Scalable Semantic Parsing with Partial Ontologies

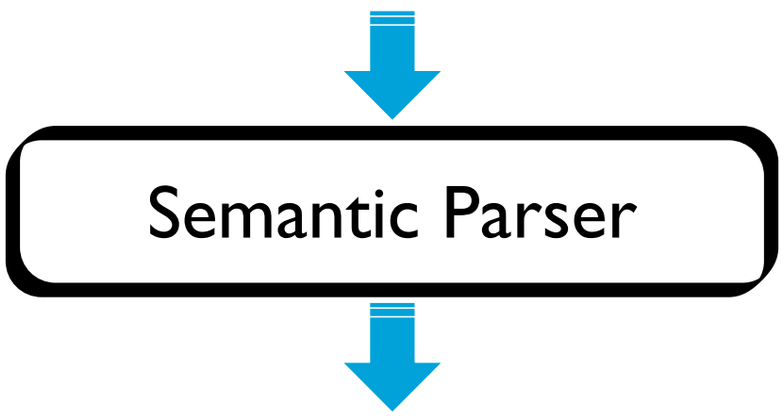
Eunsol Choi Tom Kwiatkowski Luke Zettlemoyer

ACL 2015

Semantic Parsing: Long-term Goal

Build meaning representations for open-domain texts

How many people live in Seattle?




```
SELECT Population FROM CityData
  where City=="Seattle";
```

(Kwiatkowski et.al, 13, Liang et.al. 11, Cai & Yates 2013, Berant et.al. 13,14, Reddy et. a. 14)

Semantic Parsing: Large Domain

Freebase is a large, community authored knowledge base with:

- 40 Million Entities
- 2 Billion Facts
- 20,000 Relations
- 10,000 Types
- 100 Domains

Current semantic parsers

can parse…

How many people live in Seattle?

Which college did Obama go to?

What party did Clay establish?

Current semantic parsers

can parse…

How many people live in Seattle?

Which college did Obama go to?

What party did Clay establish?

cannot parse…

How many people live in Anyang?

Which college did Eunsol go to?

Who are Russian short story writers in 19th century?

What is a popular seaside resort city in Italy?

Remaining Challenges

Fact Incompleteness

How many people live in Anyang?

Which college did Eunsol go to?

Schema Incompleteness

Who are Russian short story writers in 19th century?

What is a popular seaside resort city in Italy?

Remaining Challenges

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How many people live in Anyang?

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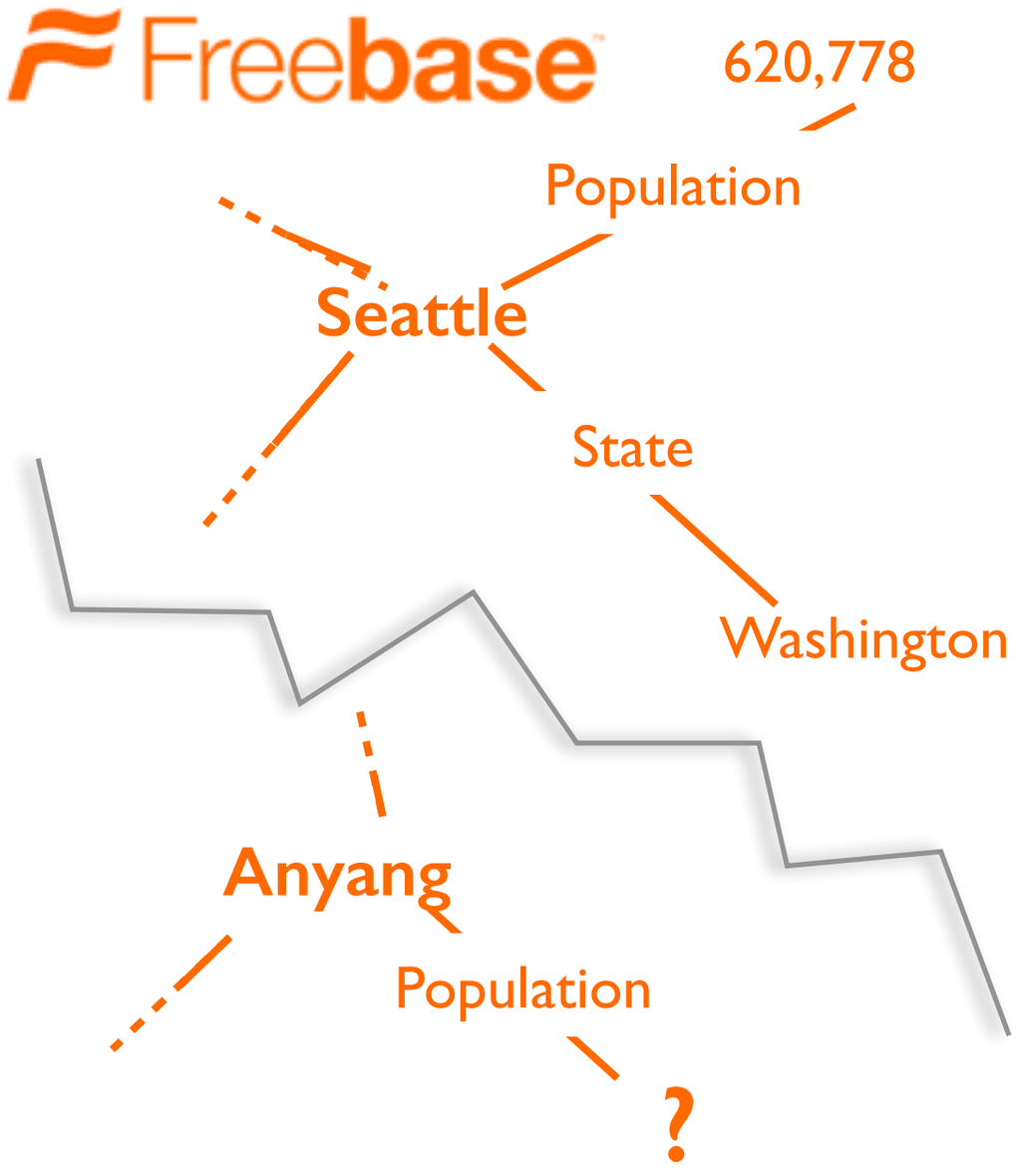
Remaining Challenges: Fact Incompleteness

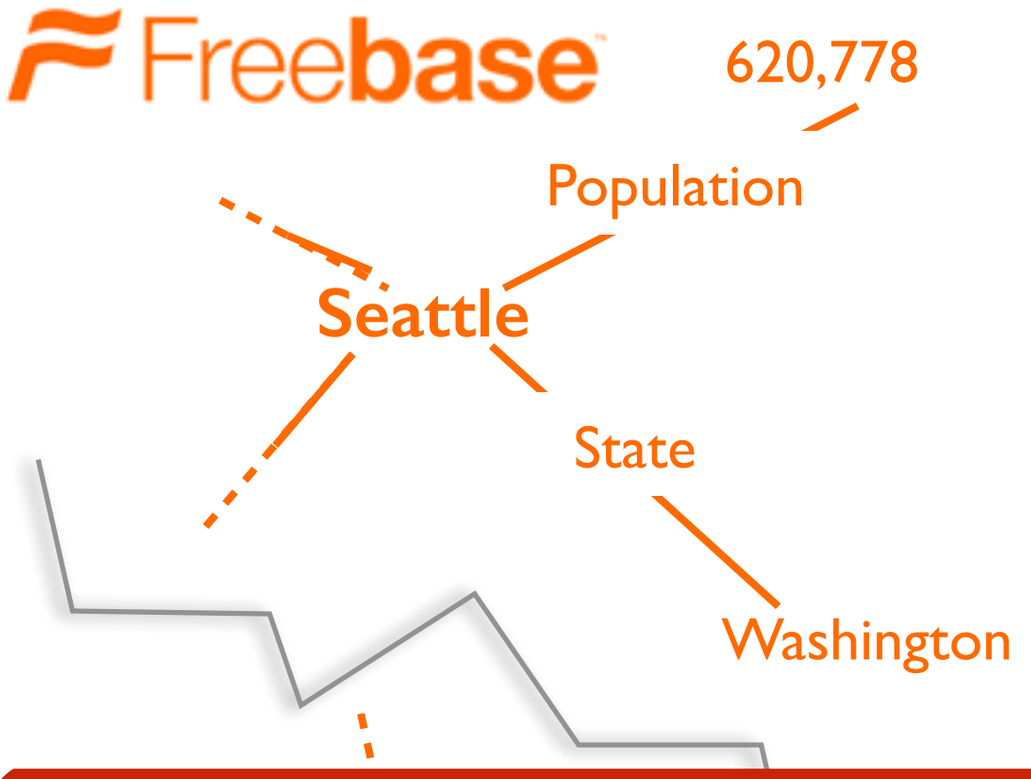


How many people live in Anyang?

Which college did Eunsol go to?

Unable to handle sentences with facts not in Freebase

Remaining Challenges: Fact Incompleteness



How many people live in Anyang?

Which college did Eunsol go to?

70% of people in FB have no birth place (West' 14)
66% of facts missing in pilot study for our dataset

Remaining Challenges

Fact Incompleteness

How many people live in Anyang

Which college did Eunsol

Schema Incompleteness

Who are Russian short story writers in 19th century?

What is a popular seaside resort city in Italy?

Remaining Challenges:
Schema Incompleteness

Who are Russian short story writers in 19th century?

What is popular seaside resort city in Italy?

Unable to handle concepts outside existing schema

Remaining Challenges: **Schema** Incompleteness

Who are Russian short story writers in 19th century?

What is popular seaside resort city in Italy?

In a pilot study on our dataset:
27.2% of sentences describe concepts not in Freebase

Previous Approach?

Existing data is filtered to ensure completeness:

- FB917 dataset is created from Freebase (Cai and Yates' 13)
- 93% of originally gathered questions cannot be answered with FB (WebQuestions, Berant' 13)

Remaining Challenges

Fact Incompleteness

New learning approach
with broad coverage lexical statistics

Schema Incompleteness

Semantic parser
with partial groundings

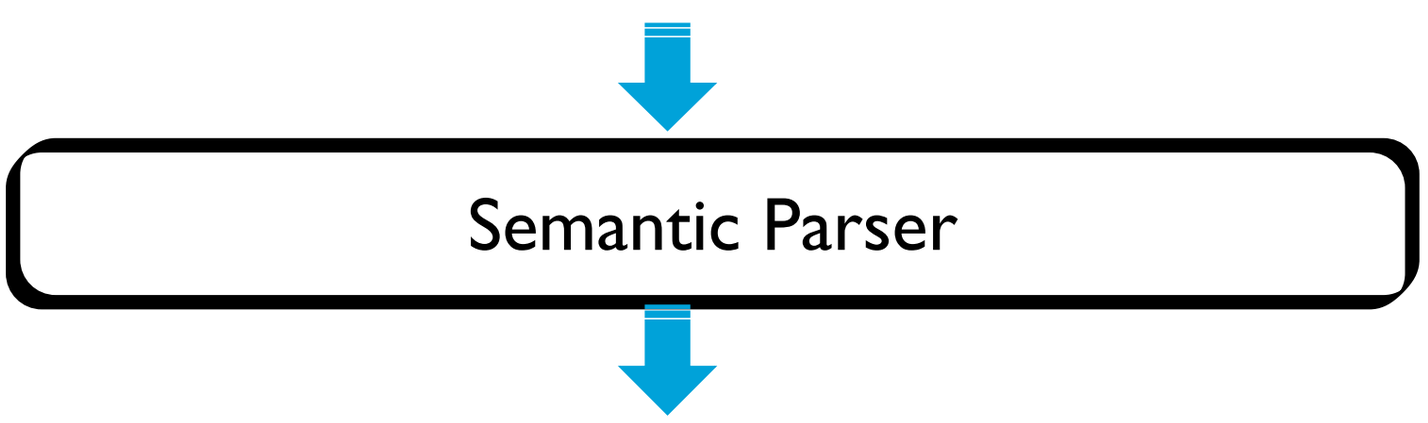
Who are Russian short story writers

city in Italy?

This Work

Build meaning representations with both Freebase concepts and open concepts

British playwright, novelist and short story writer

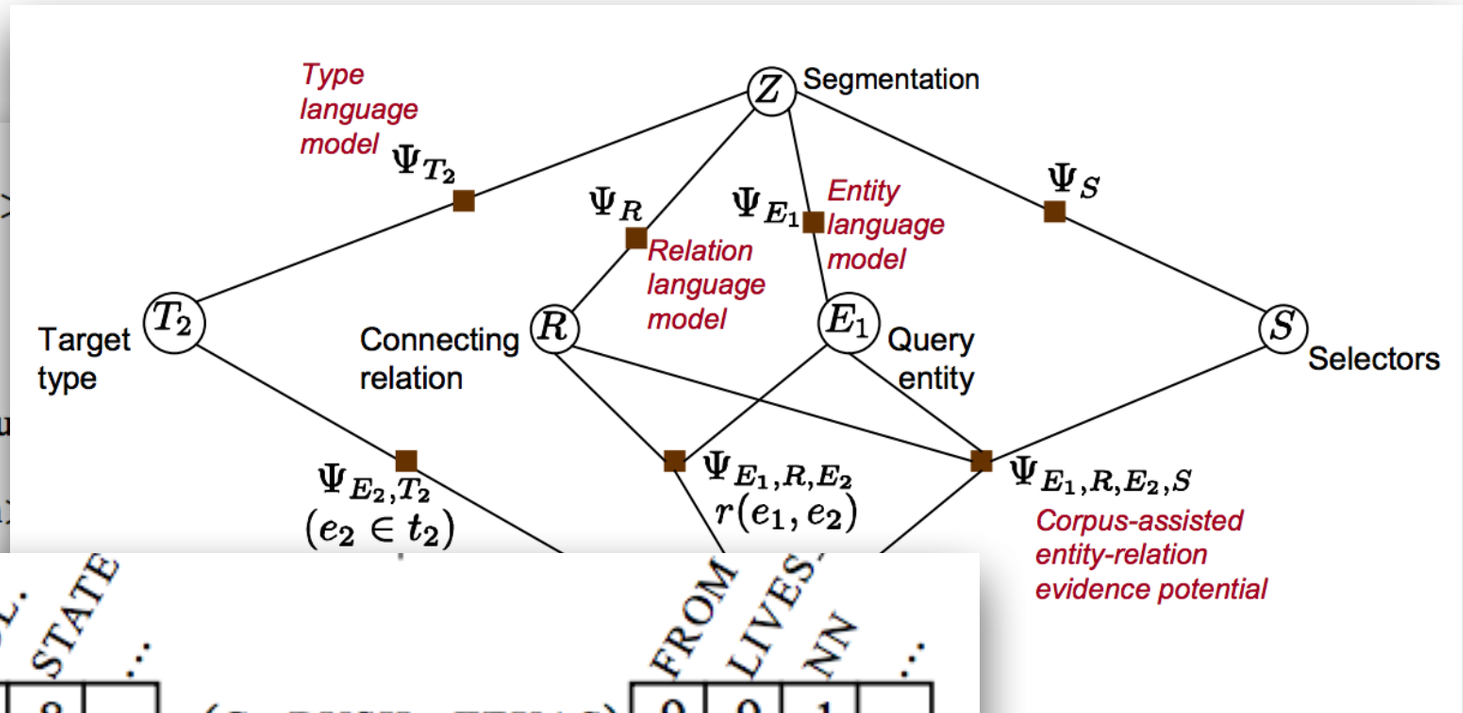


$$\lambda x.\texttt{OpenRel\_writer}(x, \texttt{short\_story})$$
$$\wedge\, \texttt{person.profession}(x, \texttt{novelist})$$
$$\wedge \texttt{person.profession}(x, \texttt{playwright})$$
$$\wedge\, \texttt{person.nationality}(x, \texttt{united\_kingdom})$$

Parsing with Incompleteness

1. Open Information Extraction (Banko et al., 07; Fader et al., 11)
2. Matrix Factorization (Riedel, 13;Krishnamurthy, 15)
3. Web Search Queries (Joshi, 14)

(<proper noun>, acquired, <proper noun>)
(<proper noun>, graduated from, <proper noun>
(<proper noun>, is author of, <proper noun>)
(<proper noun>, is based in, <proper noun>)
(<proper noun>, studied, <noun phrase>)
(<proper noun>, studied at, <proper noun>)
(<proper noun>, was developed by, <proper nou
(<proper noun>, was formed in, <year>)
(<proper noun>, was founded by, <proper noun
(<proper noun>, worked



	F.-RUN	POL.	STATE	…
TEXAS	.1	.1	.8	
REPUB.	.1	.1	.1	
G._BUSH	.9	.9	.1	
…				

	FROM	LIVES-	NN	…
(G._BUSH, TEXAS)	.9	.9	.1	
(G._BUSH, REPUB.)	.1	.1	.1	
(REPUB., G._BUSH)	.1	.1	.7	
…				

Outline

1. *Task and Applications*
2. Data
3. Semantic Parser with Partial Ontology
4. Learning
5. Evaluation

Task

Build a meaning representation with **Freebase** concepts and **concepts outside Freebase**

British playwright, novelist and short story writer

Semantic Parser

$$\lambda x.\texttt{OpenRel\_writer}(x, \texttt{short\_story})$$
$$\wedge\, \texttt{person.profession}(x, \texttt{novelist})$$
$$\wedge \texttt{person.profession}(x, \texttt{playwright})$$
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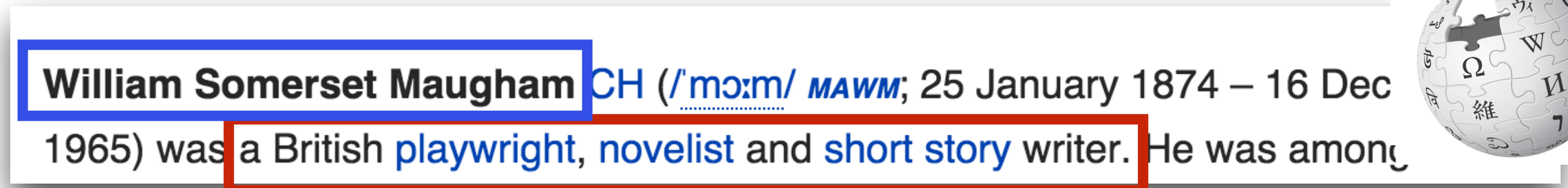
Focus: Noun Phrases

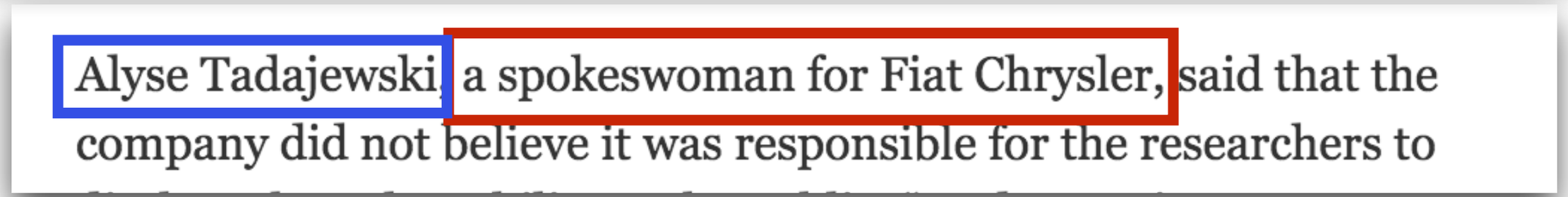
William Somerset Maugham CH (/ˈmɔːm/ *MAWM*; 25 January 1874 – 16 Dec 1965) was a British playwright, novelist and short story writer. He was among

Alyse Tadajewski, a spokeswoman for Fiat Chrysler, said that the company did not believe it was responsible for the researchers to

- Interesting noun-noun modifier, implicit relations.
- Itself is a referring expression, resembling queries.

Focus: Noun Phrases





- Interesting noun-noun modifier, implicit relations.
- Useful for information extraction, when paired with an entity.

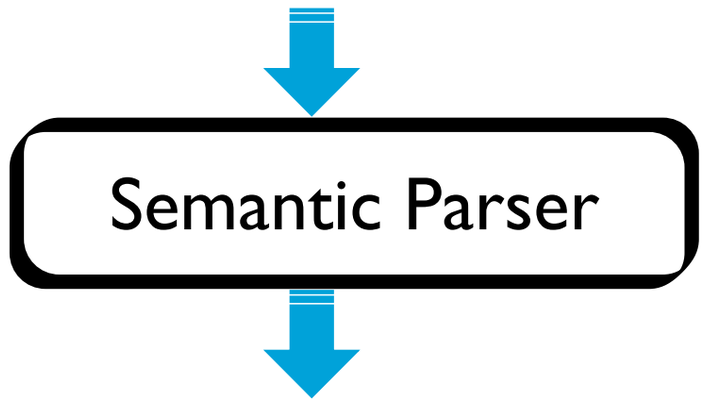
Applications

	Referring Expression Resolution (QA)	**Entity Attribute Extraction (IE)**
Input:	Noun Phrase	(Entity, Noun Phrase)
	British playwright, novelist and short story writer	*Somerset Maugham* *' British playwright, novelist and short story writer*

Output:	`Sommerset Maugham`	`(S. Maugham, Nationality, U.K)`
		`(S. Maugham, Profession, Novelist)`
		`(S. Maugham, Profession, Playwright)`

Overview: Approach

British playwright, novelist and short story writer



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Referring Expression Resolution (QA)

British playwright, novelist and short story writer

Semantic Parser

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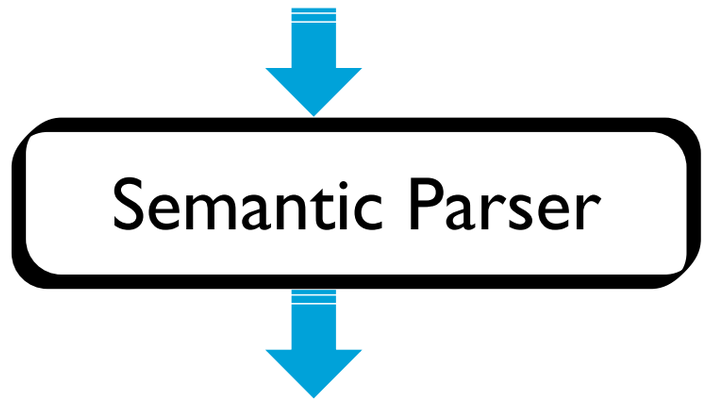
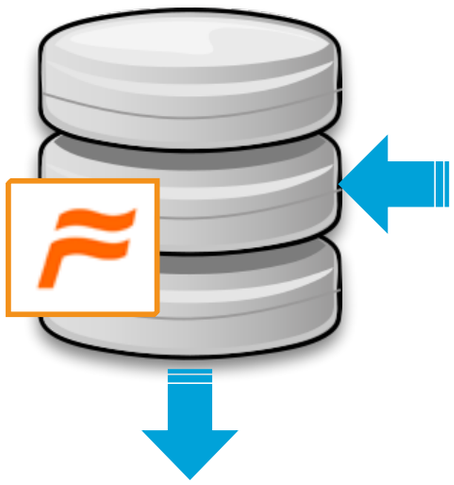
Sommerset Maugham

Referring Expression Resolution (QA)

Entity Attribute Extraction (IE)

British playwright, novelist and short story writer





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$\wedge\, \texttt{person.nationality}(x, \texttt{united\_kingdom})$

Sommerset Maugham

(x, Nationality, U.K)
(x, Profession, Novelist)
(x, Profession, Playwright)

Referring Expression Resolution (QA)

Entity Attribute Extraction (IE)

Somerset Maugham , *British playwright, novelist and short story writer*

Semantic Parser

$\lambda x.\texttt{OpenRel\_writer}(x, \texttt{short\_story})$
$\wedge\, \texttt{person.profession}(x, \texttt{novelist})$
$\wedge \texttt{person.profession}(x, \texttt{playwright})$
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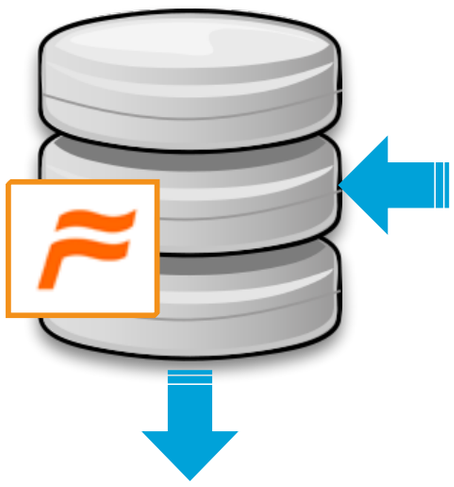

Sommerset Maugham

(S.Maugham, Nationality, U.K)
(S.Maugham, Profession, Novelist)
(S.Maugham, Profession, Playwright)

Outline

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2. *Data*
3. Semantic Parser with Partial Ontology
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Wikipedia Category

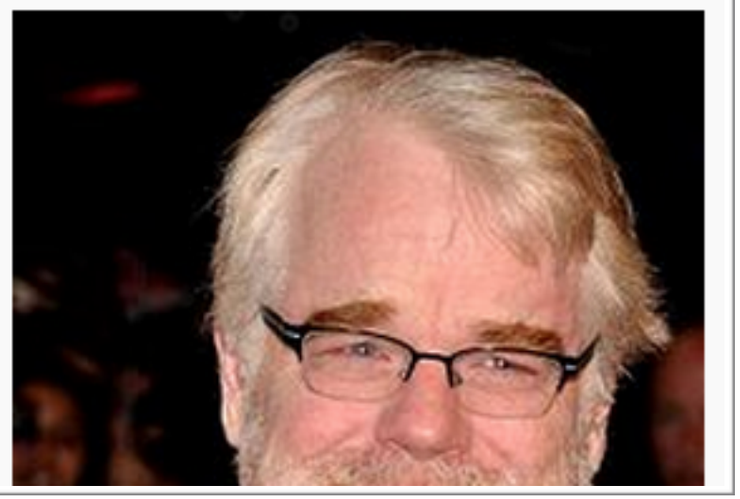
Philip Seymour Hoffman

From Wikipedia, the free encyclopedia

Philip Seymour Hoffman (July 23, 1967 – February 2, 2014) was an American actor and director. He was prolific in both film and theater from the early 1990s until his death at age 46, after which *The New York Times* declared him "perhaps the most ambitious and widely admired American actor of his generation".[1]

Raised in Fairport, New York, Hoffman studied acting at the New York State Summer School of the Arts and the Tisch School of the Arts. He began his career in 1991 playing a defendant in a rape case in an episode of *Law &*

Philip Seymour Hoffman



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acto
Rais
Sur
care

Philip Seymour Hoffman

Categories: 1967 births | 2014 deaths | 20th-century American male actors | 21st-century American male actors | American film producers | American film directors | American male film actors | American male stage actors | American male television actors | American male voice actors | American people of Dutch descent | American people of English descent | American people of German descent | American people of Irish descent | American theatre directors | BAFTA winners (people) | Best Actor Academy Award winners | Best Actor BAFTA Award winners | Best Drama Actor Golden Globe (film) winners | Circle in the Square Theatre School alumni | Cocaine-related deaths in New York | Drug-related deaths in New York | Film directors from New York | Film directors from New York City

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[Film directors from New York]

Wikipedia Category

Philip Seymour Hoffman

From Wikipedia, the free encyclopedia

Philip Seymour Ho
American actor and
the early 1990s until
dec
act
Rais
Sun
care

Categories
21st-cent
American
American
American
American
Best Acto
Best Drar
Cocaine-

Pages in category "Film directors from New York City"

The following 196 pages are in this category, out of 196 total. This list may not reflect recent

A

- George Abbott
- J. J. Abrams
- Ivan Abramson
- Jus Addiss
- John G. Adolfi
- Irwin Allen
- Woody Allen
- Roy Lee
- Spike Lee
- Marc Levin
- Jonathan Levine
- Joseph H. Lewis
- Doug Liman
- Victoria Linchong
- Fred J. Lincoln
- Steven Lisberger

from New York City

[Film directors from New York]

Wikipedia Category

Philip Seymour Hoffman

From Wikipedia, the free encyclopedia

On average, 15% entity overlap with Freebase

Exciting opportunity for information extraction

Challenge for existing learning techniques

Film directors from New York

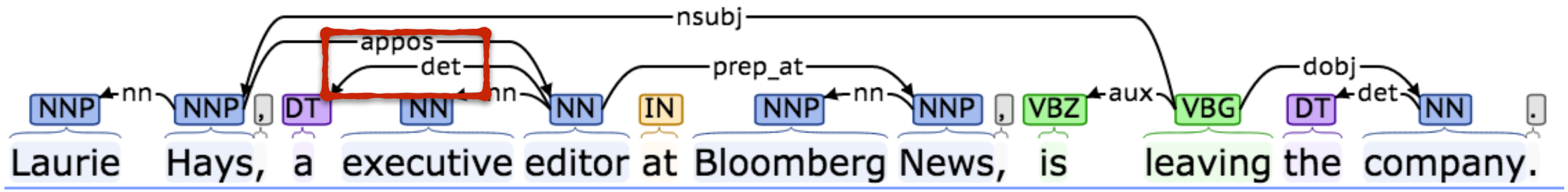
Wikipedia Category: Data statistics

	Entire Set
Number of Category	365 K
Number of words per category	4.1
Number of entity-category pair	7 million

Appositives

Relation between a named entity and a nominal.

- Laurie Hays, a executive editor at Bloomberg News, is leaving the company.



Laurie Hays ,

a executive editor at Bloomberg News

Appositives

Extracted from open texts such as news articles

- Malta, an EU outpost in the Mediterranean, decided today…
- Richard Nixon, a former president of the United States…
- Maputo, the relaxed seaside capital of Mozambique, …

Appositives

Extracted from open texts such as news articles

- Malta, an **EU outpost** in the Mediterranean, decided today…
- Richard Nixon, a **former** president of the United States…
- Maputo, the **relaxed seaside** capital of Mozambique, …

Appositives: Data statistics

	Entire Set
Number of apposition	67 K
vocab	25 K
Number of words per apposition	5.73

Outline

1. Task and Applications
2. Data
3. *Semantic Parser with Partial Ontology*
4. Learning
5. Evaluation

Two Stage Semantic Parsing (EMNLP 13)

British playwright, novelist and short story writer

Domain Independent Parse

Ontology Match

Two Stage Semantic Parsing (EMNLP 13)

British playwright, novelist and short story writer

Domain Independent Parse

$$\lambda x. \quad \text{British}(x) \wedge \text{Playwright}(x) \wedge \text{Novelist}(x) \wedge \text{Writer}(x, \text{Short Story})$$

Ontology Match

Two Stage Semantic Parsing (EMNLP 13)

British playwright, novelist and short story writer

Domain Independent Parse

$\lambda x.$ British(x) $\wedge$ Playwright(x)
Novelist(x) $\wedge$ Writer(x, Short Story)

Ontology Match

$\lambda x.$ person.profession(x, novelist)
$\wedge$person.profession(x, playwright)
$\wedge$ person.nationality(x, united_kingdom)

Two Stage Semantic Parsing with Partial Grounding

British playwright, novelist and short story writer

Domain Independent Parse

$$\lambda x. \quad \text{British}(x) \ \wedge \ \text{Playwright}(x)$$
$$\text{Novelist}(x) \ \wedge \ \text{Writer}(x, \text{Short Story})$$

Ontology Match

$$\lambda x.\texttt{OpenRel\_writer}(x, \texttt{short\_story})$$
$$\wedge\, \texttt{person.profession}(x, \texttt{novelist})$$
$$\wedge \texttt{person.profession}(x, \texttt{playwright})$$
$$\wedge\, \texttt{person.nationality}(x, \texttt{united\_kingdom})$$

Partial Grounding:
Open Schema

Explicitly model concepts not in Knowledge base
as OpenRel and OpenType

Plants described in 1891

$\lambda x.$ `Lower_classification(plant, x)`
`OpenRel_described_in(x, 1891)`

Former municipalities in Brandenburg

$\lambda x.$ `OpenType_Former(x)`
`OpenRel(x, Municipality)`
`Located_In(x, Brandenburg)`

Partial Grounding: Open Schema

Benefits of open schema:

- Help learn String-Freebase concepts
- Allow partial execution
- Capture useful information, although not grounded

(x, Located_In, Brandenburg)

Two Stage Semantic Parsing with Partial Grounding

Domain Independent Parse

$$\dfrac{\dfrac{\text{Former}}{\dfrac{N/N}{\lambda f \lambda x.f(x) \wedge former(x)}} \quad \dfrac{\text{municipalities}}{\dfrac{N}{\lambda x.municipalities(x)}}}{\dfrac{N}{\lambda x.former(x) \wedge municipalities(x)}}> \quad \dfrac{\dfrac{\text{in}}{\dfrac{N\backslash N/NP}{\lambda f \lambda x \lambda y.f(y) \wedge in(y,x)}} \quad \dfrac{\dfrac{\text{Brandenburgh}}{NP}}{Brandenburg}}{\dfrac{N\backslash N}{\lambda f \lambda y.f(y) \wedge in(y, Brandenburg)}}>$$

$$\dfrac{\text{Former municipalities in Brandenburgh}}{l_0 = \lambda x.former(x) \wedge municipalities(x) \wedge in(x, Brandenburg)}<$$

Ontology Match

Structure Match Constant Matches for ≈. OPEN Constant Matches

$$\lambda x.\text{OpenType}(x) \wedge \text{OpenRel}(x, \text{Municipality}) \wedge \text{Location.ContainedBy}(x, \text{Brandenburg})$$

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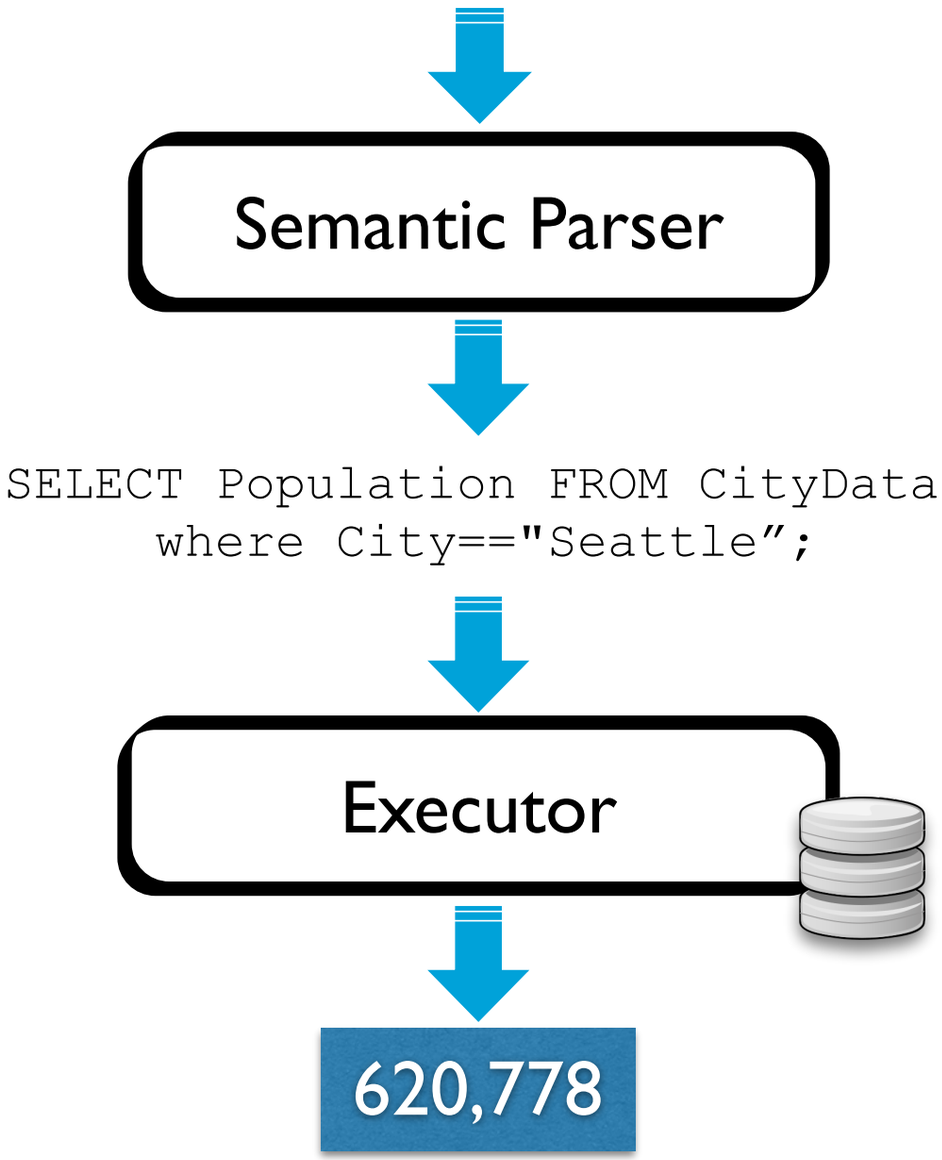
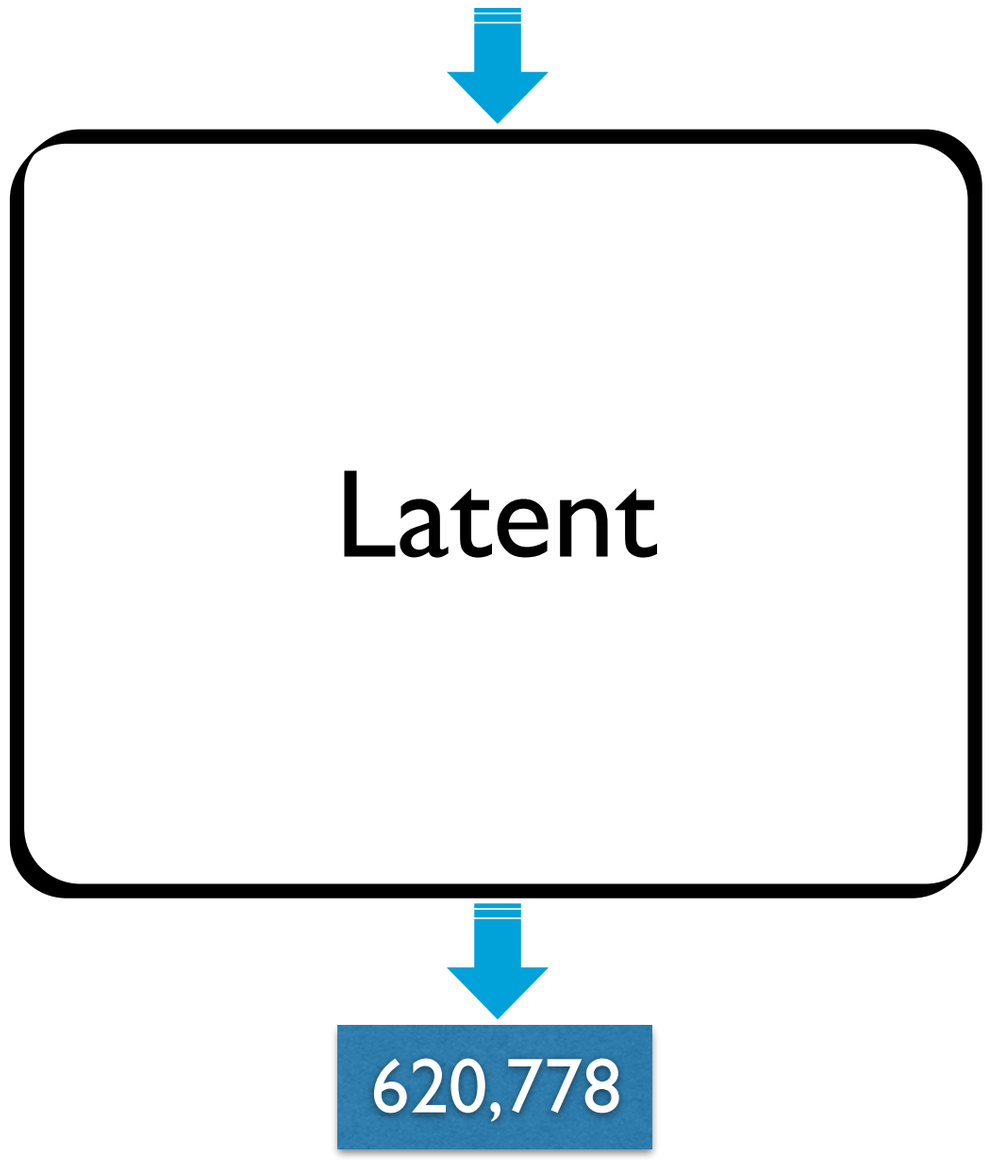
Previous Work: Direct Supervision

How many people live in Seattle?



How many people live in Seattle?



Supervision from Unfiltered Data

Pages in category "Social democratic parties in Greece"

The following 23 pages are in this category, out of 23 total. This list may not reflect recent changes (learn more).

A

- Agreement for the New Greece
- Agricultural and Labour Party

D

- Democratic Left (Greece)
- Democratic Regional Union
- Democratic Socialist Party of Greece

F

- Free Citizens

G

- Georgios Papandreou Party

M

- Movement of Democratic Socialists

O

- Olive Tree (Greece)

P

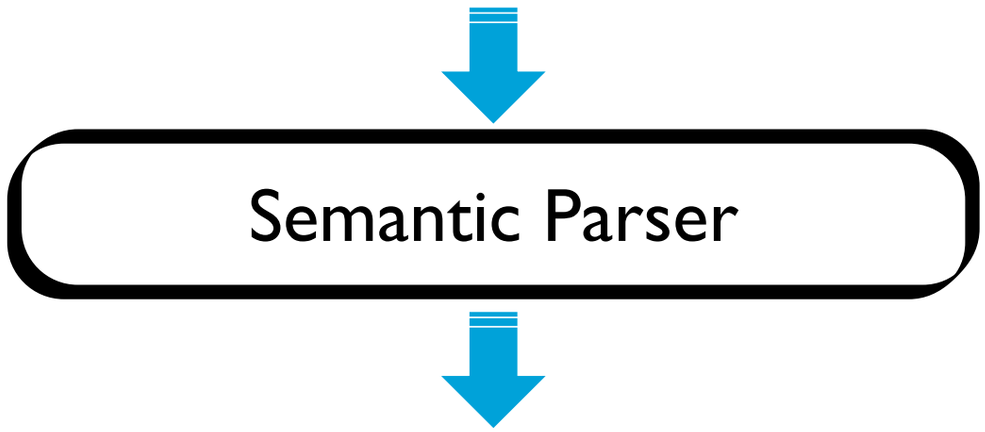
- Panhellenic Citizen Chariot
- Panhellenic Socialist Movement
- Party of Democratic Socialism (Greece)
- Popular Unions of Bipartisan Social Groups

R

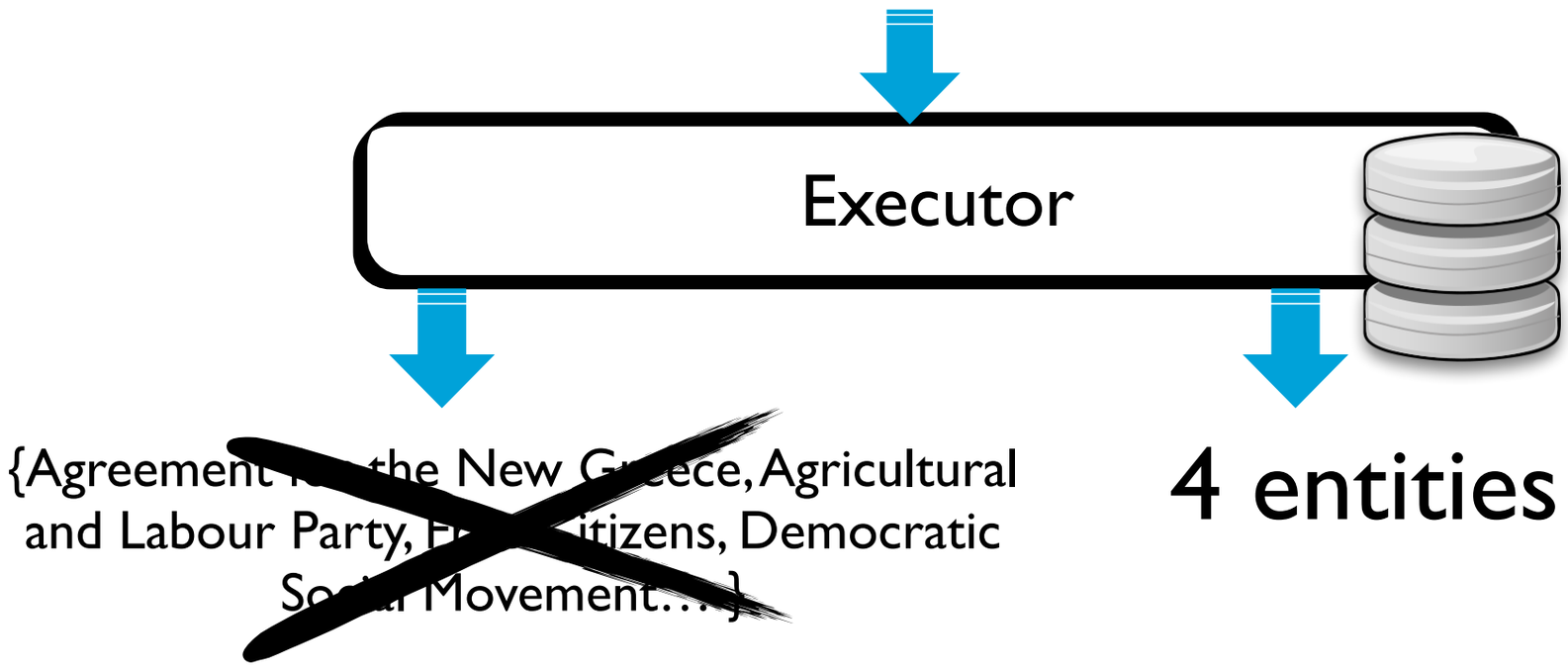
- Radical Movement of Social Democratic Allia

Supervision from Unfiltered Data

Social democratic parties in Greece



$\lambda x.\texttt{political\_party.ideology}(x, \texttt{social\_democratic})$
$\wedge \texttt{political\_party.country}(x, \texttt{greece})$



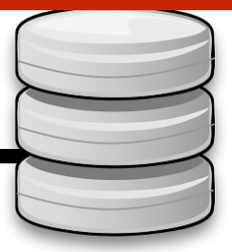
Supervision from Unfiltered Data

Social democratic parties in Greece

Semantic Parser

Missing facts make direct supervision difficult.

Executor

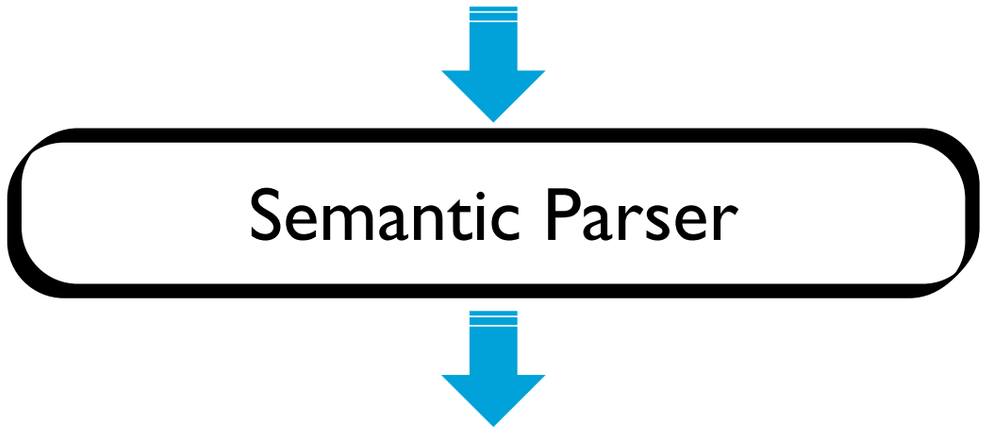


{Agreement for the New Greece, Agricultural and Labour Party, For Citizens, Democratic Social Movement…}

4 entities

Supervision from Unfiltered Data

Social democratic parties in Greece



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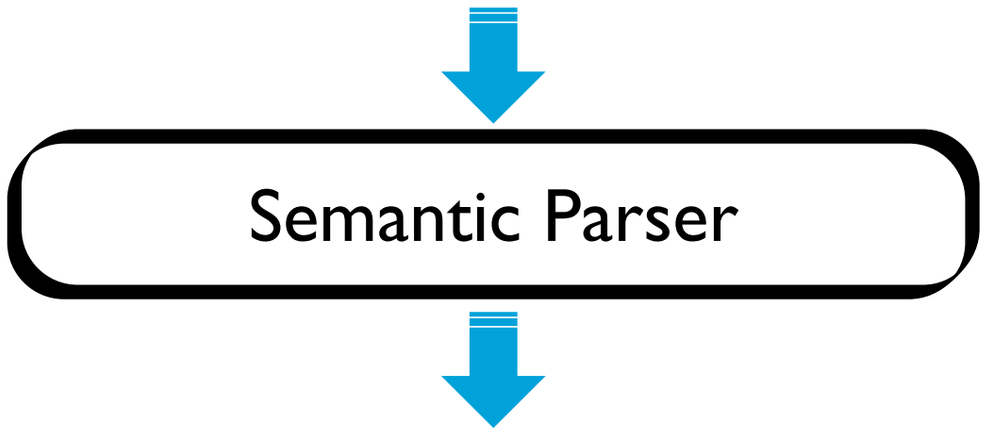
Supervision from Unfiltered Data

Social democratic parties in Greece



$\lambda x.\texttt{political\_party.ideology}(x, \texttt{social\_democratic})$
$\wedge\texttt{political\_party.country}(x, \texttt{greece})$

Gold mapping is expensive to gather large scale.

Learning with Fact Incompleteness

1. Two-Stage Learning
2. Two kinds of data
    i. Small Annotated Dataset
    ii. Broad Coverage Lexical Statistics

Two-Stage Learning

Social democratic parties in Greece

CCG

Domain Independent Parse

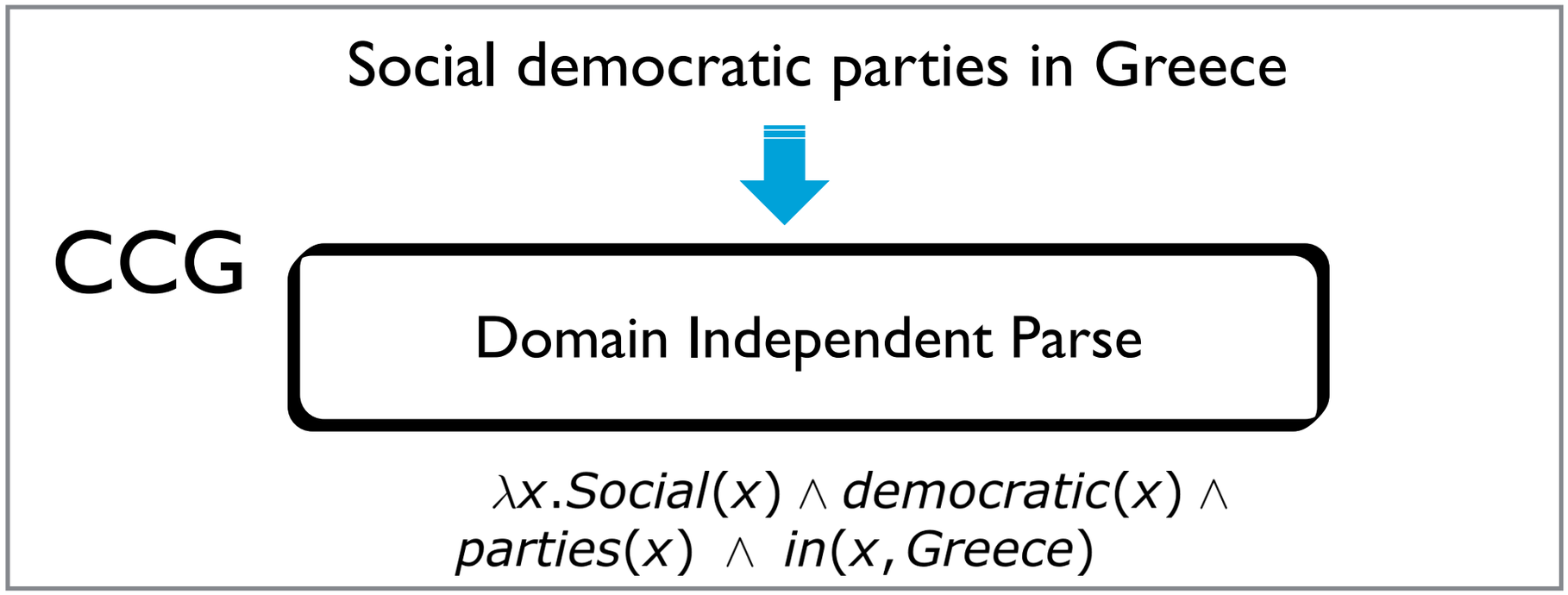
$\lambda x.Social(x) \wedge democratic(x) \wedge$
$parties(x) \wedge in(x, Greece)$

Ontology Matcher

ONT

$\lambda x.\texttt{political\_party.ideology}(x, \texttt{social\_democratic})$
$\wedge \texttt{political\_party.country}(x, \texttt{greece})$

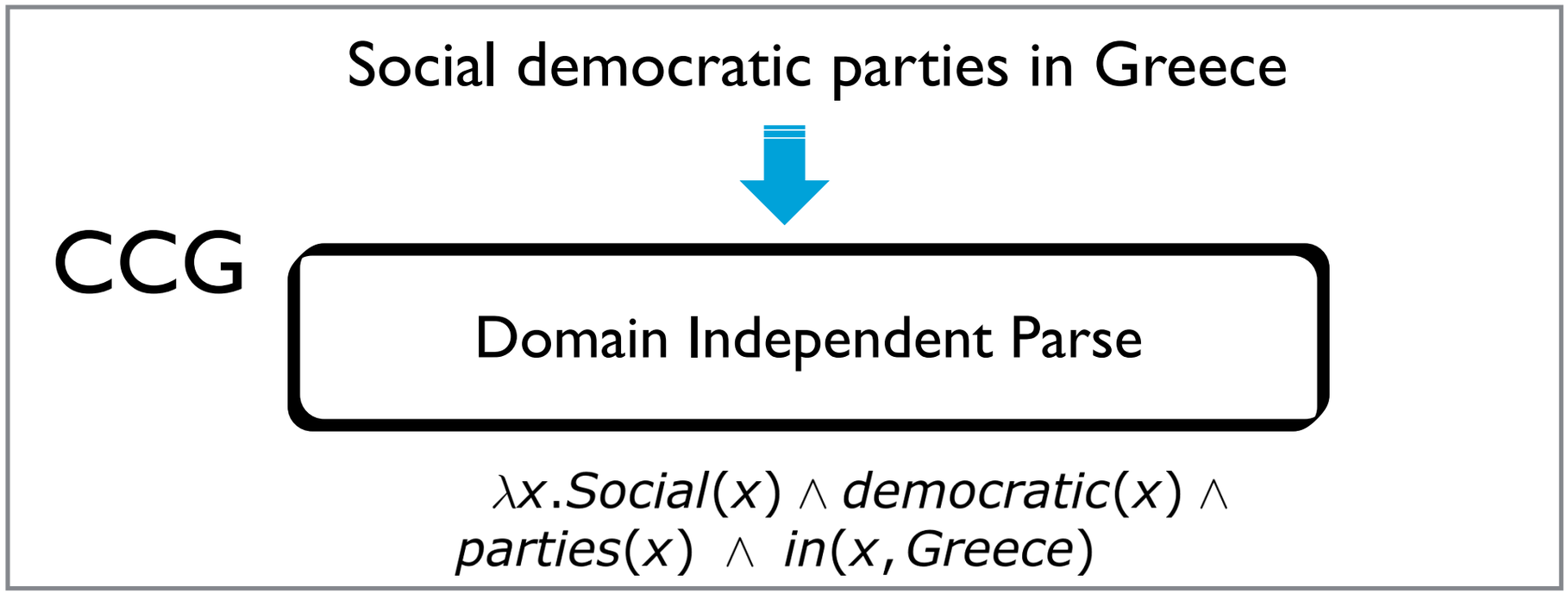
Two-Stage Learning



Small training set with logical form

(*British playwright, novelist and short story writer* , $\lambda x.\texttt{OpenRel\_writer}(x, \texttt{short\_story}) \wedge \texttt{person.profession}(x, \texttt{novelist}) \wedge \texttt{person.profession}(x, \texttt{playwright}) \wedge \texttt{person.nationality}(x, \texttt{united\_kingdom})$) x 500

Two-Stage Learning



Derivations l are scored using a linear model

Highest scoring logical form(l^*) is passed to the second stage

$$\text{score}(l) = \phi_{ccg}(l) \cdot \theta$$

$$l^* = \arg \max_{l \in \text{CCG}(x)} (\theta_p \cdot \phi_p(l))$$

Two-Stage Learning

$\lambda x.Social(x) \wedge democratic(x) \wedge$
$parties(x) \wedge in(x, Greece)$

ONT → Ontology Matcher

$\lambda x.\texttt{political\_party.ideology}(x, \texttt{social\_democratic})$
$\wedge \texttt{political\_party.country}(x, \texttt{greece})$

Freebase is a large, community authored knowledge base with:

- 20,000 Relations
- 10,000 Types
- 100 Domains

Broad Coverage Lexical Statistics : Wikipedia Category dataset

85 K vocabulary

365 K category

2.5 M entity

7 M category-entity pair

Mapping words to Freebase Attribute

Pixar Feature Films
Animation Films from Pixar
Pixar songs

Mapping words to Freebase Attribute

Pixar Feature Films
Animation Films from Pixar
Pixar songs

Ratatouille
Wall-E
Finding Nemo
Toy Story
Monster Inc.
Just keep swimming

Mapping words to Freebase Attribute

Pixar Feature Films
Animation Films from Pixar
Pixar songs

Ratatouille	**(film.production_companies, Pixar)**
Wall-E	(film.film.produced_by, John Lasseter)
Finding Nemo	(film.film.directed_by, John Lasseter)
Toy Story	(film.film.film_festivals, 2011 Anima Mundi)
Monster Inc.	(film.film.starring.actor, Bob Peterson)
Just keep swimming	

Mapping words to Freebase Attribute

Pixar Feature Films

A

Large amount of information
for String - Entity - Freebase attribute alignment

Toy Story
Monster Inc.
Just keep swimming

(film.film.directed_by, John Lasseter)
(film.film.film_festivals, 2011 Anima Mundi)
(film.film.starring.actor, Bob Peterson)

Mapping words to Freebase Attribute

Pointwise Mutual Information(PMI)=

$$\log\left(\frac{P(\text{String, Freebase Attribute})}{P(\text{String})\quad P(\text{Freebase Attribute})}\right)$$

as a feature

Features

Domain Independent Parse

Ontology Match

Parse Features:
CCG Lexicon, Capitalization

String -> Freebase features
Wikipedia Lexical Statistics

Surface Lexical Features
String Match, Stem Match

KnowledgeBase Features

Outline

1. Task and Applications
2. Data
3. Semantic Parser with Partial Ontology
4. Learning
5. *Evaluation*

Experimental Setup

Training Set:

500 annotated Wikipedia Category

Test Set (Manual Evaluation):

500 unseen Wikipedia Category

300 appositives

Baseline:

SVM Classifier trained with annotated logical forms

Applications

	Referring Expression Resolution (QA)	Entity Attribute Extraction (IE)
Input:	Noun Phrase	(Entity, Noun Phrase)
	British playwright, novelist and short story writer	*Somerset Maugham ' British playwright, novelist and short story writer*
Output:	$\lambda x.\texttt{OpenRel\_writer}(x, \texttt{short\_story})$ $\wedge\, \texttt{person.profession}(x, \texttt{novelist})$ $\wedge \texttt{person.profession}(x, \texttt{playwright})$ $\wedge\, \texttt{person.nationality}(x, \texttt{united\_kingdom})$	Entity attributes for Freebase
	Sommerset Maugham	

S. Maugham	Nationality	U.K
S. Maugham	Profession	Novelist
S. Maugham	Profession	Playwright

Evaluation Metric: Referring Expression Resolution

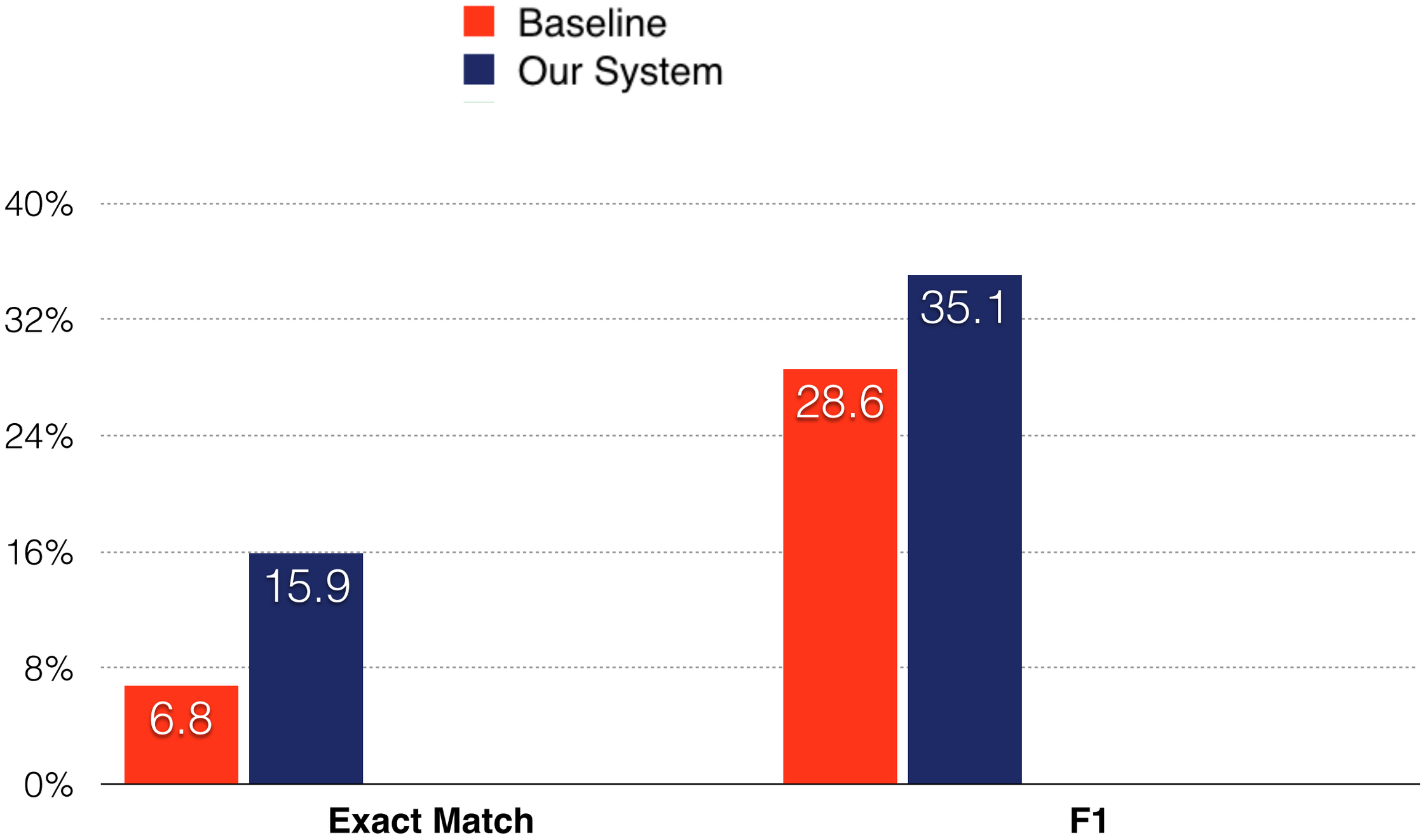
Alternative Rock Groups from Nevada

Gold	music group(x) ∧ music.artist.origin(x, NEVADA) ∧ music.genre.artist(alternative rock, x)	✗ ✓ ✗
Output	music.artist.origin(x, NEVADA) ∧ music.genre.artist(hard rock, x)	✓ ✗

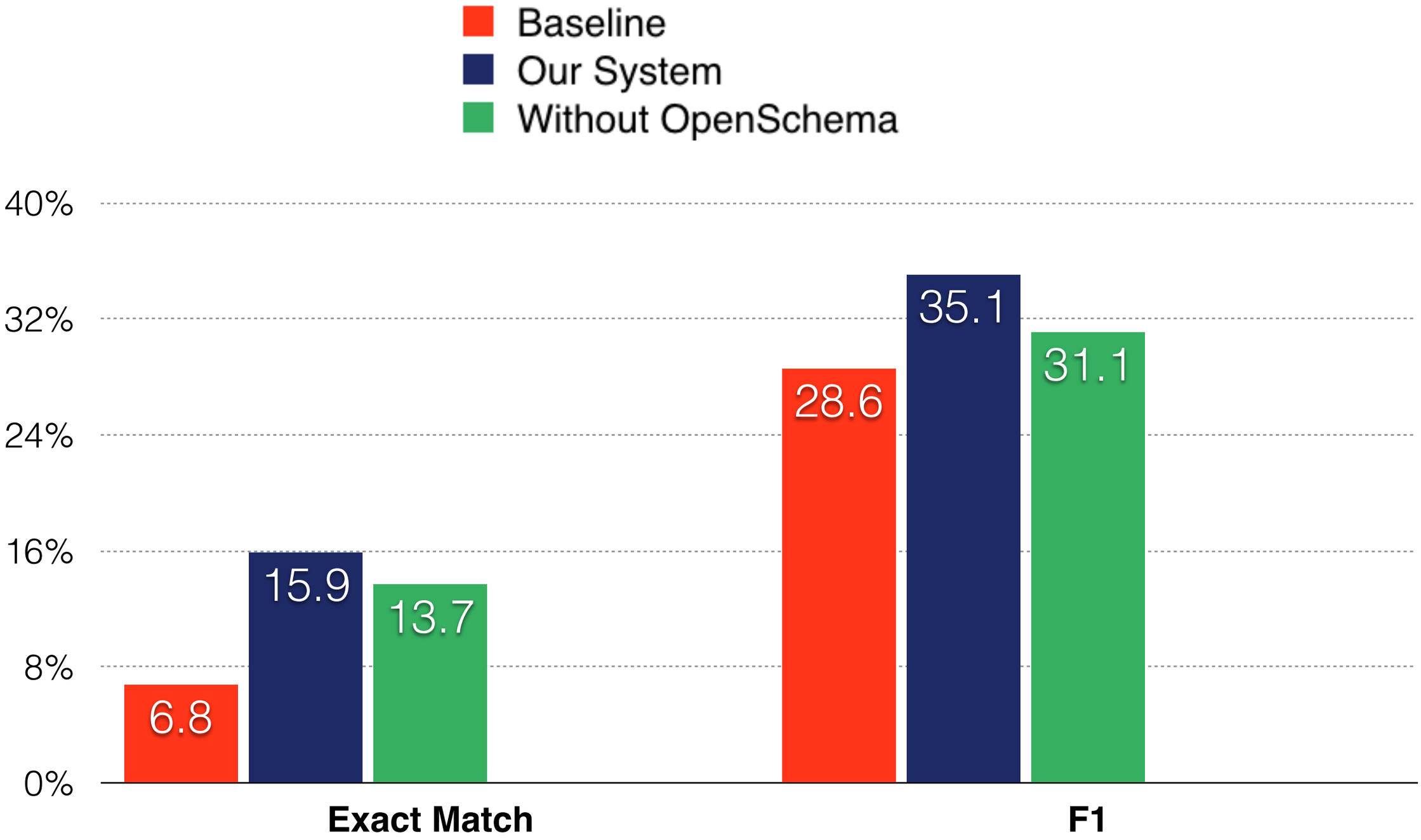
Precision: 0.5 Recall: 0.3 F1:0.375

Exact Match: False

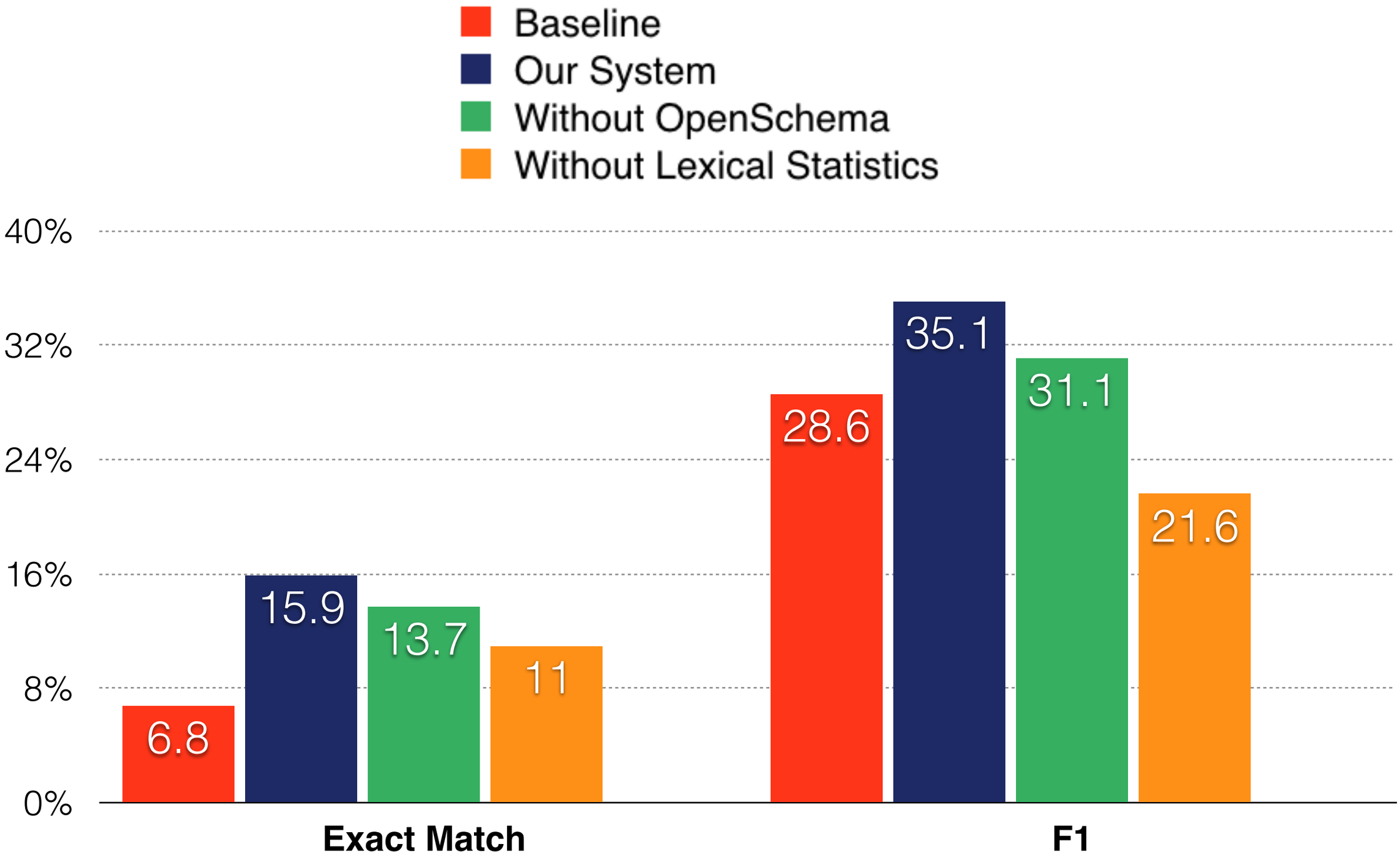
Referring Expression Resolution: (5 fold cross validation on Training Set)



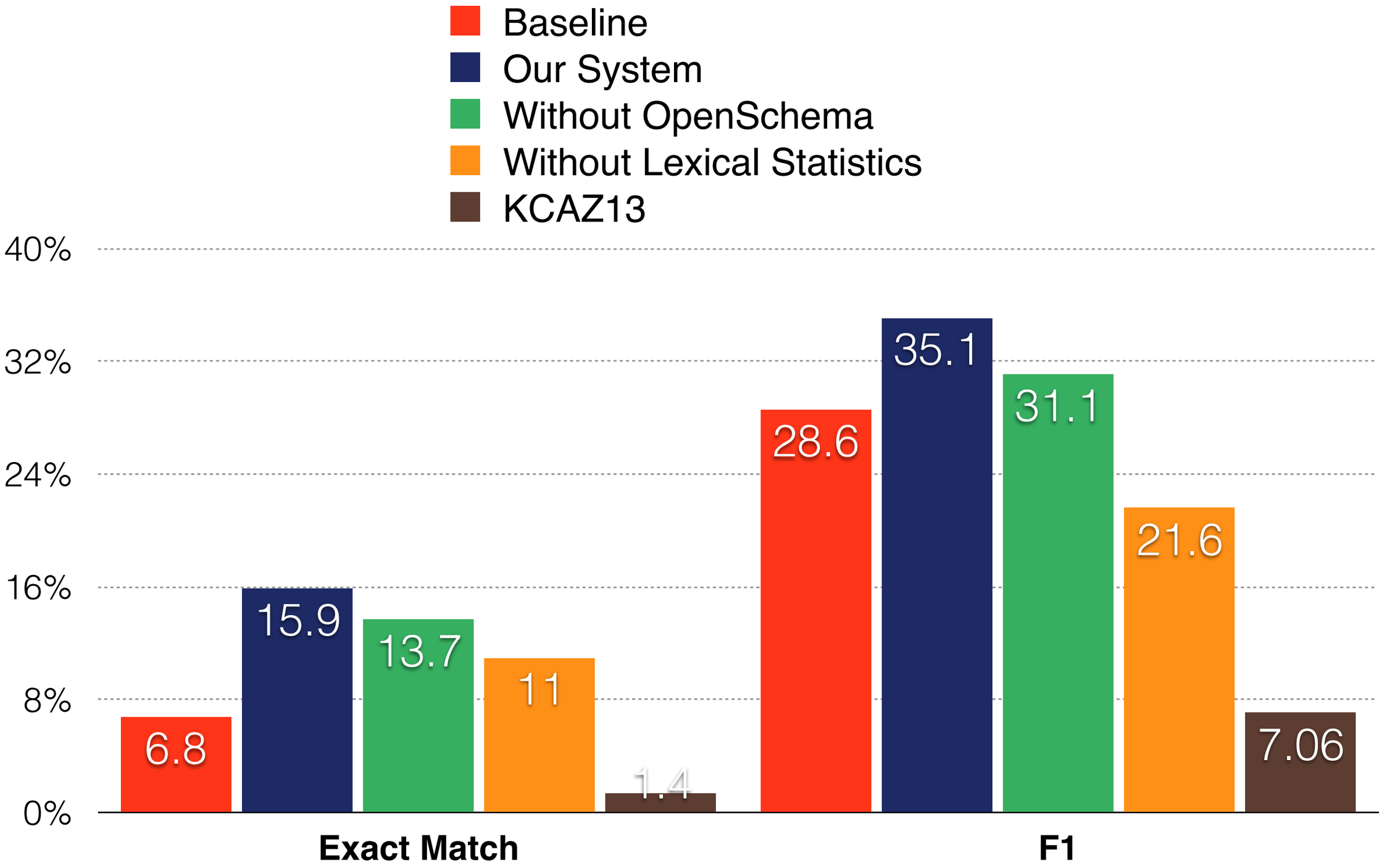
Referring Expression Resolution: (5 fold cross validation on Training Set)



Referring Expression Resolution: (5 fold cross validation on Training Set)



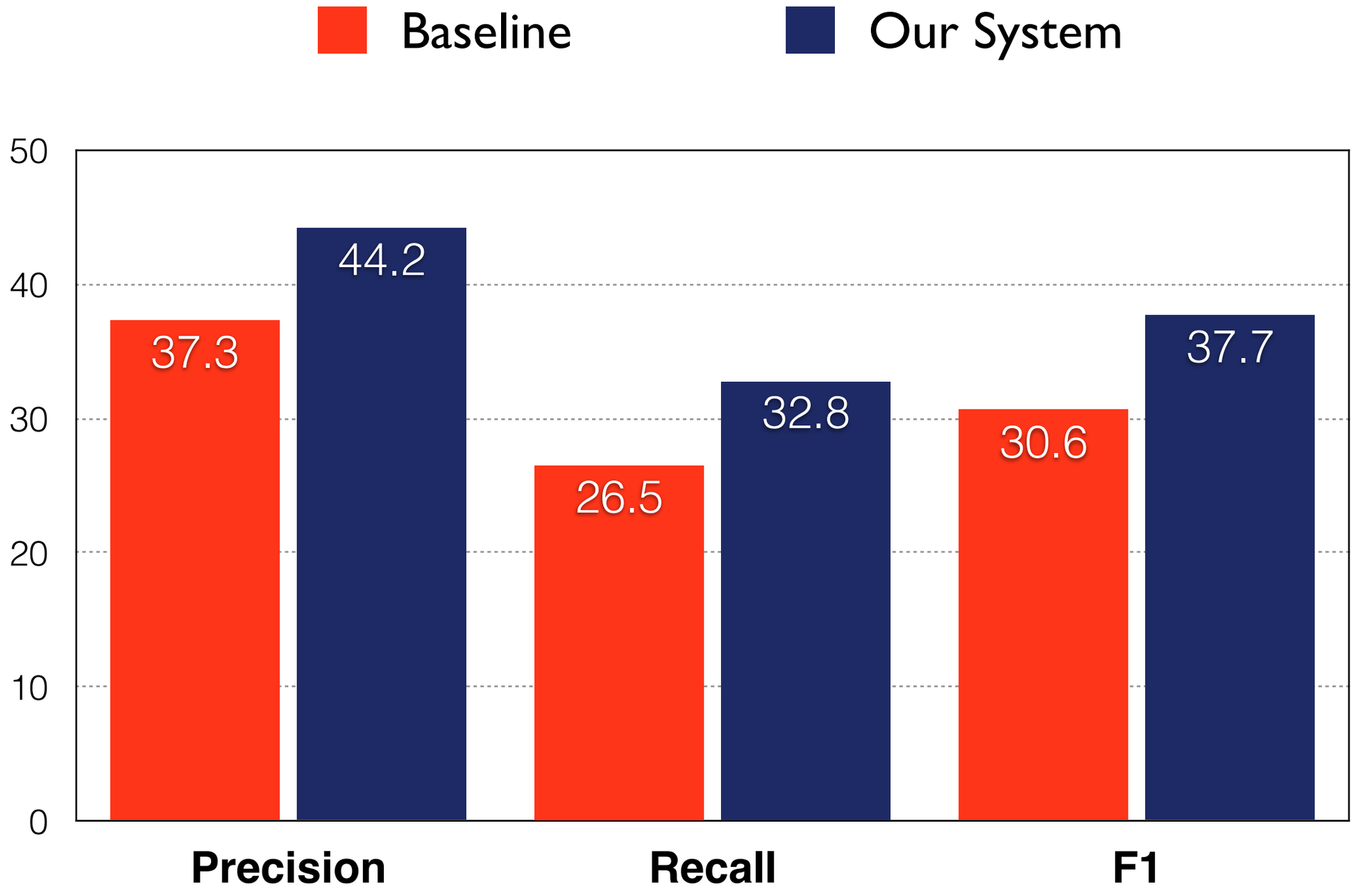
Referring Expression Resolution: (5 fold cross validation on Training Set)



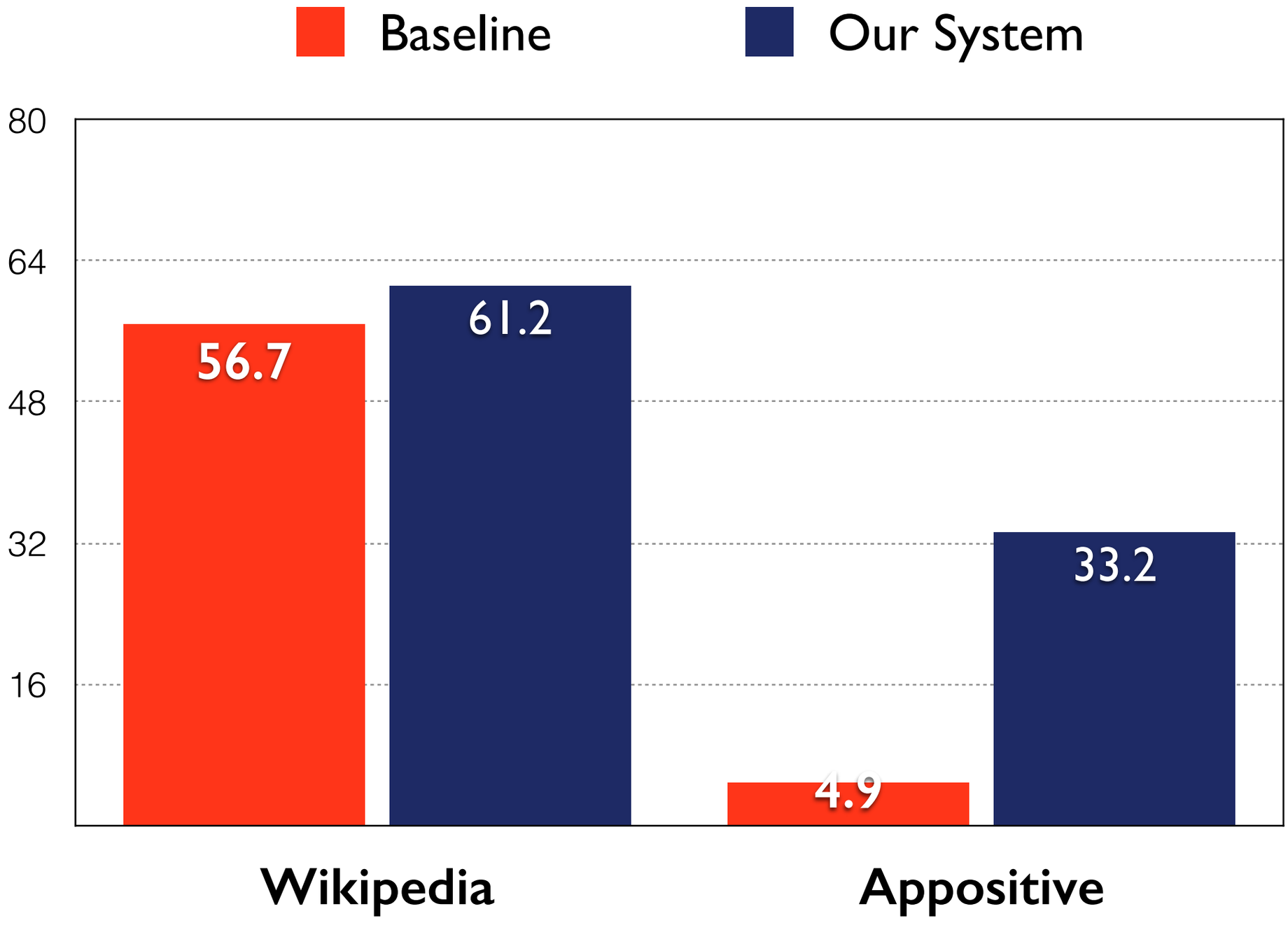
Applications

	Referring Expression Resolution (QA)	**Entity Attribute Extraction (IE)**
Input:	Noun Phrase	(Entity, Noun Phrase)
	British playwright, novelist and short story writer	*Somerset Maugham ' British playwright, novelist and short story writer*
Output:	$\lambda x.\texttt{OpenRel\_writer}(x, \texttt{short\_story})$ $\wedge\, \texttt{person.profession}(x, \texttt{novelist})$ $\wedge \texttt{person.profession}(x, \texttt{playwright})$ $\wedge\, \texttt{person.nationality}(x, \texttt{united\_kingdom})$	Entity attributes for Freebase **(S. Maugham, Nationality, U.K)** **(S. Maugham, Profession, Novelist)** **(S. Maugham, Profession, Playwright)**
	Sommerset Maugham	

Entity Attribute Extraction:
(5 fold cross validation on Training Set)



Entity Attribute Extraction: Test Result



Error analysis

10% : named entity retrieving failure

10% : spurious lexical match

10% : looking at different domain

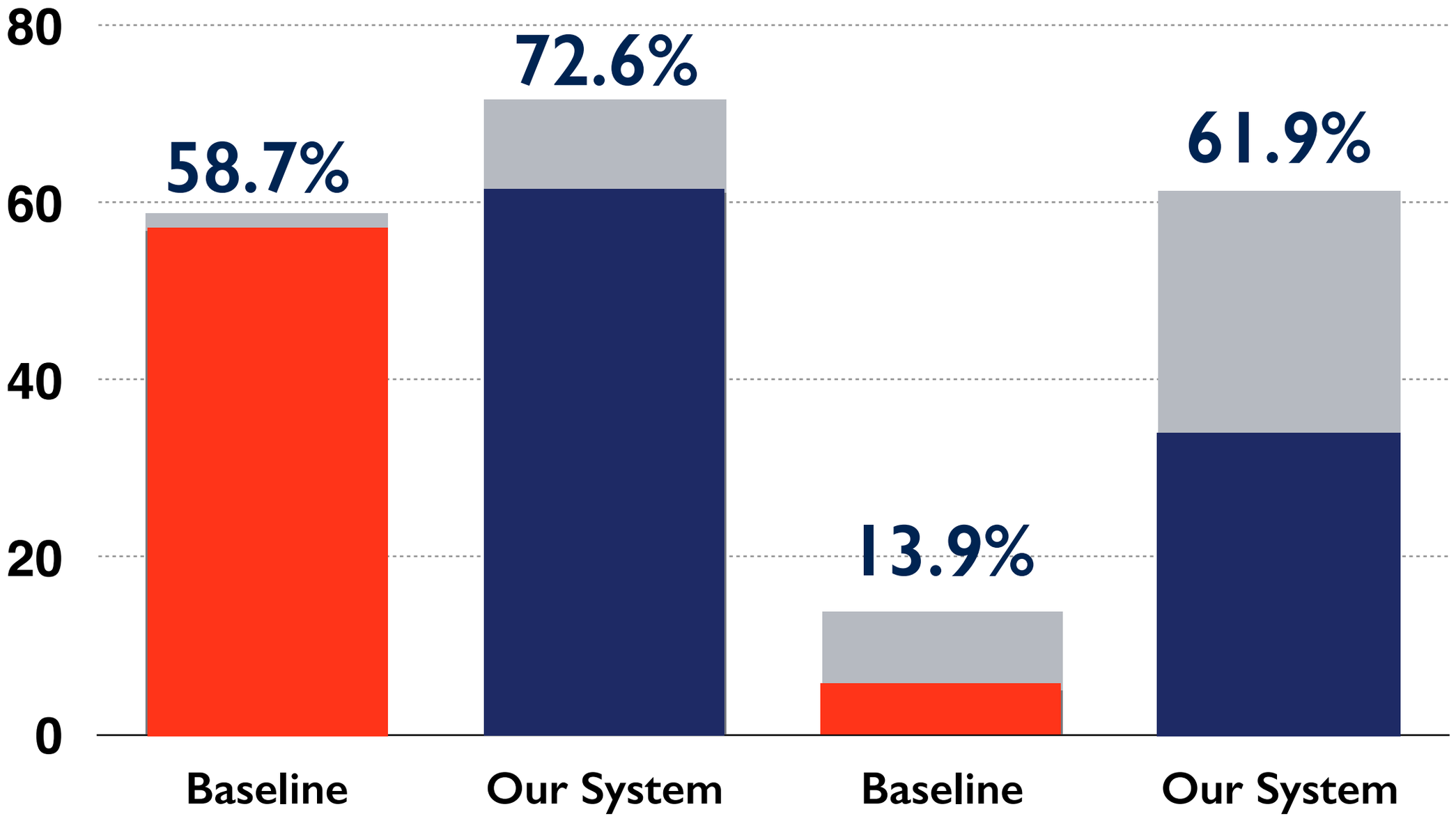
e.g: “stage actor” to “film.actor”

15% : wrong underspecified logical form

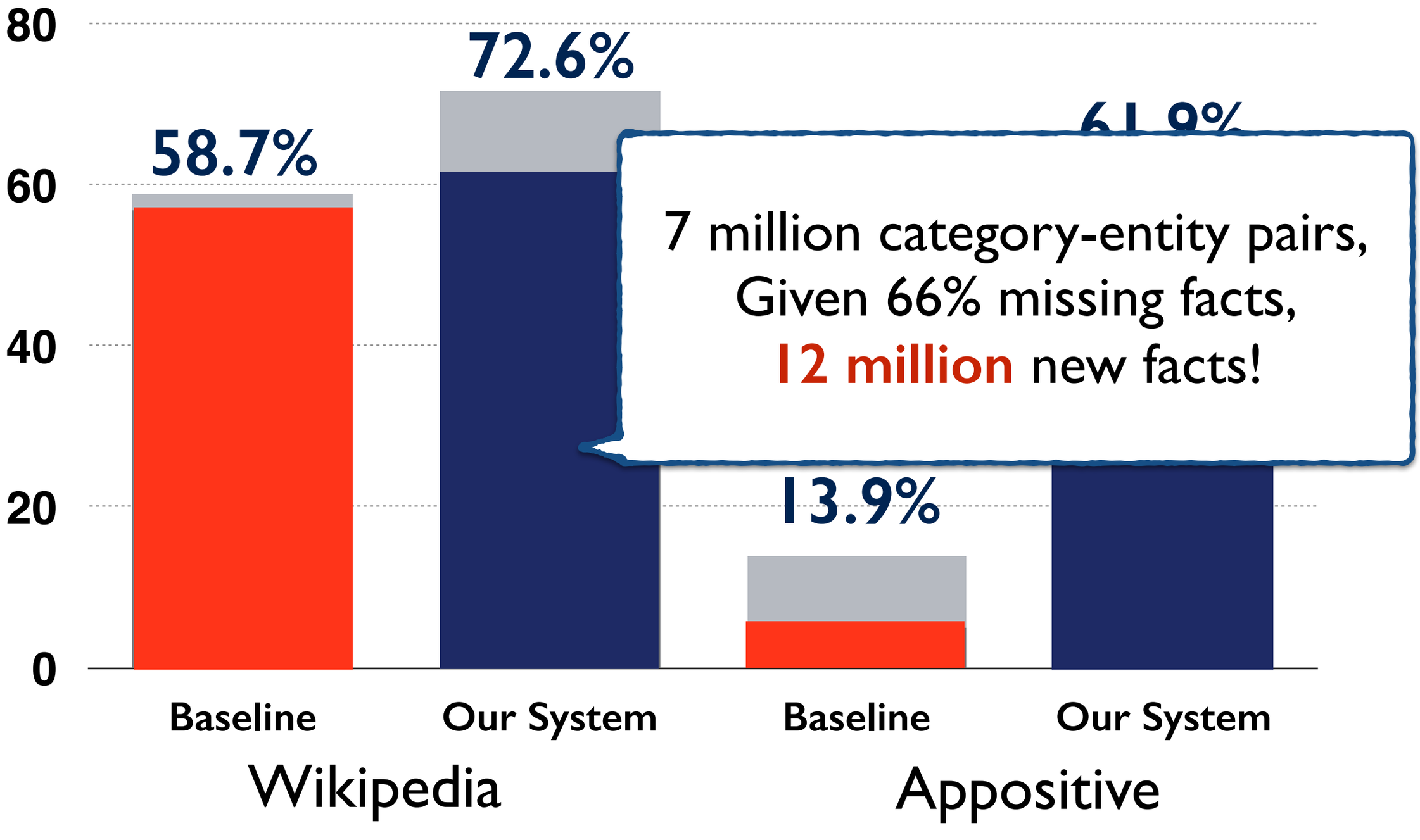
30% : mapping to superset or subset

e.g: “novel” to “book”

Entity Attribute Extraction: Test Result



Entity Attribute Extraction: Test Result



Contributions

- Introduce large-scale semantic parsing datasets
- Partial grounding to large knowledge base
- Learn from two kinds of supervision: large-scale co-occurence statistics and small labeled tuning set

Future work

Barack Hussein Obama is the 44th and current President of the United States, the first African American to hold the office.

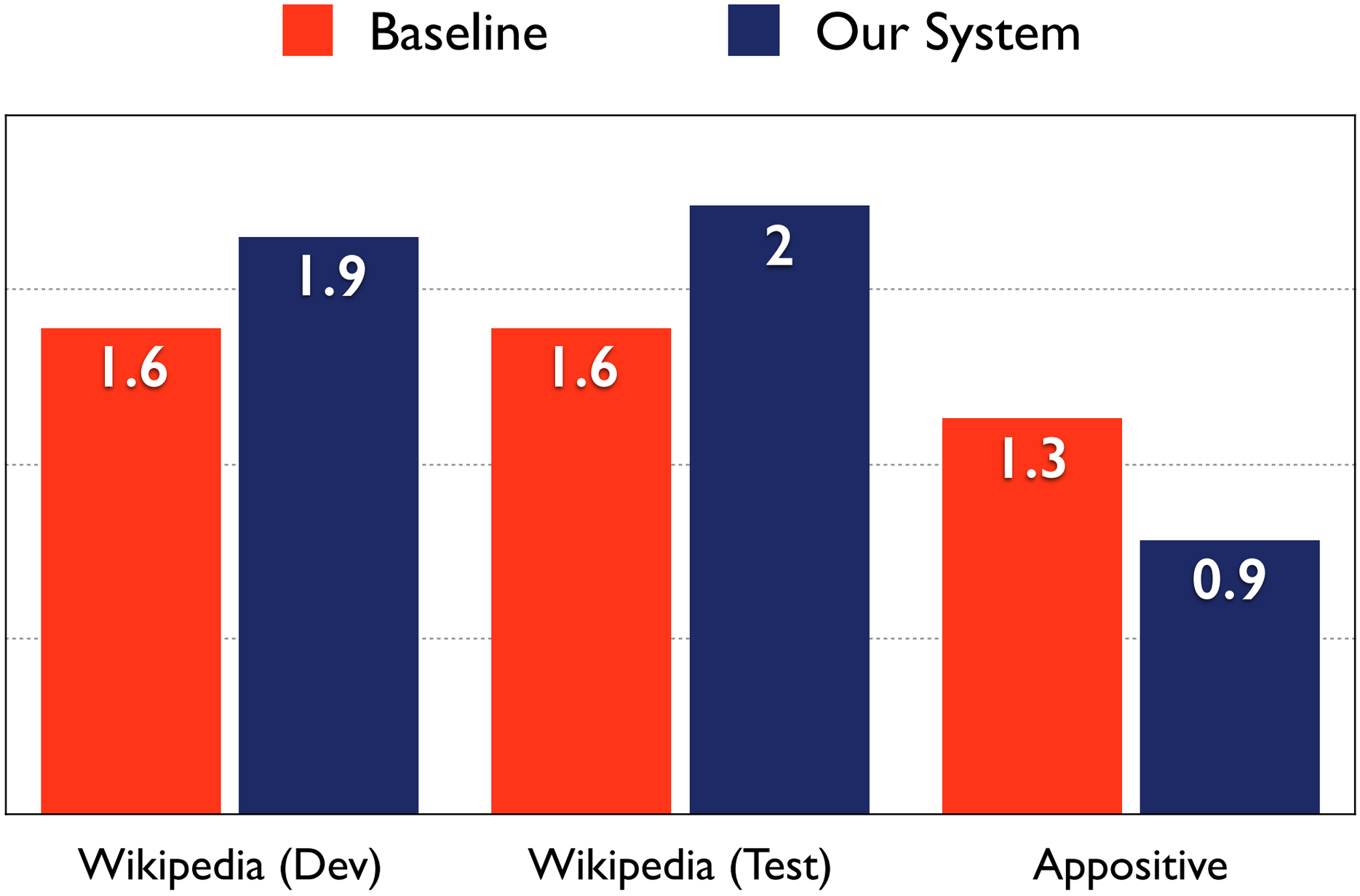
$$\texttt{president\_number}(\texttt{BO}, 44) \wedge \exists \texttt{e}.\texttt{position\_held}(\texttt{BO}, \texttt{e}) \wedge \texttt{office}(\texttt{e}, \texttt{PotUS}) \wedge$$
$$\exists \texttt{t}.\texttt{from}(\texttt{e}, \texttt{t}) \wedge (\texttt{t} < \texttt{NOW}) \wedge \texttt{to}(\texttt{e}, \texttt{NULL}) \wedge \texttt{african\_american}(\texttt{BO}) \wedge$$
$$\nexists \texttt{x} \exists \texttt{e}'.\texttt{position\_held}(\texttt{x}, \texttt{e}') \wedge \texttt{office}(\texttt{e}', \texttt{PotUS}) \wedge \texttt{african\_american}(\texttt{x}) \wedge$$
$$\exists \texttt{t}'.\texttt{from}(\texttt{e}, \texttt{t}') \wedge (\texttt{t}' < \texttt{t})$$

Freebase

- More compositional and complicated structures: orders, comparison, min, max, range
- Extending to declarative sentences

Questions?

The Number of Extracted Facts



Referring Expression Resolution: Test Set