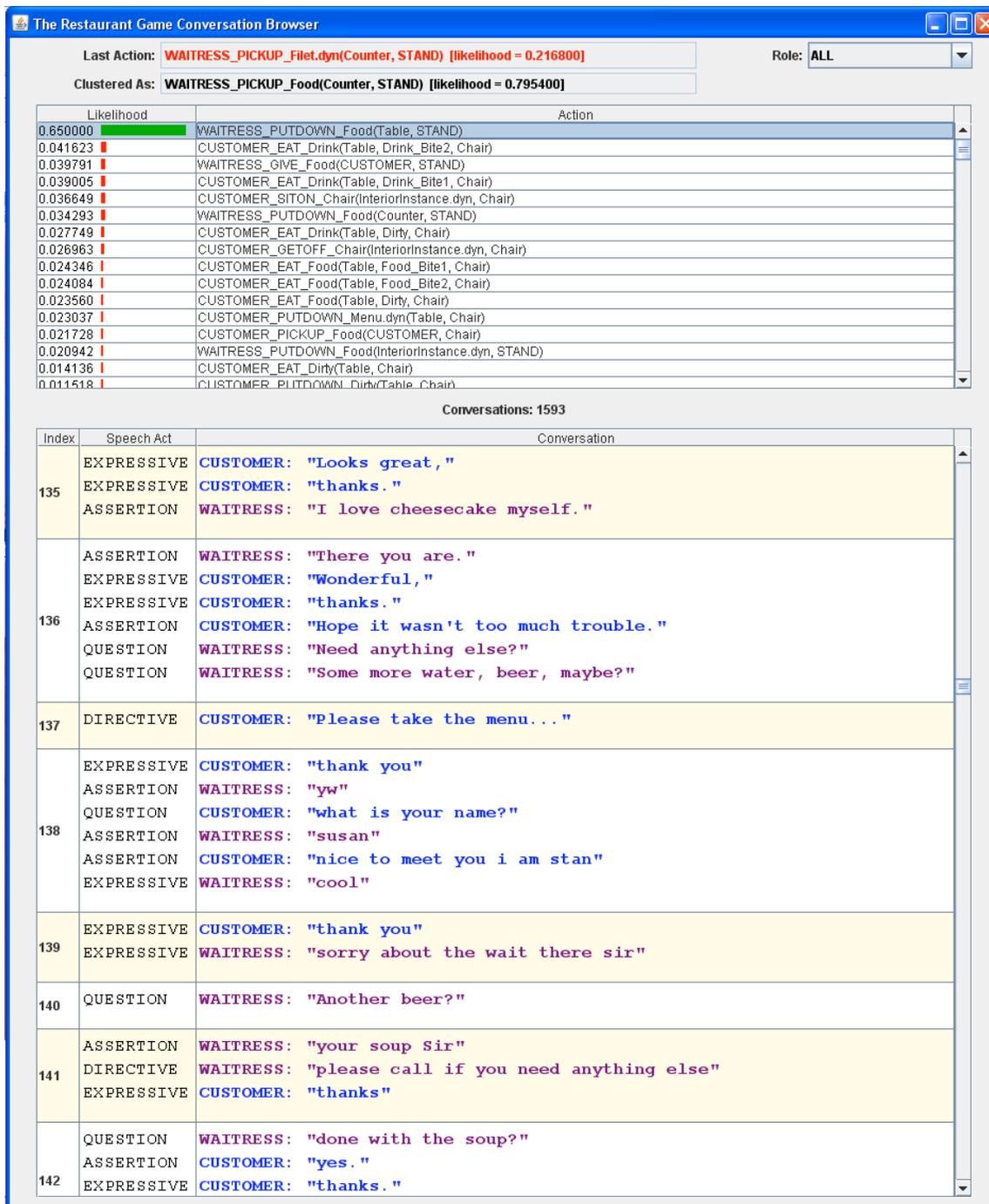


Figure 4-13: Browsing conversations after picking up food, captured from 5,000 games.

Once the waitress puts down the dish, the next action is less certain, and language plays a larger role in determining which branch of the physical graph is taken. Similar to the role-specific filtering of physical behavior graphs, the browser allows the user to focus on one social role when browsing conversations. Focusing on the waitress, there are several highly likely branches. She might clean up some dirty dishes, pick up a drink from the bar, bring more food, or ring up the customer at the register. If the user selects touching the cash register (to create a bill) as the next action, the browser displays 316 unique examples of conversations that precede the waitress

getting the bill. These conversations typically include directives from the customer referring to a check or bill.

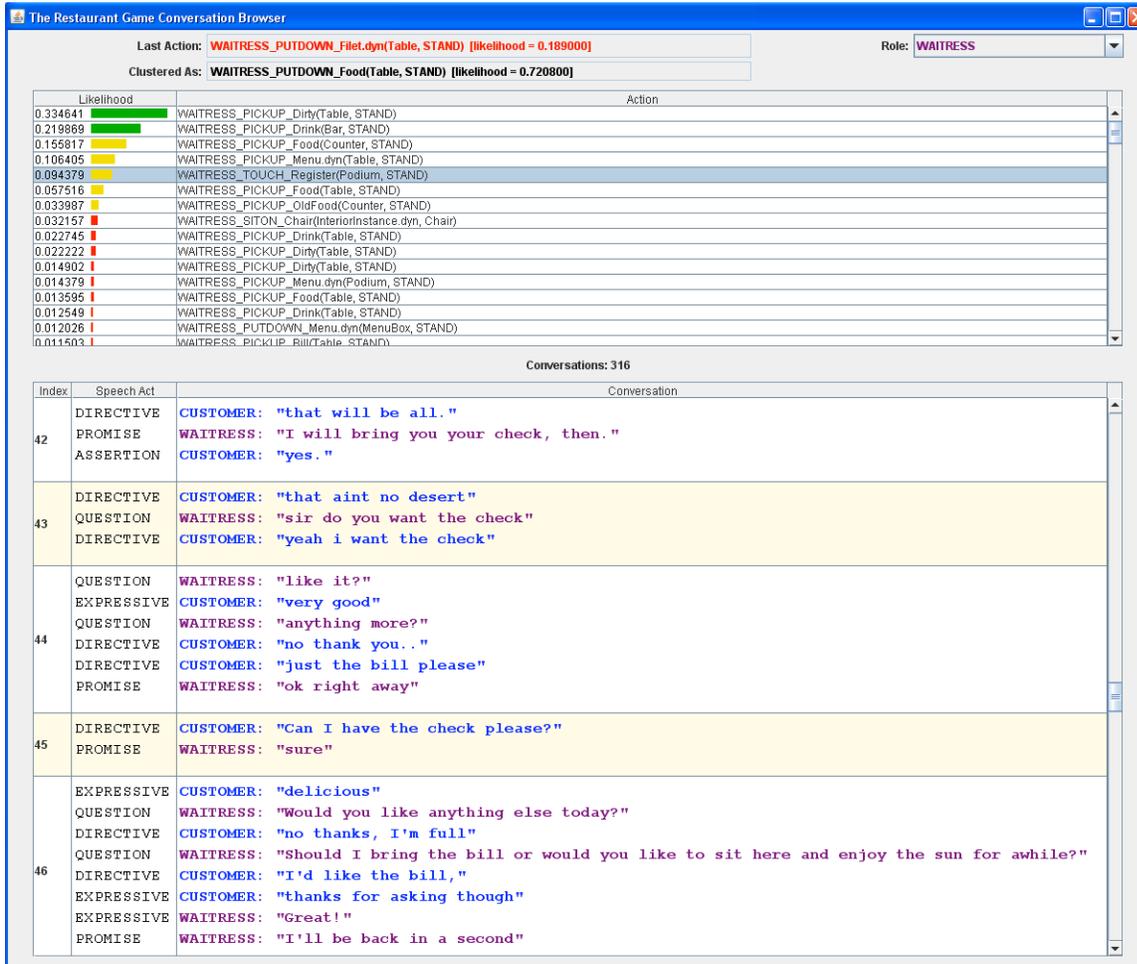


Figure 4-14: Browsing conversations after putting down food, captured from 5,000 games.

Equally as interesting as the conversations clustered within the likely branches of the physical action model are those that exist within unlikely branches. The following example bolsters the claim that capturing behavior from human players produces a more robust model than hand authored scripts. There is a fruit bowl in the back of the kitchen sitting on the dish washer. This is a purely decorative prop that would be non-interactive in most games, or at best physically simulated to fall down when pushed. The following screenshot shows that the system recognizes that the waitress picking up the fruit bowl is highly unlikely. However, in the event that she does pick it up, the system predicts that she is most likely going to place it on a table, and displays 37 examples of conversations that occur when she does.

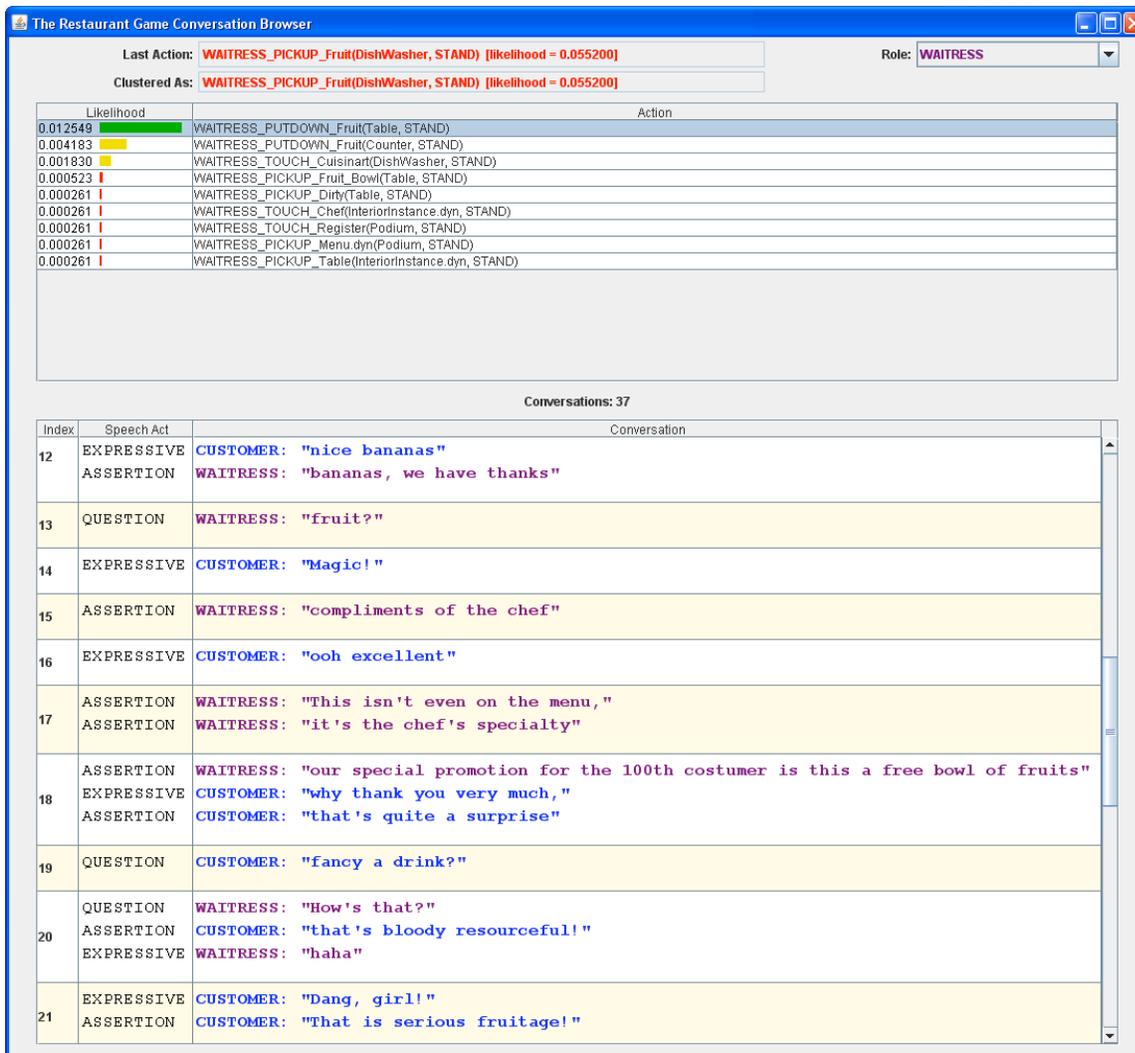


Figure 4-15: Browsing conversations after picking up fruit bowl, captured from 5,000 games.

In one game the customer compliments the bananas. In others the waitress offers a complimentary bowl of fruit. The Plan Network captures dialogue that human scripters are unlikely to include, because the Plan Network captures what people really do, rather than scripting in anticipation of what they are likely to do.

4.2 Building Plan Networks

I will now describe the process of constructing a Plan Network. The first step is to compile a lexicon of physical actions and a lexicon of words. Next physical actions are automatically clustered to simplify the network. Finally, frequencies are computed for atoms in both of the lexicons, where an atom refers to an individual action or word, and for transitions between atoms.

4.2.1 Terminology and Representation

We need to define the terms action, action lexicon, language lexicon, and word before we can proceed. An action is a manipulation of the world performed by an agent, the structure of which will be examined shortly. An action lexicon is a catalogue of all unique actions observed in 5,000 games. We define word in the usual way, as an atomic unit of language with which players construct speech acts. A language lexicon is a catalogue of all unique words we have observed in 5,000 games, including slang, typos, abbreviations, and multiple tenses.

An action is represented in a logical format similar to a STRIPS operator, as described in Russell and Norvig (1995). Each action is defined by a set of preconditions and effects, where preconditions are world state variable criteria that must be met to activate this action, and effects are assignments to world state variables upon completion. In addition, each action has a social role requirement, and an interaction object. Actions are typically initiated through the user interface when a player (of some social role) clicks on an object and selects an action from the pop-up menu. Actions represent preconditions with a short list of variables localized to describing only the actor and the interaction object.

Here is an example of an action representing a customer picking up a salad (with one bite taken) from a table while sitting in a chair:

```
ACTION: PICKUP
REQUIREMENTS:
  ROLE = CUSTOMER
  OBJECT = Salad
PRECONDITIONS:
  ACTOR::SITTINGON = Chair
  OBJECT::ATTACHEDTO = NULL
  OBJECT::DELETED = FALSE
  OBJECT::ON = Table
  OBJECT::SHAPE = Bite1
EFFECTS:
  OBJECT::ATTACHEDTO = CUSTOMER
  OBJECT::ON = NULL
```

Actions are learned automatically from data, and preconditions are assigned based on the current state of the world at the time the action's execution was observed. The scope of the world state considered for preconditions is limited to the acting agent and the object being acted upon. This agent-centric world state representation is similar to that described in Orkin (2004, 2005, 2006). No assumptions are made about which subset of preconditions are required for each type of action. In other words, every action includes preconditions for `SittingOn`, `AttachedTo`, `Deleted`, `On`, and `Shape`. The system does not have any prior knowledge of these actions, or restaurant behavior in general. Learning restaurant behavior should be no different to the system than learning behavior for hospitals, banks, or grocery stores. This leads to under-generalization, meaning that the above action is unique from another action where the customer picks up the salad while sitting on a stool, or standing, or picks up a salad with two bites taken. I will explain shortly how opportunities can be exploited to cluster actions.

4.2.2 Building an Action Lexicon

As each gameplay log file is processed, unique actions that we have not previously observed are added to the action lexicon. The first action observed is index one, the next non-identical action is index 2 and so on. The action lexicon indices are used to compile gameplay logs down to a compact form, more convenient for statistic analysis. Below is a graph of how the size of the action lexicon grows as the system processes 5,000 games.

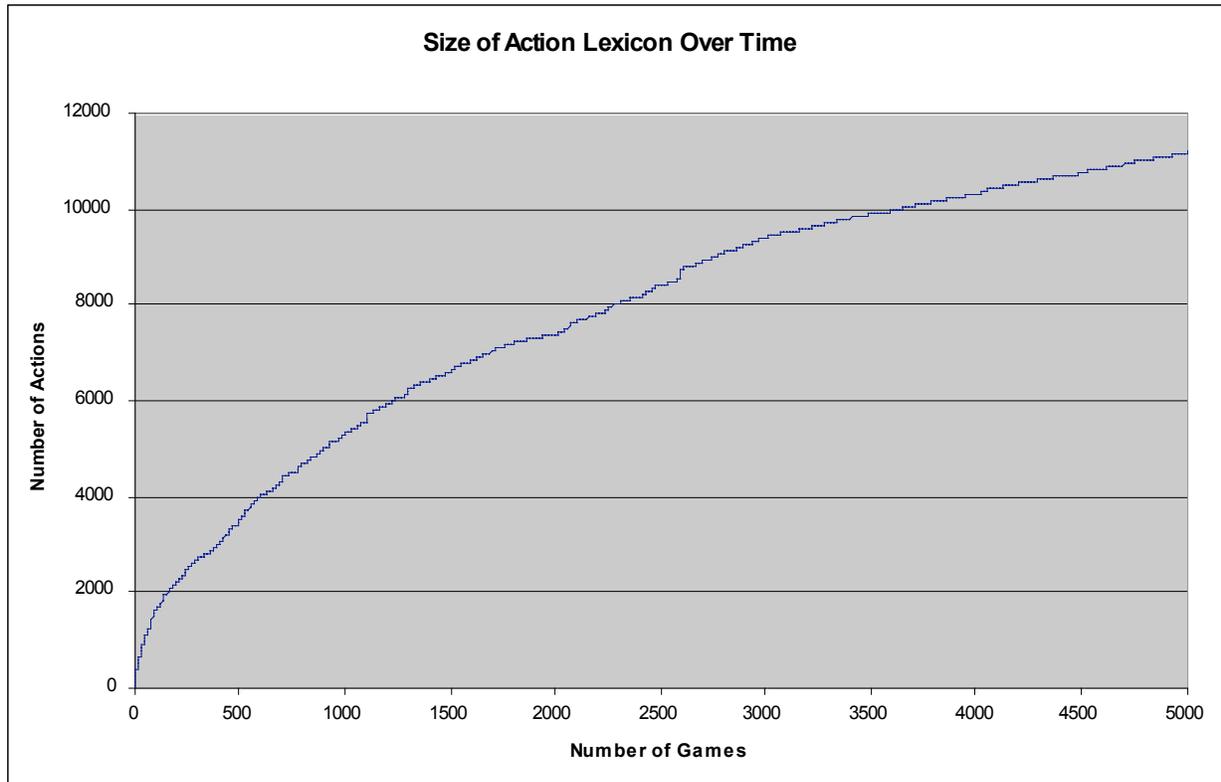


Figure 4-16: Growth of action lexicon over 5,000 games.

After 5,000 games the action lexicon grows to 11,206 unique actions, and has not plateaued in size. The maximum action lexicon size is 107,468, due to all possible combinations of variables (e.g. eating salmon while sitting on a chair vs. eating salmon sitting on the microwave vs. eating salmon sitting on the counter, etc). Details of calculating the maximum action lexicon size can be found in Appendix B. After 5,000 games the action lexicon has only covered about 10% of the possibility space (computed by dividing the observed 11,206 by the maximum 107,468). Fortunately, social conventions lead the majority of combinations to be statistically unlikely, hence the less than linear growth. Table 4-1 gives some statistics of game length.

	Mean	Median	Mode	Max
Actions per Game	84.96	77	75	919

Table 4-1: Game length statistics, based on 5,000 games.

4.2.3 Clustering Actions

Many of the objects in the world of the restaurant are functionally similar. If these objects can be clustered, then the actions that refer to those objects can also be clustered, greatly reducing the size of our action lexicon.

Objects are clustered in a bottom-up fashion following these steps: First, count how many games include someone interacting with each object. Next, tabulate in how many games each action is applied to each object. For example, count how many times a customer eats steak while sitting at the table. Finally, count how many times an object provides context for an action taken on another object. In the previous example, the table and chair are providing context for the action of eating steak. Dividing the action and context counts by the total interaction count gives the probability of an action being taken on an object, or an object providing context for an action. Actions with probabilities above some chosen threshold are considered to be the affordances of the object. Objects that have an identical list of affordances are clustered. For instance, chairs are clustered with stools because customers sit on them, and salmon with steak because customers eat them and waitresses pick them up from the counter. Keep in mind that actions themselves are role-dependent, allowing the system to learn role-dependent affordances. Once the clustering process is complete, clusters are manually inspected and assigned labels for visualization purposes. Labels include concepts such as food, drinks, chairs, and dirty dishes.

Discriminating between the counter and the bar presents a problem for the method described thus far. The system will not recognize that we pick up food from the counter and drinks from the bar. The problem is that there are six types of beverages and nine types of food. The probability of the bar or counter providing context is roughly equal for each of these items, and when divided six or nine ways the probability of picking up any single item is low. To remedy this, the action probabilities are normalized by the probability of the most likely interaction. The most frequent interaction becomes 100% likely, and the rest are scaled proportionately. Now the system can recognize that the bar provides context for picking up drinks, and the counter provides context for food. This works because it is the relative frequencies of interaction that are important in clustering.

There are still some objects that do not cluster well due to lack of data, such as pots and pans, blenders and food processors. This is not much of a problem, because the lack of data indicates that these items are less significant to the scenario we are trying to learn.

The benefit of clustering is that the number actions in our action lexicon can now be greatly reduced by referencing clusters rather than individual items. A clustered action is a new action that has a number of children, where the child actions are the original unclustered actions. Eating salmon at the table is clustered with eating steak at the table, as children of a new action for eating *food* at the table. After 5,000 games the clustered action lexicon has 7,086 actions. The maximum possible action lexicon size is now 31,014 actions, as calculated in Appendix B. Coverage of the possibility space has doubled to over 20% (computed by dividing the observed 7,086 by the maximum 31,014). The graph below illustrates the benefit of clustering on action lexicon size.

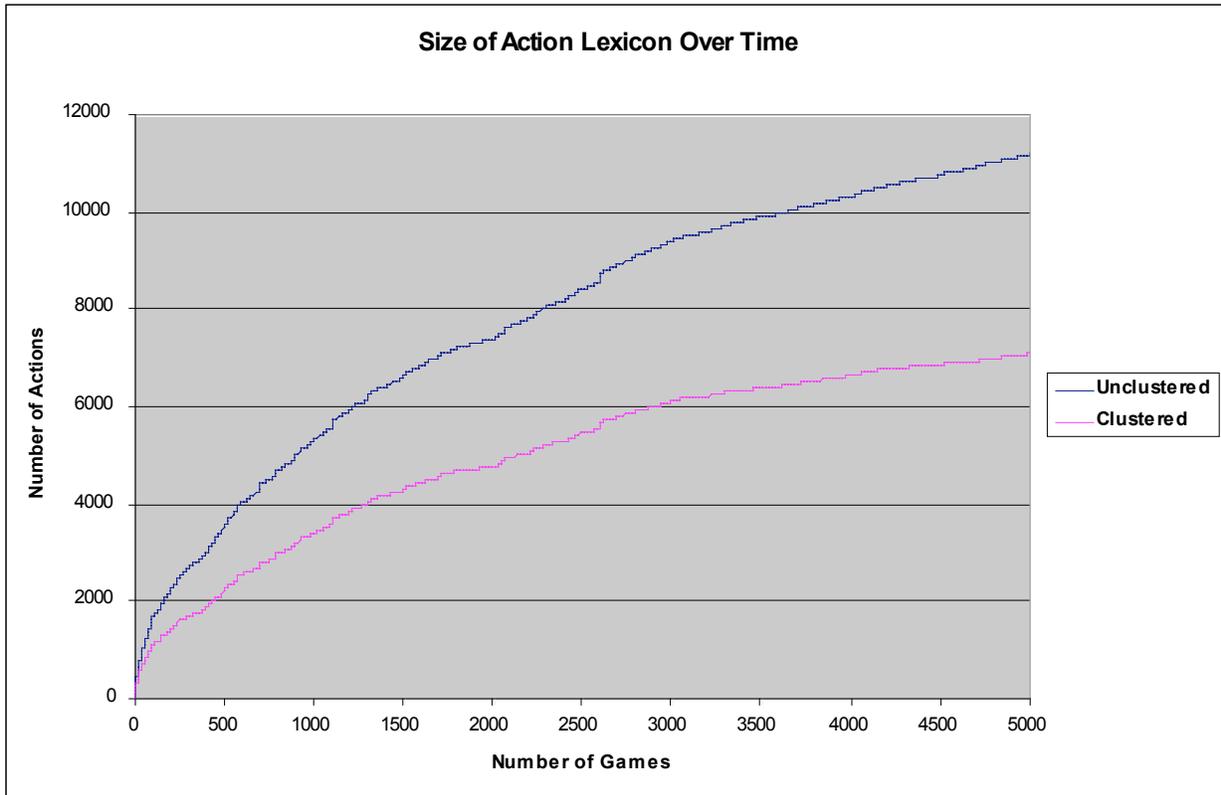


Figure 4-17: Growth of action lexicon, clustered and unclustered, over 5,000 games.

4.2.4 Building a Language Lexicon

Building a language lexicon is a more straight forward process. As new words are encountered while processing gameplay logs, these words are added to the language lexicon. After 5,000 games, the language lexicon has 23,691 words. The maximum language lexicon size is literally infinite due to slang, typos, abbreviations, tenses, and multiple languages. However, the growth is less than linear due to some limitation on the range of words people typically use in a restaurant scenario.

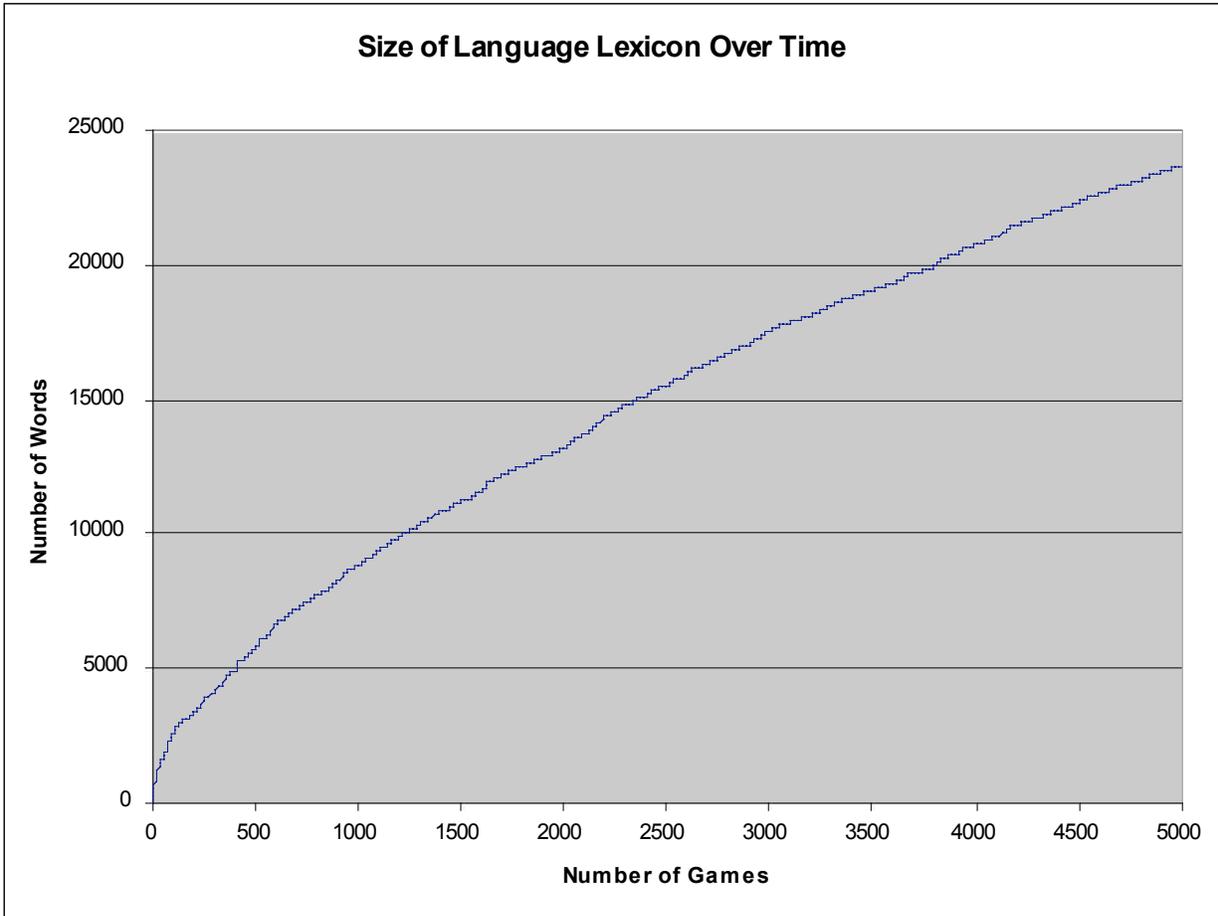


Figure 4-18: Growth of language lexicon over 5,000 games.

Table 4-2 details statistics about speech acts and words in 5,000 games. The number of words per speech act is limited by the interface’s limit on the number of characters typed.

	Mean	Median	Mode	Max
Speech Acts per Game (All)	40.28	32	22	438
Speech Acts per Game (Waitress)	20.71	21	13	271
Speech Acts per Game (Customer)	19.72	15	8	320
Words per Speech Act (All)	4.07	3	1	31
Words per Speech Act (Waitress)	4.16	4	1	21
Words per Speech Act (Customer)	3.97	3	1	31
Total Number of Speech Acts		244,845		

Table 4-2: Speech act statistics, based on 5,000 games.

4.2.5 N-gram Models of Language and Behavior

N-gram models refer to a statistical modeling technique from the field of Natural Language Processing. Borrowing this technique, and applying it to both the language lexicon and action

lexicon gives a means of estimating the likelihood of new gameplay sessions, and quantitatively evaluating how well the learned model of restaurant behavior and language correlates with humans’.

An n-gram model estimates the likelihood of a sequence of words of length N by counting the frequency of this sequence in a training corpus, and dividing by the total number of unique n-grams. Unigrams estimate the likelihood of atomic words. Bigrams estimate the likelihood of pairs of words. Trigrams estimate triplets and so on. The likelihood of an entire sentence can be estimated by iterating over every sequence of N words, and multiplying the n-gram probabilities together. For example, estimating the likelihood of the sentence “The dog laughs.” with trigrams looks like this:

$$\begin{aligned} P(\text{the, dog, laughs}) &= P(\text{the} \mid \text{START}) \\ &\quad \times P(\text{dog} \mid \text{START, the}) \\ &\quad \times P(\text{laughs} \mid \text{the, dog}) \\ &\quad \times P(\text{STOP} \mid \text{dog, laughs}) \end{aligned}$$

The trigram $P(\text{laughs} \mid \text{the, dog})$ is the probability of seeing “laughs” given that we have already seen “the dog”. Enclosing each sentence in START and STOP markers captures the probability of starting or ending a sentence with a particular n-gram. In practice, instead of looking at the product of probabilities, looking at the sum of the log probabilities keeps the likelihood from going to zero. The above example becomes:

$$\begin{aligned} \log P(\text{the, dog, laughs}) &= \log P(\text{the} \mid \text{START}) \\ &\quad + \log P(\text{dog} \mid \text{START, the}) \\ &\quad + \log P(\text{laughs} \mid \text{the, dog}) \\ &\quad + \log P(\text{STOP} \mid \text{dog, laughs}) \end{aligned}$$

If all of the actions in an entire gameplay session are treated as one sentence, an n-gram model can be used to estimate the likelihood of this sequence. Similarly, all of the words in all of the speech acts in one gameplay session can be concatenated into one long sentence, to estimate the likelihood of the sequence of words in one game. This provides two *lenses* through which new gameplay sessions can be examined to assess their typicality. If the likelihoods assigned by the action and language models correlate well with ratings of typicality by humans, then this quantitatively shows that the learned Plan Network is a good representation of how humans think about the restaurant scenario.

As illustrated by the figures this section, even after 5,000 games, the action lexicon and language lexicon are still growing. Words could be clustered by lexical similarity, or by leveraging an external source such as WordNet (1998), to gain similar benefits to those achieved in clustering actions. This would decrease the rate of growth of the language lexicon, but would not eliminate the growth. The probability calculations need to incorporate discounting and smoothing techniques to counter the effects of data sparsity. In order to estimate the likelihood of previously unseen action or word sequences or atoms, true counts are discounted in some way, and the missing probability mass is distributed among previously unseen n-grams. I

implemented Katz Back-Off smoothing as described in Jurafsky & Martin (2000) and Manning & Schütze (1999).

The Katz method computes a discounted maximum likelihood estimate for bigrams that do exist in the corpus, and backs-off to an estimate defined in terms of unigram maximum likelihoods for previously unseen bigrams. In the Katz formula, Count* refers to the true count discounted by subtracting some discount factor.

Define two sets:

$$A(w_{i-1}) = \{w : \text{Count}(w_{i-1}, w) > 0\}$$

$$B(w_{i-1}) = \{w : \text{Count}(w_{i-1}, w) = 0\}$$

The bigram model:

$$P_{KATZ}(w_i | w_{i-1}) = \begin{cases} \frac{\text{Count}^*(w_{i-1}, w_i)}{\text{Count}(w_{i-1})} & \text{If } w_i \in A(w_{i-1}) \\ \alpha(w_{i-1}) \frac{P_{ML}(w_i)}{\sum_{w \in B(w_{i-1})} P_{ML}(w)} & \text{If } w_i \in B(w_{i-1}) \end{cases}$$

where $\alpha(w_{i-1}) = 1 - \sum_{w \in A(w_{i-1})} \frac{\text{Count}^*(w_{i-1}, w)}{\text{Count}(w_{i-1})}$

Figure 4-19: Katz back-off model for bigrams.

Similarly, the Katz method computes a discounted maximum likelihood estimate for existing trigrams, and backs-off to an estimate defined in terms of Katz bigrams for previously unseen trigrams. This back-off technique continues up to the desired length of n-grams, each backing-off to an estimate defined in terms of Katz n-grams one word smaller.

Define two sets:

$$A(w_{i-2}, w_{i-1}) = \{w : \text{Count}(w_{i-2}, w_{i-1}, w) > 0\}$$

$$B(w_{i-2}, w_{i-1}) = \{w : \text{Count}(w_{i-2}, w_{i-1}, w) = 0\}$$

The trigram model is defined in terms of the bigram model:

$$P_{KATZ}(w_i | w_{i-2}, w_{i-1}) = \begin{cases} \frac{\text{Count}^*(w_{i-2}, w_{i-1}, w_i)}{\text{Count}(w_{i-2}, w_{i-1})} & \text{If } w_i \in A(w_{i-2}, w_{i-1}) \\ \alpha(w_{i-2}, w_{i-1}) \frac{P_{KATZ}(w_i | w_{i-1})}{\sum_{w \in B(w_{i-2}, w_{i-1})} P_{KATZ}(w | w_{i-1})} & \text{If } w_i \in B(w_{i-2}, w_{i-1}) \end{cases}$$

where $\alpha(w_{i-2}, w_{i-1}) = 1 - \sum_{w \in A(w_{i-2}, w_{i-1})} \frac{\text{Count}^*(w_{i-2}, w_{i-1}, w)}{\text{Count}(w_{i-2}, w_{i-1})}$

Figure 4-20: Katz back-off model for trigrams.

Chapter 5

Evaluation, Results, and Discussion

I evaluated the system quantitatively by computing likelihood estimates for gameplay sessions based on a combination of physical actions and words, and correlating these scores with human ratings of the same sessions. The intuition is that if the system has learned a high quality Plan Network for the restaurant scenario, it should exhibit a human-like ability to judge typical and atypical behavior in the restaurant environment. The ability to judge typicality is a powerful asset of a Plan Network that enables users of the system to automatically detect off-script behavior; irregularities which would be undetectable with a hand crafted script. Behavior and language estimated to be highly likely by the Plan Network represents the behavior and language that can be expected from an agent driven by the learned model. Behavior and language estimated to be unlikely provides a red flag, indicating that some action may be required on the part of an agent to direct the scenario back towards typical behavior.

5.1 Tuning the System for Optimal Correlation

I randomly selected 200 log files that I set aside for validation and testing, and trained the system on the remaining 5,000. I created a validation set by rating 100 of the set aside files on a one to seven scale indicating how typical I felt the interaction was, with respect to typical restaurant behavior and language in an English speaking country. Below are the guidelines I set for evaluating typicality.

Rating	Description
7	Perfect example of what you would expect to witness in a restaurant.
6	Pretty good example, with a couple of out of the ordinary events.
5	Generally what happens in a restaurant, with a handful of out of the ordinary events.
4	A fair amount of out of the ordinary behavior, while generally going through expected events.
3	Lots of out of the ordinary behavior, while generally going through expected events
2	Very little ordinary behavior for a restaurant
1	Not at all what people do in a restaurant

Table 5-1: Descriptions of typicality ratings given to raters.

I rated the games by reading the filtered log files, which look like the script illustrated in Figure 4-2, and assigning a single rating between one and seven. It took about six hours to rate 100 games. Below is a histogram of the ratings that I assigned.

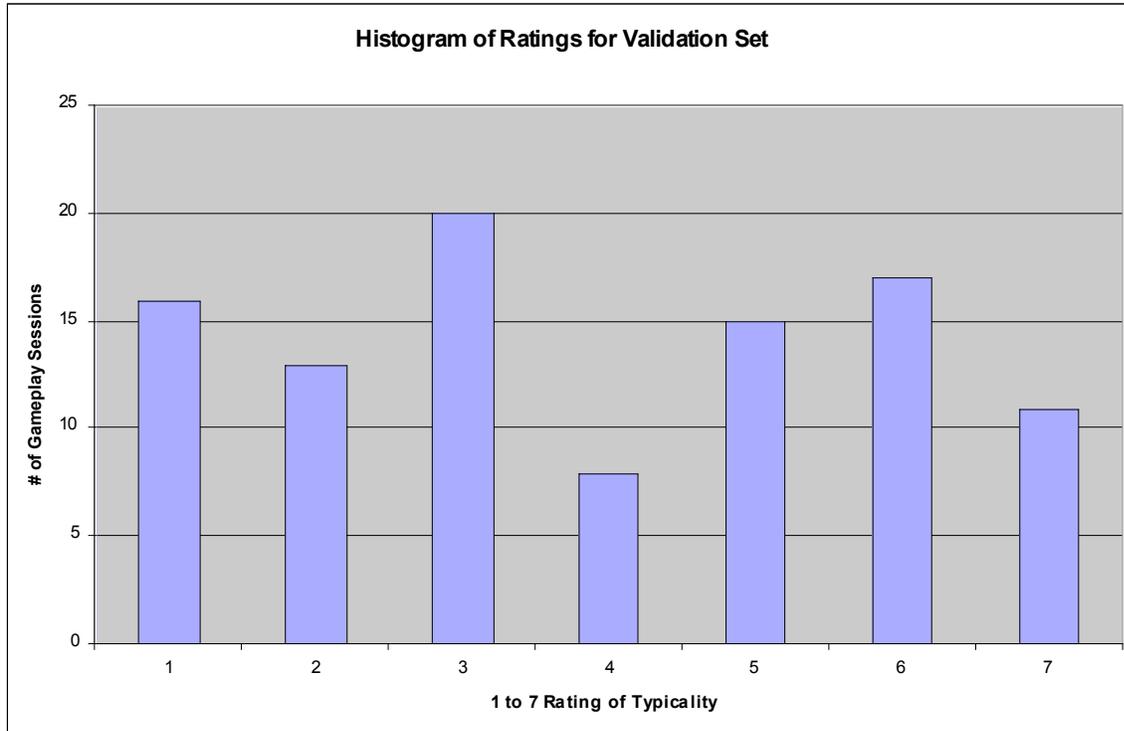


Figure 5-1: Histogram of human ratings for validation set.

I computed likelihood scores for games by building an n-gram action model from the action lexicon and an n-gram language model from the language lexicon, based on the 5,000 games in the training set. The n-gram models estimated likelihood scores with Katz Back-Off smoothing and a constant discount factor. I interpolated between the scores from the action model and the language model to find an overall likelihood estimate for each game. I ran a number of experiments to find the best combination of action and word n-grams of various lengths, and to select the discount factor. The goal of the experiments was to maximize the correlation between the likelihood scores and my ratings for the 100 games. Correlation was measured by computing the Pearson's R correlation coefficient.

Figure 5-2 illustrates the effect of different discount factors on the correlation for various lengths of n-grams of physical actions. I found that a discount of subtracting 0.5 from the true count gave the best correlation over the variety of n-gram lengths. I used the discount factor of 0.5 in all experiments from this point on in validation and testing.

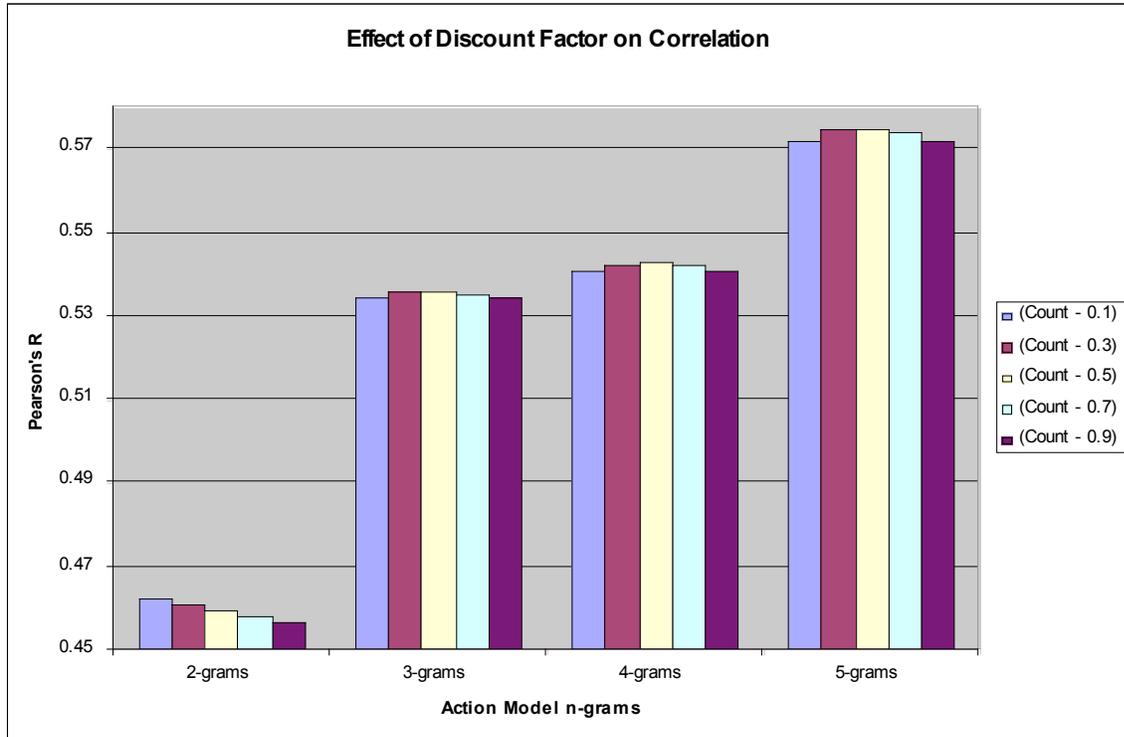


Figure 5-2: Effect of discount factor on correlation.

I estimated the likelihood of each game three times for each length of action model n-grams. First, I estimated the likelihood based on the interleaved model containing actions from both the customer and waitress. Next, I estimated the likelihood based on the role-specific model for each social role, once ignoring customer actions and next ignoring waitress actions. Figure 5-3 shows that averaging the likelihoods of the separate models leads to a better correlation than can be achieved with the interleaved model. Much of the time the two actors are engaging in behavior in parallel, so the interleaved model is subjected to a great deal of noise in the transition probabilities between actions. The separate models identify strange behavior on the part of either character, and averaging the likelihoods from each separate model yields the best overall perspective on typicality. The best correlation found overall was $R = 0.633$, based on averaging likelihoods of action model 4-grams from separate waitress and customer models.

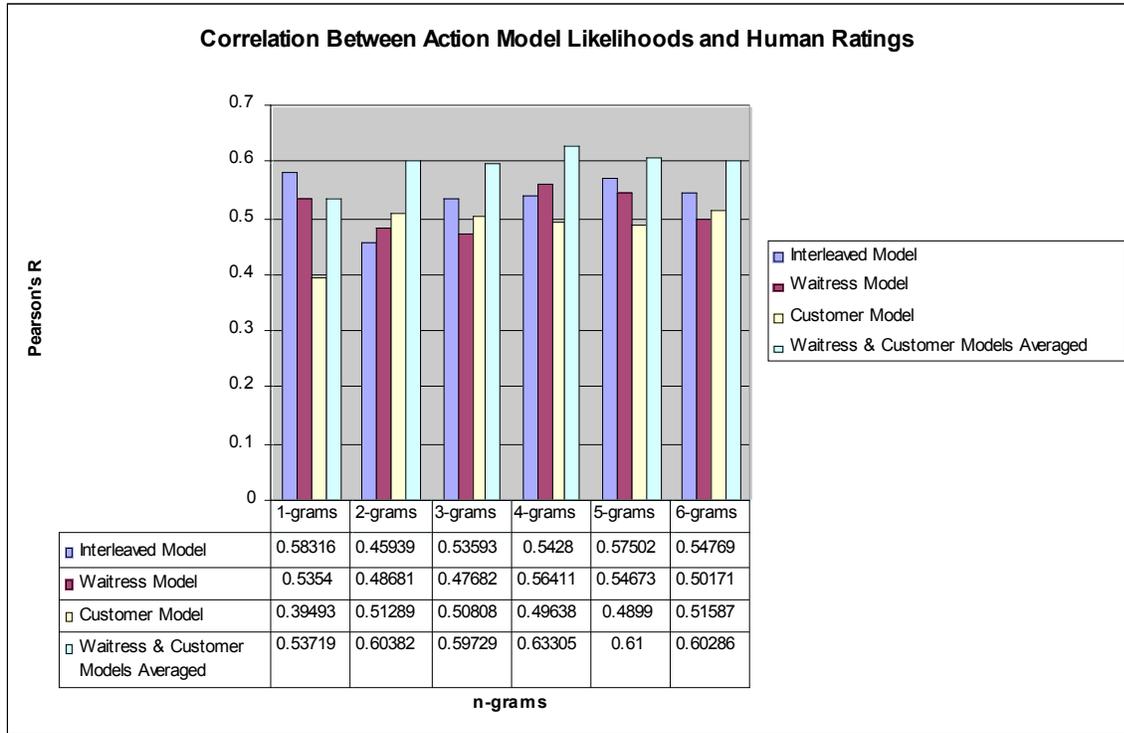


Figure 5-3: Correlation between action model likelihoods and human ratings.

Figure 5-4 contains the top 20 action 4-gram plan fragments for the waitress found in the validation set, and Figure 5-5 contains the top 20 action 4-gram plan fragments for the customer.

Waitress 4-gram Plan Fragments
PUTDOWN_OldFood(Counter) EAT_OldFood(Counter) PICKUP_OldFood(Counter) PUTDOWN_OldFood(Counter)
PICKUP_OldFood(Counter) PUTDOWN_OldFood(Counter) EAT_OldFood(Counter) PICKUP_OldFood(Counter)
PUTDOWN_Beverage(Table) LOOKAT_MenuBox(Floor) PICKUP_Food(Counter) PUTDOWN_Food(Table)
EAT_OldFood(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter)
PICKUP_Flower(Table) PUTDOWN_Flower(Table) PICKUP_Food(Counter) PUTDOWN_Food(Table)
TOUCH_Fridge(Floor) PICKUP_DirtyDish(Table) EAT_DirtyDish(WAITRESS) PUTDOWN_DirtyDish(Counter)
PICKUP_DirtyDish(Counter) PUTDOWN_DirtyDish(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter)
PICKUP_Beverage(Table) PUTDOWN_Beverage(Counter) PICKUP_DirtyDish(Table) PUTDOWN_DirtyDish(Counter)
PICKUP_DirtyDish(Table) PUTDOWN_DirtyDish(Counter) PICKUP_DirtyDish(Table) PUTDOWN_DirtyDish(Counter)
PUTDOWN_DirtyDish(Counter) PICKUP_DirtyDish(Table) PICKUP_Counter(Floor) PUTDOWN_DirtyDish(Counter)
PUTDOWN_DirtyDish(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter)
PUTDOWN_Food(Table) PUTDOWN_Menu(MenuBox) PICKUP_Food(Counter) PUTDOWN_Food(Table)
PICKUP_Food(Table) PUTDOWN_Food(Table) PICKUP_Food(Counter) PUTDOWN_Food(Table)
GIVE_Bill(Hand, UNPAID) PUTDOWN_Bill(Register, PAID) PICKUP_Menu(Table) PUTDOWN_Menu(MenuBox)
EAT_OldFood(Counter) EAT_OldFood(Counter) EAT_Food(Counter) EAT_Food(Counter)
TOUCH_Microwave(DishWasher) PUTDOWN_Flower(Table) PICKUP_Food(Counter) PUTDOWN_Food(Table)
PICKUP_DirtyDish(Table) PUTDOWN_DirtyDish(Counter) EAT_DirtyDish(Table) PICKUP_DirtyDish(Table)
EAT_Food(Counter) EAT_Food(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter)
PICKUP_Beverage(Bar) PUTDOWN_Beverage(Floor) PICKUP_Food(Counter) PUTDOWN_Food(Table)
PICKUP_DirtyDish(Bar) PUTDOWN_DirtyDish(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter)

Figure 5-4: Top 20 waitress 4-gram plan fragments.

Customer 4-gram Plan Fragments
EAT_Beverage(Table) EAT_Beverage(Table) PICKUP_Food(Table) PUTDOWN_Food(Table)
EAT_Food(Table) EAT_Beverage(Table) LOOKAT_Bill(Hand, UNPAID) PAY_Bill(Hand, PAID)
EAT_Chef(Floor) EAT_Fruit(DishWasher) EAT_FoodPrep(TrashCompactor) EAT_FoodPrep(TrashCompactor)
EAT_Fruit(DishWasher) EAT_FoodPrep(TrashCompactor) EAT_FoodPrep(TrashCompactor) EAT_FoodPrep(TrashCompactor)
PICKUP_DirtyDish(Table) PUTDOWN_DirtyDish(Table) PICKUP_Food(Table) PUTDOWN_Food(Table)
EAT_Beverage(Table) PICKUP_Food(Hand) PUTDOWN_Food(Table) EAT_Food(Table)
GIVE_Bill(WAITRESS, UNPAID) EAT_Trash(Hand) EAT_Trash(Hand) EAT_Trash(Hand)
EAT_Food(Table) EAT_Food(Table) PICKUP_Bill(Table, UNPAID) LOOKAT_Bill(Hand, UNPAID)
GETOFF_Chair(Floor) SITON_Menu(Table, Menu) GETOFF_Menu(Table, Menu) SITON_Chair(Floor)
EAT_DirtyDish(Counter) EAT_Microwave(DishWasher) EAT_FoodPrep(TrashCompactor) EAT_FoodPrep(TrashCompactor)
TOUCH_Fridge(Floor) TOUCH_Counter(Floor) EAT_FoodPrep(TrashCompactor) EAT_FoodPrep(TrashCompactor)
EAT_Beverage(Hand) PUTDOWN_DirtyDish(Table) PICKUP_Bill(Table, UNPAID) LOOKAT_Bill(Hand, UNPAID)
EAT_DirtyDish(Table) EAT_DirtyDish(Table) EAT_Food(Table) EAT_Food(Table)
EAT_OldFood(Counter) EAT_Wine(Bar) EAT_Wine(Bar) EAT_Wine(Bar)
EAT_Beverage(Hand) GIVE_DirtyDish(WAITRESS) LOOKAT_Bill(Hand, UNPAID) PAY_Bill(Hand, PAID)
EAT_DirtyDish(Table) EAT_DirtyDish(Table) EAT_Food(DirtyDish) EAT_Food(DirtyDish)
EAT_Counter(Floor) EAT_OldFood(Counter) EAT_OldFood(Counter) EAT_OldFood(Counter)
PICKUP_OldFood(Counter) EAT_OldFood(Hand) EAT_OldFood(Hand) EAT_OldFood(Hand)
LOOKAT_Food(Table) EAT_Beverage(Table) PICKUP_Food(Table) PUTDOWN_Food(Table)
EAT_Wine(Table) EAT_Beverage(Table) PICKUP_Food(Table) PUTDOWN_Food(Table)

Figure 5-5: Top 20 customer 4-gram plan fragments.

I repeated these experiments with the language model, and again found that averaging the likelihoods from separate models yields a better correlation than that achieved by the interleaved model. The average of the likelihoods from separate bigram models yields the best combined correlation with $R = 0.546$. Interestingly, this is slightly lower than the best correlation for the waitress-only bigram model, possibly indicating that the waitress's speech is more informative than the customer's or their combined dialogue. However, due to the tiny discrepancy between the two best R values, I chose to continue using the averaged bigram model for future experiments to ensure that the customer speech was being taken into account.

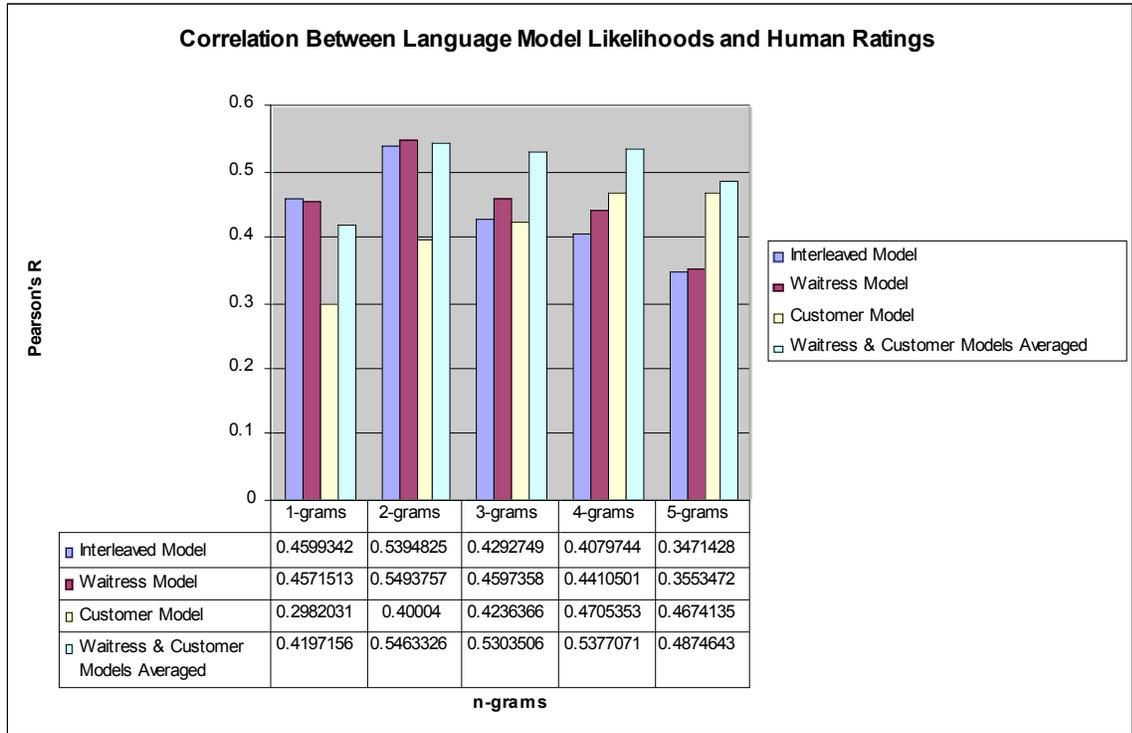


Figure 5-6: Correlation between language model likelihoods and human ratings.

Table 5-2 lists the top 40 most probable bigrams for waitresses and customers found in the validation set. Note that punctuation has been removed, all words have been forced to lowercase, and misspellings come directly from the data.

Waitress Bigrams	Customer Bigrams
folow me	excuse me
follow me	supposed to
supposed to	thank you
thank you	berry pie
excuse me	du jour
restrount plz	followed by
trying to	cobb salad
vegetable soup	grilled salmon
nectarine tart	vegetable soup
interest you	trying to
berry pie	nectarine tart
por favor	piece of
let me	may i
du jour	glass of
sort of	iced tea
cobb salad	veg soup
grilled salmon	let me
youd like	slice of
hold on	cob salad
anyhting else	id like
twilight zone	cup of
blueberry pie	white wine
white wine	shut up
red wine	de jour
anyting else	refuse to
would you	red wine
may i	thatll be
show you	allergic to
glass of	charge me
woud you	kind of
shut up	bring me
help you	cheese cake
main course	filet mignon
serving you	worked here
such a	r u
helo thar	meet you
anything else	main course
cup of	can i
calling the	going to
united states	cherry cheesecake

Table 5-2: Top 40 bigrams for waitresses and customers.

Next I ran experiments to investigate the effect of averaging the likelihoods from the action and language models. The likelihoods for each model are themselves computed by averaging the likelihoods of the separate role-specific models. Figure 5-7 illustrates that for any length of n-grams, averaging the action and language models leads to better correlation with human ratings than either model alone.

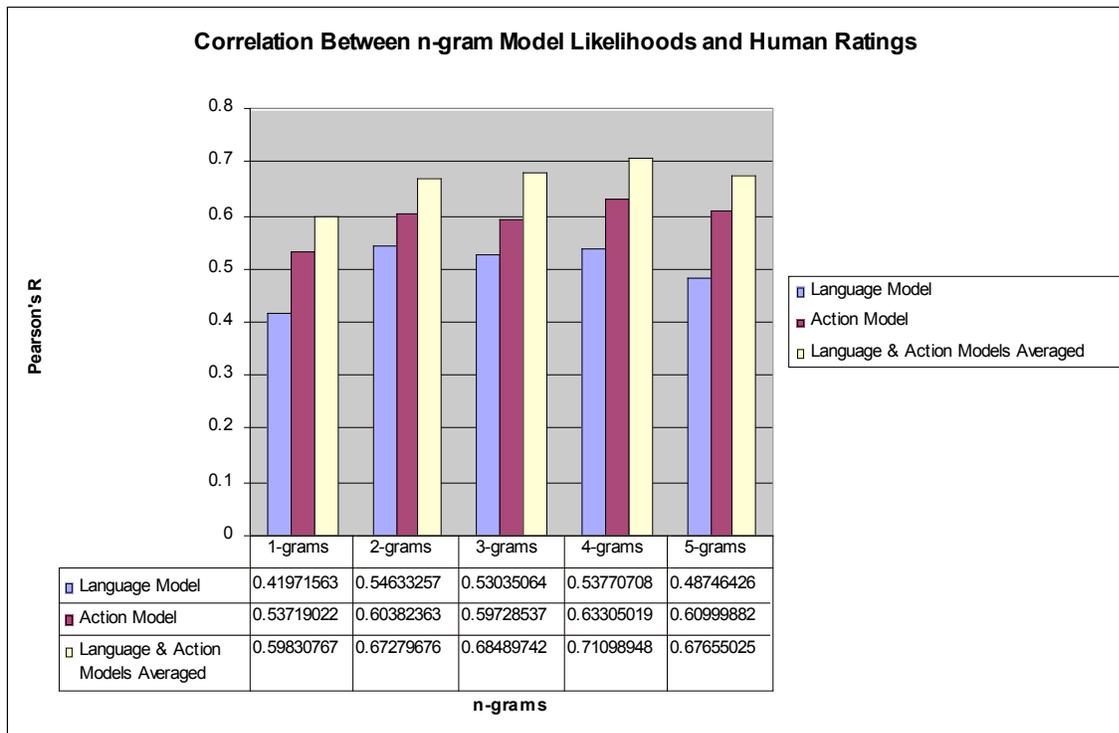


Figure 5-7: Correlation between n-gram model likelihoods and human ratings.

Having determined that averaging likelihoods from action model 4-grams, and language model bigrams yields the best respective correlations with human ratings, and averaging action and language models outperforms either model alone, my next goal was to find the best overall combination achievable by interpolating between likelihoods for actions and language. Figure 5-8 details various combinations of actions and language, with the peak at $R = 0.782$ with 25% physical actions and 75% words. The extents of the graph show the correlation based on only language on the left and actions only on the right.

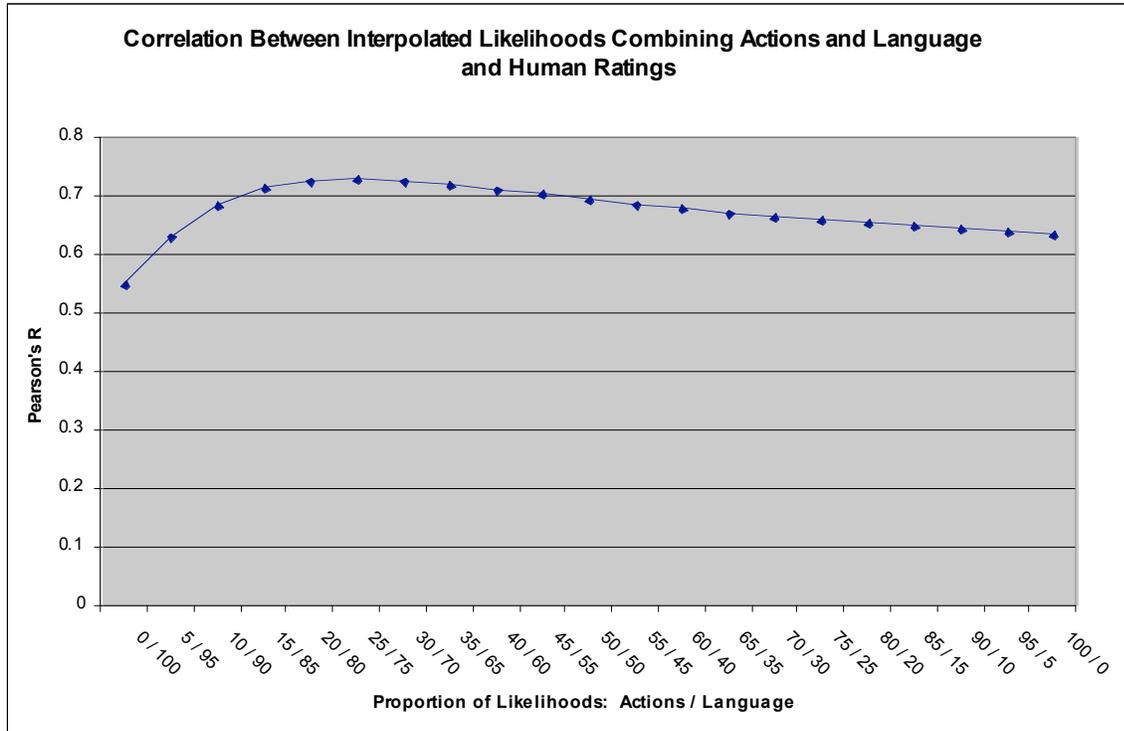


Figure 5-8: Correlation between interpolated likelihoods combining actions and language and human ratings.

Figure 5-9 re-presents these results more clearly, challenging the old adage that actions speak louder than words. On their own, the likelihoods estimated by the action model do correlate better with human ratings than the language model, but the combination of the two correlates significantly better, with an interpolation that favors the language model 75 to 25. This is an interesting counter-intuitive result, given that Figure 5-7 shows the action model consistently outperforming the language model.

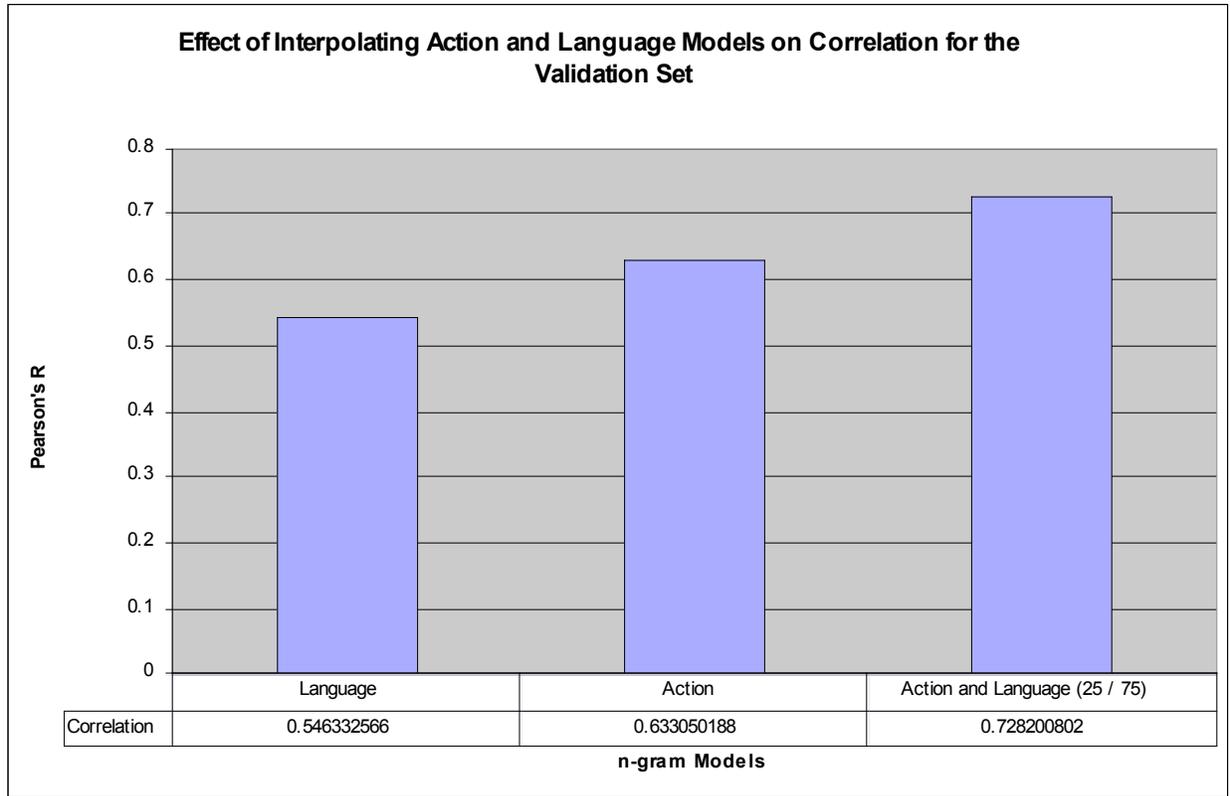


Figure 5-9: Effect of interpolating action and language models on correlation for the validation set.

The final figure in this section renders the scatter plot of the relationship between likelihood scores estimated by the best interpolated combination from above and human ratings. Pearson's $R = 0.782$ shows a strongly significant correlation for 100 games. With 100 games, a correlation of .254 or greater is significant at the .01 level ($p < .01$).

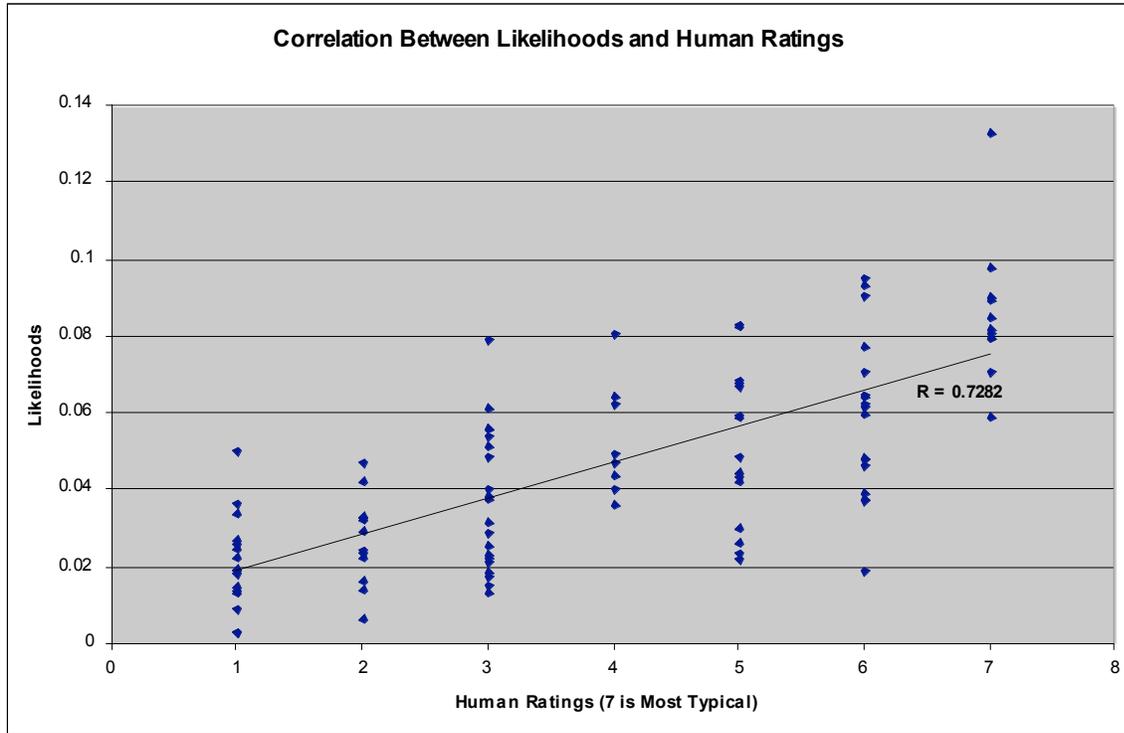


Figure 5-10: Scatter plot of correlation between likelihoods and human ratings.

Based on the scatter plot, it looks like 0.04 is a good threshold for discriminating between typical and atypical gameplay sessions. Ignoring the eight games that I rated as neutral, and considering anything above four to be typical, and below four atypical, the model’s binary classification results are presented in Table 5-3.

	Rating > 4 (Typical)	Rating < 4 (Atypical)
Likelihood > 0.04 (Typical)	35 True Positives	11 False Positives
Likelihood <= 0.04 (Atypical)	8 False Alarms	38 True Negatives

Table 5-3: Binary classification matrix comparing estimated likelihoods to human ratings.

If the likelihood threshold of 0.04 was used as the criteria for filtering which gameplay sessions to include in the visualization graphs described in Chapter 4, 81% of games that I rated as typical would be incorporated into the graphs, and 78% of atypical examples would be filtered out.

5.2 Testing the System

The evaluation demonstrated that the likelihood scores estimated by the Plan Network correlate well with my ratings of 100 games. To test the system, I had 10 people who were not involved with the development of the project rate 300 games. These ratings were compared to likelihoods estimated using the best parameters found in the evaluation.

I randomly selected 200 gameplay log files from the training set to add to the 100 I had originally set aside for testing, for a total of 300 test games. I kept the 100 games from the validation set out completely so as not to introduce any bias during testing, and retrained a new Plan Network with the remaining 4,800 games. None of the 300 games used for testing were included in the 4,800 games used to train the new Plan network. Each of the ten raters received 40 games to rate on a one to seven scale of typicality. Everyone was given the same ten games from the validation set, and a unique set of 30 games from the test set. I hand selected the ten games from the validation set to ensure raters were given an even spread of typical and atypical games. The overlapping ratings of validation set games gave me some means of ensuring that all of the raters understood and followed instructions.

5.2.1 Inter-Rater Agreement

Figure 5-11 displays the ratings that each of the ten raters assigned to each of the ten games in the validation set. Overall, the raters generally agreed within one unit of typicality. Game four caused raters the most confusion due to people playing the game in a foreign language. Despite explicit instructions to rate typicality based on expected behavior in a restaurant in an English speaking country, rating varied widely from two to six. My own rating for this game was two.

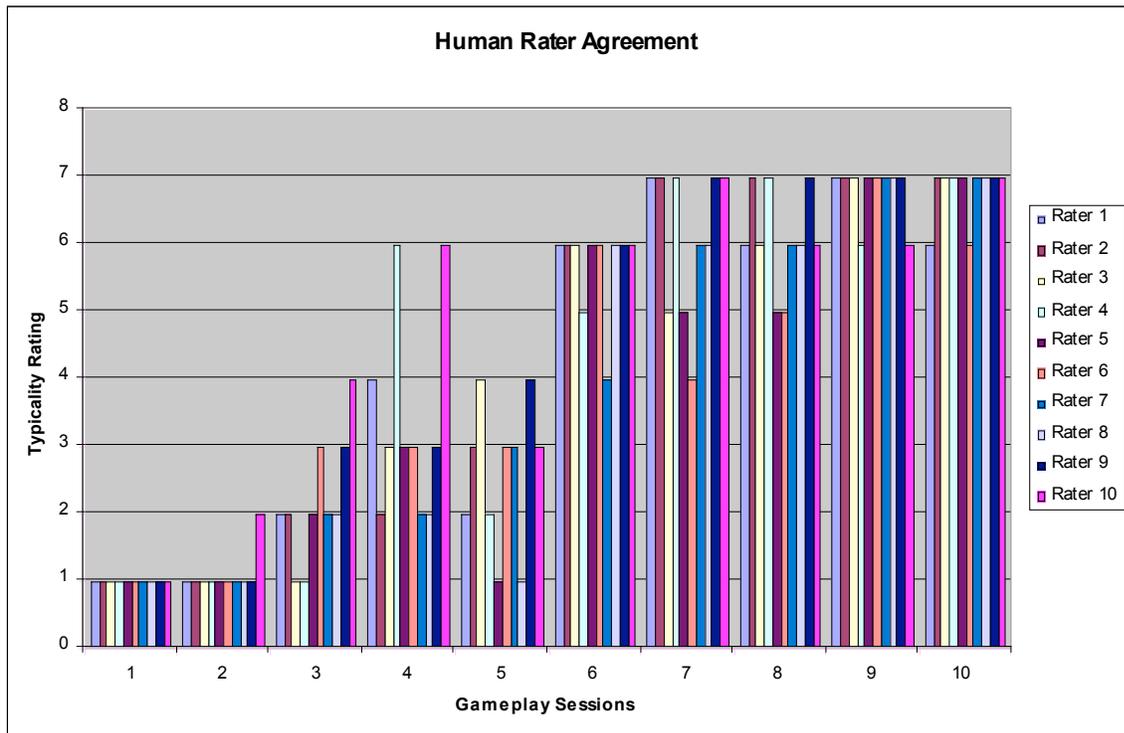


Figure 5-11: Human inter-rater agreement.

I formally measured inter-rater agreement with the R statistical package’s implementation of Light’s weighted Kappa for N raters. This is a metric of inter-annotator agreement between 0.0

and 1.0 for non-categorical, real valued ratings. I found Kappa = 0.8643515. I also computed the average correlation between any pair of raters, and found the mean Pearson's R = 0.899.



Figure 5-12: Rater agreement with my ratings, based on mode of 10 rater's ratings.

Figure 5-12 shows how well the ten raters agreed with my ratings. Based on the mode of ten ratings for each game, the raters generally agree with my ratings. However, comparing the histogram of ratings in Figure 5-13 to the histogram of my ratings in Figure 5-1 uncovers a discrepancy in the handling of neutral ratings for games. I tended to rate games above or below four, choosing not to rate games as neutral, while the other raters chose neutral most often. This is a notable difference in the way games were rated during validation and testing that may have contributed to a slight difference in the final correlation found between the system's likelihood rating and human ratings of typicality during validation and testing.

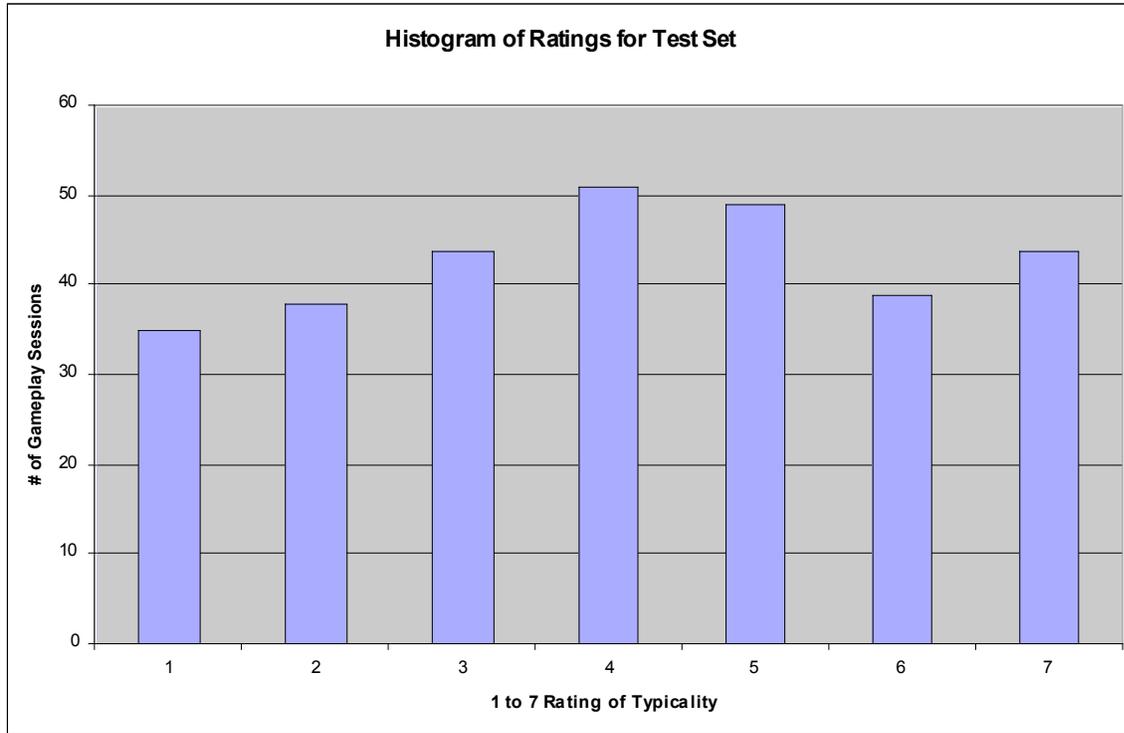


Figure 5-13: Histogram of human ratings for test set.

5.2.2 Test Results

I computed the correlation between the human ratings for the 300 games in the test set, and the likelihood scores estimated with the parameters found experimentally in the evaluation – the 25 / 75 combination of likelihoods from the action model and language model, with action 4-grams averaged over social roles, and language bigrams averaged over social roles. The result was a Pearson’s $R = 0.576$ correlation coefficient, which is strongly significant for 300 games. With 300 games, a correlation of .147 or greater is significant at the .01 level ($p < .01$).

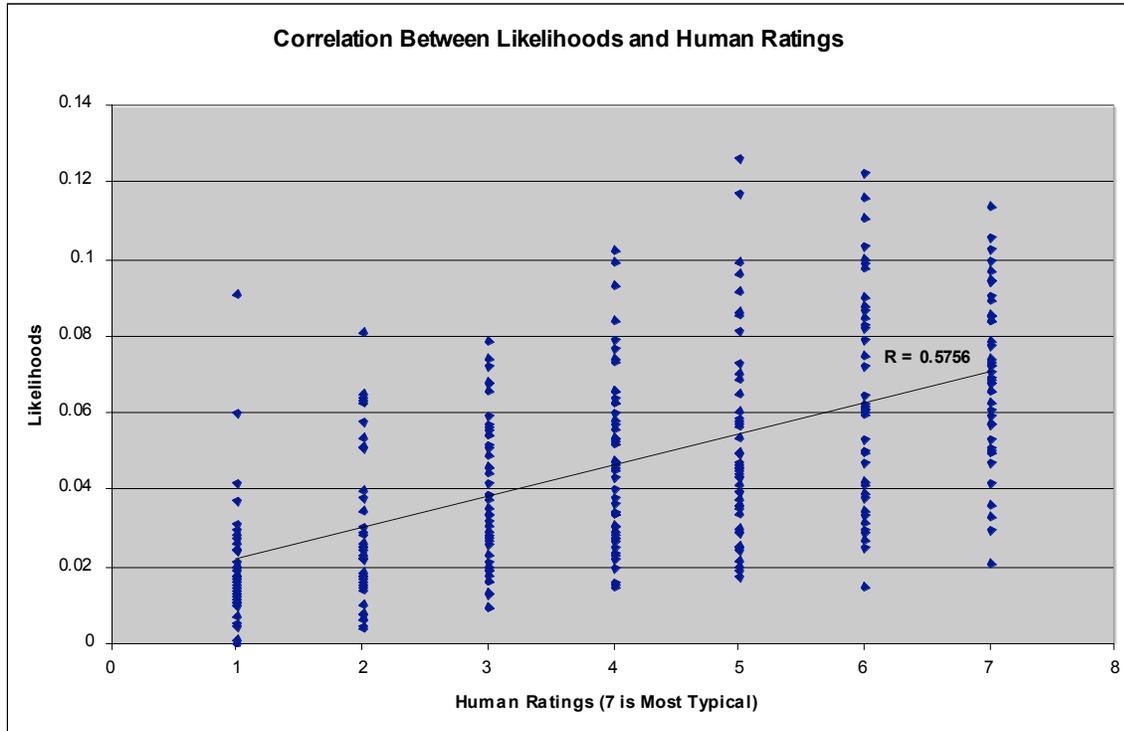


Figure 5-14: Scatter plot of correlation between likelihoods and human ratings.

The correlation in the test set is slightly lower than in the validation set, which can be attributed to a number of causes. The test set is three times as large, and may have contained more variation. The raters were unfamiliar with the data, and did not share my intimate knowledge of the game and learning process. Regardless of these issues, there was still a strong correlation, indicating that it is possible to learn a Plan Network from video game data that does reflect human judgment of typicality. Figure 5-15 illustrates that the test set follows the same progression of improvement when comparing correlation with the language model, the action model, and the interpolated model.

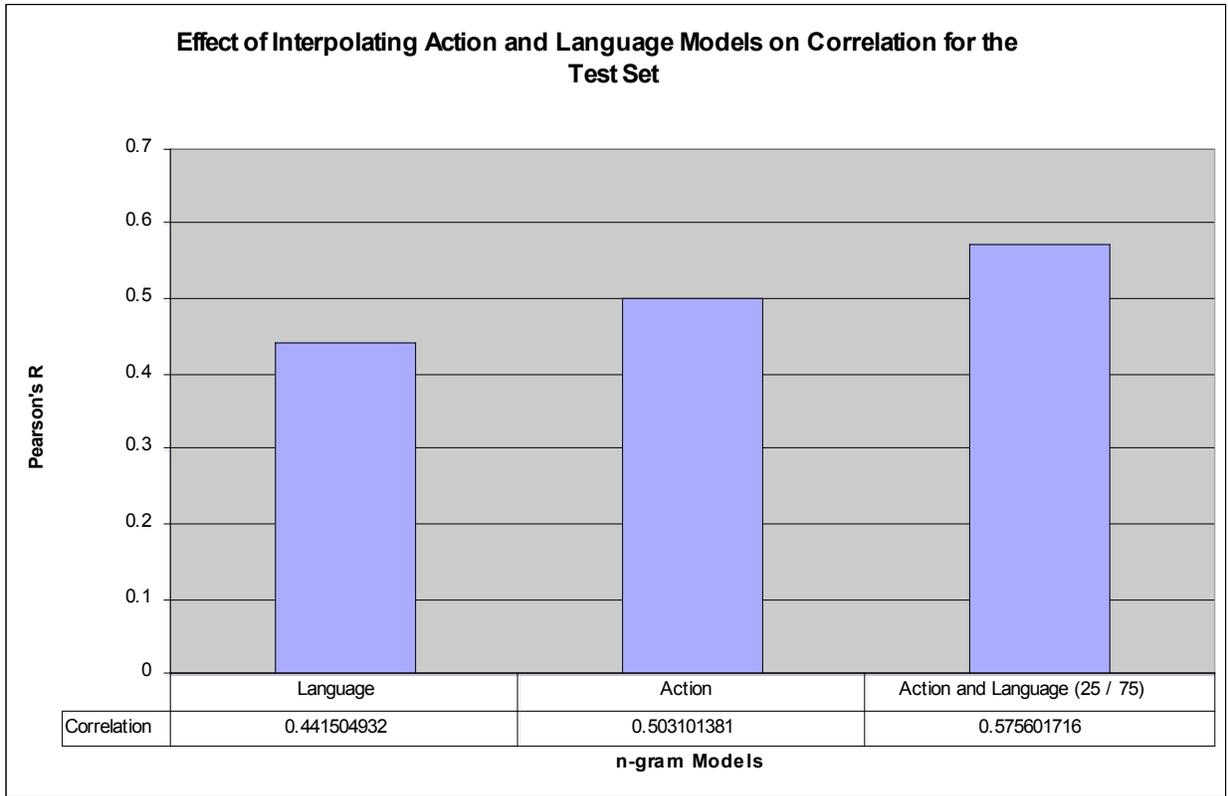


Figure 5-15: Effect of interpolating action and language models on correlation for the test set.

If the likelihood threshold of 0.04 is applied to the test set, Table 5-4 details the system’s performance on the binary classification task of identifying typical and atypical gameplay sessions. The Plan Network correctly identifies 75% of the games that humans rated as typical, and filters out 75% of the games that humans found to be atypical.

	Rating > 4 (Typical)	Rating < 4 (Atypical)
Likelihood > 0.04 (Typical)	99 True Positives	32 False Positives
Likelihood <= 0.04 (Atypical)	33 False Alarms	85 True Negatives

Table 5-4: Binary classification matrix comparing estimated likelihoods to human ratings.

5.3 System Successes and Failures

Figure 5-16 is a graph visualization of customer behavior in a game rated as a seven by a human, with a high likelihood estimate from the system (above 0.1). The player’s actions are highlighted by the blue nodes, connected with bold edges. The player’s actual behavior follows an existing path in the customer Plan Network.

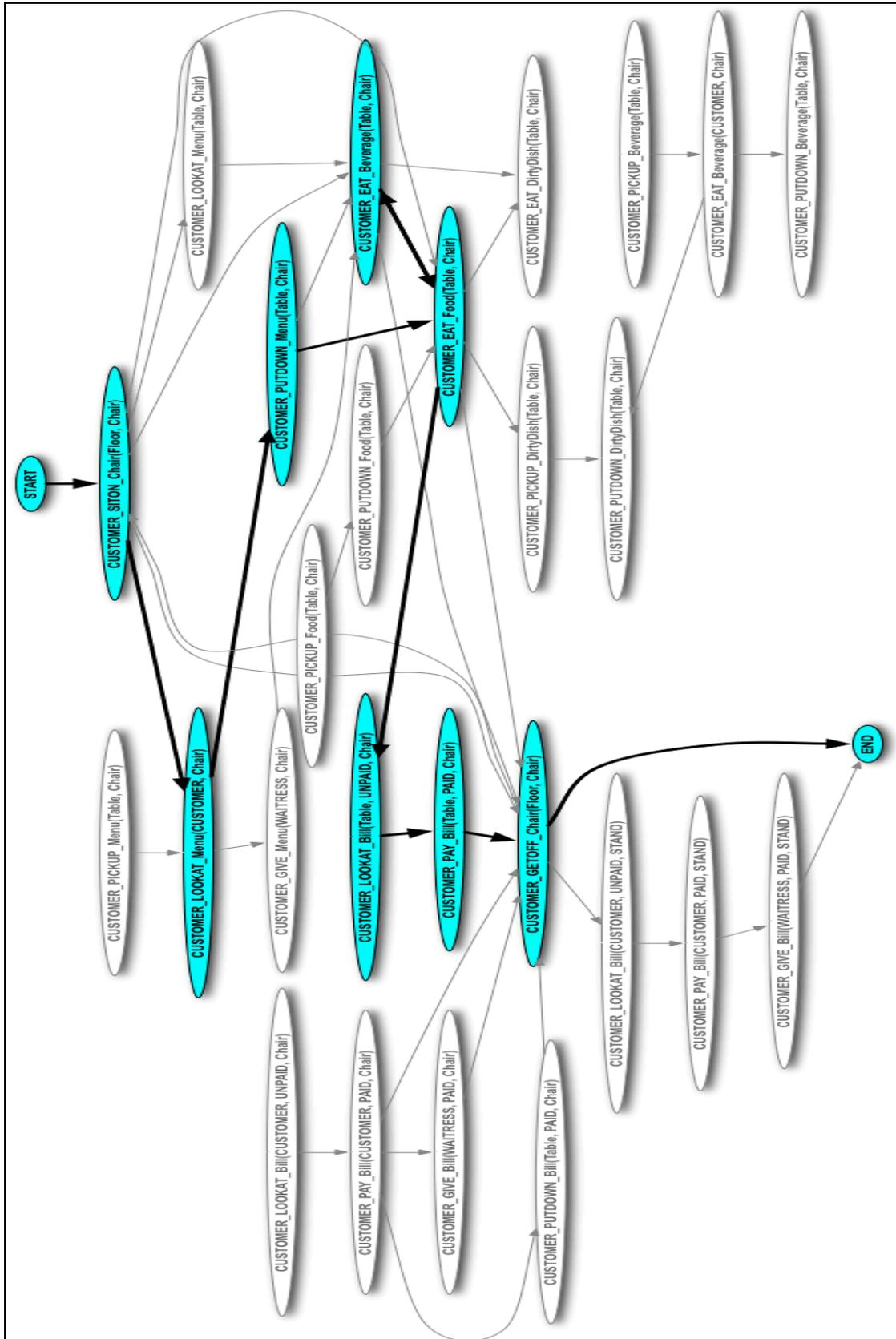


Figure 5-16: Graph of customer behavior in a game rated typical by humans and the system.

The graph only represents the physical behavior. It is possible to find games where the physical behavior is typical, but the language is not, and the system can successfully identify these as well. Figure 5-17 contains an excerpt from a game where the waitress and customer engage in ordinary behavior such as eating food and paying bills, but the dialogue between them reveals that the customer is trying to leave without paying, and trying to take the waitress home with him. Here the human rating is two, and the system estimates a likelihood of below 0.03. The typicality of physical behavior is estimated as highly likely with a score over 0.09, but the unusual language forces the combined likelihood below the threshold of typical behavior. In a similar manner, games played in a foreign language can be easily identified. The system is also sensitive to out of the ordinary word ordering, allowing detection of games containing broken English.

39319352 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
39319352 WAITRESS: "welcome!!"
39345836 CUSTOMER: "i wanna eat some food"
39354274 CUSTOMER: "i havent eaten in eight days"
39355633 WAITRESS: "have a sit... and enjoy!"
39359992 CUSTOMER: "stupid heroin addiction"

39361211 CUSTOMER WALKS TO table1
39365742 CUSTOMER SITSON chair3
39373102 WAITRESS PICKSUP Menu
39374055 WAITRESS WALKS TO table1
39379024 WAITRESS GIVES Menu TO CUSTOMER
39383039 CUSTOMER LOOKSAT Menu

39394539 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
39394539 WAITRESS: "hungry ah?"
39403071 CUSTOMER: "gimme a filet mignon and six beers"
39408461 WAITRESS: "six???"
39411117 CUSTOMER: "yes i've had a very bad day"

39422242 CUSTOMER GIVES Menu TO WAITRESS

39428539 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
39428539 WAITRESS: "well.. ok... but it's better to drink one at a time..."
39453727 CUSTOMER: "what are you, my mother"
39456836 WAITRESS: "or they'll get warm!!!"

. . .

39777071 [CONVERSATION BETWEEN CUSTOMER AND WAITRESS]
39784742 WAITRESS: "are leaving so fast???"
39794430 CUSTOMER: "i'm an american baby, I do whatever I want"
39808024 WAITRESS: "ok... but I thought... you... would want me to"
39829117 WAITRESS: "come with you for a walk after work..."
39833649 CUSTOMER: "I'll give you a "tip," if thats what you're asking for"
39856274 WAITRESS: "well... to be honest... you still have to pay the bill!"
39865242 CUSTOMER: "lets go back inside so you can get paid, then you come home with m"

39869227 CUSTOMER WALKS TO podium
39871742 WAITRESS WALKS TO podium

39881071 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
39881071 WAITRESS: "ok... wait a minute..."

39895680 WAITRESS TOUCHES Register
39917242 Bill APPEARS ON Podium
39917242 ITEM0="FILET MIGNON"
39917242 ITEM1="LOBSTER THERMADOR"
39917242 ITEM2="BERRY PIE"
39917242 ITEM3="BEER"

39922352 WAITRESS PICKSUP Bill
39926633 WAITRESS GIVES Bill TO CUSTOMER
39937336 CUSTOMER UNDERPAYS Bill BY \$0.29
39945586 CUSTOMER GIVES Bill TO WAITRESS

39945867 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
39957836 WAITRESS: "I think it's ok!"
39964852 CUSTOMER: "look lady, you're hot to trot, and we're going to shower together now"
39965992 WAITRESS: "you've been very kind..."

39982649 WAITRESS WALKS TO podium
39990117 WAITRESS PUTSDOWN Bill ON Register
39990217 WAITRESS EARNS \$25.28

40054992 [CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
40054992 WAITRESS: "moron!!!! I'm not coming with you..."
40081321 WAITRESS: " it was a trick to convince you to PAY!!!"

Figure 5-17: Game with typical physical behavior, but atypical language.

Figure 5-18 illustrates the Plan Network detecting off-script behavior in a game rated as a three by a human, and below 0.04 by the system. The customer stands up after looking at the menu, then sits down again. Even more alarming, the customer picks up the flower from his table, and then grabs the cash register before exiting the restaurant (without paying his bill)! The off-script actions and decisions are illustrated with red nodes and edges inserted manually into the automatically generated visualization.

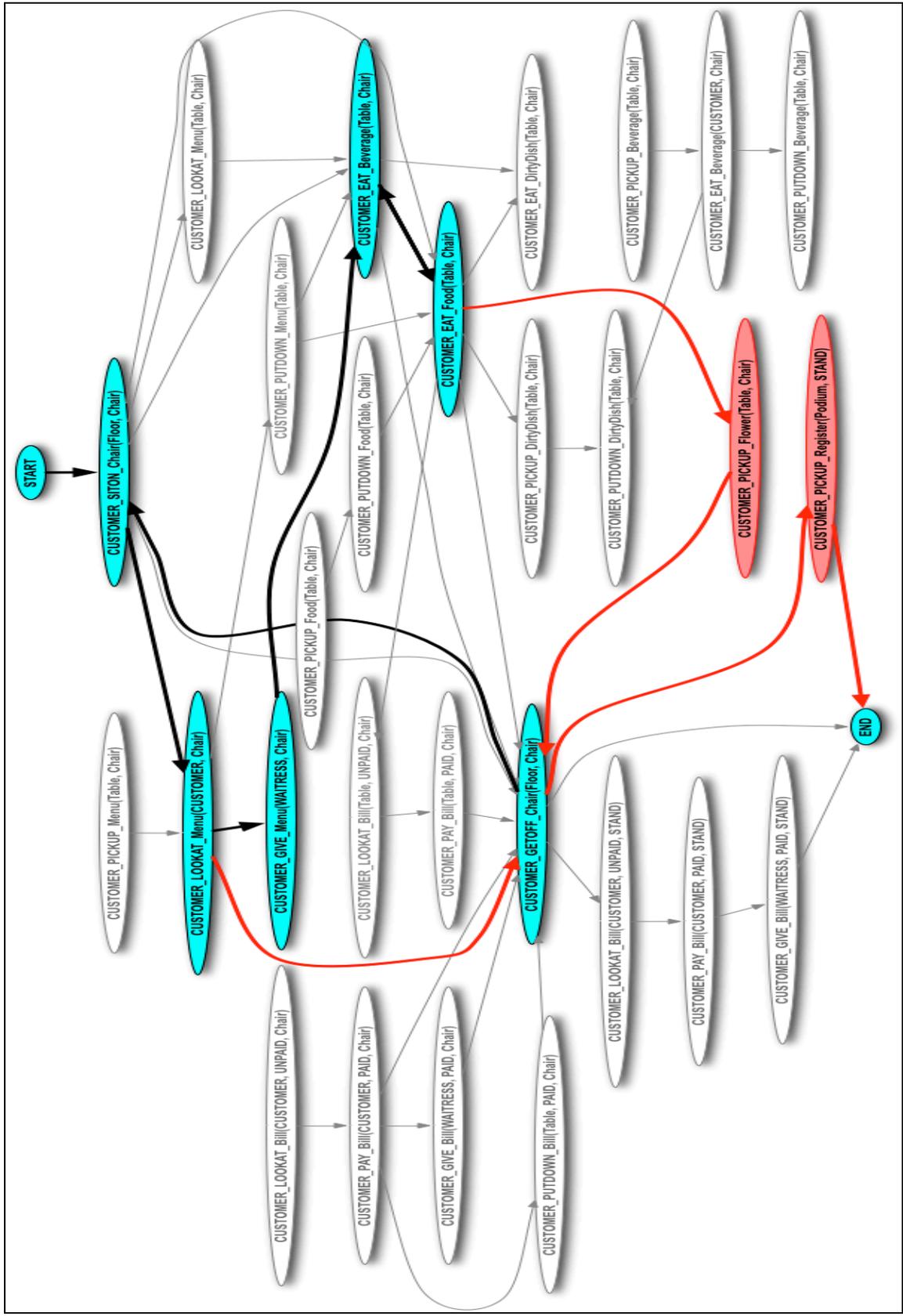


Figure 5-18: Graph of customer behavior in a game rated atypical by humans and the system.

The figures above demonstrate system successes, however relying on statistics and Markovian assumptions will not always lead to successful detection of typical behavior. There are a number of ways to confuse the system. Sometimes players engage in conversation about topics outside of the scope of the scenario, introducing new vocabulary in an otherwise typical play through. The unrecognized words lead the system to assign a low likelihood to a game that humans rate as typical. Other times, players repeat typical restaurant language and behavior an atypical number of times.

7790428	[CONVERSATION BETWEEN WAITRESS AND CHEF]
7790428	WAITRESS: "cherry pie"
7791428	Pie APPEARS ON Counter
7792398	[CONVERSATION BETWEEN WAITRESS AND CHEF]
7792398	WAITRESS: "cherry pie"
7793398	Pie APPEARS ON Counter
7795368	[CONVERSATION BETWEEN WAITRESS AND CHEF]
7795368	WAITRESS: "cherry pie"
7796368	Pie APPEARS ON Counter
7799388	[CONVERSATION BETWEEN CUSTOMER, WAITRESS, AND CHEF]
7799388	CUSTOMER: "big fun. How about beer?"
7805449	WAITRESS: "Sure"
7806563	WAITRESS WALKS TO bar
7808035	CUSTOMER WALKS TO bar
7809897	[CONVERSATION BETWEEN WAITRESS AND BARTENDER]
7809897	WAITRESS: "beer"
7810897	Beer APPEARS ON Bar
7814023	[CONVERSATION BETWEEN CUSTOMER, WAITRESS, AND BARTENDER]
7814023	CUSTOMER: "beer"
7815004	CUSTOMER: "beer"
7815023	Beer APPEARS ON Bar
7816004	Beer APPEARS ON Bar
7816252	[CONVERSATION BETWEEN CUSTOMER, WAITRESS, AND BARTENDER]
7816252	CUSTOMER: "beer"
7817252	Beer APPEARS ON Bar

Figure 5-19: Waitress and customer order lots of pie and beer.

Figure 5-19 displays an excerpt from a game where the waitress and customer cooperatively fill the restaurant with pie and beer. The human rater rated this game a two, but the system's failure to assign a low likelihood supports Chomsky's observation (1957) that statistics can never fully capture the potentially infinitely recursive nature of language. The action model fails to recognize this odd behavior due to the fact that the repeated physical behavior is actually performed by the staff, placing items on the counter and bar, but the Plan Network only models the customer and waitress. Even if the Plan Network incorporated a model of the staff, ordering several dishes or beverages is not out of the ordinary, but ordering the *same* item multiple, times is. This is one case where the loss of precision due to clustering leads to a false positive.

The Plan Network also has trouble with games that are atypically short or truncated. Figure 5-20 contains an entire script for a short game.

10276248	WAITRESS APPEARS ON Floor
10290546	WAITRESS WALKS TO podium
10314559	WAITRESS PICKSUP Menu
10327579	WAITRESS PUTSDOWN Menu ON MenuBox
10328814	WAITRESS WALKS TO table4
10331098	CUSTOMER APPEARS ON Terrain
10333102	WAITRESS PICKSUP OLD_Salad_Bite3
10334051	WAITRESS WALKS BETWEEN counter AND table2
10338177	WAITRESS PUTSDOWN OLD_Salad_Bite3 ON Counter
10338646	CUSTOMER WALKS BETWEEN table1 AND table4
10339216	WAITRESS WALKS TO table4
10340177	OLD_Salad_Bite3 DISAPPEARS
10343134	WAITRESS PICKSUP table4
10349884	[CONVERSATION BETWEEN CUSTOMER AND WAITRESS]
10349884	CUSTOMER: "hello?"
10350317	WAITRESS PICKSUP OLD_Bill
10351548	WAITRESS WALKS TO podium
10354500	WAITRESS PUTSDOWN OLD_Bill ON Register
10354600	WAITRESS EARNS \$21.05
10354600	OLD_Bill DISAPPEARS
10357340	WAITRESS WALKS TO table4
10363532	CUSTOMER SITSON chair3
10372758	[CONVERSATION BETWEEN WAITRESS AND CUSTOMER]
10372758	WAITRESS: "hi sir, can i get you a drink?"
10385635	CUSTOMER: "hello?"
10395154	WAITRESS: "can i get you a drink?"
10401162	CUSTOMER: "no!"
10406013	WAITRESS: "nice one"
10414001	CUSTOMER STANDSUP FROM chair3
10438580	CUSTOMER WALKS TO ExitTrigger(ExitTrigger)

Figure 5-20: Complete script for a very short game.

A human can recognize that this is not a typical restaurant experience, even though the actions and words it is composed of are typical. Humans evaluate games based on both what did and what did *not* happen, and they are aware that this game is strange because the customer refused service and exited the restaurant without ordering, eating, or paying a bill. The system needs some representation of the typical structure of a game to recognize that it is out of the ordinary for a customer to just stand up and exit without having a meal. The current Plan Network implementation only has access to a local representation of the expected sequence of events. It cannot identify gross absences.

Chapter 6

Contributions and Future Work

This thesis has demonstrated that it is possible to not only collect a large quantity of data with a multiplayer video game, but also data of high quality that accurately reflects typical human behavior and language. A methodology has been described to learn a Plan Network from this data that can be visualized as a graph, and interactively browsed to view conversations clustered by context. A quantitative measure has been applied to a random selection of 300 games, positively correlating the Plan Network's estimate of likelihood with ratings from ten humans.

The Restaurant Game was quickly constructed for data collection purposes, and is hardly a game at all. Yet, this restaurant simulation provided enough entertainment to capture behavior from over 5,000 people. With hundreds of thousands of people online in *Second Life*, and millions playing *The Sims* and *World of Warcraft*, the potential for using games to learn about humans is enormous.

The data analysis performed so far only scratches the surface of a rich research area. The system failures in Chapter 5 illustrate the need for additional representations of learned behavior that capture the large scale structure of the narrative, possibly in the form of a plan grammar. A context-sensitive grammar may be able to detect games with atypical omissions of behavior, such as exiting the restaurant without paying the bill.

Even a perfect representation of the scenario learned from *The Restaurant Game* will not fully reflect all that humans know about restaurants. The Plan Network only provides representations of *observable* intentions, such as eating food, and paying bills. The data provided from log files does not explicitly indicate whether the customer left a large tip because he was trying to impress the waitress, or was just happy with his experience. A more robust model would incorporate knowledge from other sources as well; perhaps transcripts from films and television shows, or text from web sites about restaurants. These additional sources of knowledge could allow the system to make inferences about unobservable intentions.

This thesis began with the statement that conversation is a collaboration, yet the best likelihood estimations are achieved by learning separate models for the two social roles. Ultimately, an additional unified model of the interaction dynamics between the customer and waitress is desirable, because an agent who's behavior is driven by the Plan Network will need to understand when to expect the other actor to take a turn. The nodes of the Plan Network already contain the knowledge required to build the unified model, in the form of action preconditions. For example, the customer's behavior model includes an edge from looking at the menu to eating food. In between, a waitress must put food on the table for the customer to eat. The preconditions of eating food require food to be on the table, providing the required knowledge that interaction between the waitress and customer is required between looking at the menu and

eating food. Implementation of the unified model of interaction dynamics remains for future work. Ideally the Plan Network will also scale to handle more than two simultaneous actors.

Despite the issues raised above, the Plan Network in its current form is already useful. Plan Networks allow humans to visualize norms that emerge from thousands of people interacting in the same environment, and may expose unexpected behavior or user interface confusion. A system that can predict and suggest socially appropriate actions and utterances could open the door to new types of communication aids, assisting people with Autism or other neurological disorders affecting social behavior. The ability to recognize atypical behavior and language not only enhances visualizations, but can also filter data used to teach an agent appropriate behavior, and to recognize off-script behavior in real-time. Perhaps the chef starts a small fire in the kitchen to distract a player who was detected taking the scenario in an atypical direction with erratic behavior or out of vocabulary language. Course correction like this may improve games, but would be especially useful in training simulations; one of the many potential application areas for socially aware, conversational role-playing agents. In the future, conversational agents powered by Plan Networks may provide new experiences in gameplay and training, allow new ways to practice foreign languages, and act as digital extras in animated films and machinima.

Of course, there is more work to be done before Plan Networks can drive agents in interactive applications. A future goal for this work is to automate conversational characters in a new single-player restaurant game, fulfilling the promise made to participants on the project web page.

Appendix A

Clusters

Below are the clusters found with the method described in section 4.2.3. The cluster names in brackets after the items are assigned manually by inspecting the automatically generated clusters. These labels are only used for visualization purposes.

Items that are created after the game starts are tagged as dynamic objects with the addition of “.dyn” to their names. Note that the restaurant always starts in the same state, with one dirty table covered with half eaten salad, salmon, beer, and wine, and a paid bill. Also, an old pie and lobster are always sitting on the counter when the game starts.

This clustering technique does a good job of clustering the objects most commonly interacted with in the restaurant scenario: food, drinks, and dirty dishes. This technique also successfully distinguishes between the half eaten salad, salmon, beer and wine that are already on the dirty table from fresh items ordered from the chef.

CLUSTER0=Brandy,Wine,Bottle [Liquor]
CLUSTER1=DishWasher [DishWasher]
CLUSTER2=Stove [Stove]
CLUSTER3=Bar [Bar]
CLUSTER4=Stool,Chair [Chair]
CLUSTER5=Cuisinart [Cuisinart]
CLUSTER6=FoodPrep [FoodPrep]
CLUSTER7=Microwave [Microwave]
CLUSTER8=Pan [Pan]
CLUSTER9=Pot [Pot]
CLUSTER10=Fridge [Fridge]
CLUSTER11=TrashCompactor [TrashCompactor]
CLUSTER12=Table [Table]
CLUSTER13=Lobster,Pie [OldFood]
CLUSTER14=Counter [Counter]
CLUSTER15=Trash [Trash]
CLUSTER16=Podium [Podium]
CLUSTER17=Fruit [Fruit]
CLUSTER18=Flower [Flower]
CLUSTER19=Blender [Blender]
CLUSTER20=Register [Register]
CLUSTER21=Chef [Chef]
CLUSTER22=Bartender [Bartender]
CLUSTER23=Salmon,RedWine,Salad,Beer,Glass,Plate,WineGlass,Bowl,TeaCup,Mug [DirtyDish]
CLUSTER24=Bill [OldBill]
CLUSTER25=Interior [Interior]
CLUSTER26=WAITRESS [WAITRESS]
CLUSTER27=CUSTOMER [CUSTOMER]
CLUSTER28=Menu.dyn [Menu]
CLUSTER29=Vase [Vase]
CLUSTER30=Filet.dyn,Spaghetti.dyn,Salmon.dyn,Salad.dyn,Lobster.dyn,Soup.dyn,
Cheesecake.dyn,Tart.dyn,Pie.dyn [Food]
CLUSTER31=Beer.dyn,RedWine.dyn,Water.dyn,WhiteWine.dyn,Tea.dyn,Coffee.dyn [Beverage]
CLUSTER32=Wine_Empty [Wine_Empty]

CLUSTER33=Bill.dyn [Bill]
CLUSTER34=Trash_Empty,[Trash_Empty]
CLUSTER35=Fruit_Bowl [Fruit_Bowl]
CLUSTER36=Terrain [Terrain]
CLUSTER37=FoodPrep_Empty [FoodPrep_Empty]
CLUSTER38=Brandy_Empty [Brandy_Empty]
CLUSTER39=Bottle_Empty [Bottle_Empty]

Appendix B

Maximum Action Lexicon Size

This appendix details the calculation of the total number of possible combinations and permutations of action types, roles, and variable assignments that define the maximum size of the action lexicon. This process is repeated for unclustered and clustered actions.

The full list of objects is available in Appendix A. These objects can be divided into groups based on whether they are consumable, movable, or immovable. Consumable objects change shape with each bite, and can also be moved.

Players may take nine different actions: PickUp, PutDown, Give, SitOn, GetOff, LookAt, Eat, Touch, and Pay. PutDown and Give only apply to objects that can be picked up. Pay only applied to bills. The other six actions may be applied to any object.

B.1 Unclustered Actions

The restaurant has a total of 28 consumable objects, 50 moveable objects, and 14 immovable objects. Any non-dynamic object may be treated as a surface to put something down on top of. There are 50 possible surfaces.

Variations of PutDown and Give:

Moveable: $2 \text{ roles} \times 50 \text{ objects} \times 50 \text{ surfaces} = 5,000$

Consumable: $2 \text{ roles} \times 28 \text{ objects} \times 50 \text{ surfaces} \times 3 \text{ states} = 8,400$

Total number of actions: $2 \times (5,000 + 8,400) = 26,800$

Variations of PickUp, SitOn, GetOff, LookAt, Eat, and Touch:

Immovable: $2 \text{ roles} \times 14 \text{ objects} = 28$

Moveable: $2 \text{ roles} \times 50 \text{ objects} \times 50 \text{ surfaces} = 5,000$

Consumable: $2 \text{ roles} \times 28 \text{ objects} \times 50 \text{ surfaces} \times 3 \text{ states} = 8,400$

Total number of actions: $6 \times (28 + 5,000 + 8,400) = 80,568$

Variations of Pay:

Bills: $2 \text{ roles} \times 50 \text{ surfaces} = 100$

Total number of possible actions:

$26,800 + 80,568 + 100 = 107,468$

The system observed 11,206 actions in 5,000 games, which covers 10.43% of the possibility space.

B.2 Clustered Actions

Once objects are clustered, there are 9 clusters of consumable objects, 25 clusters of moveable objects, and 13 clusters of immovable objects. There are 37 clusters for possible surfaces.

Variations of PutDown and Give:

Moveable: $2 \text{ roles} \times 25 \text{ clusters} \times 37 \text{ surface clusters} = 1,850$

Consumable: $2 \text{ roles} \times 9 \text{ clusters} \times 37 \text{ surface clusters} \times 3 \text{ states} = 1,998$

Total number of actions: $2 \times (1,850 + 1,998) = 7,696$

Variations of PickUp, SitOn, GetOff, LookAt, Eat, and Touch:

Immovable: $2 \text{ roles} \times 13 \text{ clusters} = 26$

Moveable: $2 \text{ roles} \times 25 \text{ clusters} \times 37 \text{ surface clusters} = 1,850$

Consumable: $2 \text{ roles} \times 9 \text{ clusters} \times 37 \text{ surface clusters} \times 3 \text{ states} = 1,998$

Total number of actions: $6 \times (26 + 1,850 + 1,998) = 23,244$

Variations of Pay:

Bills: $2 \text{ roles} \times 37 \text{ surface clusters} = 74$

Total number of possible actions:

$7,696 + 23,244 + 74 = 31,014$

The system observed 7,086 clustered actions in 5,000 games, which covers 22.85% of the possibility space. The coverage of the possibility space has more than doubled by clustering.

Appendix C

Learned Language Lexicon

This appendix contains the complete learned language lexicon, sorted by word frequency. Words have been forced to lowercase, and punctuation has been stripped.

[4649] you [4596] i [4543] a [4198] the [4192] please [3980] have [3918] to [3731] and [3434] like [3403] can [3284] me [3212] is [3189] for [3114] your [3010] would [3006] yes [2971] what [2965] no, thank [2956] hello [2914] are [2888] get [2839] that [2837] of [2780] it [2743] ok [2597] thanks [2571] im [2500] here [2453] do [2441] my [2435] ill [2430] sir [2383] wine [2376] be [2329] beer [2286] menu [2281] good [2255] this [2251] drink [2237] with [2187] anything [2112] just [2080] else [2057] on [2029] right [2005] water [1991] there [1987] how [1982] go [1975] will [1960] one [1946] bill [1932] in [1926] some [1902] soup [1880] take [1875] sure [1871] hi [1825] check [1819] sorry [1789] want [1784] table [1770] not [1738] was [1737] now [1726] so [1658] seat [1656] welcome [1615] dont [1592] red [1552] up [1547] nice [1540] its [1532] sit [1516] salad [1513] or [1475] oh, well [1459] all [1390] come [1370] very [1365] glass [1350] but [1328] we [1325] if [1321] order [1315] more [1308] lobster [1299] back [1276] may [1273] see [1260] eat [1256] pie [1238] where [1219] u [1202] know [1200] day [1191] then [1187] thats [1173] something [1169] too [1166] bye [1165] at [1160] am [1136] white [1113] think [1079] did [1068] great [1064] need [1056] could [1045] out [1040] ready [1037] much [1036] another, from [1034] start [1025] about [1014] pay [1010] again [982] hey [976] file! [971] dessert [960] coffee [955] spaghetti [954] follow [952] any [950] today [906] salmon [901] let [898] youre [894] enjoy [874] coming [872] give [871] tart [866] okay [842] time [834] fine, food [815] cheesecake [808] way [800] why [791] steak [789] lol [773] yeah [765] problem [760] away [753] course [752] look [743] cobb [730] down [722] mignon [717] tea [705] our [697] as [695] meal [689] help [688] off [685] when [665] id [651] didnt [646] berry [639] house [638] really [634] got [620] bring [615] first, going [610] evening [606] name [598] an, thing [590] hope, were [586] done [583] flowers, had [582] waitress [580] moment [579] cant [552] by [547] tip [544] whats [533] grilled, nectarine [531] alright, only [527] over [524] free [521] jour [519] money [515] wait [506] chef [505] make [504] try [496] tell [492] lets [491] say [485] vegetable [484] should [482] everything [479] looks [476] been [460] ya [455] put [453] specials [452] maybe [446] delicious [444] restaurant [440] they [436] du [431] leave [430] haha [424] hungry, wow [417] cake [415] cool [414] excuse [413] dinner [411] ah, heres [410] cherry, desert [402] game [399] anywhere [394] ive [392] love [390] ask [387] excellent [382] little [377] also, better, kind [373] doing [367] bit, sounds, work [363] old [361] hear [358] guess [357] soon [356] mean [354] place, though [353] he [350] choice [346] tonight [345] new [340] service, special [339] hmm [335] before [334] them [333] mind [332] certainly [331] main [325] still, ur [320] call [319] actually [318] while [317] night [315] must, said [314] marinara [312] o [310] bar [308] r [307] thankyou [305] other [303] long [301] yourself [300] customer, theres [298] two [293] cheese [288] care [287] shall, um [286] thought, yet [282] after, pretty [280] lovely [279] man [278] finished [277] these [275] pick [273] bad [268] wanna [265] quite [263] recommend [262] around, never [261] has, perhaps [260] minute [253] job [252] goodbye [251] cup [247] fun, real, wont [245] window [241] does [240] lot, nope [239] best, register [237] miss [236] ate, k [234] later [233] spaghetti, those [232] second [230] wonderful [229] d, isnt [227] even, find [226] already, youd [224] who [223] last, people [222] big, bitch, us [221] de [220] yea [219] enjoyed, gonna [218] bottle [216] many [215] might, use [214] serve [213] plate [211] paid, than [210] eating [209] enough, hehe, next [208] mmm [207] ever, girl [206] made, nothing, talk [205] cash, coffe [204] beers [202] guy, hot, outside [201] trying [200] plz [199] feel [197] myself [196] bartender, stop [195] tasty [194] always, huh, show [193] play [192] wrong [191] doesnt [190] few [187] home [186] ha, same [185] maam [184] anyway [182] fuck [181] live [179] sweet [178] customers, having [177] forgot [176] because, drunk, glad [175] life [174] fruit, oops [173] funny, getting [172] full, hmmm, uh, wanted [171] ass, looking, things [170] decided, havent [169] him, indeed, working, yo [168] keep, meet, y [167] hows, left, starter [165] thermador, yep [164] refill, wish [163] youll [162] bite [161] drinks [160] join [158] wat [157] paying [155] which [154] boy [153] p, pleasure, umm, youve [152] finish [150] being, stuff, yours [149] hold [148] fresh [147] charge, seem [146] mine [145] clean, dear, t [144] afraid, move [143] dishes, offer, ordered, s, someone [142] gave, yummy [140] cheers, stay [139] ahh [137] believe, eh, hard, hurry [136] gotta [135] seems [134] into [133] god, yup [132] taste, wheres [131] cold, w [130] speak [129] baby, trash [128] slow [127] arent, fillet, nah, todays [126] hahaha, run [125] empty, his, most [124] fast, talking [123] behind [122] choose, hell, since [121] person [120] head, thx [119] busy, damn [118] board, both, mam, starters, walk [117] playing, sec [116] fish, leaving [115] perfect, prefer, whatever [114] cheesecake, idea, once, waiting [113] clear, cook, happy, worry, yum [112] awesome, hes, read, shit [111] mmmm, watch [110] compliments, minutes [109] sitting, wasnt [108] english, ouch, understand, view, wherever [106] asked, grab, three, told, took [105] vase, whenever [104] chair, far [103] ahead, catch [102] heard, remember, seated, used, waiter, whine [101] flower, kitchen, says, sex, such [100] brandy, decide, glasses, pasta, started [99] rather, rude, theyre [98] crazy, e, interesting, m, own, years [97] buy, gimme, probably, suggest, tables, wouldnt [96] asking, forget [95] breakfast, her [94] friend, quick, survey [93] beautiful, instead, taking, without [92] lady, she, weird [91] afternoon, couldnt, microwave, woman [90] shortly, tried [89] bet, extra, question, rest [88] came, either, face, fantastic [87] open, server, thatll, through [86] bon, c, drinking, every, male, pleas, ty [85] dude, piece, police, went [84] cheque, friends, hand, kinda [83] alrighty, bowl, cute, thirsty [82] ago, alone, cause, end, room [81] heh, kidding, type [80] suppose, true [79] business, dollars, female, garbage, makes, set [78] bathroom, chance, floor, hit, interest, meat, part, year [77] bout, close, eaten [76] appetizer, lunch, morning, near, touch [75] b, change, counter, eyes, favorite, hate, school, stupid, wall [74] entree, guys, n, serving, town, ummm, vodka, world [73] anyone, ow, student, tastes, till, xd [72] almost, inside, sound, win [71] absolutely, computer, date, mistake, played, road, ta, texas [70] break, desserts, gone, hon, ice, sexy [69] anymore, bored, days, dish, least, lots, manager, ohh, thanx, trouble [68] add, babe, front, ooh, st, suck, wtf [67] age, dirty, england, fucking, hurt, pardon, seen, times [66] alot, fill, quiet, stand, supposed, whole [65] correct, er, expensive, meant, medium, rare, square, staff, starving [64] ahhh, beverage, college, drive, number, pls, saw [63] cream, deal, fat, kids, late, oi, omg, ones, poor [62] gets, hair, high, party, pass, repeat, shame, strange, their, usually, wines [61] followed, kill, liked, madam, missed, self, silly, top, wife [60] broke, click, comes, meeting, often, tree, yay [59] alcohol, goes, la, lost, phone, th, until [58] appreciate, aww, chat, found, heavy, hm, lobsters, saying, slice [57] aint, charged, dining, erm, honey, lunch, matter, shouldnt [56] boss, brb, cannot, die, shift, sometimes [55] boring, different, games, hands, kk, mmmmm, possible, week, young [54] asshole, called, case, cheap, everyone, french, juice, making, plates, rush, wash, word, worked [53] alright, california, cooked, each, mr, resturant, under, usa, veggie, visit

[52] black, careful, country, crap, drank, fair, green, hang, hehehe, ll, problems, small, sucks, sweetie, thar, vegetable [51] allergic, beef, cob, dead, fancy, kiss, married, payed, terrible, toast [50] amazing, coke, complimentary, cya, exactly, finest, horrible, il, mm, point, prob, si, sire, sort, straight, uk, unfortunately [49] able, car, chefs, chicken, easy, happen, means, non, pies, round, sup, thinking, unless [48] bastard, cofee, helo, men, objective, questions, re, recommend, soda, sometime, stuffed, together [47] don, giving, l, milk, mother, np, served, weve, whiskey [46] afford, appetit, biting, champagne, city, cut, driving, martini, mom, return, stuck, sugar [45] anyways, apologize, bills, cops, dick, fly, liking, ofcourse, quit, tomorrow, treat, wonder, worries [44] allison, apologies, com, comming, dance, dog, door, dunno, enjoying, family, half, living, ring, turn [43] brought, da, five, gay, handsome, ho, min, names, ran, remove, restroom, running, sick, somewhere, stole, suit [42] agree, along, anytime, bucks, canada, company, g, gift, hah, hahahaha, met, ohhh, oo, seeing, shut, steal, uhh, weather [41] nd, nevermind, ooooh, outta, sry, tab, tarts, teh, ugly [40] booze, buddy, feeling, figure, knew, lemme, odd, plus, whoa [39] aw, bear, body, burp, fact, fired, generous, happens, howdy, noticed, okey, prepare, reccomend, sad, spot, whoops, wondering, yellow [38] boyfriend, card, comin, doin, je, lmao, looked, mingon, mister, plese, serious, share, shes, single, smells, speaking, studying, teach, tips, women, write [37] answer, closed, cost, couple, dine, feed, girlfriend, girls, goodnight, greetings, hahah, liek, magic, minion, owe, pants, short, street, tanks, text, worth, yah [36] although, apple, area, butt, chocolate, dare, definitely, eggs, four, happened, hum, jk, less, light, ma, mate, needs, somethin, step, te [35] allowed, btw, calling, diner, hmmm, honest, itll, joke, london, middle, needed, oke, send, trick, virtual [34] act, berr, complete, em, forward, goin, husband, idiot, lue, none, rich, smoking, soo, strong, thief, tired, wink, works, yeh [33] cafe, earlier, earn, f, listen, ou, sauce, sign, son, standing, taken, thermidor, wants, waters, zou [32] allow, delightful, dumb, edible, err, establishment, fire, fix, h, kindly, language, moved, personal, price, trust, veg, watching, wot, ye [31] apparently, appetite, blender, choices, email, especially, fridge, heart, hiya, hour, lucky, madame, okie, orange, seriously, teacher, terribly, ticket, touched, tough, vegatable [30] accident, american, bee, boo, carry, chop, cutie, dat, elementary, eles, jesus, joe, joking, learn, north, notice, please, sat, secret, sigh, smile, spend, sry, study, surely, wallet, warm, wil [29] available, between, darling, dollar, dropped, duh, except, expect, hallo, knows, large, likes, marry, menus, mess, mit, msn, music, older, plan, polite, reservation, restaurants, sald, samon, selection, sleep, telling, ther, throw, x, yer, york [28] alcoholic, beeer, besides, bin, brazil, corner, depends, fabulous, feet, floating, form, glas, hav, hide, iam, interested, jerk, merlot, migon, mouth, pee, ru, state, stealing, waitresses, werent [27] across, aim, bob, bother, comfortable, confused, cuz, florida, flying, fool, fuckin, grade, health, lie, lonely, merci, ordering, pleasant, smell, test, tho, toots, tutorial [26] ahhhh, america, awww, begin, children, gives, hahahahaha, huge, imagine, months, moving, obviously, ot, places, refills, safe, save, scared, shot, sister, smart, teeth, turned, uhm, vegetarian, waitressng, wats, woah, words [25] air, appears, aswell, bed, boobs, ciao, conversation, diet, double, fit, france, given, goodness, gosh, insist, items, kid, local, mood, occupation, prepared, sense, shoot, sims, something, super, sweetheart, university, whisky, whit, whos [24] ahem, blind, blue, burger, cents, dokey, education, experience, favor, however, nasty, nooo, peace, pei, personally, plant, quickly, reason, rock, six, sooo, stick, takes, vegetables, wear, yu [23] anybody, australia, banana, basket, belgium, ber, bought, box, bread, brother, character, cheapskate, child, closer, cmon, cock, cups, doctor, fucker, germany, gin, hic, holy, hopefully, human, important, lap, longer, lookin, month, opps, owner, paper, reach, redwine, seconds, sell, shout, skip, soups, starting, toilet, ugh, un, visiting, wearing, whore [22] aha, blood, bloody, blush, bug, changed, chez, chose, clothes, cunt, curious, dash, discount, disgusting, earned, eye, feels, freak, fruits, furniture, hola, holding, internet, jack, joining, jus, kick, killed, knife, laugh, loved, low, machine, mad, movie, normal, nowhere, nuts, online, ooo, pizza, pm, popular, putting, que, robbery, salade, screw, se, sink, speciality, spell, star, thatd, third, tonic, total, totally, voila, yr [21] agian, barman, birthday, coffie, count, definately, delay, delicious, deserts, during, early, farewell, finally, foods, friendly, future, gratuity, hee, helping, heya, highly, hours, italian, italy, james, john, legs, list, lord, management, neat, nobody, penis, pudding, rid, sam, sing, speghetti, surprise, tasted, touching, tu, ure, whatll [20] accent, adios, al, balls, button, byebye, cab, chairs, checking, cocktail, compliment, consider, cow, damnit, darlin, darn, deaf, degree, deserve, died, enter, ew, expecting, fall, fault, favourite, goodevening, jump, liquor, lived, mi, moments, naw, others, payment, pig, pleased, press, promise, rite, rofl, screen, sip, spanish, sweetie, tank, ten, ti, twice, using, ways [19] ai, assume, bringing, buffet, butter, cry, custom, dad, etc, exit, fan, father, fetch, filled, hoping, ja, kinds, kno, margarita, meals, ne, neither, nicer, noooo, ook, orders, oyu, parents, pi, plenty, poop, pussy, rape, relax, report, roof, sea, south, states, sucker, wellcome, woo, worst [18] accept, against, attention, barkeep, beat, become, bigger, bud, building, bunch, burn, cereal, checks, chosen, clearly, closing, color, cooking, creepy, drop, easier, facing, faster, forgive, gorgeous, graders, ground, guest, invisible, joint, lake, le, loser, mention, na, note, nvm, policy, professional, refil, regular, rubbish, sandwich, seafood, settle, smoke, somebody, space, spaggetti, staring, style, superb, talked, tap, teaching, tempt, tender, tipsy, tracksuit, truth, twenty, urs, waste, yesterday, yh, yummm [17] aids, anthing, blowjob, brilliant, caught, christ, common, complements, dancing, demand, difficult, doubt, due, eater, fake, familiar, fell, fo, fries, graduated, hadnt, halo, handle, hay, helpful, hiding, honestly, ima, ohio, pan, past, paula, picked, pity, potatoes, refuse, research, ride, rocks, salads, san, smiles, som, soooo, speciality, stomach, stopping, tha, thaks, thin, thnx, tits, tnx, track, uhhh, vine, wa, weight, west, wit, worse, wud [16] ahhhhh, alive, appear, arm, art, bacon, born, british, broken, bus, ca, cashier, cat, chief, courses, dizzy, en, europe, figured, gracias, gross, hamburger, harder, hat, havnt, heat, holland, holler, ik, kisses, loves, lueshi, mighty, minion, mspace, needing, net, nick, noise, oui, particular, playin, pop, probs, proper, quality, random, raw, shoes, shop, shy, site, spit, splendid, story, tie, trashcan, vous, walking, weeks, wha, won [15] attitude, au, awesome, aye, band, bien, block, bottom, bum, carolina, certain, chips, class, coast, code, cola, completely, cough, cover, dammit, dogs, east, entire, excelent, fag, frank, freshly, giv, graduate, healthy, helps, hoe, hole, hug, ie, jsut, lead, liar, lying, mostly, mouse, nearby, nother, offering, opened, otherwise, oy, per, picking, piepie, piss, player, por, preference, pregnant, present, reading, realize, request, retarded, satisfaction, season, shell, sis, spaghetti, spent, stack, sum, swear, tht, tooth, trip, typing, virginia, wel, welcom, wherever, whilst, woops [14] amanda, apetit, appreciated, awful, ay, beach, ben, blonde, blow, bonjour, bowtie, breasts, brings, build, byee, cani, chatting, cheff, china, choice, cleaning, comfy, costumer, credit, di, dutch, earth, ehm, ends, esle, explain, file, forgotten, further, hehehehe, kaila, latley, laughing, law, lives, marina, marvelous, meatballs, mignon, mo, monkey, nectarine, nigga, office, oki, onto, plea, portuguese, position, problemo, processor, pull, rate, resist, restaraunt, restraunt, righto, rob, rough, russia, scotch, slap, slave, sou, soz, spegetti, sphagetti, sun, thermadore, tipper, ummmm, verry, wee, younger, yw [13] alas, ale, anyhow, anything, appetizers, asl, awhile, balancing, bil, boat, bottles, brown, chease, chesecake, currently, decision, deposit, doll, dress, dressing, dry, escape, escort, following, goo, gotcha, grand, hahahah, heck, hellow, hottie, iced, idk, impressive, item, keeps, knock, kool, lame, leftovers, likewise, lose, maar, mac, manage, messed, mission, mmmmmmm, nactarine, natural, naughty, news, noone, ny, oder, ol, options, originally, pain, pal, park, pas, pc, personality, phew, piep, pinot, plaese, poison, poo, pot, reccomend, refrain, replace, restuarant, restauraunt, robbing, roll, rules, sadly, salt, scary, science, scotland, scrumptious, seating, seats, shirt, sight, sky, slamon, slut, somehow, song, sory, soupe, steaks, stronger, sue, taht, tall, tasting, thak, tony, tower, uniform, usual, waht, wasted, wate, wen, wet, whered, wise, woud, woul, www, yoink [12] abouts, account, acting, address, advice, ahoy, angry, apetite, ar, assure, attractive, awkward, beerb, beg, behavior, belive, book, boys, cent, chesse, chinese, cleaned, clever, climb, club, clumsy, co, command, complain, considered, control, cum, dam, dan, dang, death, deciding, delectable, delish, desk, doo, ello, entre, euh, everywhere, eww, feast, felt, fight, folow, francais, gal, gee, gettin, gimmie, grew, grill, het, himself, horse, hum, immediately, include, keeping, key, known, lazy, leg, lemon, limit, lo, lolol, mcdonalds, million, motherfucker, nights, noo, nooooo, normally, object, oky, particularly, payin, physics, pint, plait, planning, portugal, possibly, pounds, pour, pronto, region, relationship, revoir, rly, robot, rum, sarah, saved, seemed, sent, several, shake, shitty, smoothie, snappy, soft, someday, spahgetti, spelling, sr, stock, store, sur, tag, thans, thinks, thnks, tis, tom, tonite, training, trapped, travel, turns, united, universe, vege, walls, willing, wnat,

wut, yikes [11] aah, added, afterwards, aight, amount, angel, annoying, apologise, arrive, babies, bag, basically, beverages, blame, blueberry, bot, bow, bro, buttsecks, buying, calm, charging, cheeky, cheesecake, chest, chick, client, clue, comp, cooks, cos, costs, crab, cu, cyber, dis, docks, duty, een, egg, ending, ere, everybody, ewww, experiment, exquisite, faith, foot, fork, ga, gotten, grow, grub, guessing, hop, hte, hullo, included, j, jobs, jst, kay, keyboard, land, laws, lettuce, lift, lobster, lolz, maine, matt, mee, menu, missing, monsieur, mountains, movies, mum, naked, nervous, netherlands, niet, nite, nu, oooo, parts, peoples, pic, pieces, plase, plastic, players, power, program, project, q, race, rain, realy, recommendation, review, sa, scare, seeya, sexual, shove, shrimp, sil, similar, simply, snap, sob, software, soul, spare, specific, summer, system, tahnk, tar, thang, theyll, tomato, unusual, upset, valley, ve, vegetable, warn, wild, yknow, yor [10] acceptable, accidentally, ahve, else, anything, anywere, apart, aware, awfully, bah, bank, beauty, berries, bottled, brasil, buh, cak, cali, cars, certianly, che, cheery, chris, clearing, clock, comeing, complementary, confusing, congratulations, controls, den, didn, difference, direct, download, dream, dreams, drugs, dump, ed, ehh, famous, fav, favorites, fellow, field, final, finding, flavor, force, francisco, freaking, fried, frozen, garden, gasp, geez, george, grown, guessed, gurl, gym, ham, hawt, heaven, heheh, hello, helped, hihi, hill, hint, hotel, howd, ihave, insult, ipe, ir, issue, iv, joined, juicy, jumpsuit, kept, kewl, king, kinky, laughs, learned, legal, lied, lies, lik, limited, line, loose, loud, lousy, luesser, mains, mama, mark, mary, master, meh, meny, miles, mw, named, neck, nicely, noir, noodles, nop, nor, offended, offense, ooops, op, option, passed, passing, pays, pelase, pepper, pepsi, pretend, prices, profile, provide, punk, rd, reasonable, recently, regards, reminds, reservations, restrooms, retard, ridiculous, river, salada, salty, satisfied, senior, senor, shows, skills, sounded, spaghetti, spagueti, starve, stove, sucked, sunday, supper, support, tak, takin, tequila, thnaks, thru, trees, tres, tryin, types, v, va, vacation, voice, walked, washington, wer, wher, whys, wierd, windows, workin, woudl, wrote, yuck, yummm [9] above, accountant, admit, allergies, arse, ashamed, av, bananas, beans, berrypie, bf, bi, blend, bless, brain, brains, brooke, browse, calls, canadian, cats, cell, cest, charming, cheat, cheating, chicago, crack, cross, crowded, crying, curse, czech, damage, das, data, daughter, decent, divine, dnt, doke, else, els, enjoyable, everthing, exciting, extremely, excuse, fab, faggot, flat, fok, forever, gday, german, git, gmail, google, government, graduating, grass, gt, hahahahaha, handy, heading, hmmm, holla, horny, hs, hurts, icecream, ich, ii, incredible, instant, interface, jeez, jeff, jor, judge, kan, kiddin, kl, lay, lemonade, lesbian, lil, listed, lob, los, magnon, meaning, message, messy, mins, moves, murder, nada, natalie, nectarines, nectorine, ohhhh, omfg, ops, organic, outfit, pancakes, patience, patient, paul, pe, peeing, pissed, plane, please, pocket, ppl, practice, prick, prove, punch, purpose, push, racist, reserved, rice, rip, rule, salamon, salas, salomon, satisfactory, services, shellfish, shucks, skirt, sleeping, soem, someones, something, sos, sour, spagettie, spin, split, spoon, spring, stake, stalker, standard, starts, steve, stopped, strict, students, suggestion, suits, sushi, swing, tasty, taxi, tells, tes, theif, thi, thingy, thnk, throat, train, uni, vampire, variety, vases, vegan, version, vest, vintage, wanting, weirdo, whatcha, whew, wich, wind, wishes, wonderfull, ww, xx, yall, yess, yoiu, yuo [8] aahh, accidentally, advise, alabama, ant, anything, arms, asks, assist, attend, ave, bang, bartenders, basic, bay, beats, behave, bend, berrie, biatch, brad, brew, budget, bull, burgers, bush, bze, cakes, carrots, cashed, certanly, charles, checked, cheer, cheeseburger, cherries, chew, chill, choosing, chrissy, circus, classic, closest, cobbsalad, colour, connection, cookie, correctly, corse, crappy, crashed, cuppa, cutting, dark, disappointed, dokie, driver, duck, dying, eats, el, ended, epic, et, everyday, everythings, evil, exams, fear, fed, filit, firm, forty, freedom, gaan, ge, gentleman, gots, greatly, grey, guide, hahahaha, har, hardly, heheheh, hero, hier, hilarious, hire, hook, hospital, hospitality, hotmail, iget, imma, impossible, info, ingredients, ireland, irl, jacket, jersey, jogging, killing, laptop, lawyer, lick, lips, lke, lobser, lobster, lovley, mail, major, manners, mature, melissa, memory, messing, mexico, mhmm, michigan, migion, mike, mingnon, mint, missy, mistakes, mix, momentarily, mountain, ms, mz, nao, ni, nl, nog, noon, nooooo, nose, nothin, objectives, okk, onion, ought, outrage, oven, oww, pease, perfection, perfectly, picture, pile, pink, pl, plans, plse, pork, prepares, properly, proud, public, raised, rat, realise, respect, rl, role, saled, sally, scuse, seek, ser, seven, sharing, sheesh, simple, singing, slad, smack, sold, spag, spaggeti, spagghetti, spinning, stat, stiff, stolen, strike, suprise, susan, switch, taller, team, teehee, tempting, tend, thirst, thnak, tight, tipped, token, tongue, tonights, tries, troubles, truly, tx, ull, understandable, understood, upon, urself, vagina, wan, washed, wath, wave, website, weed, weekends, whont, wht, wood, woohoo, worker, worried, yawn, yell, zealard [7] action, actress, advantage, alergic, als, americans, angeles, appropriate, argh, attack, bac, baked, balance, barely, baseball, bere, beside, biggest, bits, bord, britain, buisness, byeeee, cancel, candy, carefull, cares, carried, celebrating, changes, cheak, chees, chery, chese, christine, cigarette, classy, clicked, clouds, coffeee, collect, como, considering, corn, cries, crust, cus, daily, danke, dave, david, dc, decoration, denmark, dessert, distracted, disturbing, dock, dosent, drag, drin, drinker, drove, dull, dumbass, eachother, ear, eatin, edge, eighteen, energy, anything, error, errr, es, est, eten, evenin, excited, exist, expected, eyou, famished, farm, fatty, fifty, filling, filthy, finger, fingers, fist, flattered, flavour, flew, flies, foo, freakin, fro, fucked, garcon, gender, general, georgia, giant, goddamn, goodday, goody, grape, grazie, gtg, gulp, gun, gunna, habit, hablo, hahaa, hahahahah, hai, hanging, hasnt, hates, higher, hitting, hoped, hrm, humm, hunny, ignoring, imported, inappropriate, inspector, interact, invented, isn, jealous, jenny, jessica, jo, joes, jou, junior, kansas, kindness, kyrie, lack, lag, learning, lease, likely, loads, lobster, lololol, loss, lyk, magician, mais, mans, maria, marks, medication, meee, member, mentioned, mhm, michael, midnight, migno, mines, mints, mixed, moar, momma, moms, mug, muy, nectarin, nee, nine, nj, noes, ocean, offcourse, offered, outa, outrageous, pad, painful, parle, partner, peckish, pet, pets, pierre, placed, planet, plays, please, plesae, plis, podium, pray, preferably, president, pricey, pushy, rachel, rawr, realised, recommendations, recommended, record, redo, redy, remind, respond, restraunt, righth, roast, safety, sake, salmo, sausage, sayin, screaming, security, servey, shane, showed, situation, size, skin, slight, slightly, sober, social, somemore, somewhat, spageti, spaghtti, spahetti, specialities, spicy, spotted, spy, squeeze, stare, stood, stool, studies, subject, suggested, suitable, sunny, tae, tail, talkative, tast, tat, teachers, technical, tempted, terrific, thankx, thee, til, tou, towards, trade, tray, tricks, trump, turning, twat, typical, uit, ummmmm, uncle, undercooked, une, unfortunate, unique, urine, vegas, virgin, waited, walmart, war, wassup, wasting, wating, waves, weak, weeee, weekend, welll, wench, weres, whether, whot, whyd, wi, wnt, yahoo, yeahh, yelling, yessir, yous, ys, yur, ze [6] aa, aaaa, abby, abeer, absolutley, according, ack, actual, actualy, ad, adds, agent, ages, ahaa, ahahahaha, alex, alice, analyst, animal, animals, anothe, anything, anywher, apologize, arnt, arrow, artist, athletic, august, awake, awwww, bare, barossa, based, batch, bath, becky, becuase, beerr, beginning, bein, bey, bitches, bloke, boston, brand, bright, bucket, built, byeeeee, cabernet, chardonnay, cheaper, cheapest, cheif, chesecake, chianti, chow, chuckles, church, cleaner, clients, cn, cocktails, coffees, cognac, combination, comment, comped, completed, concept, contact, coob, cookies, costumers, critic, damed, dandy, dank, dating, dentist, department, design, desire, developer, devil, difficulties, dig, directly, disappeared, distance, dit, dive, doe, dolce, donald, dot, dough, dr, draft, dressed, dropping, drug, dumped, eatery, eer, eight, embarrassed, emm, engaged, engineering, enought, entirely, espanol, european, ewwww, ex, example, explore, ey, fart, fastest, featuring, feelings, fella, fielt, fifteen, financial, finished, fishing, flight, flirt, folks, forced, fortune, foul, frankly, fred, freezing, freshest, fruity, frying, gain, garlic, gd, gladly, glitch, gold, gr, graag, grr, guitar, hahha, harm, haw, headed, hearing, hearty, hebben, hehehehehe, helloooo, hellp, hence, heyey, hiccup, hired, history, homosexual, honor, hose, houses, howre, humor, hv, hve, ican, ight, ignore, ike, incase, including, inconvenience, incorrect, indiana, ine, inform, information, insane, intelligence, issues, ist, itd, jaja, jew, jiffy, jim, joel, jokes, joy, kelly, kwl, labor, lager, lapdance, lawl, level, license, lime, listening, lmfao, load, location, lol, lool, lover, luckily, mah, mall, maranara, mariana, maryland, mas, massive, matters, meanie, messenger, mexican, miami, mignons, mijn, mineral, minut, mirror, misunderstanding, mmmmmmm, mon, moron, mrs, mysterious, naar, nam, native, nc, nectar, nectartine, noe, nty, offence, og, okaz, okeydokey, opinion, orderd, orleans, orly, oz, paint, pair, parched, patronage, peek, pennsylvania, pervert, plain, pleaes, poie, porn, portion, post, posted, previous, pro, products, pub, purchase, pure, quest, range, reality, realized, recipe, reg, republic, requested, restart, robber, robots, ruin, runs, russian, ryt, sail, salat, sale, saturday, scene, schools, scientist, screwed, sed, seet, select,

erves, shabby, shack, shag, shifts, shocking, sittin, skinny, slide, slipped, slowly, snack, sniff, sod, sooooo, sopu, sorrrz, sorts, spagehtti, spagethi, spain, spam, speech, spelled, spice, spoke, sprite, stab, staek, staying, stea, steel, stew, studied, suicide, suis, surprised, suspect, sweetcheeks, swell, tah, tale, tally, teas, technically, tee, thanku, thank, therefore, thick, threat, threw, thts, tim, tiny, tofu, toodles, tour, traditional, traffic, trained, treated, turbo, tv, unable, unreasonable, ups, useless, van, vc, veggies, vegi, vet, vie, vino, visited, wah, waiters, washing, wed, weee, whatd, whitewine, wicked, winw, wisconsin, witha, within, wo, woa, wooo, writing, yeap, yey, yoo, youa, ypu, yub, zone, zour [5] actor, addiction, ae, affect, agen, agreed, alan, alaska, alberta, alike, alles, allows, alternative, amen, amenu, amy, anna, answered, answers, anything, apology, appetiser, appetizing, appologies, army, arrange, ash, assistance, atleast, atmosphere, auf, aussie, australian, automatically, avatar, avoid, avoiding, bak, beacuse, bears, beerplease, befor, below, bent, berrz, beter, beyond, bie, bier, billed, bites, bj, blah, blank, blast, bleu, blushing, bomb, boobies, bourbon, bowls, br, breast, brewed, brian, brick, brothers, bu, bub, buhbye, burned, burning, burnt, caffè, captain, carmen, caroline, cashregister, caused, ce, cerry, chalkboard, characters, chase, cheasecake, chec, cheeks, cheesecak, choosen, cliff, cna, coca, cockroach, cofe, combo, complicated, concerned, congrats, consume, contest, cooler, county, cours, couse, cracker, crunchy, cucumber, cuisine, curiosity, custumer, daffodils, daisy, dancer, dangerous, debt, dee, deep, deeply, depressed, dident, digits, dink, doh, dontt, downloaded, draw, dring, dum, dummy, dun, dus, dust, ea, easily, easter, eastern, ei, elses, entered, entertainment, enu, eny, equals, eu, evan, eve, exact, exchange, excellent, fail, falling, favour, fee, finnished, fits, float, fluently, focus, fond, foor, freshen, friday, frm, froze, fuk, funds, galss, gas, geld, generally, gf, gg, gimmi, gnight, gnite, golden, golf, gona, goon, goood, grandma, gratitude, greece, greedy, growing, gues, guests, guns, habe, halp, harassment, harbor, havea, haven, hellooooo, heloo, hesitate, hh, holly, homeless, hu, hump, hundred, hunger, hungry, hurting, hvae, ic, iceland, ideas, illinois, ill, mastered, improve, india, industry, ingles, inglish, int, intend, interest, io, irish, iz, jam, janet, jeremy, jerks, jess, johnny, josh, jur, kicks, killer, lalala, lamb, lass, ld, leads, leftover, lekker, letting, levels, levitating, li, lines, lit, loaded, lobstar, locked, loke, loool, lotsa, louis, lovly, mag, magazine, magical, maincourse, mango, marinar, marinera, mars, mass, match, math, max, meantime, meanwhile, meatball, medicine, meen, memories, ment, mentally, meow, micro, mij, mis, misplaced, mistaken, modern, monday, monster, montreal, mooii, mu, muah, muffin, mull, muscular, mustard, napa, napkin, napkins, ned, nerd, nibble, nigger, nonetheless, northern, nt, nurse, nut, nw, oak, obliged, oblivion, offers, ohhhhh, oldest, om, ont, ooooo, ooooo, opening, orde, original, overs, pa, package, page, pathetic, pea, peas, peruse, peu, philly, picky, piepi, plants, ple, pleace, pleasew, pleaz, plzz, points, poisoned, poisoning, powers, ppie, pplease, preferences, prego, proble, programmer, protection, psst, pulls, puts, queen, rabies, rait, rats, recoment, redr, reds, refils, refreshing, regret, related, relationships, relief, rent, require, responsible, restrount, righ, ringing, ripped, robbed, rolls, romantic, rose, sal, salaad, salda, sales, salid, sallad, salm, sample, saving, scenery, scraps, section, sei, sends, senorita, sensitive, sever, shakes, shaped, sharp, shayla, shipment, sho, shotgun, shure, sidewalk, sim, singer, sirs, sitdown, sixteen, slurp, smaller, smooth, snatch, sneaky, snow, soap, solid, somesing, somethign, sop, sor, spagehti, spaggheti, spaghetta, spank, speed, speak, spender, spill, spilled, spinach, spirit, spoken, spread, stacked, stan, standards, station, stickup, stinks, stone, stories, storm, strawberry, stress, stripper, stud, stuf, success, sucka, suddenly, suggest, summers, sumthin, suop, supervisor, survay, survery, tabl, tacos, tafel, talented, talker, talkin, tarte, tata, tats, taught, teaches, tennessee, thankye, themador, thirty, thisll, thks, thoug, thousand, thr, toi, toothpicks, treating, truck, tthank, turkey, typed, typo, uncomfortable, understanding, user, varietal, ver, via, video, virtually, visa, vu, walks, wank, wanker, warcraft, warning, washroom, watched, watre, wedding, weeeeee, weel, werever, wft, whay, whe, whee, whipped, whistles, whose, whould, wide, wiht, winne, wondered, wanna, woot, wt, wth, wuld, wy, xxx, yeahhh, yeha, yesss, yoghurt, yoru, youi, yourre, youu, youy, yuor, zes, zitten, zo [4] aaaaaaa, aaaah, aan, abou, acutally, adam, addy, advance, aged, agh, agin, agood, agua, ahah, ahahaha, ahhhhhhh, alert, ales, already, alredy, andreza, anithing, ans, ants, anythig, apologizes, appealing, appeared, appointment, appologize, apron, aright, arizona, arranged, arrived, artificial, ashley, ashole, aside, askin, asleep, asparagus, assault, asshat, assistant, assumed, atable, atea, authorities, autumn, avec, average, avocado, ba, babes, backwards, bai, ball, bankrupt, bargain, bars, bathrooms, bber, bck, becomes, beeing, belch, belungs, bene, beautiful, bich, bird, birth, bistro, bitte, bitter, biting, blackboard, blanc, bleh, blushes, bonus, borrow, bottoms, bouquet, boxer, bra, breaking, breaks, breath, brewery, broccoli, brotha, buck, bugger, bummer, bumped, buona, busboy, bushes, cal, calamari, cam, cambridge, cancer, cannibal, capital, caps, cards, casa, cauz, ccan, ceiling, celebrate, century, ch, chap, chasing, cheapo, cheek, chek, chesscake, chicks, chili, chillin, choke, chump, cigarettes, clam, classes, cleared, clown, cnt, coach, cobbler, cobbs, colleagues, comme, commin, companion, compensate, complaining, compulsive, computers, con, confusion, conta, continue, conto, coo, cop, costomer, cou, countries, counts, courtesy, cousin, covered, covers, cowboy, cows, crabs, created, creative, crikey, crotch, cruise, culinary, cuming, daccord, dah, daisies, dashing, dated, dats, dawg, def, definetly, definition, delays, delivery, dem, dentists, der, des, describe, designed, designer, despite, details, developers, devine, deze, diff, diffrent, direction, disappointing, disaster, discover, disease, disgraceful, disguised, dishwasher, disturbance, docter, doent, doesn, doller, donkey, dou, doyou, drinken, drown, dujour, ebay, echt, effects, effort, ehhh, ein, elizabeth, employees, emty, engineer, enjoz, entertaining, entrees, enuff, environment, epi, epic, ermm, erotic, estas, euros, eveing, eventually, everythin, everytime, evry, exception, exelent, expectations, experienced, explains, fa, factor, fags, failed, fairly, fait, fallen, fallow, fanx, fare, farted, fattie, fd, thanks, fi, fifth, figuring, fink, finland, firs, firt, fixing, fl, flesh, fliet, florist, fools, fore, fraid, fre, frickin, frosty, frustrated, fully, gah, garbag, geen, gentle, gib, giggle, girlfriends, glarus, goed, golly, goober, goodburger, goood, gos, grabbed, gracious, grapes, graphic, graphics, grateful, greens, griled, grin, groovy, grumbles, grumpy, gte, gtf, gud, guten, haa, haaa, hace, hahahahahaha, haircut, hank, happening, harry, haste, heads, heated, hed, heee, height, heineken, hello, heyyyy, hez, highschool, hike, hip, hiring, holmes, homie, homo, hoor, horses, hott, hovering, hr, hummm, humph, hungry, hurr, hy, idiots, illegal, illusion, imber, impatient, incident, inconviene, indulge, inspecting, insulted, interactions, intersting, introduce, involve, involved, iron, island, jai, jajaja, jane, janette, japan, jason, jean, jen, jes, jet, jij, jimmy, jolly, joseph, journey, jr, julia, jumped, jumpy, juste, ka, kate, kayla, kentucky, keys, kicked, kiding, knees, knowing, knowledge, knw, knwo, ko, kthxbai, kued, kyou, label, ladies, lagging, laid, languages, las, lawyers, leak, leau, leaves, leavin, les, letter, licked, licks, lifes, lifting, lip, lisa, little, livin, lmaoo, loabster, loading, lobster, lobs, located, lodster, log, loo, losbter, losing, lov, loving, lower, luelinks, luk, lulz, lush, lyrics, maby, maddam, madness, maintain, maker, mal, manchester, manly, market, martinis, marvellous, masculine, masters, medical, meds, meer, melbourne, melted, meneer, mental, menucard, messin, michelle, minus, miranda, miserable, mkay, mmh, model, moet, moi, monies, mor, motel, motherfucking, mroe, mud, multiple, mumbling, mush, musical, mwah, nacterine, nae, naturally, nearby, necessary, neitrine, nederlands, netarine, nickname, nm, nom, nonalcoholic, nono, nonsmoking, noooooo, notch, nou, nyc, objects, officially, okee, okies, oks, olds, operation, ora, orkin, os, oups, ours, par, parent, parler, parmesan, parting, peach, pen, pencil, penny, perv, peter, petit, phil, physical, physically, pice, pickles, piggy, pine, piping, pis, pixels, plaease, planned, pleasent, po, poisonous, positive, powerful, prayers, pre, precious, prefers, prehaps, pretending, print, privacy, private, probleme, profession, professor, promotion, prompt, proof, property, propose, prostitute, protect, protein, ps, psychic, puta, pyramid, quarter, qui, quitting, ranch, raping, rapist, recall, reckon, redwhine, reflect, refund, registers, rekening, rember, remeber, remote, reported, required, res, resaurant, resent, reveal, riddance, rien, righty, rnt, robs, rong, roses, rub, ruined, ryan, safely, sah, salary, salem, salmons, salom, sarcastic, sashimi, satan, satisfying, sauteed, schnell, screwdriver, sd, search, servers, sh, shaken, shi, ship, shiraz, shithead, showing, shutup, silent, silver, silverware, siting, sits, sixty, slices, slip, slompt, smelly, smiling, smith, snail, snake, snakes, sneakers, sneeze, soccer, socks, soep, solved, sono, sooner, sore, sorrow, sorryy, southern, souvenir, sp, spagethi, spagethii, spaghetii, spaghetiii, species, spectacular, spghetti, sphagheti, spose, sta, stacking, stale, stars, starved, starvin, stated, sticks, sticky, strangely, stranger, streets, strive, substitute, sucking, suppose, surgery, surveys, sweden, switched, sworn, tabel,

tahnks, tangerine, tanked, tard, tastier, tavern, tears, teat, teenager, tellin, tere, terets, term, tex, texture, thanku, themselves, thermodor, theyd, thqnks, thus, tic, tick, tidy, tiger, tipping, toasted, toch, tok, tolerate, tomatoes, tommorow, tooo, tourist, toy, tr, travelled, treatment, trek, tt, tyt!, tuesday, tummy, tut, twas, twin, unacceptable, uncalled, underneath, unfortunately, unhappy, upgrade, useful, varietals, vegetable, veggy, veiw, violent, waiter, waitress, wake, wang, warmer, watere, watever, watter, waz, weeeeee, weeeeeeee, weer, weg, weirdest, western, whaddya, whant, whater, wheeeeee, wherver, whie, whip, wiedersehen, wilt, winston, wipe, witch, wite, wold, wolverhampton, wooooo, woooooo, worlds, wots, xp, yas, yeas, yessss, yopu, youe, yourself, yoy, ypur, yrs, yuk, yummi, yummmm, z, zeg, zero, zombie [3] aaa, aaaaa, aaaaah, aaahhh, aahh, abit, absolutly, absynth, abuse, abut, accen, accepted, achoo, acid, actully, adams, additional, admiring, adorable, adress, adult, adventure, afk, africa, african, afterall, afterward, ain, airport, aj, albert, alcoholic, alittle, alley, allora, aloud, alrigh, alrite, alstubleft, alt, altro, amazingly, amber, ambiance, amd, ame, among, amsterdam, anal, ancestors, andrea, andsome, anice, ankle, anns, anoter, anothr, anser, antoher, antonio, anus, aol, apartment, apeterizer, appearance, appetising, apples, appliances, appreciation, appricated, aqui, areyou, argentina, aroma, arrested, arrows, arts, asap, asear, assigned, associate, assuming, asswipe, atm, aub, aunts, austin, avez, awater, aways, awwww, babysitting, background, badly, bagel, bambi, banker, barbie, basement, basil, basketball, bb, bbeer, bc, beast, beautiful, beating, beautiful, became, beee, beery, beet, begging, behalf, behaviour, beleive, belly, belong, benny, bery, beryy, betcha, betta, betty, beware, bibi, biento, biggie, bike, billl, bing, biology, biotch, bizarre, bk, blackett, bleed, bleeding, blew, blink, blocking, blond, blouse, blown, blows, bneer, bo, boats, bod, boi, boiled, bol, bone, boob, booked, books, booth, booty, booz, boredom, bossy, bothering, bounce, boundaries, boxes, brave, brazilian, breakfast, breaky, breat, breathe, britney, bubbly, bubba, bueno, buke, bun, burns, burst, bustier, busted, butcher, butts, buuuurp, camera, cancon, cannibalism, cap, caring, carpet, catching, caucasian, causes, causing, cd, celery, center, central, ces, cha, chaching, chalk, challenge, champagne, champion, changing, charity, charlotte, charmer, chatbot, chateu, cheack, cheddar, cheddar, cheering, cheerio, cheesecake, chekc, cheques, cheryl, chesee, chickens, chicken, chile, choked, chomp, christian, christina, chuckle, chug, cindy, civil, cka, ckeck, clicking, closet, cluttered, cocaine, cocksucker, codd, cofffee, collection, colored, colt, comeback, comfort, comida, communist, companies, complaints, complet, concern, condition, conlan, considerate, construction, consumed, contain, contains, convenient, conversations, coolio, coool, copper, copperfield, corked, cosa, costumes, coul, countryside, coup, cousins, coz, crash, crashes, craving, crawl, crayons, creamy, create, creating, creator, credits, crisis, crockery, croutons, crunk, cuenta, culture, cure, current, cursed, cutlery, daddy, dads, dag, dal, dale, dallas, dangit, danku, dar, daydreaming, daylight, ddrink, deadly, dears, deathly, debil, decaf, december, decor, deer, delaware, delcious, delicacy, delicious, delights, delivered, denver, dere, derick, derset, designers, develop, device, dey, dial, dicks, didt, diego, differnt, digital, ding, dint, diploma, disappear, discipline, discovered, discuss, disguise, disorder, ditch, ditto, divorced, doby, doggie, doggy, dollface, dolls, donde, donna, donw, doomed, doors, dotn, doup, dour, dove, dow, drain, drawn, dred, drik, drill, drives, drops, drums, duel, eager, earl, ears, eated, ebeer, economics, ee, eek, eheh, ehehe, electronics, embarrassing, emnu, emo, employeee, energetic, engine, english, ensure, eraan, escargot, espresso, eta, eternal, etre, euhm, everything, everyone, evilavator, ewwww, exam, exceptional, exclusive, excuses, exists, exited, exotic, expansive, expert, explicitly, exploded, expresso, eyebrows, eyup, faces, facture, failure, fala, fame, familar, families, fantabulous, fantasies, fap, farther, fatass, fate, fatten, features, feelin, fer, fiance, fiber, fiesta, fiesty, fighting, filets, fille, filler, fillets, fills, fult, finance, finds, finished, finishing, fishy, fixed, flattering, flattery, flippin, flipping, floats, flow, flowwers, flustered, forks, fot, fourth, fox, francaise, freeze, frustrating, fu, fuckface, funeral, funky, fur, fuzz, fuzzy, gang, gamish, gather, gbye, gedaan, geek, generic, geography, geta, getcha, geven, ggood, ghost, gie, gimlet, gip, girly, glares, glue, goat, godd, gods, godspeed, goig, gon, goodnite, goods, goof, goofy, gordon, gourmet, grad, grandmother, grat, gratis, greasy, greeting, groups, grrr, grrrrr, guinness, gusta, haev, hahaaa, hahaaaa, hahaa, hahahaah, haldo, halt, hamburgers, hammered, handed, hannah, handsome, happend, hardcore, harvard, hassle, hated, havr, hawaii, hawk, hax, hazard, headache, heavens, heb, heey, hehee, heights, held, hellooo, helloooooo, helmet, herself, heylo, hha, hick, highway, hii, hiii, hiiii, hing, hink, hm, hobo, hoi, holiday, hom, homemade, honour, hoo, horde, host, hottt, hou, house, houswives, hoy, hoz, hre, hthat, htis, hugo, humans, hungary, hungrey, hunt, hunting, ia, ici, icq, idd, identity, ididnt, iep, iepie, iets, iis, ile, image, imagination, immediatly, impress, ina, inches, includes, inconvinience, incredibly, indoors, inedible, infact, informed, infront, ingredient, inhaled, init, innocent, inspection, installation, instructor, insulting, insurance, intelligent, intended, interaction, interactive, interests, international, internets, interview, investment, invite, ip, ironic, ish, itself, ittt, iwill, iwould, iyou, jak, jazz, jeeves, jerkoff, jewels, jj, joey, jog, joker, jonathan, jones, joure, ju, juggle, juggling, june, kanpai, karate, keg, kein, keine, ketchup, kingdom, kissing, kitcken, kitten, kiwi, knee, knocked, kom, korean, kosher, krijg, kung, kus, labster, lad, laddition, laggy, lala, landscapes, lard, larry, later, latest, latte, latter, laura, lesson, lest, letters, levitation, lighter, likee, likw, lily, limits, limp, link, liquid, liquids, liverpool, ll, lmaooo, lobby, lobseter, lobst, locally, lock, loks, lol, lone, looka, loosen, lour, lovely, luke, luv, lv, macaroni, maes, mafia, magnificent, magnum, magon, mai, maiden, mainly, maison, makin, managment, map, maranaria, march, marie, massachusetts, massage, matches, matey, mayb, mayo, mc, meaningless, med, meeeeee, mei, meme, menuuuu, mere, metta, me, mignom, mignot, milady, mildly, military, milkshake, miller, millionaire, minit, minogn, minor, mio, misses, misspelled, mmhmm, mmkay, mn, mode, models, mofo, momen, momento, mone, monica, moo, moon, mornay, mot, motherland, msut, muc, muffins, mugged, munch, muppet, murdered, muscle, muscles, museum, mushroom, musician, mute, muther, nacht, nahh, nap, nas, nate, national, nay, nebraska, necartine, necrarine, nectarinetart, negative, neighborhood, neva, nevar, newspaper, niece, nin, nineteen, ninja, nipples, noble, nods, noisy, noooooo, notify, nova, november, nowadays, noz, nutty, oaky, obey, observe, obvious, oc, occasionally, october, odnt, oe, oeps, ofcourse, offend, offensive, ohhhhhh, ooohhh, ooohhh, ooohh, oop, opium, opposite, oral, oranges, ord, organization, orgasm, othe, ould, ourselves, outrageous, outstanding, ovens, overseas, owned, owns, oxford, pacific, painting, palace, palce, paris, particular, partying, passes, passion, pastry, payd, paz, peaceful, peaches, peanut, peanuts, peekaboo, peie, percent, perchance, period, permission, persons, pete, petes, peut, phd, philadelphia, philippines, philosophy, picks, pics, pictures, pier, pills, pimp, pineapple, pirates, pisses, pit, platter, pleasw, please, plez, pliz, pointless, pointy, political, pool, popped, pops, poptarts, porfavor, portions, posh, potato, pots, pound, preferred, prefrnce, pregnancy, premises, pressing, pressure, presume, prettier, pride, primary, prison, probly, produce, produced, product, proposal, protest, psh, psych, psychiatrist, psycho, psychology, pue, puke, pulled, pulling, pun, purchases, purse, quebec, quer, questionnaire, questioning, quicker, quiz, rabbit, racial, rack, rad, raining, raising, ram, randomly, rank, raped, raven, ray, rdy, reaching, rear, reasons, recommendation, receipt, receive, recent, receipt, recieve, recognize, recommended, recorded, redheads, redred, reduced, reed, refresh, refused, registr, relatively, released, religion, rely, remain, reminder, remodeling, rendered, rep, replaced, replacement, reply, response, restuarnt, result, retrieve, riding, rings, roles, rom, romania, root, rotfl, row, royal, rpg, rudeness, runner, runnin, rustle, sabrina, sacrifice, sala, salard, salmom, salsa, salted, samantha, sammich, sandra, sandwich, sandwiches, santa, saucepan, saucy, saumon, scaring, score, scotia, scotty, scream, seak, sean, secon, secretive, secrets, seizure, selected, selena, selfservice, semester, sentences, seperate, servant, setak, seu, severe, sexist, shagheti, shaking, shant, shirts, shithole, shock, shoo, shopping, shorter, shoud, shoulda, shoulder, shouting, sin, singapore, sins, sirt, sisters, skeet, skill, slack, sleepy, slim, slit, sloshed, sn, snuck, sof, softly, solo, something, songs, sooooo, sophomore, sori, sorry, sould, sow, soy, spa, spagati, spagatti, spagattie, spagette, spagethi, spaghatt, spaghetin, spaghetis, spaghetto, spaghitti, spanking, sparkling, sparta, special, speaker, speccail, speedys, speedy, spegetti, speccails, spel, spher, spiffy, splash, spoons, sports, sporty, spoup, stage, severe, stalk, stalking, statements, stays, steake, stealin, stek, stella, stephen, steven, stfu, sticking, stiffed, stiller, stingy, stinky, stoppit, strangest, stretch, strength, strip, stroll, struggling, stumbled, stunning, sub, subjects, sucky, sugartits, suggesting, suggestions, suk, supe, supporting, suprised, surf, surgeon,

surprising, sux, svp, swearing, sweaty, sweetest, sweets, swimming, swore, sydney, syndrome, syrah, systems, taart, taco, tad, tada, talent, tape, tavolo, tax, tear, tech, telephone, tell, tends, tense, testicles, testing, thailand, thanks, thankies, thankss, thankz, thanls, thant, thatnk, thax, thea, theory, thier, thingie, thirteen, thankyou, thoughts, thought, thre, threesome, throws, ths, thsi, thirsty, tink, tire, tlol, toda, toes, toilets, toke, tone, tons, tont, tonts, tossed, tout, tow, tragic, tranny, traveling, treasure, triple, tripped, tryna, ts, tuck, tune, twelve, twilight, twinkle, twisted, twitching, tyeah, ud, ughhh, uhhhh, uma, umbrella, una, unaware, underage, underwear, ungrateful, uniforms, unlimited, uo, urinate, url, urm, urp, ut, uve, uz, vai, vanilla, vanished, veal, veer, vegeatable, vegetarians, vegie, venezuela, verz, village, vin, vinnie, virus, vita, vol, volgens, vomit, voor, voulez, voyage, waar, waffles, wages, wai, waist, waitre, waitres, waitressed, walke, walker, warmed, warned, wather, watiress, watr, wauw, wc, wealthy, web, websites, weclome, wednesday, wein, welcoem, wenst, werid, werre, wery, whack, whar, whatre, wheat, wheeeeeee, whet, whines, whites, whoah, whold, whoop, wid, wie, wierdo, wii, wijn, wilmington, wime, winer, winks, winr, winter, wir, withe, wiv, wolf, wolves, wone, woods, woood, workout, worrys, wou, wouldn, wouldyou, wounds, wpuld, written, wrk, ws, wter, wts, wuh, wunt, xbox, xcuse, yaa, yar, yeaa, yeaah, yee, yelled, yesh, yno, yoohoo, yorkshire, yougo, youlike, youm, yourwelcome, ythank, yucky, yupp, yuppp, yyes, yyou, zeah, zet, zijn [2] aaaaaaaaa, aaaand, aare, abd, abilities, ability, abomination, abot, abotu, about, abroad, abstract, abt, acapulco, access, accidental, accomodate, accomodating, accompany, accomplished, accountants, accounting, accurate, achtung, acount, acrobat, activities, activity, acts, acually, acum, addicted, addicting, addictive, adding, addition, adesso, adieu, administration, admire, adrink, advances, advertising, afara, affecting, affor, afterdinner, afters, ag, againg, agile, agrilled, ahahah, ahahha, ahha, ahhhhhhhhh, ahm, aid, aieee, aiming, airplane, ak, aked, akward, ala, alaskan, alcohol, alcoholic, alcoholics, alcool, algorithm, alien, alison, alla, allergy, alligator, allision, allo, allowing, allrighty, ally, almighty, almonds, aloha, already, alryt, alter, altogether, ambience, amiga, amminute, amnesia, amuse, amused, amusing, anbd, anda, anders, andrew, andyou, anger, angle, angus, anhow, animation, ann, annie, annoy, ano, anos, annoying, answering, anticipation, antsy, antwerp, anyfing, anything, anytime, anythng, anywheres, anywho, anz, ao, aoup, aout, apatete, apatizer, ape, aperitif, aplogies, apointment, appetite, appitizers, application, apply, appogaise, architect, architecture, areas, argument, ariel, arn, aroun, arr, arre, arrivederci, arround, ars, arsehole, arsenic, artistic, asi, assface, asthma, astronaut, athe, atl, atlanta, atlantic, atrocious, attached, attempt, attimo, auch, aunt, aurevoir, aus, auss, austria, aut, authentic, author, auto, autograph, aux, avatars, awa, awaken, awaz, aweosme, awesomeness, awfull, awhole, az, bab, bacardi, backs, badass, bakersfield, bakewell, balanced, ballerina, balloon, bandaid, banging, banna, banned, barf, bark, barkeeper, barmans, barmen, barn, barrier, barry, base, basis, basura, bbe, bbq, bbye, bday, bea, bead, beam, beaten, beaucoup, beaux, beb, bebe, becoming, beeeeeee, beeeer, beeerb, beerp, beerbeer, beerd, bees, beforehand, begining, begone, behindthe, beijing, belgian, believer, bella, belle, bello, bem, bending, bends, beneath, benissimo, bern, berri, betalen, bethe, betsy, bettys, bible, bid, biertje, bij, bikini, billet, billing, billion, billy, binge, bint, bio, biochemistry, birds, birmingham, biscuit, biscuits, bisogno, bisque, biter, bladder, bland, blanket, blargh, bleach, blech, blending, blessed, blessing, blijven, blimey, bll, bloated, blocks, bloem, bloemen, blog, blondes, blondie, blowjob, blueberries, blunt, blurry, boards, bobs, bodies, boger, bold, bollocks, bond, bonne, boof, boogie, boost, bootle, booye, bordeaux, bore, borrowing, bosom, bothers, botle, boutique, bouts, bows, bowties, boxers, boyardee, boyfriend, boyfriends, brady, braised, brash, brasileiro, brasilian, bravo, brazilians, breakdance, brewski, bribe, bricks, bridge, brighton, brit, broad, brokd, brooklyn, browneyes, bruce, brunello, bruno, bto, bub, buddies, buddz, bude, buenos, buggy, bugs, buisy, buiten, bullshit, bump, bunches, bunny, buns, buon, burbon, burped, busines, bussed, bussiness, bust, butterworth, buttons, buuurp, bwa, bwah, byeeee, byer, byte, bywe, cabbage, cable, cach, caesar, cakce, calculate, calgary, calif, calories, camel, canaria, canhelp, canibal, cans, cantonese, canu, capisco, carbonara, cardboard, cardiff, career, carefully, carlita, carly, carne, carol, carrot, carrying, cashing, casino, cassie, castle, castles, cataracts, catholic, caunt, cavern, cech, celebrity, certified, certinally, cervesa, cf, chack, challenging, chamange, champ, champaign, champain, champagne, champayne, champions, channel, chantelle, char, chardonay, charges, charlie, charm, chased, chaser, chateau, chatin, chatty, cheaks, cheapass, cheapsake, chears, checke, checkout, checkplease, checkpoint, cheecake, cheeers, cheep, cheerios, cheerleading, cheeseake, cheesea, cheeseckae, cheeseckae, cheesesteak, cheeskake, cheeze, cheffy, cher, cherie, cherr, cherrios, cherry, cheseecake, chewing, chewy, chheers, chi, chien, childhood, childish, childrens, chilis, chipped, chk, choking, cholesterol, chooo, chopping, choppy, chops, chowder, christmas, chrisyu, chronic, chuck, chunk, churches, ci, cibo, cinema, cipriani, circles, cities, clarify, claude, claw, clawed, clears, cliente, klik, climbed, clinic, clinton, closely, closes, cloth, clothing, cloud, clubs, clutz, cobbc, coctail, codeword, coem, coff, coffeeee, coffeee, coiming, colada, colder, coli, colleague, collecting, colleges, colleagues, colon, colorado, combine, comedian, comer, comic, comments, communication, community, companionship, compare, compared, compensation, competent, compleat, complement, completly, complex, complimentary, complimentary, compost, compsci, compte, compute, conditions, confidence, confortable, confuse, connais, connected, connections, connor, considerably, consumption, cont, contents, continued, controlling, convenience, convention, convince, convinced, convo, coofe, cooker, coolest, cooling, coop, cooperate, coordination, coors, cope, copy, corners, corrected, cosi, coughs, counted, counters, court, coy, cpa, cpr, cr, crackalacking, crackers, crawling, craziest, creatively, creators, creep, creeped, creeping, crisp, crook, crossing, crouton, cruel, crummy, crunching, crushed, crusty, cruz, crystal, cuanto, cud, cuisinart, culo, cultural, cumin, cumslut, curses, cuss, cust, customar, customors, cutiepie, cuts, cuzz, cycle, dacht, dairy, daj, dakujem, dalla, damit, dammi, dancers, dances, dandelion, danielle, dared, darned, ddint, deadbeat, dealer, dealing, dearest, debating, debbie, debts, decidous, decieving, decisions, declare, decline, decorations, dedicated, deeper, dees, defeat, defying, degrees, dehydrated, deja, dejour, del, delectious, delete, delicios, delight, delte, demanding, denk, dente, dentistry, depart, dept, derby, deser, deserv, deserved, desery, deset, desires, desktop, desrt, desssert, destroyed, deutsch, developed, development, dew, df, dickens, didnot, didu, dieing, dies, dieting, differant, differently, differnet, digest, digestion, digg, dikes, dilicious, dinners, dinning, dire, dirt, disability, disagree, disappearing, disclaimer, discombobulated, disconnected, discounts, discussing, disgrace, dished, disposed, disrespectful, distinctive, district, distro, djour, dno, doctors, dod, dodgy, doen, dogg, doi, dokay, doki, doky, dollors, domestic, donate, doning, donne, dony, doobie, doorway, dor, dork, dorsia, dose, dosnt, douche, douchebag, dovi, dowqn, dozen, dp, dpc, drab, drama, dramatic, drats, drawing, dreadfully, dressin, dri, drinke, drinkl, druck, drunken, drunnk, druuuunk, dud, dujor, duke, dumbells, dumbo, dumps, duno, duper, dustbin, dusty, duuuude, dw, dya, dynamite, eagle, earlyer, eascape, ease, eateries, eau, eccentric, ecco, economy, ecuador, ecuse, eddie, edges, ednet, eer, eeh, eerb, eet, effect, efficient, egregious, egypt, eheheh, ehmm, ehrm, eine, eipe, elaborate, elas, elase, elce, elder, eleven, ell, ella, elle, elope, elvis, emails, embarrassed, emergency, emilion, emily, emotional, enchanting, encounter, eney, enforcing, engagement, englishman, enjoyment, enlighten, enough, entertain, entertained, entry, enuf, environmental, enyoy, enysing, episode, equal, erd, eres, eric, erik, erin, erious, ermmm, ermm, escaped, ese, espana, essex, esta, establishments, este, eternity, etes, ether, eugenio, eugh, euro, ev, evaluation, eveinig, evenings, everithing, evidence, evildude, evning, examine, examines, excellent, excused, exept, exhausted, expanding, explode, exploding, exploring, expression, excuse, extraordinary, extras, exwife, eyed, facilities, factory, faithful, falls, fancypants, fantas, fantastico, fapfapfap, farmed, farts, fatso, fatter, fave, fdp, feces, federal, feedback, feeds, fee, feel, feisty, felit, felling, females, fence, feng, fernanda, ferrari, fields, fiet, figaro, figures, filed, filer, filete, filiet, fillat, fillin, filtet, filwt, fina, finals, fing, fini, finishd, finito, finsh, firts, fisherman, fishermen, fitness, flair, flakes, flash, flee, fleet, fleigh, flet, flip, flirting, floors, floral, flour, flowes, flown, flu, fluent, flowers, fock, folo, foood, foood, foood, football, fora, foreigners, foreplay, forest, forgetful, forgiven, forgotten, forklift, formular, forr, fortified, fortytwo, forum, fourteen, fowl, fr, fransisco, fraud, freebie, freebies, freeeee, freezer, freind, frend, fresher, frig, frige, friggin, frighten, frightfully, frinds, fringe, frink, frisbee, frisky, friut, frosted, fruti, fry, ft, fucktard, fuker, fulfilling, fullscreen, function, fungus, funhouse, funk, funner, funy, gae, gaem, gag, gald, gam, gambling, gamefaqs, gamer, gaming, gangster, ganna,

gardener, gassy, gauti, geeft, geesh, genius, genre, gente, gently, gess, getin, geting, getta, getti, gewoon, gfd, gh, gheti, ghetto, gig, giggles, gilled, gimp, ginger, ginny, giornata, givin, glaasje, glade, glasse, glasss, glassy, glaze, glory, gloves, glss, glued, gna, goal, gobble, goggles, goign, gonan, gonig, goodafternoon, goodbuy, goodlooking, gooey, gooo, goooooood, goooooood, goose, gor, gorgous, gorjeta, gota, goto, gp, grabs, grades, graduatin, grammar, gran, grandfather, grandmothers, gravity, greatday, greate, greatest, greets, grief, grigio, grille, grinding, grins, gris, groans, groundhog, grrrr, grrrrr, grunting, guessin, guinness, gulps, gum, gums, gustavo, gut, guts, gwenna, haaha, hab, habits, hablas, hable, hacve, hagma, hahahaaaa, hahahahahah, hahahahahahahahaha, hahahahahha, hahahahaha, hahahahaha, hahahahaha, hahhah, hail, haired, hairstyle, hairy, halfeaten, hallooo, hammer, han, handicapped, handicaps, handjob, hangin, hangover, hanks, happily, hardest, harhar, harrassment, hash, hasta, haunted, haus, hava, have, hayfever, hd, hea, headin, headless, healthier, heare, hears, heather, hectic, Hector, hedgehog, heeft, heel, heer, heheheheh, hehehe, hehhe, hel, helll, helllllooooo, helllllooooo, hellloooo, helllooooo, helllooooo, helllooooo, hells, heloooo, hem, hen, henry, hense, herbs, herd, heree, herer, hermit, heroin, herpes, heure, heve, hgave, hhah, hhaha, hhahaha, hhehe, hhi, hhmm, hhow, hid, hiiiiii, hik, hiking, hilary, hilly, hits, hittin, hlo, hobbies, hobby, holdin, holidays, hollywood, homer, homework, homey, honeymoon, hong, honk, honored, hooch, hooked, hooker, hoop, hooray, hooters, hopes, hor, horizon, horribly, horrid, hotstuff, hotter, houston, howzat, hqve, hmmm, ht, htat, http, huckleberry, hugs, huhu, hummer, humour, hung, hunh, huni, hunk, hunter, hunters, hurl, hurrah, hurricane, husbands, hussy, hustle, hw, hwat, hwllo, hye, hyper, ian, icant, icarus, icon, idc, ideia, idol, idont, iesi, ig, ignorant, ignores, iii, iim, ij, ijust, illhave, illiterate, ilove, ily, imaginary, imm, immature, imperial, impersonator, imply, importantly, impression, inch, inclined, incompetent, inconveniences, inconvenience, indeedy, indian, indigestion, industrial, ineed, informing, injuries, inner, innocently, innuendo, ino, inquiring, ins, insanely, insisted, inspectors, institute, intense, intensive, interim, interior, interpret, interrogations, interrupting, interst, intrigued, intriguing, intuition, inventive, iowa, iq, ironically, isee, islands, ismy, isso, italiano, itch, itss, iu, iwll, iyes, iyt, jackass, jacked, jackson, jacksonville, jacques, jail, jaket, jako, jamie, january, japanese, jar, jasmine, jawesome, jax, jay, jays, jebus, jeden, jeej, jeepers, jeeze, jeffrey, jelly, jenni, jennie, jep, jer, jewish, jif, jimbob, jin, jocking, johnson, jon, jordan, jose, josephine, jours, jow, jsi, juan, juicer, july, jumping, juor, jup, jure, juss, justice, jw, kalika, kassa, katie, katy, keen, keepem, keisha, kekekekeke, kerri, keyboards, kg, kia, kiki, kisha, kissed, kitties, kkk, kkt, klaar, klant, kleptomaniac, km, knickers, knoe, knowwhat, kobe, koi, koke, komt, kona, korea, kosten, kow, ks, kvety, kyoober, kytky, laa, labas, labels, lachen, ladder, lads, lagers, lags, lah, lahe, lalalala, lalalalala, lambrusco, lamp, lar, larger, laten, latin, latino, laughed, laundry, laut, lava, laying, lbster, leche, leek, legend, lei, leisure, lend, ler, letme, leve, lez, lhave, licour, lying, lier, lighten, lighting, lightning, lights, likea, limonade, lina, linguini, linkin, lipstick, liquidity, lisbon, hate, liter, literally, liver, llamo, ller, lobster, lobster, loco, logged, logging, logic, logs, loike, lok, lolll, lololololol, lololololol, lolyou, lombster, loneliness, lonley, lookat, lookit, lookout, loop, losing, lordaeron, lorfma, lotta, lottery, lou, loudly, louise, lovee, lovel, lovelz, lovelly, lovingly, lowly, lpease, lu, lobster, lucy, lump, lust, luvvy, lz, maan, mabye, macdonalds, mace, machines, madaam, madamme, mademoiselle, margarita, magnetron, magnifique, making, maken, malt, mamma, mamn, managed, managers, mandarin, mandl, mangiare, manhattan, manicure, manner, manu, marathon, margerita, marianara, married, marihuana, marinari, marinata, mario, marked, marmalade, marninara, marty, marys, mast, matched, maudit, maury, maybey, mccartney, mdear, mea, meatloaf, meditate, mediumrare, meeee, meetin, meine, melons, members, menacular, meni, menion, meno, mens, mer, merry, meself, messages, messanger, meta, meter, meth, metro, mgmt, mhave, mhmmm, mian, mice, mich, michelin, mick, microware, microwaves, midlands, migh, migron, mile, millionth, milon, minded, minds, mineraly, mini, minimal, minimum, mino, minors, mintues, minues, minuts, mirana, mirrors, missions, missouri, missus, mixer, mmmh, mmmhhh, mmmmmmm, mnam, mname, mnu, mobile, mocha, mock, moeten, mogan, mognon, mojito, molest, molesting, molto, moneys, mongoose, monsieur, mony, mooie, moonlight, mooore, moove, morels, moreso, mosaic, motherfuckin, moustache, movements, mozes, mt, muhahahaha, muhahahahaha, muto, mumble, mums, munchies, mustnt, mustve, mutt, mutter, mutters, mwaha, mwahaha, mwahahaha, myslef, naah, nachos, naco, nai, nailed, nails, nametag, napis, nathan, nation, nature, natuurlijk, nayhting, nearer, nearest, neather, necatarine, necatrine, necessary, neco, nect, nedd, nederlanders, neer, neighbor, neighbourhood, nein, neisha, nej, nerds, nerves, nervously, neverland, nevim, newb, newport, newscientist, nic, niceeee, nich, nicotine, nie, niente, niether, nifty, niggas, nigh, nightmares, nignon, niinii, nile, nip, nish, nit, nive, nix, nobodys, noce, nod, noi, noises, nonono, nonsense, nookie, noones, nooooooo, normaly, norway, nous, nout, nowwww, ns, nuclear, nude, nudge, num, numb, numbers, numerous, nurses, nursing, nutritious, nuttin, obrigado, occured, oclock, occupation, od, oddly, ofen, offerro, ofzo, ohhhhhhh, ohi, ohk, ohw, ohyeha, oj, oka, okidoki, okkk, okm, okok, okydoky, ole, oliver, omdat, ome, ontario, onze, ood, oof, oohhh, ookay, oooooohhh, oooooooo, oooooooo, oooooooo, oopsie, openings, operate, opie, opportunities, optional, oreder, oregon, orer, organize, ornaments, orrible, osry, othet, ough, oughta, outback, outdoors, outlandish, overcooked, overflow, overhere, overlook, overly, overthere, overworked, owed, owh, owuld, owww, oyyyy, pace, pack, pagare, pages, pai, painted, paintings, pairs, pale, panda, pane, panties, para, parden, pardus, pariu, parked, parles, parlez, parrot, partake, partay, partly, passenger, pastas, paste, pastime, pate, path, patio, patron, payments, payyy, peak, pecan, peculiar, pedo, peed, peepee, peice, peppered, perfer, perfetto, perform, performance, perfume, perha, perhaps, perrier, peru, perve, pest, peta, petty, peux, pey, pff, pffff, pfft, phat, phobia, phrase, piano, pica, picket, picnic, piee, pieee, pigs, pilaf, pill, pilot, pils, pina, pino, pints, pioe, pipe, pir, pirate, pire, pissing, pitch, pitt, piu, piue, pivo, pixelated, plaats, placard, placement, platinum, please, pleaseeee, pleaseeee, pleaser, pleash, pleasr, pleasre, pleasurable, pleaswe, pleasee, pleaseee, pleaseeeeee, pleez, pleqse, plesa, plesse, plesure, plkease, plox, plum, plump, plwase, plx, poco, people, poi, pointing, poisons, pokes, pole, politics, polly, pond, pony, pooped, poorly, popart, porridge, portal, porter, porti, porto, portugese, portugues, posible, positively, possibility, posso, poste, posto, potatoe, potatos, potential, potter, poured, pourrais, powdered, powered, pplz, pra, practical, practicing, prank, prasau, prattville, prease, precarious, precies, preferred, preffer, preppers, premisis, preparation, preparing, preposterous, presence, presentation, pressed, preston, prett, prettiest, prety, prevent, previously, pricing, pricy, priest, principle, pritty, prize, probably, probelm, problamo, processed, processing, procreate, programmed, programming, progress, promised, promote, promoted, pronunciation, proove, proplem, protecting, provided, pry, pu, pubic, puddings, pukes, punani, punctuation, puny, purely, purple, purty, pushing, puss, pwned, py, pyramide, psychology, qualified, quando, quantities, queer, quel, quench, quickie, quiero, qw, races, racket, rae, raincheck, rains, rainy, raise, ralph, ramsay, ramsey, randy, rap, rash, rasist, rating, rea, reached, realli, reallz, rebel, reccoment, receipt, recognise, recommended, recoment, recommended, recompense, recovering, redbull, rede, redi, redre, reduce, reeses, referring, referring, refilled, refreshment, refurbishment, refusing, regard, regester, regi, regist, registrar, regularly, regulars, regulations, rehab, reheat, reject, relate, relative, relatives, relaxed, relaxing, relieve, relieved, remembered, remembering, reminded, rendering, renovated, renovating, renovation, repent, repet, reporting, represent, reputation, reserve, reside, resolved, resourceful, respectable, respectful, responce, responding, restarant, restaruant, restaurant, restless, restrant, restricted, restrunt, restaurnts, ret, retarted, returning, reversal, revise, revision, rew, ribs, richard, rick, ricky, riesling, riight, rik, ripping, risk, rit, rith, ro, roach, roasted, robert, robis, rocked, roep, roger, roleplay, romance, ronald, roommate, rooms, ros, rosso, rotten, roughly, rowdy, rows, rr, rubber, rudy, ruining, runescape, rushed, rushing, rustig, rusty, ry, rying, saa, sacramento, sahara, saint, salald, salate, salinas, salmen, salmin, salmonm, salutes, saman, sammiches, sandolery, sapggetti, sara, sarcasm, sars, sassy, sauv, saves, savior, sb, scale, scelto, scenario, scent, schedule, schon, sciences, scientific, scientists, scoliosis, scored, scoth, scottish, scratch, screams, screenshots, scrummy, scurvyy, scusi, searching, seas, seasonal, seattle, sebastian, secks, secretary, secs, selfish, selling, selves, semesters, sempre, senile, sensible, sentence, separately, september, series, seriousness, servin, session, sessions, seta, sets, settled, settles, seventy, severely, sevice, sexes, shade, shadows, shaggy, shakin, shal, shape, shared, shaved, sheep, shelter, shezams, shine, shipped, shipping, shiffaced, shitting, shoe, shoop,

considers, consilerous, console, constant, constantly, constitutes, constraints, constricting, constructed, constructive, consued, consulting, consumers, consuming, contained, contaminated, contamination, content, contenta, conter, continent, continental, contingency, continoue, continu, continues, continuez, contractor, contractors, contradictory, contributing, contribution, controlled, contract, convain, conveniently, converted, convesation, convict, convinent, convos, convulse, coocaracha, coock, coocked, cood, coofee, coofeeccoffcoofee, cooffee, coofffffee, cookers, cookery, cooki, coolaid, coolector, cooled, coolness, coome, coming, coome, coooollllll, coosinard, cooper, cooperating, cooperative, coarse, coosen, coosinard, copacabana, copeter, copious, coplete, copliments, copmpanynice, copping, coppola, corbin, cordial, cordoroy, corect, cork, corkscrew, corncern, corndog, cornered, cornfields, corny, corporate, corporation, corr, corrcr, correcctly, corret, cosin, cosmo, cosmogony, coss, costermer, costo, costuner, cottage, cotte, cotter, cottonpicking, couch, coudent, coughed, coughing, cought, coulda, couldent, couldn, couldwe, counfuse, counrty, counseling, countertop, counting, countrie, countrybumpkin, countrybumpkinsevenfoureight, coupled, couples, cource, coures, courese, courser, courtesee, courts, cous, couser, cousre, coustomer, coustumer, cout, cove, coworker, coworkers, coze, cozy, cpbb, cqke, cqre, cra, cracka, cracked, cracking, crafted, crafting, crai, cram, cramped, cramping, cramps, cranberry, cranial, cranked, crapped, crappivers, craps, crashing, crasy, crawled, crawlin, crayz, crazed, crazies, crazsy, crazypeople, crazyy, creame, creapy, creater, creates, creepin, creey, creme, crest, crevettes, crevices, crew, crick, cricket, criing, crilleed, crime, cripple, crisps, crispy, critical, critically, criticisms, crizz, crob, croix, crossed, crossroads, crouch, crowdad, crowding, crown, crrey, crucified, crumbs, crumpets, crunch, crustacean, crustesian, crutch, cruton, cryptic, crystalina, crzz, cs, cso, ct, ctarine, ctrl, cual, cuantos, cuase, cube, cubist, cuddlier, cue, cuesta, cui, cuisanart, cuisart, cuisnart, cully, cult, cultivated, cultures, cumbersome, cummin, cumming, cumon, cumonnnnn, cumshots, cunningly, cunt, cuoca, cuoco, cupa, cupboards, cupcake, cupstacker, curacao, curiosity, currency, curricula, curriculum, curry, curtain, curtains, curteous, curve, cushty, cussing, custard, custermer, custmaro, custo, custody, custoer, custoi, customary, customerlol, customerrrrrrrrrr, customise, customr, customer, customor, customore, cuter, cutes, cutomer, cutre, cwater, cwhat, cxountry, cyaa, cyaaaaa, cyanide, cylindrical, cylon, cyinga, cynthia, cyuww, daaa, daaaaaaaamnn, daaaaays, daaaaayyyoooo, daaaaayyyoooo, daaaang, daaaayyyoooo, daar, daarna, dabord, dadadam, dadmakes, daffodil, daffodills, dahh, dahling, daiquiri, dakilo, dakota, dalad, dallors, dalmation, dalring, damagingour, damd, dame, damfdujuvuvkbsghjfklsjklfghaaajdlkhkjasnzbcmnbzvcmmzvmnbc, damien, dammint, damnable, damners, damnnnn, danc, dancar, dandelions, danemark, danged, danger, danicng, daniela, danika, danish, dankeschoen, dankhje, dankje, dankjewel, danks, dankuu, danm, dann, dans, dansen, dansk, dap, daphne, dapper, daquri, darbo, dareye, dargent, daring, darjeeling, darkness, darlen, darren, darwin, daryt, dashers, dasie, dates, datew, dauernd, daug, daugiau, davaj, davexxx, davina, davvero, dawn, daydream, dayis, daysh, dayu, daz, dazze, dba, dd, dday, ddcide, ddddddd, ddddiiddnnnttt, ddeceafff, ddi, ddoing, dduuhh, deak, deals, dealt, deart, deary, debeating, debris, dec, decadance, decarating, deci, decides, decie, deciede, decieded, deciso, declaring, decorate, decorated, decoratih, decorating, decreases, dedication, dedichi, deduct, deducted, deedee, deeeelicious, deefery, deepest, deeppurplesea, default, defeating, defeats, defense, deffinitely, deffintley, defiantaltly, deficile, defies, definatley, define, definitely, definitily, definiria, definite, definitions, definitivamente, defo, defrosted, deftly, degtineles, dehors, dehydration, dein, deinking, deipsly, deirdre, dejourir, dejur, dekuji, delcious, delectible, delej, delema, deleted, deleware, deli, delic, delicacies, delicate, delicias, delicious, delicio, delicioso, delicios, deliciously, deliciousss, delicioussssss, delicious, delicioos, delicioos, delictable, delightfull, delilicious, delious, delire, delishious, delishous, delishus, delisioso, delisos, delisous, deliver, delivering, dellorkin, dellux, deloris, delt, deltime, delue, delusion, delux, deluxe, demad, demeanor, demise, democracy, democrat, demolay, demons, demonstrate, demure, denare, denis, denise, denist, denn, dennis, dennys, dental, dentistryyyy, deny, depend, depending, depens, depiction, depositing, depotism, depp, depravity, depressing, deputy, deranged, derekdaisey, derest, deret, derivative, derivitives, derp, derriere, derrr, desaid, desc, descecrated, descision, described, describes, description, deseart, deseat, deseert, deserrrrt, deserted, desertrs, deserves, deserving, desiato, deside, desided, desidera, desighn, designated, designe, designing, desiray, desired, desirez, deskth, desnt, desolate, desolee, desperate, despise, desrert, desse, desserti, dessertje, dessery, dessetr, dessets, dessrt, dessrts, destert, destined, destract, destroy, destroying, det, detached, detail, detailed, detection, detective, detector, determine, determined, detroit, detto, deucth, deupty, deutsche, deux, devasted, developpe, devi, devilish, devo, dezert, dfdsa, dfg, dfs, dfw, dgf, dgjf, dgoin, dh, dhe, dhrtgs, dht, dhtat, diamond, diamondbacks, diamonds, diane, diaper, diarrer, diasies, dica, diches, dici, dicjs, dickbeard, dickhead, dickheads, dickheed, dickinson, dicksucker, dictate, diddly, diddy, dided, diden, didi, didint, didntunderstand, didntyou, didny, didyoy, didzyasias, diediedie, dietro, dif, difficulty, diffe, differ, different, differen, differences, difficultie, difficulty, diffivcult, difficult, difrence, digestive, digger, diggin, digging, digitally, dihydrogen, diidnt, dike, diky, dildo, dill, dillars, dille, dillema, dillydally, dillys, dim, dimmer, dimwit, din, dina, dindt, dined, dineer, dinener, dinenr, diners, dines, dingaling, dinher, dinna, dinne, dinnerware, dinner, dinosaurs, dio, diooo, dioooo, diooooo, diplomatic, dipper, dipping, dipset, dipshit, dir, directement, directions, director, direkt, dirnking, dirrrrry, dirrty, disabled, disagrees, disapered, disappea, disappered, disapproval, disapproves, disassociative, disasterous, disbanded, disconnected, disconnect, discounted, discovery, discreetly, discrete, discussed, discusting, diseased, diseases, diserves, disgraced, disgust, disgusts, disher, dishy, disicion, designer, disiple, disk, dismissed, disney, disneyland, disorganized, dispenser, displazed, displease, displeased, disposal, dispose, disquisting, disrespect, disrespectin, disrupt, diss, disagree, dissapeared, dissappointed, dissatisfied, dissed, dissert, dissssssgusting, dissszy, distancedinner, distant, distilled, distract, distracting, distraction, distribute, destroyed, distubing, disturb, disturbed, ditzy, diverso, divertido, divided, diving, divorce, dizendo, dizer, dizionario, dizzle, dj, dknorthkorea, dlae, dlike, dmanit, dmore, dmv, dmwahahahahah, dn, dne, dnesni, dnot, doar, dobre, dobreeeee, doc, doch, docters, document, documentary, documents, dodge, dodgers, dododododo, doent, doesent, doest, doet, doevres, dofus, doggies, doggystyle, dogshit, doign, doinn, doing, doings, doinh, doint, doit, doiung, dojete, doka, dokaly, dokedy, dokiey, dokkee, dokken, dolacov, dolarow, dolarz, dollar, dollari, dollas, dollers, dollari, dolores, dom, domain, domdadom, dome, dominicangemini, donals, donated, donc, doncha, dondt, donesol, donn, donnt, dono, donot, donr, dontcha, dontgive, dontknow, dontn, donts, donttouch, dontry, dontwanna, donty, dood, doody, doofus, doolars, doom, dooo, doooo, doooooomed, doorbakken, doot, doozo, doozy, dop, dopey, dora, dorien, doris, dorry, dos, dost, dostanu, dostat, dots, doublecheck, doubled, doubleteeeeff, doubly, doubtful, doubts, doughnuts, douds, dovere, dovrei, downm, downed, downing, downloads, downn, downnnn, downstairs, downtown, downunder, dpo, dpois, dqnitm, dracula, drafts, drafted, dragged, dragon, dragqueen, drags, drained, dramaaaa, dran, drankz, drapes, drat, drawers, dray, dre, dreadful, dreamed, dreaming, dreamster, dreamy, dreg, drenk, dresseing, dresser, dressers, dresses, dressign, dribe, dribk, drie, dried, drift, drifte, driiiiink, drimk, drinck, drind, drinkers, drinkgin, drinkie, drinkin, drinkings, drinl, drinlk, drinx, drip, drips, drimk, driunk, driv, drivebys, driven, drivers, drivethru, drnk, droid, droits, dronk, dronken, dropdown, dropkick, drunkkk, drudgery, druggy, druhe, druk, drukn, drun, drunkard, drunkenness, drunkkkk, drunkkkkk, drunkship, drunkz, drunmkmcaklernal, drunkkkk, dsalad, dsfg, dsg, dsl, dsssss, dt, dthx, duckbeard, duct, duddt, dudes, dudre, dududum, duff, duhh, duhhhhhh, duhj, duing, dullest, dumbkopf, dumby, dumdidumm, dummies, dumping, dumpster, dumster, dundundun, dunnn, dunoe, dunt, dupont, dur, duran, dure, durrry, durty, dusk, dusnt, dusst, dutc, duthch, duties, duur, duurt, duuuuur, duvod, dvd, dvours, dvr, dwarf, dwednesday, dweeb, dwell, dwelling, dwest, dww, dx, dxa, dyas, dye, dyed, dyou, dysentary, dyslexic, dzrt, eaaaagrrrrhhhhh, eaat, eachoth, eady, eagerly, eally, empty, earler, earler, earnerly, earnings, earnt, earthing, earthlings, eas, easat, easiet, eastenders, easting, easier, eate, eaters, eatingg, eatings, eatlets, eatings, eating, eatt, eattuing, eave, eawt, eay, eb, ebbbeer, ebb, ebee, ebeerrrrrrsssb, eber, ebertythink, ebough, ebr, ebtree, ebtter, ebut, ec, ecae, ecak, ecake, excellent, eccoti, eccuse, echoes, echte, ecosystem, ecstasy, ecumenical, ecver, edible, edinburgh, edition, editor, edoing, edredred, eduardo, eesaily, eeee, eeeee, eeeeeat, eeeeeeeaaaaa, eeet, eeexcellent,

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