When DoomJezter Met AngelBlossom: Virtual World Language Use and Real World Identity

Guest Lecture by Dr. Aaron Lawson, SRI International
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Presented by the Department of Communication
Dr. Nick Taylor and Dr. Ken Zagacki
Virtual Environment Real User Study (Verus)

Study of how people interact and communicate in Massively Multiplayer Online Games (MMOGs) -- and what this says about their real life characteristics
VERUS (2009-2012)

1346 participants in schools, public gaming events, and university labs:

- Surveys
- Screen recordings of small-group play in multiple online games
- Interviews
- Observations
- Instrumented play in a specially-designed browser-based online game
The “synchronized swim” of (high-end) MMOG play

How to infer ‘real world’ characteristics from online play when in-game behavior is so informed, constrained and elicited by the design of the particular game?
“GingerJesus”
When DoomJezter Met AngelBlossom: Virtual World Language Use and Real World Identity

Aaron Lawson
SRI International
Speech Technology and Research Lab
About SRI (Stanford Research Institute) International

• Non-profit research institution, created at Stanford University in 1946, currently 2,200 employees

• Wide range of research areas, including
  – Picked site for Disney World in Anaheim, CA
  – Developed Technicolor
  – Tide detergent
  – Invented magnetic ink character recognition (still used on all US checks)
  – Invented computer mouse
  – Invented Ink jet printer
  – Developed first computer network
  – Made first internet transmission (to UCLA)
  – Developed SIRI personal assistant (acquired by Apple in 2010)
Speech Technology and Research (STAR) Lab

- Thirty researchers (with 50% of all SRI’s computer resources!)
  - Combination of engineers, computer scientists and linguists
- Lots of work in speech recognition (speech to text)
  - Spun off the Nuance speech recognition company
- Personal Digital Assistants
  - Developed SIRI and working on LOLA
- Automatic language and speaker identification from speech
  - Doing a lot of work for DARPA and IARPA and government agencies
- Machine translation and making machine translation useful is a major focus.
  - Developed two-way speech to speech translation for the Army
- The future lies in multi-modal research – combining speech, text, video, imagery into something that works
VERUS Background

• This work is part of the VERUS project, which explores the relationship between virtual world (VW) behaviors and real world (RW) demographics

• This presentation provides results, observations and new directions based on analysis of chat data and avatar names across four virtual worlds
  – Guardian Academy
  – Sherwood
  – Second Life
  – World of Warcraft

• Main emphasis has been on two areas:
  – Applying sociolinguistic claims and observations to develop discourse features for characterizing gender within online chat
  – Looking at other linguistic factors, such as choice of avatar name, to detect gender trends
Language Based Features and Rules

• Our language data came from two sources that span several virtual worlds:
  – In-game messaging and chat
  – Character/avatar name choices

• Goal was to develop predictive features that were largely independent of particular VW environments

• Our approach was to generate hypotheses about sub-group behavior based on the established body of linguistic research
  – Idea was that part of the trends in the data could be explained by rules based on real world observed behavior

• We also looked for factors that were unique to virtual world activity
Language Data: From Theoretical Concepts to Rules

- **Women tend to use modal verbs and terms of uncertainty**
- **Men tend to swear and use aggressive language**
- **Females are associated with high frequency sounds like 'sh'**
- **Males are associated with closed syllables and obstruents**
- **Females correlate with nature terms**
- **Males correlate with terms connoting self-aggrandizement**
- **Females are more likely to ask questions**
- **Males are more likely to use command forms**

**Phonology and Sound Symbolism**

**Discourse Analysis**

**Sociolinguistic Theories**

**Hypotheses**

**Avatar names**

**Chat data**

**Features + Machine Learning**

**Rules**

**Avatar names**

**Chat data**

**Features + Machine Learning**

**Rules**
Language and Gender in Virtual World Chat
Background

- This presentation provides results, observations and new directions based on analysis of chat data across four virtual worlds (VW)
  - Guadian Academy
  - Sherwood
  - Second Life
  - World of Warcraft
- **Main emphasis has been on two areas:**
  - Applying sociolinguistic claims and observations to develop discourse features for characterizing *gender* on a *turn* basis
  - Looking at other linguistics factors, such as choice of avatar name, to detect gender trends
  - See if it is possible to detect real world (RW) gender even if VW avatar gender is different
Gendered Speech

• Theoretical Background
  – There is a long history of language and gender studies in the field of sociolinguistics
  – This began with Robin Lakoff in the early 70’s and continues today with research by Deborah Tannen, Deborah Cameron and specifically in computer-mediated language use by Susan Herring.
  – This research makes empirical claims about the differences between male and female speech at the discourse level.

• Research Evolution
  – Early research focus on observing the role of gender in speech as a way of characterizing mens’ vs. womens’ behaviors, be it innate or learned
  – Later work has come to see many of these linguistic differences in speech as manifestations of power, status or role differences, rather than as purely gender-based ones.
Earlier Work on Language and Gender

• Lakoff (1975) Seminal work on language and gender, lays out specific features of women’s speech
  – Hedging, hesitation, uncertainty
  – More polite forms
  – More question
  – Apologizes more
  – More modal verbs (can, could, would, should)

• Tannen (1984, 1994)
  – Student of Lakoff; looks at these factors in terms of dominance in conversation, and not necessarily gender per se

• O’ Barr and Atkins (1980)
  – Found that those characteristics identified as “woman’s language” by Lakoff were not confined to women, but more reflected power differences in a situation
More Recent Research

• Keith and Shuttleworth (2000) Distinguish traits more common to women and traits more common to men
  – Women: more talk, polite language, ask questions, supportive statements, empathy
  – Men: more swears, more insults, give commands

• Herring (1994, 2006)
  – Male: adversariality: put-downs, strong, often contentious assertions, lengthy and/or frequent postings, self-promotion, and sarcasm, name calling, personal insults, challenging “face”.
  – Female: attenuation -- hedging, apologizing, asking questions rather than making assertions, thanking, agreeing
Initial “Top-down” Features for Gendered Speech in the Virtual World

• Feature Motivation
  – Many of the features identified by the field of sociolinguistics has the potential to apply more broadly to gender, leadership, experience in the VW and other areas.
  – Furthermore, this body of work makes specific claims that can easily be tested in our chat data

• Feature Categories
  – Based on a consensus from the literature several categories were used from which features were developed
  – Lexical level: swears, insults, slurs, modal verbs
  – Expression level: uncertainty, apologizing, empathy, questions
  – Inter-turn and discourse level features are clear target and planned for future work
Features Explained

• Lexical Features
  – Swearing: swear words, broken into strong (damn) and attenuated (darn)
  – Insults: generic terms directed at individuals (jerk)
  – Slurs: terms picking out a specific group (homo)
  – Modals: qualifying/modifying verbs (can, should, would, etc.)

• Expression-level Features
  – Uncertainty: not knowing “don’t/don’t know”, “not sure”, surprise, “oh”, etc.
  – Apologizing: Direct -“I’m sorry”, Indirect: “Ooops”, “my bad”
  – Empathy: compliments: “I like X”, “I love”, hope, agreement
  – Questions: any WH-question phrase, phrases ending in “?”

• In total these features occurred in 1,464 turns.
Description of Results

• Analysis Approach
  – Given the expression of a feature, what is the probability that the turn came from a male or female?
  – The unit of analysis is the turn, rather than all the turns for a given player

• Interpretation
  – These results are expressed as precision for a single feature, to provide an understanding of how each element might contribute to a predictive model of gender
  – Because the probability of a male turn (55%) is higher than a female turn (45%) a further chart shows the adjusted predictive power of the feature
Results: Scaled Contribution of Features

Absolute Probability above Random For Each Feature

Random

- Uncert: 0.15
- Strong Swears: 0.05
- Light Swears: 0.07
- Insults: 0.00
- Slurs: 0.44
- Question: 0.09
- Modals: 0.08
- Empathy: 0.11
- Strong Apology: 0.14
- Indirect Apology: 0.06
Gender: Discussion

- **Socio-linguistic predictions about gender and language**
  - The “top-down” application of generic findings from the linguistic literature do generalize to the VW language to a certain extent
  - This is a bit surprising since the genres are quite different, though they are both “conversational”

- **Analysis**
  - Most important features in this data were higher-level, non-lexical traits, such as uncertainty, empathy and strong apologies
  - Though slurs were highly predictive, they were relatively scarce compared with the expression-level features
  - Of interest is the difference between direct and indirect apologies, men robustly favored indirect apologies, which women were much more direct in this area.
Predicting Age from Chat
Age Analysis of Chat

• Looked at typographic and linguistic factors to identify features that pattern clearly with an age group

• Looked at issues dealing with
  – Lexicon (word choice)
  – Orthography (capitalization, special characters)
  – Punctuation (commas, ellipsis, etc.)
  – Grammatical elements (pronouns)
  – Phatic elements (emoticons, laughter)

• We broke the data into three age groups:
  – 1-Under 18 (Youth)
  – 2-18-24 (Yough Adult)
  – 3-Over 24 (Adult)
Some Age in Chat Conclusions

* For groups 1 and 2, use of lowercase “i” for “I” and “u” for “you” is 20-30% greater than for adults.
* Adults tend to use personal pronouns at a higher rate than youth
  * Group 3's use of pronouns is double group 1's.
* Adults are twice as likely to use traditional emoticons as minors and 3-4 times more likely to use ellipsis
  * However, emoticons such as :D :P not used by adults but are fairly common among youth (2.2%)
* Likelihood of using two or more special typographic characters in a row is doubled for adults/young adults vs minors.
Some More Age in Chat Conclusions

- Minors tend to use **single word utterances** at a rate almost double adults and to use **shorter phrases** in general.
- Minors tend to use more **uppercase** (shouting) words and are less likely to use **final punctuation and commas**.
- There is also an interesting variation in **laughter**:
  - The use of ‘lol’ is consistent across all age groups
  - ‘haha’ is just as frequently used among minors and young adults, but is very rarely used by adults.
- The older one is, the higher the use of proper **contractions** “im” vs “I'm”
# Socio-linguistic Chat Trends for Gender and Age

<table>
<thead>
<tr>
<th>Behavior</th>
<th>Class</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedging/Uncertainty</td>
<td>Female</td>
<td>Questions, ‘I don’t know’</td>
</tr>
<tr>
<td>Command forms</td>
<td>Male</td>
<td>“Heal me!”</td>
</tr>
<tr>
<td>Use of slurs</td>
<td>Male</td>
<td>“You homo!”</td>
</tr>
<tr>
<td>Direct apologies</td>
<td>Female</td>
<td>“I’m sorry”</td>
</tr>
<tr>
<td>Indirect apologies</td>
<td>Male</td>
<td>“Ooops”, “my bad”</td>
</tr>
<tr>
<td>Empathy</td>
<td>Female</td>
<td>“I like X”, “u OK?”</td>
</tr>
<tr>
<td>Use of modal verbs</td>
<td>Female</td>
<td>can, could, would, should, etc.</td>
</tr>
<tr>
<td>Use of all caps</td>
<td>Youth</td>
<td>“STOP BEING DUMB”</td>
</tr>
<tr>
<td>Frequent use of ellipsis</td>
<td>Adult</td>
<td>“if you bring up your questlog...”</td>
</tr>
<tr>
<td>Using commas, apostrophes</td>
<td>Adult</td>
<td>“we're done. let's turn in”</td>
</tr>
<tr>
<td>Lowercase ‘i’ for ‘l’ and ‘u’ for</td>
<td>Youth</td>
<td>“u losted to 4 pokemno”</td>
</tr>
<tr>
<td>‘you’</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single word utterances</td>
<td>Youth</td>
<td>“come”, “yo”</td>
</tr>
</tbody>
</table>
Lots in a Name: Avatar Names in the Virtual World
Avatar and Naming Features

• In the VW, every participant chooses an avatar or character, which can be either male or female.
• Our goal in this part of the study was to use the avatar name as a source of data to identify RW gender using phonological factors, semantic factors, etc.
• Additional goal is to use the features developed for gender ID based on avatar names to identify the gender of those whose RW gender and VW gender is different.
• Since avatar names are minimally VW dependent they also make for carriers of ‘traveling characteristics’ that enable individuals to be traced across different VW environments.
Avatar Naming Conventions

• Avatar feature development was informed by sound symbolism research, linguistic trends in RW naming, and observation of trends.
  – Ford vs Chevrolet phenomenon
  – Female names ending in ‘a’ in many European and Semitic languages

• A total of 24 different behavioral indicators were developed based on naming
  – Cover factors such as capitalization, numbers and special characters and relationship to RW names and words

• Some of these are highly predictive on their own, while other contribute in conjunction with other observables

• Most of these trends apply across VW environments
## Initial Avatar Rules from Phase 1 Data

<table>
<thead>
<tr>
<th>Rule</th>
<th>Gender</th>
<th>Rule</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Female</td>
<td>Ends in “a”</td>
</tr>
<tr>
<td>2</td>
<td>Male</td>
<td>Ends in back vowel</td>
</tr>
<tr>
<td>3</td>
<td>Female</td>
<td>Ends in “y”</td>
</tr>
<tr>
<td>4</td>
<td>Male</td>
<td>Ends in “er”</td>
</tr>
<tr>
<td>5</td>
<td>Male</td>
<td>Ends in back or alveolar stop</td>
</tr>
<tr>
<td>6</td>
<td>Male</td>
<td>Ends in any consonant</td>
</tr>
<tr>
<td>7</td>
<td>Male</td>
<td>Ends in fricative consonant</td>
</tr>
<tr>
<td>8</td>
<td>Male</td>
<td>Begins with capital letter</td>
</tr>
<tr>
<td>9</td>
<td>Male</td>
<td>Contains “x” or “z”</td>
</tr>
<tr>
<td>10</td>
<td>Female</td>
<td>Contains palatal fricative “sh”</td>
</tr>
<tr>
<td>11</td>
<td>Male</td>
<td>Contains title of nobility</td>
</tr>
<tr>
<td>12</td>
<td>Male</td>
<td>Is a male census name</td>
</tr>
<tr>
<td>13</td>
<td>Female</td>
<td>Is a female census name</td>
</tr>
</tbody>
</table>
Best Performing Single Naming Features on all Instrumented VWs (N=977)

<table>
<thead>
<tr>
<th>Rule</th>
<th>Class</th>
<th>P</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is female name</td>
<td>F</td>
<td>100%</td>
<td>8%</td>
</tr>
<tr>
<td>Contains female name</td>
<td>F</td>
<td>97%</td>
<td>16%</td>
</tr>
<tr>
<td>Ends in “a”</td>
<td>F</td>
<td>74%</td>
<td>23%</td>
</tr>
<tr>
<td>Contains special character (new rule)</td>
<td>M</td>
<td>84%</td>
<td>5%</td>
</tr>
<tr>
<td>Contains male name</td>
<td>M</td>
<td>83%</td>
<td>7%</td>
</tr>
<tr>
<td>Ends in back, stop consonant</td>
<td>M</td>
<td>77%</td>
<td>15%</td>
</tr>
<tr>
<td>Contains ‘x’ or ‘z’</td>
<td>M</td>
<td>76%</td>
<td>8%</td>
</tr>
</tbody>
</table>
Avatar Results Combining Best Rules

- For evaluation purpose we are using precision and recall measures, ‘best’ rule set was determined by prioritizing precision over recall

<table>
<thead>
<tr>
<th>Rule Set</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Female Rules</td>
<td>.75</td>
<td>.59</td>
</tr>
<tr>
<td>All Male Rules</td>
<td>.71</td>
<td>.81</td>
</tr>
<tr>
<td>Best Female Rules</td>
<td>.75</td>
<td>.59</td>
</tr>
<tr>
<td>Best Male Rules</td>
<td>.78</td>
<td>.70</td>
</tr>
</tbody>
</table>
Gender Switchers

• Let’s apply these rules to participants whose RW gender and VW gender are different
• Can we still detect the RW gender? Do they change their avatar naming behavior when they change gender?
• Results:
  – Applying the same rules we find that the pattern is largely the same as with matched gender avatars

<table>
<thead>
<tr>
<th></th>
<th>P</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female/Female</td>
<td>.75</td>
<td>.59</td>
</tr>
<tr>
<td>Male/Male</td>
<td>.78</td>
<td>.70</td>
</tr>
<tr>
<td>Female/Male</td>
<td>.71</td>
<td>.71</td>
</tr>
<tr>
<td>Male/Female</td>
<td>.76</td>
<td>.74</td>
</tr>
</tbody>
</table>
Traveling Characteristics: Avatar Naming across Virtual Worlds

• Avatars are the primary means by which players navigate and interact in most virtual worlds.
• Players choose what to name their avatars and this allows for a certain level of personal continuity and identity across virtual environments.
• One might expect that this could take the form of reusing names, or devising names that share some elements in common with past avatar names.
• In this study quantitative analysis was performed to determine the extent to which avatar names maintain cohesion for the same player across multiple sessions.
Avatar Naming Example

• This user shows many of the kinds of ‘traveling’ behavior we identify
  – Palabill
  – UncleBill
  – Itfunclebill
  – 2tfluffy
  – Im2tfrost
  – 2tbehindyou

• This type of character repetition was observed across many individuals, as well as semantic repetition
  – Im2tfrost
  – 2tbehindyou
  – Biilyy
  – Parusensis
  – Killsforfood
  – Priestigans

Approach to Analysis

• Our goal was to quantify theses traveling characteristics to identify how prevalent this practice was across gamers

• Looked at the co-occurrence of two character strings (bigrams) across names from same RW identity and random RW identity

• Used number of bigrams per name pair to measure cohesion.
Same Player Player vs. Random Name Comparison

Difference in Subsegments Shared per Name between Avatar Names from the Same RW Identity vs. Random

Average 83% greater characters in common for same vs. different

<table>
<thead>
<tr>
<th></th>
<th>Same</th>
<th>Random</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>2.9</td>
<td>0.66</td>
</tr>
<tr>
<td>F</td>
<td>3.4</td>
<td>0.53</td>
</tr>
<tr>
<td>Ave</td>
<td>3.2</td>
<td>0.59</td>
</tr>
</tbody>
</table>

VERUS™
SRI International
Multi-Modal Rules
Rule Combinations across Modalities

• The VERUS project acquired data not just from names and text chat, but from movement, combat, questing and economic activity.
• Our final rules combined information from all these modalities to make a prediction of the player’s attributes.
• This required thinking globally about all we had discovered about VW activity during the course of the project.
• We ended up with several “meta-hypotheses” to help explain why certain phenomena predict certain categories when combined.
Language Rule Combination: Age

- Very young participants tend to use a ‘telegraphic’ chat style with low use of articles and other grammatical particles, low use of overt pronouns (when the meaning is understandable), and frequent use of “shouting” (all CAPS) in both names and chat.
- Adults have a chat style that conforms much more closely to standard written language, use of overt pronouns, qualifiers and articles, and flourishes of written language such as ellipses, etc.

<table>
<thead>
<tr>
<th>Rule</th>
<th>Class</th>
<th>P</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avatar name is all caps + low use of articles</td>
<td>Youth</td>
<td>92%</td>
<td>12%</td>
</tr>
<tr>
<td>Frequent use of articles but low use of pronouns</td>
<td>Young Adult</td>
<td>80%</td>
<td>20%</td>
</tr>
<tr>
<td>Frequent use of both articles and qualifiers/tentative language</td>
<td>Adults</td>
<td>83%</td>
<td>14%</td>
</tr>
</tbody>
</table>
Rule Combination: Minors and Socio-Economic Status

• Those with low SES display ‘neophyte’ gaming behaviors, due to lack of access to gaming experience/PCs because of socio-economic factors
  – This manifests itself with ‘noobie’ behavioral traits, such as strong RW impact on avatar name choices and dueling other players
• Those with high SES exhibit game behaviors associated with experienced gamers
  – This includes ‘abstract’ or non-RW based naming conventions and group-based gaming activities

<table>
<thead>
<tr>
<th>Rules</th>
<th>Class</th>
<th>P</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very high arena kills + avatar name contains dictionary word</td>
<td>Low</td>
<td>83%</td>
<td>20%</td>
</tr>
<tr>
<td>Avatar name contains number + avatar name contains dictionary word</td>
<td>Low</td>
<td>80%</td>
<td>16%</td>
</tr>
<tr>
<td>Lots of time spent in group or lots of questing or abstract avatar name</td>
<td>High</td>
<td>81%</td>
<td>94%</td>
</tr>
</tbody>
</table>
Native Speaker

- Native speakers are captured by combining two rules from the chat behavior rules.
- High frequency of utterances conforming to a ‘good syntax’ measure were correlated with native speakers
  - This was derived using the confidence measures from part of speech tagging
- High use of expressive, florid or adjective-rich lexicon, based on high DAL score for imagery and expressiveness

<table>
<thead>
<tr>
<th>Rule</th>
<th>Class</th>
<th>P</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>High global good syntax + high use of expressive lexicon</td>
<td>Native Speaker</td>
<td>83%</td>
<td>12%</td>
</tr>
</tbody>
</table>
Conclusions and Next Steps

• Classic socio-linguistics literature provided a lot of good ideas that held true in the VW environment.

• This was also true of ideas taken from the sound symbolism research (Jespersen, Ohala among others)

• Most interesting aspect was the utility of “little things”: names, punctuation, use of emoticons, orthography, duration and capitalization were also very useful.

• Much more that can be done with names! Currently planning to use Wikipedia and other free resources to produce features based on general cultural phenomena and intertextuality.

• Pronouns are an area that showed some strong age dependencies, 10-13 year olds seem to be exhibiting “acquisition of literacy” effects.