From Language to the Mind: Learning to Read Deception, Connotation, and Literary Success

Yejin Choi
Computer Science & Engineering

UNIVERSITY of WASHINGTON
Three Different Layers of Reading

- Information
- Intent
- Identity

Reading the author’s mind
films are if anyone wants to help dig under the snow for them."

Soon a small party with a lantern dashed out into the howling darkness where Blackie's memory suggested that a box of film had been left during the rush to get settled for the winter. Working like wild men to beat the cold, they dug a hole six feet deep into the snow and finally located the missing box.

The show, an old Charlie Chaplin release, was given right there in the mess hall where a stove and the kitchen filled half of one side of the room and bunks lined the other side. In the center was a long table and on either side of this were benches. Those in the crowd that were too young to sleep in the upper bunks were47, they crowded onto the long table below.

What was said about the actors and actresses would have made them forget their cues could they but have heard. Comments were rough. If the members of the expedition didn't like anyone on the screen they told him so in unmistakable terms of disapproval. Often they named the actors after some of those present, and yells of derision greeted their appearance on the screen. For instance, "Bill" Vander Veer, on account of his...
films are if anyone wants to help dig under the snow for them.”

Soon a small party with a lantern dashed out into the howling darkness with a Blackie's men's soup and a box of tea. They had to hunt for the entrance and when they found it, they were met with a wall of cold that was pushing like wild men to beat the cold, they dug a hole six feet deep into the snow in a circle and the wind blew.

The show, an old Charlie Chaplin release, was given right under the ice. The room was packed and the smell of one side of the room and bunks lined the other side. In the center was a fire that had been going all night. There were benches. Those who could not sit anywhere else stretched out on the upper benches. They could not read and the wind blew below.

When the fire died down, they decided to leave. One made them forget their coats and they had heard. Over the road were rough. If they told him so in unmistakable terms of anyone on the screen. For instance.

Alexa Wilding

Alexa Wilding was one of the favourite models of the Pre-Raphaelite artist Dante Gabriel Rossetti, featuring in some of his finest paintings of the later 1860s and early 1870s. Wikipedia

Born: United Kingdom

People also search for

Fanny Cornforth  Jane Morris  Elizabeth Siddal  Annie Miller

Total Tweets: 22,365
films are if anyone wants to help dig under the snow for them.”

Soon a small party with a lantern dashed out into the howling darkness where Blackie’s memory suggested that a box of film had been left during the rush to get settled for the winter. Working like wild men to beat the cold, they dug a hole six feet deep into the snow and finally located the missing box.

The show, an old Charlie Chaplin release, was given right there in the mess hall where a stove and the kitchen filled half of one side of the room and bunks lined the other side. In the center was a long table and on either side of this were benches. Those who could not sit on the benches stretched out on the upper bunks where they could lean against the heads of those below.

What was said about the actors and actresses would have made them forget their cues could they but have heard. Comments were rough. If the members of the expedition didn’t like anyone on the screen they told him so in unmistakable terms of disapproval. Often they named the actors after some of those present, and yells of derision greeted their appearance on the screen. For instance, “Bill” Vander Veer, on account of his
framing in media & political discourse (Yano et al., 2010) (Recasens et al., 2013)

dodging (Nguyen et al 2013)

hedging (Choi et al. 2012) (Ganter and Strube, 2009) (Kilicoglu and Bergler 2008)

syntactic packaging
"My toy broke"
instead of
"I broke my toy"
(Greene and Resnik 2009)

dodging (Nguyen et al 2013)

hedging (Choi et al. 2012) (Ganter and Strube, 2009) (Kilicoglu and Bergler 2008)

syntactic packaging
"My toy broke"
instead of
"I broke my toy"
(Greene and Resnik 2009)

dodging (Nguyen et al 2013)

hedging (Choi et al. 2012) (Ganter and Strube, 2009) (Kilicoglu and Bergler 2008)

syntactic packaging
"My toy broke"
instead of
"I broke my toy"
(Greene and Resnik 2009)

syntactic packaging
"My toy broke"
instead of
"I broke my toy"
(Greene and Resnik 2009)
films are if anyone wants to help dig under the snow for them.”

Soon a small party with a lantern dashed out into the howling darkness where Blackie’s memory suggested that a box of film had been left during the rush to get settled for the winter. Working like wild men to beat the cold, they dug a hole six feet deep into the snow and finally located the missing box.

The show, an old Charlie Chaplin release, was given right there in the mess hall where a stove and the kitchen filled half of one side of the room and bunks lined the other side. In the center was a long table and on either side of this were benches. Those who could not sit on the floor crowded out on the upper bunks where they would peer down at the heads of those below.

What was said about the actors and actresses would have made them forget their cues could they but have heard. Comments were rough. If the members of the expedition didn’t like anyone on the screen they told him so in unmistakable terms of disapproval. Often they named the actors after some of those present, and yells of derision greeted their appearance on the screen. For instance, “Bill” Vander Veer, on account of his
authorship verification

authorship obfuscation

demographics: gender, nationality, age, vocation

personality, psychological state: happy, authoritative, depressed...

intellectual traits & development: literary success
From Language to the Mind
From Language to the Mind

Is it even possible? (without full semantic understanding)

- It is more about “HOW” it is said than “WHAT” is said.

“HOW” it is said
i.e., Writing Style

Information
“WHAT”

Intent
“WHY”

Identity
“WHO”
Is it even possible? (without full semantic understanding)

⇒ It is more about “HOW” it is said than “WHAT” is said.

(Harpalani et al., ACL 2011)

• Wikipedia
  – Community-based knowledge forums (collective intelligence)
  – anybody can edit
  – susceptible to vandalism --- 7% are vandal edits

• Wikipedia Vandalism
  – ill-intentioned edits to compromise the integrity of Wikipedia.
  – E.g., irrelevant obscenities, humor, or obvious nonsense.
Wikipedia Vandalism

<Edit Title: Harry Potter>

- Harry Potter is a teenage boy who likes to smoke crack with his buds. They also run an illegal smuggling business to their headmaster dumbledore. He is dumb!
Wikipedia Vandalism

<Edit Title: Harry Potter>
- Harry Potter is a teenage boy who likes to smoke crack with his buds. They also run an illegal smuggling business to their headmaster dumbledore. He is dumb!

<Edit Title: Global Warming>
- Another popular theory involving global warming is the concept that global warming is not caused by greenhouse gases. The theory is that Carlos Boozer is the one preventing the infrared heat from escaping the atmosphere. Therefore, the Golden State Warriors will win next season.
Wikipedia Vandalism

<Edit Title: Harry Potter>
• Harry Potter is a teenage boy who likes to smoke crack with his buds. They also run an illegal smuggling business to their headmaster dumbledore. He is dumb!

<Edit Title: Global Warming>
• Another popular theory involving global warming is the concept that global warming is not caused by greenhouse gases. The theory is that Carlos Boozer is the one preventing the infrared heat from escaping the atmosphere. Therefore, the Golden State Warriors will win next season.
Wikipedia Manual of Style

Formatting / Grammar Standards:
- layout, acronyms, punctuations, etc

Content Standards:
- *Neutral point of view*,
- *No original research* (always include citation)
- Verifiability
- “What Wikipedia is Not”:
  - propaganda, opinion, promotion, advertising
<Edit Title: *Harry Potter*>  
- Harry Potter is a teenage boy who likes to smoke crack with his buds. They also run an illegal smuggling business to their headmaster Dumbledore. He is dumb!

<Edit Title: *Global Warming*>  
- Another popular theory involving global warming is the concept that global warming is not caused by greenhouse gases. *The theory is that* Carlos Boozer *is the one preventing* the infrared heat from escaping the atmosphere. *Therefore*, the Golden State Warriors *will win* next season.
1. N-gram Language Models
   -- most popular choice

2. PCFG Language Models
   -- Chelba (1997), Raghavan et al. (2010),

\[
P(w_1^n) = \prod_{k=1}^{n} P(w_k \mid w_{k-1})
\]

\[
P(w_1^n) = \prod P(A \rightarrow \beta)
\]
Writing style: can detect vandalism better

Heuristics: keywords, spelling, ...

+ shallow lexicosyntactic (Wang and McKeown 2010)

Baseline: 52.6
Baseline + ngram LM: 53.5
Baseline + PCFG LM: 57.9

+ deep syntactic (Our work, ACL 2011)
From Language to the Mind

Is it even possible? (without full semantic understanding)

• It is more about “HOW” it is said than “WHAT” is said.
• We --humans-- also often rely on “overall impression”.

“HOW” it is said
i.e., Writing Style

Information
“WHAT”

Intent
“WHY”

Identity
“WHO”
We --humans-- also often rely on “overall impression”.

Part sculpture, part table, all artisanal. Craftspeople in Jaipur, India, hand carved the delicate rosettes on this low-lying solid mango wood table, which takes its original inspiration from a ceremonial stool used by Bamileke royalty in the African country of Cameroon.
Part sculpture, part table, all artisanal. Craftspeople in Jaipur, India, hand carved the delicate rosettes on this low-lying solid mango wood table, which takes its original inspiration from a ceremonial stool used by Bamileke royalty in the African country of Cameroon.
Part sculpture, part table, all artisanal. Craftspeople in Jaipur, India, hand carved the delicate rosettes on this low-lying solid mango wood table, which takes its original inspiration from a ceremonial stool used by Bamileke royalty in the African country of Cameroon.
From Language to the Mind

Is it even possible? (without full semantic understanding)

• It is more about “HOW” it is said than “WHAT” is said.
• We --humans-- also often rely on “overall impression”.

Computers at times can do better than humans!
What is “Writing Style”? 

"HOW" it is said i.e., Writing Style

Information "WHAT"

Intent "WHY"

Identity "WHO"
“So how can you spot a fake review? Unfortunately, it’s difficult, but with some technology there are a few warning signs:

“To obtain a deeper understanding of the nature of deceptive reviews, we examine the relative utility of three potentially complementary framings of our problems.

“As online retailers increasingly depend on reviews as a sales tool, an industry of fibbers and promoters has sprung up to buy and sell raves for a pittance.”
What is “Writing Style”? 

Genre Categorization:
Petrenz and Webber, 2011; Finn et al., 2006; Argamon et al., 2003; Kessler et al., 1997

Authorship Attribution:
Holmes 1985, Raghavan et al., 2010; Koppel and Shler, 2004; Gamon, 2004;

Many more possibilities...
Swanson and Charniak, 2012; Xu et al., 2012; Iyyer et al., 2014; Hardisty et al., 2010

“HOW” it is said i.e., Writing Style

Intent: “WHY”
Identity: “WHO”

Alan Ritter
From Language to the Mind

Outline of the talk:

"HOW" it is said i.e., Writing Style

Information "WHAT"

Intent "WHY"

Identity "WHO"
From Language to the Mind

Outline of the talk:

I. Deceptive Reviews and Essays
II. Success of Novels
III. Connotation of Words

“HOW” it is said
i.e., Writing Style

Information
“WHAT”

Intent
“WHY”

Identity
“WHO”
Motivation

Online reviews = shopping tool

Potential target for fake reviews!
“My husband and I stayed at the James Chicago Hotel for our anniversary. This place is fantastic! We knew as soon as we arrived we made the right choice! The rooms are BEAUTIFUL and the staff very attentive and wonderful! The area of the hotel is great, since I love to shop I couldn’t ask for more! We will definitely be back to Chicago and we will for sure be back to the James Chicago.”

Deceptive or Truthful?
“My husband and I stayed at the James Chicago Hotel for our anniversary. This place is fantastic! We knew as soon as we arrived we made the right choice! The rooms are BEAUTIFUL and the staff very attentive and wonderful! The area of the hotel is great, since I love to shop I couldn’t ask for more! We will definitely be back to Chicago and we will for sure be back to the James Chicago.”

“I have stayed at many hotels traveling for both business and pleasure and I can honestly say that The James is tops. The service at the hotel is first class. The rooms are modern and very comfortable. The location is perfect within walking distance to all of the great sights and restaurants. Highly recommend to both business travellers and couples.”
Gathering Data

• Label existing reviews?
  – Can’t manually do this
Gathering Data

• Label existing reviews?
  – Can’t manually do this

☐ Instead, create new reviews
  – By hiring people to write fake positive reviews
  – Amazon Mechanical Turk
    • 20 hotels
    • 20 reviews / hotel
    • Offer $1 / review
    • 400 reviews
How good are humans in detecting deceptive reviews?

- 80 truthful and 80 deceptive reviews
- 3 undergraduate judges
Human Performance

Aligns with previous studies in deception literature: humans typically perform barely better than chance. trained experts may perform at ~70%

Accuracy

- Judge 1: 61.9 (performed at chance, p-value = 0.1)
- Judge 2: 56.9
- Judge 3: 53.1 (performed at chance, p-value = 0.5)
How Well Can Computers Do?
Classifier Performance (SVM with 5-fold CV)

By analyzing *only* the distribution of part-of-speech (e.g., nouns, verbs, adjectives), already performs much better than human judges!
Classifier Performance (SVM with 5-fold CV)

Accuracy

- Best Human Variant: 61.9
- Classifier: Part-of-Speech: 73
- Classifier: Words: 89.8

→ No human performs at this level in deception literature!
Data-driven Discovery of Insights into Deceptive Writings
Informative writing (left) --- nouns, adjectives, prepositions
Imaginative writing (right) --- verbs, adverbs, pronouns
Rayson et. al. (2001)
<table>
<thead>
<tr>
<th>Category</th>
<th>Variant</th>
<th>Weight</th>
<th>Category</th>
<th>Variant</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truthful/Informative Writing</td>
<td></td>
<td></td>
<td>Deceptive/Imaginative Writing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nouns</td>
<td>Singular</td>
<td>0.008</td>
<td>Verbs</td>
<td>Base</td>
<td>-0.057</td>
</tr>
<tr>
<td></td>
<td>Plural</td>
<td>0.002</td>
<td></td>
<td>Past tense</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>Proper, singular</td>
<td>-0.041</td>
<td></td>
<td>Present participle</td>
<td>-0.089</td>
</tr>
<tr>
<td></td>
<td>Proper, plural</td>
<td>0.091</td>
<td></td>
<td>Singular, present</td>
<td>-0.031</td>
</tr>
<tr>
<td>Adjectives</td>
<td>General</td>
<td>0.002</td>
<td></td>
<td>Third person</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>Comparative</td>
<td>0.058</td>
<td></td>
<td>singular, present</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Superlative</td>
<td>-0.164</td>
<td></td>
<td>Modal</td>
<td>-0.063</td>
</tr>
<tr>
<td>Prepositions</td>
<td>General</td>
<td>0.064</td>
<td></td>
<td>General</td>
<td>0.001</td>
</tr>
<tr>
<td>Determiners</td>
<td>General</td>
<td>0.009</td>
<td></td>
<td>Comparative</td>
<td>-0.035</td>
</tr>
<tr>
<td>Coords. Conj.</td>
<td>General</td>
<td>0.094</td>
<td></td>
<td>Personal</td>
<td>-0.098</td>
</tr>
<tr>
<td>Verbs</td>
<td>Past participle</td>
<td>0.053</td>
<td></td>
<td>Possessive</td>
<td>-0.303</td>
</tr>
<tr>
<td>Adverbs</td>
<td>Superlative</td>
<td>-0.094</td>
<td></td>
<td>General</td>
<td>0.017</td>
</tr>
<tr>
<td>Pronouns</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-determiners</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Truthful Reviews ≈ Informative Writing (Journalism)

Deceptive Reviews ≈ Imaginative Writing (Novels)
STRONG DECEPTIVE INDICATORS

A focus on who they were with
In this example, “My husband;” also words like “family.”

Greater use of first-person singular
Fake reviews tend to use “I” and “me” more often.

Direct mention of where they stayed
Hotel and city names were less common in truthful reviews, which focus more on details about the hotel itself, like “small” or “bathroom.”

“My husband and I stayed in the [hotel name] Chicago and had a very nice stay! The rooms were large and comfortable. The view of Lake Michigan from our room was gorgeous. Room service was really good and quick, eating in the room looking at that view, awesome! The pool was really nice but we didn’t get a chance to use it. Great location for all of the downtown Chicago attractions such as theaters and museums. Very friendly staff and knowledgeable, you can’t go wrong staying here.”

SLIGHT DECEPTIVE INDICATORS

High adverb use
“Very” and “really” are both used twice; “here” is used once.

High verb use
“Get”, “go”, “use”, “can’t”, “didn’t”, “eating”, “had”, “looking”, “stayed”, “was” (three times), “were.”

Use of “!?” and positive emotion
Deceptive reviews tend to use exclamation points, while truthful reviews used more punctuation of other kinds, including “.”
lack of spatial, sensorial details (Vrij et al., 2009)
lack of descriptive adjectives: low, small, shiny
less use of prepositions
instead, story telling:

-- why they were there: “vacation”, “business”, “anniversary”
-- whom they were with: “husband”, “family”
exaggeration, words over the top: “fantastic”, “luxurious”, “gorgeous”, “awesome”

superlatives: “the most”, “best”, “ever”

certainty: “absolutely”, “definitely”, “for sure”

and had a very nice stay! The room was clean and comfortable. The view of Lake Michigan from our room was gorgeous. Room service was really good and quick, eating in the room looking at that view, awesome! The pool was really nice but we didn’t get a chance to use it. Great location for all of the downtown Chicago attractions such as theaters and museums. Very friendly staff and knowledgable, you can’t go wrong staying here.”

SLIGHT DECEPTIVE INDICATORS
High adverb use
“Very” and “really” are both used twice; “here” is used once.

High verb use
“Get”, “go”, “use”, “can’t”, “didn’t”, “eating”, “had”, “looking”, “stayed”, “was” (three times), “were.”

Use of “!” and positive emotion
Deceptive reviews tend to use exclamation points, while truthful reviews used more punctuation of other kinds, including “.”
Increased level of “first person singular”
“I”, “me”, “my”, “mine”

In contrast to psychological distancing (Newman et al., 2003)
→ deception cues are domain dependent
Two Follow-up Work
① Syntax Improves Deception Detection  
(Feng et al., ACL 2012)  
--- 3 product review dataset  
--- 1 essay dataset (Mihalcea and Strapparava (2009))

② Natural V.S. Distorted Distributions of Opinions  
(Feng et al., ICWSM 2012, best paper runner up)
I was visiting Chicago for a christening with my fiancé. I was impressed with this hotel from the moment I checked in. The lobby was exceptionally modern with color and furnishings. Front desk staff was pleasant and helpful, especially Susan, who quickly suggested and reserved a table for us at Keefer's Steakhouse for a late dinner. The room itself was fabulous. Extremely comfortable King sized bed, dual head shower, breathtakingly beautiful views, I couldn't ask for more. Next I was treated to a facial as my fiancé took a short run through the city. After a day full of shopping we retired to our room and ordered room service that was on time and delicious.
Conclusion (Part I – Deception)

- Learning to read the “intent” of the author, even a hidden one.
- Humans not good at this task.
- Computers may at times perform better than humans, even without full blown semantic understanding.
- Data-driven discovery of insights to complement hypothesis-driven research
- Domain-dependency of deception cues

Ganganath, Jurafsky, McFarland (EMNLP 2009)

➔ computers predict flirtation intention better than humans can, despite humans having access to vastly richer information (visual features, gesture, etc.).
Conclusion (Part I – Deception)

• Much revelation in “HOW” it is said.
  ➔ Deceptive reviewers write like novelists,
  ➔ truthful reviewers write like journalists,
  ➔ even POS distribution alone can achieve over 70%.
• Syntactic patterns require more attention.
• Need more expressive statistical models to analyze a richer set of elements in writing style

Ott et al. ACL 2011; Feng et al. ICWSM 2012; Feng et al. ACL 2012
I really loved my stay at the Talbott. My room was amazing! The bathroom (and I am VERY picky about hotel bathrooms) had ample room for all of my stuff, which is a bonus for me. The staff treated me really well and they were very friendly. I was afraid that I'd get a little lost, since it was my first trip to Chicago, but the staff helped me navigate to the downtown area (Rush St./Michigan Ave.-- which are *very* close by). The room service is 24 hours, which for me, was a bonus because I am up mostly during the nights. This is the *only* place I will ever stay if I visit Chicago again...

Stayed at the Monaco for a romantic weekend getaway and it was simply fantastic. Very convenient for walking to museums, shopping and park nearby. The room has a great box window that you can sit in and enjoy the view. We also requested a goldfish which was a pleasant surprise and added to the charm and uniqueness of the hotel. Helpful staff, wifi, Aveda products, decent restaurant downstairs for brunch, easy to get a taxi and nothing beats the location. I would definitely recommend staying at this hotel, for business or pleasure.
From Language to the Mind

Outline of the talk:
I. Deceptive Reviews and Essays
   Success of Novels
II. Connotation of Words

"HOW" it is said i.e., Writing Style

Information "WHAT"

Intent "WHY"

Identity "WHO"
Predicting the success of novels

Novelty
Style of writing
Story line

Social context
Luck!
Can Computers Predict the Success of Novels without Really Reading the Book?

- based only on writing style
- stylistic correlates of successful novels?
Publishers do make mistakes

Paul Harding’s “Tinkers” that won 2010 Pulitzer Prize for Fiction was rejected couple times before publication.

Rejected ~12 times before publication.
Can Computers Predict the Success of Novels without Really Reading the Book?

• based only on writing style
• stylistic correlates of successful novels?
How to define success
How to quantify success
Popularity v.s. Literary Quality

**Downloaded**

- 2013710710
- 143540
- last 7 days
- 1099579
- last 30 days

---

**Best Seller**

*THE NEW YORK TIMES BOOK REVIEW*

**Best Sellers**

<table>
<thead>
<tr>
<th>FICTION</th>
<th>NONFICTION</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Sunbather</em></td>
<td><em>Cracked Like Toast</em></td>
</tr>
<tr>
<td>Pamela MacLaughlin</td>
<td>Dexter Eagan (Morrow, $25.95)</td>
</tr>
<tr>
<td><em>Ragknights of Darkness</em></td>
<td><em>Empanadas in Worcester</em></td>
</tr>
<tr>
<td></td>
<td><em>Wrong: The Liberal Plan to Hijack Your Life and Pervert Your Kids</em></td>
</tr>
<tr>
<td><em>The Ballyhoo Table</em></td>
<td><em>The Usual Suspects</em></td>
</tr>
<tr>
<td>Tim Drye</td>
<td><em>Manhunt at Madison Square</em></td>
</tr>
<tr>
<td><em>Great Fish</em></td>
<td><em>Need for Speed</em></td>
</tr>
<tr>
<td>Liz Martin</td>
<td>(Simon &amp; Schuster, $25.95)</td>
</tr>
<tr>
<td><em>Narcotics: A Shock Blade</em></td>
<td><em>The Usual Suspects</em></td>
</tr>
<tr>
<td>Nick Boccieri, Nick Moskovitz</td>
<td><em>Need for Speed</em></td>
</tr>
</tbody>
</table>

---

**Project Gutenberg**

Downloads

- 2013-10-10
- last 7 days
- last 30 days

---

**Nobel Prize**

- Literature
- Economics
- Peace
- Chemistry
- Physics
- Physiology or Medicine
Dataset

- Project Gutenberg
  - free ebooks.
  - Title, author, genre, download count.
- 50 books per class, 8 genres.
Dataset

• Project Gutenberg
  – offers over 40,000 free ebooks.
  – Title, author, genre, download count.
• 50 books per class, 8 genres.
• \( \leq 2 \) books per author.

⚠️ Authorship attribution
Stylistic Elements as Features

• Lexical Choices
  – unigrams / bigrams

• Word Categories
  – Distribution of POS tags

• Constituents
  – Distribution of Phrasal & Clausal tags in PCFG trees

• Grammatical Rules
  – CFG rules (e.g. NP^VP → NP PP , SBAR → S WHNP )
Experiments

• Setup
  – Feature encoding: tf-idf
  – 80% training, 20% testing
  – 5-fold cross validation
  – LIBLINEAR (Fan et al., 2008) with L2-regulization
Prediction Results

- Adventure: 84
- Mysterious: 75
- Fiction: 75
- History: 61
- Love: 82
- Poetry: 76
- Sci-fi: 77
- Short story: 78
This is Surprising Because…

• Not considering any other influencing factor, not actually understanding the story, only looking at writing styles

• Different writers have wildly different writing styles. Should there even be stylistic commonalities shared by those different individuals?

• Testing: only the books by previously unseen authors (who presumably have his/her own unique writing style)
Secret Elements in Successful Novels

(only as correlates, not to be confused as causality)
Distribution of Tree (PCFG) Components

- Adventure
- Mystery
- Fiction
- History
- Love
- Poetry
- Sci-Fi
- Story
Writing Style of Journalism
(Douglas and Broussard 2000, Rayson et al. 2001)
Readability & Literary Success

Easier to Read

Harder to Read

More Successful

Less Successful
Readability & Literary Success

Success in Academic Journals (best paper awards)

Easier to Read → More Successful

Harder to Read → Less Successful

Sawyer et al (2008) @ Journal of Marketing
Readability & Literary Success

Easier to Read

Harder to Read

More Successful

Less Successful
Readability & Literary Success

1. Increased use of VP = better readability (Pitler and Nenkova (2008))
2. Readability Indices:

<table>
<thead>
<tr>
<th>METRIC</th>
<th>More Successful</th>
<th>Less Successful</th>
</tr>
</thead>
<tbody>
<tr>
<td>FOG index</td>
<td>9.88</td>
<td>9.80</td>
</tr>
<tr>
<td>Flesch index</td>
<td>87.48</td>
<td>87.64</td>
</tr>
</tbody>
</table>
Less successful: **telling**

- verbs that are **explicitly descriptive** of actions and emotions: want, went, took, promise, cry, shout, jump, glare, urge
- **extreme** words: never, very, breathless, absolutely, perfectly
- **cliche**: love (desires, affair), body parts (face, arms, skin), obvious locations (beach, room, boat, avenue)

More successful: **showing**

- verbs that describe **thought-processing**: recognized, remembered
- verbs for **reports** or quotes: said
- **prepositions**: up, into, out, after, in, within
- **discourse connectives**: and, which, though, that, as, after

Insights into Lexical Choices (w.r.t. Adventure Genre)
Testing on Literature beyond Project Gutenberg

To validate whether the “download” counts of Project Gutenberg is a reasonable quantification of success
Training on Project Gutenberg, testing on...

<table>
<thead>
<tr>
<th>More Successful</th>
<th>Less Successful</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train</td>
<td>#Download (400)</td>
</tr>
<tr>
<td>Test</td>
<td>(10)</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Training on Project Gutenburg, testing on...

Content:

- More Successful
- Less Successful

Download counts at Project Gutenburg reflect more on literary quality than commercial success.
Three Classifiers

- KL-divergence based
  - Distribution of phrasal & clausal tags of PCFG trees
  - Only 26 features, no lexical information
  - Deliberately deficient information to check whether “high-level syntactic commonalities” exist among highly successful novels.
  - Classification based on KL divergence

- Unigram-feature based

- PCFG-grammar rule based
  - including rules covering leaf nodes
**Prediction Results** = avg 80%  
(all results, no cherry picking)

![More Successful](image1.png)

<table>
<thead>
<tr>
<th>Classifier used</th>
<th># of correct prediction / 10 books</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL Divergence</td>
<td>8/10</td>
</tr>
<tr>
<td>SVM with Unigram features</td>
<td>10/10</td>
</tr>
<tr>
<td>SVM with PCFG features</td>
<td>10/10</td>
</tr>
</tbody>
</table>

![Less Successful](image2.png)

<table>
<thead>
<tr>
<th>Classifier used</th>
<th># of correct prediction / 10 books</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL Divergence</td>
<td>3/4</td>
</tr>
<tr>
<td>SVM with Unigram features</td>
<td>3/4</td>
</tr>
<tr>
<td>SVM with PCFG features</td>
<td>2/4</td>
</tr>
</tbody>
</table>
“The old man and the sea” by Ernest Hemingway

Signature style: minimalism
70% simple sentences.

<table>
<thead>
<tr>
<th>Classifier used</th>
<th>correct prediction?</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL Divergence</td>
<td>no</td>
</tr>
<tr>
<td>SVM with Unigram features</td>
<td>yes</td>
</tr>
<tr>
<td>SVM with PCFG features</td>
<td>yes</td>
</tr>
</tbody>
</table>
“The lost symbol” by Dan Brown

Significant criticisms on the quality of writing despite the commercial success

<table>
<thead>
<tr>
<th>Classifier used</th>
<th>correct prediction?</th>
</tr>
</thead>
<tbody>
<tr>
<td>KL Divergence</td>
<td>yes</td>
</tr>
<tr>
<td>SVM with Unigram features</td>
<td>yes</td>
</tr>
<tr>
<td>SVM with PCFG features</td>
<td>yes</td>
</tr>
</tbody>
</table>
How about Movie Scripts?
Predicting the Success of Movie Scripts

- movie script dataset (Danescu-Niculescu-Mizil and Lee, 2011)
- quantifying success: IMDb ratings
  - More successful: $\geq 8$
  - Less successful: $\leq 5.5$
- over 11 genres
- 15 movies per class, per genre

- good perf in some genres, but not all. more investigation with larger dataset needed
- additional factors (actors, directors, budgets) are likely to be more important in this domain
From Language to the Mind

Outline of the talk:
I. Deceptive Reviews and Essays
II. Success of Novels
III. Connotation of Words

“HOW” it is said i.e., Writing Style
Connotation

“com-” (“together or with”) | “notare” (“to mark”)

Commonly understood cultural or emotional association that some word carries, in addition to its explicit or literal meaning (denotation).

<table>
<thead>
<tr>
<th>Words</th>
<th>Connotation</th>
</tr>
</thead>
<tbody>
<tr>
<td>music, scientist</td>
<td>positive</td>
</tr>
<tr>
<td>surfing, rose</td>
<td></td>
</tr>
<tr>
<td>flu, emission</td>
<td>negative</td>
</tr>
<tr>
<td>deforestation, bedbug</td>
<td></td>
</tr>
</tbody>
</table>
Part sculpture, part table, all artisanal. Craftspeople in Jaipur, India, hand carved the delicate rosettes on this low-lying solid mango wood table, which takes its original inspiration from a ceremonial stool used by Bamileke royalty in the African country of Cameroon.

Creating an exotic feeling by “showing” the most elegant and unique table that you will never find anywhere else, this absolute exotic beauty will add an antique warmth to your living room.

More explicit “telling”
Connotation: a Dash of Sentiment beneath the Surface Meaning

Motivation:

1. Intent
   ➔ overtone / undertone of the writing that the author intends to deliver

2. An element of writing style
   ➔ showing v.s. telling

In comparison to sentiment analysis:
   ➔ more nuanced sentiment
   ➔ subjectivity via seemingly objective descriptions

“HOW” it is said i.e., Writing Style

Intent “WHY”

Identity “WHO”
Sentiment vs. Connotation

- **positive sentiment**: surfing
- **negative sentiment**: flu
- **positive connotation**: happy
- **negative connotation**: unhappy
Key Insight: “Connotative Predicate”

A predicate that has *selectional preference* on the connotative polarity of some of its semantic arguments.


<table>
<thead>
<tr>
<th>Connotative Predicate</th>
<th>Sentiment of predicate</th>
<th>Preference on arguments</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>suffer</td>
<td></td>
<td></td>
<td>“suffer coldness”</td>
</tr>
<tr>
<td>cure</td>
<td></td>
<td></td>
<td>“cure cancer”</td>
</tr>
<tr>
<td>cause</td>
<td></td>
<td></td>
<td>“cause emission”</td>
</tr>
</tbody>
</table>

(Feng et al. 2011)
20 Positive Connotative Predicates
accomplish, achieve, advance, advocate, admire, applaud, appreciate, compliment, congratulate, develop, desire, enhance, enjoy, improve, praise, promote, respect, save, support, win

20 Negative Connotative Predicates
alleviate, accuse, avert, avoid, cause, complain, condemn, criticize, detect, eliminate, eradicate, mitigate, overcome, prevent, prohibit, protest, refrain, suffer, tolerate, withstand

Feng et al. 2011
Network of Words

Semantic prosody
(Connotative Predicates – Arguments)

- prevent
  - tax
  - preventing

- suffer
  - loss

- enjoy
  - writing
  - profit

- thank
  - preventing

prosody
Network of Words

Semantic Parallelism across coordination (X and Y)
Network of Words

- prevent
- suffer
- enjoy
- thank

- tax
- loss
- bonus
- writing
- investment
- profit
- preventing
- flu
- cold

Dictionary-based Semantic Relations

- synonyms
- antonyms
- prosody
- coordination
Network of Words

- prevent
- suffer
- enjoy
- thank

- tax
- loss
- writing
- profit
- preventing

- bonus
- investment
- cold
- flu

- gain

prosody
synonyms
coordination
antonyms
Connotation Assignment as Constraint Optimization

1. Integer Linear Programming
2. Linear Programming

\[ F = \Phi^{prosody} + \Phi^{coord} + \Phi^{syn} + \Phi^{ant} + \Phi^{neu} \]

\[ \Phi^{prosody} = \sum_{i,j}^{\mathcal{R}^{\text{pred}^+}} w_{i,j}^{\text{pred}^+} \cdot x_j + \sum_{i,j}^{\mathcal{R}^{\text{pred}^-}} w_{i,j}^{\text{pred}^-} \cdot y_j \]

\[ \Phi^{coord} = \sum_{i,j} \mathcal{R}^{\text{coord}} w_{i,j}^{\text{coord}} \cdot (dc_{i,j}^{++} + dc_{i,j}^{--}) \]

\[ \Phi^{syn} = W^{\text{syn}} \sum_{i,j}^{\mathcal{R}^{\text{syn}}} (ds_{i,j}^{++} + ds_{i,j}^{--}) \]

\[ \Phi^{ant} = W^{\text{ant}} \sum_{i,j}^{\mathcal{R}^{\text{ant}}} (da_{i,j}^{++} + da_{i,j}^{--}) \]

\[ \Phi^{neu} = \alpha \sum_{i,j} w_{i,j}^{\text{pred}} \cdot z_j \]

\[ ds_{i,j}^{++} \leq x_i - x_j, \quad ds_{i,j}^{++} \leq x_j - x_i \]

\[ ds_{i,j}^{--} \leq y_i - y_j, \quad ds_{i,j}^{--} \leq y_j - y_i \]

\[ da_{i,j}^{++} \leq x_i - (1 - x_j), \quad da_{i,j}^{++} \leq (1 - x_j) - x_i \]

\[ da_{i,j}^{--} \leq y_i - (1 - y_j), \quad da_{i,j}^{--} \leq (1 - y_j) - y_i \]
ILP/LP Comparison with MPQA

Recall  | Precision  | F-score
---|---|---
Pred+Syn+Ant  |  |  |
Pred+Syn+Ant+Coord  |  |  |
Pred+Syn+Ant  |  |  |
Pred+Syn+Ant+Coord  |  |  |
Learning connotation of real world entities

<table>
<thead>
<tr>
<th>Positive</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>FEMA, Mandela, Intel, Google, Python, Sony, Pulitzer, Harvard, Duke, Einstein, Shakespeare, Elizabeth, Clooney, Hoover, Goldman, Swarovski, Hawaii, Yellowstone</td>
<td>Katrina, Monsanto, Halliburton, Enron, Teflon, Hiroshima, Holocaust, Afghanistan, Mugabe, Hutu, Saddam, Osama, Qaeda, Kosovo, Helicobacter, HIV</td>
</tr>
</tbody>
</table>
Potential Application - I

• Learning public perception on named entities.
Choosing the right word:

“Jack the Giant Killer” v.s. “Jack the Giant Slayer”
– Slayer has more of “fantasy” connotation
– Killer has more of “crime” connotation
Potential Applications - III

Tracking the connotation of words over time:
• e.g., “geek”
Conclusions & Future Work

• First broad coverage connotation lexicon
• Comparative evaluations of multiple algorithms.
• Available at
• http://homes.cs.washington.edu/~yejin/connotation

Need work for:
• Dealing with WSD and MWE issues in learning
• More interesting dimensions of connotations
I. Deceptive Reviews (ACL 2011)

II. Success of Novels (EMNLP 2013)

III. Connotation of Words

intellectual traits (~ cognitive identity)
Research Outlook

1. Many more surprising and impactful applications --- yet to be discovered, formulated, and explored!
2. Computers may at times perform better than humans.
3. NLP for Digital Humanities (... and for Humanities) --- Data-driven discovery of insights vs. hypothesis-driven

"HOW" it is said i.e., **Writing Style**

**WHAT**

**WHY**

**WHO**
NLP for Social Good

• When our work was first published in 2011, no clear legal regulations against fake reviews.
• Not any more! New York law enforcement charged 19 firms $350,000 for facilitating fake reviews (Sep 2013).
  – (not based on automatic detection)
NLP for Social Good

EMNLP 2013:

“Where Not to Eat? Improving Public Policy by Predicting Hygiene Inspections Using Online Reviews.”

Using inspection records from https://Data.KingCounty.gov/

--- collaboration with Mike Luca @ Harvard Business School

Featured in (Jun 19, 2013)

The Atlantic
Research Outlook

1. Many more surprising and impactful applications --- yet to be discovered, formulated, and explored!
2. Computers may at times perform better than humans.
3. NLP for Digital Humanities (... and for Humanities) --- Data-driven discovery of insights vs. hypothesis-driven
4. Expressive statistical models to analyze a richer set of stylistic elements in writing style: “deep syntax”, “discourse”, “plot”
Bibliography (2011 – 2013)

I. Deception & Public Opinion
   - EMNLP 2013 Where Not to Eat? Improving Public Policy by Predicting Hygiene...
   - ICWSM 2012 Distributional Footprints of Deceptive Product Reviews.
   - ACL 2012 Syntactic Stylometry for Deception Detection

II. Authorship & Writing Style
   - EMNLP 2012 Characterizing Stylistic Elements in Syntactic Structure.
   - CoNLL 2011 Gender Attribution: Tracing Stylometric Evidence Beyond Topic...
   - ACL 2011 Language of Vandalism: Improving Wikipedia Vandalism Detection..

III. Connotation
   - ACL 2013 Connotation Lexicon: A Dash of Sentiment Beneath the Surface Meaning.
   - EMNLP 2011 Learning General Connotation of Words using Graph-based Algorithms.

IV. Literary Success & Linguistic Creativity
   - EMNLP 2013 Success with Style: Using Writing Style to Predict the Success of Novels.
   - EMNLP 2013 Understanding and Quantifying Creativity in Lexical Composition.
Media Coverage (Highlights 2011-2014)


- [EMNLP 2013] Success with Style: Using Writing Style to Predict the Success of Novels.

- [EMNLP 2013] Where Not to Eat? Improving Public Policy by Predicting Hygiene...
Acknowledgements

- **My PhD**
  - Ritwik Banerjee, Song Feng, Jun Seok Kang, Polina Kuznetsova

- **Other PhD**
  - Vikas Ashok, Ritwik Bose, Jianfu Chen

- **MS**
  - Manoj Harpalani, Kailash Gajulapalli, Anupam Gogar, Rohith Menon, Ruchita Sarawgi, Sandesh Singh, Longfei Xing

- **Professor**
  - Claire Cardie, Jeffrey Hancock, Rob Johnson, Michael Luca

- **Industry**
  - Michael Hart, Myle Ott

- **Institutions**
  - Google
  - University of Washington