Comparison of Corpora through Narrative Structure

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Overview

Introduction

Background

Corpus Selection

Algorithm

Comparing Corpora

Results

In Progress

End Remarks
How this started?

2013 Capitol Hill “Shooting”

News sources presented the events in two different ways:

- Fox News/MSNBC: Strong Moral Leaning, Provocative

Analysis by hand.
As a computational linguist, I can study $10^6$—instead of $10^{0.6}$—documents.
Goals

- Compare police narratives *en masse* from different news sources.

Available data: New York Times Corpus [Sandhaus 2008].
Goals

- Compare police narratives *en masse* from different news sources.

What might have caused changes in the way police are talked about in that time frame?
Goals

- Compare police narratives *en masse* from different news sources.
  ...before and after September 11th. [Balko 2012]

Were there significant changes in how police were discussed before and after September 11th?
What is a narrative schema?

- [Chambers and Jurafsky 2008], [Chambers and Jurafsky 2009]

Examples: **Firing of Employee** and **Executive Resigns**

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>accused</td>
<td>X</td>
<td>W</td>
</tr>
<tr>
<td>X</td>
<td>claimed</td>
<td></td>
<td>W</td>
</tr>
<tr>
<td>X</td>
<td>denied</td>
<td></td>
<td>W</td>
</tr>
<tr>
<td>Y</td>
<td>dismissed</td>
<td>X</td>
<td>W</td>
</tr>
</tbody>
</table>

X (employee), Y (supervisor), W (executive), and V (company) represent co-referent in the argument slots.
Previous Work

[Chambers and Jurafsky 2008] and [Chambers and Jurafsky 2009]

- Use coreference chains and dependency parses to extract narrative event chains/schema.

- [Webber, Egg, and Kordoni 2012] cites those as the first such work in a long time, and a few follow ups.
An Example

Our whole corpus:

“he barricaded himself in.”
Coreference

“he barricaded himself in.”

\{he_0, himself_2\}
"he barricaded himself in."

- $\{(subj, barricade, he), (obj, barricade, himself)\}$
Narrative Event Chain

“he barricaded himself in.”

- \{(barricade, subj), (barricade, obj)\}

Originally included a temporal ordering step.
- This was irrelevant here.
Pointwise Mutual Information

When two events are independent:

\[ p(x)p(y) = p(x, y) \]  \hspace{1cm} (1)

Therefore,

\[ pmi(x, y) \equiv \frac{p(x, y)}{p(x)p(y)} \]  \hspace{1cm} (2)

In our case, \( x \) and \( y \) are verb-dependency pairs.

- \( p(x, y) \) indicates the probability that a coreference chain is an argument to both \( x \) and \( y \).
Using $pmi$

The next candidate verb-dependency pair:

$$\max_{j:0<j<m} \sum_{i=0}^{n} pmi(e_i, f_j)$$  \hspace{1cm} (3)

$e_i$ is our chain as it stands. $f_j$ that maximizes is our next candidate.
Coreference is Slow

“Honey, I shrunk the corpus!”

- 1.6 million documents was too many to process in a reasonable time.
- Shrinking the corpus in a systematic way may help us focus on our target data as well.
Corpus Shrinking

- Keyword Selection — is the word “police” in the document? (That’s it.)
- Categorical Selection
Categorical Selection

Table: Number documents per category retained from the “police” subset. There were many more; they were not explicitly excluded.

<table>
<thead>
<tr>
<th>Category</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Murders and Attempted Murders</td>
<td>22,640</td>
</tr>
<tr>
<td>Crime and Criminals</td>
<td>21,315</td>
</tr>
<tr>
<td>Terrorism</td>
<td>17,565</td>
</tr>
<tr>
<td>Demonstrations and Riots</td>
<td>9,443</td>
</tr>
<tr>
<td>Accidents and Safety</td>
<td>8,742</td>
</tr>
<tr>
<td>World Trade Center (NYC)</td>
<td>7,128</td>
</tr>
<tr>
<td>Blacks</td>
<td>6,786</td>
</tr>
<tr>
<td>Law and Legislation</td>
<td>6,695</td>
</tr>
<tr>
<td>Violence</td>
<td>6,059</td>
</tr>
<tr>
<td>Police Brutality and Misconduct</td>
<td>4,823</td>
</tr>
<tr>
<td>Attacks on Police</td>
<td>2,583</td>
</tr>
<tr>
<td>Frauds and Swindling</td>
<td>2,247</td>
</tr>
<tr>
<td>Cocaine and Crack Cocaine</td>
<td>1,487</td>
</tr>
<tr>
<td>Organized Crime</td>
<td>1,434</td>
</tr>
<tr>
<td>Serial Murders</td>
<td>1,136</td>
</tr>
<tr>
<td>Suburbs</td>
<td>296</td>
</tr>
<tr>
<td>Noise</td>
<td>294</td>
</tr>
<tr>
<td>Prison Escapes</td>
<td>270</td>
</tr>
</tbody>
</table>
Time Periods

Four time periods:

- Three years in size (1095 days, technically).
- Retained two before/two after 9/11.
People Selection

Still too big!

- People Metadata from NYT Corpus [Sandhaus 2008].
- Chose people who appeared 10 and 15 times per time period.
- Kept the documents they appeared in.

Most questionable reduction?

- Ensures we have coherent narratives from the handful of individuals selected.
- Worst case scenario, this is equivalent to random selection.
Coreference Chains, Dependency Parses, etc.

- Stanford CoreNLP\(^2\)
- corenlp-python\(^3\) serverlet — allowed for marginally graceful crashes.

Took two weeks on “Wisdom.”

\(^2\)http://nlp.stanford.edu/software/corenlp.shtml
\(^3\)https://pypi.python.org/pypi/corenlp-python
Counter-Training

Inspired by [Yangarber 2003]:

- Document classification algorithm
- If multiple categories choose the same document, then that selection is a poor fit for the category.

This intuition is applied to our verb-dependency pairs and growing event chains.
Probabilistic Rationale

How can this be justified?

- We’re producing a discrete representation of a continuous space.
- A $< v, d >$ choice may assign a disproportionate probability mass to our approximation.
- Penalizing prevents that disproportionality from becoming absurd.

Creates maximally distant schema.
Counter-Training

chosen by others (quantity varies)

next \(< v, d >\) added

(removed from future consideration)
Counter-Training

\(\chi\) penalties (dotted lines)

\(\gamma\) penalties

\(\langle v, d \rangle\)'s with scores below zero.
(removed from future consideration)
Starting the Train

Something has to seed the counter-training process.

- Single \(< v, d >\) Pairs
- Existing \(< v, d >\) Pairs

[Chambers and Jurafsky 2008] is a bit vague about this aspect of the process:

\[
\max_{j: 0 < j < m} \sum_{i=0}^{n} \text{pmi}(e_i, f_j) \tag{4}
\]
Comparing Event Chains

There are many levels of comparison:

- verb-dependency pair × verb-dependency pair
- event chain × event chain
- corpus × corpus
Verb-Dependency Pair

- WordNet [Princeton 2010]
- Leacock-Chodorow Distance: $- \log \frac{p_{a,b}}{2D}$ [Leacock and Chodorow 1998]
- Penalize for mismatched dependencies—scale the path length.
Event Chains and Corpora

- Assume the closest possible match.
- corpora : event chains :: event chains : verb deps

\[
\text{this level}(A, B) = \text{norm} \sum_{b \in B} \max_{a \in A} \text{lower level}(a, b) \quad (5)
\]
Tentative Results

Figure: $p_n(P_j) = \text{period}(P_n, P_j)$, where $n$ refers to period index of the series under consideration. Each series contains a common $i$ value. The peaks are where $n = j$ or $n = j_r$—e.g. self-comparison. The left plot represents the periodic test; the second, the randomized test. The randomized $i$ values are denoted with the subscript $r$. 
Hypothesis? Nay!

The distributions are about the same.

- **periodic**: $2.750 (\sigma = 0.306)$
- **randomize**: $2.752 (\sigma = 0.304)$

On the bright side, this indicates that the narrative schema are quite stable across the New York Times!
Event Chains? Yay!

**Table:** Computation of mean of the difference set $D$ for each test. $p_n(P_i)$ is short-hand here for $period(P_n, P_i)$. $D_p$ and $D_r$ refer to the difference set for the periodic and randomized tests, respectively. Each $d \in D$ is $p_n(P_i) - p_n(P_j)$ with respect to the row it is contained in.

<table>
<thead>
<tr>
<th>periodic</th>
<th>randomized</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n$</td>
<td>$i$</td>
</tr>
<tr>
<td>-1</td>
<td>-2</td>
</tr>
<tr>
<td>-1</td>
<td>-2</td>
</tr>
<tr>
<td>0</td>
<td>-2</td>
</tr>
<tr>
<td>0</td>
<td>-1</td>
</tr>
</tbody>
</table>

Mean of $D_p = 0.072$  Mean of $D_r = 0.002$
Continuing Work

Upgrading from event chains to the schema as given in [Chambers and Jurafsky 2009].

- Start with typed event chains.
Examples

Type **PERSON**: comes from the CoreNLP NamedEntityRecognizer/pronouns in the chain.

<table>
<thead>
<tr>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>arraign</td>
</tr>
<tr>
<td>arrest</td>
</tr>
<tr>
<td>brag</td>
</tr>
<tr>
<td>charge</td>
</tr>
<tr>
<td>plead</td>
</tr>
</tbody>
</table>
Examples

Type SELF: 1st person pronouns appear in the coreference chain.

- I believe
- I feel
- I hear
- I see
- I think
- I want
Examples

Type judge: a preferred type.

- X adopt
- X chide
- X come
- X reprimand
Examples

Type diallo: a preferred type.

<table>
<thead>
<tr>
<th>Type</th>
<th>X crouch</th>
</tr>
</thead>
<tbody>
<tr>
<td>fire</td>
<td>X*</td>
</tr>
<tr>
<td>hit</td>
<td>X</td>
</tr>
<tr>
<td>kill</td>
<td>X</td>
</tr>
<tr>
<td>shoot</td>
<td>X</td>
</tr>
<tr>
<td>stand</td>
<td>X</td>
</tr>
</tbody>
</table>

* = PREP, not OBJ
What’s Next?

Finalize this project.

- The schema, and improved comparison, should give more interesting results.

Product reviews are stories.

- What are their schema like?
- Can schema similarity classify product reviews?

Infuse schema with other features.

- Modality — are the events described hypothetical?
Acknowledgements

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References


