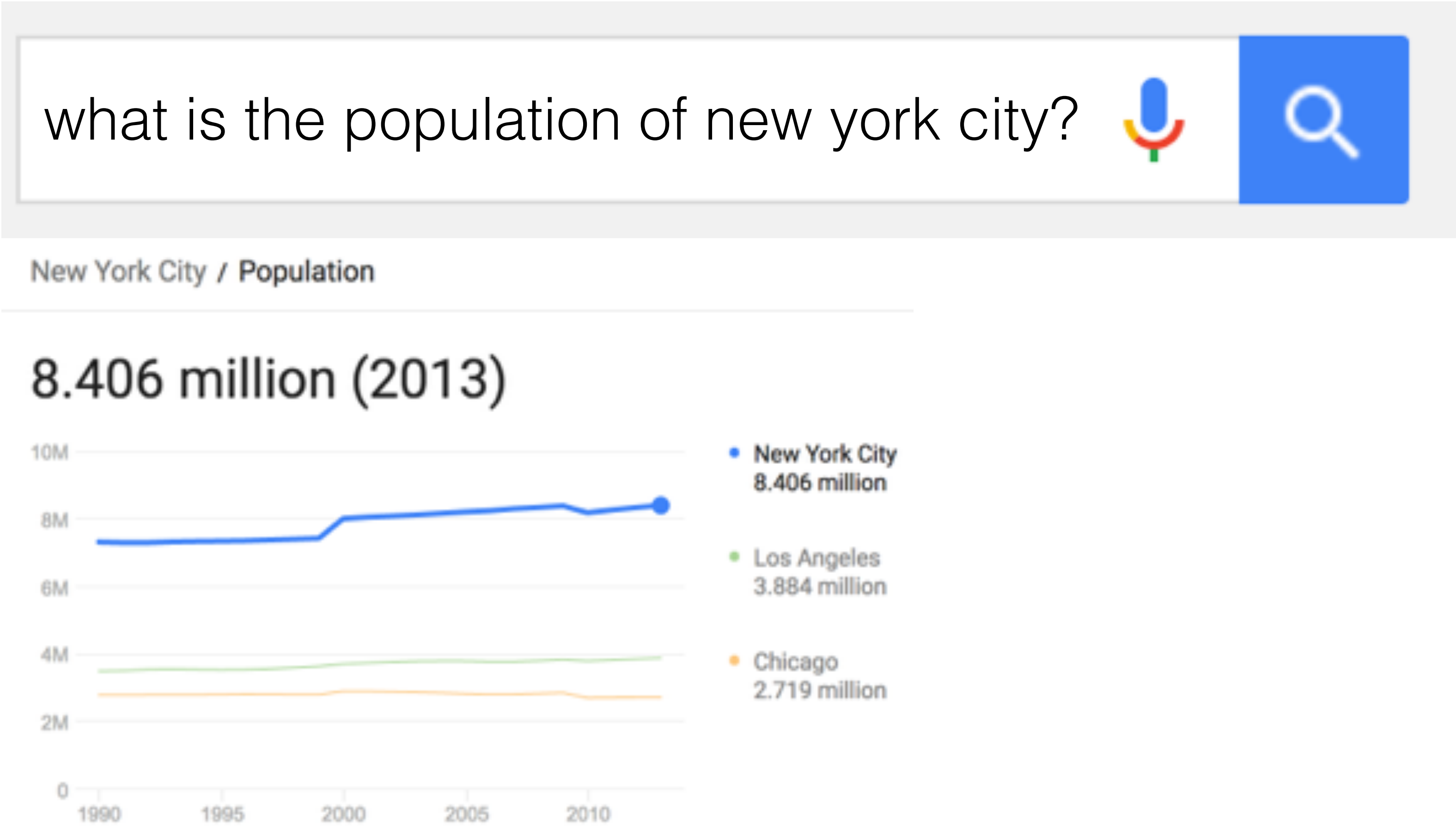
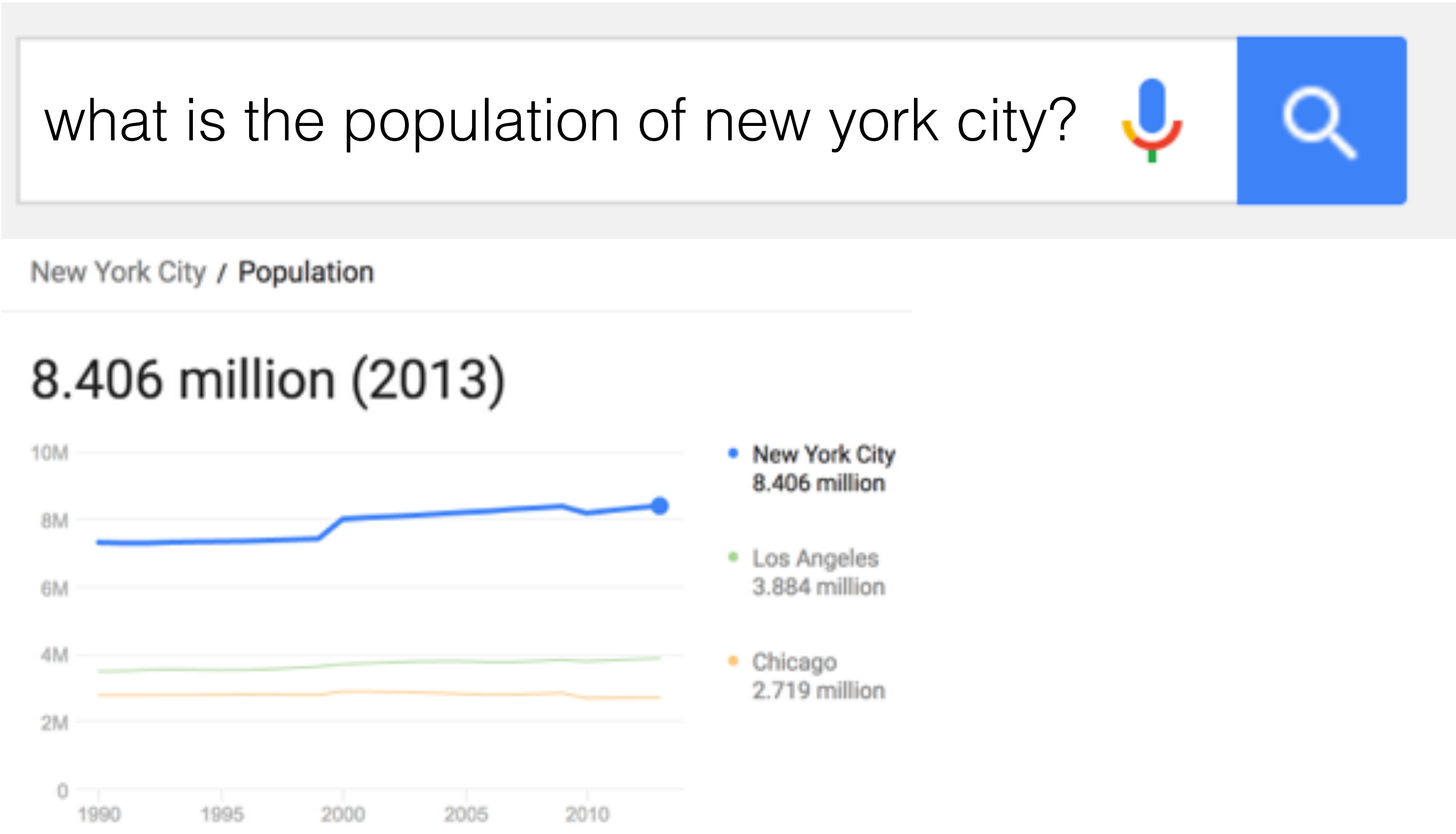
Compositional Lexical Semantics for Natural Language Inference

Thesis Defense

Ellie Pavlick
Department of Computer and Information Science
University of Pennsylvania


what is the population of new york city?
New York City / Population
8.406 million (2013)
10M
8M
6M
4M
2M
0
1990
1995
2000
2005
2010
New York City
8.406 million
Los Angeles
3.884 million
Chicago
2.719 million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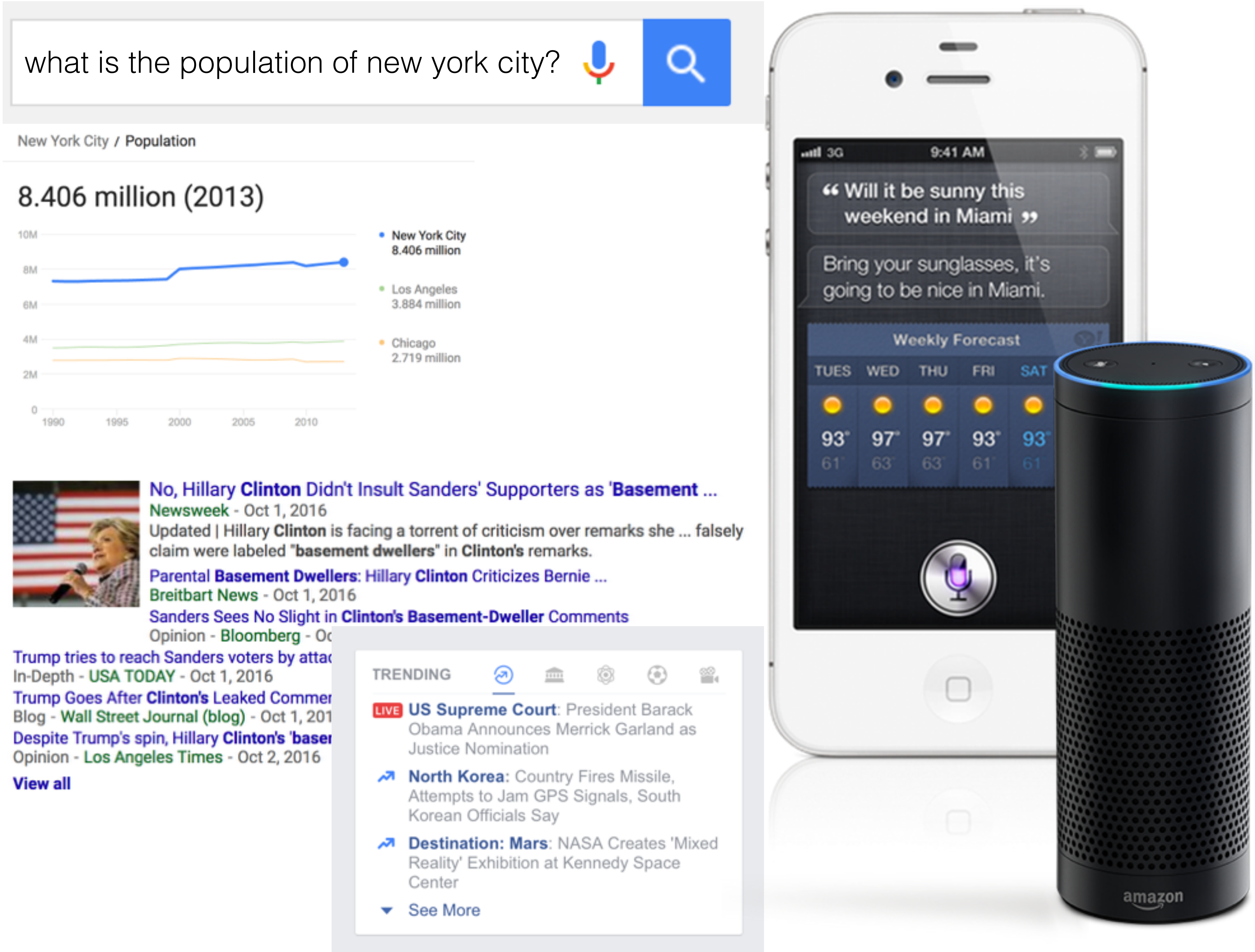
3G
9:41 AM
“Will it be sunny this weekend in Miami”
Bring your sunglasses, it's going to be nice in Miami.
Weekly Forecast
TUES
WED
THU
FRI
SAT
93°
97°
97°
93°
93°
61°
63°
63°
61°
61°
amazon



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No, Hillary Clinton Didn't Insult Sanders' Supporters as 'Basement ...
Newsweek - Oct 1, 2016
Updated | Hillary Clinton is facing a torrent of criticism over remarks she ... falsely claim were labeled "basement dwellers" in Clinton's remarks.
Parental Basement Dwellers: Hillary Clinton Criticizes Bernie ...
Breitbart News - Oct 1, 2016
Sanders Sees No Slight in Clinton's Basement-Dweller Comments
Opinion - Bloomberg - Oc
Trump tries to reach Sanders voters by attac
In-Depth - USA TODAY - Oct 1, 2016
Trump Goes After Clinton's Leaked Commen
Blog - Wall Street Journal (blog) - Oct 1, 201
Despite Trump's spin, Hillary Clinton's 'baser
Opinion - Los Angeles Times - Oct 2, 2016
View all
TRENDING
LIVE US Supreme Court: President Barack Obama Announces Merrick Garland as Justice Nomination
North Korea: Country Fires Missile, Attempts to Jam GPS Signals, South Korean Officials Say
Destination: Mars: NASA Creates 'Mixed Reality' Exhibition at Kennedy Space Center
See More
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TUES WED THU FRI SAT
93° 97° 97° 93° 93°
61° 63° 63° 61° 61°
amazon


what is the population of new york city?
New York City / Population
8.406 million (2013)
how many people live in nyc?
number of residents of nyc
new york city population
how big is new york city?
how crowded is ny?
Human language is highly variable.
"Will it be sunny this weekend in Miami?"
"What's the weather going to be like this weekend?"
"What is Saturday afternoon's forecast?"
"Is it going to be nice out on Saturday?"
Clinton gives frank take on Sanders supporters in audio from hacked email
October 1, 2016
Hillary caught on tape mocking millennials living in parents' basement and wanting free college
In Leaked Audio, Clinton Talks About Sanders Supporters 'Living in Parents' Basement'
by Josh Feldman | 11:17 pm, September 30th, 2016
HILLARY CALLS BERNIE SUPPORTERS LOSERS WHO LIVE IN THEIR PARENTS' BASEMENTS
OCTOBER 1, 2016 I BY BRIAN ANDERSON

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


in hacked fundraiser recording • in leaked recording • in audio from hacked email • privately • hacked audio:
mocks • said • insults • characterizes • comments on • gives frank take on • slams • calls • knocks • describes
Hillary • Hillary Clinton • HRC
In leaked audio, Clinton talks about Sanders supporters “living in basement”
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 hacked fundraiser recording • in leaked recording • in audio from hacked email • privately • hacked audio:

Hillary • Hillary Clinton • HRC

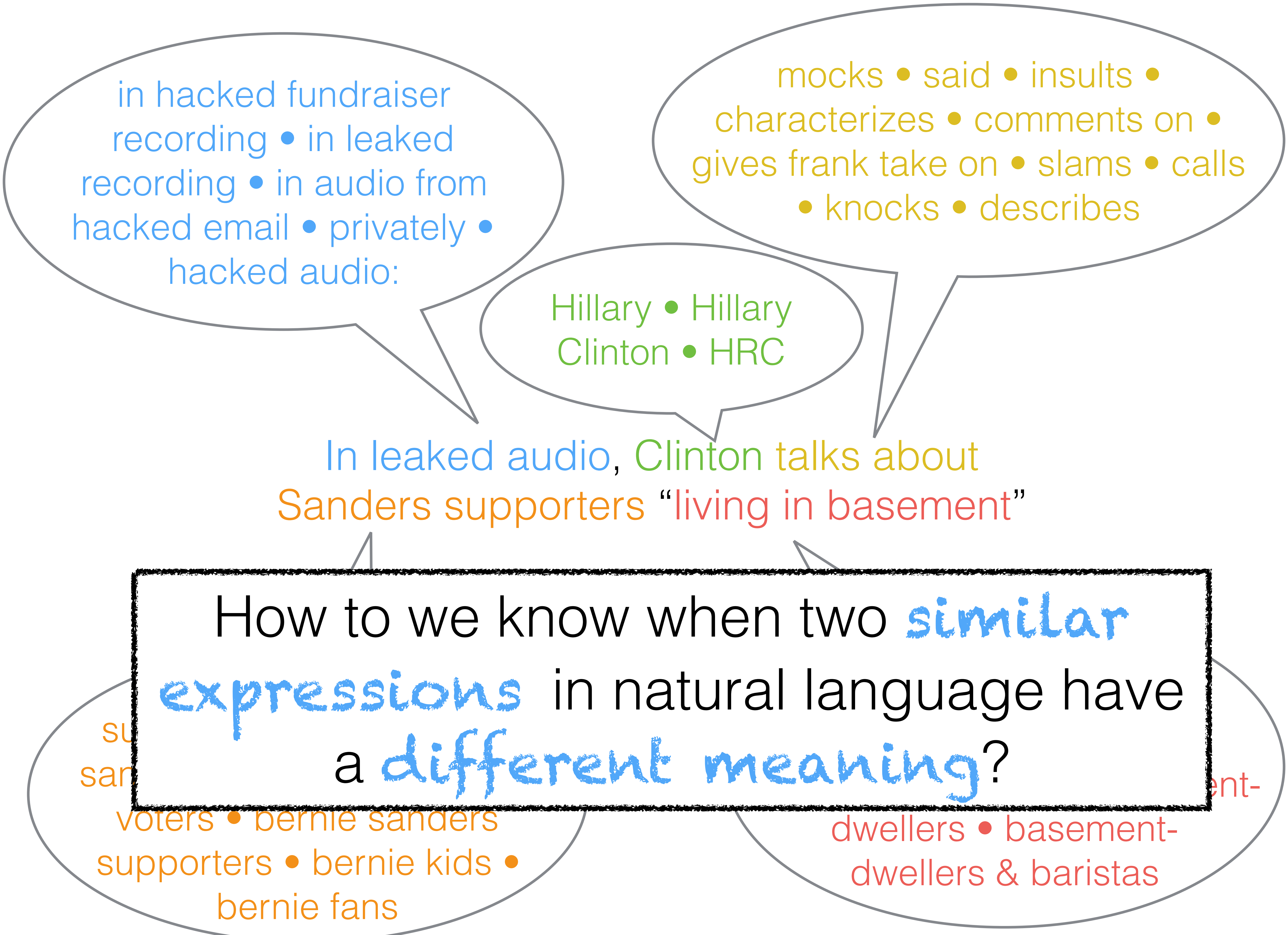
mocks • said • insults • characterizes • comments on • gives frank take on • slams • calls • knocks • describes

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*?

su
sar
voters • bernie sanders supporters • bernie kids • bernie fans

ent-
dwellers • basement-dwellers & baristas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In leaked audio, Clinton talks about Sanders supporters "living in basement"
voters • bernie sanders supporters • bernie kids • bernie fans
dwellers • basement-dwellers & baristas
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

||

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

Logical Inference

In hacked fundraiser recording $\subset$ In leaked recording

$\parallel$

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

Logical Inference

In hacked fundraiser recording $\subset$ In leaked recording $\subset$ Privately

$\parallel$

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

Logical Inference

In hacked fundraiser recording $\subset$ In leaked recording $\subset$ Privately

$\parallel$

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

Common Sense Inference

Logical Inference

In hacked fundraiser recording $\subset$ In leaked recording $\subset$ Privately

$\parallel$

In leaked audio, Clinton talks about Sanders supporters “living in parents’ basement”

$\parallel$

basement-dwellers

Common Sense Inference

Stylistics

Logical Inference

In hacked fundraiser recording $\subset$ In leaked recording $\subset$ Privately

$\|$

In leaked audio, Clinton talks about
Sanders supporters “living in parents’ basement”

$\|$

basement-dwellers

Common Sense Inference

Stylistics

Natural Language Inference

Natural Language Inference

(aka Recognizing Textual Entailment)

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(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

premise

Hillary Clinton privately slams millennials as
basement-dwellers

hypothesis

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 entails h if "typically, a human reading p would infer that h 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.
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Summary and Future Work

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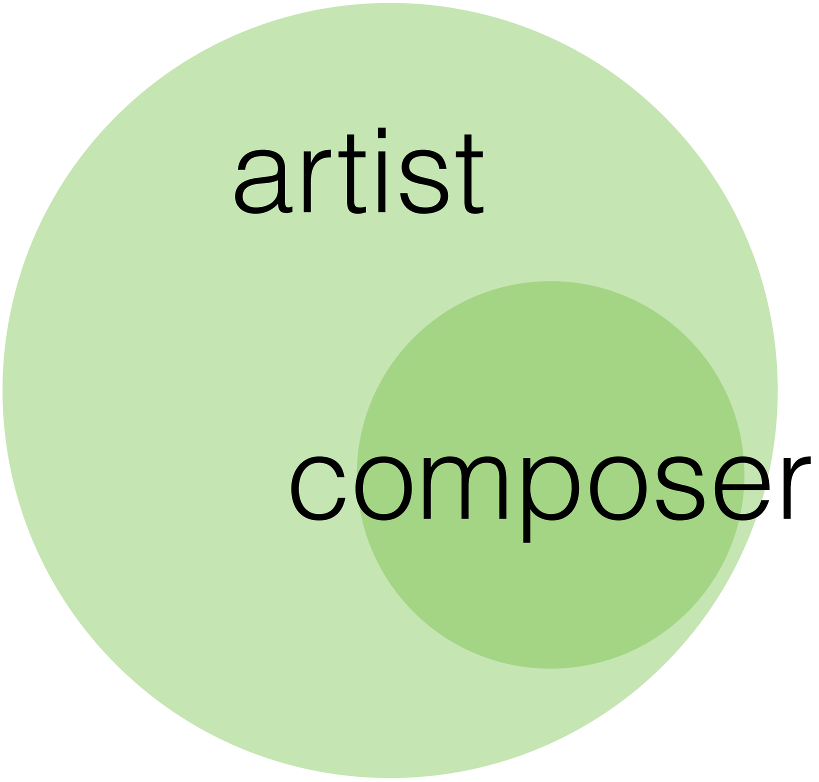

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American composer

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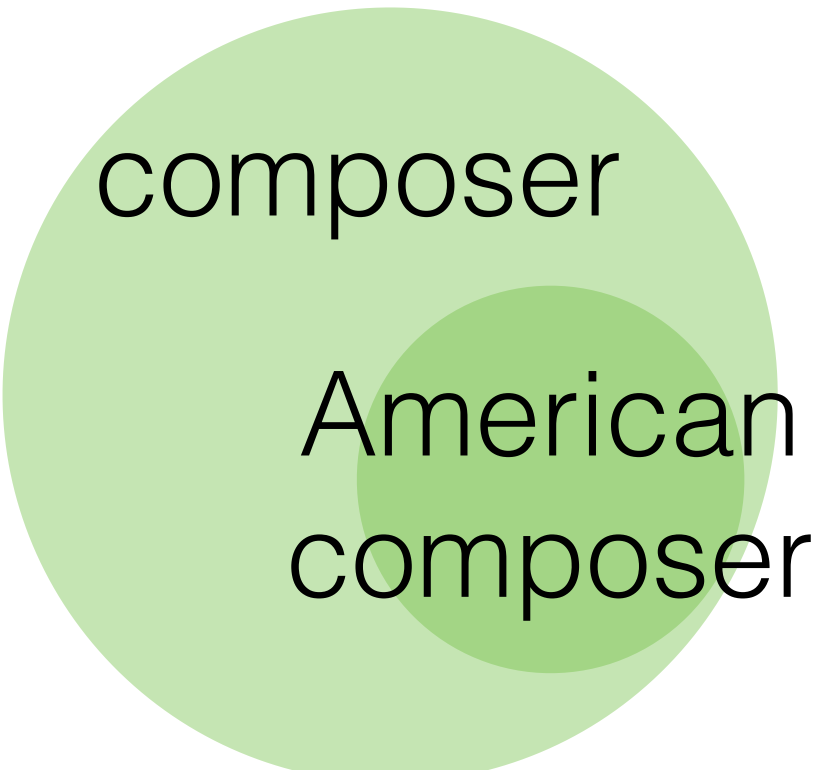

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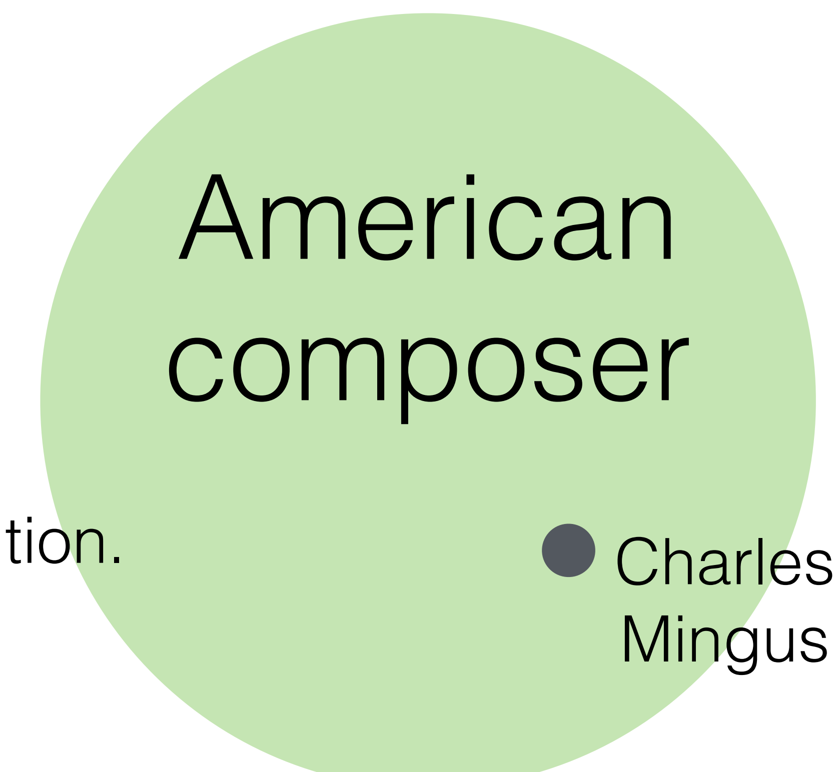

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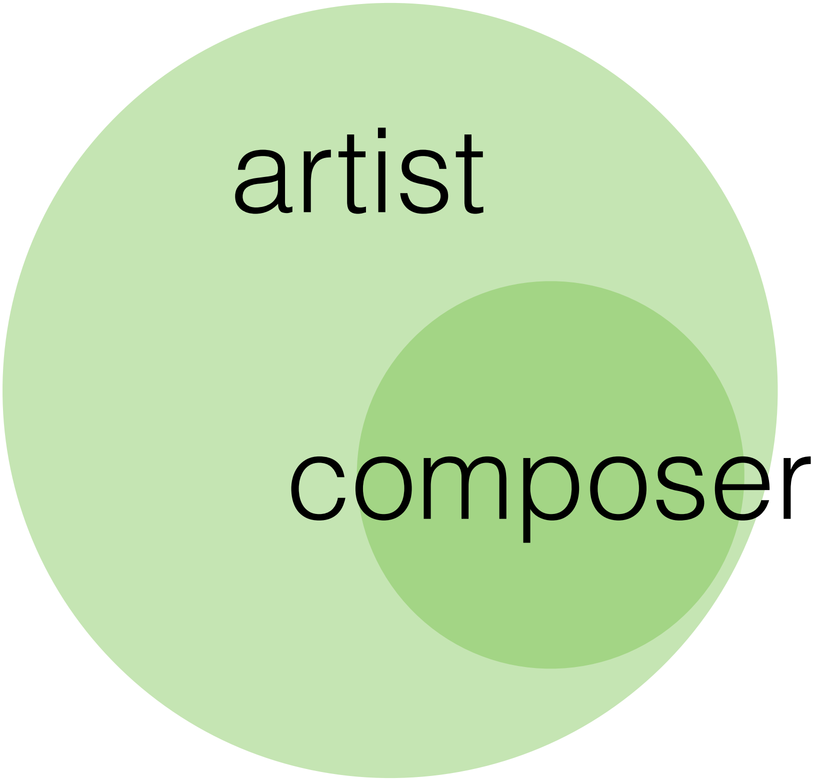

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Natural Language Inference

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

Hillary Clinton privately slams millennials as
basement-dwellers

Natural Language Inference

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

Hillary Clinton privately slams millennials as
basement-dwellers

Equivalence

Natural Language Inference

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

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

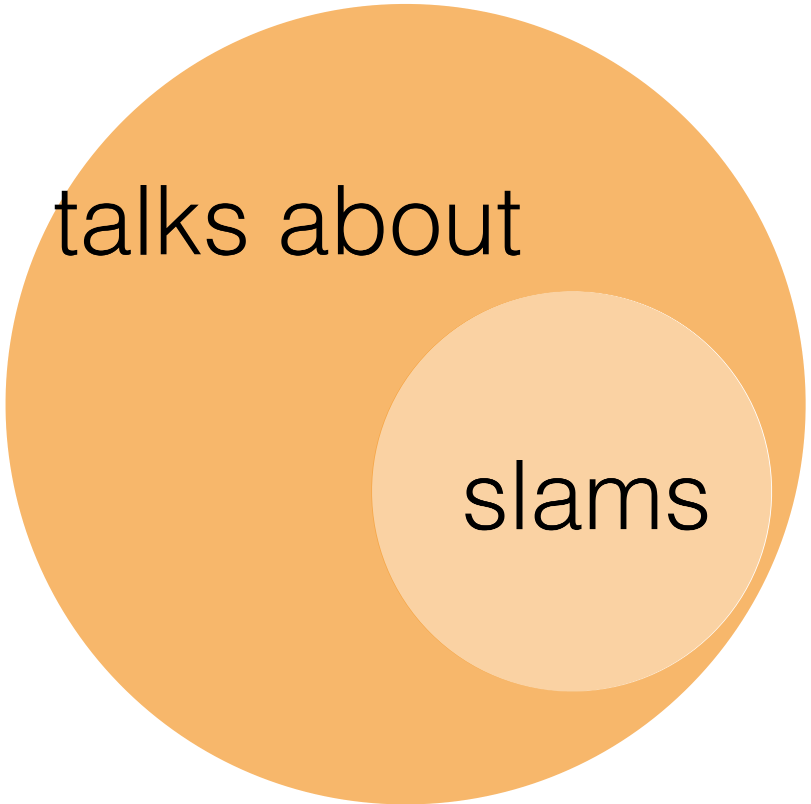
Forward Entailment

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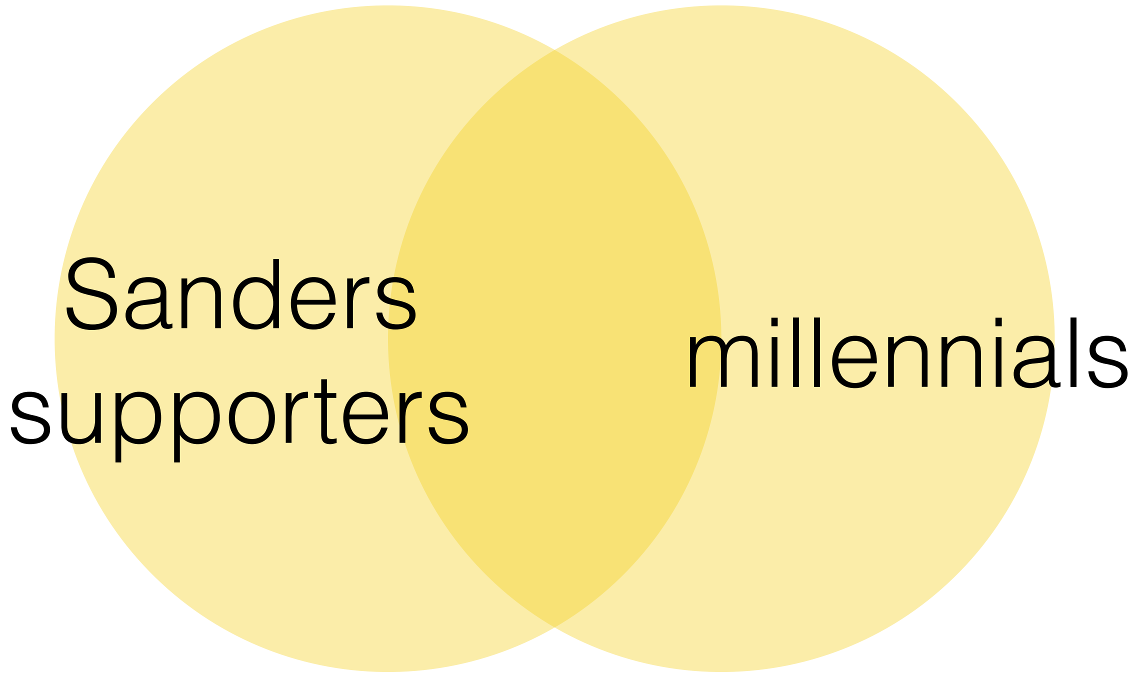
Hillary Clinton privately slams **millennials** as
basement-dwellers

Independent

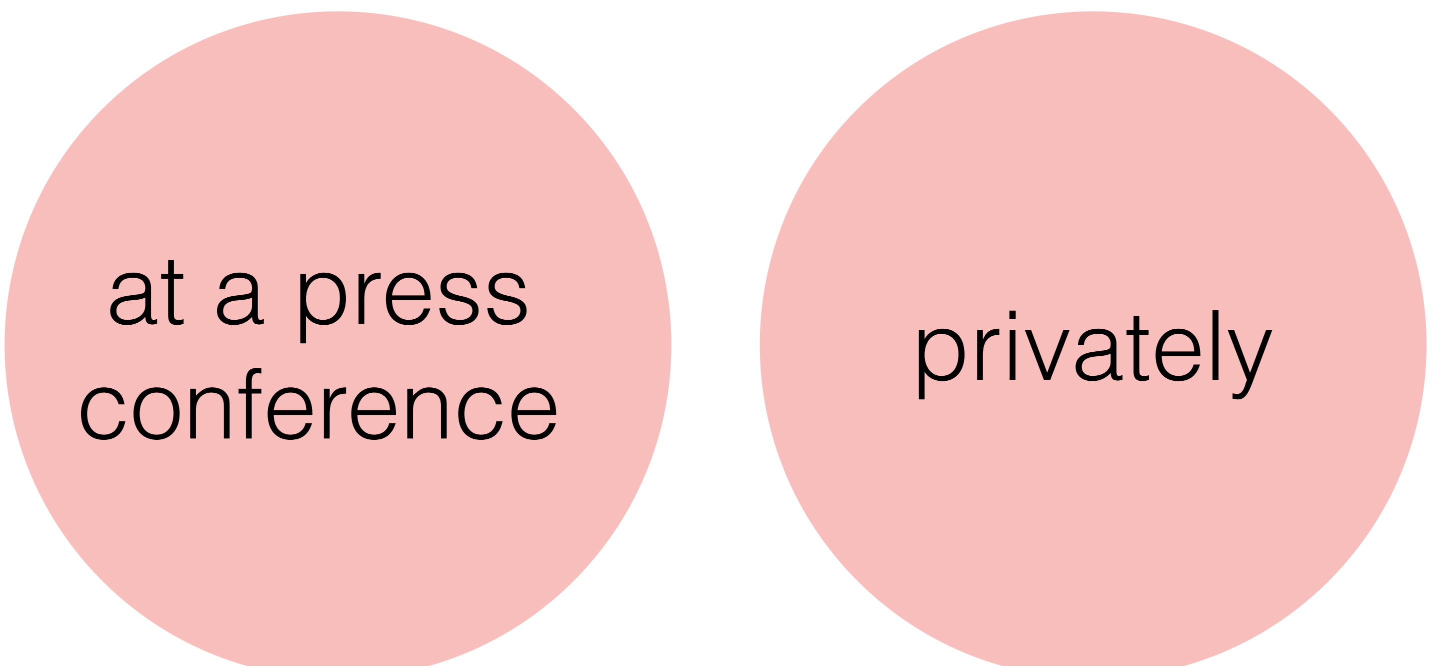


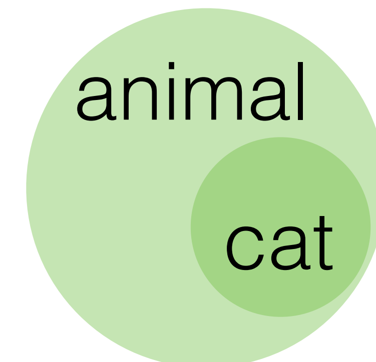
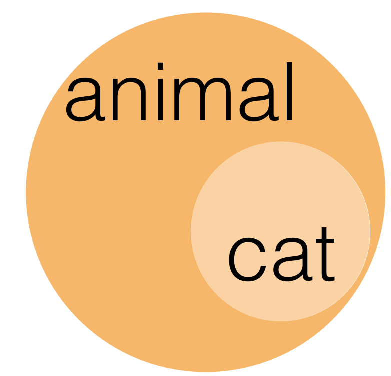
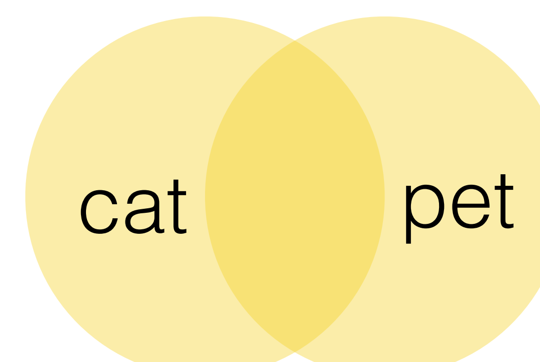
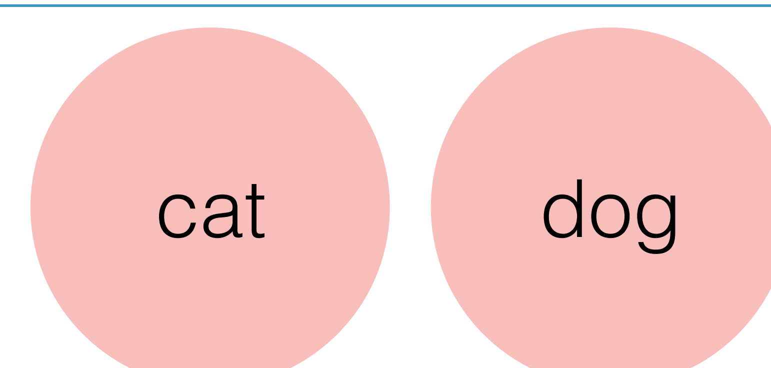
Natural Language Inference

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

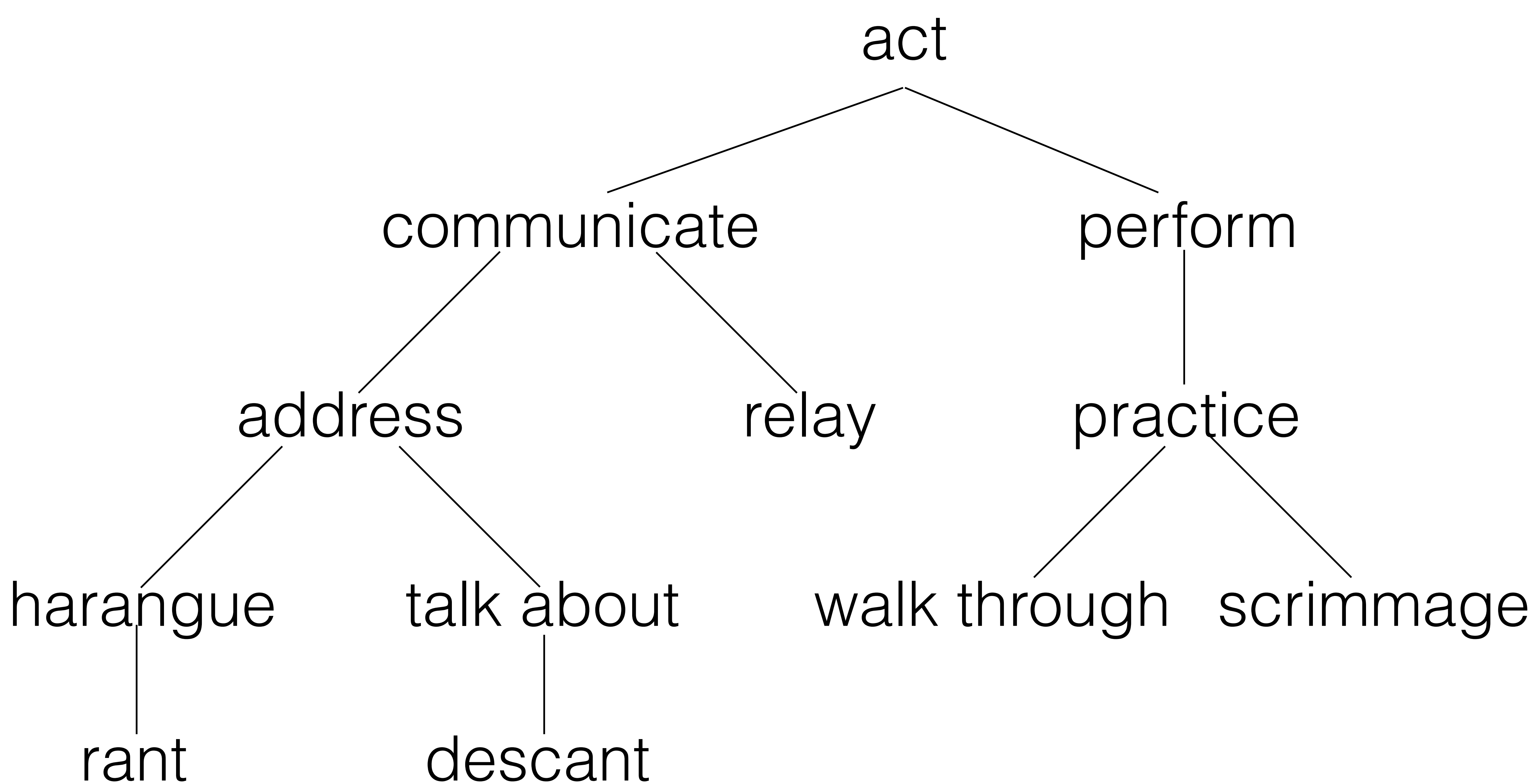
Hillary Clinton **privately** slams millennials as basement-dwellers

Exclusion



Equivalence	$x \iff y$	
Reverse Entailment	$x \Rightarrow y$	
Forward Entailment	$y \Rightarrow x$	
Independence	$x \nRightarrow y \wedge y \nRightarrow x$	
Exclusion	$x \Rightarrow \neg y \wedge y \Rightarrow \neg x$	

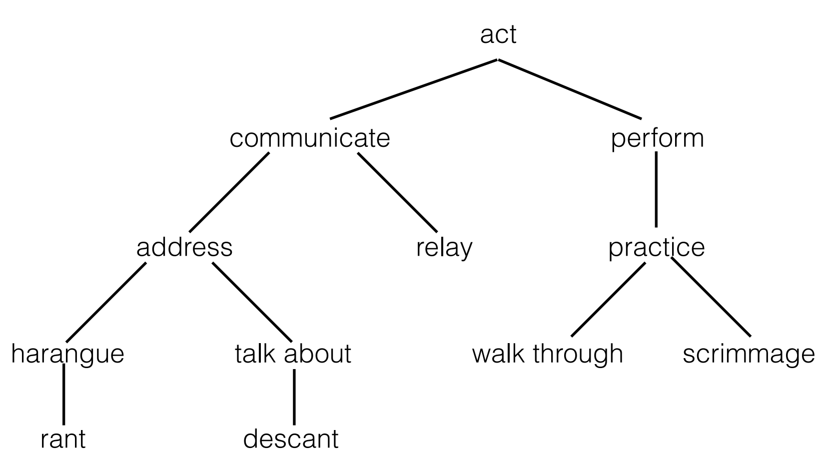
Lexical Semantics Resources



WordNet

WordNet. *Fellbaum (1998)*

Lexical Semantics Resources



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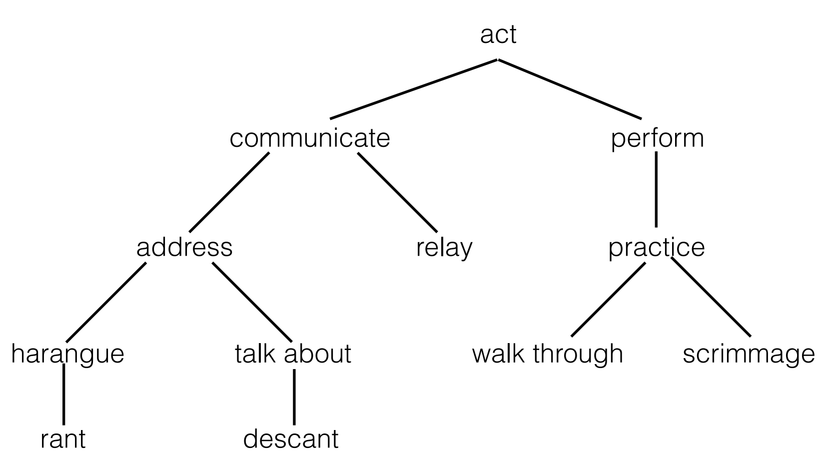

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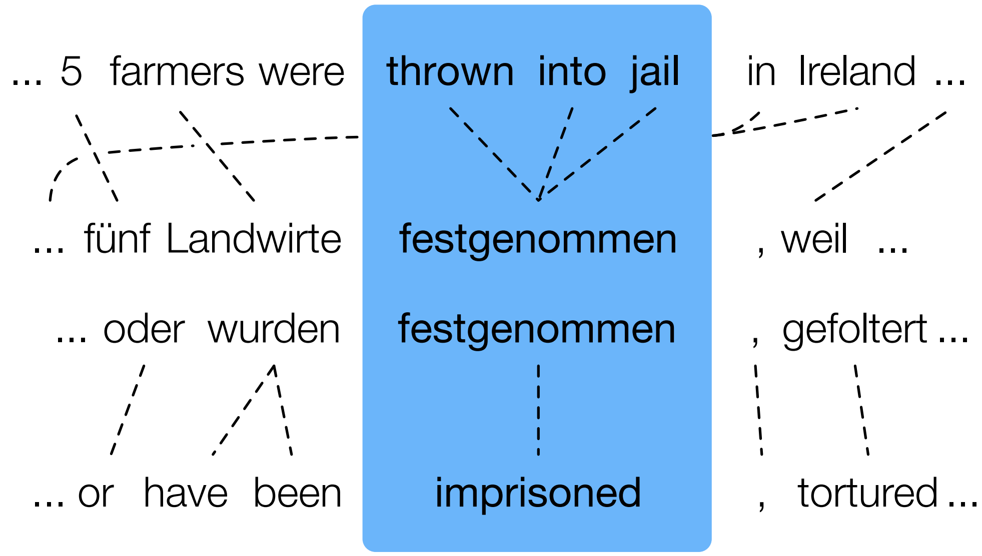
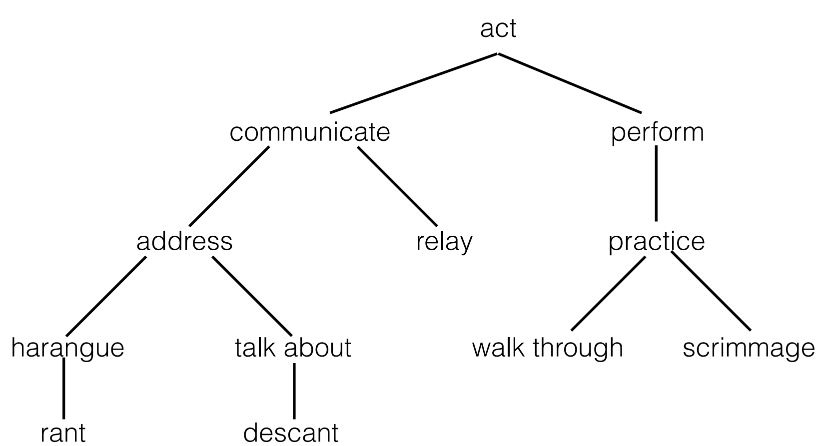


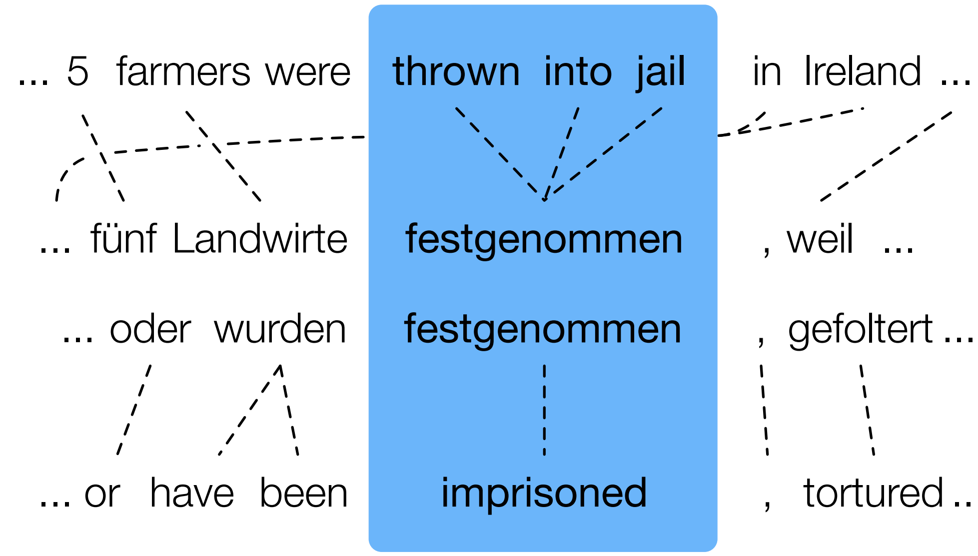
Bilingual Pivoting

Paraphrasing with bilingual parallel corpora. *Bannard and Callison-Burch (2005)*

Lexical Semantics Resources



WordNet



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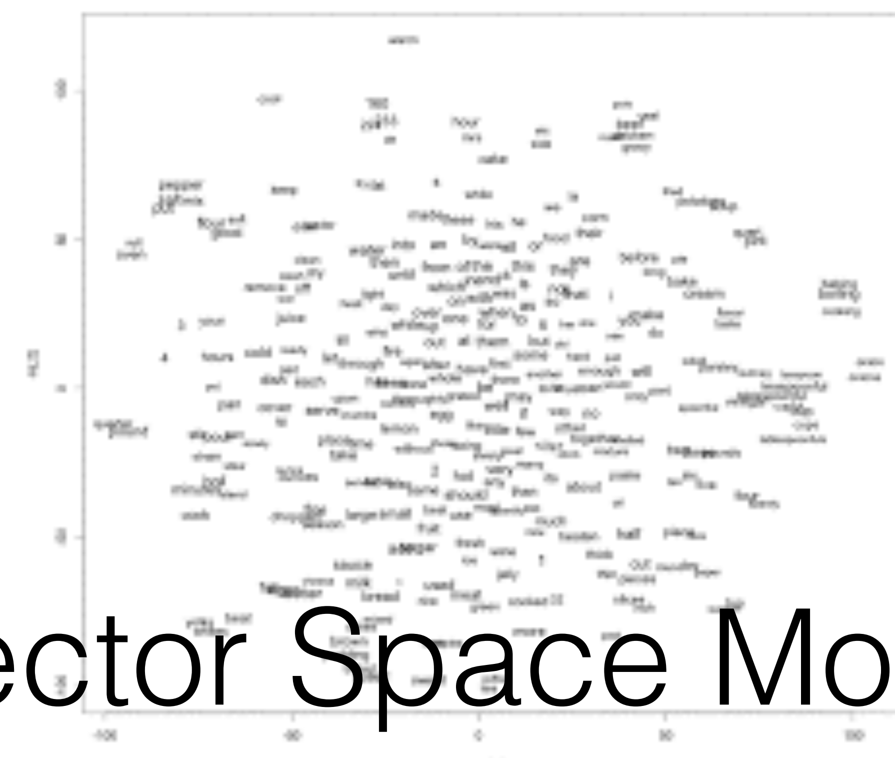
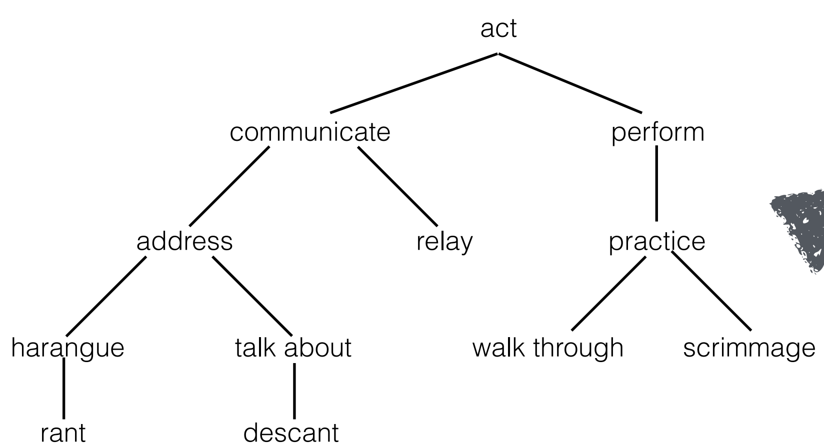
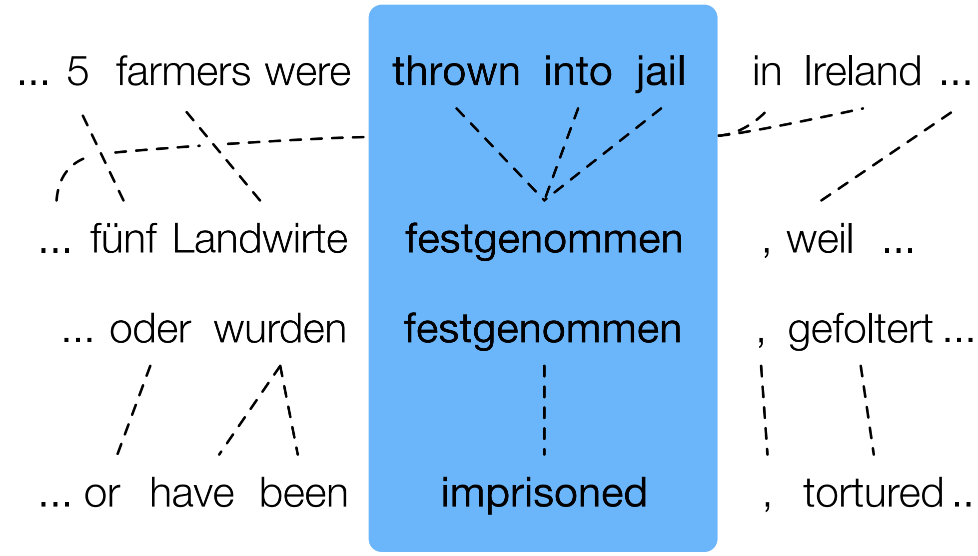


Vector Space Models

Lexical Semantics Resources



WordNet



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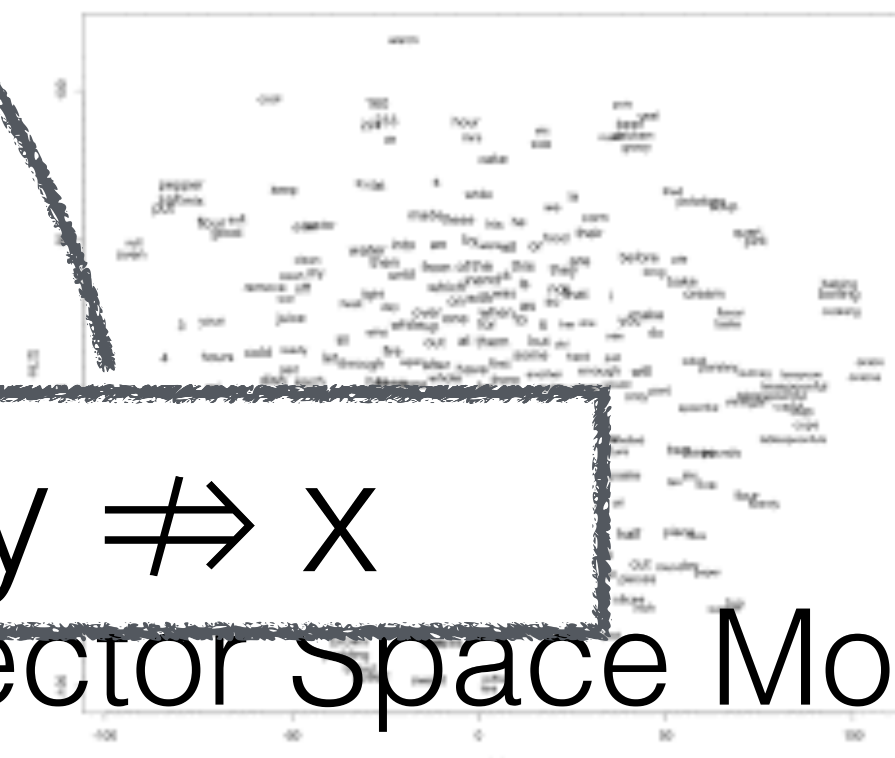
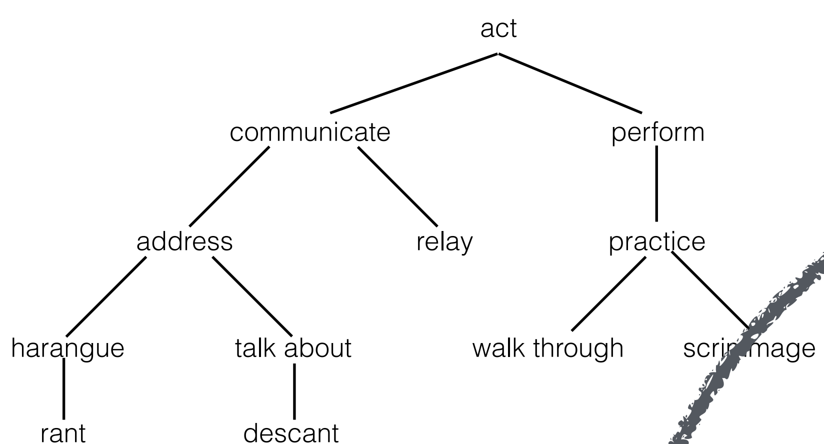


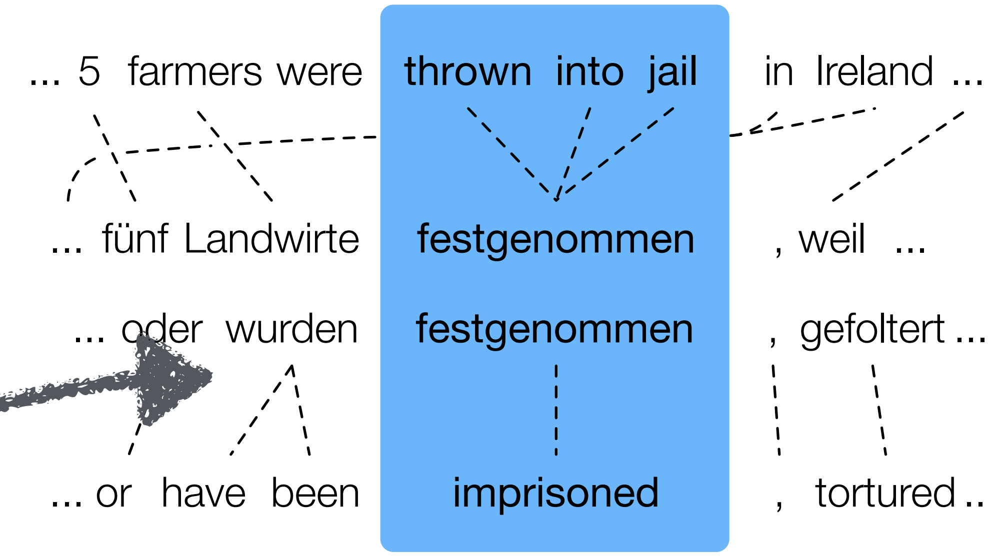
Vector Space Models

$$x \Rightarrow y \land y \not\Rightarrow x$$

Lexical Semantics Resources



WordNet



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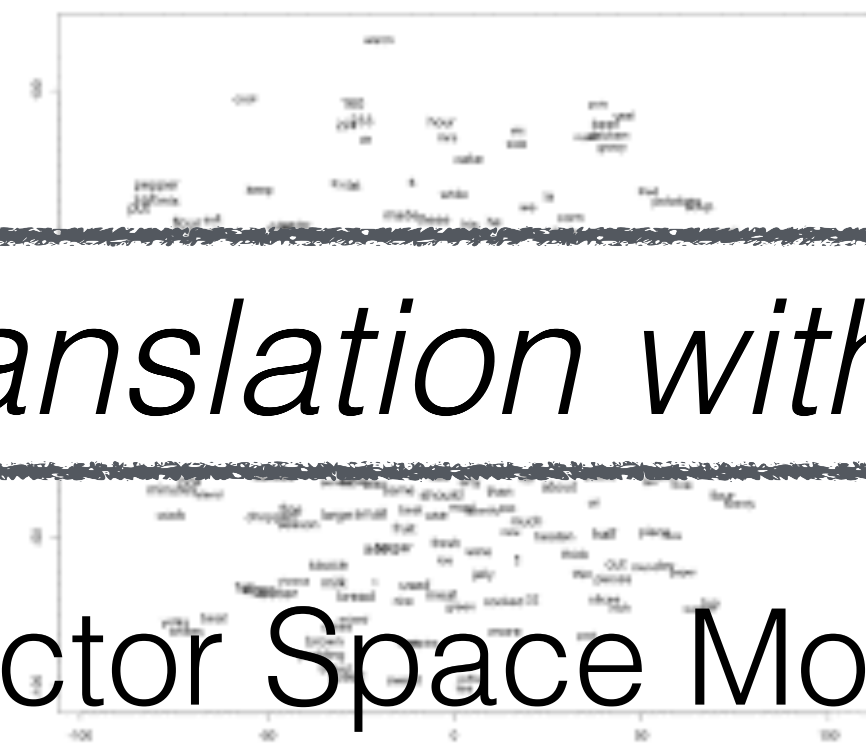
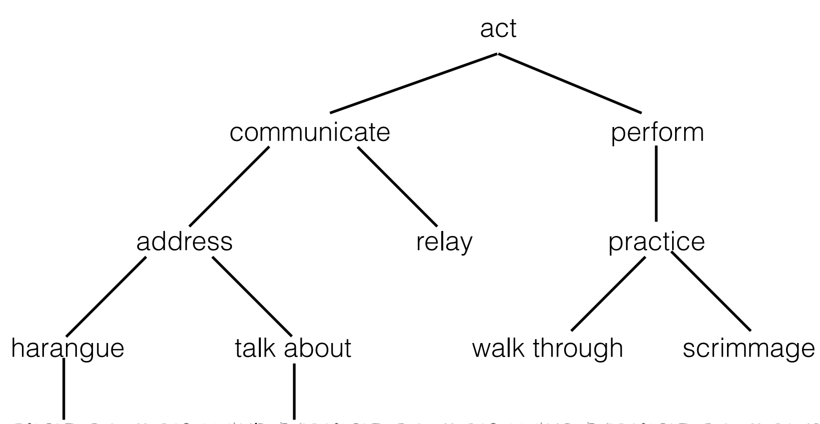
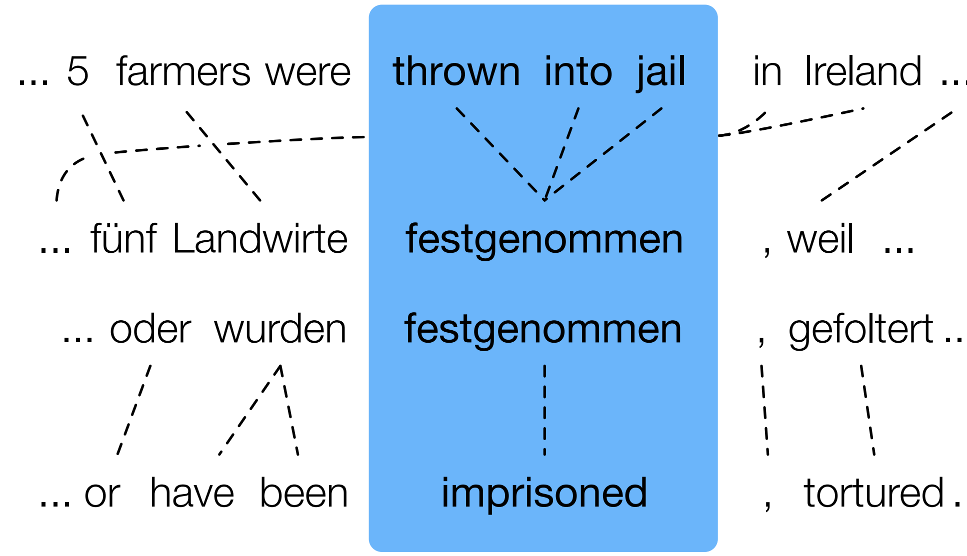


x *shares some translation with* y

Vector Space Models

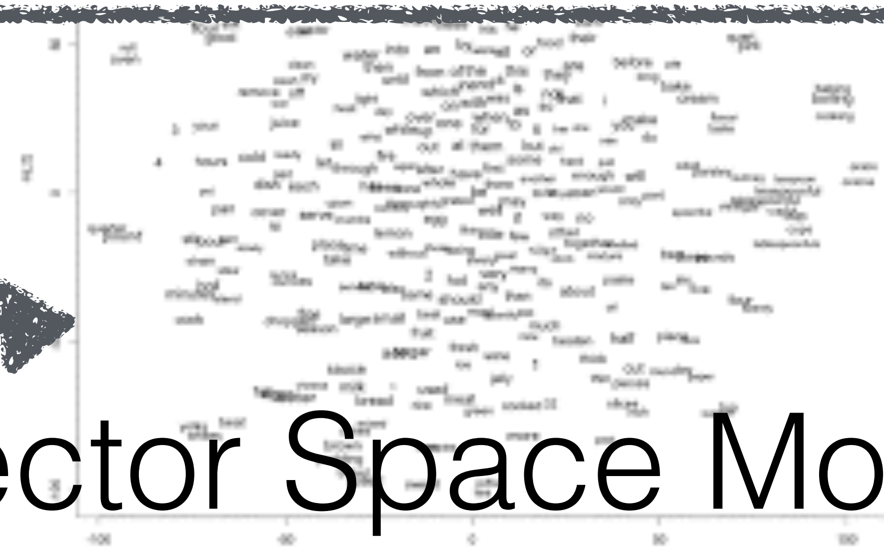
Lexical Semantics Resources





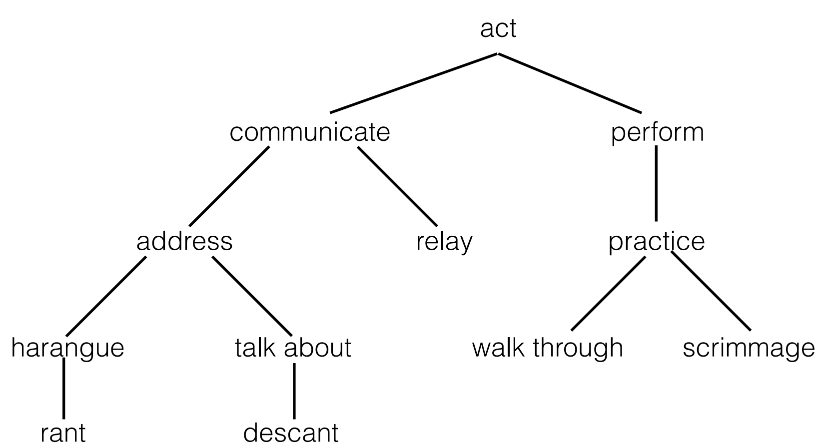
Bilingual Pivoting

x *appears in similar contexts as* y

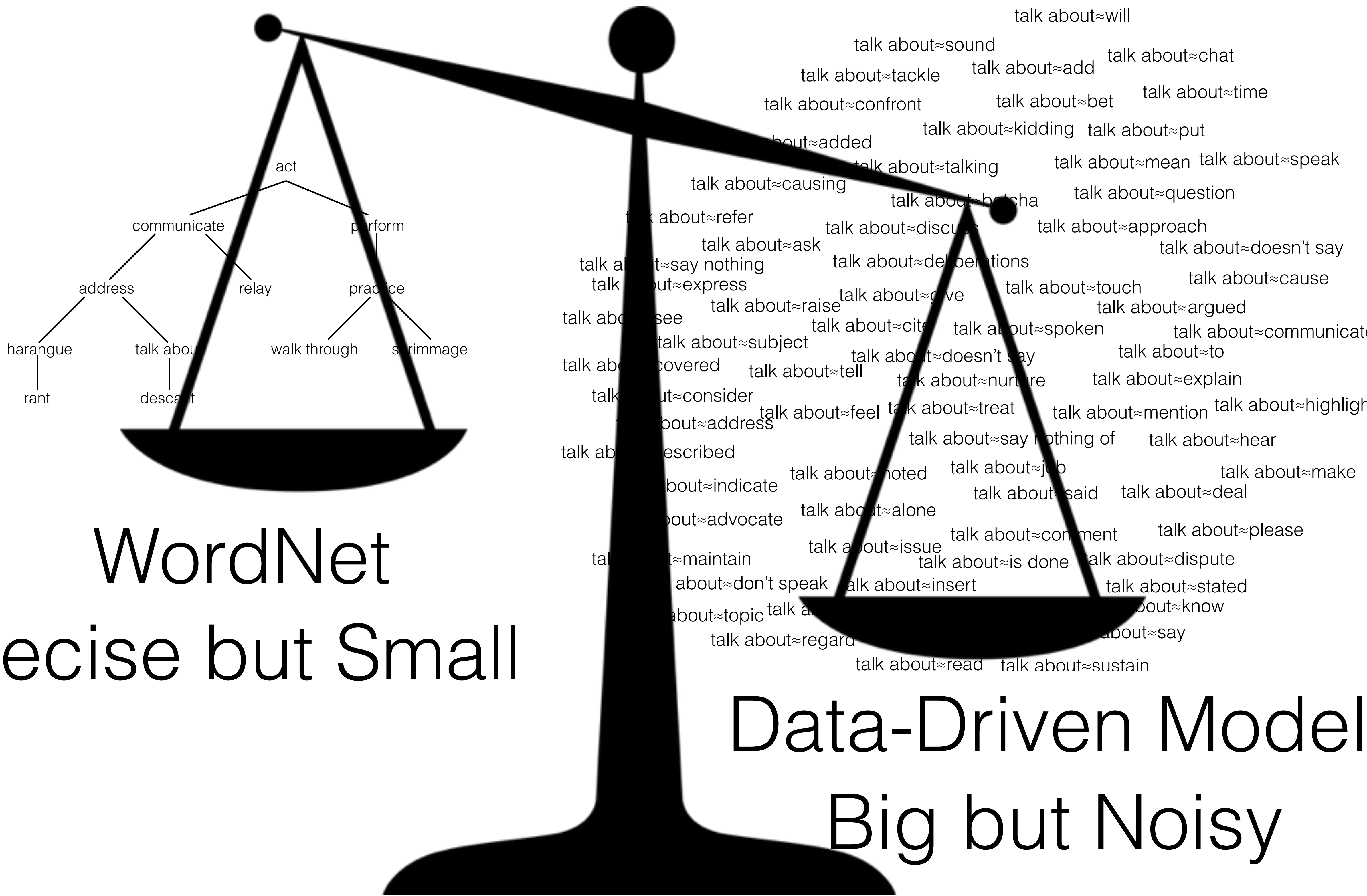


Vector Space Models

Lexical Semantics Resources



Lexical Semantics Resources



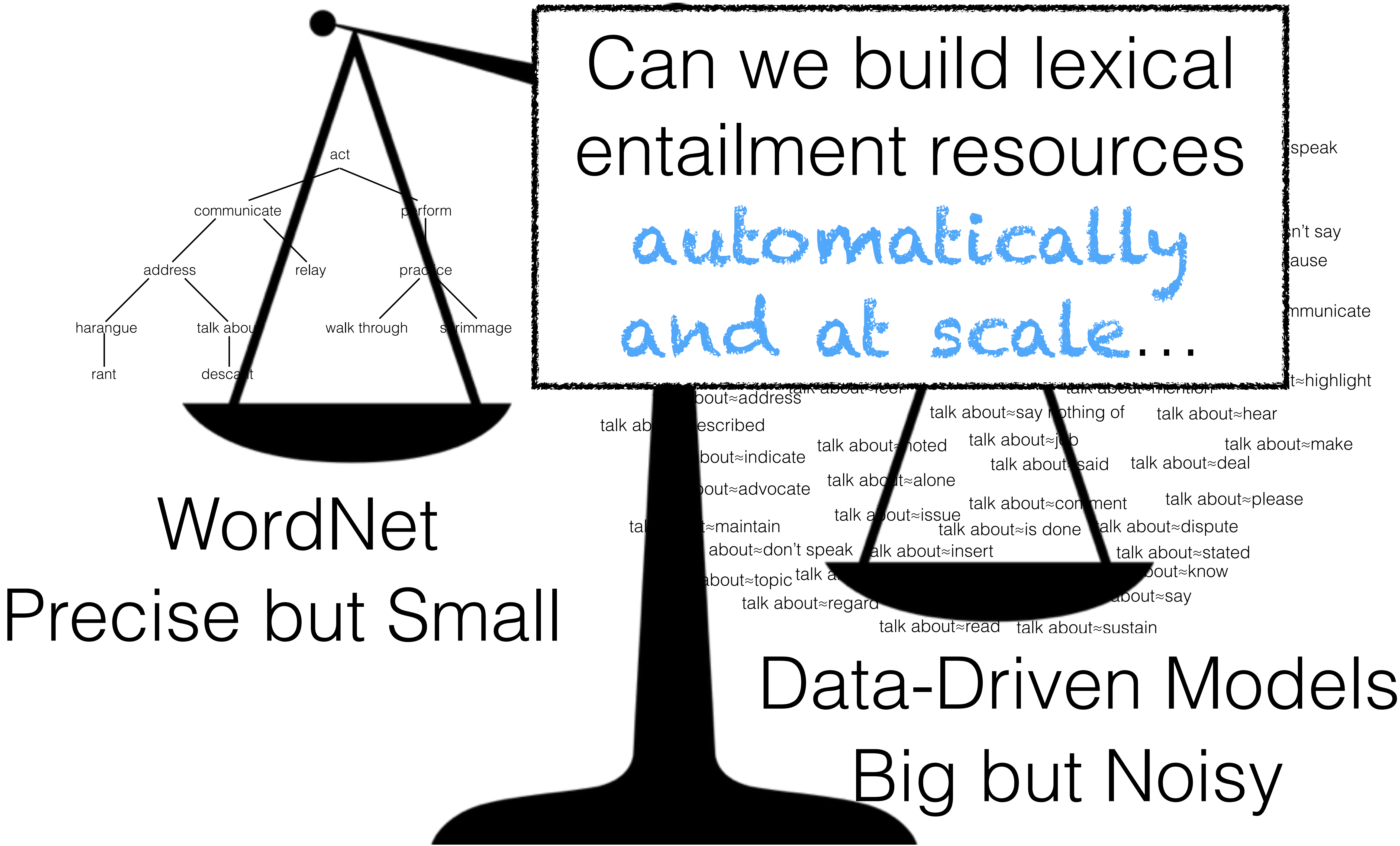
WordNet

Precise but Small

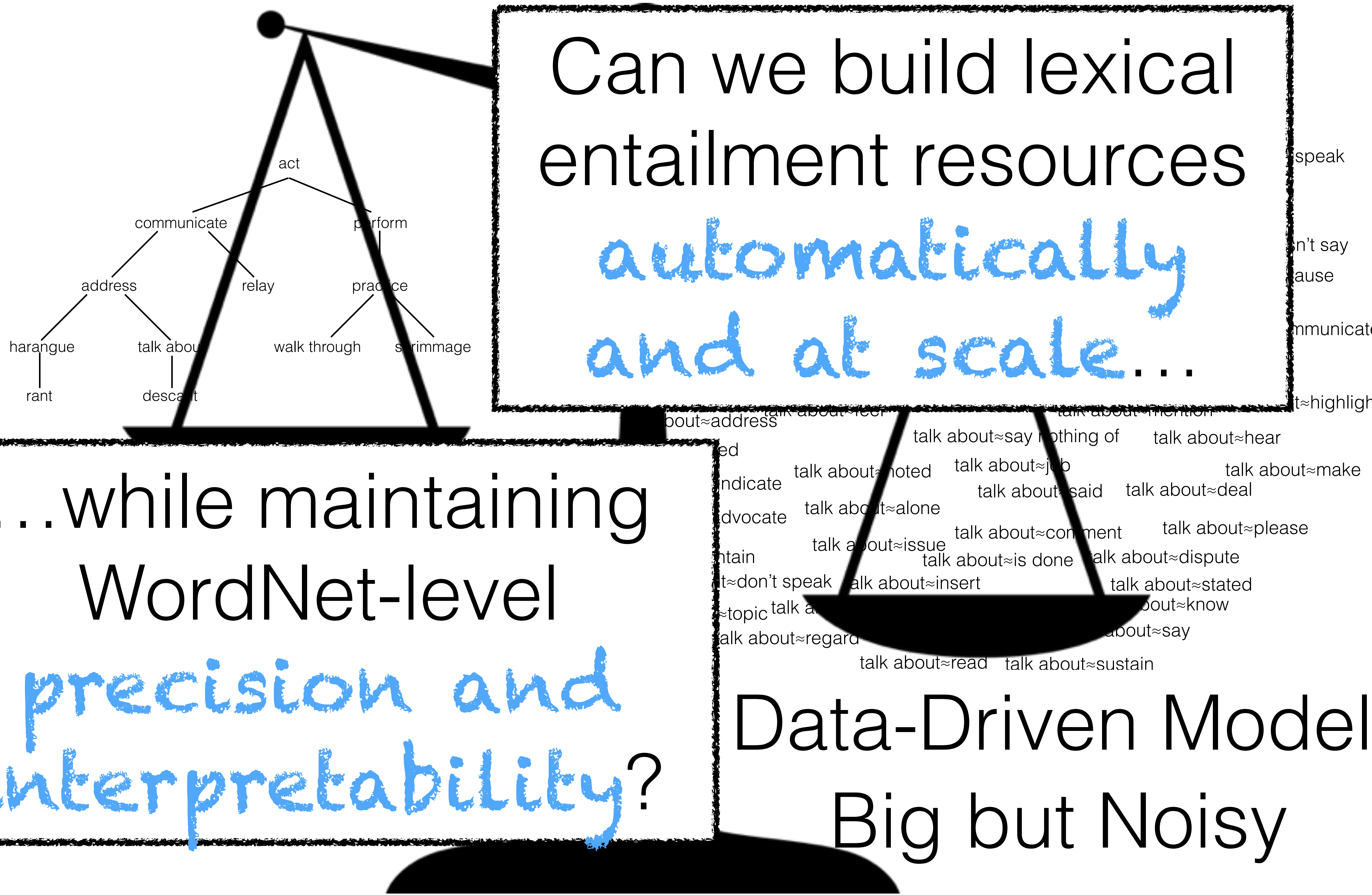
Data-Driven Models

Big but Noisy

Lexical Semantics Resources



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

talk about≈will
talk about≈sound
talk about≈chat
talk about≈betcha
talk about≈added
talk about≈time
talk about≈add
talk about≈confront
talk about≈kidding
talk about≈bet
talk about≈doesn't say
talk about≈put
talk about≈speak
talk about≈tackle
talk about≈mean
talk about≈causing
talk about≈nurture
talk about≈ask
talk about≈talking
talk about≈approach
talk about≈refer
talk about≈discuss
talk about≈say nothing
talk about≈doesn't say
talk about≈deliberations
talk about≈cause
talk about≈raise
talk about≈express
talk about≈covered
talk about≈argued
talk about≈subject
talk about≈touch
talk about≈spoken
talk about≈to
talk about≈consider
talk about≈highlight
talk about≈tell
talk about≈explain
talk about≈see
talk about≈mention
talk about≈address
talk about≈hear
talk about≈communicate
talk about≈described
talk about≈job
talk about≈noted
talk about≈make
talk about≈said
talk about≈alone
talk about≈indicate
talk about≈maintain
talk about≈comment
talk about≈advocate
talk about≈please
talk about≈is done
talk about≈issue
talk about≈topic
talk about≈stated
talk about≈dispute
talk about≈about
talk about≈say
talk about≈don't speak
talk about≈told
talk about≈know
talk about≈relate
talk about≈insert
talk about≈debate
talk about≈sustain
talk about≈give
talk about≈say nothing of
talk about≈treat
talk about≈feel
talk about≈read
talk about≈question

PPDB: The Paraphrase Database. *Ganitkevich et al. (2013)*

The Paraphrase D e

Entailment

Independent

Equivalence

Exclusion

talk about≈chat

talk about≈see

talk about≈say

talk about≈say nothing of

talk about≈sound
talk about≈betcha
talk about≈added
talk about≈will
talk about≈add
talk about≈time
talk about≈kidding
talk about≈bet
talk about≈put
talk about≈speak
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The Paraphrase Database

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Distributional Signals of Semantics

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Monolingual Contextual Similarities

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Mikolov et al., 2013 (Google)
Pennington et al., 2014 (Stanford)

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…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…

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Contextual Similarities

Strengths

Weaknesses

Contextual
Similarities

Strengths

dad/father
vs.
dad/lychee

Weaknesses

Contextual Similarities

Strengths

dad/father
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dad/lychee

Weaknesses

dad/father
vs.
dad/mom

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…to favour the position of **artists** who have to travel throughout the community…	…favoriser la position des artistes qui doivent voyager à travers la communauté…

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Distributional Signals of Semantics

Lexico-Syntactic Patterns

Hearst, 1992 (Berkeley)
Snow et al., 2006 (Stanford)
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Logistic Regression

$$\begin{bmatrix} P(\text{equivalent}) \\ P(\text{entailment}) \\ P(\text{exclusion}) \\ P(\text{independent}) \end{bmatrix} = \frac{1}{1 + e^{\begin{bmatrix} w1 \\ w2 \\ w3 \end{bmatrix} \cdot \begin{bmatrix} \text{Contextual Similarities} \\ \text{Bilingual Translations} \\ \text{Lexico-Syntactic Patterns} \end{bmatrix}}}$$

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Predict a probability distribution
based over entailment relations...

Logistic Regression

$$\begin{bmatrix} \text{P(equivalent)} \\ \text{P(entailment)} \\ \text{P(exclusion)} \\ \text{P(independent)} \end{bmatrix} = \frac{1}{1 + e^{\begin{bmatrix} w1 \\ w2 \\ w3 \end{bmatrix} \cdot \begin{bmatrix} \text{Contextual Similarities} \\ \text{Bilingual Translations} \\ \text{Lexico-Syntactic Patterns} \end{bmatrix}}}$$

...based on all of the data-driven signals available.

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talk about≈cov
about≈express
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talk ab
talk about≈se
alk about≈explain
talk about≈c
out≈communicate
talk about≈r
talk about≈indicate

Can we build a resource like WordNet automatically, **at scale**, and **without loss of precision**?

talk about≈advocate
talk about≈is done
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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 entails h if typically, a human reading p would infer that h is most likely true.

↓

No

Improving End-to-End RTE

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

x1
man(x1)

x2 x3
patient(x2,x3) agent(x2,x1) have(x2) conversation(x3)

x1 x2
agent(x1,x2) talk(x1) woman(x2)

Improving End-to-End RTE

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

```
x1
----------
man(x1)
```

```
x2 x3
----------
patient(x2,x3)
agent(x2,x1)
have(x2)
conversation(x3)
```

```
x1 x2
----------
agent(x1,x2)
talk(x1)
woman(x2)
```

$$\forall x(man(x) \Rightarrow \neg woman(x))$$

Improving End-to-End RTE

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

```
x1
--------
man(x1)
```

```
x2 x3
--------
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conversation(x3)
```
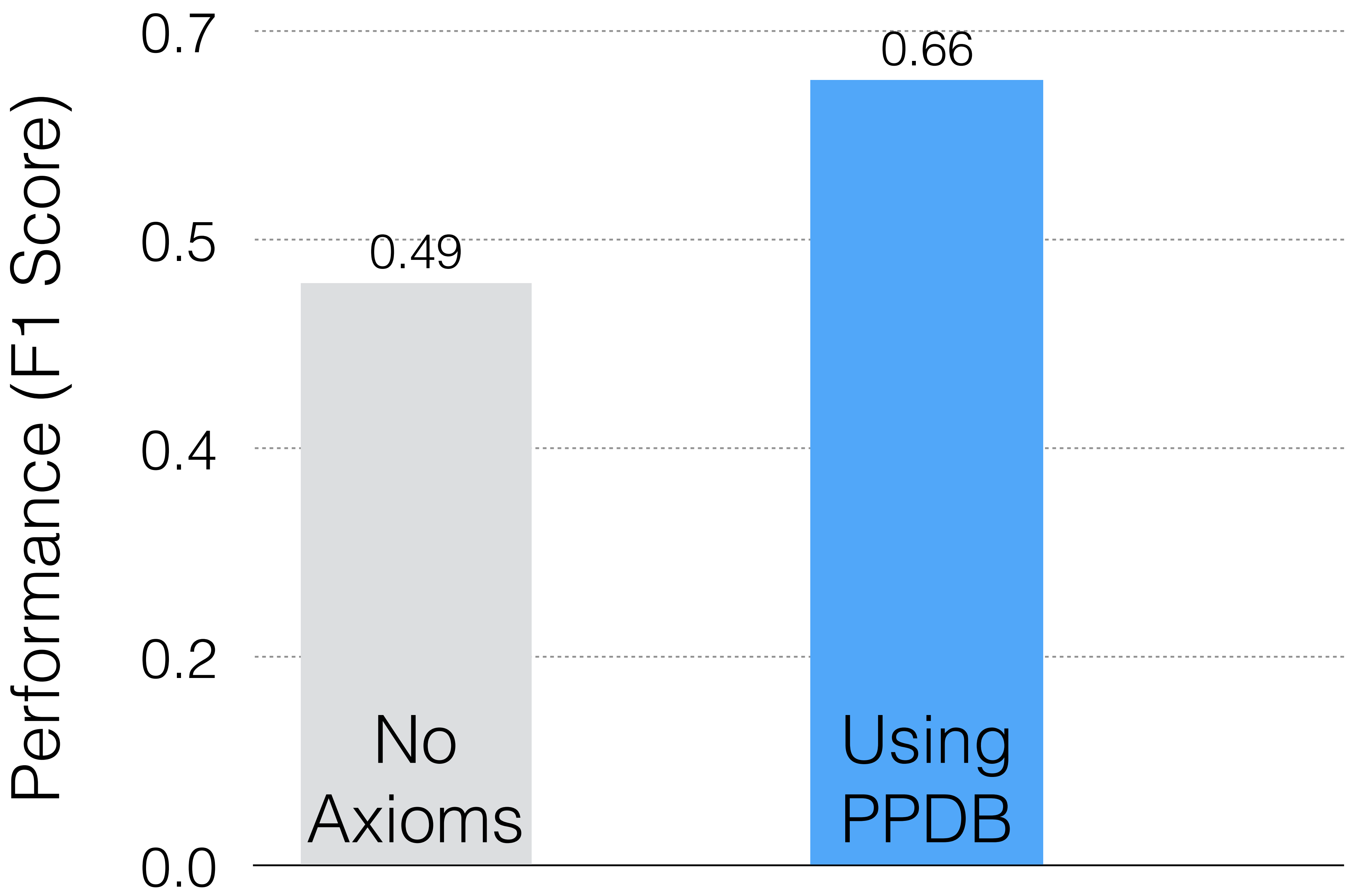

```
x1 x2
--------
agent(x1,x2)
talk(x1)
woman(x2)
```

$$\forall x,h,c,t\,(have(h) \land conversation(c) \land talk(t) \land agent(h,x) \Rightarrow agent(t,x))$$

Improving End-to-End RTE



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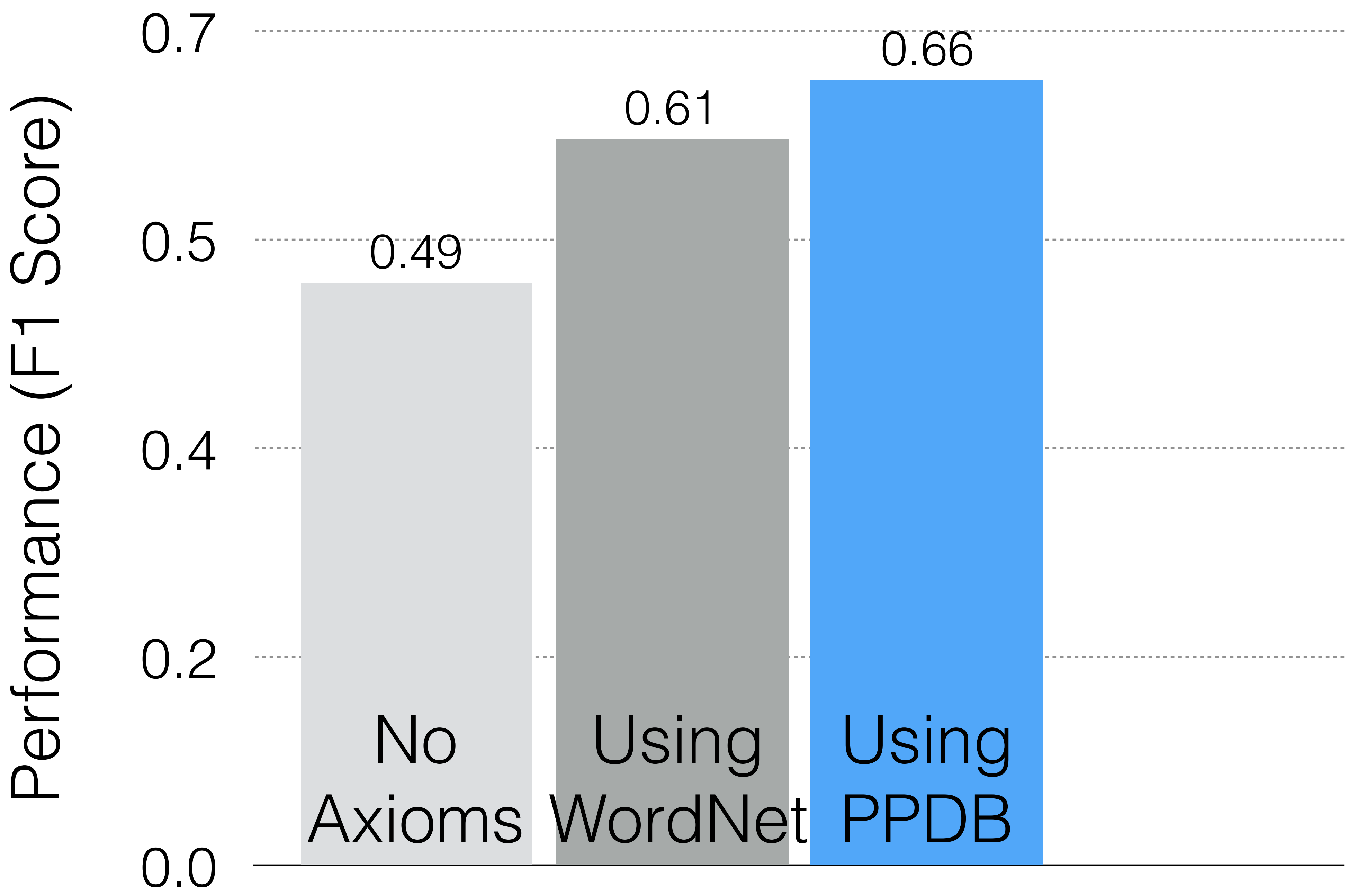

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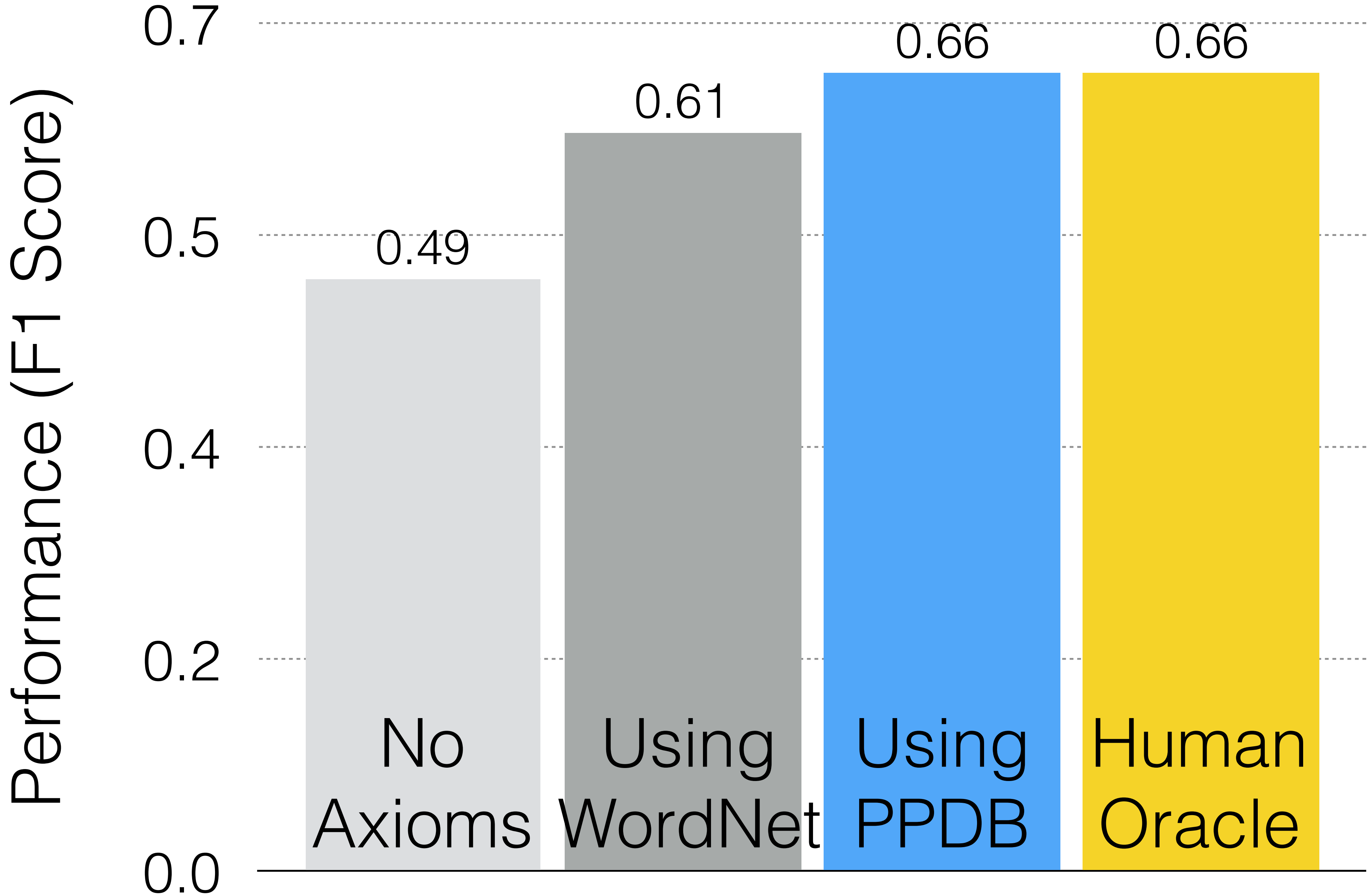
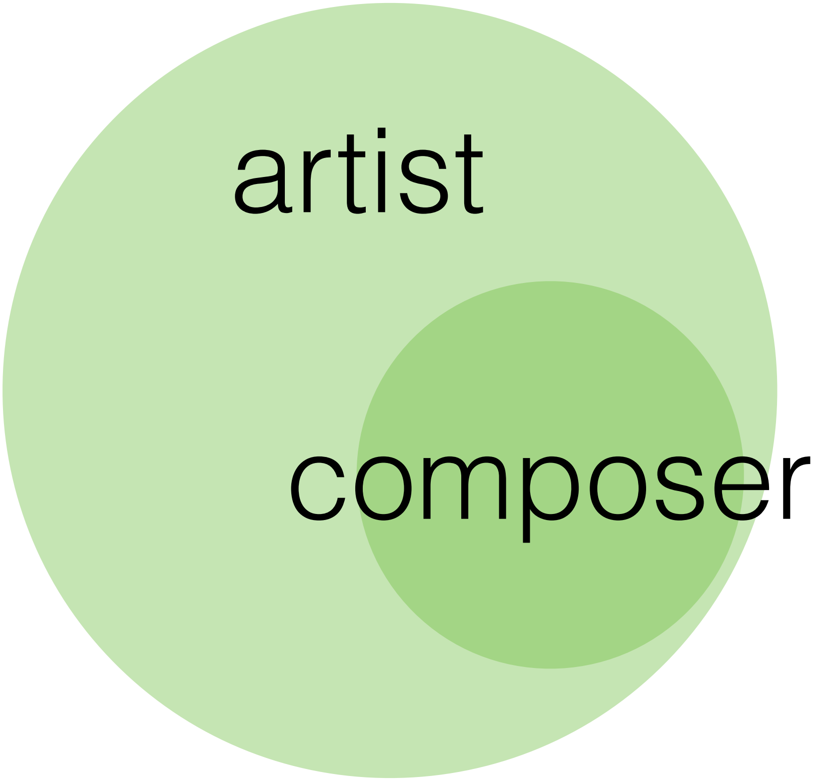


Introduction

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.
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Summary and Future Work

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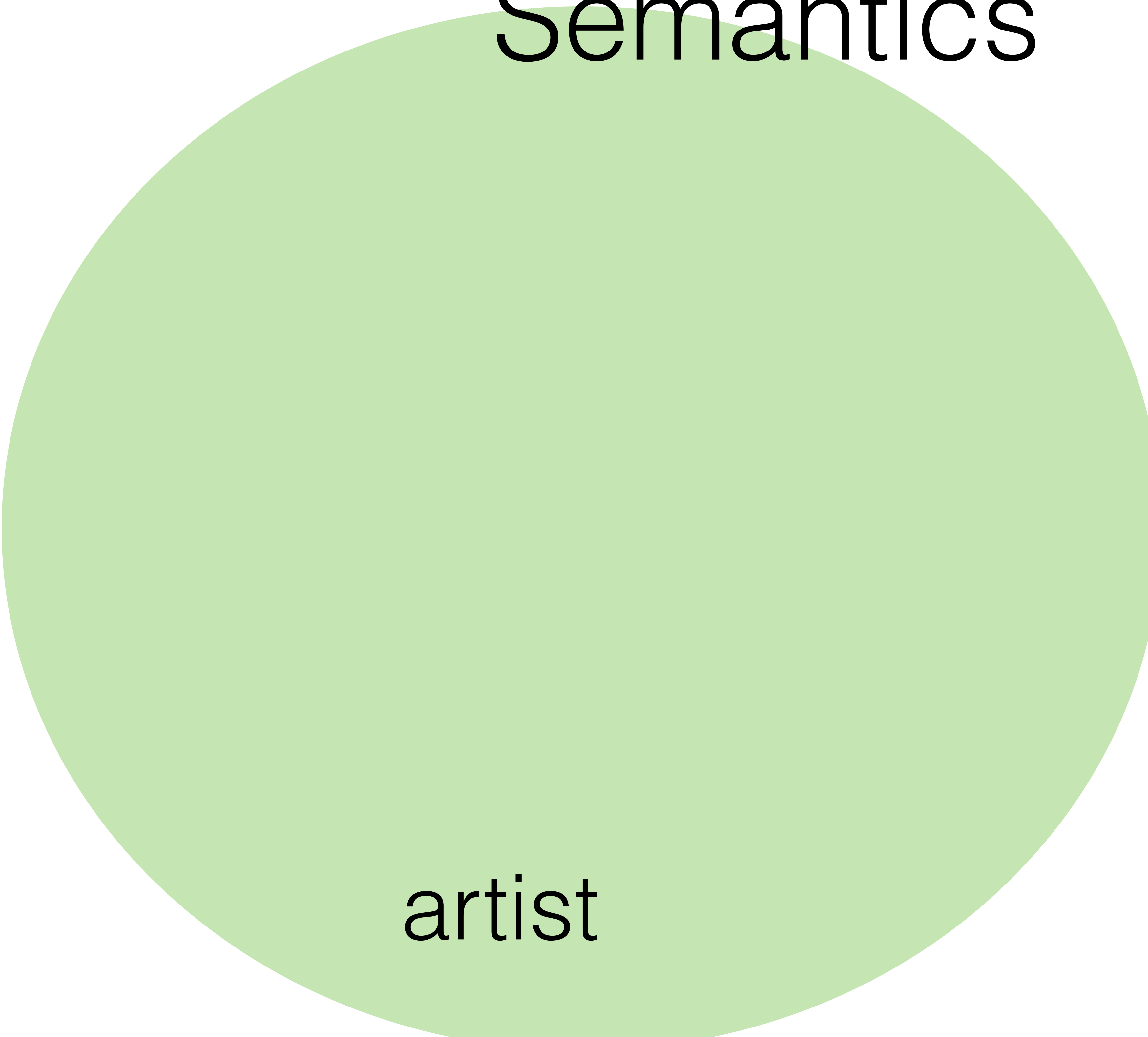
American composer

Non-Compositional Semantics



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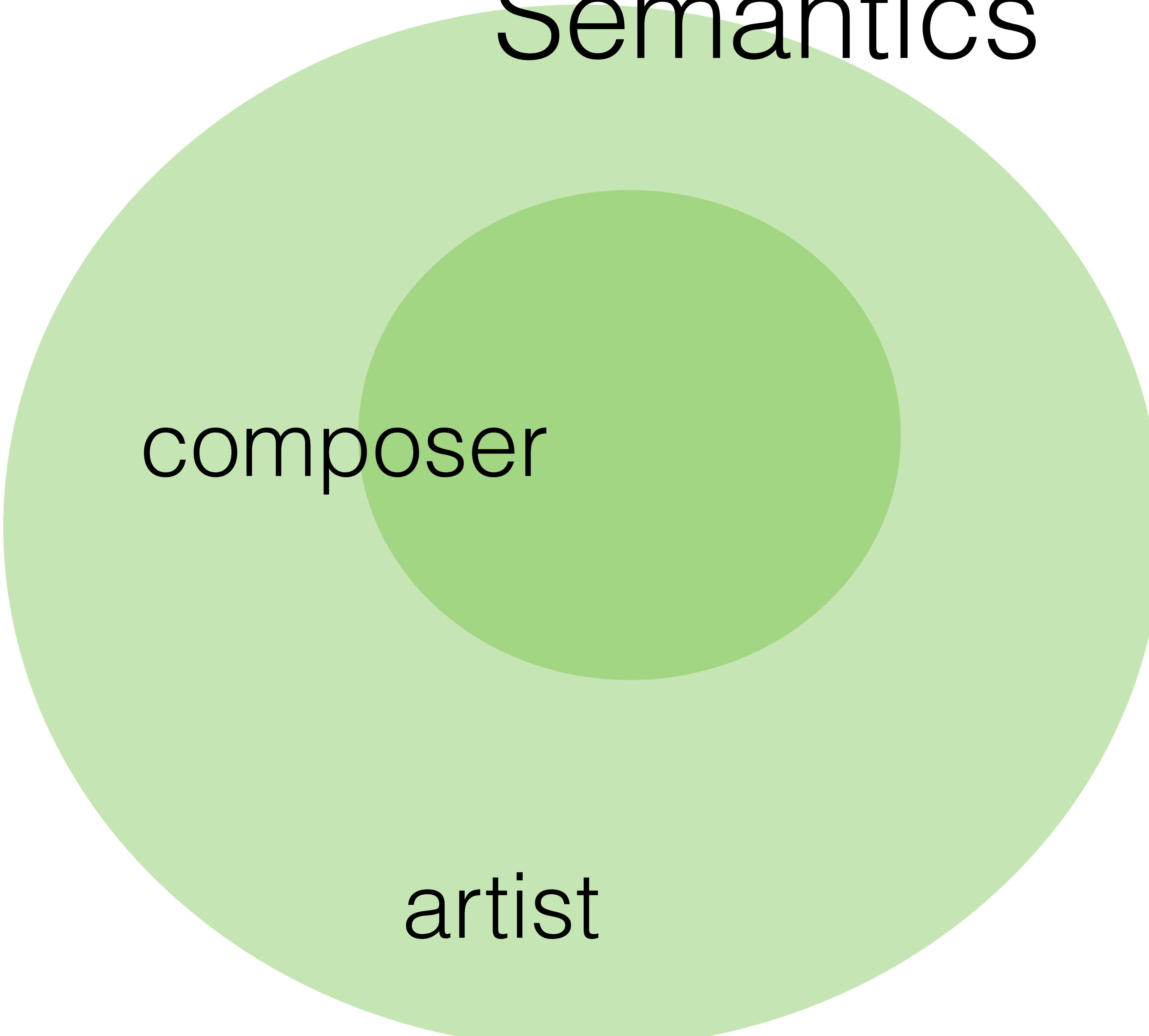

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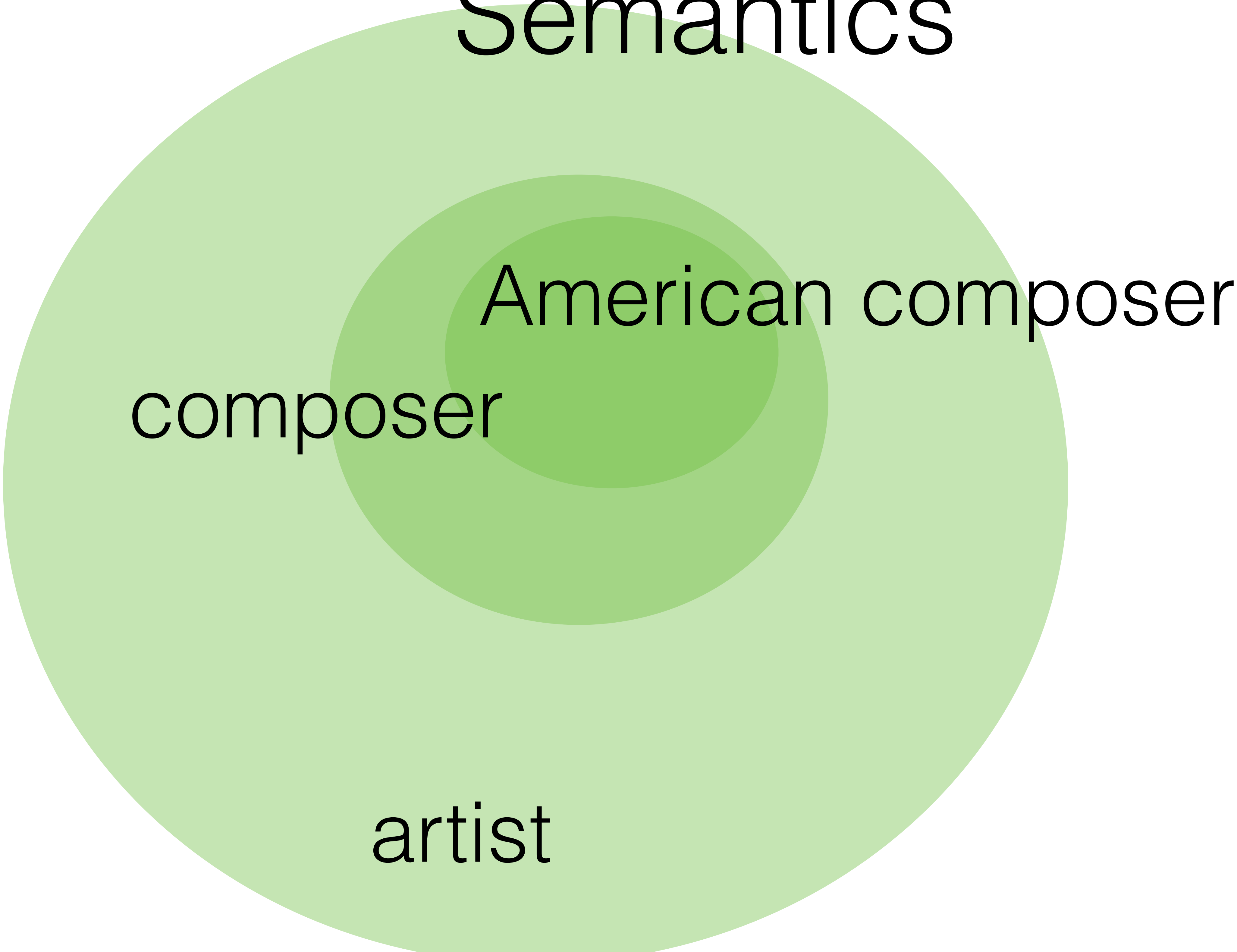

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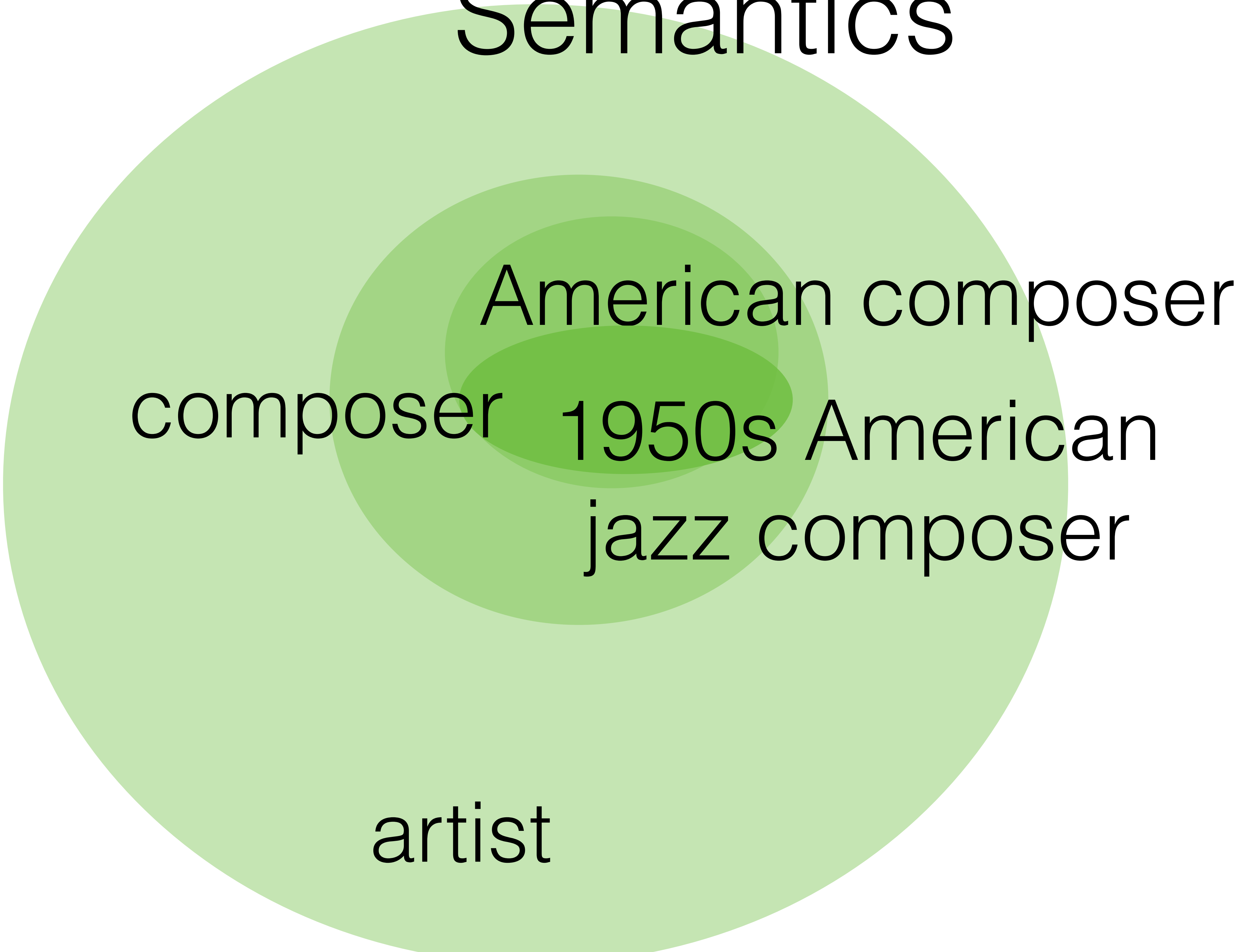


Non-Compositional Semantics

$[\![\text{modifier}_1 \text{ modifier}_2 \ldots \text{ modifier}_k \text{ noun}]\!]$

Non-Compositional Semantics

$$O(NM^{k})$$

Non-Compositional Semantics

American jazz composer

$O(NM^k)$

~270,000,000,000,000

Non-Compositional Semantics

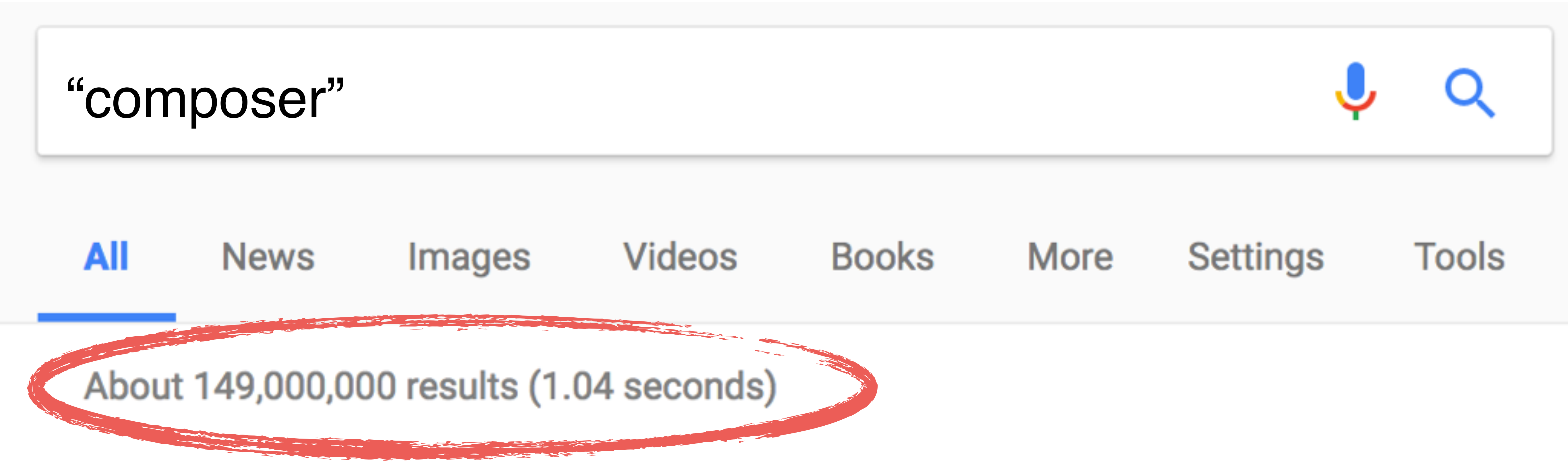
American jazz composer

$$O(NM^k)$$

~270,000,000,000,000,000

Problem #1: scalability

Non-Compositional Semantics



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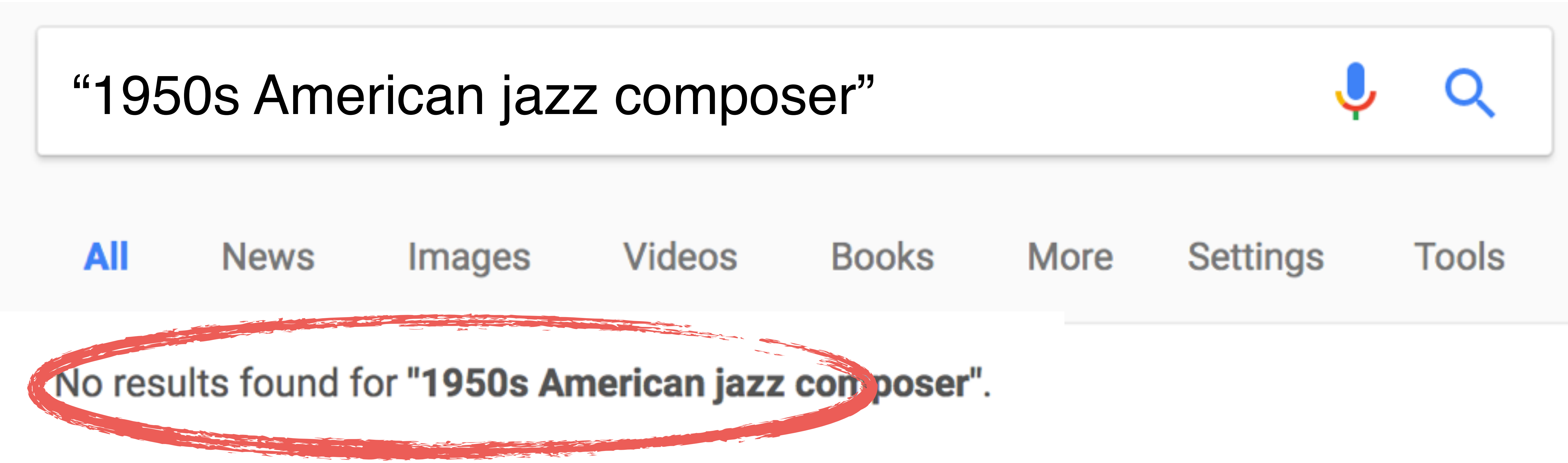

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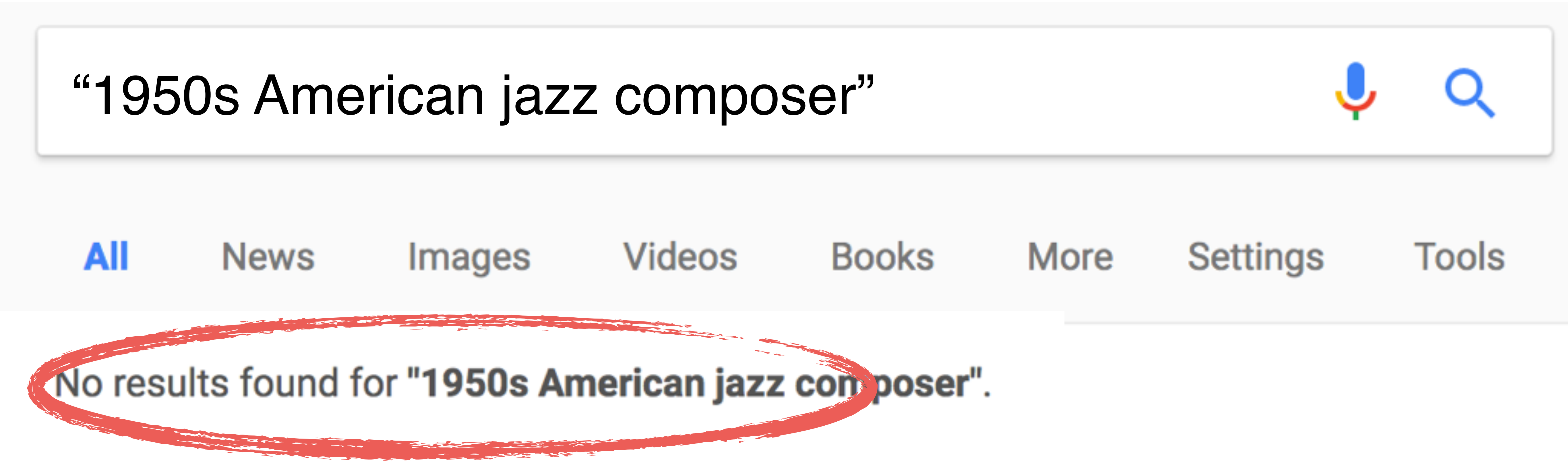
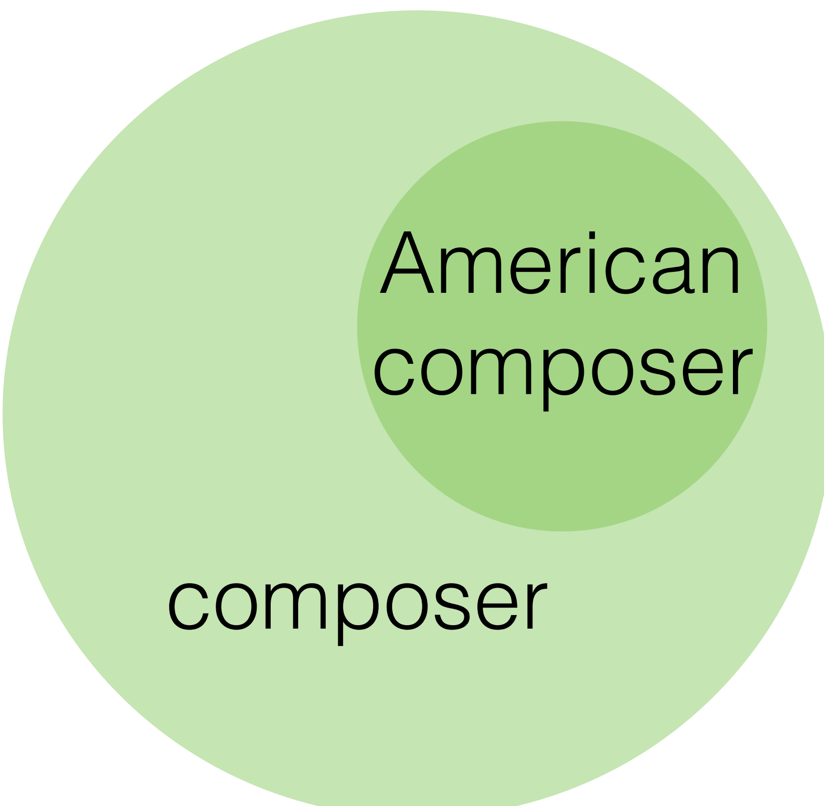


Problem #2: sparsity

Non-Compositional Semantics



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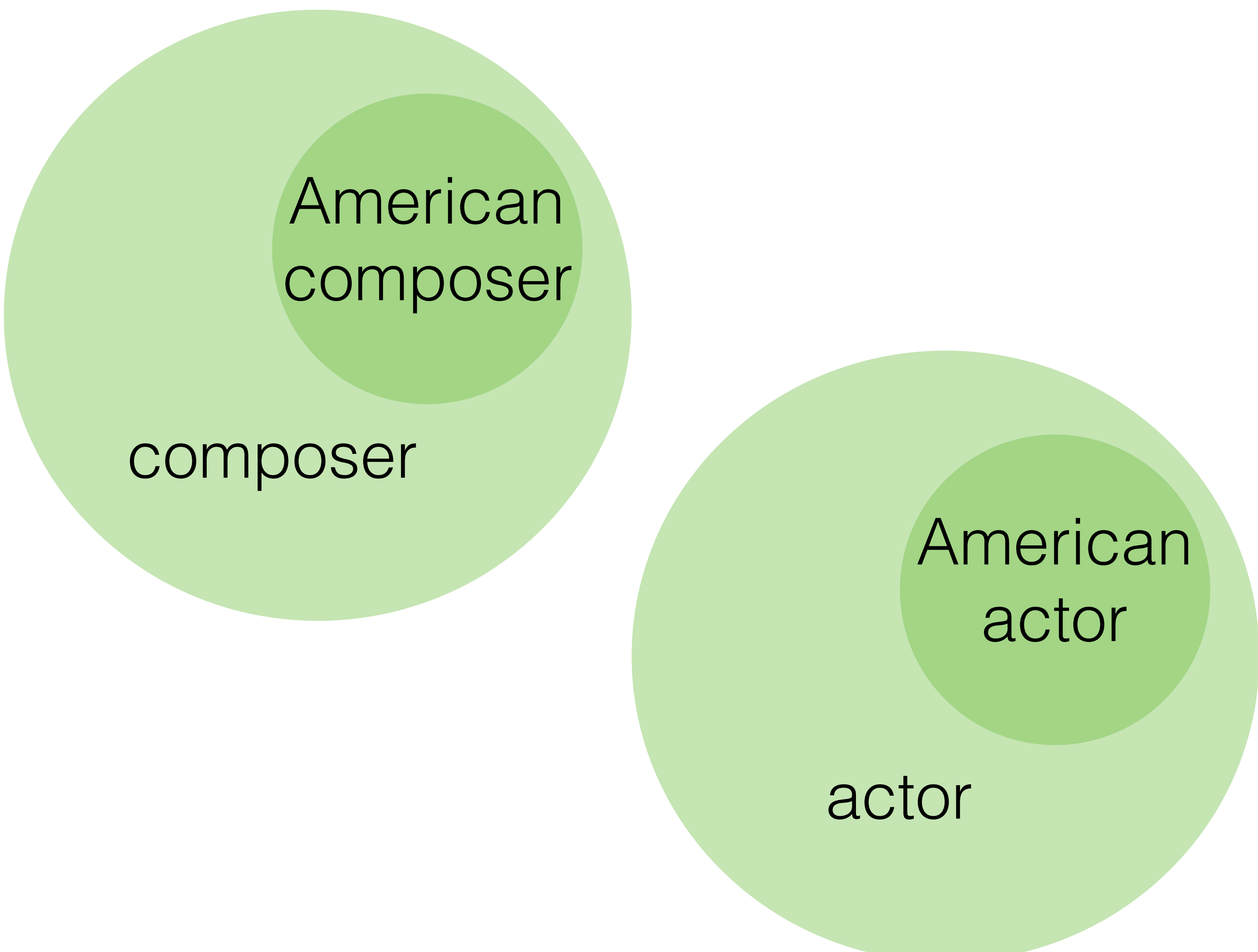

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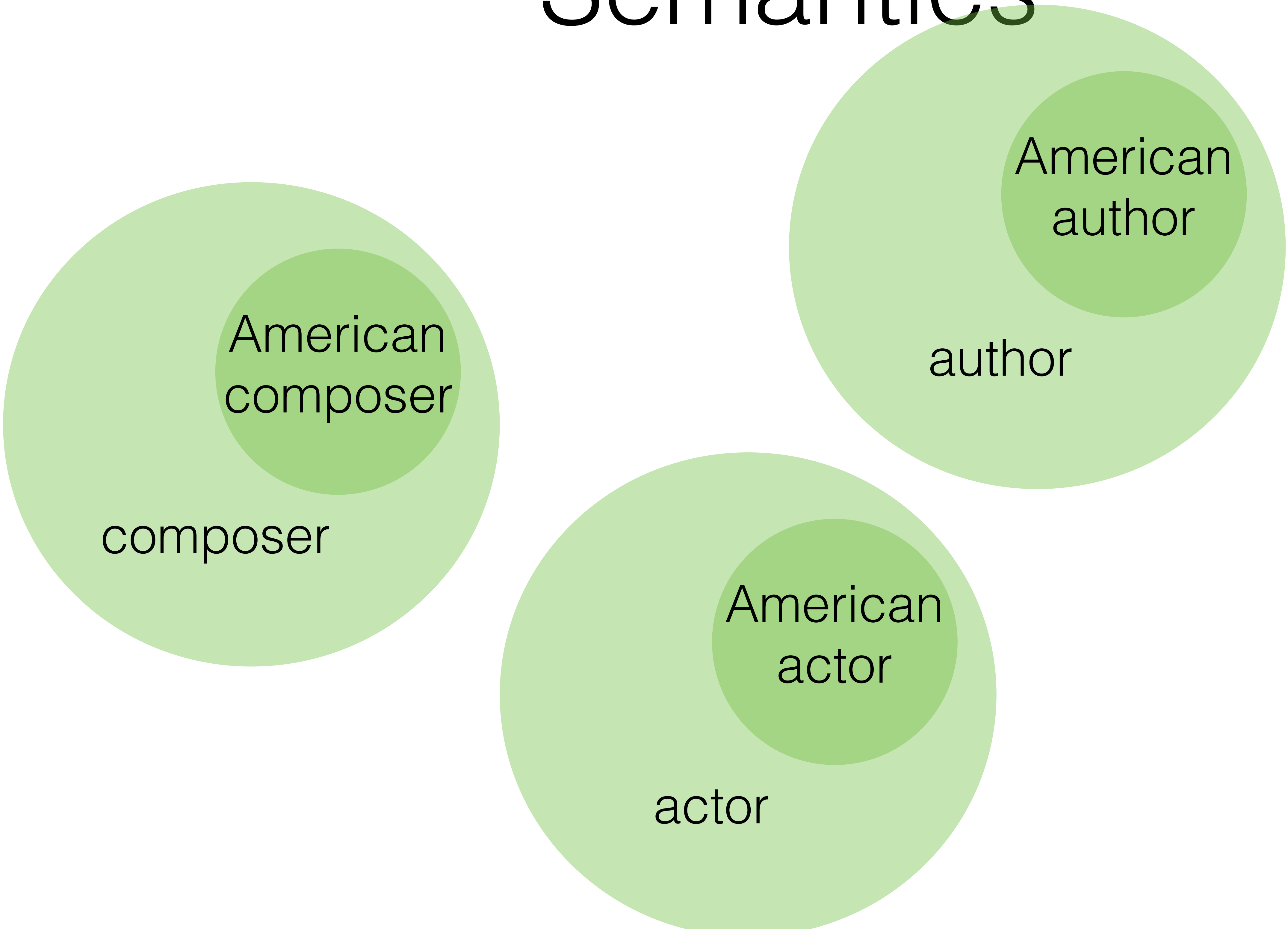

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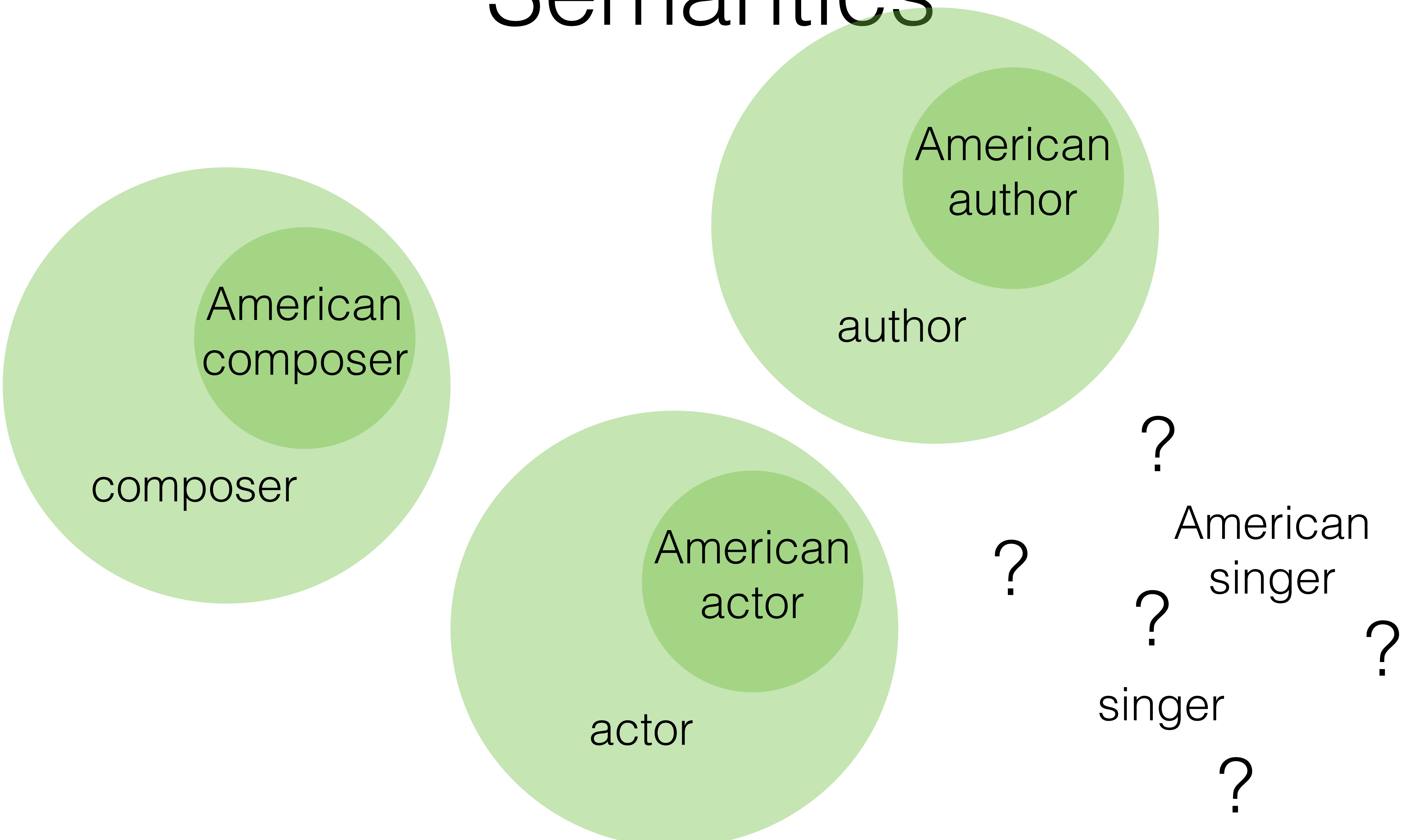

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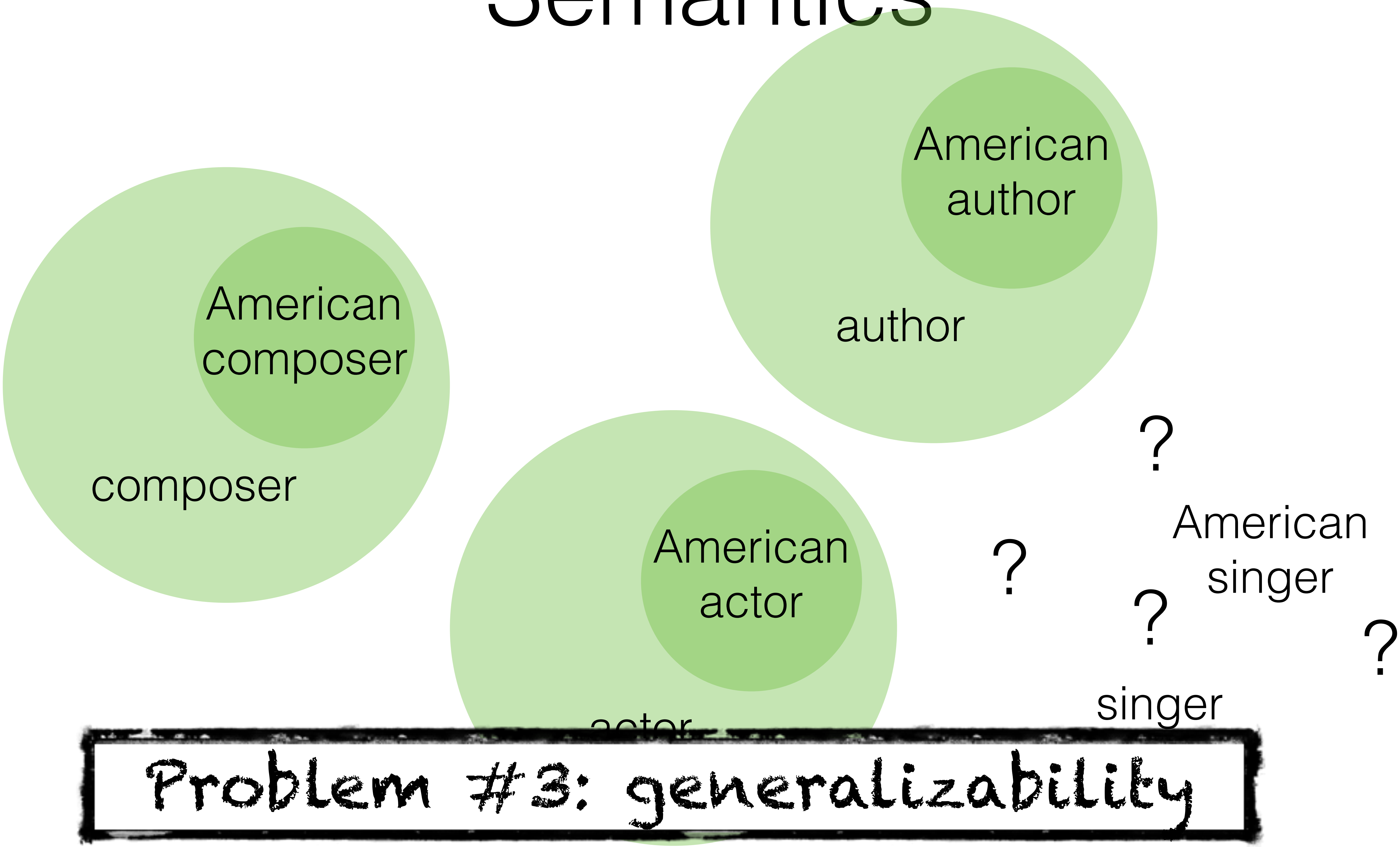
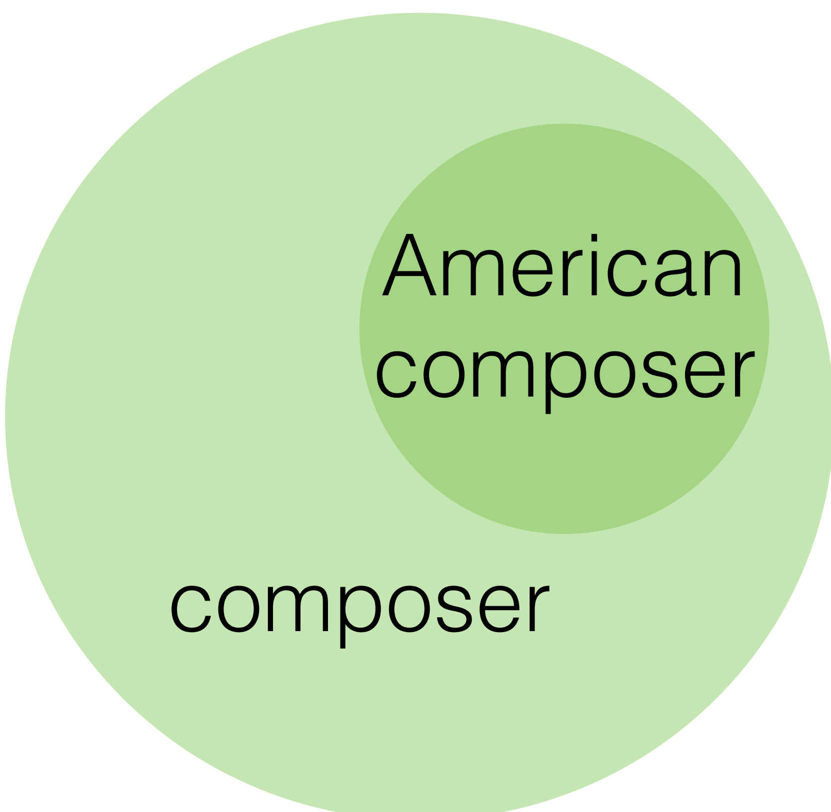


Problem #3: generalizability

Compositional Semantics



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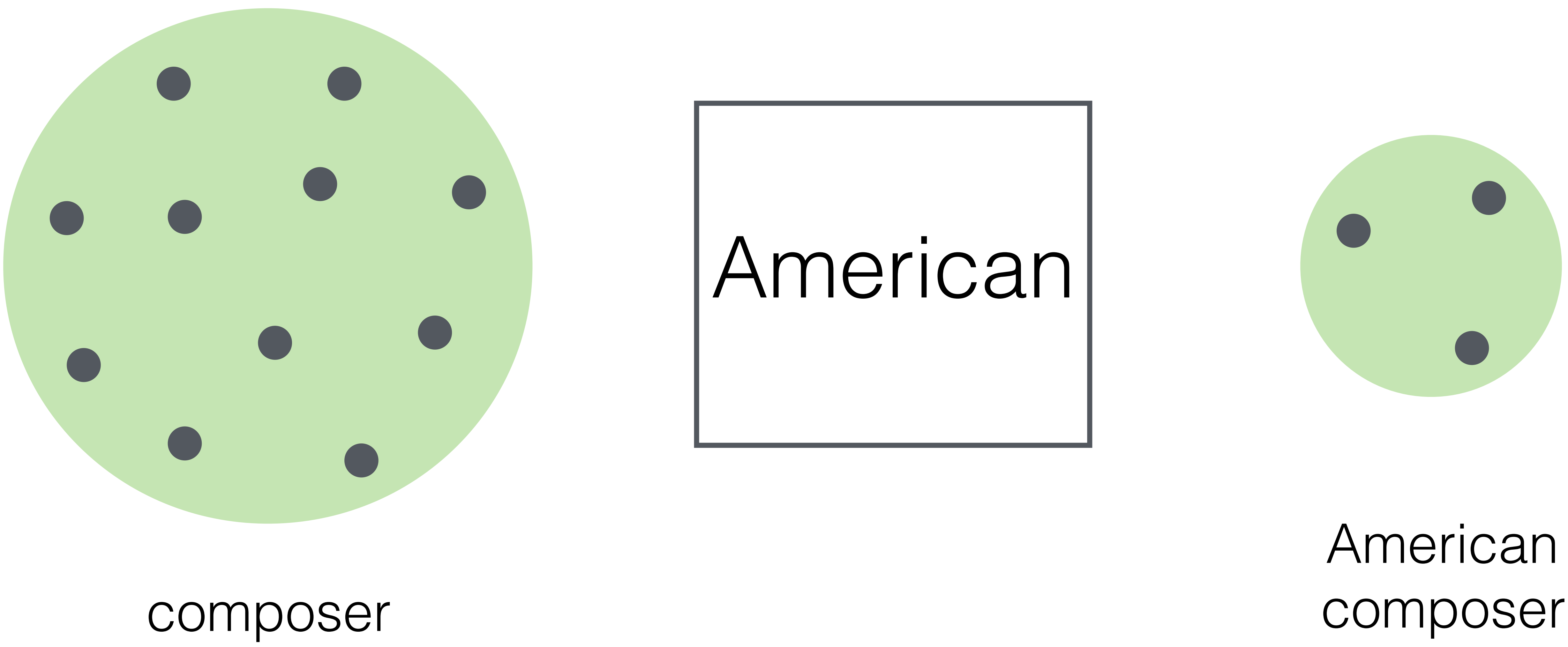

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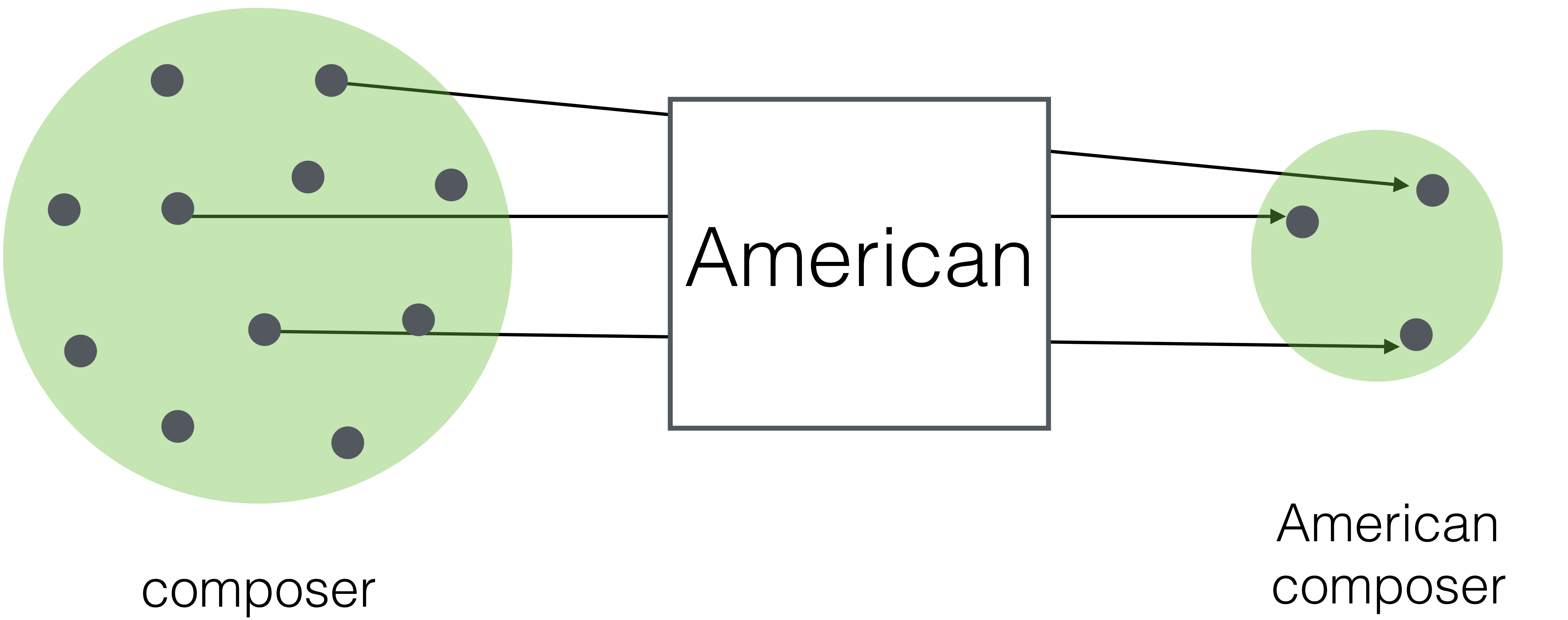

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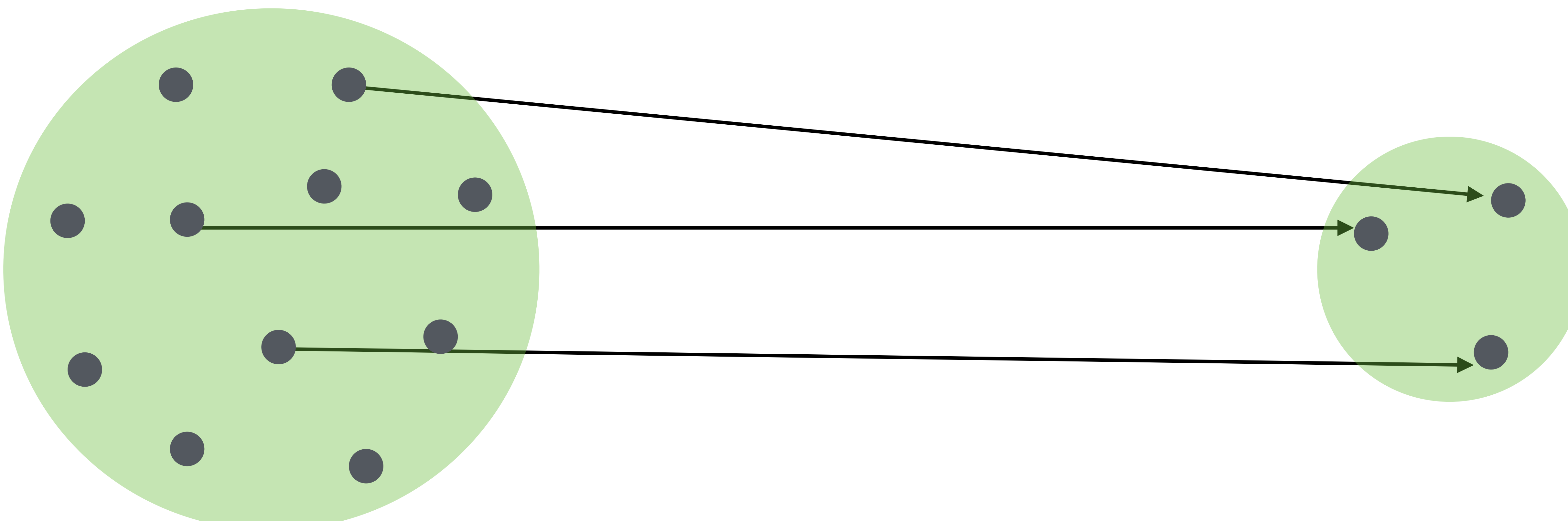
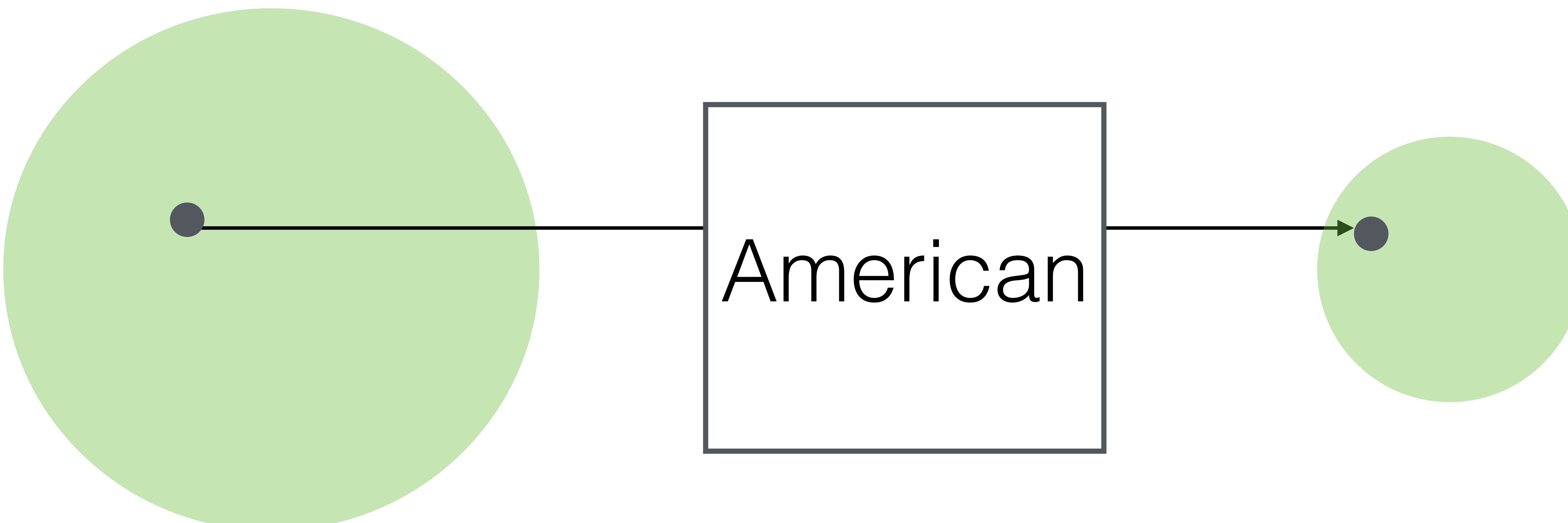


composer

American composer

Semantic Containment

Compositional Semantics



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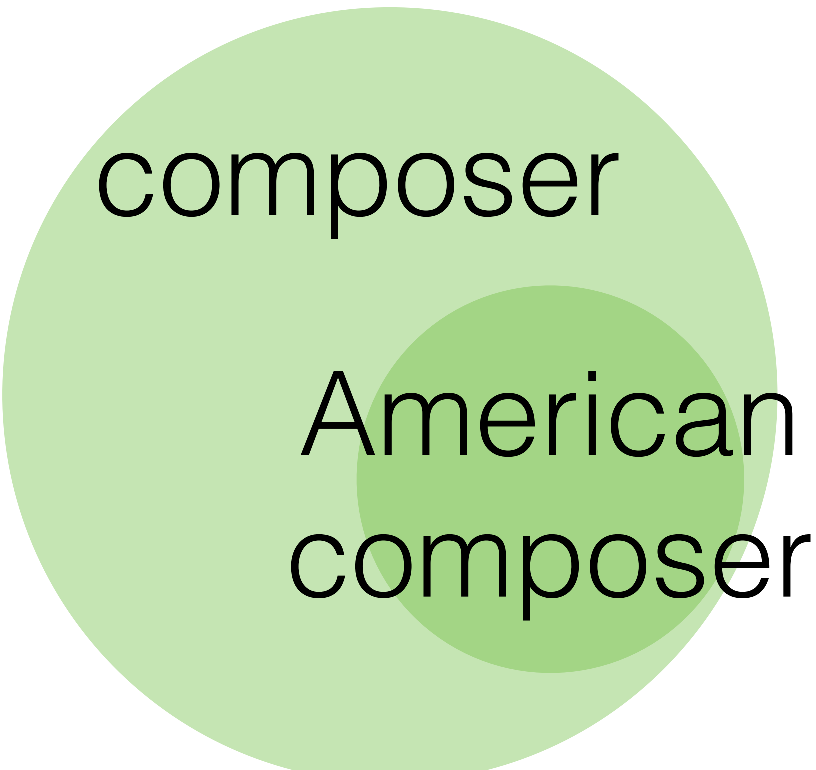
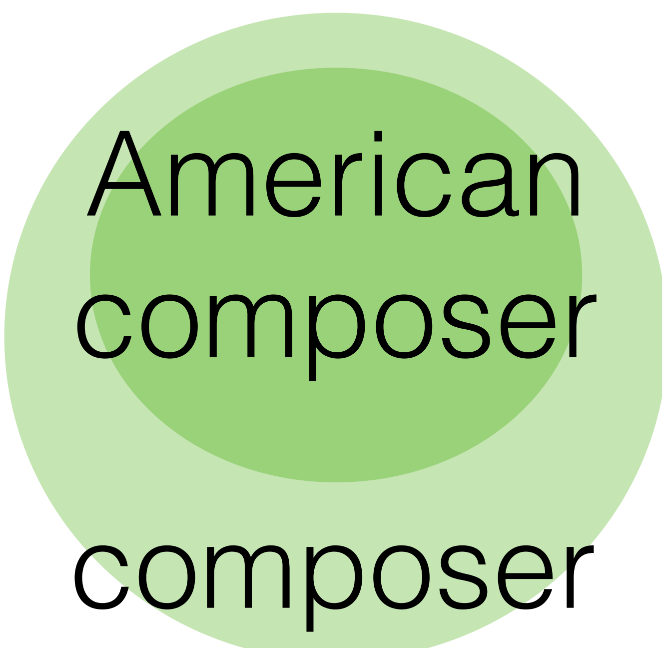


Class-Instance Identification

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

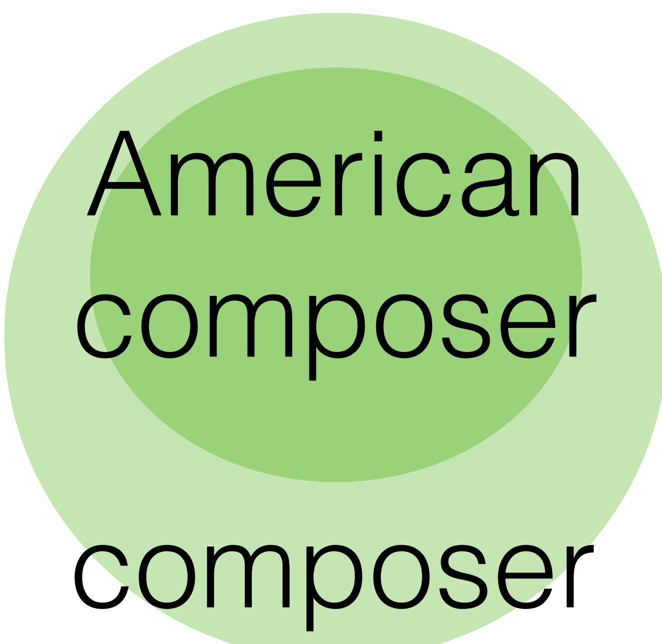
Summary and Future Work

Classes of Modifiers



Classes of Modifiers

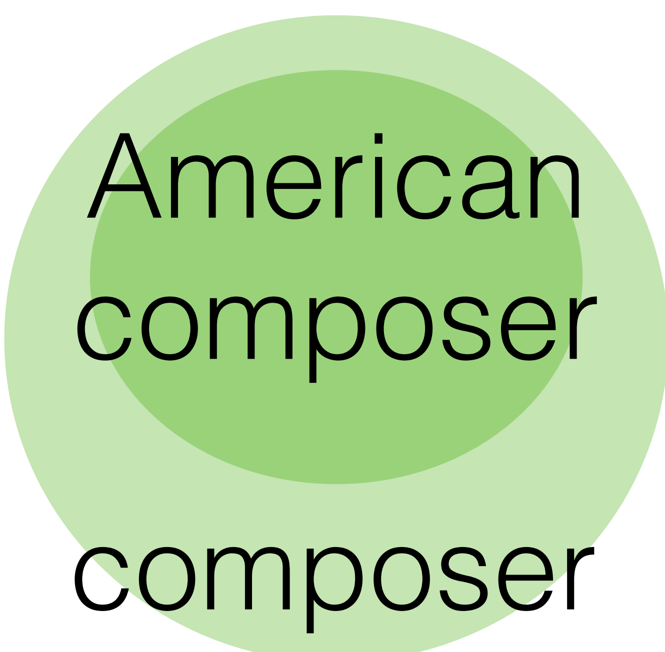
MH ⇒ H



Subsective

Classes of Modifiers

$MH \Rightarrow H$



Subsective

$MH \nRightarrow H$

Plain Non-Subsective

Classes of Modifiers

$MH \Rightarrow H$ | $MH \not\Rightarrow H$ | $MH \Rightarrow \neg H$

Subsective | Plain Non-Subsective | Privative

Equivalence	$MH \Leftrightarrow H$	It is her favorite book in the **entire world**.
Reverse Entailment	$MH \Rightarrow H \land H \nRightarrow MH$	She is an **American composer**.
Forward Entailment	$MH \nRightarrow H \land H \Rightarrow MH$	She is the president's **potential successor**.
Independence	$MH \nRightarrow H \land H \nRightarrow MH$	She is the **alleged hacker**.
Exclusion	$MH \Rightarrow \neg H \land H \Rightarrow \neg MH$	She is a **former senator**.

Natural Language Inference

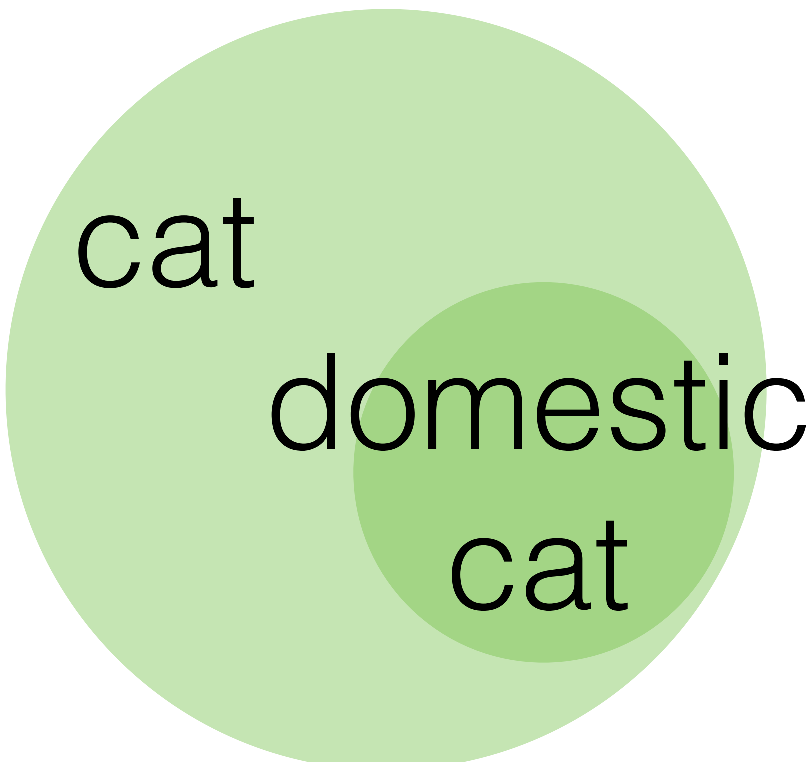
Eddy is a **cat**.

Natural Language Inference

Eddy is a **cat**.

Eddy is a **domestic cat**.

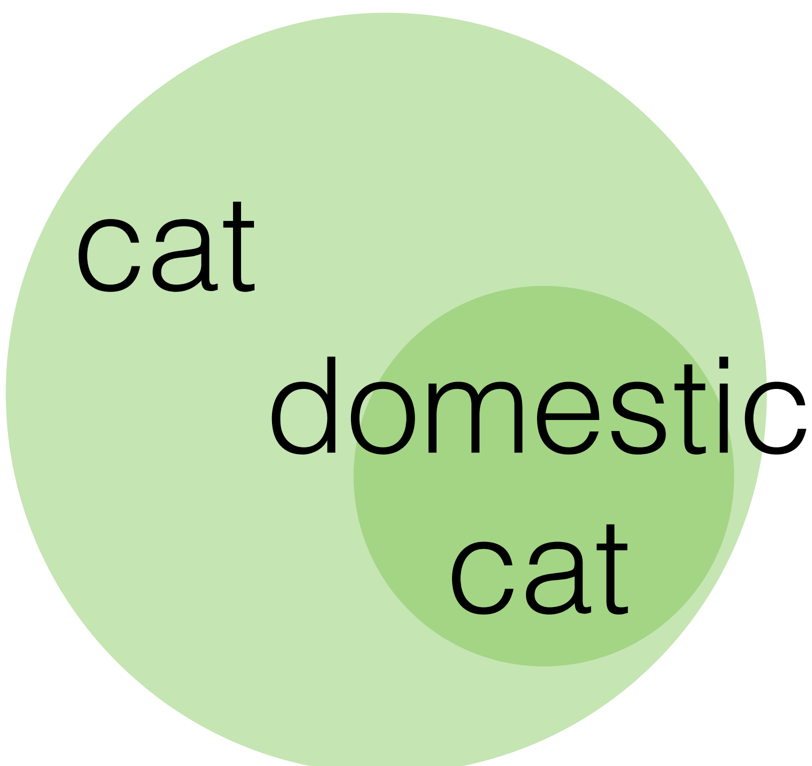
Natural Language Inference



Eddy is a **cat**.

Eddy is a **domestic cat**.

Natural Language Inference



Eddy is a **cat**.

$$\not\Downarrow$$

Eddy is a **domestic cat**.

Natural Language Inference

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

$$\not\Downarrow$$

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.

$$\not\Downarrow$$

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.

Natural Language Inference

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

$\Downarrow$

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?

e Inference

e ground looking
oor screen.

$\Downarrow$

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**?

e Inference

e ground looking

oor screen.

What, if any, **generalizations** can be made to aide systems in performing natural language inference?

Eddy is a **dom** ... d

looking out t

p ent

read

most likely true.

Human Annotation of MH Compositions

Human Annotation of MH Compositions

$$H \Rightarrow MH?$$

Eddy is a **cat**.

Eddy is a **domestic cat**.

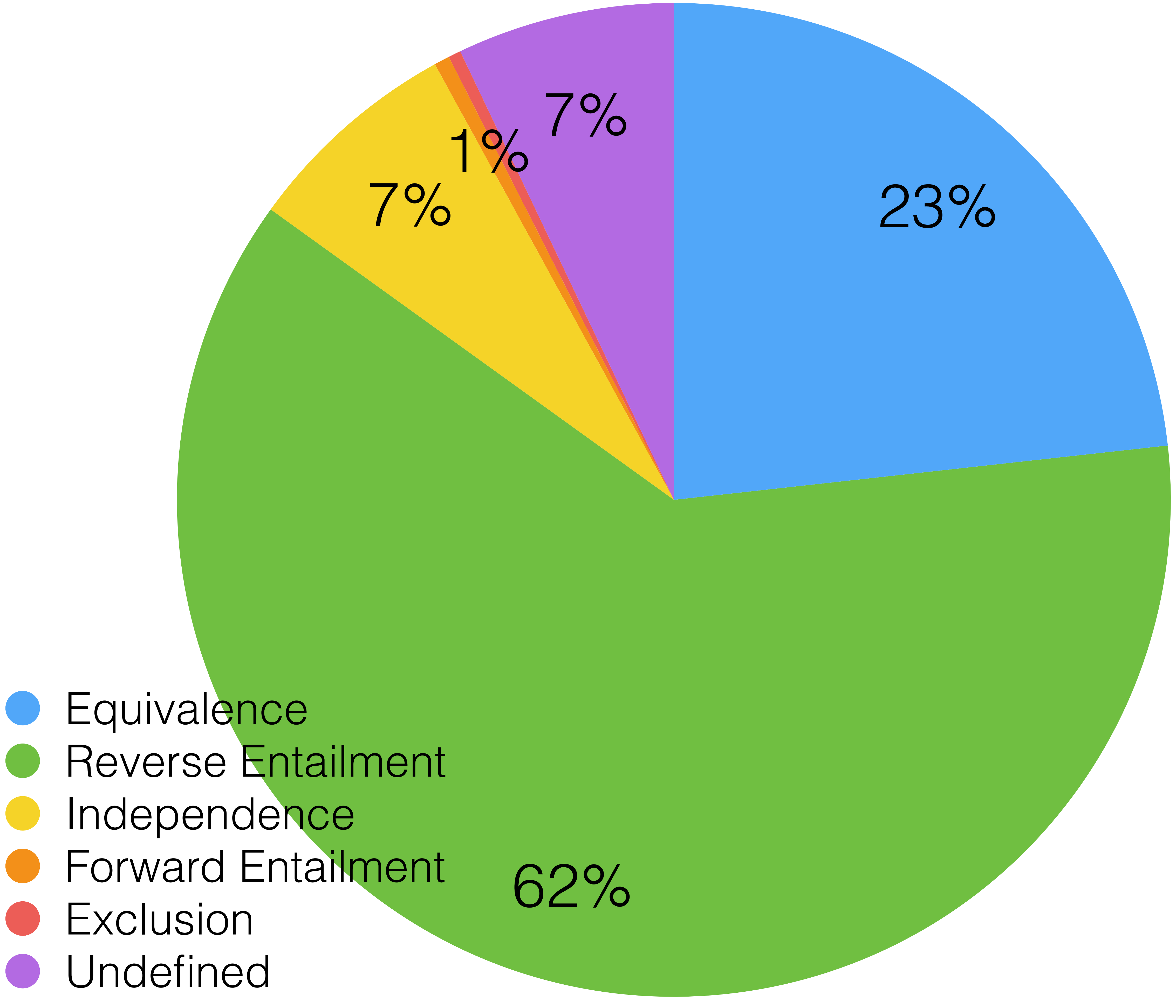
Human Annotation of MH Compositions

$$MH \Rightarrow H?$$

Eddy is a **domestic cat**.

Eddy is a **cat**.

	$MH \Rightarrow H$	$H \Rightarrow MH$	
Equiv.	Yes	Yes	It is her favorite book in the **entire world**.
Rev. Ent.	Yes	Unk	Eddy is a **gray cat**.
For. Ent.	Unk	Yes	She is the president's **potential successor**.
Indep.	Unk	Unk	She is the **alleged hacker**.
Excl.	No	No	She is a **former senator**.


23%
62%
7%
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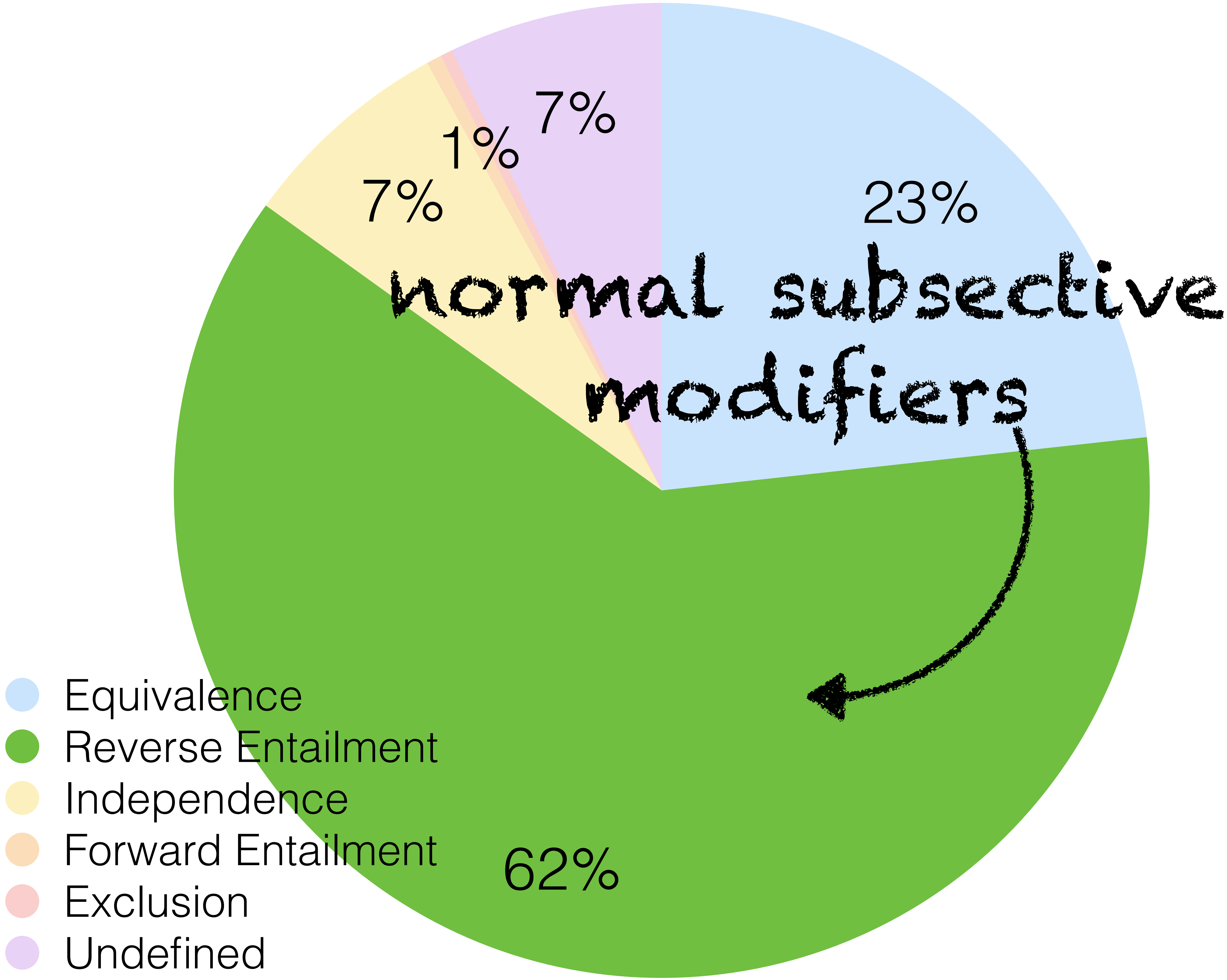
7%
Equivalence
Reverse Entailment
Independence
Forward Entailment
Exclusion
Undefined


7%
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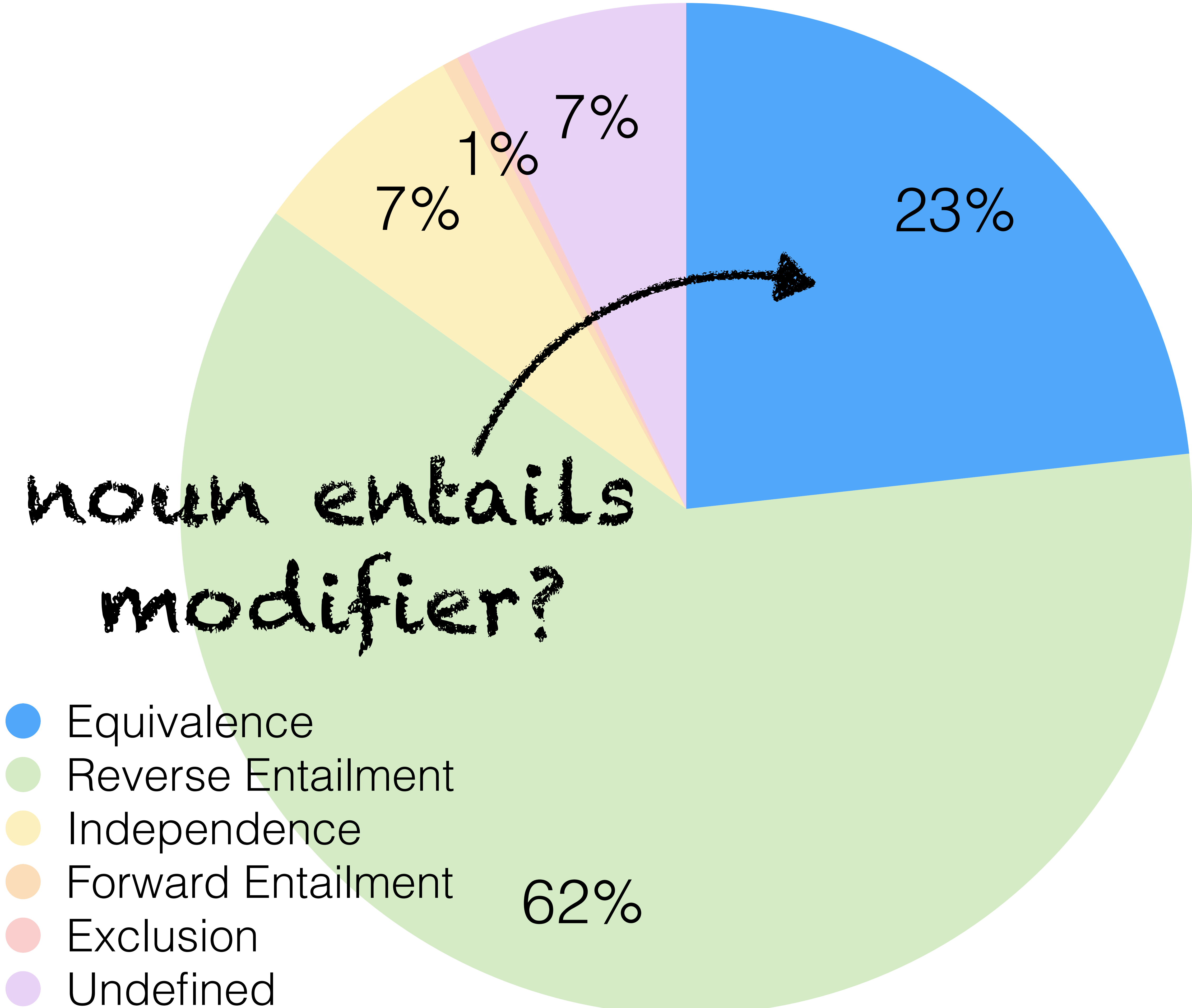
normal subsective modifiers
62%
Equivalence
Reverse Entailment
Independence
Forward Entailment
Exclusion
Undefined


7%
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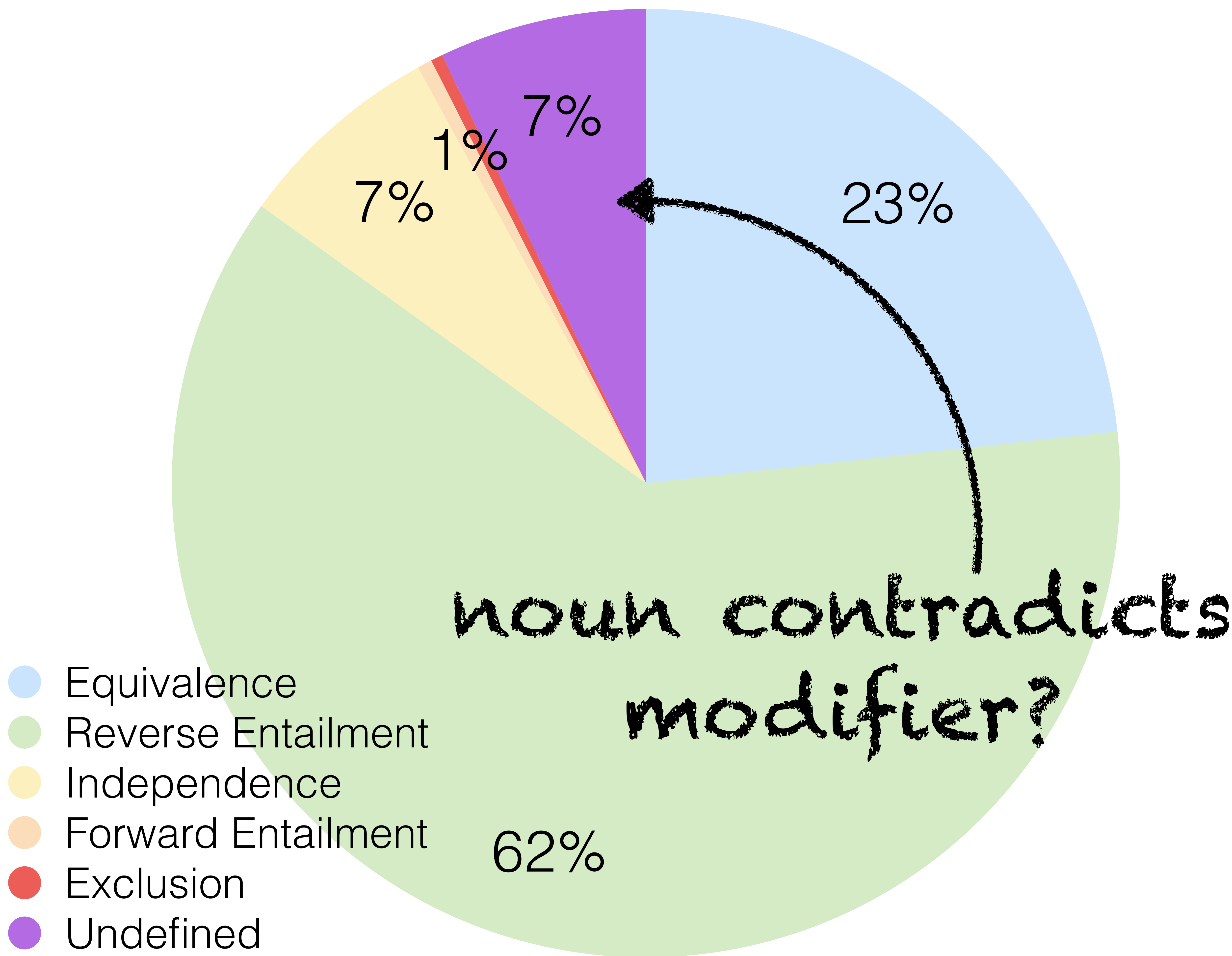
noun entails modifier?
62%
Equivalence
Reverse Entailment
Independence
Forward Entailment
Exclusion
Undefined


7%
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noun contradicts modifier?
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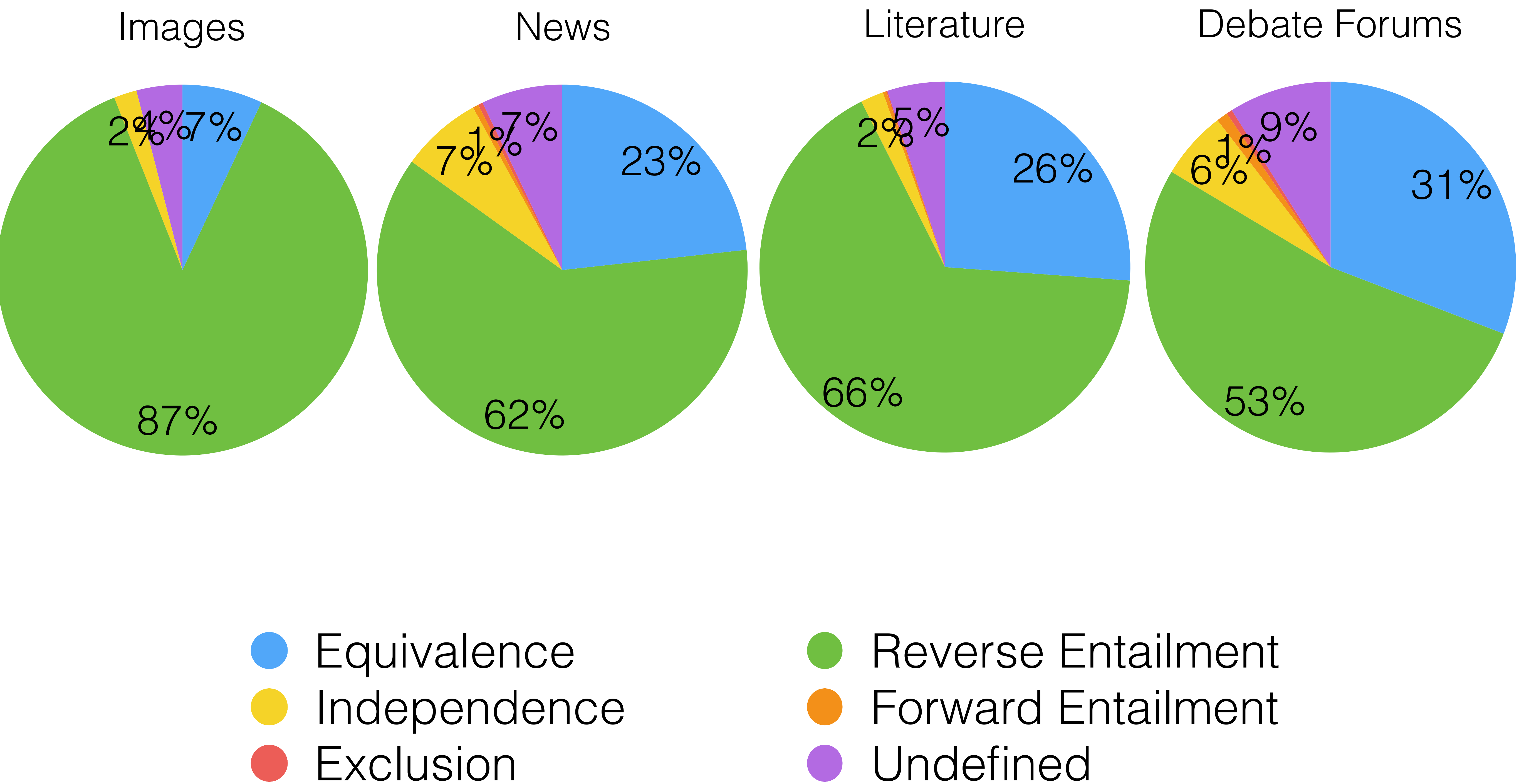
Equivalence
Reverse Entailment
Independence
Forward Entailment
Exclusion
Undefined


Images
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News
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Literature
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66%
Debate Forums
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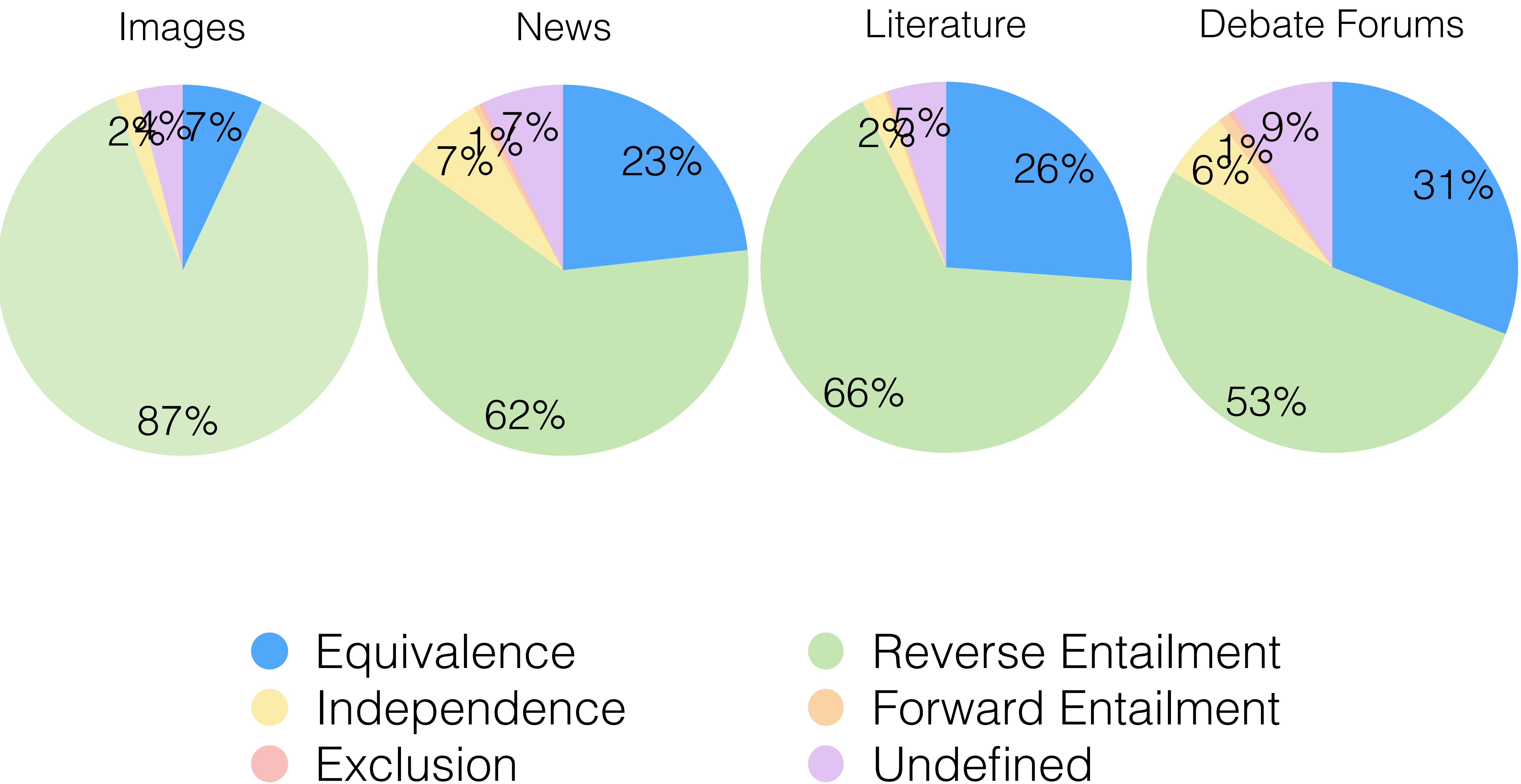
9%
31%
53%
Equivalence
Independence
Exclusion
Reverse Entailment
Forward Entailment
Undefined

H ⇒ MH?


Images
News
Literature
Debate Forums
2%
4%
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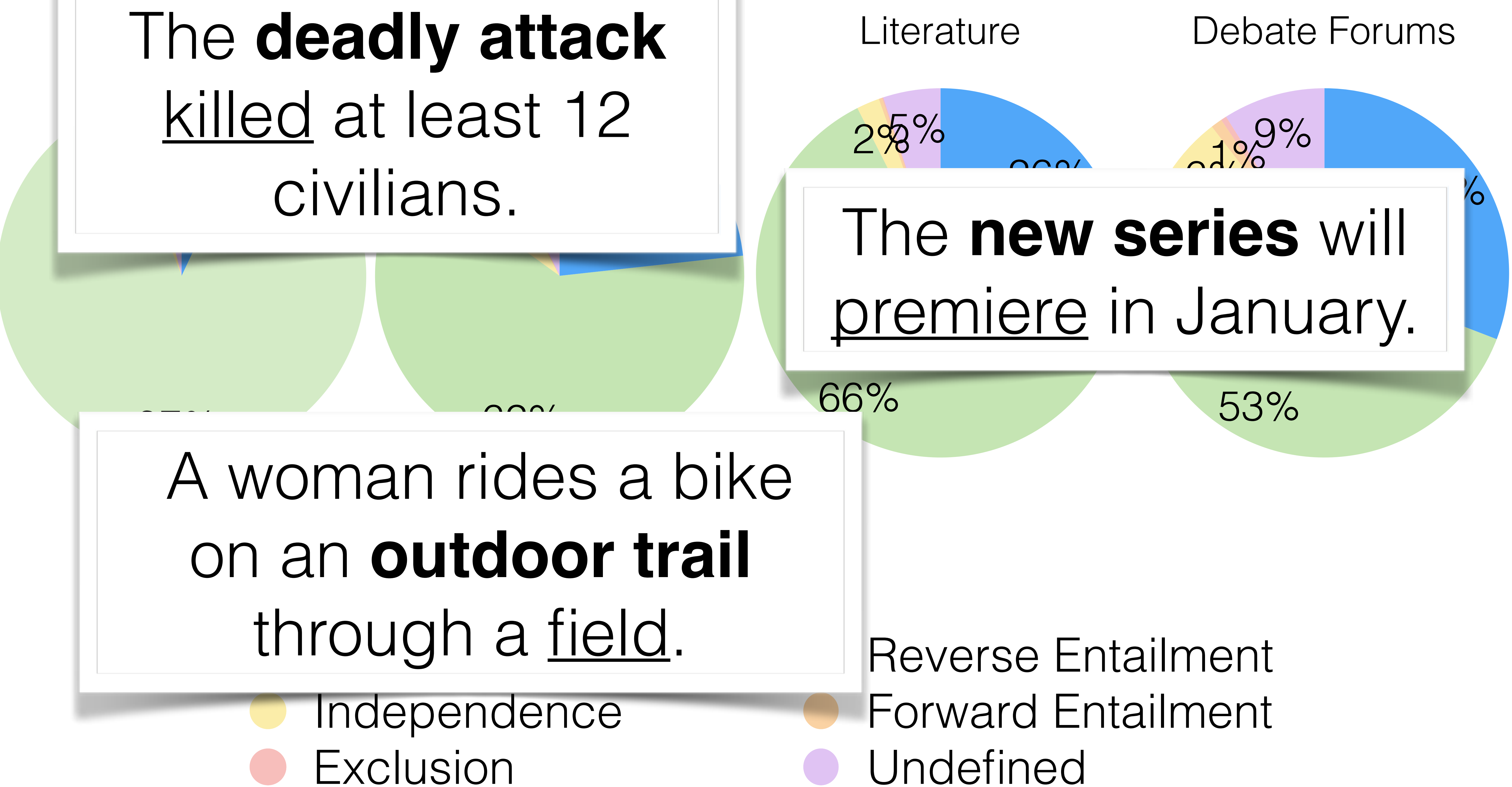
5%
26%
66%
6%
1%
9%
31%
53%
Equivalence
Independence
Exclusion
Reverse Entailment
Forward Entailment
Undefined

H ⇒ MH?

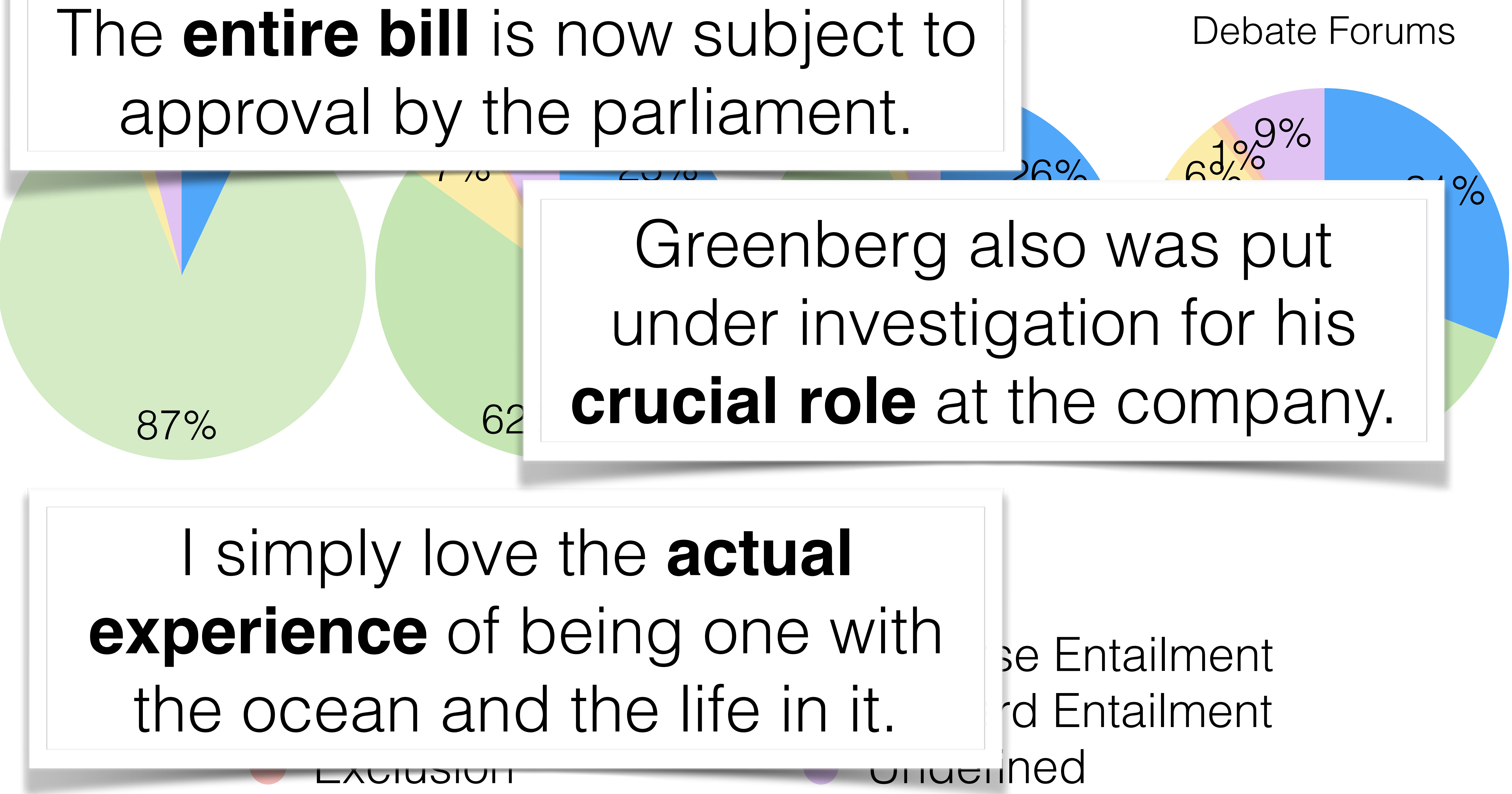
The **deadly attack** killed at least 12 civilians.

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

A woman rides a bike on an **outdoor trail** through a field.



H ⇒ MH?

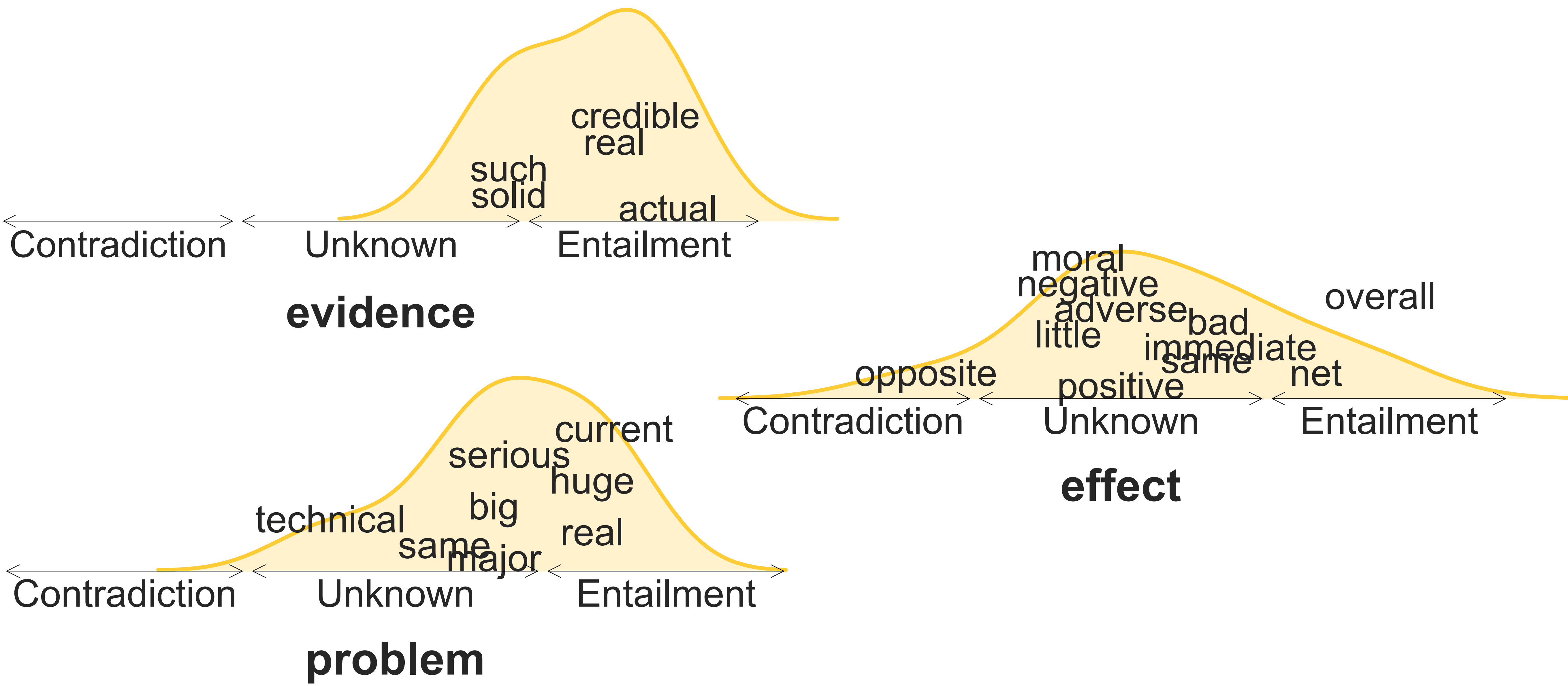


The **entire bill** is now subject to approval by the parliament.

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

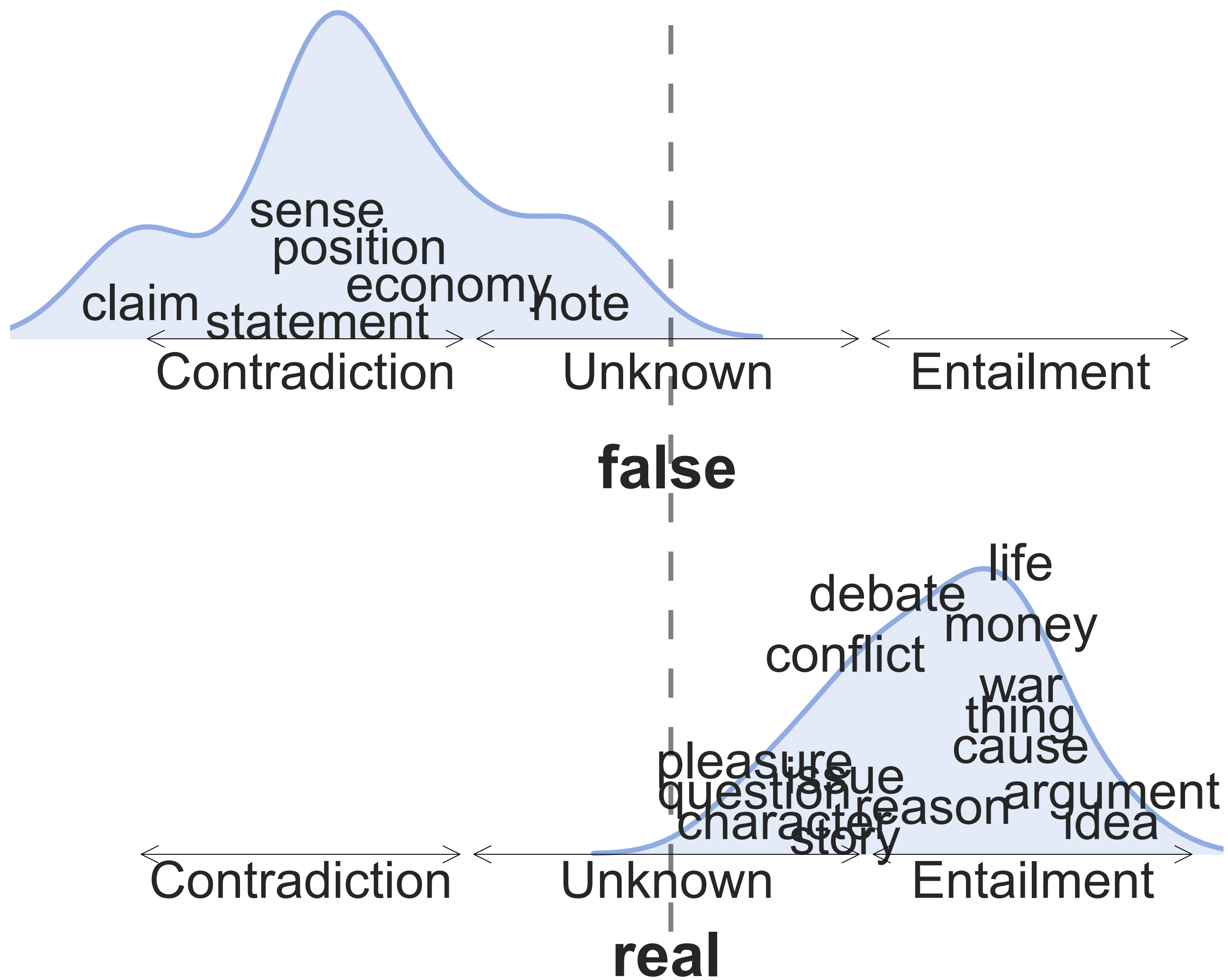
I simply love the **actual experience** of being one with the ocean and the life in it.

$H \Rightarrow MH?$



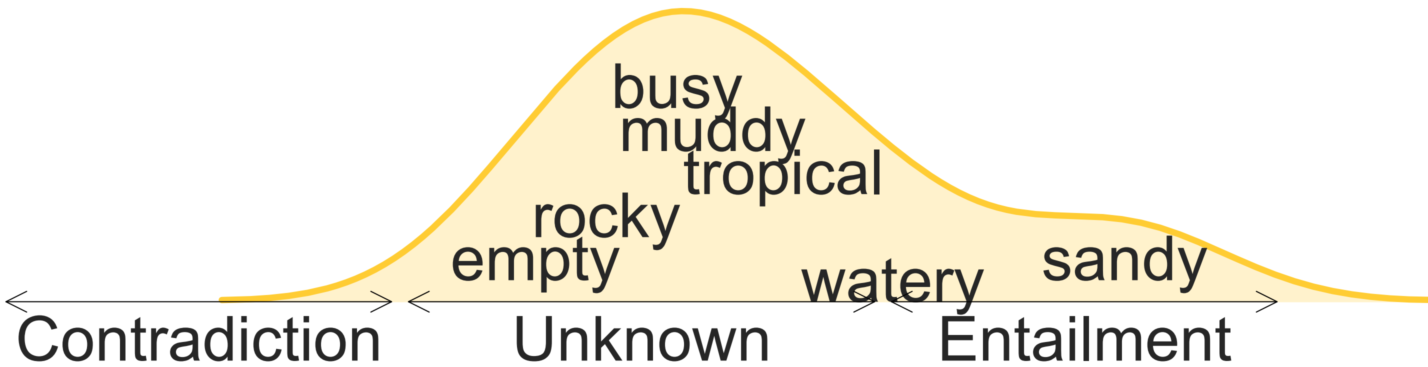
Entities are assumed to be real and relevant.

$H \Rightarrow MH?$

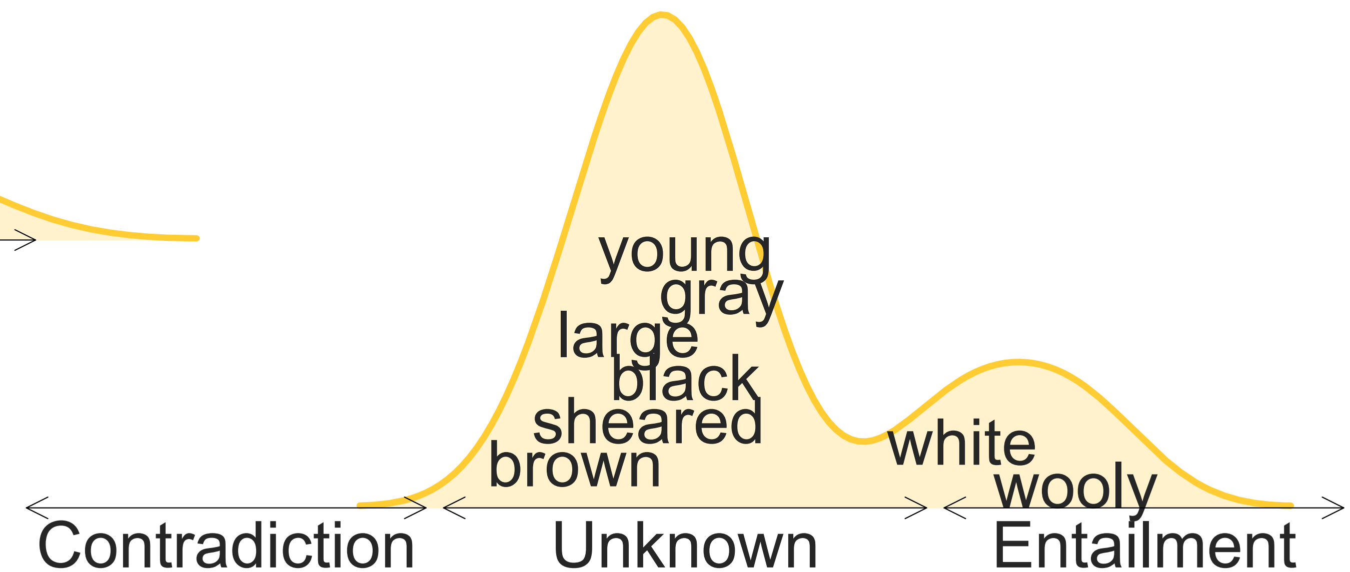


Entities are assumed to be real and relevant.

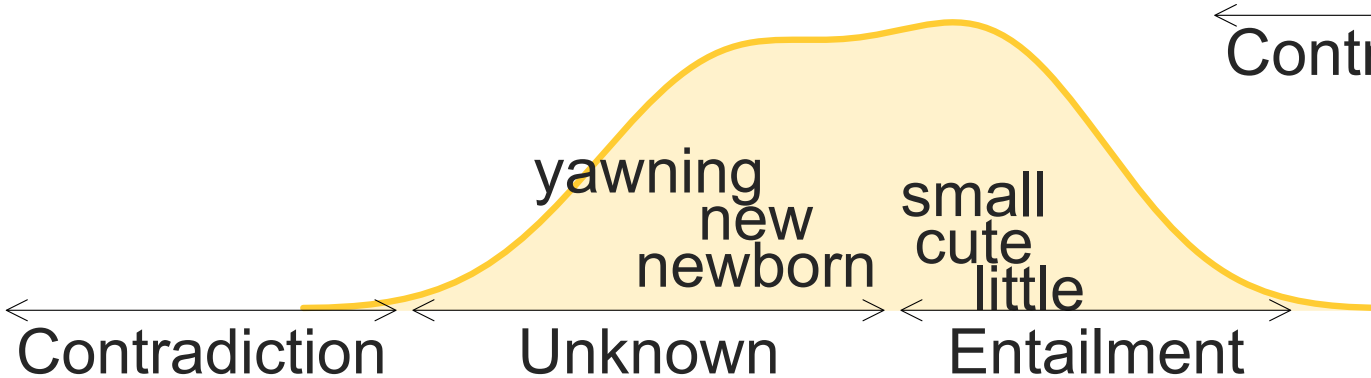
$H \Rightarrow MH$?



beach



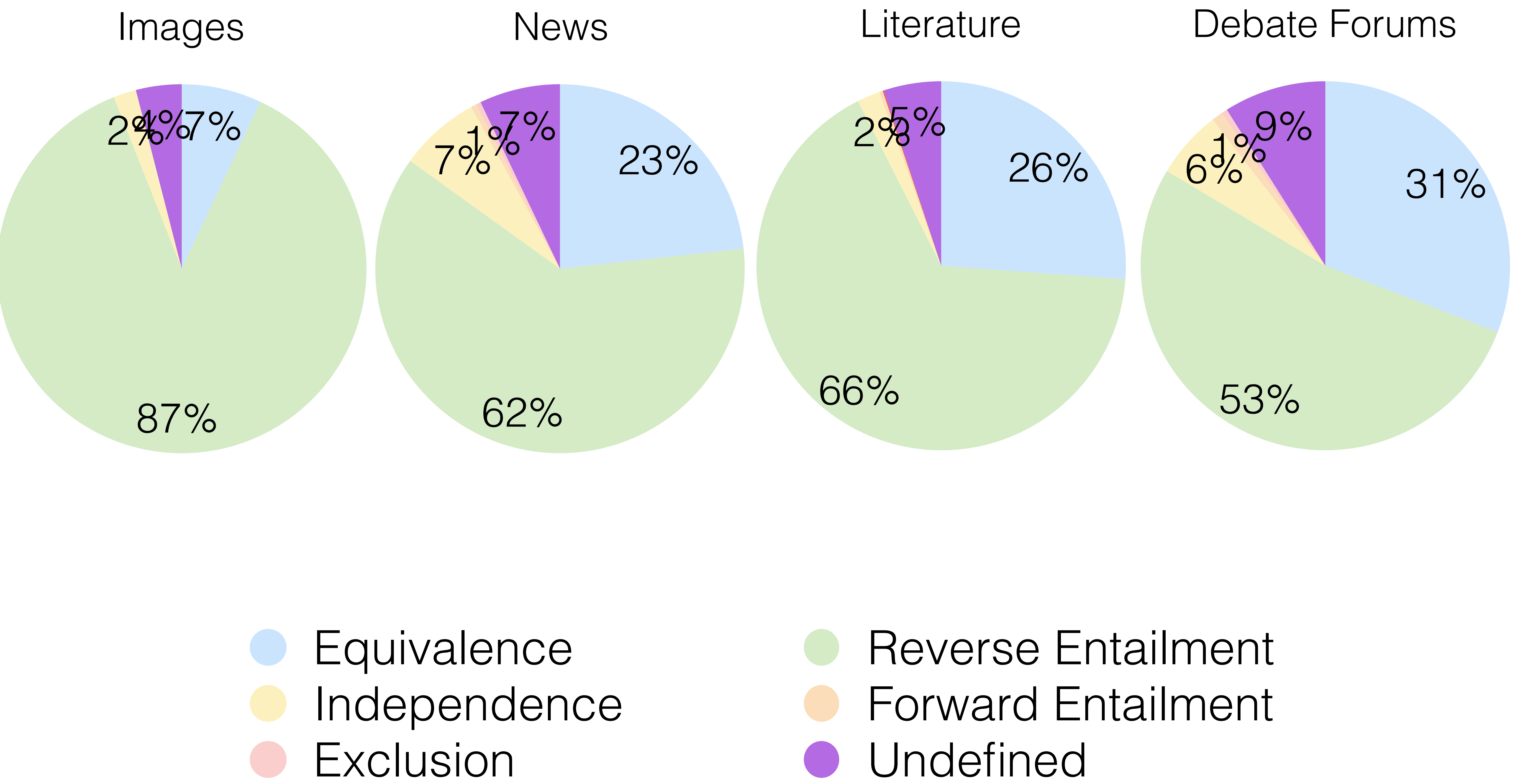
sheep



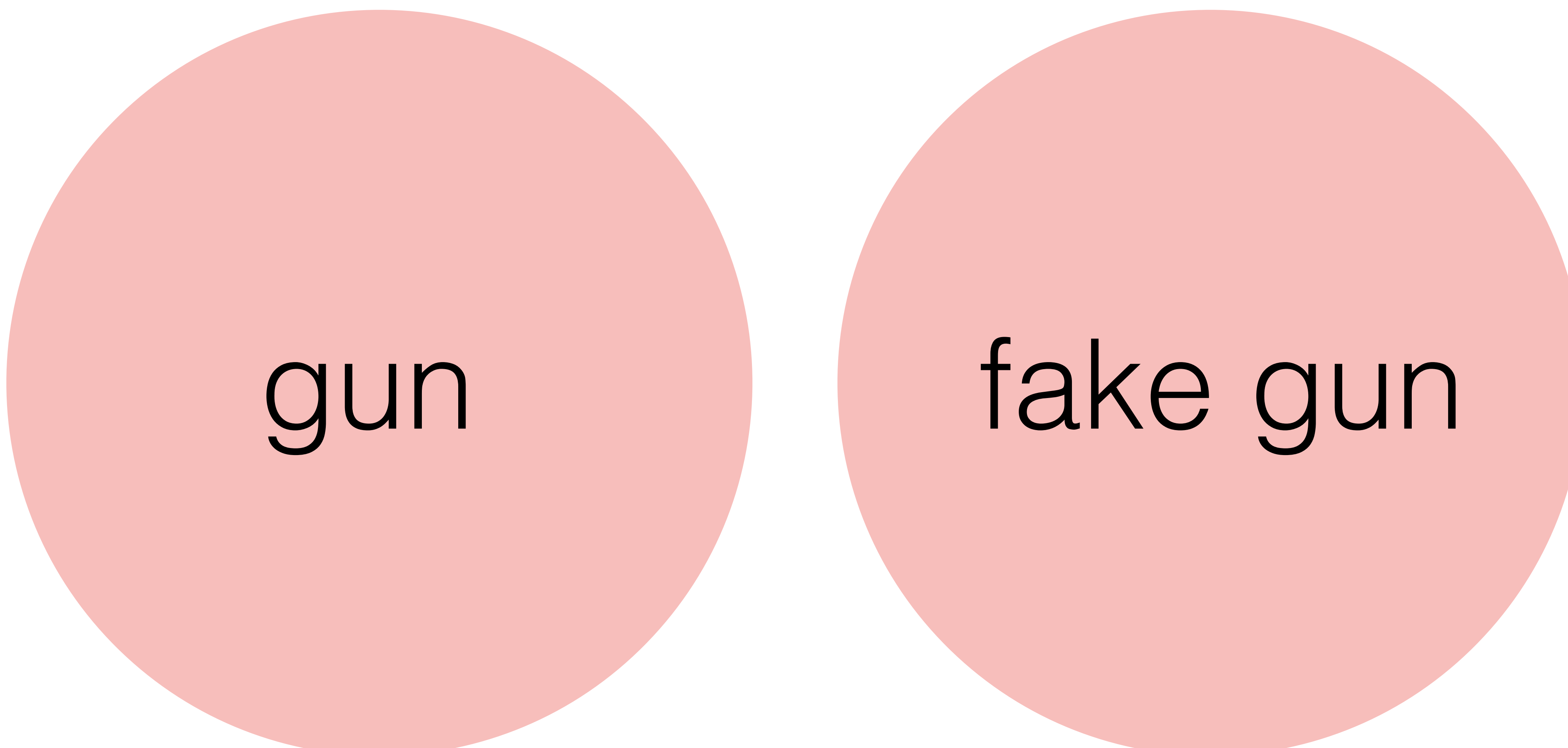
baby

Entities are assumed to be prototypical.

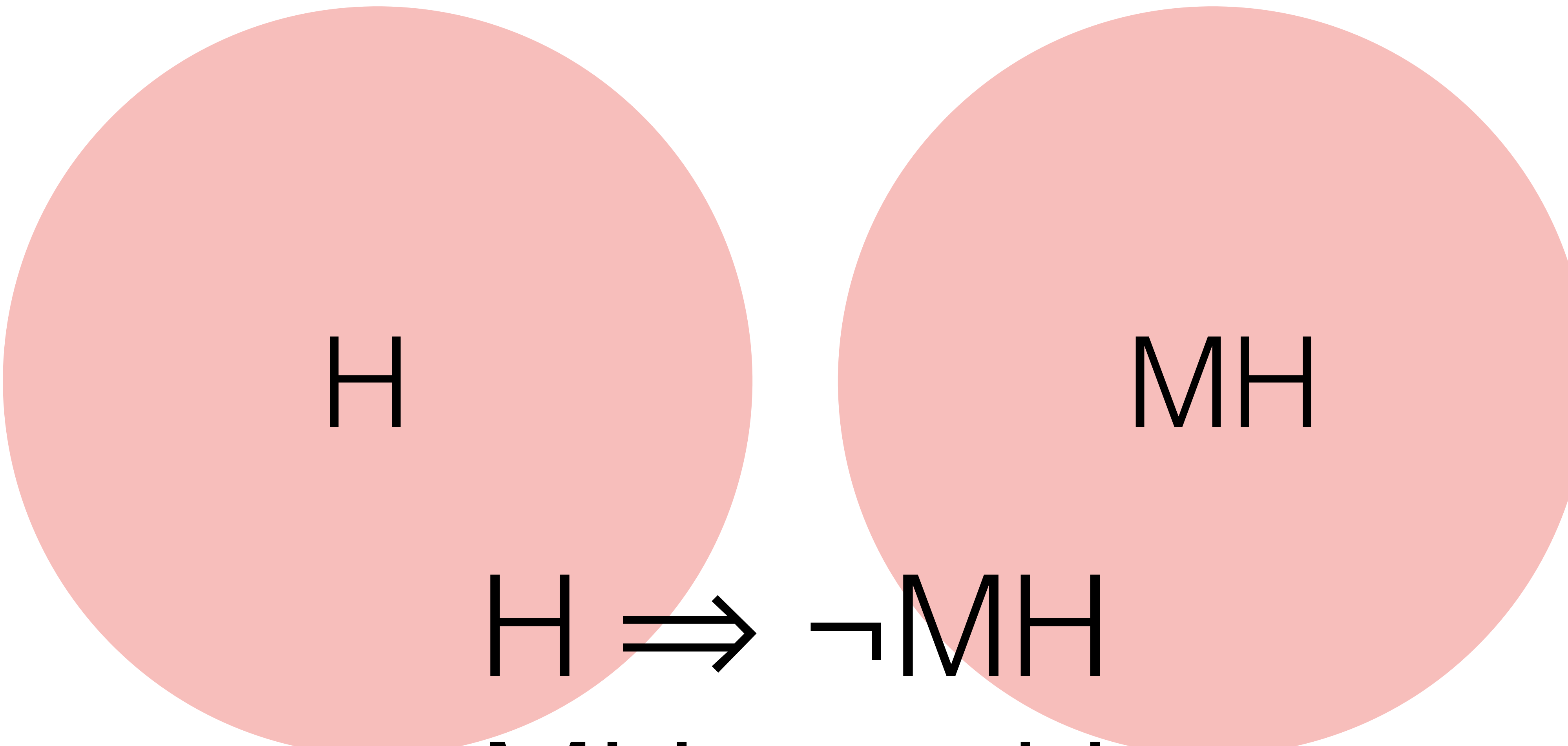
$H \Rightarrow \neg MH$?



$H \Rightarrow \neg MH$?



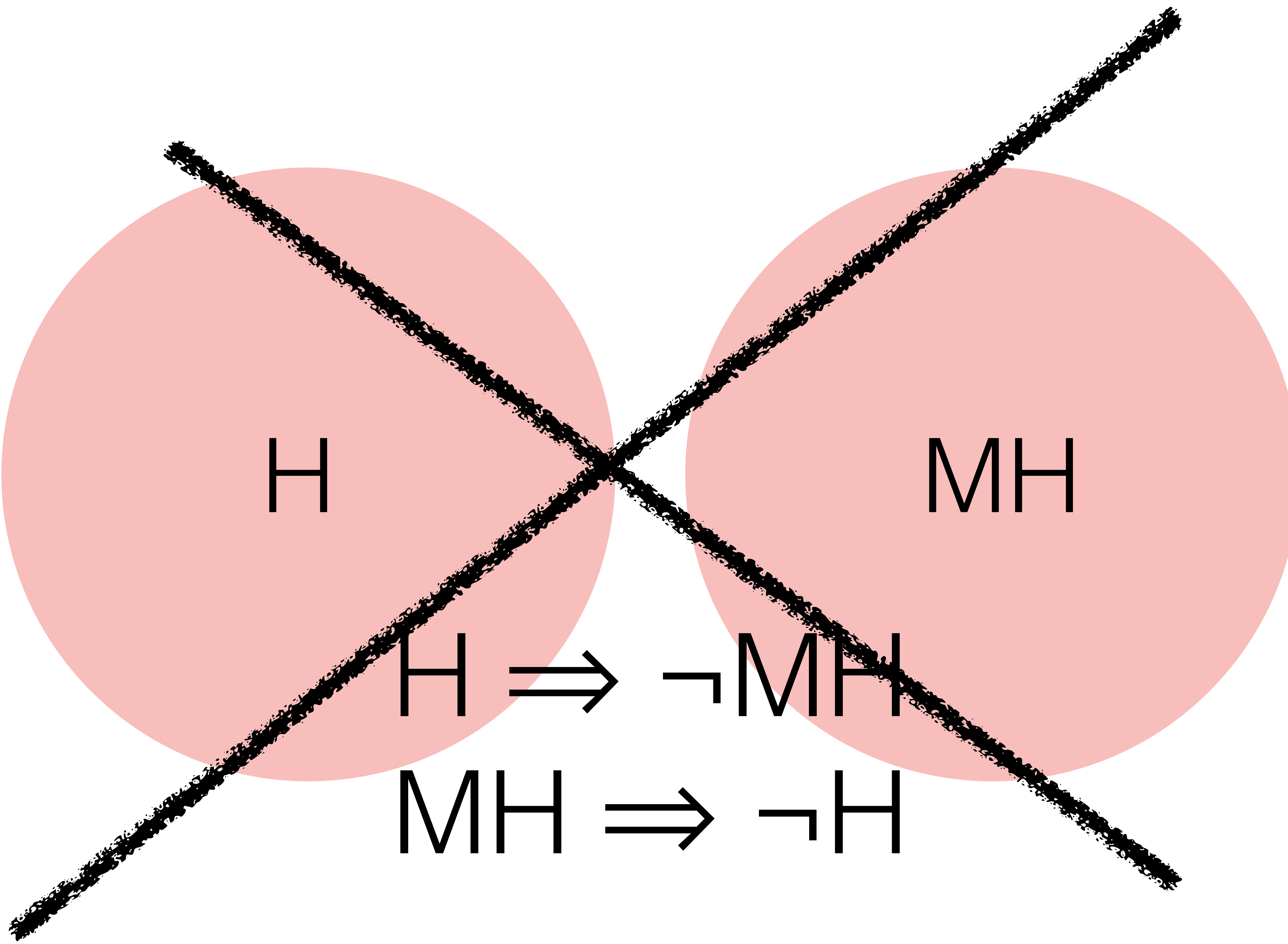
$$H \Rightarrow \neg MH?$$



$$H \Rightarrow \neg MH$$

$$MH \Rightarrow \neg H$$

$H \Rightarrow \neg MH$?

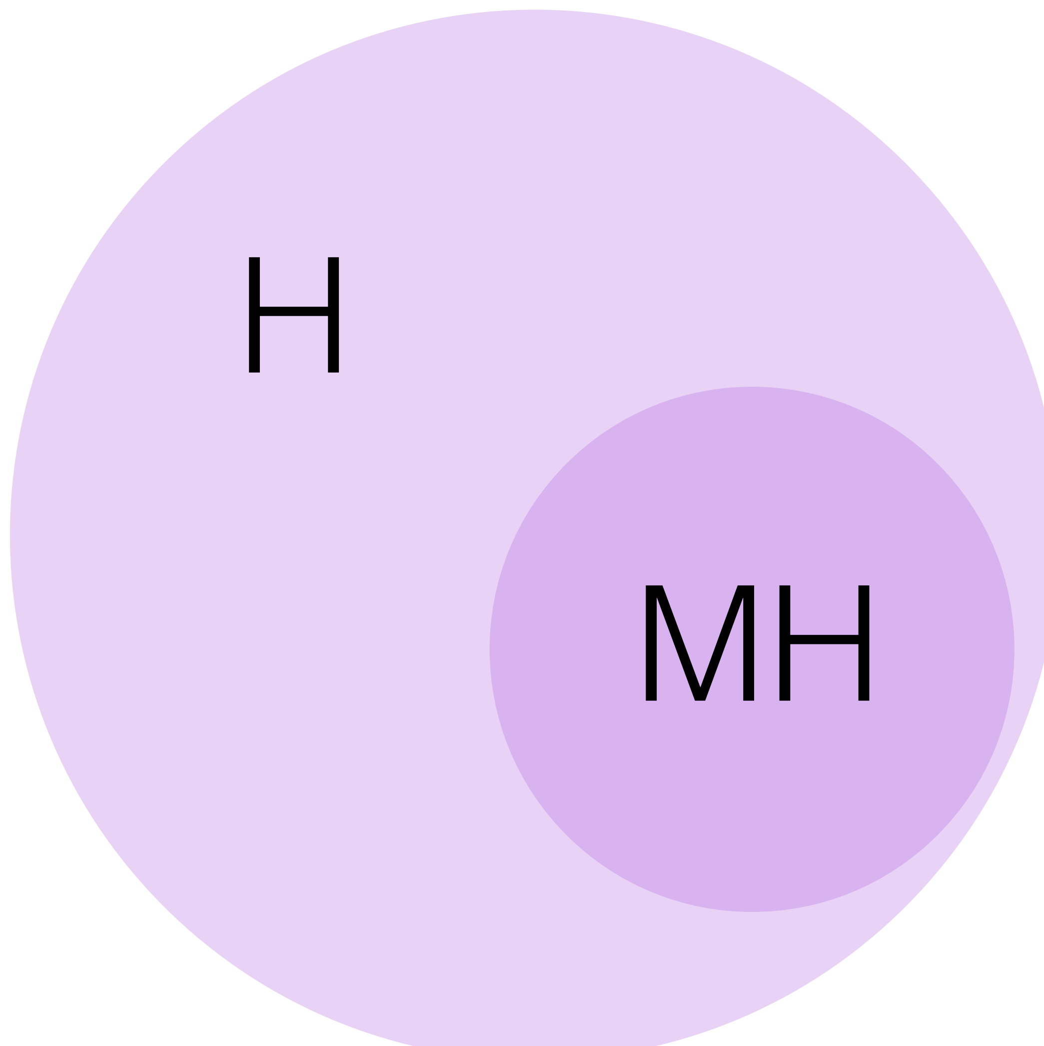


$H \Rightarrow \neg MH$

$MH \Rightarrow \neg H$

Undefined Relations

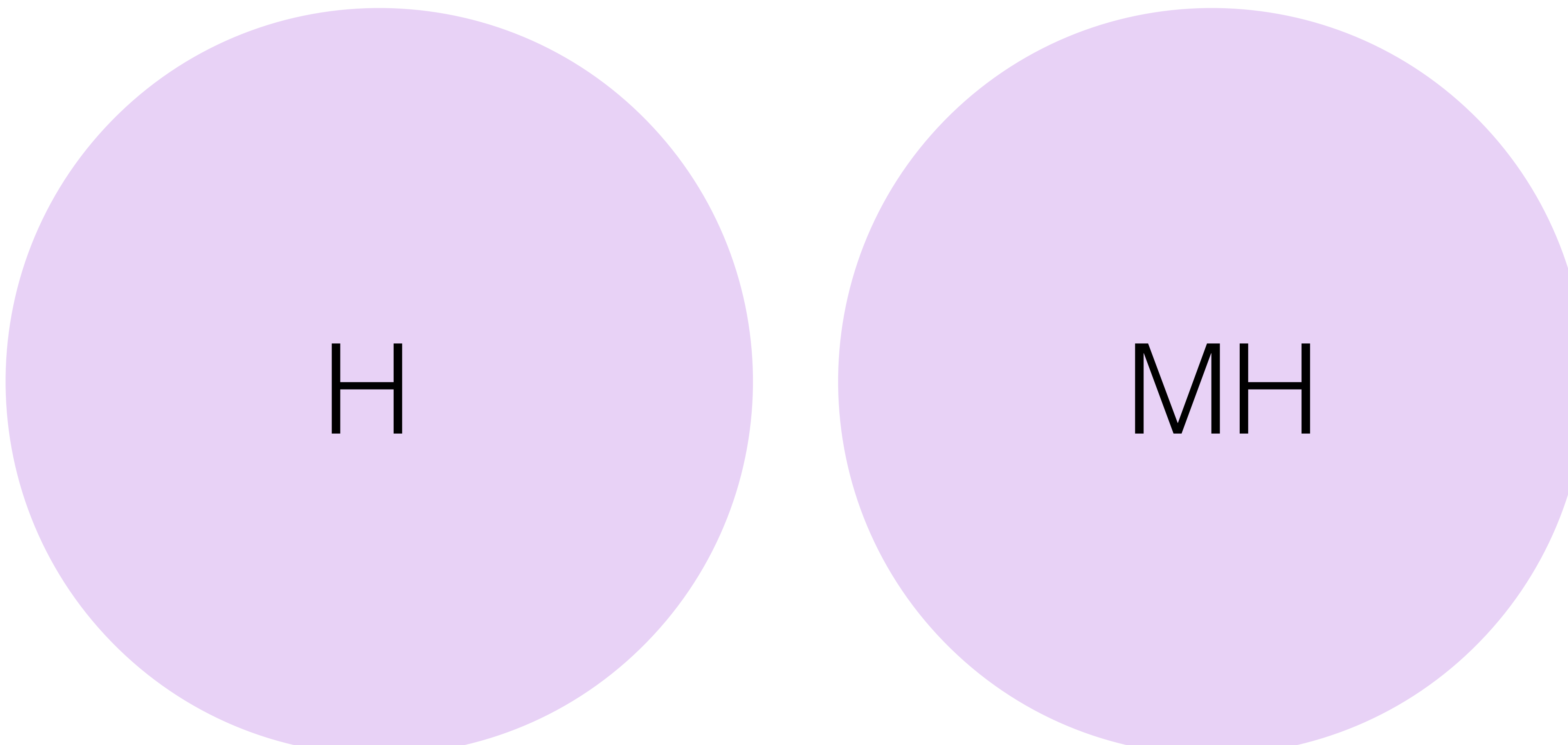
Undefined Relations



$$MH \Rightarrow H$$

(like subsective)

Undefined Relations



$$H \Rightarrow \neg MH$$

(like privative)

	$MH \Rightarrow H$	$H \Rightarrow MH$	
Equiv.	Yes	Yes	It is her favorite book in the **entire world**.
Rev. Ent.	Yes	Unk	Eddy is a **gray cat**.
For. Ent.	Unk	Yes	She is the president's **potential successor**.
Indep.	Unk	Unk	She is the **alleged hacker**.
Excl.	No	No	She is a **former senator**.
Undef.	Yes	No	**?????**

Undefined Relations

$$H \Rightarrow \neg MH$$

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

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

Undefined Relations

$$\mathrm{MH} \Rightarrow \mathrm{H}$$

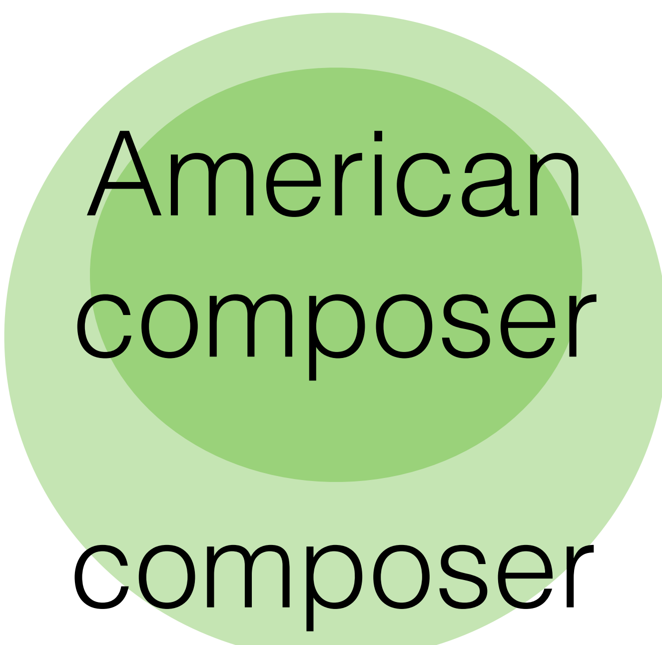
Bush travels Monday to Michigan to remark on the **Japanese economy**.

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

Classes of Modifiers Revisited

Subsective

$MH \Rightarrow H$



Plain Non-Subsective

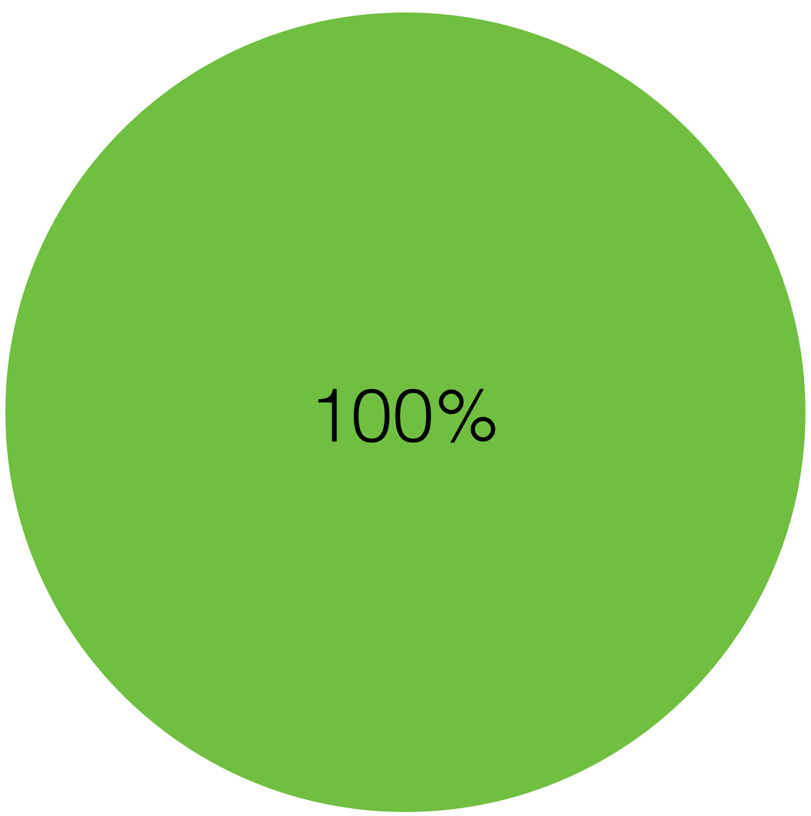
$MH \nRightarrow H$

Privative

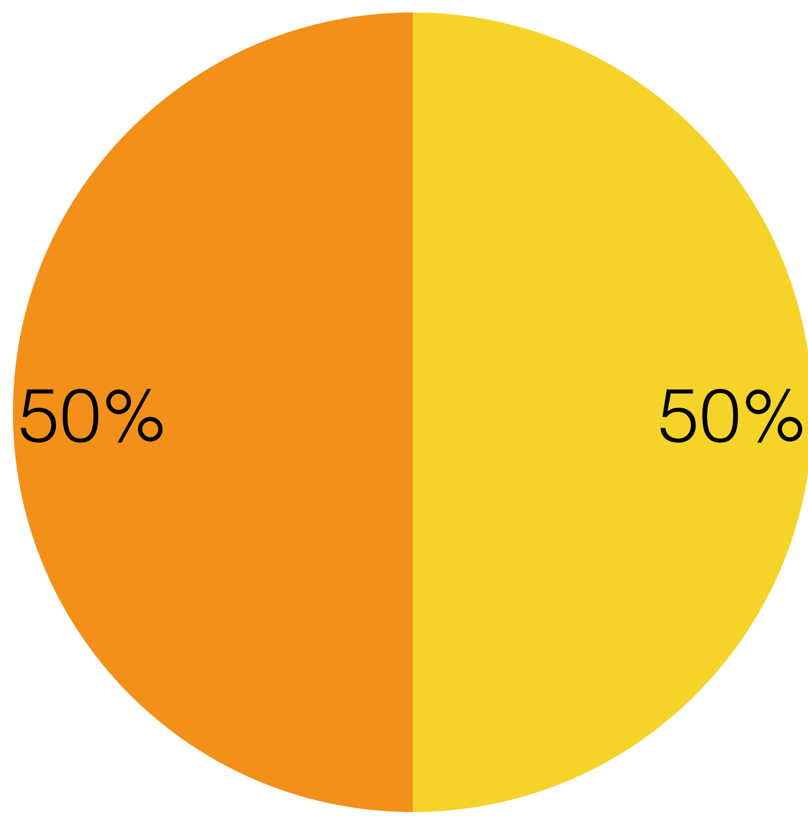
$MH \Rightarrow \neg H$

Classes of Modifiers Revisited

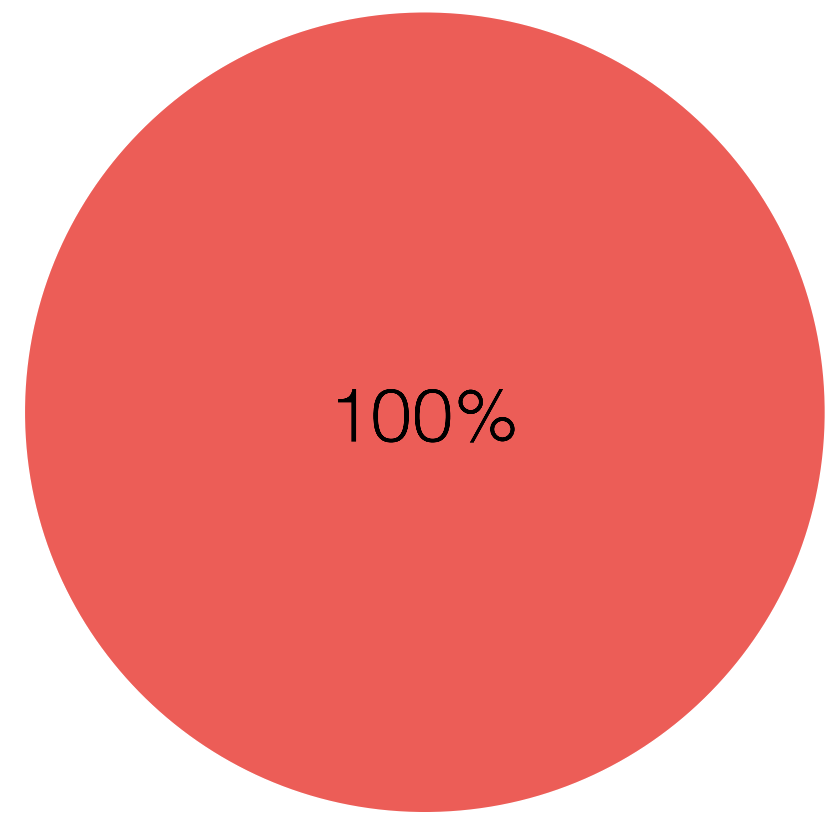
Subsective
$MH \Rightarrow H$



Plain Non-Subsective
$MH \nRightarrow H$

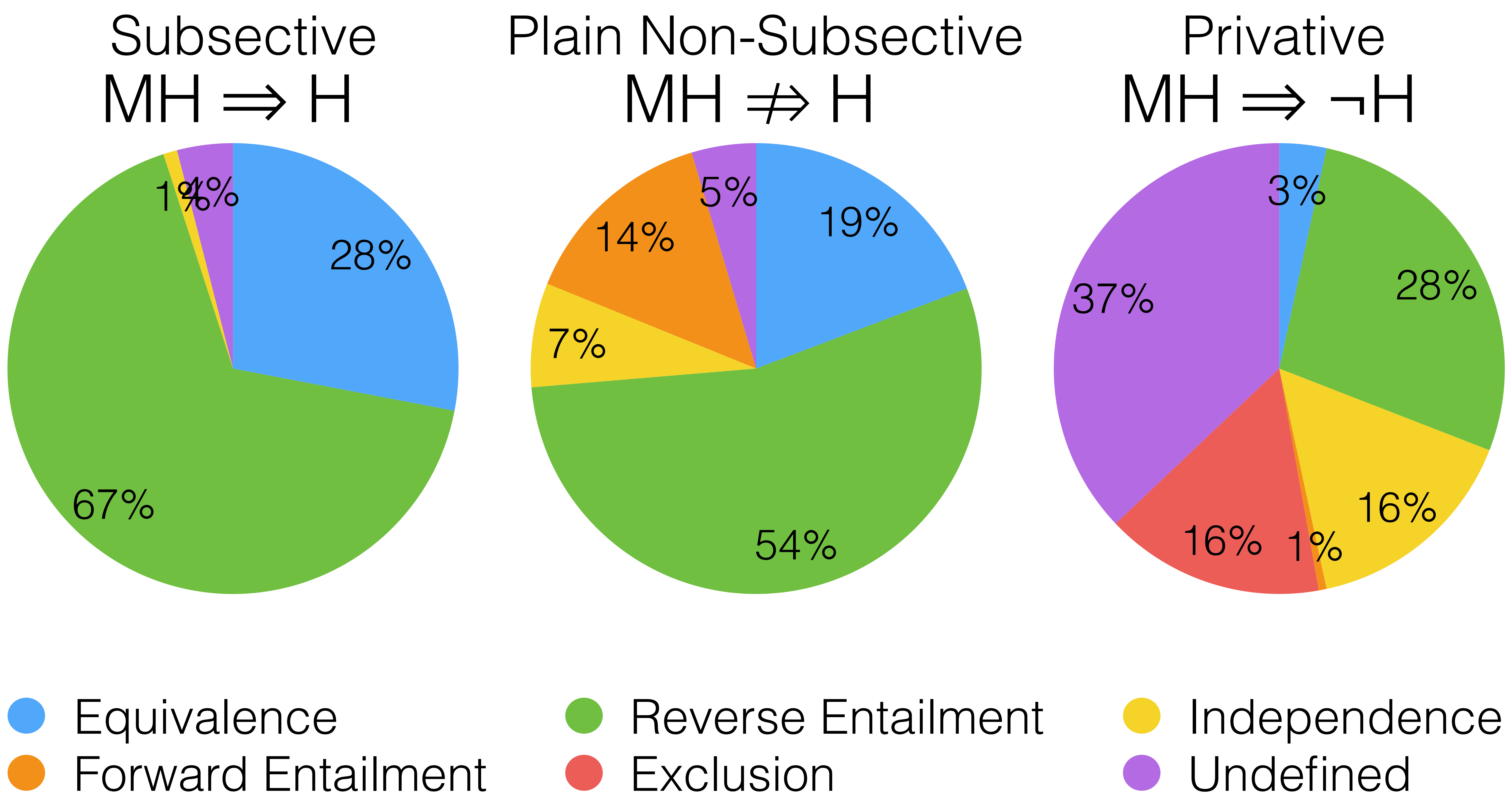


Privative
$MH \Rightarrow \neg H$



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

Classes of Modifiers Revisited



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**.

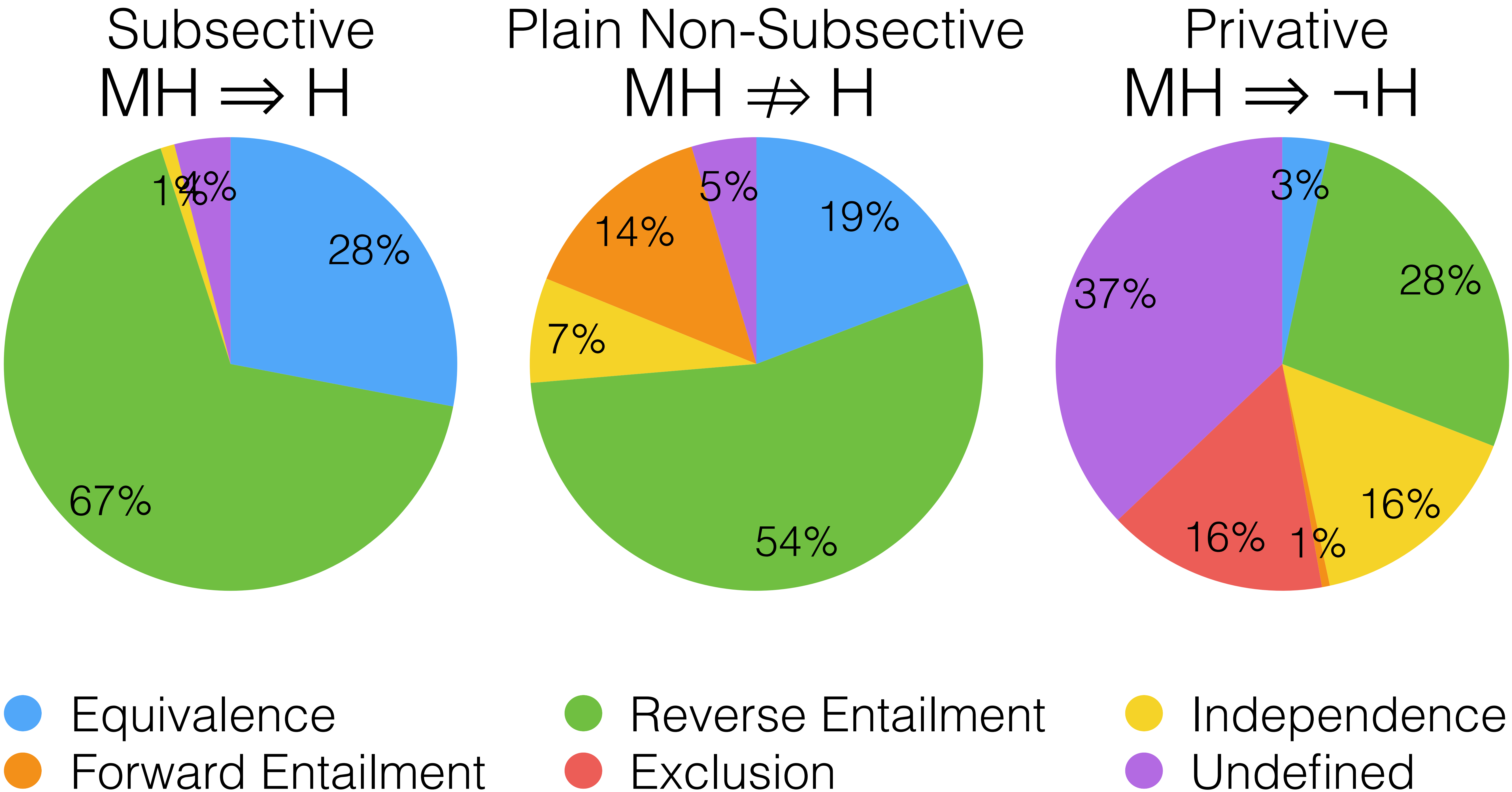
Privative Modifiers

$$MH \not\Rightarrow H$$

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

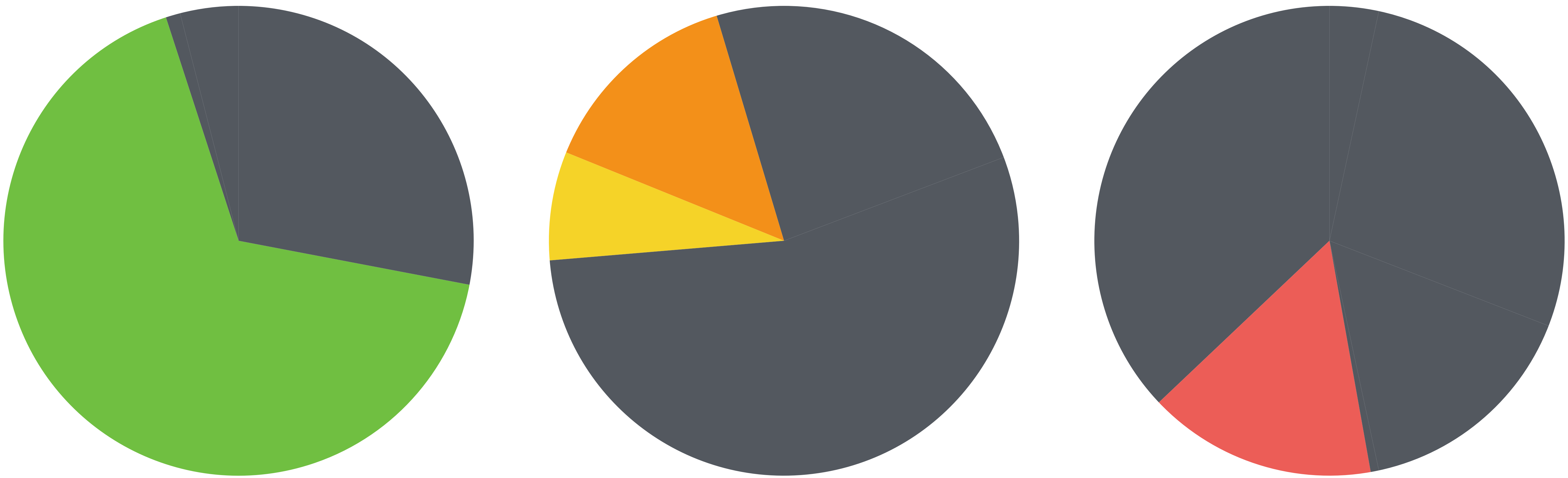
Wilson signed off to pay the debts to the **company**.

Classes of Modifiers Revisited



Classes of Modifiers Revisited

Subsective	Plain Non-Subsective	Privative
$MH \Rightarrow H$	$MH \not\Rightarrow H$	$MH \Rightarrow \neg H$



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 = “The crowd roared.”

h = “The enthusiastic crowd roared.”

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

Modern Inference Systems

p = “The crowd roared.”

h = “The enthusiastic crowd roared.”

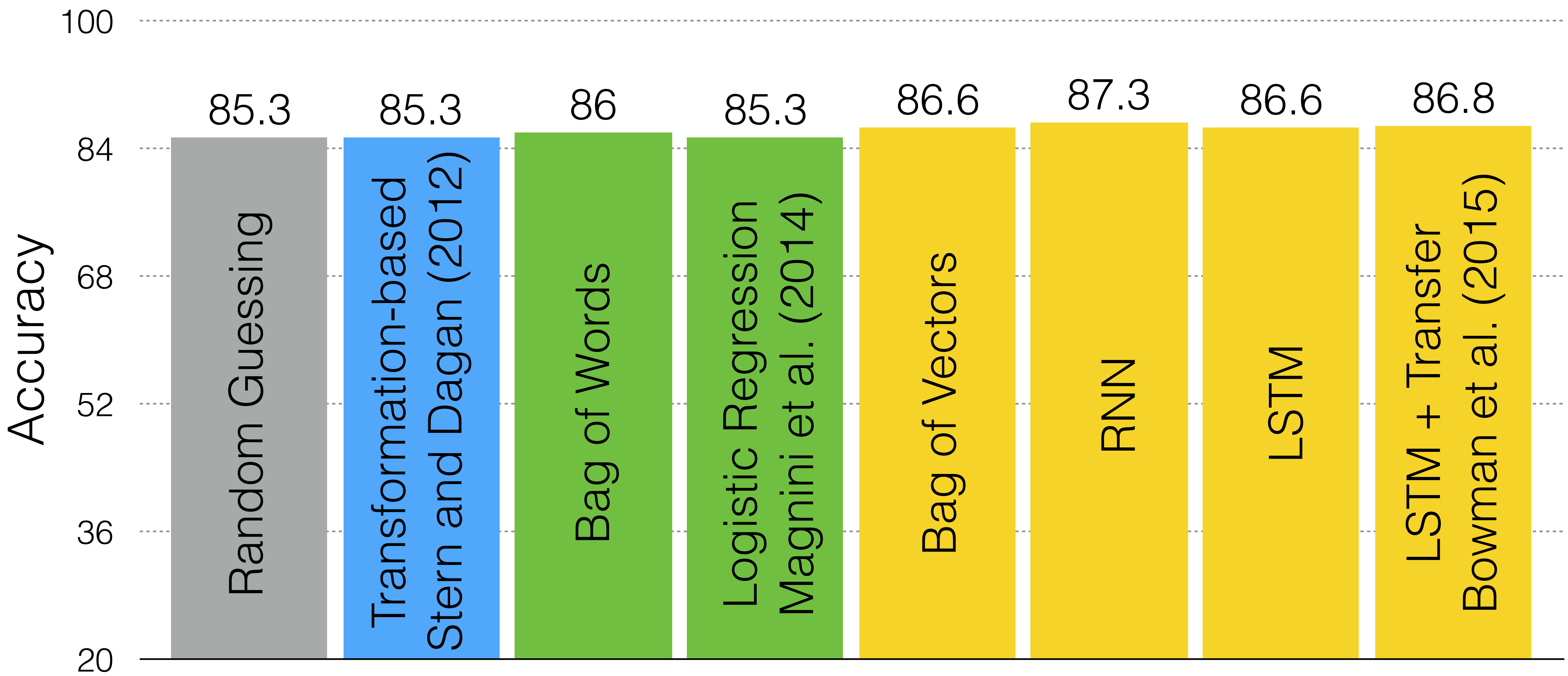
↓

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

↓

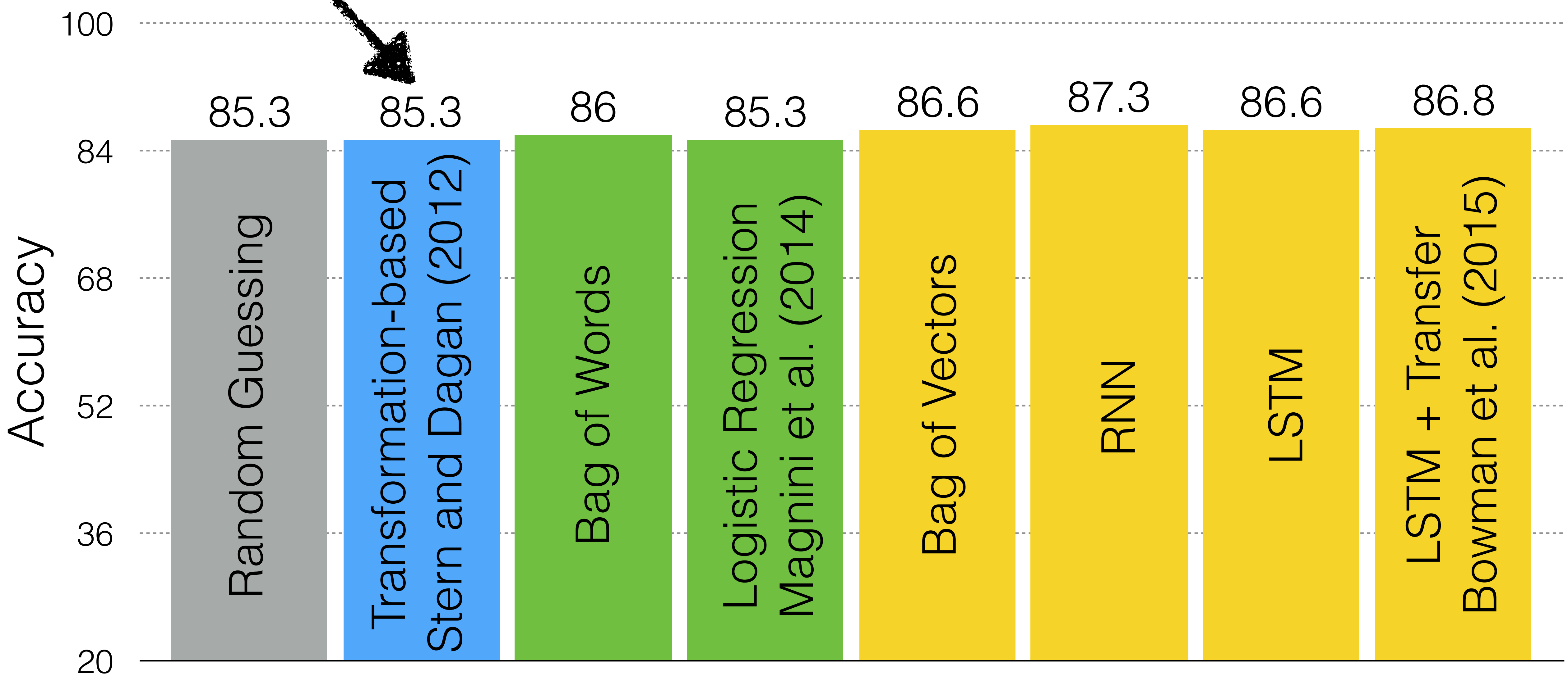
Yes

Modern Inference Systems

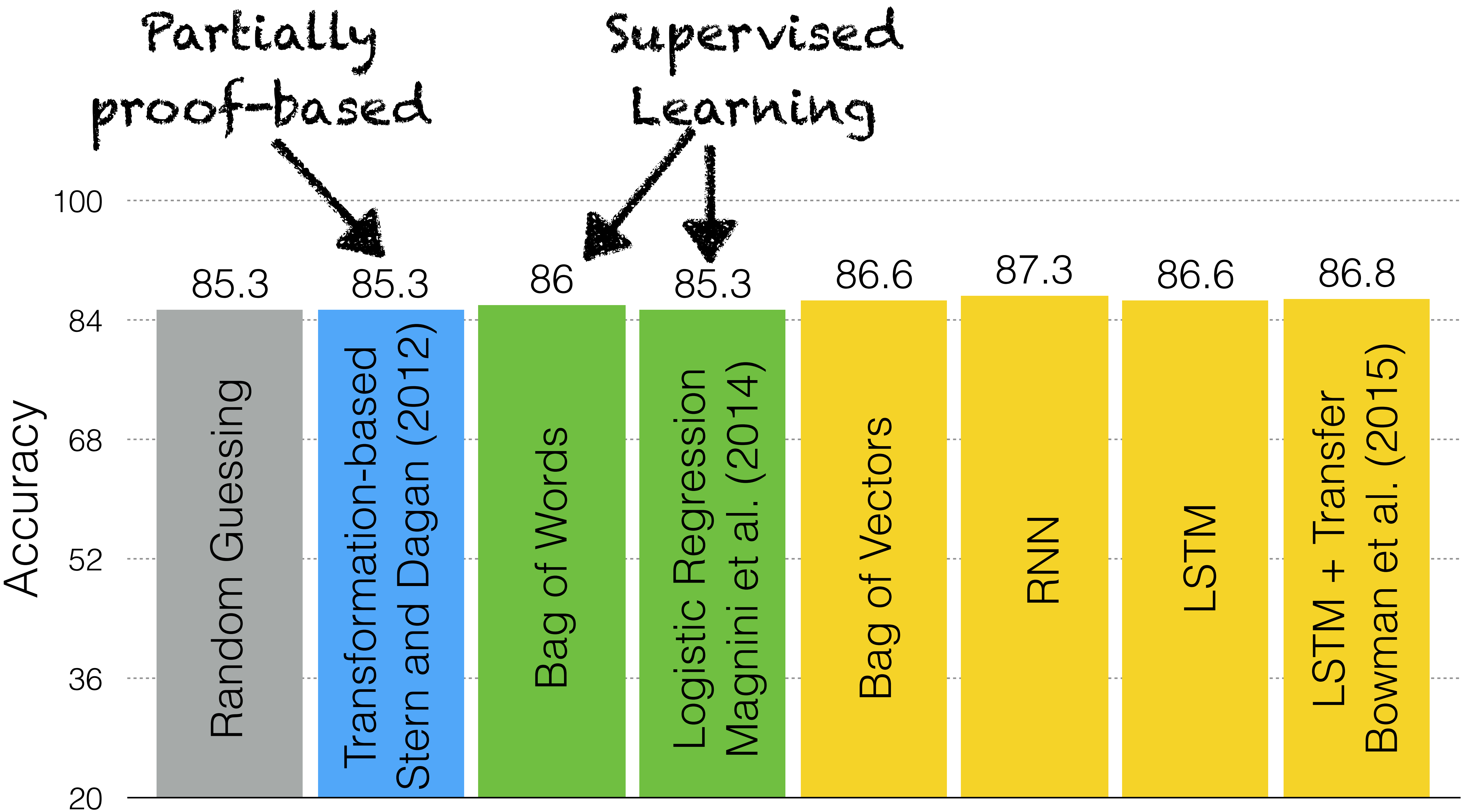


Modern Inference Systems

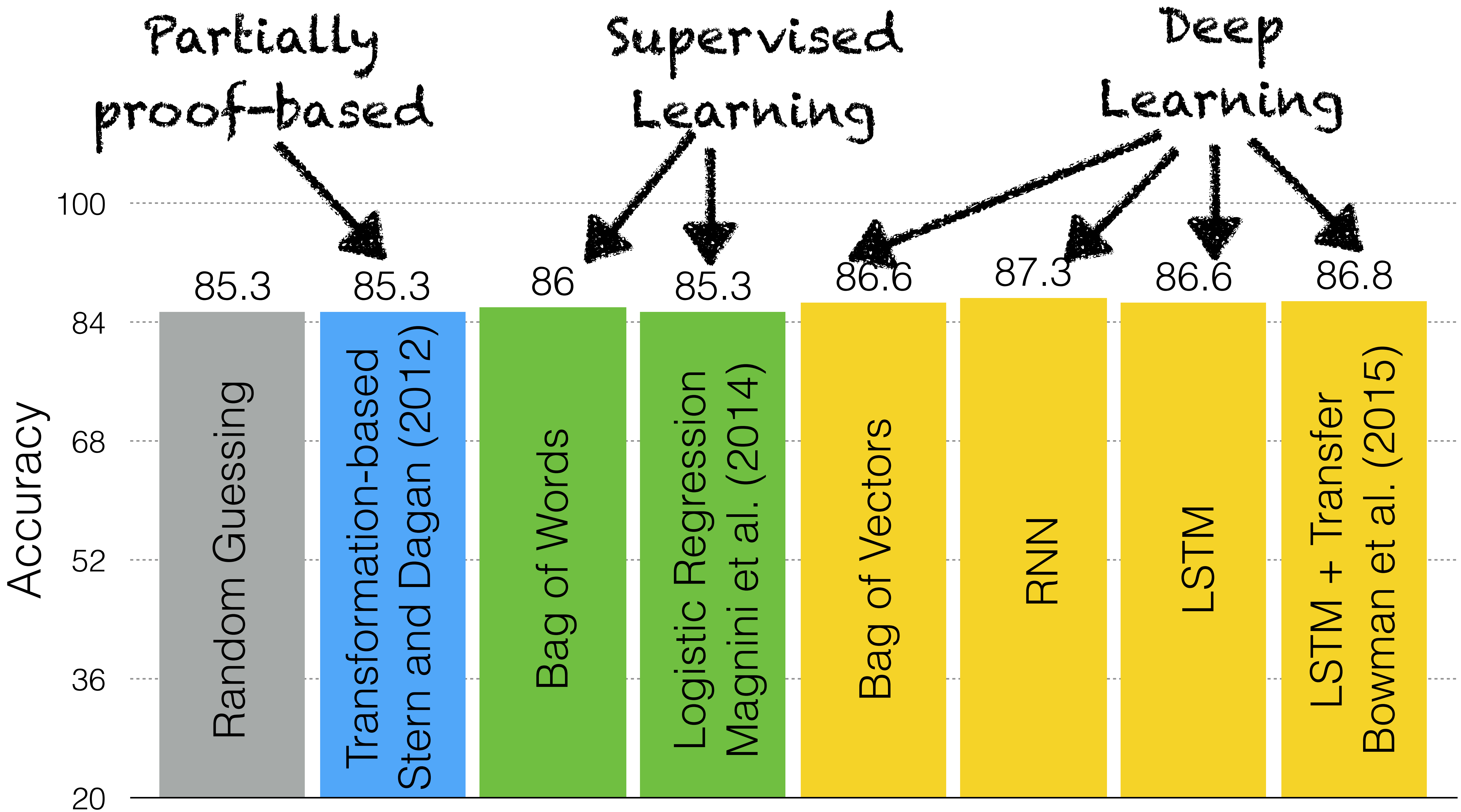
Partially
proof-based



Modern Inference Systems

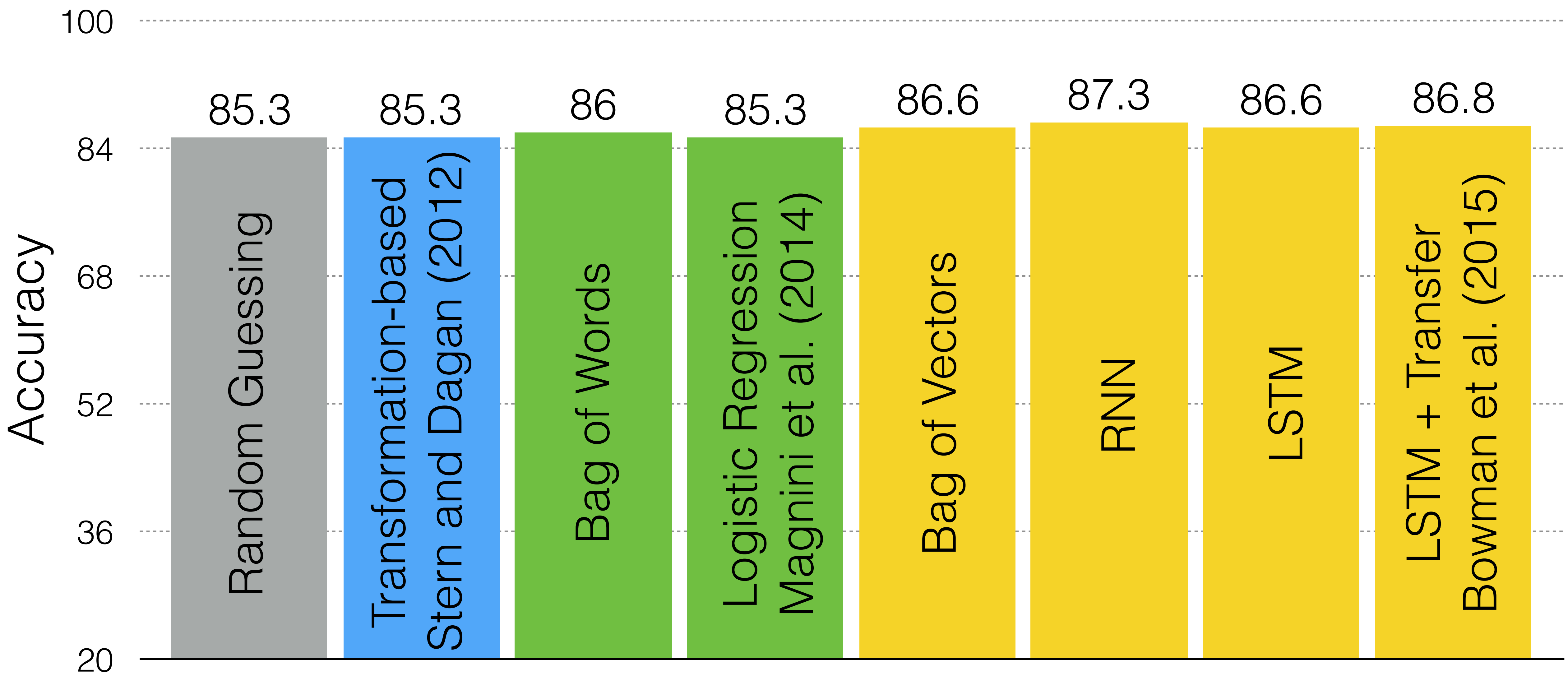


Modern Inference Systems



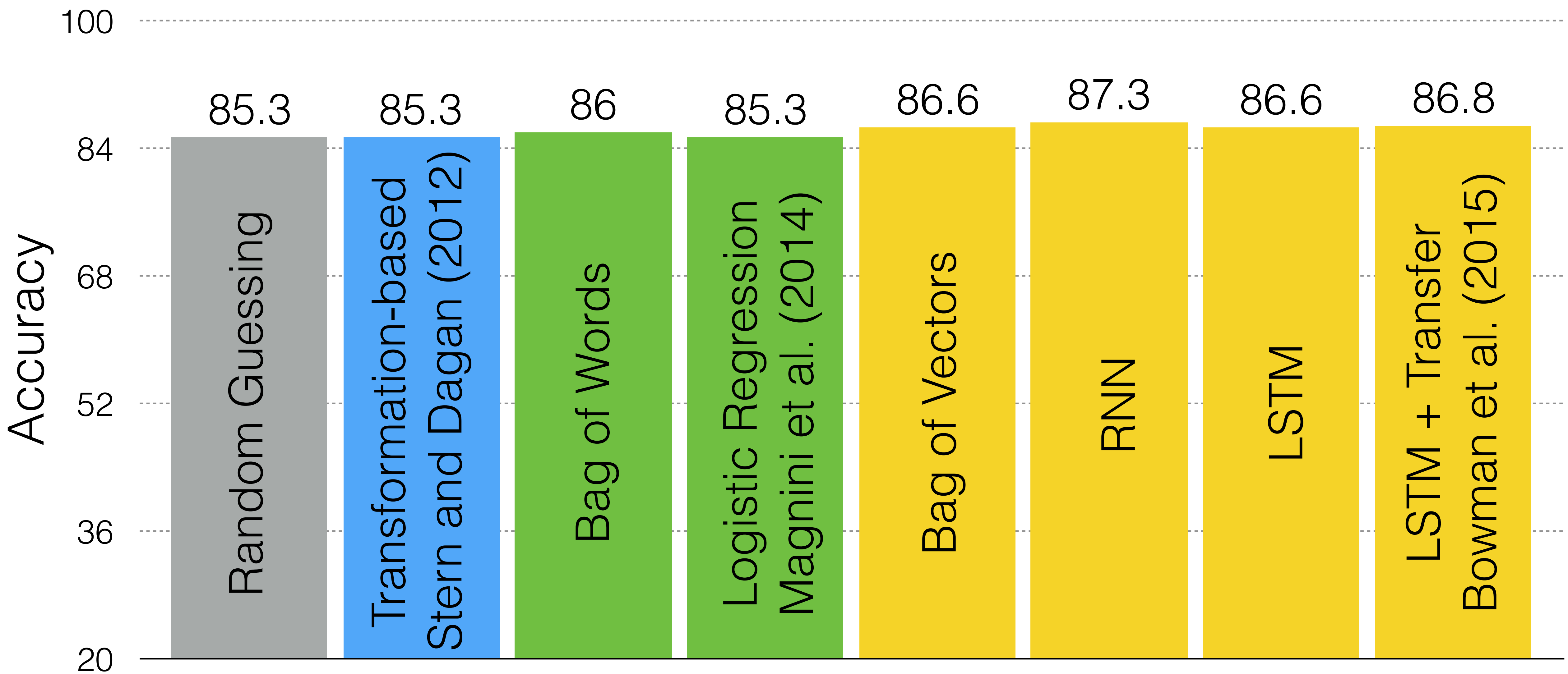
Modern Inference Systems

Correct representation is difficult to capture explicitly



Modern Inference Systems

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



Discussion

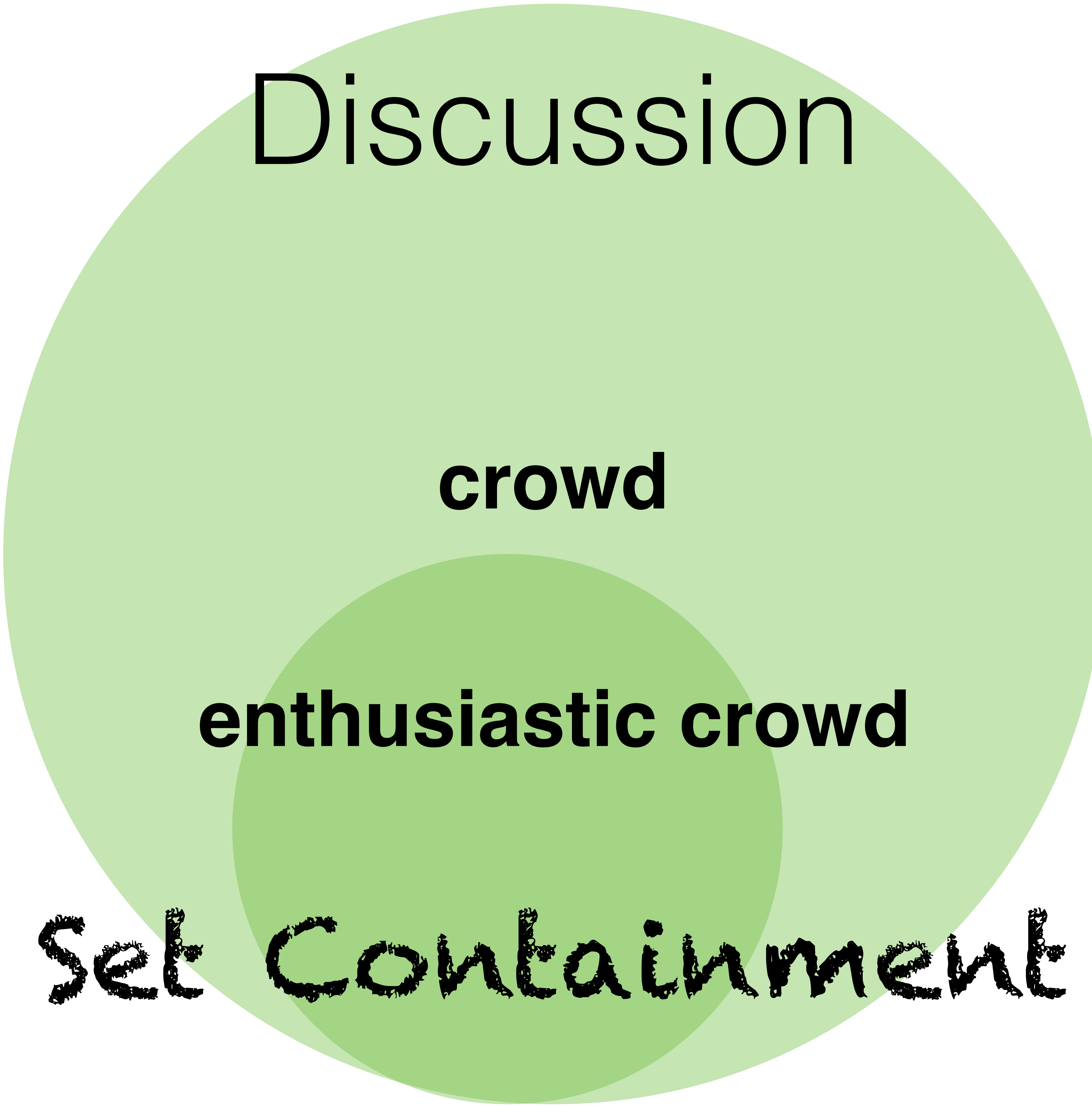
Discussion

The **crowd** roared.

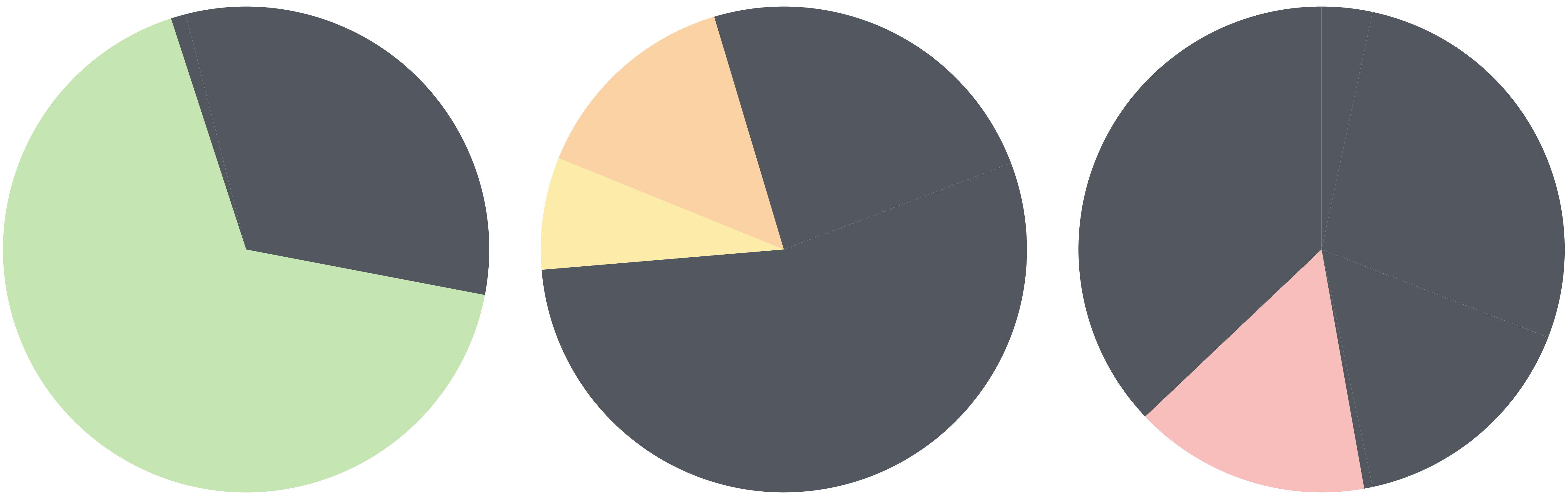
Discussion

The **crowd** roared.

enthusiastic crowd


Discussion
crowd
enthusiastic crowd
Set Containment

Discussion



Set Containment

Discussion

The **crowd** roared.

Discussion

The ___ **crowd** roared.

↓

P(enthusiastic)
P(silent)
P(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

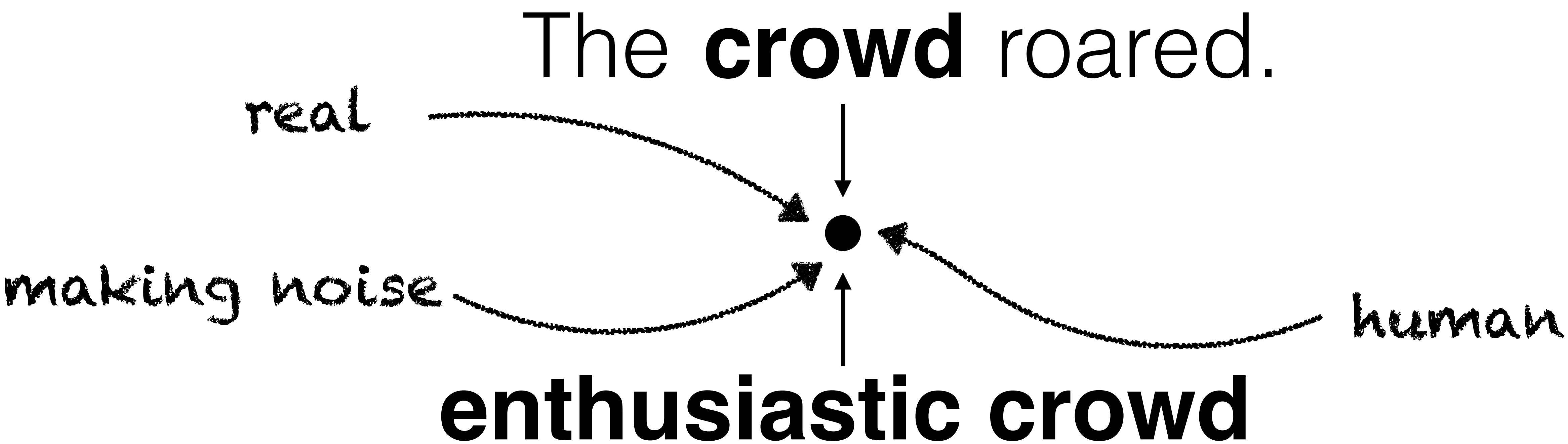
The **crowd** roared.

real

human

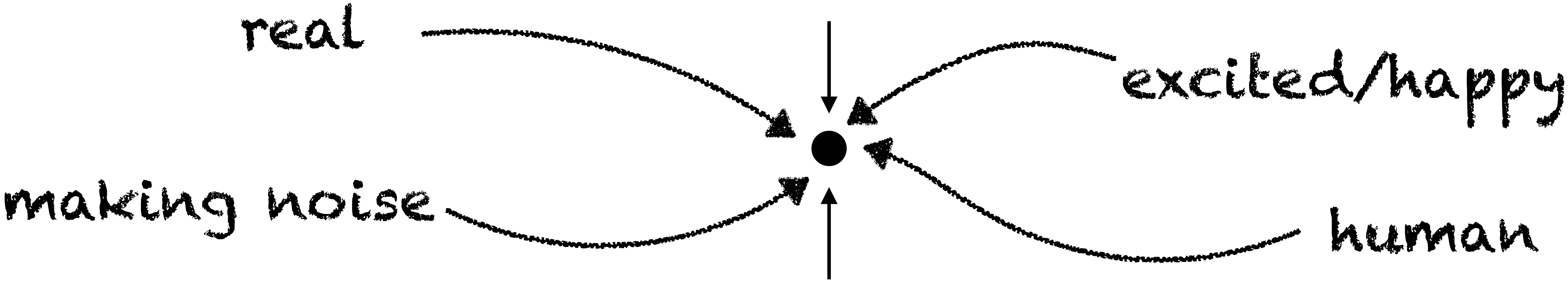
enthusiastic crowd

Discussion


The **crowd** roared.
real
making noise
human
enthusiastic crowd

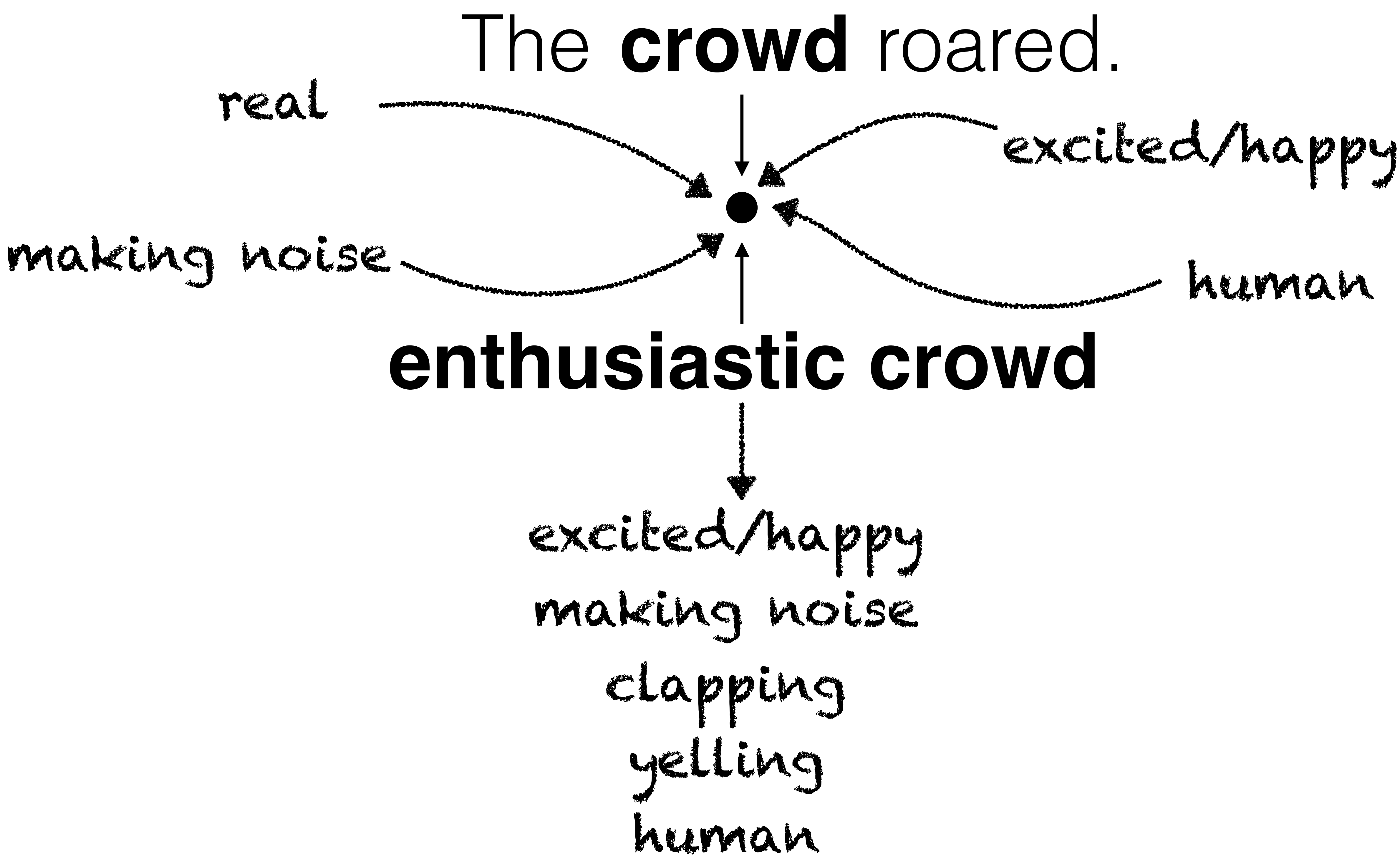
Discussion

The **crowd** roared.



enthusiastic crowd

Discussion


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

Discussion

The **crowd** roared.

real

excited/happy

making noise

human

enthusiastic crowd

excited/happy

making noise

clapping

yelling

human

Discussion

Assigning **intrinsic meaning** to modifiers…

e **crowd** roared.

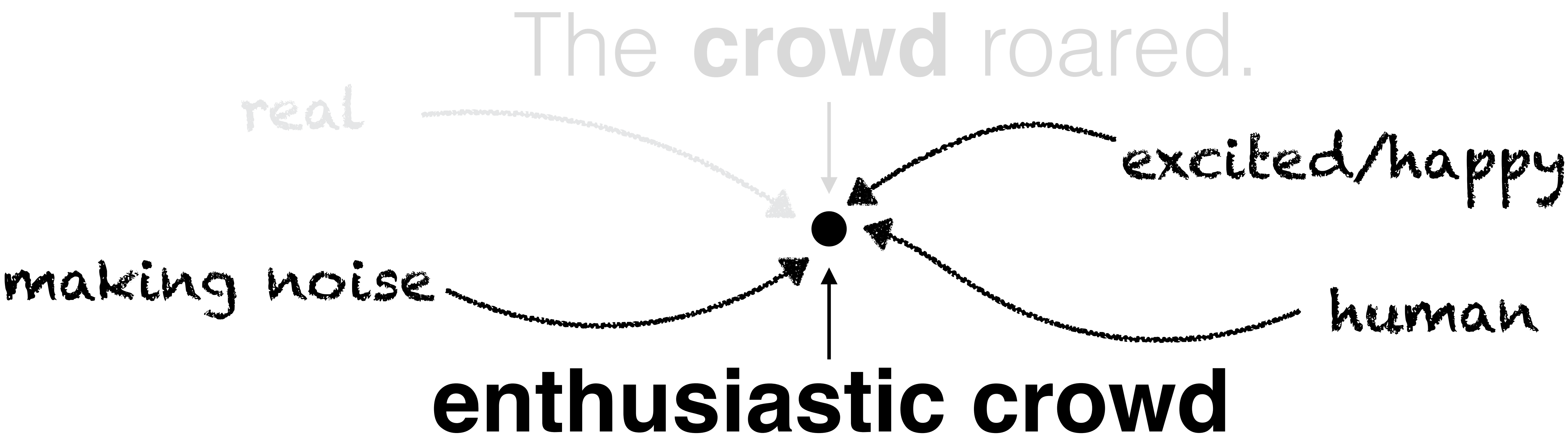
excited/happy

human

enthusiastic crowd

excited/happy
making noise
clapping
yelling
human

Discussion



Determining whether they hold for individual entities

Introduction

Lexical Entailment

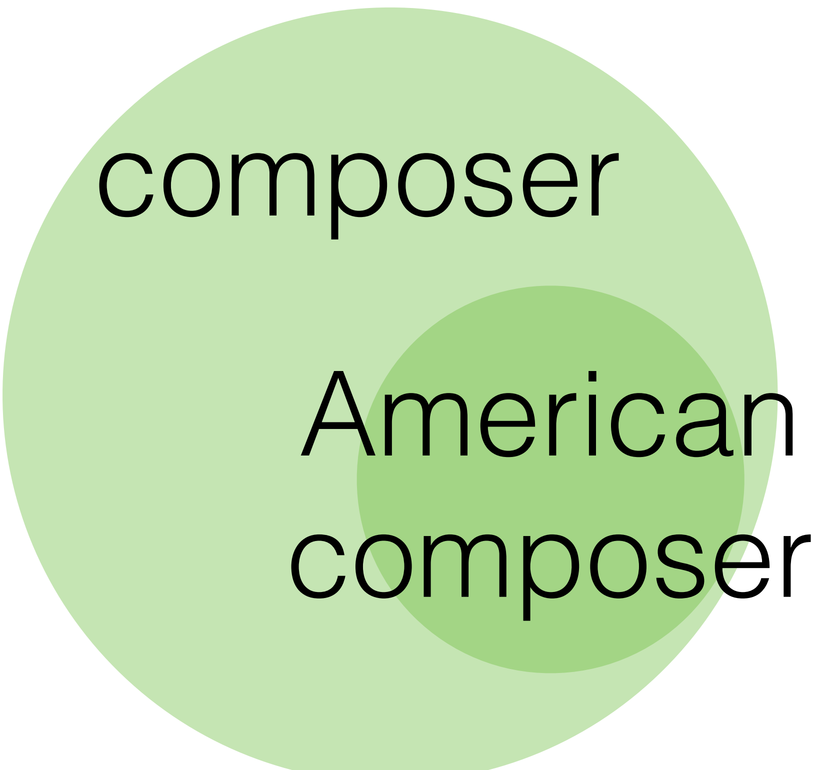
Adding Semantics to Data-Driven Paraphrasing.
Pavlick et al. ACL (2015)

Modifier-Noun Composition

Semantic Containment

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

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



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Summary and Future Work

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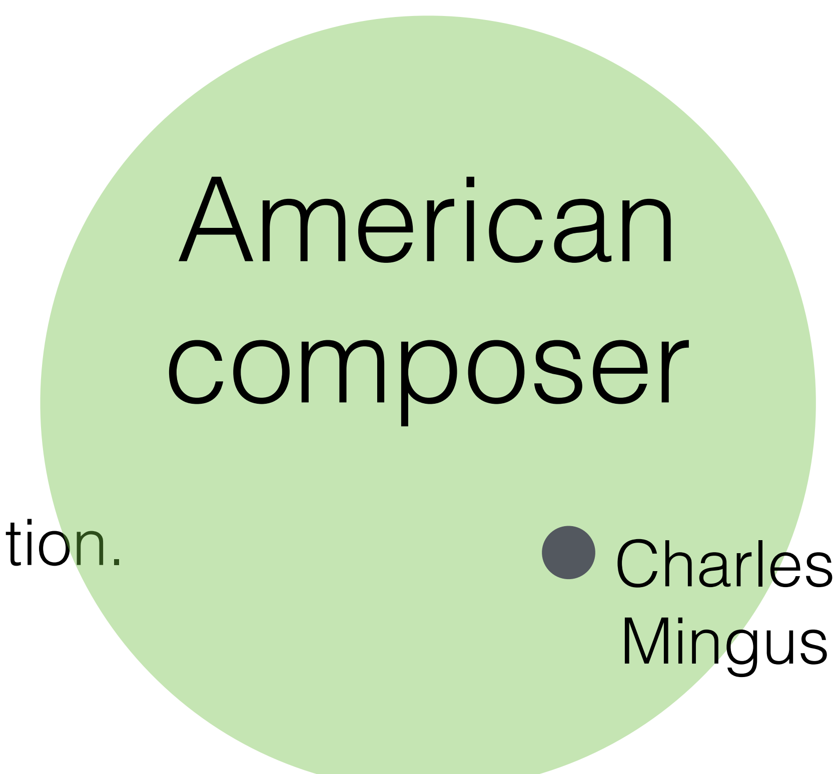
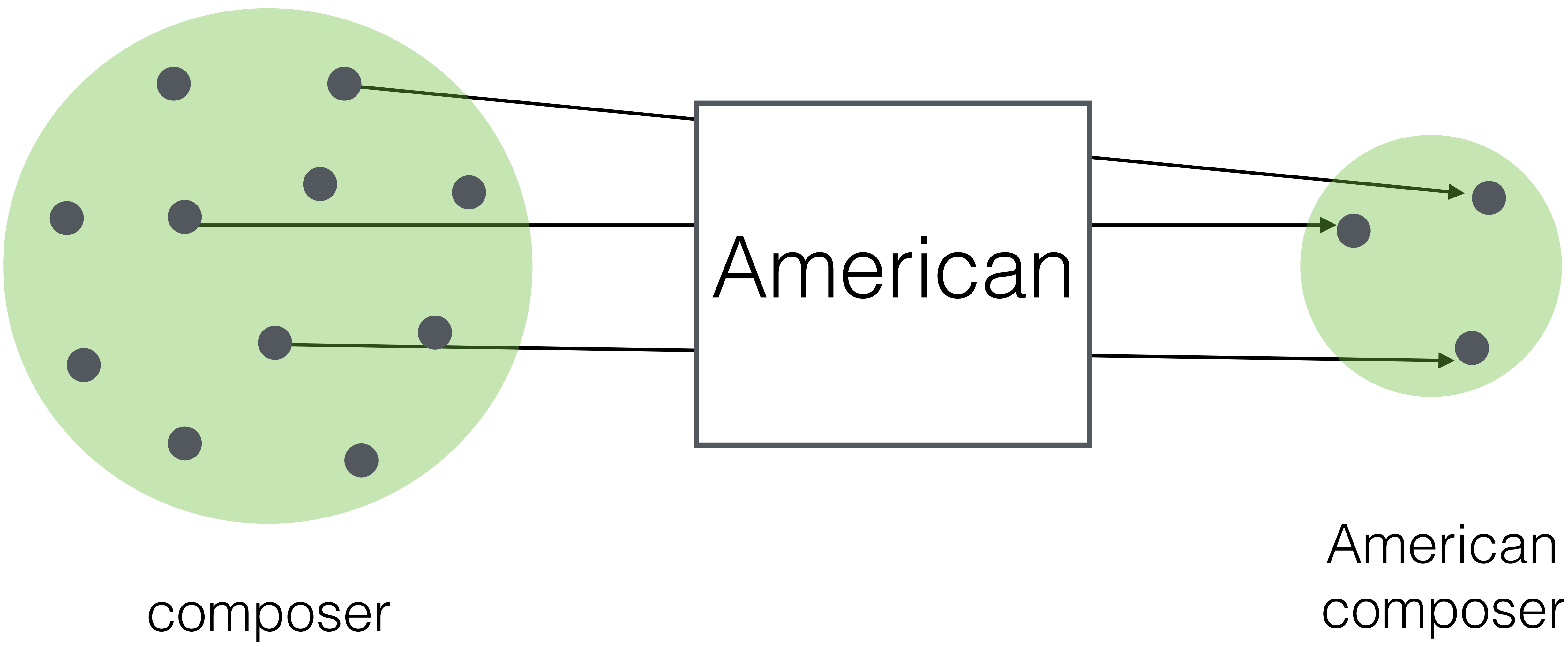
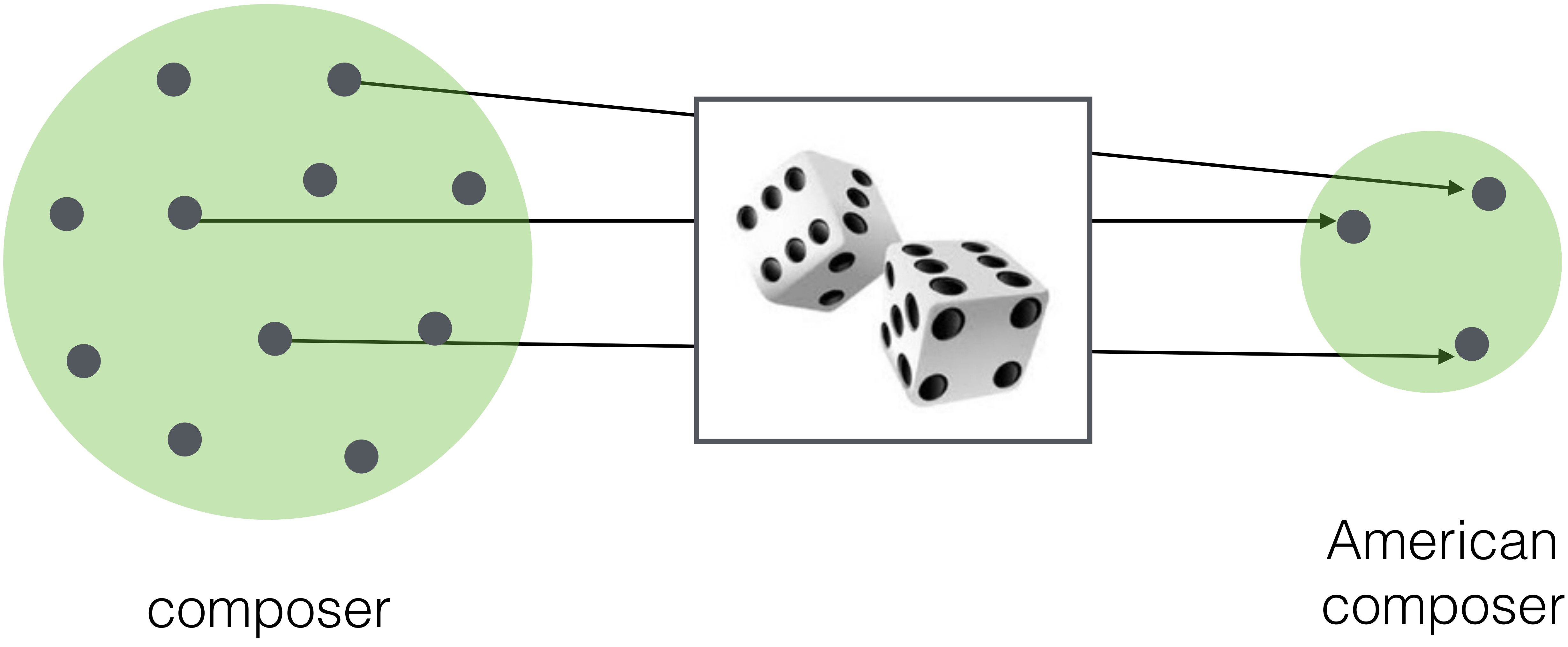


Summary and Future Work

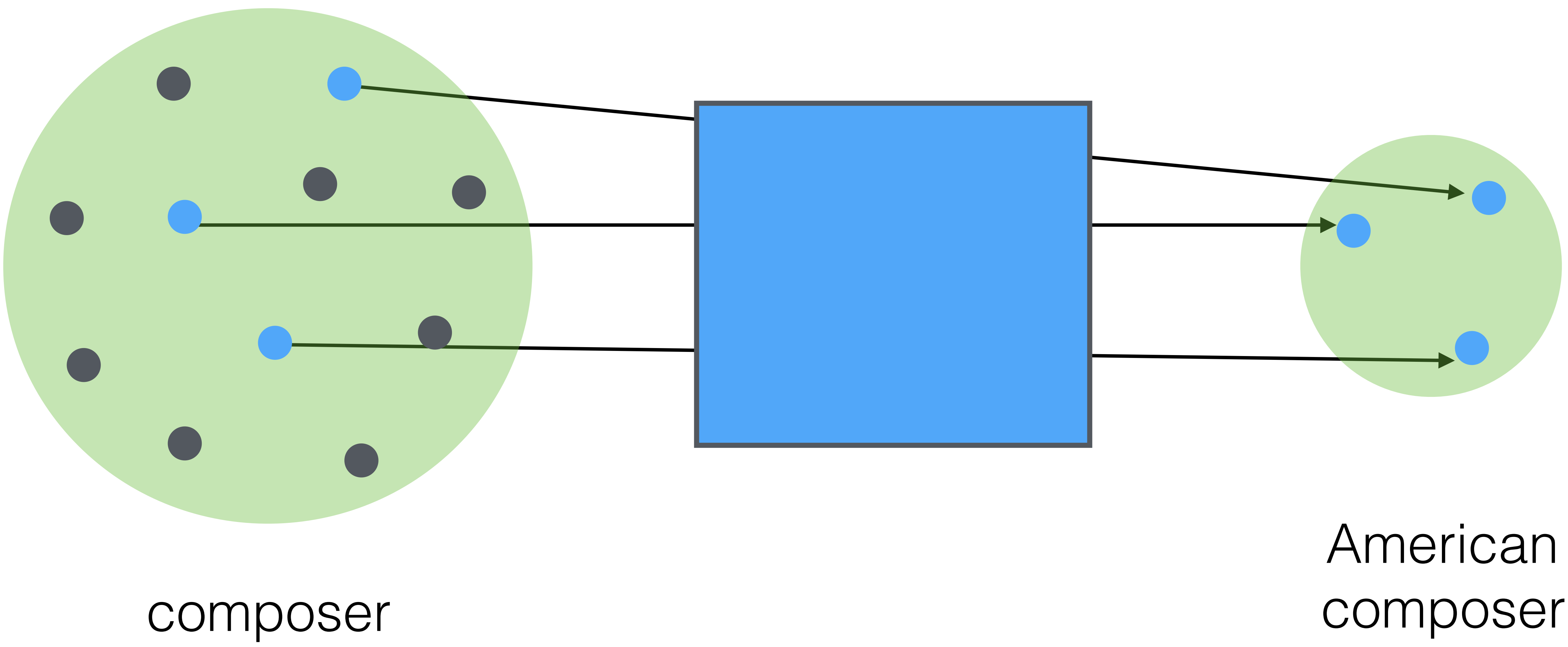
Compositional Semantics



Compositional Semantics

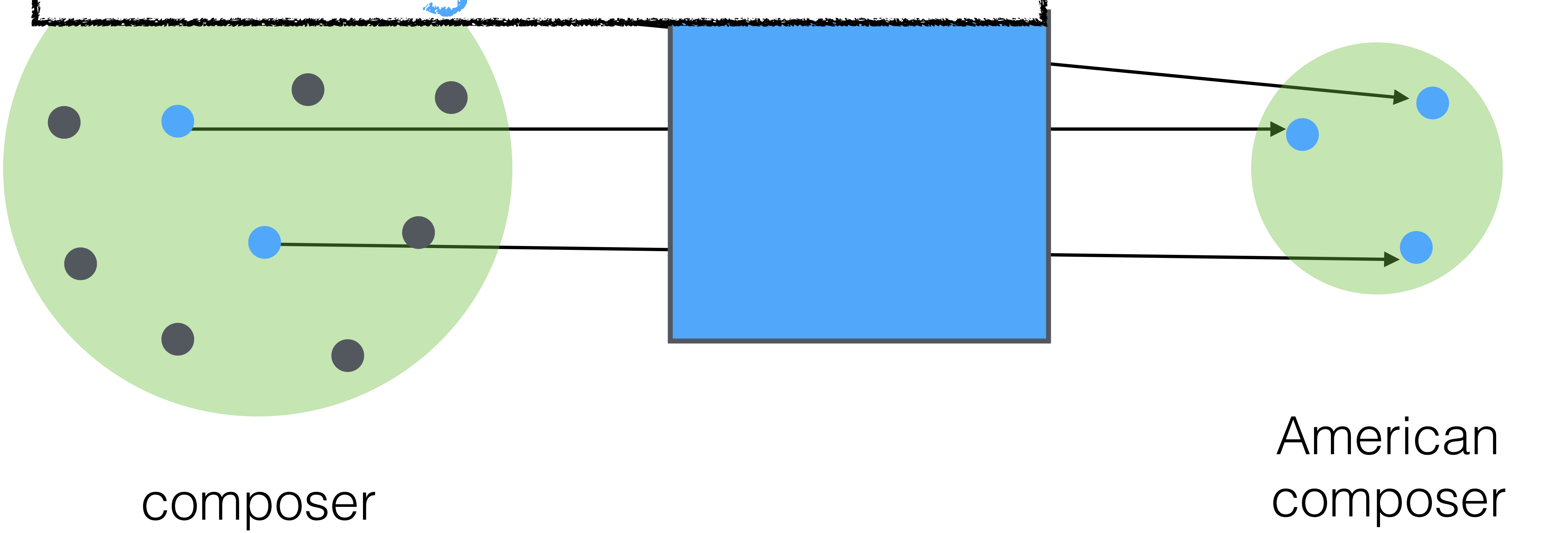


Compositional Semantics



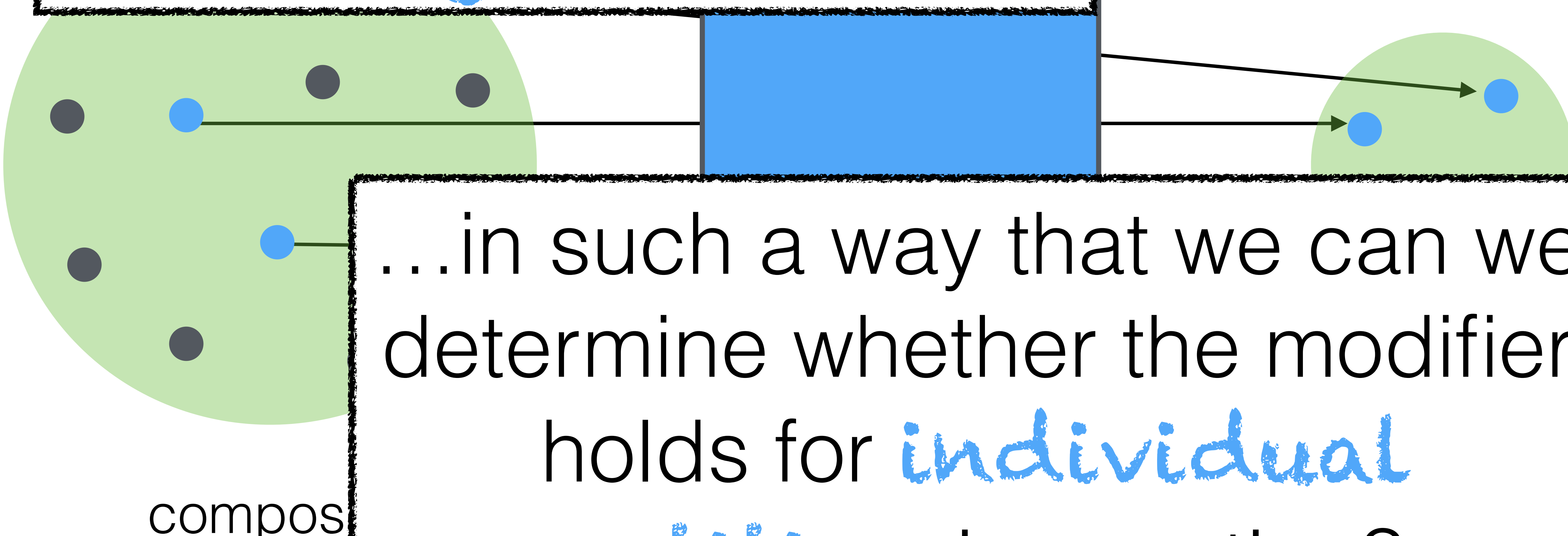
Compositional Semantics

Can we assign intrinsic meaning to modifiers…



Compositional Semantics

Can we assign intrinsic meaning to modifiers…



…in such a way that we can we 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**

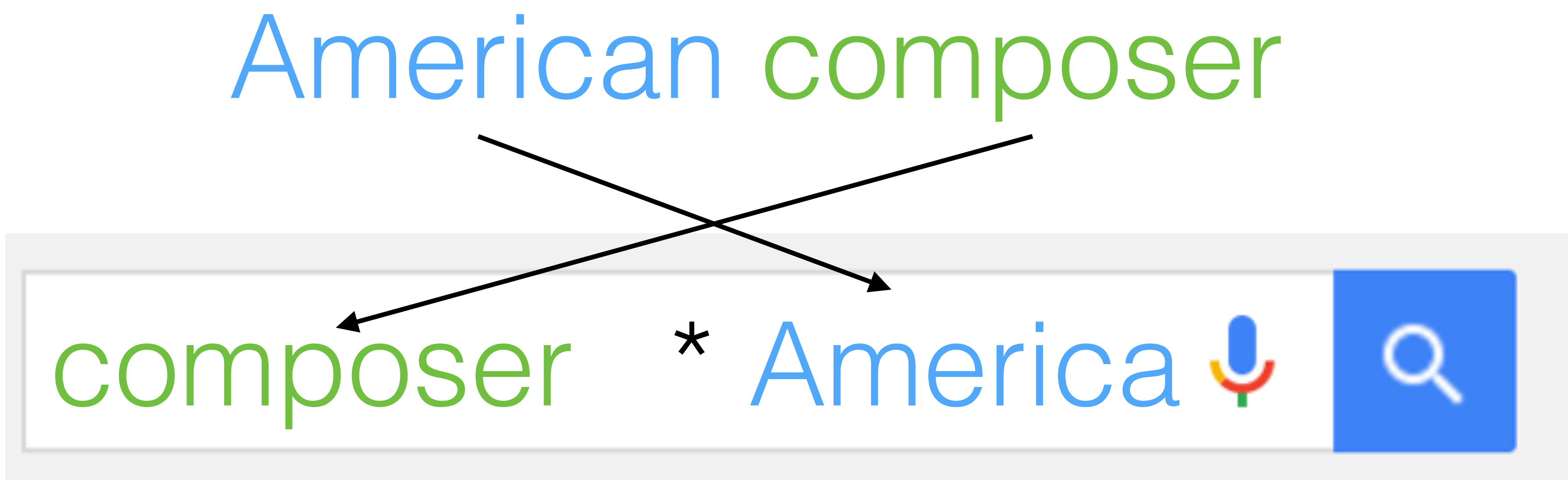
born in America
influential in America
prolific while in America
a product of America
lived in America
~~visited America~~
~~popular in America~~

…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



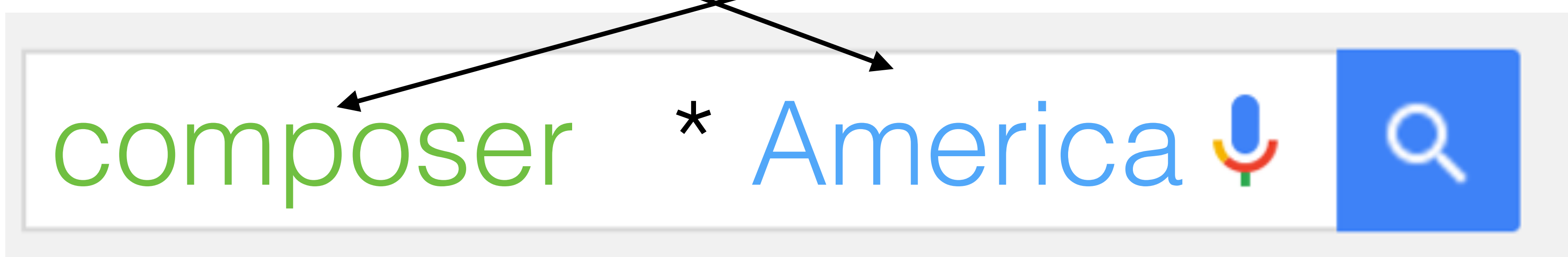
Modifier Interpretation

American composer

composer from America
composer born in America
composer popular in America
composer active in America

Modifier Interpretation

American composer



⟨composer from America, 3702⟩

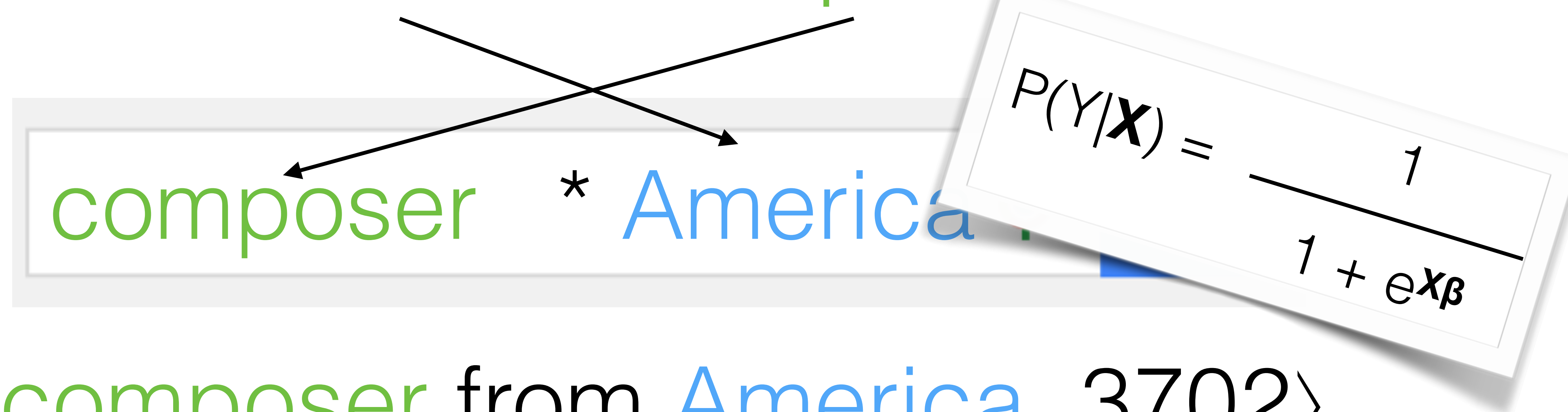
⟨composer born in America, 1389⟩

⟨composer popular in America, 1292⟩

⟨composer active in America, 2041⟩

Modifier Interpretation

American composer



⟨composer from America, 3702⟩

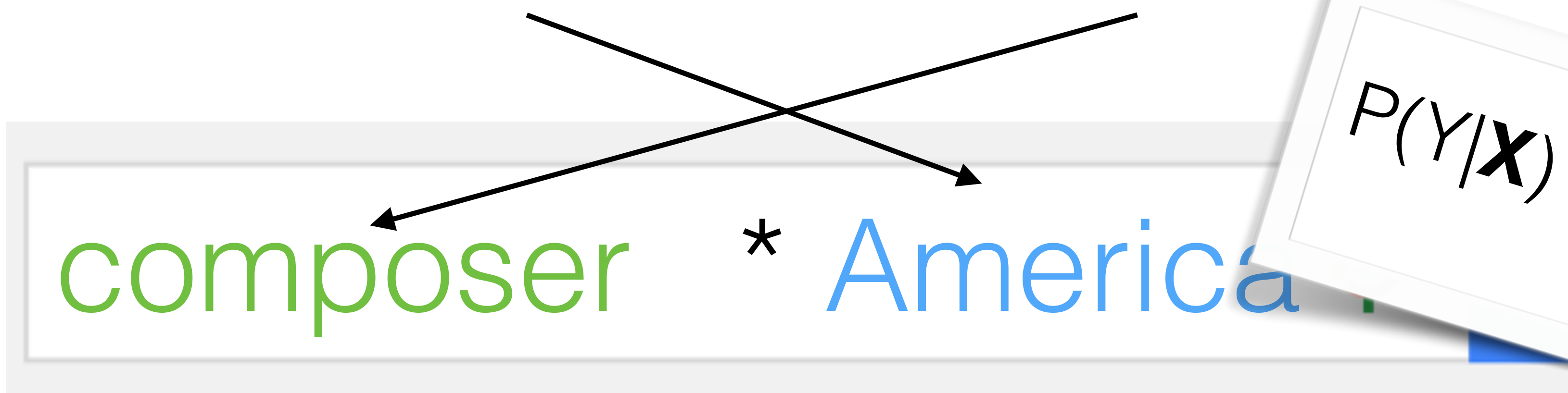
⟨composer born in America, 1389⟩

⟨composer popular in America, 1292⟩

⟨composer active in America, 2041⟩

Modifier Interpretation

American composer



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

⟨composer from America, 0.93⟩

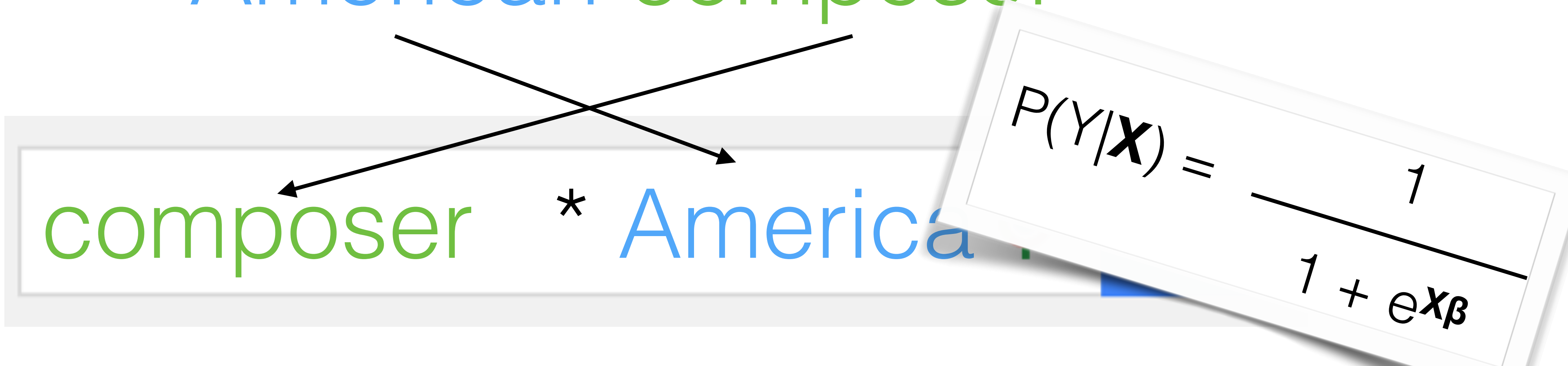
⟨composer born in America, 0.94⟩

⟨composer popular in America, 0.45⟩

⟨composer active in America, 0.52⟩

Modifier Interpretation

American composer



⟨composer born in America, 0.94⟩

⟨composer from America, 0.93⟩

⟨composer active in America, 0.52⟩

⟨composer popular in America, 0.45⟩

Modifier Interpretation

American composer $\longrightarrow$ born in America

American company $\longrightarrow$ based in America

American novel $\longrightarrow$ written in America

Produces good results...

Modifier Interpretation

child actor ⟶ has child

risk manager ⟶ takes risks

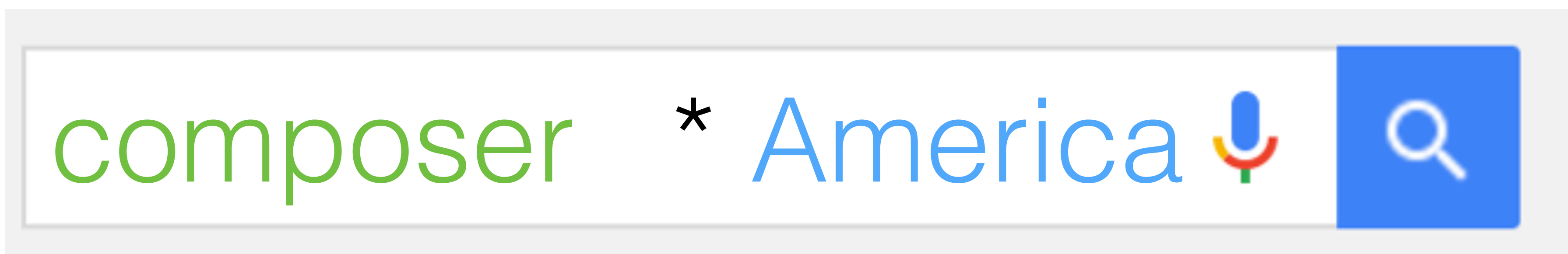
machine gun ⟶ used by machine

...but not perfect.

Class-Instance Identification

Class-Instance Identification

American composer

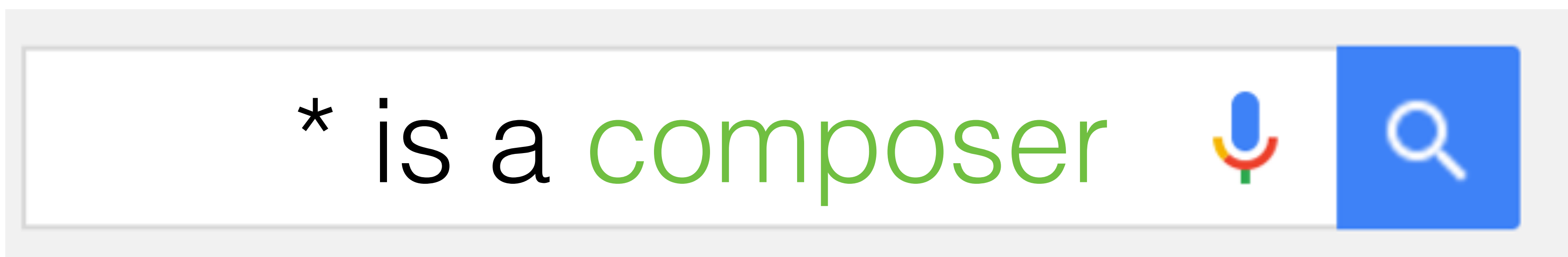


⟨___ born in America, 0.94⟩
⟨___ from America, 0.93⟩
⟨___ active in America, 0.52⟩
⟨___ popular in America, 0.45⟩

Weighted modifier
interpretations

Class-Instance Identification

American composer



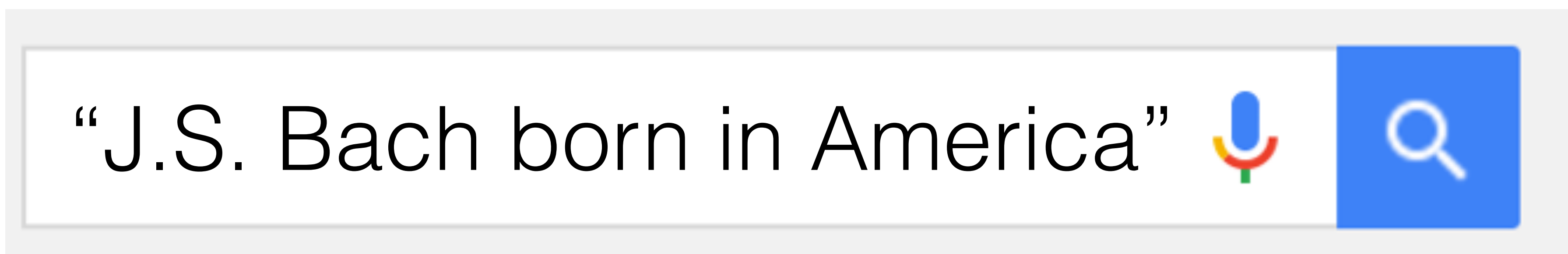
⟨___ born in America, 0.94⟩
⟨___ from America, 0.93⟩
⟨___ active in America, 0.52⟩
⟨___ popular in America, 0.45⟩

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

Candidate instances

Class-Instance Identification

American composer



⟨___ 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

Class-Instance Identification

American composer

"J.S. Bach from 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

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

	American composer	jazz composer
JS Bach	0.21	0.04
Charles Mingus	0.89	0.93
John Cage	0.96	0.52
WA Mozart	0.19	0.13
Libby Larsen	0.72	0.24
Duke Ellington	0.76	0.97
Palestrina	0.04	0.03
Ludwig van Beethoven	0.09	0.12
Morton Feldman	0.88	0.31
Frederick Chopin	0.33	0.32
Barack Obama	0.14	0.35
Herbie Hancock	0.62	0.95

Class-Instance Identification

	American jazz composer
JS Bach	0.25
Charles Mingus	1.82
John Cage	1.48
WA Mozart	0.32
Libby Larsen	0.96
Duke Ellington	1.73
Palestrina	0.07
Ludwig van Beethoven	0.21
Morton Feldman	1.19
Frederick Chopin	0.65
Barack Obama	0.49
Herbie Hancock	1.57

Class-Instance Identification

	American jazz composer
Charles Mingus	1.82
Duke Ellington	1.73
Herbie Hancock	1.57
John Cage	1.48
Morton Feldman	1.19
Libby Larsen	0.96
Frederick Chopin	0.65
Barack Obama	0.49
WA Mozart	0.32
JS Bach	0.25
Ludwig van Beethoven	0.21
Palestrina	0.07

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.

Wikimedia
media relat
temples in

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

C

- Chithurst Buddhist Monastery
- Chithurst Forest Monastery

H

- Hádegismóar Temple

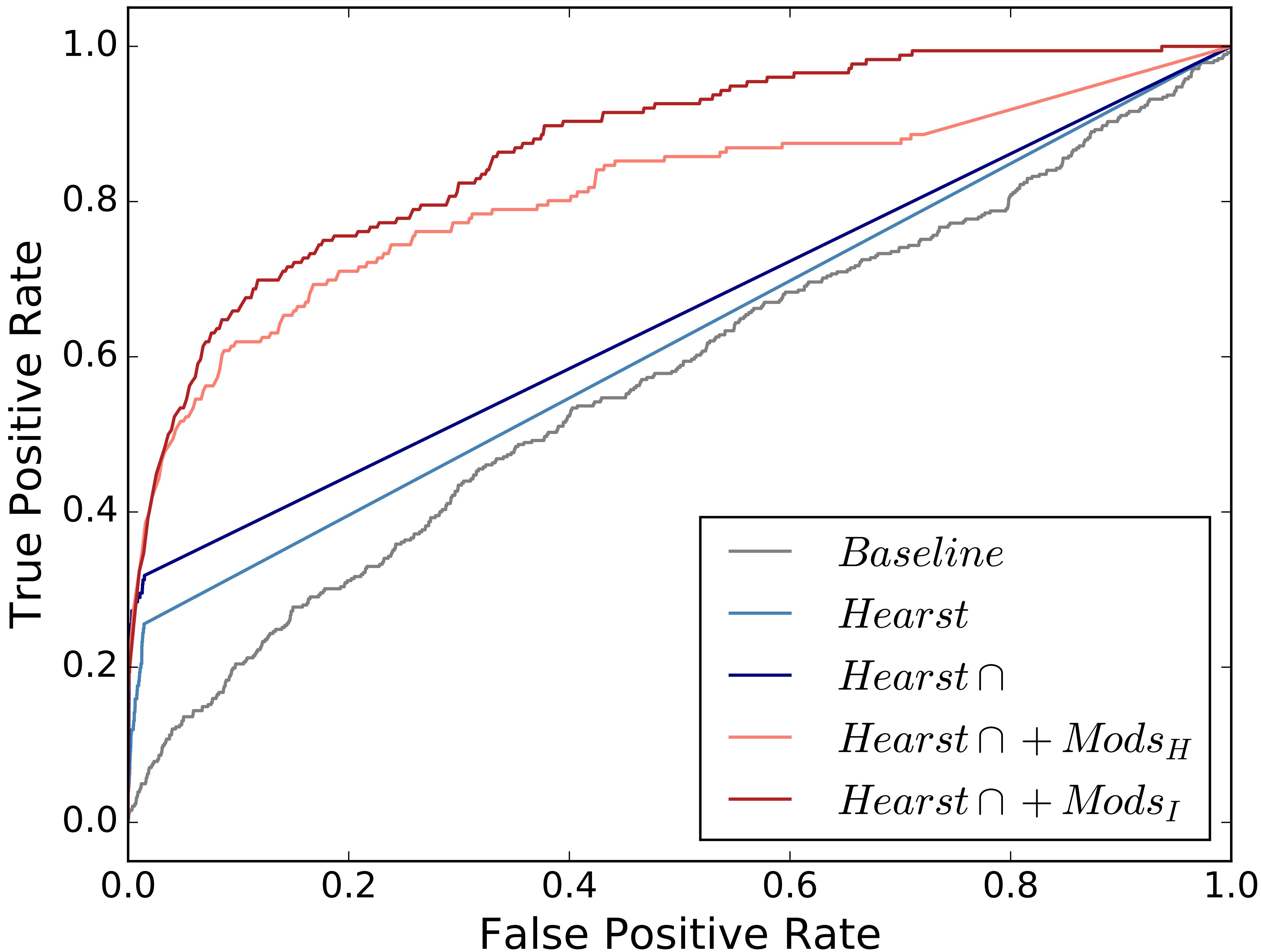
S

- Sunnataram Forest Monastery

W

- Wat Boston Buddha Vararam
- Wat Buddhananachat of Austin
- Wat Buddhanusorn
- Wat Buddhapadipa
- Wat Charoenbhavana
- Wat Chetawan
- Wat Mongkolratanaram
- Wat Nawamintararachutis
- Wat Pasantidhamma
- Wat Srinagarindravararam

Reconstructing Wikipedia



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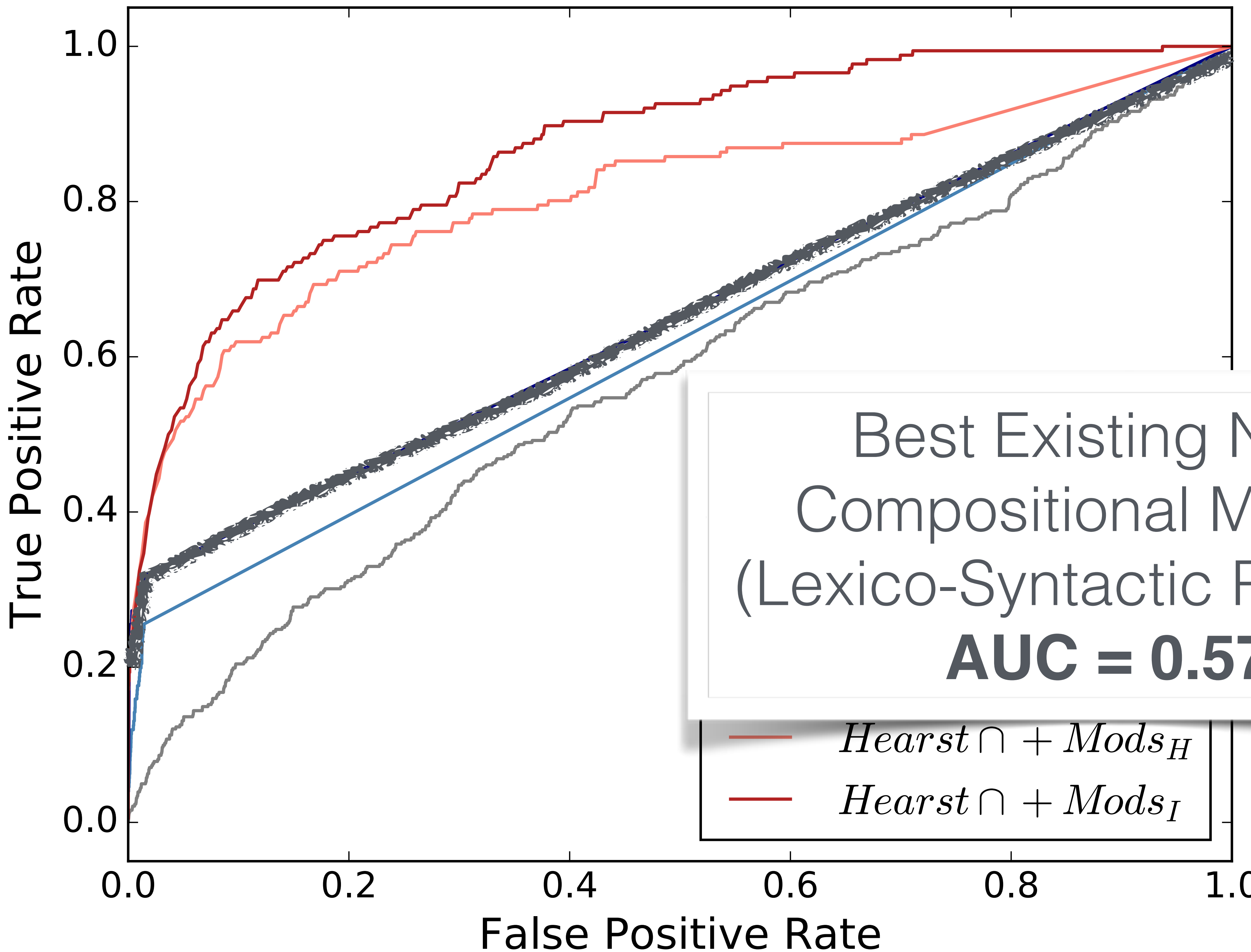
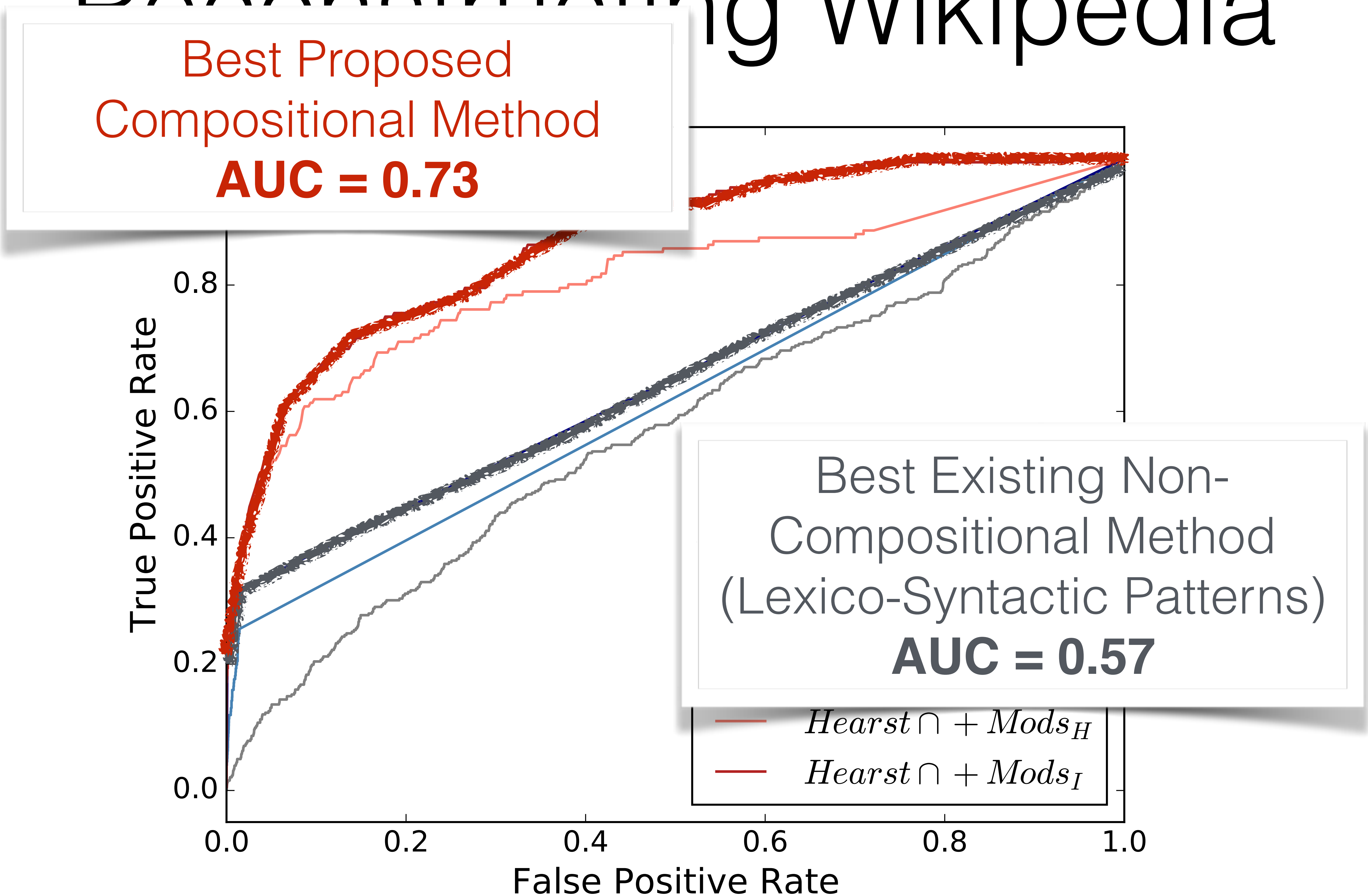


Best Existing Non-Compositional Method (Lexico-Syntactic Patterns)

AUC = 0.57

Reconstructing Wikipedia



Introduction

Lexical Entailment

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

Modifier-Noun Composition

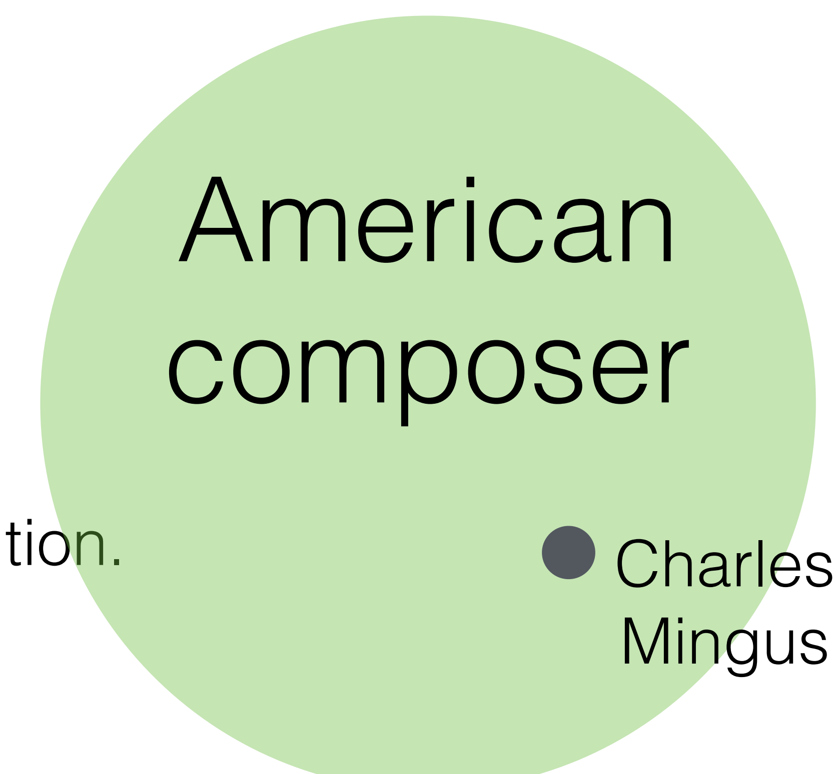
Semantic Containment

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

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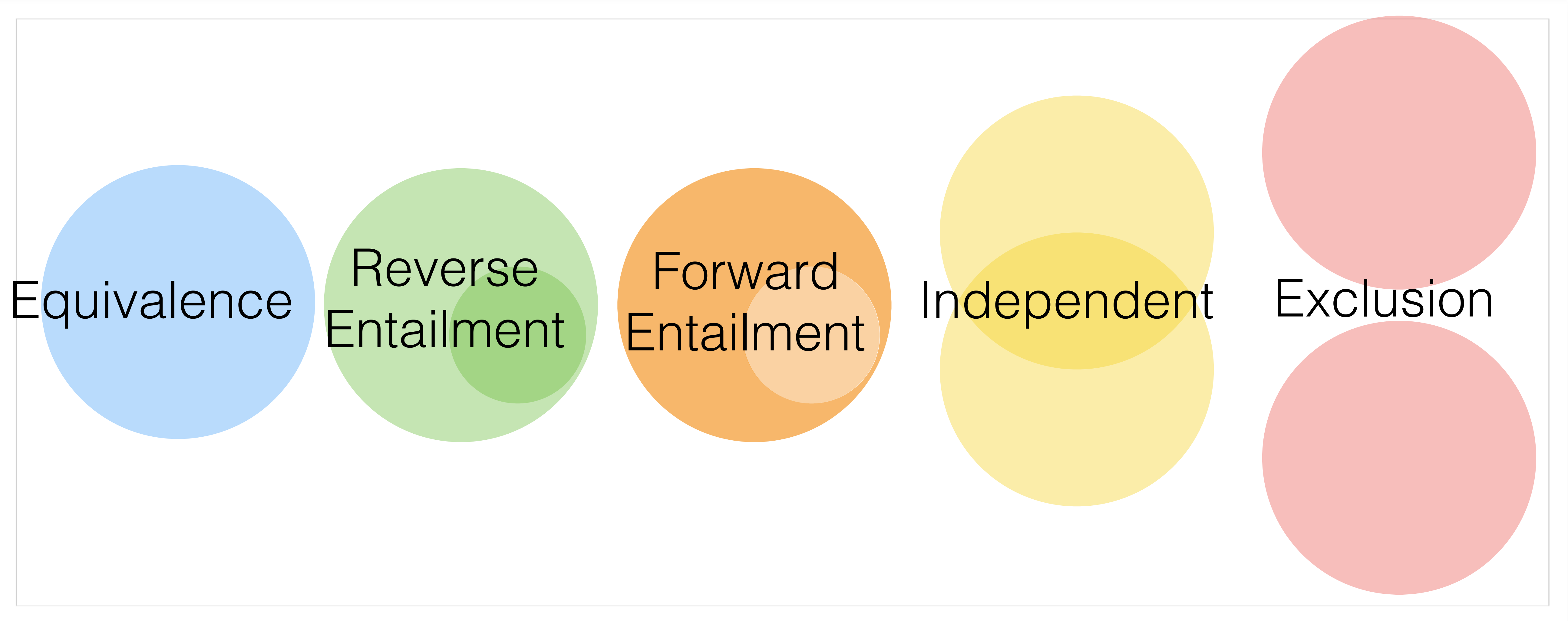

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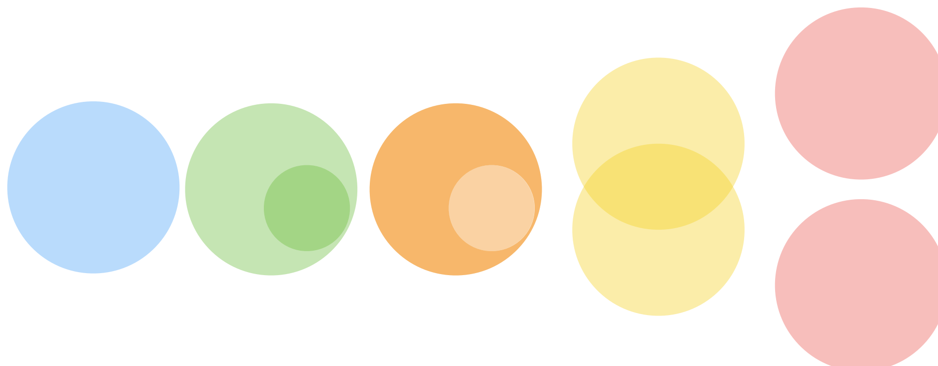
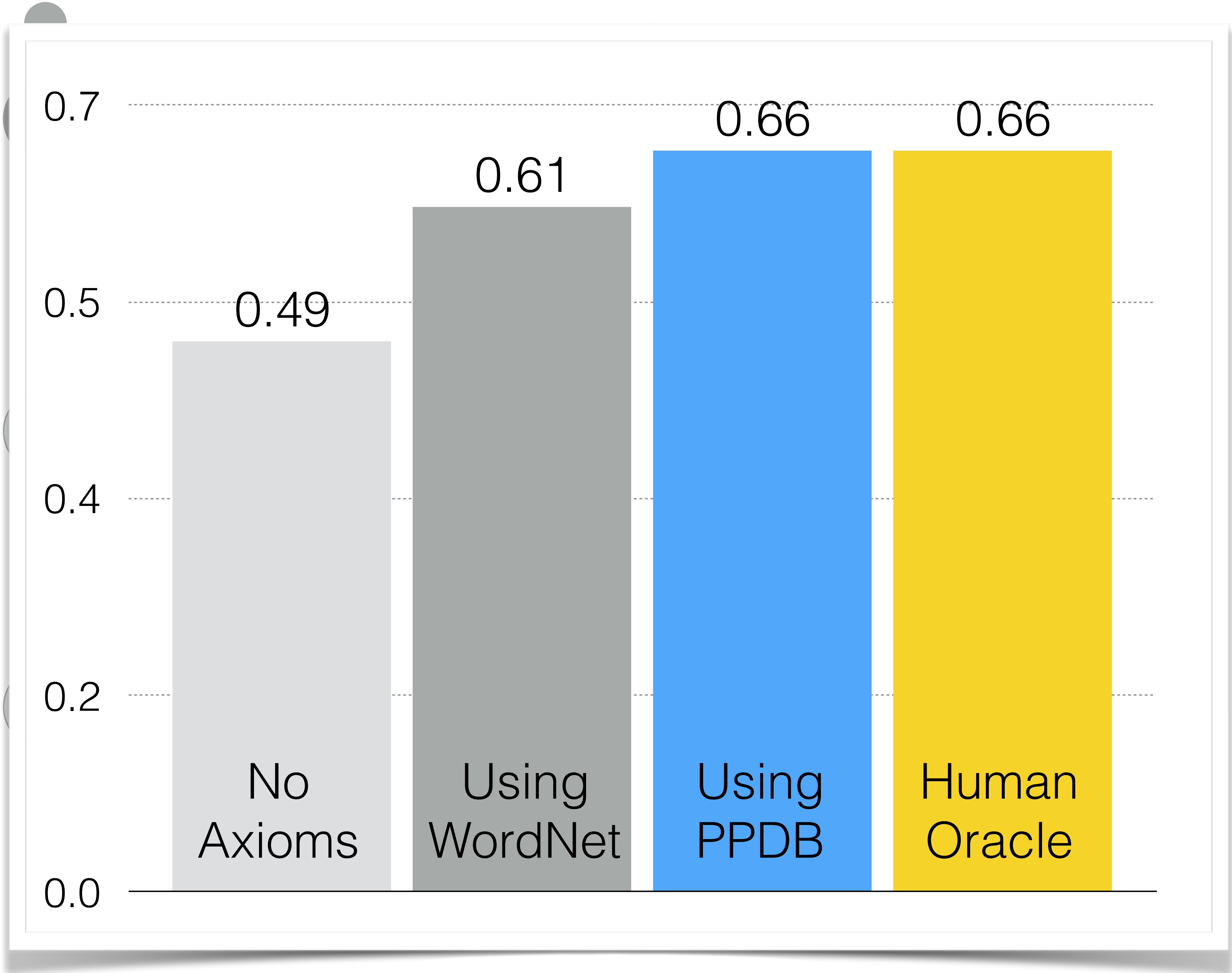
Lexical Entailment

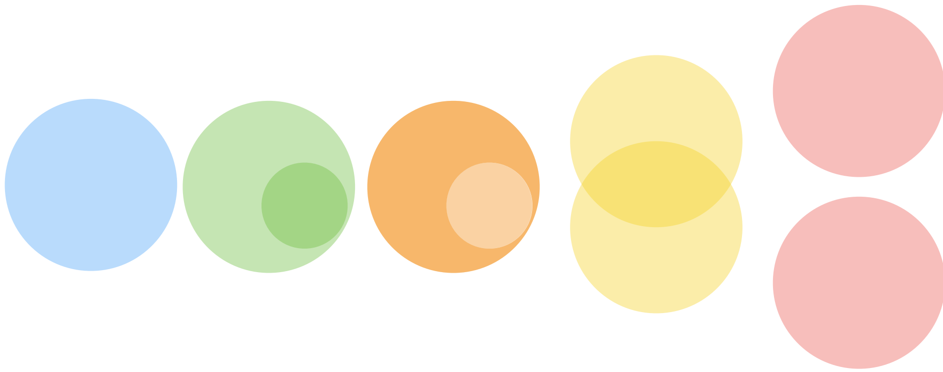


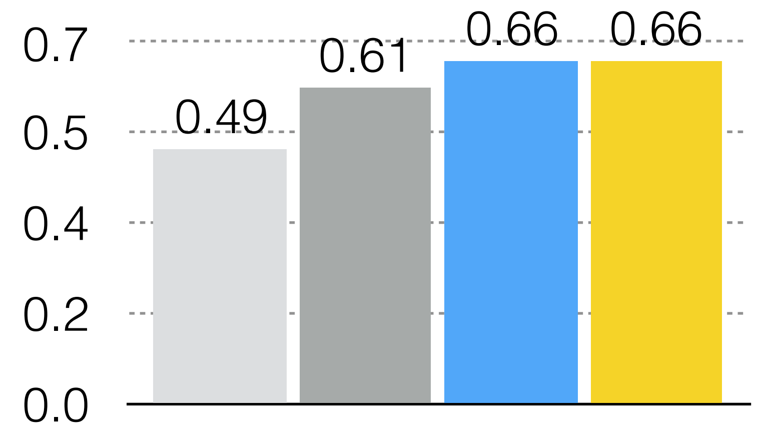
Semantic Containment

Class-Instance Identification


0.7
0.5
0.4
0.2
0.0
0.49
0.61
0.66
0.66
No Axioms
Using WordNet
Using PPDB
Human Oracle

Lexical Entailment

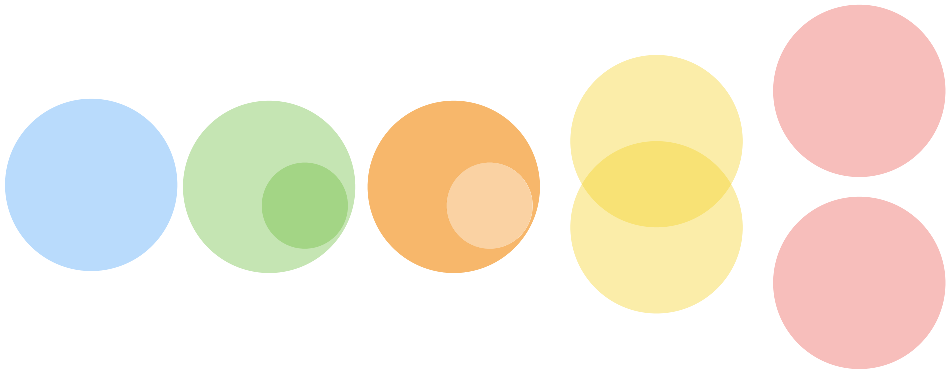


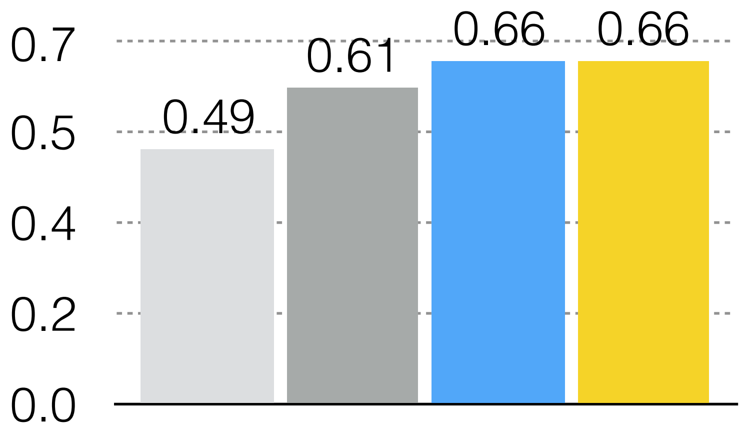


Semantic Containment

Class-Instance Identification

Lexical Entailment





Semantic Containment

Class-Instance Identification

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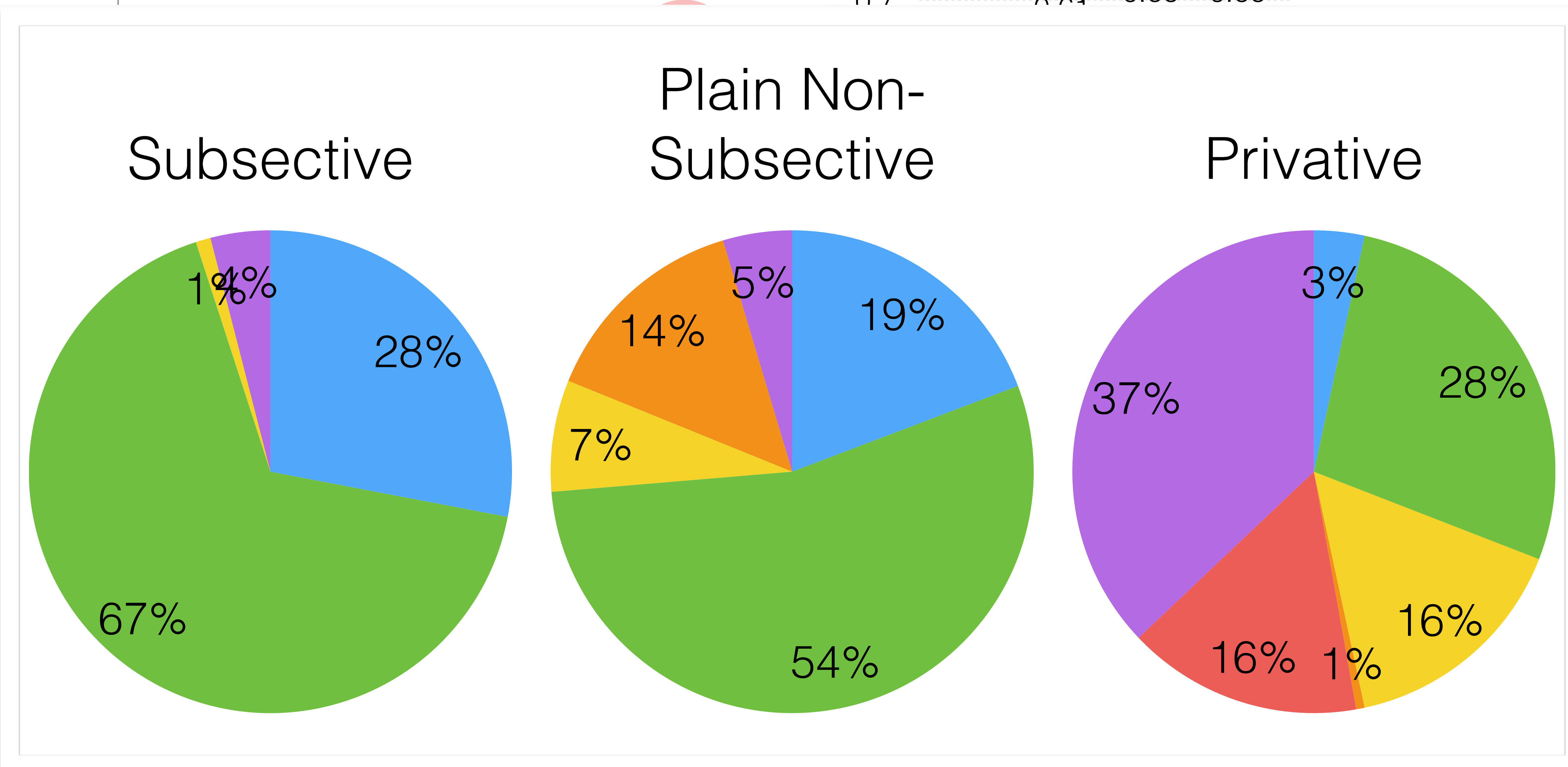
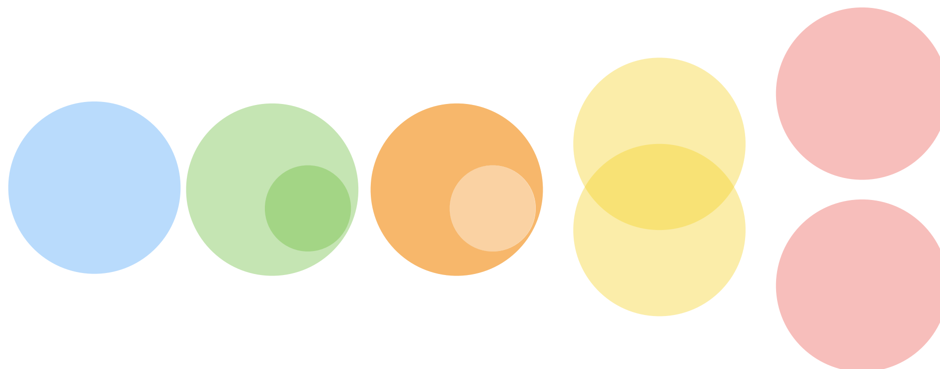
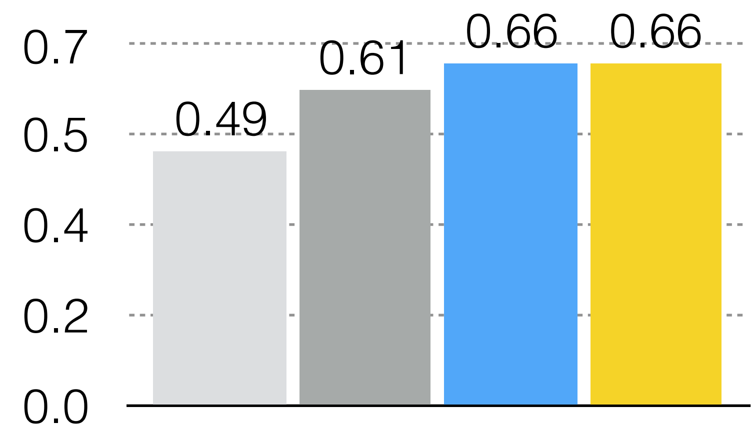
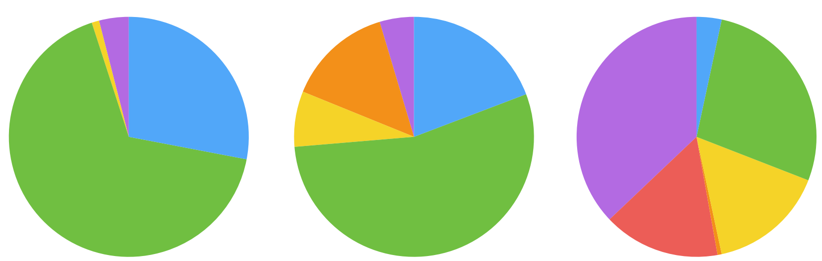


Lexical Entailment





Semantic Containment



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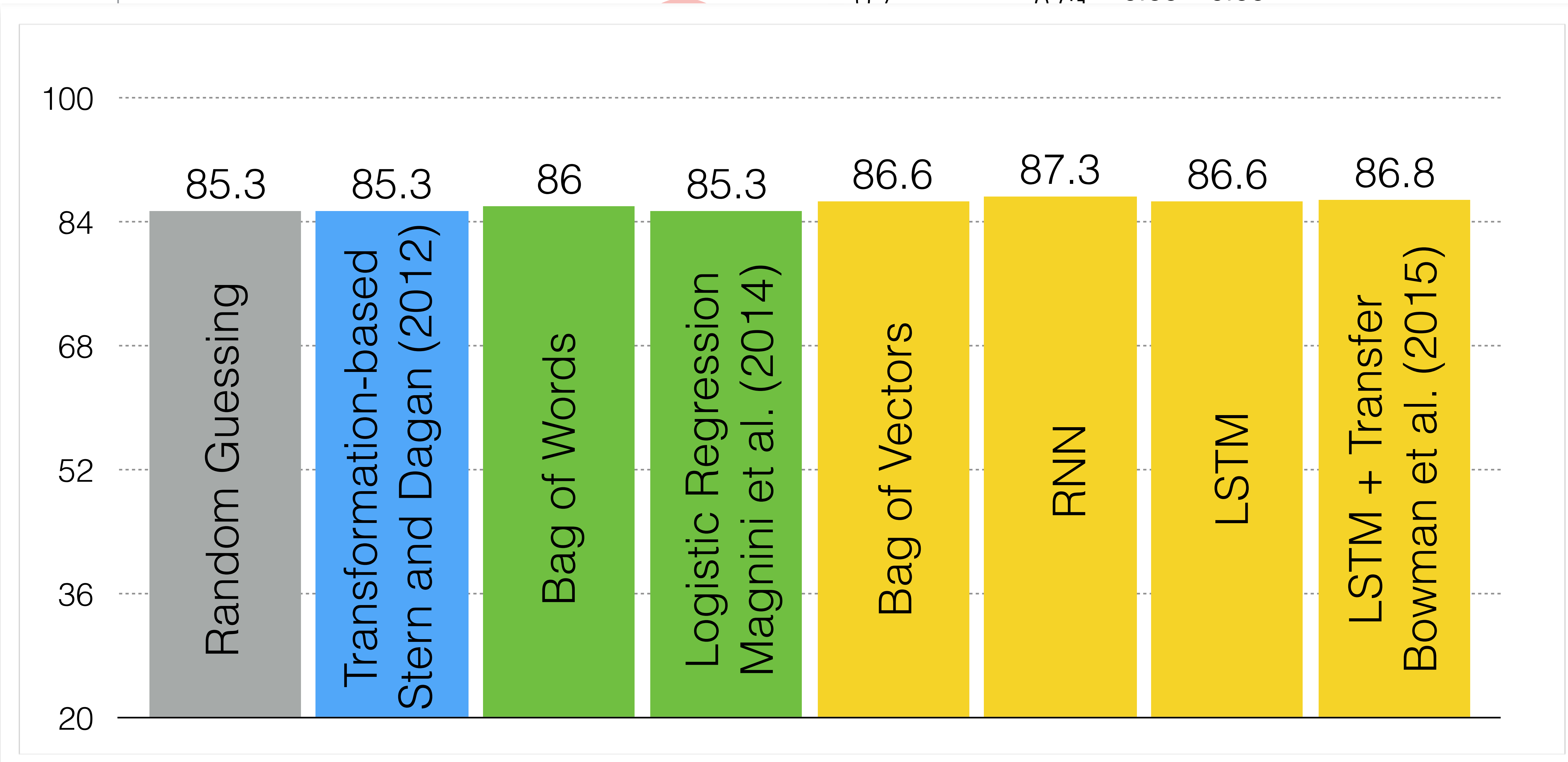

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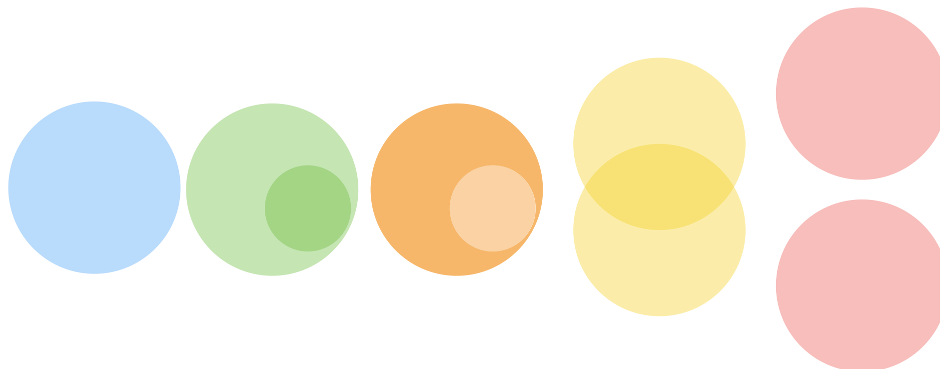

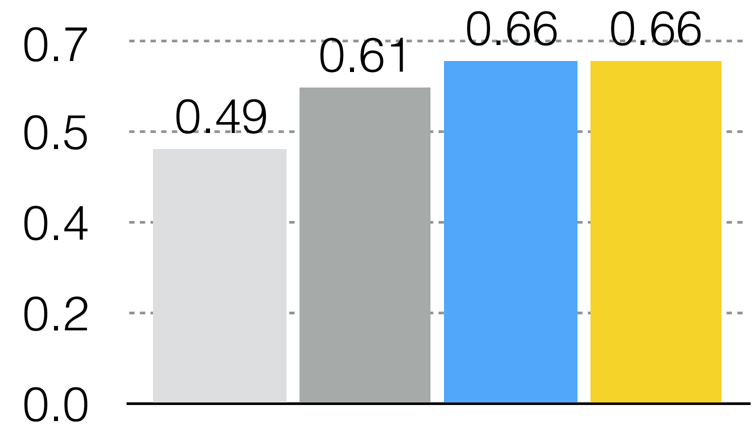

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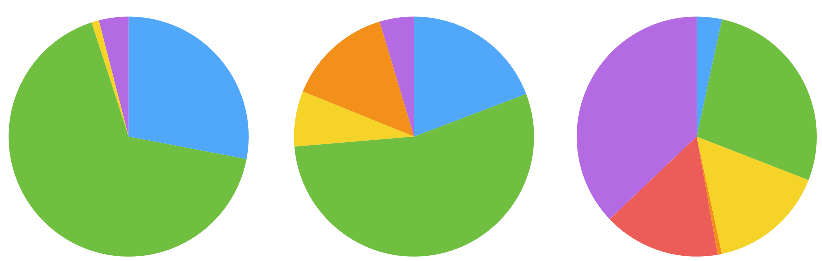

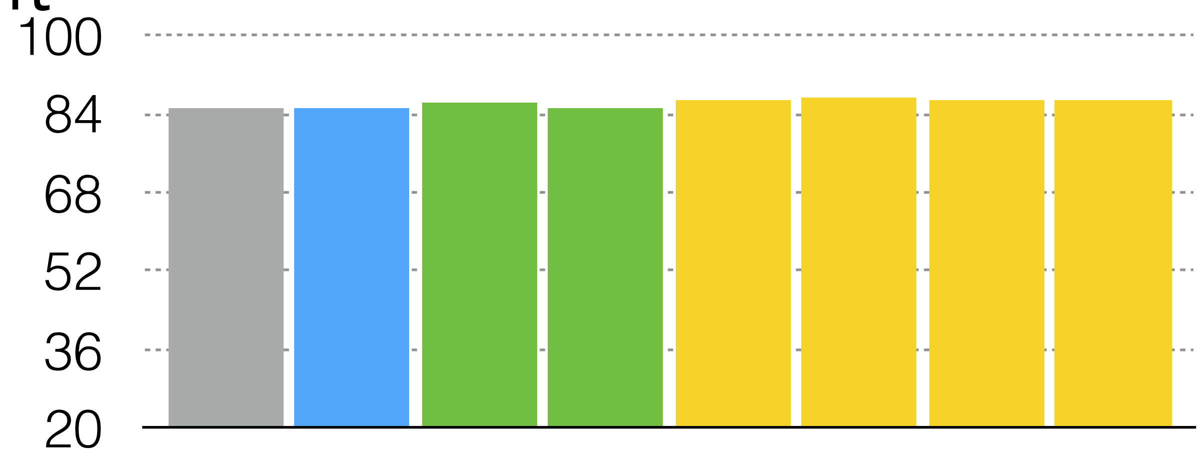

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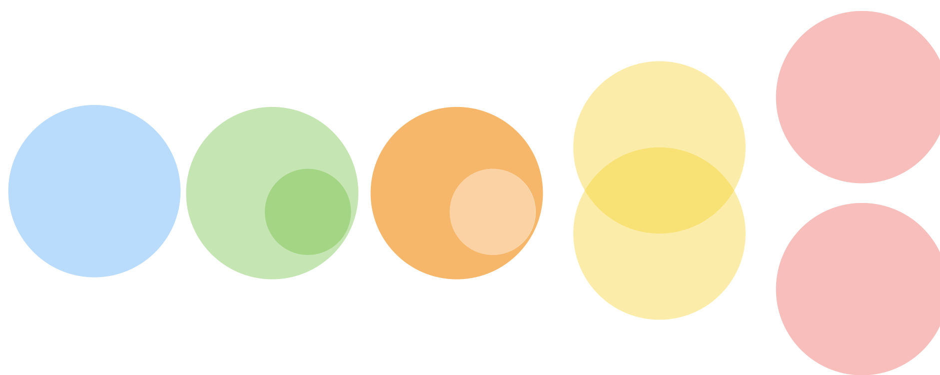
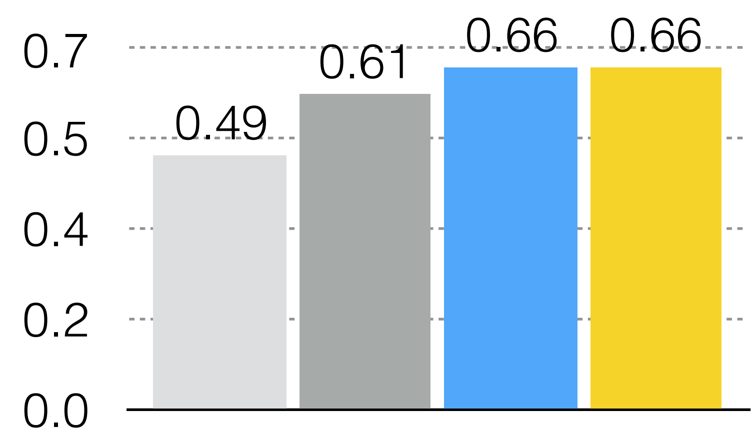
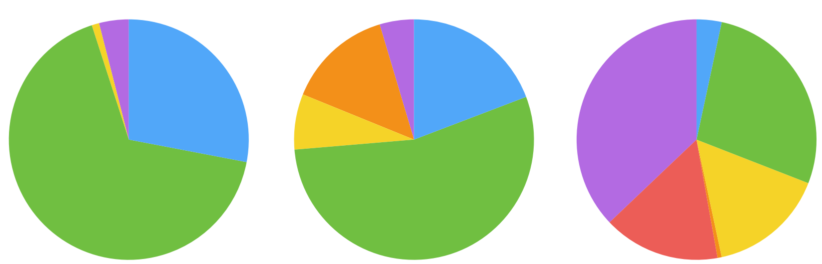
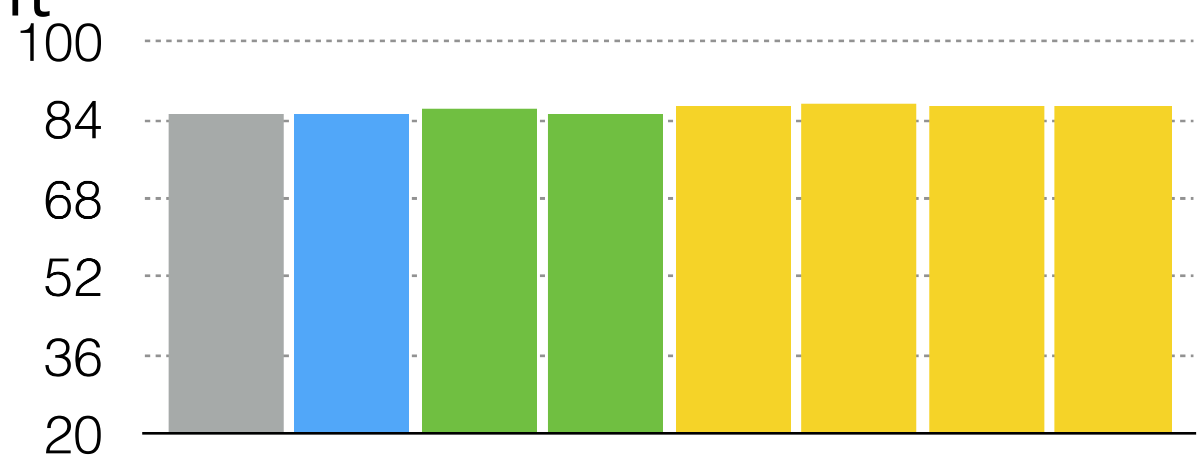




Semantic Containment





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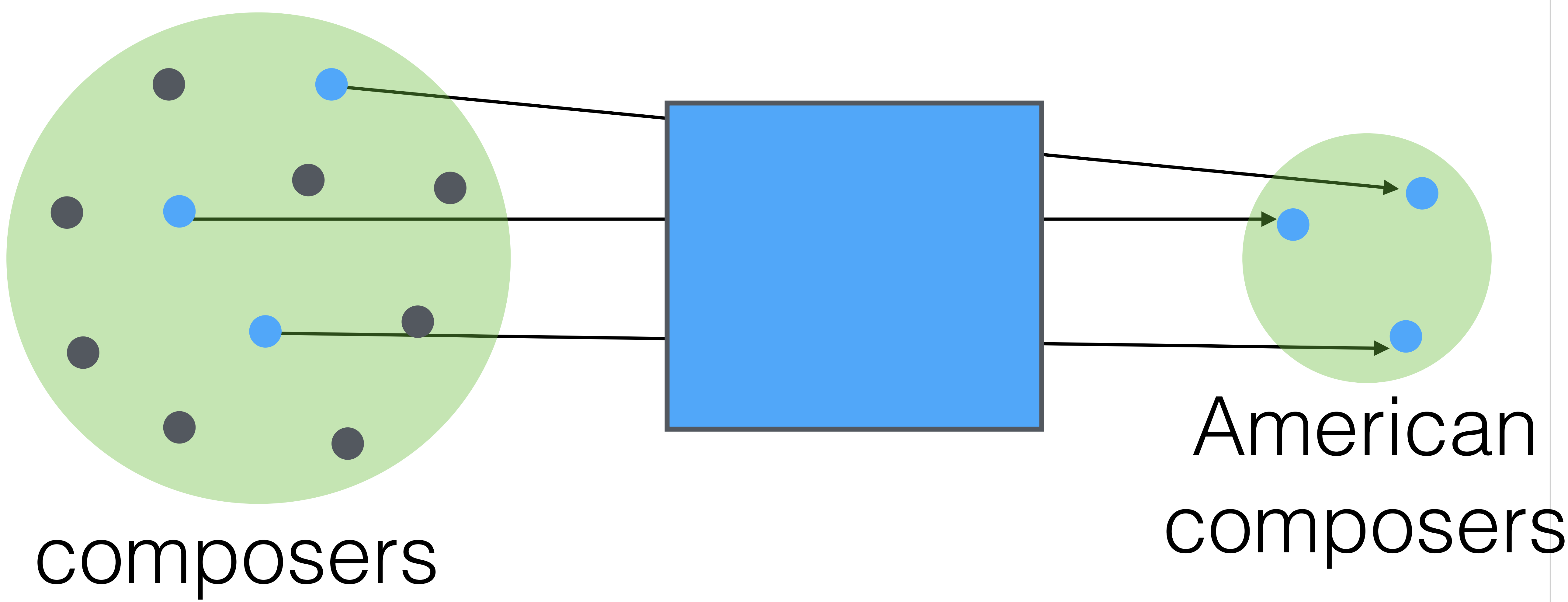
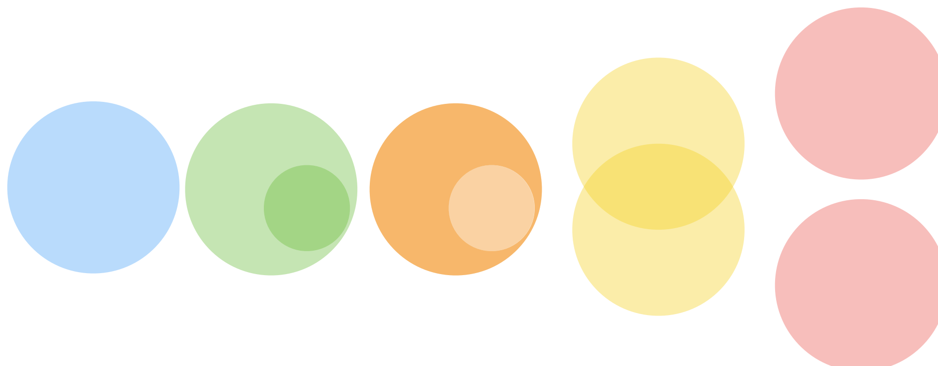
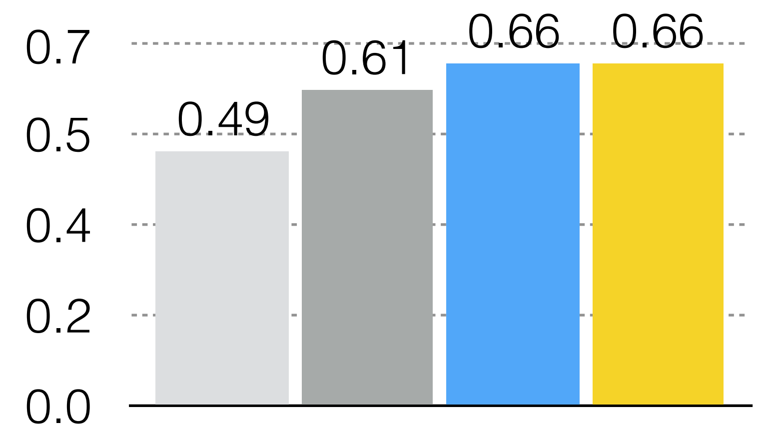
Lexical Entailment

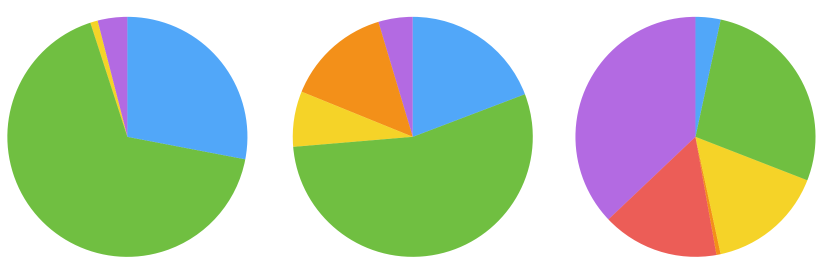


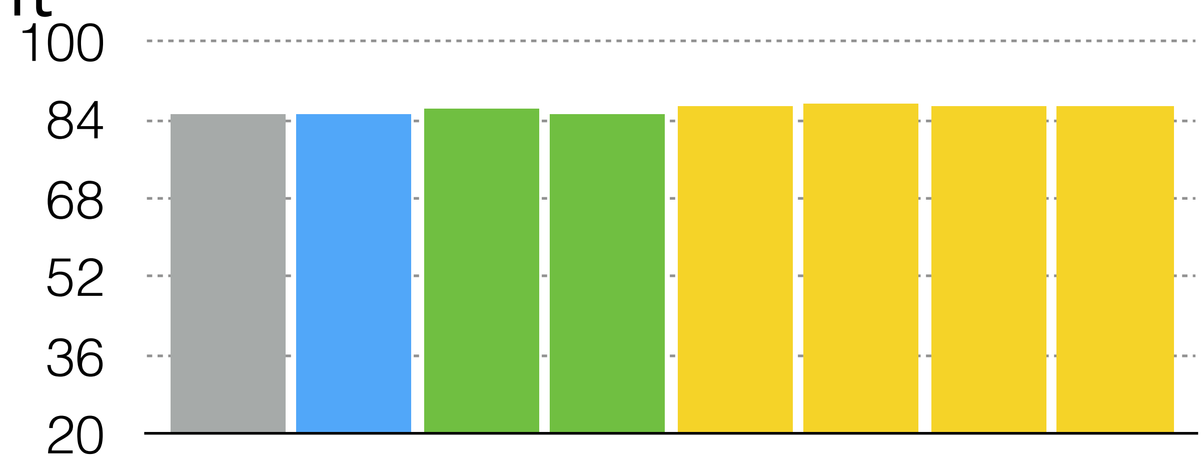
Lexical Entailment





Semantic Containment





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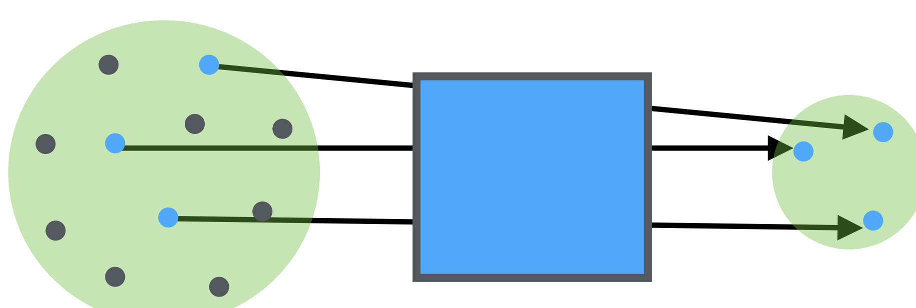
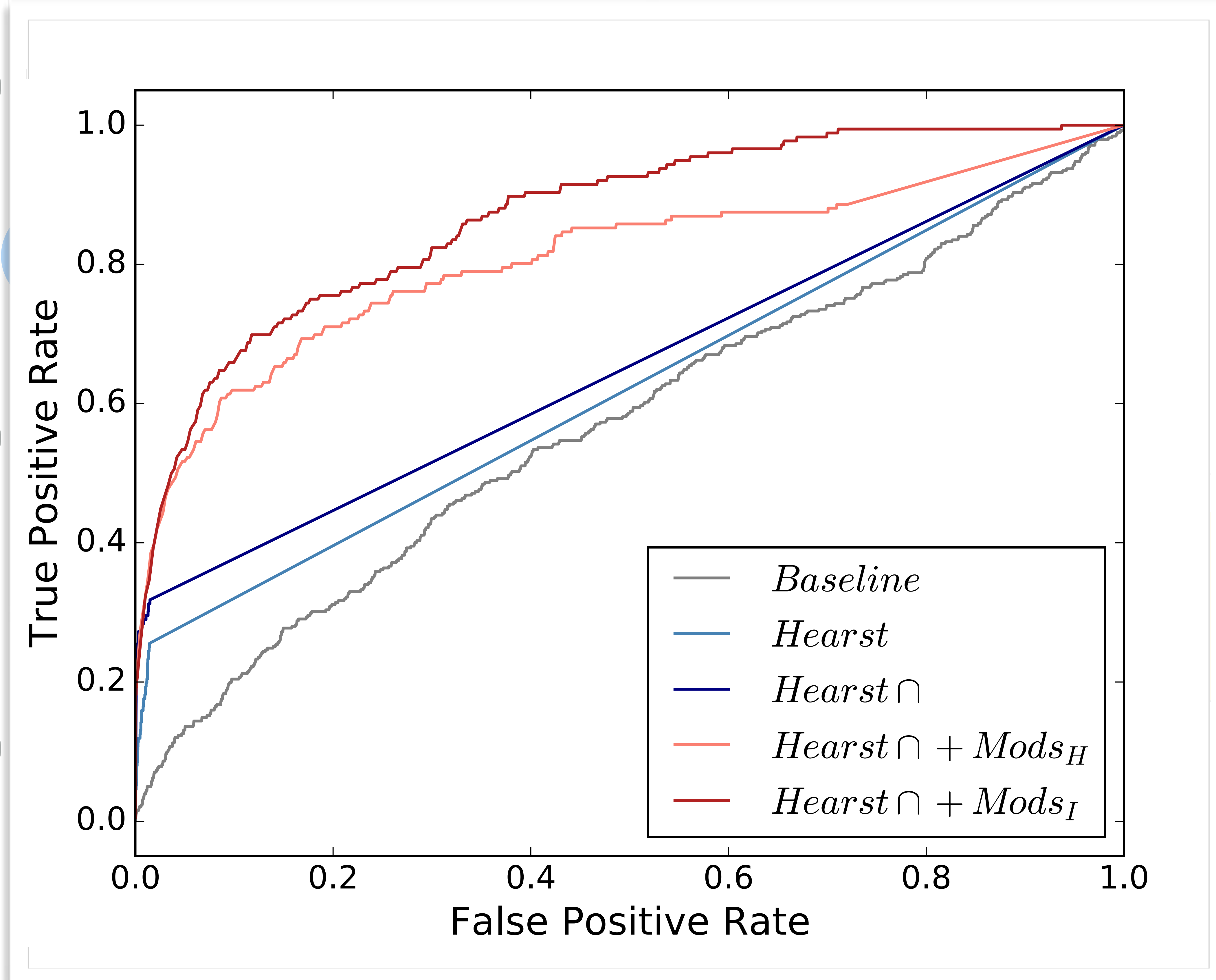
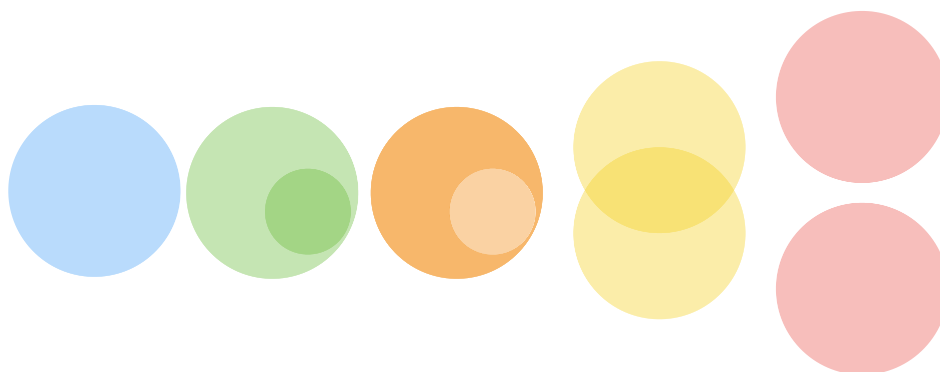
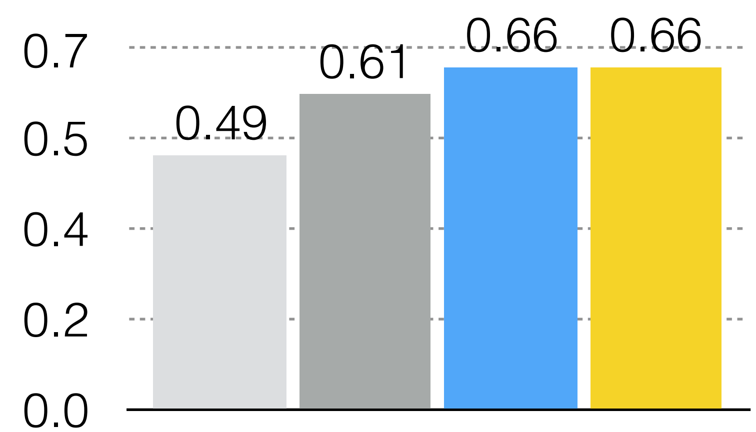




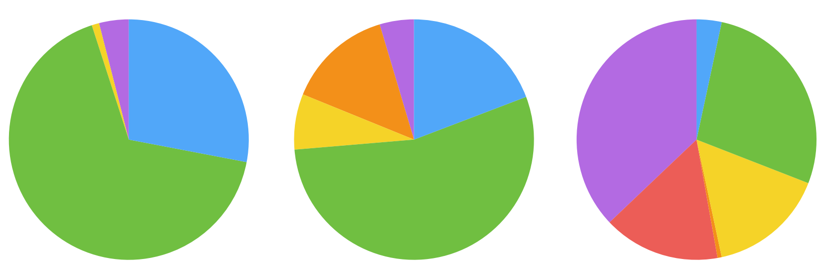
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
Baseline
Hearst
Hearst ∩
Hearst ∩ + Mods_H
Hearst ∩ + Mods_I

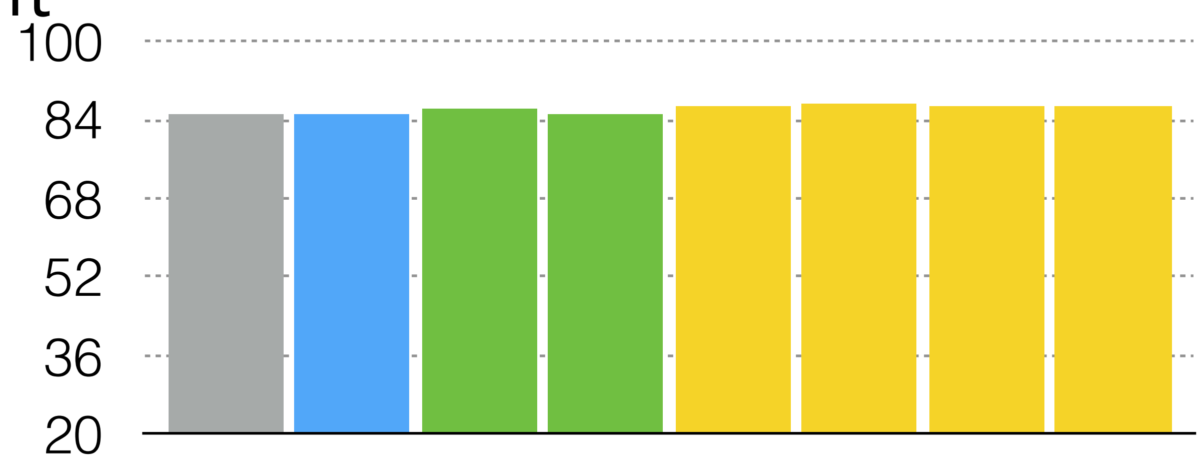
Lexical Entailment



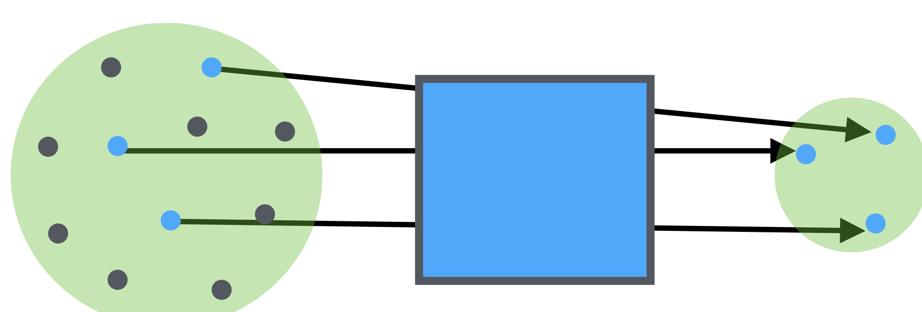


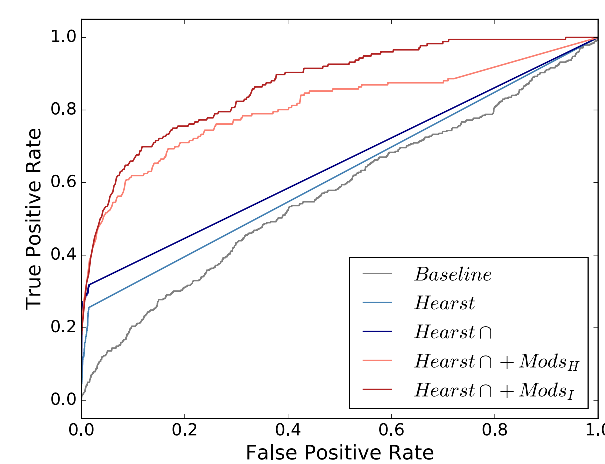
Semantic Containment





Class-Instance Identification





Future Directions

Future Directions

The **crowd** roared.

real

excited/happy

making noise

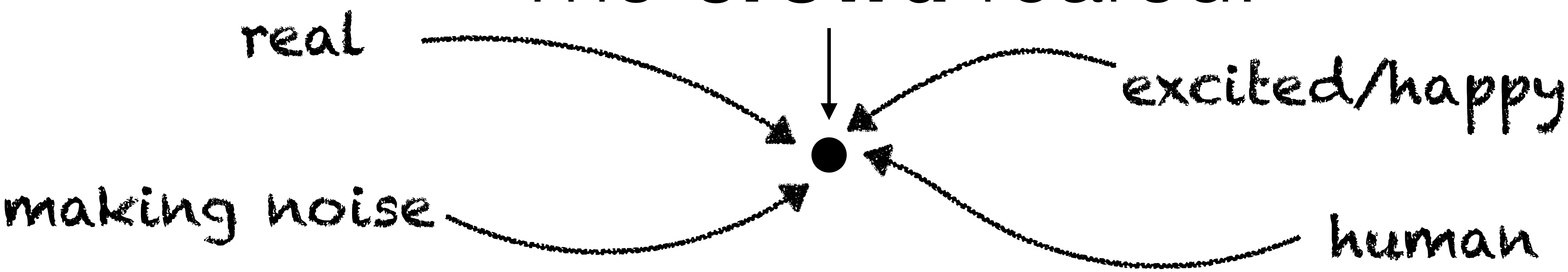
human

enthusiastic crowd

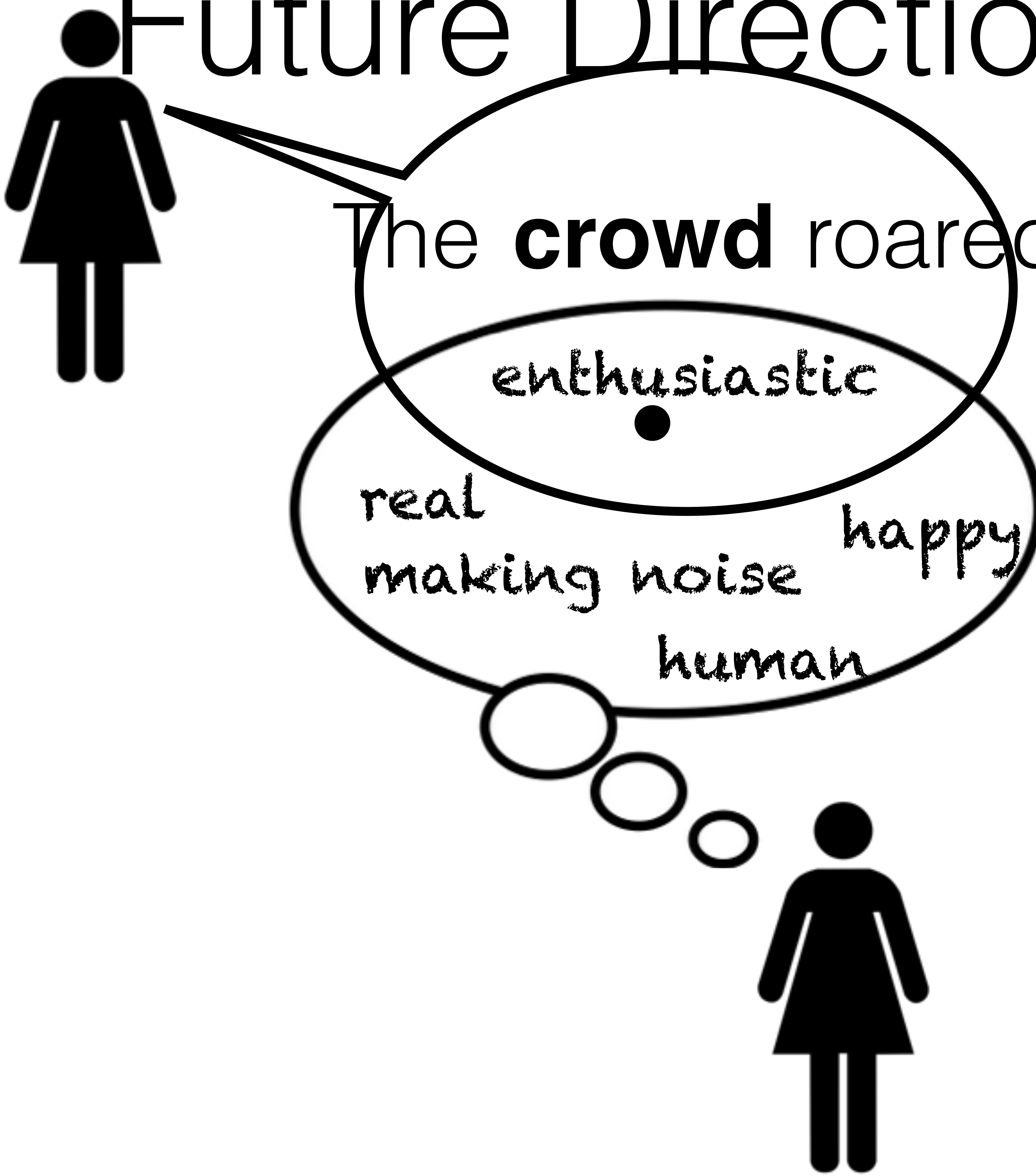
excited/happy
making noise
clapping
yelling
human

Future Directions

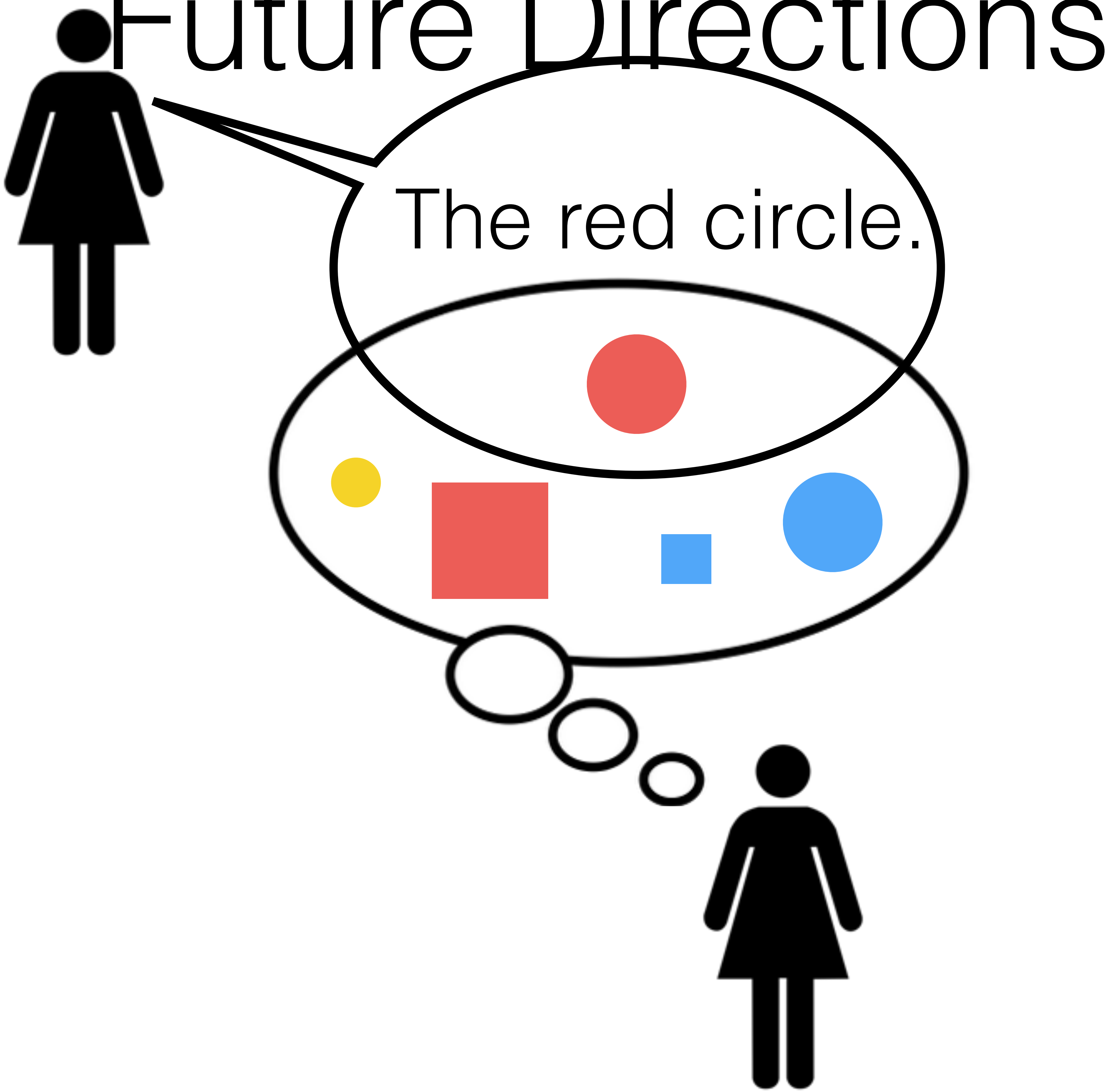
The **crowd** roared.



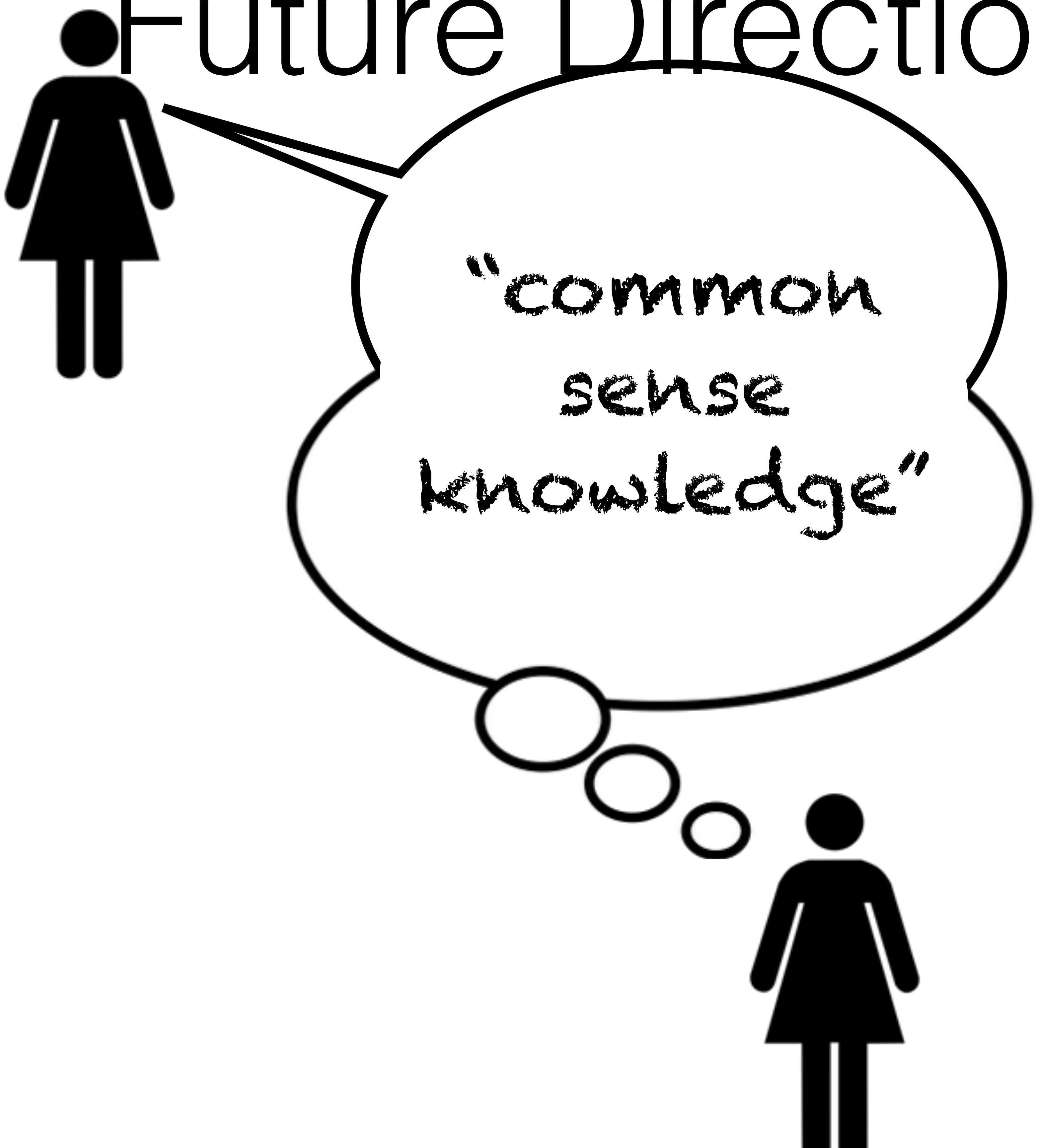
Future Directions



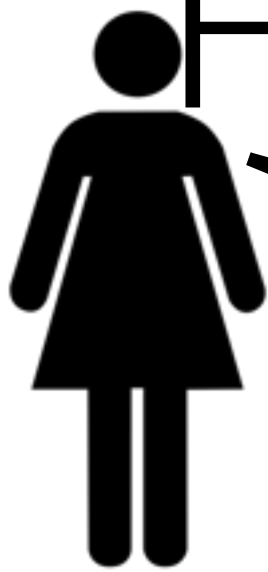
Future Directions

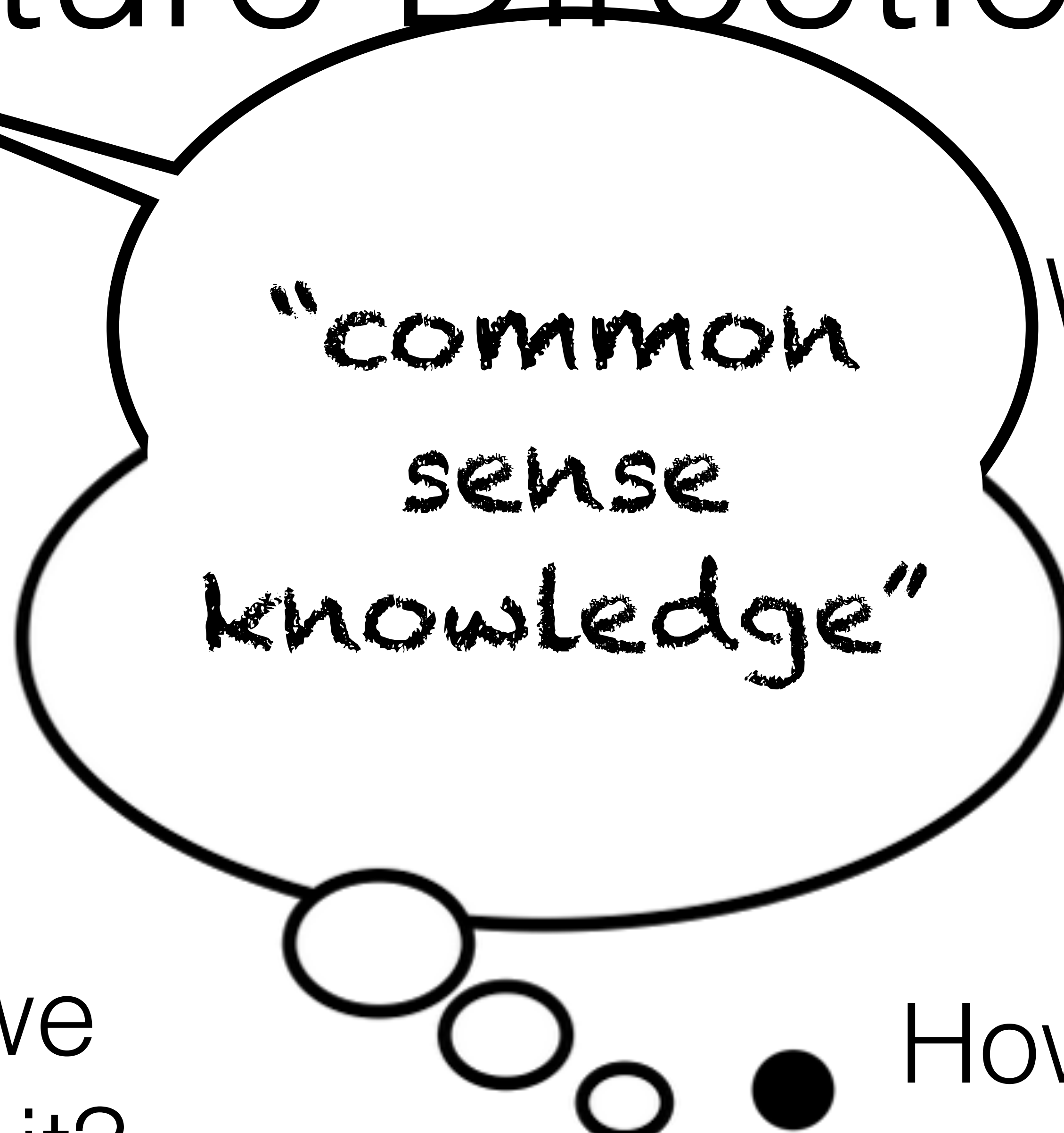


Future Directions



Future Directions





When/how is it accessed?

What can be precomputed?
What happens at “runtime”?

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?

Thank you!
Questions!