Compositional Lexical Semantics for Natural Language Inference

Thesis Defense
Ellie Pavlick
Department of Computer and Information Science
University of Pennsylvania
What is the population of New York City?

8.406 million (2013)
what is the population of new york city?

8.406 million (2013)
what is the population of new york city?

8.406 million (2013)
Human language is highly variable.
In leaked audio, Clinton talks about Sanders supporters “living in basement”
In leaked audio, Clinton talks about Sanders supporters “living in basement”

Hillary Clinton • HRC

mocks • said • insults • characterizes • comments on • gives frank take on • slams • calls • knocks • describes

In hacked fundraiser recording • in leaked recording • in audio from hacked email • privately • hacked audio:

in hacked fundraiser recording • in leaked recording • in audio from hacked email • privately • hacked audio:

bernie supporters • millennials • sanders supporters • young voters • bernie sanders supporters • bernie kids • bernie fans

losers who live in their parents' basements • basement dwellers • frustrated basement-dwellers • basement-dwellers & baristas
In leaked audio, Clinton talks about Sanders supporters “living in basement.”

How to we know when two different expressions in natural language have the same meaning?
How to we know when two similar expressions in natural language have a different meaning?
In leaked audio, Clinton talks about Sanders supporters “living in basement”
Logical Inference

In leaked recording, Clinton talks about Sanders supporters “living in basement”
Logical Inference

In hacked fundraiser recording \(\subset\) In leaked recording

\[\subset\]

In leaked audio, Clinton talks about Sanders supporters “living in basement”
Logical Inference

In hacked fundraiser recording \(\subseteq\) In leaked recording \(\subseteq\) Privately

In leaked audio, Clinton talks about Sanders supporters “living in basement”
In leaked audio, Clinton talks about Sanders supporters “living in parents’ basement”
In leaked audio, Clinton talks about Sanders supporters “living in parents’ basement”
In leaked audio, Clinton talks about Sanders supporters “living in parents’ basement”
Natural Language Inference
Natural Language Inference
(aka Recognizing Textual Entailment)
Natural Language Inference
(aka Recognizing Textual Entailment)

In leaked audio, Clinton talks about Sanders supporters living in basement
Natural Language Inference
(aka Recognizing Textual Entailment)

In leaked audio, Clinton talks about Sanders supporters living in basement

Hillary Clinton privately slams millennials as basement-dwellers
Natural Language Inference
(aka Recognizing Textual Entailment)

In leaked audio, Clinton talks about Sanders supporters living in basement

Hillary Clinton privately slams millennials as basement-dwellers
Natural Language Inference
(aka Recognizing Textual Entailment)

In leaked audio, Clinton talks about Sanders supporters living in basement

Hillary Clinton privately slams millennials as basement-dwellers

\[ p \text{ entails } h \text{ if "typically, a human reading } p \text{ would infer that } h \text{ is most likely true."} \]

The Pascal Recognising Textual Entailment Challenge.

Dagan et al. (2006)
Introduction

Lexical Entailment

Adding Semantics to Data-Driven Paraphrasing.
*Pavlick et al. ACL (2015)*

Modifier-Noun Composition

Semantic Containment

Compositional Entailment in Adjective Nouns.
*Pavlick and Callison-Burch. ACL (2016)*

So-Called Non-Subsective Adjectives.
*Pavlick and Callison-Burch. *SEM (2016)*

Class-Instance Identification

Fine-Grained Class Extraction via Modifier Composition.
*Pavlick and Pasca. ACL (2017)*

Summary and Future Work
Introduction

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing. Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment

Class-Instance Identification

Summary and Future Work
Introduction

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing.
Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment
Compositional Entailment in Adjective Nouns.
Pavlick and Callison-Burch. ACL (2016)
So-Called Non-Subsective Adjectives.

Class-Instance Identification
Fine-Grained Class Extraction via Modifier Composition.
Pavlick and Pasca. ACL (2017)

Summary and Future Work

American composer
American composer

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing.
Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment
Compositional Entailment in Adjective Nouns.
Pavlick and Callison-Burch. ACL (2016)
So-Called Non-Subsective Adjectives.

Class-Instance Identification
Fine-Grained Class Extraction via Modifier Composition.
Pavlick and Pasca. ACL (2017)

Summary and Future Work
Introduction

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing. 
Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment
Compositional Entailment in Adjective Nouns. 
Pavlick and Callison-Burch. ACL (2016)
So-Called Non-Subsective Adjectives. 

Class-Instance Identification
Fine-Grained Class Extraction via Modifier Composition. 
Pavlick and Pasca. ACL (2017)

Summary and Future Work
Introduction

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing. 
*Pavlick et al. ACL (2015)*

Modifier-Noun Composition

Semantic Containment
Compositional Entailment in Adjective Nouns.
*Pavlick and Callison-Burch. ACL (2016)*
So-Called Non-Subsective Adjectives. 
*Pavlick and Callison-Burch. *SEM (2016)*

Class-Instance Identification
Fine-Grained Class Extraction via Modifier Composition. 
*Pavlick and Pasca. ACL (2017)*

Summary and Future Work
In leaked audio, Clinton talks about Sanders supporters living in basement

Hillary Clinton privately slams millennials as basement-dwellers
In leaked audio, Clinton talks about Sanders supporters **living in basement**.

Hillary Clinton privately slams millennials as **basement-dwellers**.

**Equivalence**

- lives in basement
- is a basement-dweller
In leaked audio, Clinton talks about Sanders supporters living in basement.

Hillary Clinton *privately* slams millennials as basement-dwellers.

Forward Entailment
Natural Language Inference

In leaked audio, Clinton talks about Sanders supporters living in basement.

Hillary Clinton privately slams millennials as basement-dwellers.

Reverse Entailment
Natural Language Inference

In leaked audio, Clinton talks about Sanders supporters living in basement.

Hillary Clinton privately slams millennials as basement-dwellers.
Natural Language Inference

At a press conference, Clinton talks about Sanders supporters living in basement.

Hillary Clinton privately slams millennials as basement-dwellers.

Exclusion

- at a press conference
- privately
<table>
<thead>
<tr>
<th>Logical Relation</th>
<th>Symbolization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equivalence</td>
<td>$x \iff y$</td>
</tr>
<tr>
<td>Reverse Entailment</td>
<td>$x \Rightarrow y$</td>
</tr>
<tr>
<td>Forward Entailment</td>
<td>$y \Rightarrow x$</td>
</tr>
<tr>
<td>Independence</td>
<td>$x \not\iff y \land y \not\iff x$</td>
</tr>
<tr>
<td>Exclusion</td>
<td>$x \Rightarrow \neg y \land y \Rightarrow \neg x$</td>
</tr>
</tbody>
</table>
Lexical Semantics Resources

WordNet

act

communicate perform

address relay practice

harangue talk about walk through scrimmage

rant descant
Lexical Semantics Resources

WordNet

Diagram:
- act
  - communicate
  - address
    - harangue
    - rant
  - talk about
    - descant
  - perform
    - relay
    - walk through
  - practice
    - scrimmage
Lexical Semantics Resources

Bilingual Pivoting

WordNet

Lexical Semantics Resources

Bilingual Pivoting

WordNet

\[ x \Rightarrow y \land y \not\Rightarrow x \]

vector Space Models
Lexical Semantics Resources

WordNet

x shares some translation with y

Bilingual Pivoting

Vector Space Models
Lexical Semantics Resources

Bilingual Pivoting

x appears in similar contexts as y
Lexical Semantics Resources
Lexical Semantics Resources

WordNet
Precise but Small

Data-Driven Models
Big but Noisy
Lexical Semantics Resources

Can we build lexical entailment resources automatically and at scale...

WordNet
Precise but Small

Data-Driven Models
Big but Noisy
Lexical Semantics Resources

Can we build lexical entailment resources automatically and at scale...

...while maintaining WordNet-level precision and interpretability?

Data-Driven Models
Big but Noisy
The Paraphrase Database

PPDB: The Paraphrase Database. Ganitkevich et al. (2013)
The Paraphrase Database
Distributional Signals of Semantics
Distributional Signals of Semantics

Monolingual Contextual Similarities

Lin and Pantel, 2001 (Alberta)
Mikolov et al., 2013 (Google)
Pennington et al., 2014 (Stanford)
Distributional Signals of Semantics

Monolingual Contextual Similarities

Lin and Pantel, 2001 (Alberta)
Mikolov et al., 2013 (Google)
Pennington et al., 2014 (Stanford)

...converted from classical work to abstract expressionism after hearing Russian composer Igor Stravinsky's “Rite of Spring”...

...South African contemporary artist, with abstract expressionism work featuring key aesthetics of the most sought after artists...
Distributional Signals of Semantics

Monolingual Contextual Similarities

Lin and Pantel, 2001 (Alberta)
Mikolov et al., 2013 (Google)
Pennington et al., 2014 (Stanford)

...converted from classical work to abstract expressionism after hearing Russian composer Igor Stravinsky's "Rite of Spring"...

...South African contemporary artist with abstract expressionism work featuring key aesthetics of the most sought after artists...
Contextual Similarities

Strengths

Weaknesses
Contextual Similarities

Strengths

dad/father

vs.

dad/lychee

Weaknesses
Contextual Similarities

Strengths

- dad/father vs. dad/lychee

Weaknesses

- dad/father vs. dad/mom
Distributional Signals of Semantics

Bilingual Translational Similarity

Bannard and Callison-Burch, 2005 (Edinburgh)
Kok and Brockett, 2010 (MSR)
Ganitkevitch et al., 2013 (Hopkins)
Distributional Signals of Semantics

Bilingual Translational Similarity

Bannard and Callison-Burch, 2005 (Edinburgh)
Kok and Brockett, 2010 (MSR)
Ganitkevitch et al., 2013 (Hopkins)

…the directive include the extension to the period of protection for composers…

…to favour the position of artists who have to travel throughout the community…

…la directive comprennent la prolongation de la durée de protection pour les artistes…

…favoriser la position des artistes qui doivent voyager à travers la communauté…
Distributional Signals of Semantics

Bilingual Translational Similarity

Bannard and Callison-Burch, 2005 (Edinburgh)
Kok and Brockett, 2010 (MSR)
Ganitkevitch et al., 2013 (Hopkins)

…the directive include the extension to the period of protection for composers...

to favour the position of artists who have to travel throughout the community...

…la directive comprennent la prolongation de la durée de protection pour les artistes...

…favoriser la position des artistes qui doivent voyager à travers la communauté…
Contextual Similarities

**Strengths**

- dad/father vs. dad/lychee

**Weaknesses**

- dad/father vs. dad/mom

Bilingual Translations
**Contextual Similarities**

- dad/father vs. dad/lychee

**Bilingual Translations**

- dad/father vs. dad/mom

**Strengths**

- dad/father vs. dad/lychee

**Weaknesses**

- dad/father vs. dad/mom
Contextual Similarities

Strengths
- dad/father vs. dad/lychee
- dad/father vs. dad/mom

Weaknesses
- dad/father vs. dad/mom
- dad/parent vs. dad/lychee
Distributional Signals of Semantics

Lexico-Syntactic Patterns

Hearst, 1992 (Berkeley)
Snow et al., 2006 (Stanford)
Movshovitz-Attias and Cohen, 2015 (CMU)
How do composers and other artists survive and work in today's musical theatre scene?

As Luciano Berio did in his “Recital for Cathy”, creative artists such as composers, theatre directors, choreographers, video artists or even circus ...
How do composers and other artists survive and work in today's musical theatre scene?

As Luciano Berio did in his “Recital for Cathy”, creative artists such as composers, theatre directors, choreographers, video artists or even circus ...
Contextual Similarities

Bilingual Translations

Lexico-Syntactic Patterns

Strengths

- dad/father vs. dad/lychee
- dad/father vs. dad/mom

Weaknesses

- dad/father vs. dad/mom
- dad/parent vs. dad/lychee
**Contextual Similarities**

- **Strengths**
  - dad/father vs. dad/lychee
  - dad/father vs. dad/mom
  - dad/parent vs. dad/lychee

- **Weaknesses**
  - dad/father vs. dad/mom
  - dad/parent vs. dad/lychee

**Bilingual Translations**

**Lexico-Syntactic Patterns**
Logistic Regression

\[
\begin{bmatrix}
P(\text{equivalent}) \\
P(\text{entailment}) \\
P(\text{exclusion}) \\
P(\text{independent})
\end{bmatrix}
= \frac{1}{1 + e^{\omega_1 \cdot \begin{bmatrix}
\omega_1 \\
\omega_2 \\
\omega_3
\end{bmatrix} \cdot \begin{bmatrix}
\text{Contextual Similarities} \\
\text{Bilingual Translations} \\
\text{Lexico-Syntactic Patterns}
\end{bmatrix}}
\]
Logistic Regression

\[
\begin{bmatrix}
P(\text{equivalent}) \\
P(\text{entailment}) \\
P(\text{exclusion}) \\
P(\text{independent})
\end{bmatrix}
= \frac{1}{1 + e^{\omega_1 w_1 + \omega_2 w_2 + \omega_3 w_3}}
\begin{bmatrix}
\text{Contextual Similarities} \\
\text{Bilingual Translations} \\
\text{Lexico-Syntactic Patterns}
\end{bmatrix}
\]

Predict a probability distribution based over entailment relations...
Logistic Regression

\[
\begin{bmatrix}
P(\text{equivalent}) \\
P(\text{entailment}) \\
P(\text{exclusion}) \\
P(\text{independent})
\end{bmatrix} = \frac{1}{1 + e^{-\omega^T \cdot [\text{Contextual Similarities, Bilingual Translations, Lexico-Syntactic Patterns}]}}
\]

...based on all of the data-driven signals available.
The Paraphrase Database
The Paraphrase Database
The Paraphrase Database

Can we build a resource like WordNet automatically, at scale, and without loss of precision?
Improving End-to-End RTE

$p$ entails $h$ if typically, a human reading $p$ would infer that $h$ is most likely true.
Improving End-to-End RTE

$p = “A\ man\ is\ having\ a\ conversation.”$
$h = “Some\ women\ are\ talking.”$

$p\ entails\ h\ if\ typically,\ a\ human\ reading\ p\ would\ infer\ that\ h\ is\ most\ likely\ true.$
Improving End-to-End RTE

\[ p = "A man is having a conversation." \]

\[ h = "Some women are talking." \]

\[ p \text{ entails } h \text{ if typically, a human reading } p \text{ would infer that } h \text{ is most likely true.} \]

No
Improving End-to-End RTE

A man is having a conversation. Some woman are talking.

<table>
<thead>
<tr>
<th>x1</th>
<th>x2</th>
<th>x3</th>
</tr>
</thead>
<tbody>
<tr>
<td>man(x1)</td>
<td>patient(x2,x3)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>agent(x2,x1)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>have(x2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>conversation(x3)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>x1</th>
<th>x2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>agent(x1,x2)</td>
</tr>
<tr>
<td></td>
<td>talk(x1)</td>
</tr>
<tr>
<td></td>
<td>woman(x2)</td>
</tr>
</tbody>
</table>
Improving End-to-End RTE

A man is having a conversation. Some woman are talking.

\[
\forall x (\text{man}(x) \Rightarrow \neg \text{woman}(x))
\]
Improving End-to-End RTE

A man is having a conversation. Some woman are talking.

\[ \forall x, h, c, t (\text{have}(h) \land \text{conversation}(c) \land \text{talk}(t) \land \text{agent}(h, x) \Rightarrow \text{agent}(t, x)) \]
Improving End-to-End RTE

Performance (F1 Score)

- No Axioms: 0.49
- Using PPDB: 0.66
Improving End-to-End RTE

Performance (F1 Score)

- No Axioms: 0.49
- Using WordNet: 0.61
- Using PPDB: 0.66
Improving End-to-End RTE

Performance (F1 Score)

No Axioms: 0.49
Using WordNet: 0.61
Using PPDB: 0.66
Human Oracle: 0.66
Introduction

Lexical Entailment

Adding Semantics to Data-Driven Paraphrasing. *Pavlick et al. ACL (2015)*

Modifier-Noun Composition

Semantic Containment

Compositional Entailment in Adjective Nouns. *Pavlick and Callison-Burch. ACL (2016)*


Class-Instance Identification


Summary and Future Work
Introduction

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing. 
Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment
Compositional Entailment in Adjective Nouns. 
Pavlick and Callison-Burch. ACL (2016)
So-Called Non-Subsective Adjectives. 

Class-Instance Identification
Fine-Grained Class Extraction via Modifier Composition. 
Pavlick and Pasca. ACL (2017)

Summary and Future Work
Non-Compositional Semantics

artist

composer
Non-Compositional Semantics

American composer

composer

artist
Non-Compositional Semantics

- American composer
- composer
- 1950s American jazz composer
- artist
Non-Compositional Semantics

[[modifier_1 modifier_2 \ldots modifier_k \text{noun}]]
Non-Compositional Semantics

$O \left( N M^k \right)$
Non-Compositional Semantics

American jazz composer

$O\left(\text{NM}^k\right)$

$\sim 270,000,000,000,000,000$
Non-Compositional Semantics

American jazz composer

$O \left( N M^k \right)$

$\sim 270,000,000,000,000,000,000$

Problem #1: scalability
Non-Compositional Semantics

"composer"

About 149,000,000 results (1.04 seconds)
No results found for "1950s American jazz composer".
Non-Compositional Semantics

“1950s American jazz composer”

No results found for "1950s American jazz composer".

Problem #2: sparsity
Non-Compositional Semantics

American composer

composer
Non-Compositional Semantics

- American composer
- American actor
- composer
- actor
Non-Compositional Semantics
Non-Compositional Semantics

American composer

American actor

American author

composer

actor

singer
Non-Compositional Semantics

American composer

American actor

American author

Problem #3: generalizability
Compositional Semantics

- American composer
- composer
Compositional Semantics

composer

American composer
Compositional Semantics

composer

American

American composer
Compositional Semantics

- composer
- American

American composer
Compositional Semantics

Semantic Containment

composer

American composer
Compositional Semantics

American composer

Class-Instance Identification

composer American composer
Adding Semantics to Data-Driven Paraphrasing. 
*Pavlick et al. ACL (2015)*

Modifier-Noun Composition

Compositional Entailment in Adjective Nouns. 
*Pavlick and Callison-Burch. ACL (2016)*

So-Called Non-Subsective Adjectives. 
*Pavlick and Callison-Burch. *SEM (2016)*

Fine-Grained Class Extraction via Modifier Composition. 
*Pavlick and Pasca. ACL (2017)*

*American composer*
Introduction

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing. 
Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment
Compositional Entailment in Adjective Nouns. 
Pavlick and Callison-Burch. ACL (2016)
So-Called Non-Subsective Adjectives. 

Class-Instance Identification
Fine-Grained Class Extraction via Modifier Composition. 
Pavlick and Pasca. ACL (2017)

Summary and Future Work
Classes of Modifiers

American composer
composer
Classes of Modifiers

MH $\Rightarrow$ H

American composer

Subsective
Classes of Modifiers

MH $\Rightarrow$ H

- American composer
- composer

MH $\not\Rightarrow$ H

- alleged criminal
- criminal

Subsective

Plain Non-Subsective
Classes of Modifiers

MH $\Rightarrow H$
- American composer
- composer
- Subsective

MH $\not\Rightarrow H$
- alleged criminal
- criminal
- Plain Non-Subsective

MH $\Rightarrow \neg H$
- fake gun
- gun
- Privative
<table>
<thead>
<tr>
<th>Type</th>
<th>Condition</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equivalence</td>
<td>$\text{MH} \iff \text{H}$</td>
<td>It is her favorite book in the entire world.</td>
</tr>
<tr>
<td>Reverse Entailment</td>
<td>$\text{MH} \Rightarrow \text{H} \land \text{H} \not\Rightarrow \text{MH}$</td>
<td>She is an American composer.</td>
</tr>
<tr>
<td>Forward Entailment</td>
<td>$\text{MH} \not\Rightarrow \text{H} \land \text{H} \Rightarrow \text{MH}$</td>
<td>She is the president’s potential successor.</td>
</tr>
<tr>
<td>Independence</td>
<td>$\text{MH} \not\Rightarrow \text{H} \land \text{H} \not\Rightarrow \text{MH}$</td>
<td>She is the alleged hacker.</td>
</tr>
<tr>
<td>Exclusion</td>
<td>$\text{MH} \Rightarrow \neg \text{H} \land \text{H} \Rightarrow \neg \text{MH}$</td>
<td>She is a former senator.</td>
</tr>
</tbody>
</table>
Natural Language Inference

Eddy is a cat.
Natural Language Inference

Eddy is a cat.

Eddy is a domestic cat.
Eddy is a cat.

Eddy is a domestic cat.
Natural Language Inference

Eddy is a **cat**.

Eddy is a **domestic cat**.
Natural Language Inference

Eddy is a **cat** sitting on the ground looking out through a clear door screen.

Eddy is a **domestic cat** sitting on the ground looking out through a clear door screen.
Natural Language Inference

Eddy is a **cat** sitting on the ground looking out through a clear door screen.

文娱 →

Eddy is a **domestic cat** sitting on the ground looking out through a clear door screen.

\[ p \text{ entails } h \text{ if typically, a human reading } p \text{ would infer that } h \text{ is most likely true.} \]
Eddy is a domestic cat sitting on the ground looking out through a clear door screen.

$p$ entails $h$ if typically, a human reading $p$ would infer that $h$ is most likely true.
What types of inference rules govern human inferences in practice?

Eddy is a **domestic cat** sitting on the ground looking out through a clear door screen.

\[ p \text{ entails } h \text{ if typically, a human reading } p \text{ would infer that } h \text{ is most likely true.} \]
What types of inference rules govern human inferences in practice?

What, if any, generalizations can be made to aide systems in performing natural language inference?
Human Annotation of MH Compositions
Human Annotation of MH Compositions

H $\Rightarrow$ MH?

Eddy is a *cat*.

Eddy is a *domestic cat*. 
Human Annotation of MH Compositions

MH $\Rightarrow$ H?

Eddy is a domestic cat.

Eddy is a cat.
<table>
<thead>
<tr>
<th>Type</th>
<th>MH</th>
<th>H</th>
<th>MH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equiv.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Rev. Ent.</td>
<td>Yes</td>
<td>Unk</td>
<td></td>
</tr>
<tr>
<td>For. Ent.</td>
<td>Unk</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Indep.</td>
<td>Unk</td>
<td>Unk</td>
<td></td>
</tr>
<tr>
<td>Excl.</td>
<td>No</td>
<td>No</td>
<td></td>
</tr>
</tbody>
</table>

It is her favorite book in the **entire world**.

Eddy is a **gray cat**.

She is the president’s **potential successor**.

She is the **alleged hacker**.

She is a **former senator**.
Equivalence: 62%
Reverse Entailment: 23%
Independence: 7%
Forward Entailment: 7%
Exclusion: 1%
Undefined: 7%
noun entails modifier?

- Equivalence
- Reverse Entailment
- Independence
- Forward Entailment
- Exclusion
- Undefined

62%
noun contradicts modifier?
$H \Rightarrow MH?$

- **Images**
  - Equivalence: 2%
  - Reverse Entailment: 7%
  - Forward Entailment: 7%
  - Independence: 2%
  - Exclusion: 7%
  - Undefined: 87%

- **News**
  - Equivalence: 7%
  - Reverse Entailment: 23%
  - Forward Entailment: 7%
  - Independence: 7%
  - Exclusion: 1%
  - Undefined: 62%

- **Literature**
  - Equivalence: 2%
  - Reverse Entailment: 26%
  - Forward Entailment: 5%
  - Independence: 2%
  - Exclusion: 66%
  - Undefined: 6%

- **Debate Forums**
  - Equivalence: 9%
  - Reverse Entailment: 31%
  - Forward Entailment: 1%
  - Independence: 6%
  - Exclusion: 1%
  - Undefined: 53%
H ⇒ MH?

The **deadly attack** killed at least 12 civilians.

The **new series** will **premiere** in January.

A woman rides a bike on an **outdoor trail** through a **field**.
The entire bill is now subject to approval by the parliament.

Greenberg also was put under investigation for his crucial role at the company.

I simply love the actual experience of being one with the ocean and the life in it.
Entities are assumed to be real and relevant.
Entities are assumed to be real and relevant.
Entities are assumed to be prototypical.
$H \Rightarrow \neg MH?$
H ⇒ ¬MH?

gun

fake gun
H ⇒ ¬MH?

H ⇒ ¬MH

MH ⇒ ¬H
Undefined Relations
Undefined Relations

MH $\Rightarrow$ H

(like subsective)
Undefined Relations

H \implies \neg MH

(H \implies (\neg MH)

(like privative)
<table>
<thead>
<tr>
<th>Equiv.</th>
<th>MH $\Rightarrow$ H</th>
<th>H $\Rightarrow$ MH</th>
<th>It is her favorite book in the <strong>entire world</strong>.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rev. Ent.</td>
<td>Yes</td>
<td>Unk</td>
<td>Eddy is a <strong>gray cat</strong>.</td>
</tr>
<tr>
<td>For. Ent.</td>
<td>Unk</td>
<td>Yes</td>
<td>She is the president’s <strong>potential successor</strong>.</td>
</tr>
<tr>
<td>Indep.</td>
<td>Unk</td>
<td>Unk</td>
<td>She is the <strong>alleged hacker</strong>.</td>
</tr>
<tr>
<td>Excl.</td>
<td>No</td>
<td>No</td>
<td>She is a <strong>former senator</strong>.</td>
</tr>
<tr>
<td>Undef.</td>
<td>Yes</td>
<td>No</td>
<td>??????</td>
</tr>
</tbody>
</table>
Undefined Relations

H ⇒ ¬MH

Bush travels Monday to Michigan to remark on the economy.

Bush travels Monday to Michigan to remark on the Japanese economy.
Undefined Relations

MH $\Rightarrow$ H

Bush travels Monday to Michigan to remark on the Japanese economy.

Bush travels Monday to Michigan to remark on the economy.
Classes of Modifiers Revisited

- **Subsective**
  - $MH \Rightarrow H$
  - American composer
  - composer

- **Plain Non-Subsective**
  - $MH \not\Rightarrow H$
  - alleged criminal
  - criminal

- **Privative**
  - $MH \Rightarrow \neg H$
  - fake gun
  - gun
Classes of Modifiers Revisited

- **Subsective**
  - $MH \Rightarrow H$
  - 100%
  - **Equivalence**
  - **Forward Entailment**

- **Plain Non-Subsective**
  - $MH \not\Rightarrow H$
  - 50% Reverse Entailment
  - 50% Exclusion

- **Privative**
  - $MH \Rightarrow \neg H$
  - 100%
  - **Independence**
  - **Undefined**
Classes of Modifiers Revisited

- **Subsective**
  - $\text{MH} \Rightarrow H$
  - Equivalence: 67%
  - Reverse Entailment: 28%
  - Independence: 1%

- **Plain Non-Subsective**
  - $\text{MH} \not\Rightarrow H$
  - Equivalence: 54%
  - Reverse Entailment: 19%
  - Exclusion: 7%
  - Independence: 5%

- **Privative**
  - $\text{MH} \Rightarrow \neg H$
  - Equivalence: 37%
  - Reverse Entailment: 28%
  - Exclusion: 16%
  -Independence: 16%
  - Undefined: 3%

The diagrams illustrate the percentage distribution of each class of modifiers in the context of entailment relationships.
Privative Modifiers

\[ H \Rightarrow \neg MH \]

Wilson signed off to pay the debts to the company.

Wilson signed off to pay the debts to the fictitious company.
Privative Modifiers

MH ⇒ H

Wilson signed off to pay the debts to the **fictitious company**.

Wilson signed off to pay the debts to the **company**.
Classes of Modifiers Revisited

Subsective
MH → H
- Equivalence: 67%
- Reverse Entailment: 28%
- Independence: 1%
- Undefined: 1%

Plain Non-Subsective
MH ↔ H
- Equivalence: 54%
- Reverse Entailment: 19%
- Independence: 5%
- Exclusion: 14%
- Undefined: 7%

Privative
MH → ¬H
- Equivalence: 37%
- Reverse Entailment: 28%
- Independence: 16%
- Exclusion: 16%
- Undefined: 3%
Classes of Modifiers Revisited

Subsective
MH ⇒ H

Plain Non-Subsective
MH ⇒ H

Privative
MH ⇒ ¬H

Generalizations based on the class of the modifier lead to incorrect predictions more often than not.
Modern Inference Systems

$p$ entails $h$ if typically, a human reading $p$ would infer that $h$ is most likely true.
Modern Inference Systems

\[ p = \text{“The crowd roared.”} \]
\[ h = \text{“The enthusiastic crowd roared.”} \]

\[ p \text{ entails } h \text{ if typically, a human reading } p \text{ would infer that } h \text{ is most likely true.} \]
Modern Inference Systems

\[ p = \text{“The crowd roared.”} \]
\[ h = \text{“The enthusiastic crowd roared.”} \]

\[ p \text{ entails } h \text{ if typically, a human reading } p \text{ would infer that } h \text{ is most likely true.} \]

Yes
Modern Inference Systems

Accuracy

- Random Guessing: 85.3
- Transformation-based (Stern and Dagan, 2012): 85.3
- Bag of Words: 86
- Logistic Regression (Magnini et al., 2014): 85.3
- Bag of Vectors: 86.6
- RNN: 87.3
- LSTM: 86.6
- LSTM + Transfer (Bowman et al., 2015): 86.8
Modern Inference Systems

- Random Guessing: 85.3%
- Transformation-based: 85.3%
- Bag of Words: 86%
- Logistic Regression: 85.3%
- Bag of Vectors: 86.6%
- RNN: 87.3%
- LSTM: 86.6%
- LSTM + Transfer: 86.8%

Partially proof-based
Modern Inference Systems

- Partially proof-based
  - Random Guessing
  - Transformation-based
    - Stern and Dagan (2012)
- Supervised Learning
  - Bag of Words
  - Logistic Regression
    - Magnini et al. (2014)
  - Bag of Vectors
  - RNN
  - LSTM
  - LSTM + Transfer
    - Bowman et al. (2015)
Modern Inference Systems

- Partially proof-based
  - Random Guessing
  - Transformation-based (Stern and Dagan, 2012)
- Supervised Learning
  - Bag of Words
  - Logistic Regression (Magnini et al., 2014)
  - Bag of Vectors
- Deep Learning
  - RNN
  - LSTM
  - LSTM + Transfer (Bowman et al., 2015)
Modern Inference Systems

Correct representation is **difficult to capture explicitly**

![Accuracy Chart]

- Random Guessing: 85.3
- Transformation-based: 85.3
- Bag of Words: 86
- Logistic Regression: 85.3
- Bag of Vectors: 86.6
- RNN: 87.3
- LSTM: 86.6
- LSTM + Transfer: 86.8

Modern Inference Systems

*Correct representation is difficult to capture explicitly*
Correct representation is difficult to capture explicitly and is currently not being learned implicitly.
Discussion
Discussion

The **crowd** roared.
Discussion

The **crowd** roared.

enthusiastic crowd
Discussion

crowd

enthusiastic crowd

Set Containment
Discussion

Set Containment
Discussion

The *crowd* roared.
Discussion

The ___ **crowd** roared.

\[
P(\text{enthusiastic})
\]
\[
P(\text{silent})
\]
\[
P(\text{imaginary})
\]

Language Modeling
Discussion

The **crowd** roared.

- enthusiastic crowd
- silent crowd
- imaginary crowd

Word Sense Disambiguation
Discussion

The *crowd* roared.

Reference
Discussion

The crowd roared.

Reference
Discussion

The crowd roared.

enthusiastic crowd

Reference
Discussion

The *crowd* roared.

real

enthusiastic crowd
Discussion

The **crowd** roared.

*real*  
*enthusiastic crowd*  
*human*
Discussion

The **crowd** roared.

- real
- making noise
- human

enthusiastic crowd
Discussion

The **crowd** roared.

- real
- making noise
- excited/happy
- human

enthusiastic crowd
Discussion

The **crowd** roared.

- real
- making noise
- excited/happy
- human

**enthusiastic crowd**

- excited/happy
- making noise
- clapping
- yelling
- human
The enthusiastic crowd roared.

- Real human
- Making noise
- Excited/happy
- Human
- Excited/happy
- Making noise
- Clapping
- Yelling
The enthusiastic crowd roared.

Assigning intrinsic meaning to modifiers...

enthusiastic crowd

excited/happy
making noise
clapping
yelling
human
The **crowd** roared.

**enthusiastic crowd**

- real
- making noise
- excited/happy
- human

Determining whether they hold for **individual entities**
Introduction

Lexical Entailment

Adding Semantics to Data-Driven Paraphrasing.
Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment

Compositional Entailment in Adjective Nouns.
Pavlick and Callison-Burch. ACL (2016)

So-Called Non-Subsective Adjectives.

Class-Instance Identification

Fine-Grained Class Extraction via Modifier Composition.
Pavlick and Pasca. ACL (2017)

Summary and Future Work
Introduction

Lexical Entailment

Adding Semantics to Data-Driven Paraphrasing. 
*Pavlick et al. ACL (2015)*

Modifier-Noun Composition

Semantic Containment

Compositional Entailment in Adjective Nouns. 
*Pavlick and Callison-Burch. ACL (2016)*

So-Called Non-Subsective Adjectives. 
*Pavlick and Callison-Burch. *SEM (2016)*

Class-Instance Identification

Fine-Grained Class Extraction via Modifier Composition. 
*Pavlick and Pasca. ACL (2017)*

Summary and Future Work

American composer

Charles Mingus
American composer

Compositional Semantics

composer

American composer
Compositional Semantics

composer

American composer
Compositional Semantics

composer

American composer
Compositional Semantics

Can we assign intrinsic meaning to modifiers...

composer

American composer
Compositional Semantics

Can we assign *intrinsic meaning* to modifiers...

...in such a way that we can determine whether the modifier holds for *individual entities* in practice?
Step 1: Modifier Interpretation
Step 1: Modifier Interpretation
Determine the properties entailed by the modifier in the context of the head

American composer

- born in America
- influential in America
- prolific while in America
- a product of America
- lived in America
- visited America
- popular in America
Step 2: Class-Instance Identification
Determine, for a specific instance, whether the necessary properties hold

American composer
born in America
influential in America
prolific while in America
a product of America
lived in America
visited America
popular in America

...Mingus's intricate, complex, compositions in the genres of jazz and classical music illustrate his ability to be dynamic in both the strings and the swing. Mingus truly was a product of America in all its historic complexities. His mother, Harriet, was half black and half Chinese, and his father, Charles Sr., was half black and half Swedish, making Mingus a true reflection of the hybrid nature of our divided nation...
Modifier Interpretation

American composer
Modifier Interpretation

American composer
composer * America
Modifier Interpretation

American composer

composer from America
composer born in America
composer popular in America
composer active in America
Modifier Interpretation

American composer

composer * America

⟨composer from America, 3702⟩
⟨composer born in America, 1389⟩
⟨composer popular in America, 1292⟩
⟨composer active in America, 2041⟩
Modifier Interpretation

\[ P(Y|X) = \frac{1}{1 + e^{X\beta}} \]

American composer
composer * America

\langle \text{composer from America, 3702} \rangle
\langle \text{composer born in America, 1389} \rangle
\langle \text{composer popular in America, 1292} \rangle
\langle \text{composer active in America, 2041} \rangle
Modifier Interpretation

American composer

composer * America

\[ P(Y|X) = \frac{1}{1 + e^{X\beta}} \]

⟨composer from America, 0.93⟩
⟨composer born in America, 0.94⟩
⟨composer popular in America, 0.45⟩
⟨composer active in America, 0.52⟩
Modifier Interpretation

\[
P(Y|X) = \frac{1}{1 + e^{X_\beta}}
\]

American composer

\langle \text{composer born in America}, 0.94 \rangle
\langle \text{composer from America}, 0.93 \rangle
\langle \text{composer active in America}, 0.52 \rangle
\langle \text{composer popular in America}, 0.45 \rangle
Modifier Interpretation

American composer → born in America

American company → based in America

American novel → written in America

Produces good results...
Modifier Interpretation

child actor \(\rightarrow\) has child

risk manager \(\rightarrow\) takes risks

machine gun \(\rightarrow\) used by machine

...but not perfect.
Class-Instance Identification
Class-Instance Identification

American composer

<___ born in America, 0.94>
<___ from America, 0.93>
<___ active in America, 0.52>
<___ popular in America, 0.45>

Weighted modifier interpretations
Class-Instance Identification

American composer

* is a composer

⟨___ born in America, 0.94⟩
⟨___ from America, 0.93⟩
⟨___ active in America, 0.52⟩
⟨___ popular in America, 0.45⟩

J.S. Bach
Charles Mingus
John Cage
W.A. Mozart

Candidate instances
Class-Instance Identification

American composer

“J.S. Bach born in America”

Confidence = 0.94x21
Class-Instance Identification

American composer

“J.S. Bach from America”

Confidence = 0.94x21 + 0.93x34
Class-Instance Identification

American composer

“J.S. Bach active in America”

⟨___ born in America, 0.94⟩
⟨___ from America, 0.93⟩
⟨___ active in America, 0.52⟩
⟨___ popular in America, 0.45⟩

J.S. Bach
Charles Mingus
John Cage
W.A. Mozart

Confidence = 0.94x21 + 0.93x34 + 0.52x329
Class-Instance Identification

American composer

“J.S. Bach popular in America”

⟨___ born in America, 0.94⟩
⟨___ from America, 0.93⟩
⟨___ active in America, 0.52⟩
⟨___ popular in America, 0.45⟩

J.S. Bach
Charles Mingus
John Cage
W.A. Mozart

Confidence = 0.94x21 + 0.93x34 + 0.52x329 + 0.45x4,043
## Class-Instance Identification

<table>
<thead>
<tr>
<th>Name</th>
<th>American composer</th>
<th>Jazz composer</th>
</tr>
</thead>
<tbody>
<tr>
<td>JS Bach</td>
<td>0.21</td>
<td>0.04</td>
</tr>
<tr>
<td>Charles Mingus</td>
<td>0.89</td>
<td>0.93</td>
</tr>
<tr>
<td>John Cage</td>
<td>0.96</td>
<td>0.52</td>
</tr>
<tr>
<td>WA Mozart</td>
<td>0.19</td>
<td>0.13</td>
</tr>
<tr>
<td>Libby Larsen</td>
<td>0.72</td>
<td>0.24</td>
</tr>
<tr>
<td>Duke Ellington</td>
<td>0.76</td>
<td>0.97</td>
</tr>
<tr>
<td>Palestrina</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Ludwig van Beethoven</td>
<td>0.09</td>
<td>0.12</td>
</tr>
<tr>
<td>Morton Feldman</td>
<td>0.88</td>
<td>0.31</td>
</tr>
<tr>
<td>Frederick Chopin</td>
<td>0.33</td>
<td>0.32</td>
</tr>
<tr>
<td>Barack Obama</td>
<td>0.14</td>
<td>0.35</td>
</tr>
<tr>
<td>Herbie Hancock</td>
<td>0.62</td>
<td>0.95</td>
</tr>
<tr>
<td>Name</td>
<td>Score</td>
<td></td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>-------</td>
<td></td>
</tr>
<tr>
<td>JS Bach</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>Charles Mingus</td>
<td>1.82</td>
<td></td>
</tr>
<tr>
<td>John Cage</td>
<td>1.48</td>
<td></td>
</tr>
<tr>
<td>WA Mozart</td>
<td>0.32</td>
<td></td>
</tr>
<tr>
<td>Libby Larsen</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>Duke Ellington</td>
<td>1.73</td>
<td></td>
</tr>
<tr>
<td>Palestrina</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>Ludwig van Beethoven</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>Morton Feldman</td>
<td>1.19</td>
<td></td>
</tr>
<tr>
<td>Frederick Chopin</td>
<td>0.65</td>
<td></td>
</tr>
<tr>
<td>Barack Obama</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>Herbie Hancock</td>
<td>1.57</td>
<td></td>
</tr>
</tbody>
</table>
## Class-Instance Identification

<table>
<thead>
<tr>
<th>Name</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>American jazz composer</td>
<td></td>
</tr>
<tr>
<td>Charles Mingus</td>
<td>1.82</td>
</tr>
<tr>
<td>Duke Ellington</td>
<td>1.73</td>
</tr>
<tr>
<td>Herbie Hancock</td>
<td>1.57</td>
</tr>
<tr>
<td>John Cage</td>
<td>1.48</td>
</tr>
<tr>
<td>Morton Feldman</td>
<td>1.19</td>
</tr>
<tr>
<td>Libby Larsen</td>
<td>0.96</td>
</tr>
<tr>
<td>Frederick Chopin</td>
<td>0.65</td>
</tr>
<tr>
<td>Barack Obama</td>
<td>0.49</td>
</tr>
<tr>
<td>WA Mozart</td>
<td>0.32</td>
</tr>
<tr>
<td>JS Bach</td>
<td>0.25</td>
</tr>
<tr>
<td>Ludwig van Beethoven</td>
<td>0.21</td>
</tr>
<tr>
<td>Palestrina</td>
<td>0.07</td>
</tr>
</tbody>
</table>
Reconstructing Wikipedia

Category: Thai Buddhist temples

From Wikipedia, the free encyclopedia

This category is for temples belonging to the Thai Buddhism traditions, both in and outside of Thailand.

Pages in category "Thai Buddhist temples"

The following 18 pages are in this category, out of 18 total. This list may not reflect recent changes (learn more).

A
- Amaravati Buddhist Monastery
- Aruna Ratanagiri

B
- Birken Forest Buddhist Monastery
- Buddharama Temple

H
- Hádegismóar Temple

S
- Sunnataram Forest Monastery

W
- Wat Boston Buddha Vararam
- Wat Buddhananachat of Austin
- Wat Buddhanusorn
- Wat Buddhapatipada
- Wat Charoenbhavana
- Wat Chetawan
- Wat Mongkolratanaram
- Wat Nawamintararachutis
- Wat Pasantidhamma
- Wat Srinagarindravararam
Reconstructing Wikipedia

![ROC curve graph](image)

Legend:
- **Baseline**
- **Hearst**
- **Hearst ∩**
- **Hearst ∩ + Mods_H**
- **Hearst ∩ + Mods_I**

- **True Positive Rate**
- **False Positive Rate**

---

Table 7: Recall of instances listed on Wikipedia category pages.

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.70</td>
<td>0.09</td>
</tr>
<tr>
<td>Hearst</td>
<td>0.73</td>
<td>0.10</td>
</tr>
<tr>
<td><em>Hearst ∩</em></td>
<td>0.68</td>
<td>0.08</td>
</tr>
<tr>
<td><em>Hearst ∩ + Mods_H</em></td>
<td>0.57</td>
<td>0.04</td>
</tr>
<tr>
<td><em>Hearst ∩ + Mods_I</em></td>
<td>0.56</td>
<td>0.03</td>
</tr>
</tbody>
</table>

References:
- EACL 2017 Submission. Confidential review copy. DO NOT DISTRIBUTE.

TODO: Add two or three lines of future work.
Reconstructing Wikipedia

![ROC curve](image.png)

Best Existing Non-Compositional Method (Lexico-Syntactic Patterns)

**AUC = 0.57**
We have presented an approach to IsA extraction which we are able to populate. Significant increase in the number of fine-grained properties that it implies about the instances. This approach allows us to harness information that is spread across multiple sentences, and results in a method that takes advantage of the compositionality of the infinite number of classes describable in natural language. Existing approaches often treat class labels as atomic units which must be observed in the label individually, in terms of the properties it implies about the instances. This.

Our method works by reasoning about each modification which takes advantage of the compositionality of the infinite number of classes describable in natural language. Existing approaches often treat class labels as atomic units which must be observed in the label individually, in terms of the properties it implies about the instances. This.
Introduction

Lexical Entailment
Adding Semantics to Data-Driven Paraphrasing.
*Pavlick et al. ACL (2015)*

Modifier-Noun Composition

Semantic Containment
Compositional Entailment in Adjective Nouns.
*Pavlick and Callison-Burch. ACL (2016)*
So-Called Non-Subsective Adjectives.
*Pavlick and Callison-Burch. *SEM (2016)*

Class-Instance Identification
Fine-Grained Class Extraction via Modifier Composition.
*Pavlick and Pasca. ACL (2017)*

American composer
Charles Mingus
Introduction

Lexical Entailment

Adding Semantics to Data-Driven Paraphrasing.
*Pavlick et al. ACL (2015)*

Modifier-Noun Composition

Semantic Containment

Compositional Entailment in Adjective Nouns.
*Pavlick and Callison-Burch. ACL (2016)*

So-Called Non-Subsective Adjectives.
*Pavlick and Callison-Burch. *SEM (2016)*

Class-Instance Identification

Fine-Grained Class Extraction via Modifier Composition.
*Pavlick and Pasca. ACL (2017)*

Summary and Future Work
Lexical Entailment

Semantic Containment

Class-Instance Identification
Lexical Entailment

- Equivalence
- Reverse Entailment
- Forward Entailment
- Independent
- Exclusion

Class-Instance Identification
Lexical Entailment

Semantic Containment

Class-Instance Identification

No Axioms

Using WordNet

Using PPDB

Human Oracle

Axioms

Using PPDB

Using WordNet

Human Oracle
Lexical Entailment
Semantic Containment
Class-Instance Identification
Lexical Entailment

Subsective

- 67%
- 28%
- 1%

Plain Non-Subsective

- 54%
- 19%
- 14%
- 5%
- 7%

Privative

- 37%
- 28%
- 16%
- 16%
- 3%
- 1%
Lexical Entailment

Random Guessing: 85.3
Transformation-based Stern and Dagan (2012): 85.3
Bag of Words: 86
Logistic Regression Magnini et al. (2014): 85.3
Bag of Vectors: 86.6
RNN: 87.3
LSTM: 86.6
LSTM + Transfer Bowman et al. (2015): 86.8
Lexical Entailment

Semantic Containment

Class-Instance Identification
Lexical Entailment

Semantic Containment

Class-Instance Identification
Lexical Entailment

composers

American composers
Our method works by reasoning about each modifier in the label individually, in terms of the properties it conveys. We have presented an approach to IsA extraction which takes advantage of the compositionality of natural language, most of which never appear in text. Existing approaches often treat classes which we are able to populate. A significant increase in the number of fine-grained class labels as atomic units which must be observed in full in order to be populated with instances. As a result, it can provide non-zero scores for many more candidate instances. This enables for many more candidate instances. This enables for many more candidate instances.

Table 7: Recall of instances listed on Wikipedia

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uniform Weighted</td>
<td>0.73</td>
<td>0.10</td>
</tr>
<tr>
<td>Uniform random sample</td>
<td>0.71</td>
<td>0.09</td>
</tr>
<tr>
<td>Weighted random sample</td>
<td>0.68</td>
<td>0.08</td>
</tr>
</tbody>
</table>

The curve becomes linear once all remaining instances in the list have the same score (e.g., 0) as this makes it impossible to choose a threshold which adds true positives to the list without also including all remaining false positives. ROC curves show the relationship between the number of true positives and the number of false positives between extracting true positives versus false positives (see Figure 3).
Lexical Entailment

Semantic Containment

Class-Instance Identification
Future Directions
Future Directions

The **crowd** roared.

- real
- making noise
- enthusiastic crowd
  - excited/happy
  - human
  - making noise
  - clapping
  - yelling
  - human
The crowd roared.

- real
- making noise
- excited/happy
- human
Future Directions

The crowd roared.
Future Directions

The red circle.
Future Directions

“common sense knowledge”
Future Directions

“common sense knowledge”

What is it?
World Knowledge?
Pragmatics?

How do we represent it?
Distributional?
Symbolic? Triple stores?
Probability distributions?

How is it learned?
Is it distributional?
Is text enough?

When/how is it accessed?
What can be precomputed?
What happens at “runtime”?

How is it accessed?
What can be precomputed?
What happens at “runtime”?
Thank you!
Questions!