
Coreference Resolution Revisited



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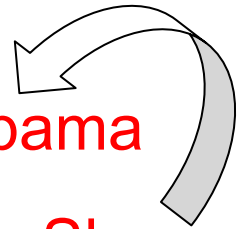
April 19th, 2013

What is it?

Coreference resolution = the task of clustering together of expressions that refer to the same entity/concept.



Michelle LaVaughn Robinson Obama
is an American lawyer and writer. **She**
is the wife of the 44th and current
President of the United States, Barack
Obama, and the first African-American
First Lady of the United States.



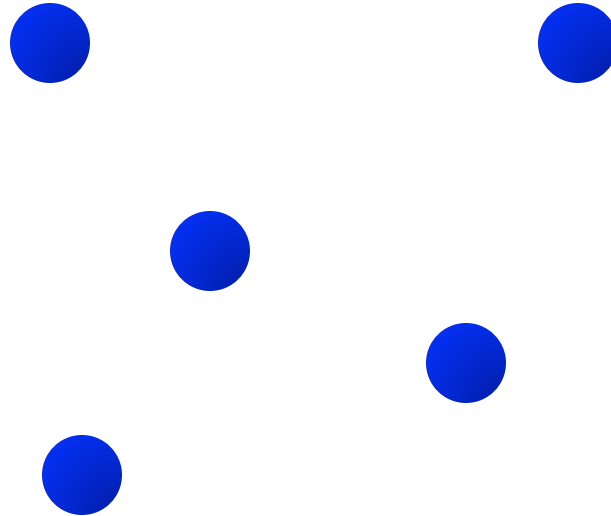
Why is it important?

- Question answering
 - “Who is Barack Obama’s spouse?”
- Information extraction
 - “Find all per:spouse relations between all named entities in this large corpus.”
- News aggregation
 - “What are recent events involving Michelle Obama?”
 - *Requires cross-document coreference resolution. More on this soon.*

Why is it important?

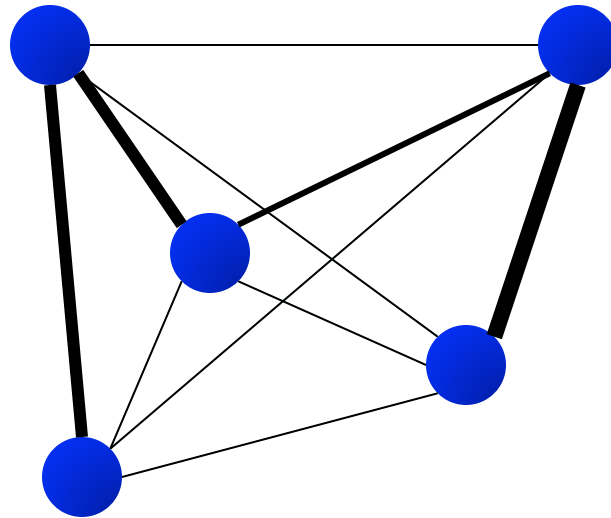
- Performance doubles for these applications when coreference resolution is used.
- See: R. Gabbard, M. Freedman, and R. Weischedel, "Coreference for Learning to Extract Relations: Yes, Virginia, Coreference Matters," ACL 2011.

A typical algorithm



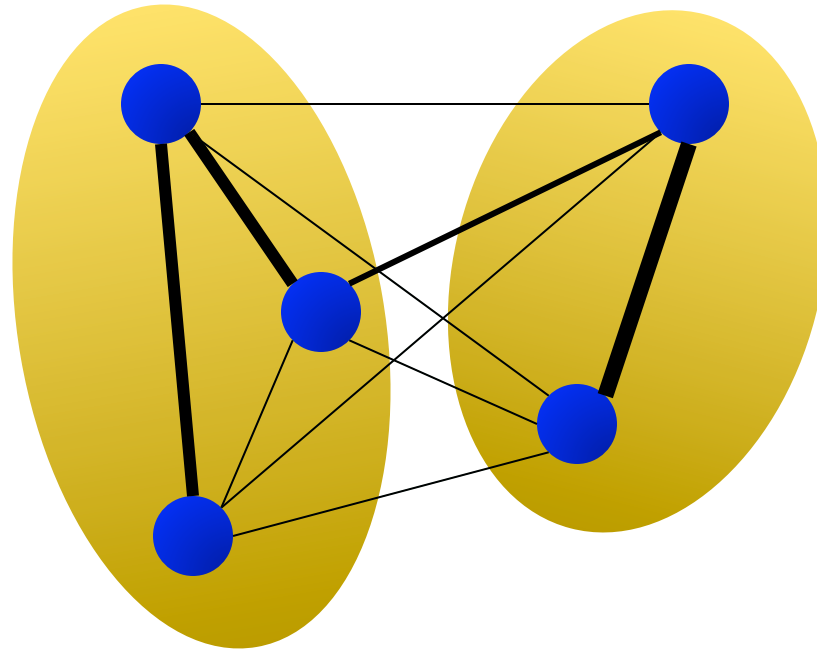
Identify all mentions

A typical algorithm



Compute link scores between all pairs

A typical algorithm



Partition this graph into entity clusters

Some insights learned

- Most algorithms focus on step 2: computing mention-pair scores using machine learning, which is a *local* operation
 - Poor representation of context: only two mentions considered
- Recent work showed that it is important to address coreference resolution as a *global* task, where all mentions are modeled jointly
 - This is hard to model using machine learning
- ML models generalize poorly to new words, domains, and languages
 - Annotating coreference is expensive

Idea I



✗ ~~machine learning~~

✓ deterministic, rule-based model

✓ “baby steps” approach

✓ global model

Entities are only part of the picture

A senior adviser to Mitt Romney lashed out at Barack Obama's re-election campaign Friday, president of waging a campaign based on "us and lies."

"They have gone from what started out as petty distortions and untruths to unbelievable exaggerations that diminish the office of the president and insult the American people," Romney senior adviser Eric Fehrstrom told reporters at a media briefing at the campaign's headquarters.

media briefing at the campaign's headquarters.

media briefing at the campaign's headquarters.

About of a third of the words mention events

Events are fundamental for cross-document news aggregation!

News aggregation is a big business



Prismatic

LinkedIn



Flipboard



Entities help event resolution



Doc 1

The New Orleans Saints placed Reggie Bush on the injured list or Wednesday.

Doc 2

Saints put Bush on I.R.

Events help entity resolution

Doc 1

*One of the key suspected Mafia bosses arrested yesterday **has hanged** himself.*

Doc 2

*Police said **Lo Presti** **had hanged** himself.*

Coreferent events have
coreferent arguments!

Idea II



✓ joint entity and event
coreference model

Overview

- Idea I – rule-based, global entity coreference resolution model
- Idea II – joint entity/event coreference resolution model

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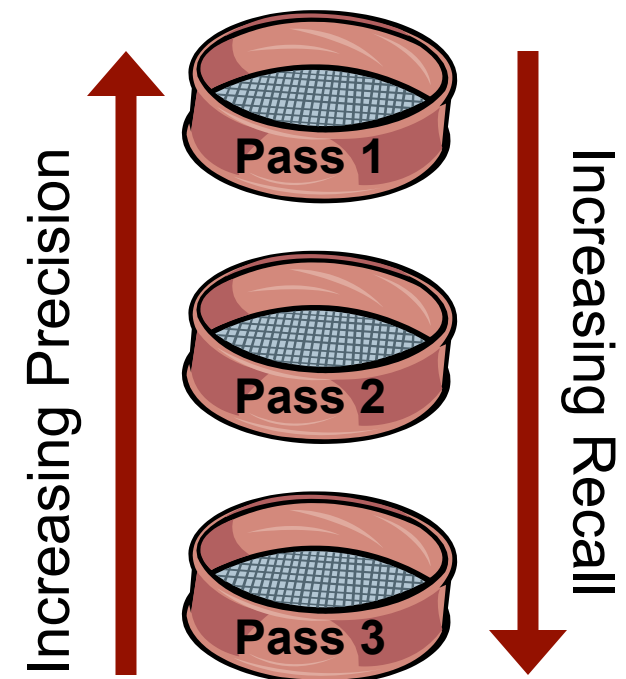
Entity coreference resolution model



- Novel architecture for coreference resolution:
 - **“Baby steps”** – accurate things first
 - **Global** – attribute sharing in clusters
 - **Deterministic** – rule-based model
- Top ranked system at CoNLL-2011 Shared Task:
 - 58.3% (open), 57.8% (closed)

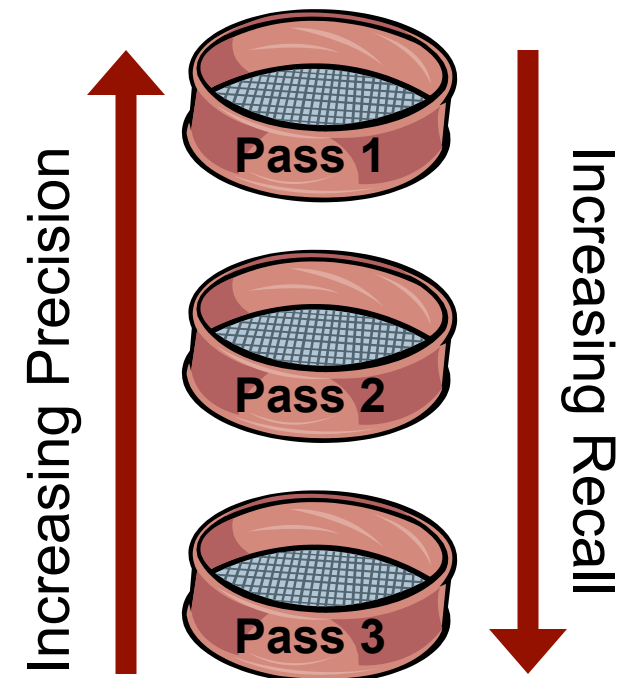
Baby-steps approach

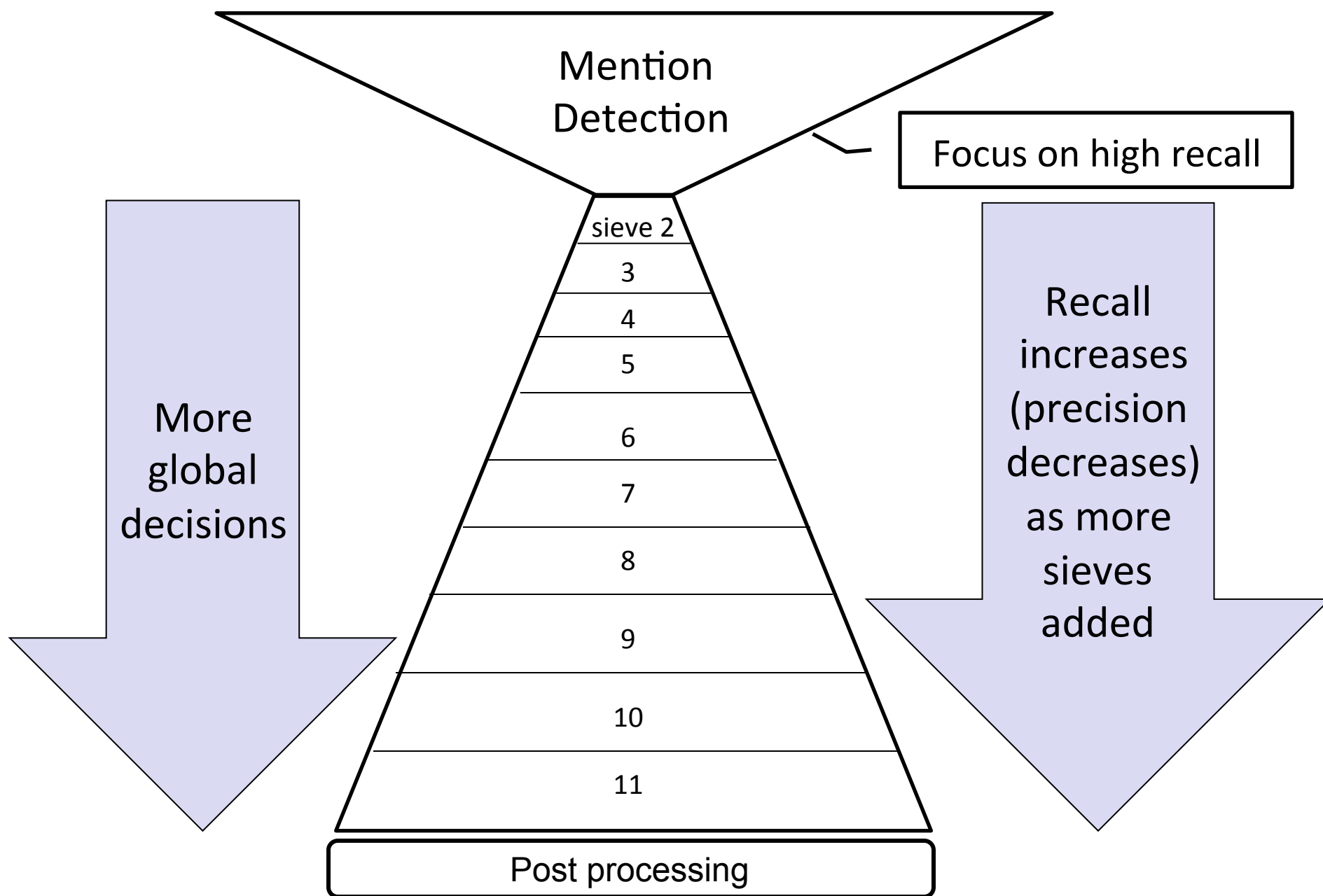
- Multiple passes (or “sieves”) over text
- Precision of each pass is smaller than preceding ones
- Recall keeps increasing with each pass
- Decisions once made cannot be modified by later passes
- Modular architecture



Baby-steps approach

- Multiple passes (or “sieves”) over text
 - Precision > Recall
 - Recall > Precision
 - Decision threshold
 - Modular architecture
- “shaping”
“cautious learning”
“scaffolding”





Why multiple sieves?

number: plural
animacy: animate

number: plural
animacy: unknown

The second attack occurred after some rocket firings aimed, apparently, toward **the israelis**, apparently in retaliation. **we**'re checking our facts on that one. ... the strike will undermine efforts by palestinian authorities to bring an end to terrorist attacks and does not contribute to the security of **israel**.

number: singular
animacy: inanimate

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number: plural, singular
animacy: inanimate

Pass I – Mention detection

- Extract all noun phrases (NP) plus pronouns and named entities even in modifier position
- Remove non-referring expressions, e.g., generic “it”, with manually written patterns
 - *E.g., **It** is possible that...*

Pass 2 – Speaker identification

- Extract speakers and use the info for resolution
 - “....”, *she* **said**.
- Positive and negative constraints for following sieves:
 - “*I* voted for **Nader** because **he** was most aligned with **my** values,” **she** said.

Pass 3 – Exact string match

Exactly the same text:

...**TWA** 's bid for **USAir** skeptically , seeing it as a ploy to pressure **USAir** into buying **TWA**.

The Shahab 3 ground-ground missile: the new addition to Iran's military capabilities ... developed **the Shahab 3 ground-ground missile** for defense purposes with capabilities ranging from ...

Pass 4 – Relaxed string match

String match after dropping the text following the head word:

**...Clinton... Clinton, whose term ends in
January...**

Pass 5 – Precise constructs

Appositives:

... but **Bob Gerson**, **video editor of This Week in Consumer Electronics**, says Sony conceives ...

Predicate nominatives:

Started three years ago, **Chemical's interest-rate options group** was **a leading force** in the field.

Role appositives:

... **[[actress] Rebecca Schaeffer]** ...
... **[[painter] Pablo Picasso]** ...

Pass 5 – Precise constructs

Relative pronouns:

... **[the finance street [which] has already formed in the Waitan district]** ...

Acronyms:

Agence France Presse ... AFP

Demonyms/Gentilics:

Israel... Israeli

Passes 6 – 9: Strict head match

The Japanese company already has 12% of the total camcorder market, ranking it third behind the RCA and Panasonic brands ... The company also plans to aggressively start marketing ... The electronics company...

- Coupled with various constraints:
 - No new information in mentions to be resolved
 - No location mismatch, “Lebanon” != “southern Lebanon”
 - No numeric mismatch, “people” != “around 200 people”
 - No i-within-i, e.g., [[Sony Corporation] of America]

Pass 10 – Relaxed head match

- Same constraints as above but anaphora head can match any word in the candidate cluster

“Sanders”

is compatible with the cluster:

{Sauls, the judge, Circuit Judge N.
Sanders Sauls}

Pass 11 – Pronoun resolution

- Attributes must agree
 - Number
 - Gender
 - Person
 - Animacy
- Assigned using POS tags, NER labels, static list of assignments for pronouns
- Improved further using gender and animacy dictionaries of Bergsma and Lin (2006), and Ji and Lin (2009)

Post processing

- Discard singleton clusters
 - This is why we could maximize recall in mention detection!
- Discard shorter mentions in appositive patterns
- Discard mentions that appear later in copulative relations
- Implemented to comply with OntoNotes annotations

A run-through example

John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.

A run-through example

John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.

A diagram showing a horizontal line with a small peak in the middle, representing a mention detection process. Below the line is a rounded rectangular box containing the text "Mention detection".

Mention detection

A run-through example

John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.

A diagram showing a speaker identification process. It features a white box with a black border and a small triangular shape on top, resembling a speech bubble or a callout. The text "Speaker identification" is centered inside the box.

Speaker identification

A run-through example

John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.

A diagram consisting of a horizontal rectangle with rounded ends, topped by a triangular roof-like shape. The text "String match" is centered within the rectangle.

String match

A run-through example

John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.

A diagram consisting of a horizontal rectangle with rounded ends, and a triangle pointing upwards from its top center. The text "Precise constructs" is centered within the rectangle.

Precise constructs

A run-through example

John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.



Strict head match

A run-through example

John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.



Pronoun resolution

A run-through example

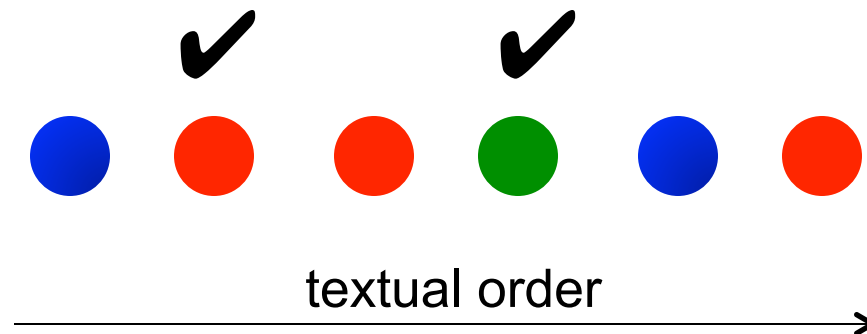
John is a musician. He played a new song. A girl was listening to the song. “It is my favorite,” John said to her.

A white rectangular box with a black border and rounded corners, containing the text "Post processing".

Post processing

Mention selection in a given sieve

- In each sieve, we consider for resolution only mentions that are currently first in textual order in their cluster.
- Most informative!



Features are shared within clusters

- Within a cluster:
 - Union of all modifiers
 - Union of all head words
 - Union of all attributes: number, gender, animacy
- Robustness to missing/incorrect attributes

“a group of students”

number: singular

“five students”

number: plural

number: singular, plural

EXPERIMENTS

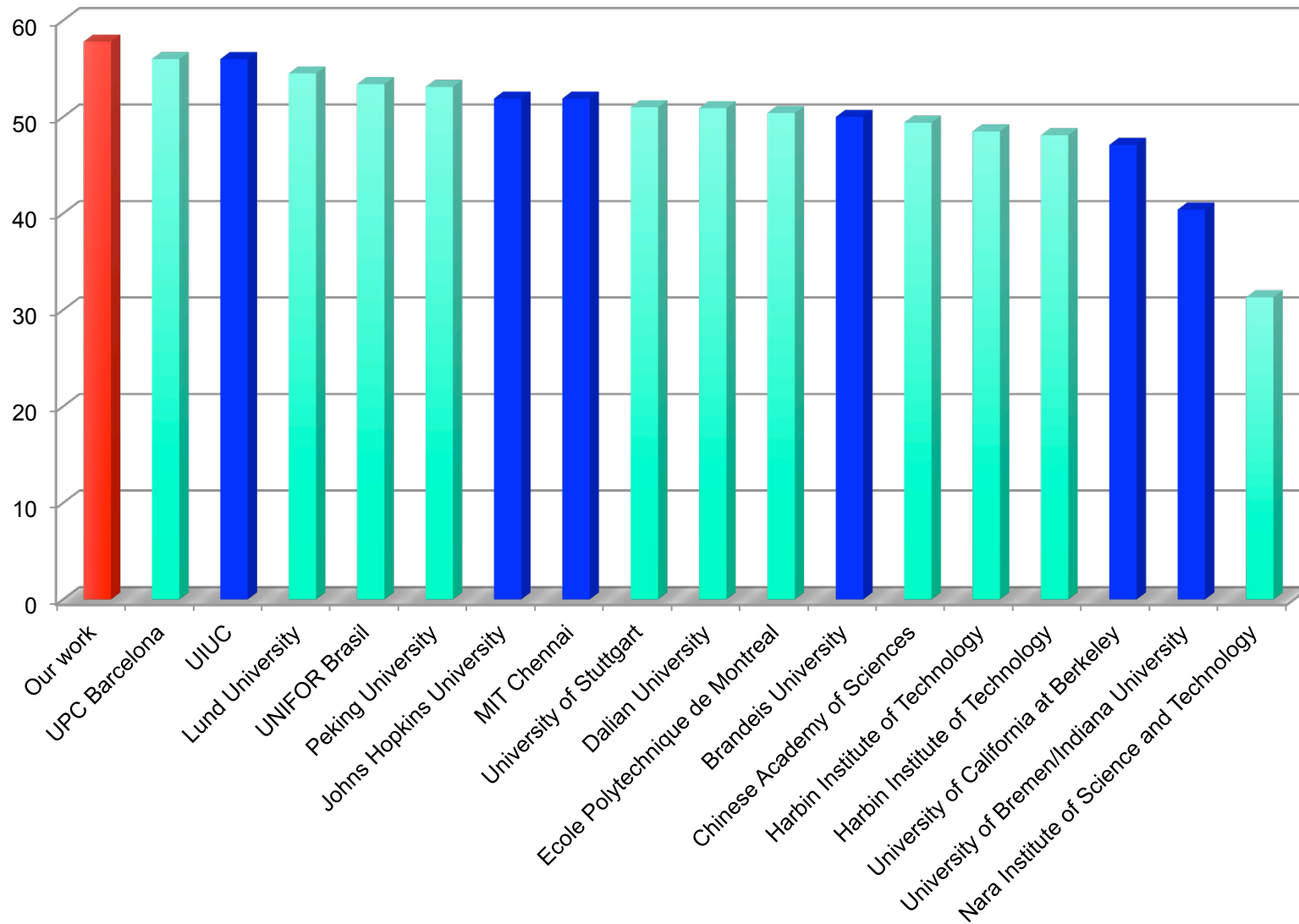
Results on older corpora

UNSUPERVISED	ACE 2004 Test	ACE NWIRE	MUC6
This work	81	80.2	74.4
Haghighi and Klein (2009)	79.0	76.9	75.0

SUPERVISED	Ace 2004 Test	ACE NWIRE	MUC6
Culotta et al. (2007)	79.3	-	-
Bengston and Roth (2008)	80.8	-	-
Finkel and Manning (2008) +G	-	74.5	64.3

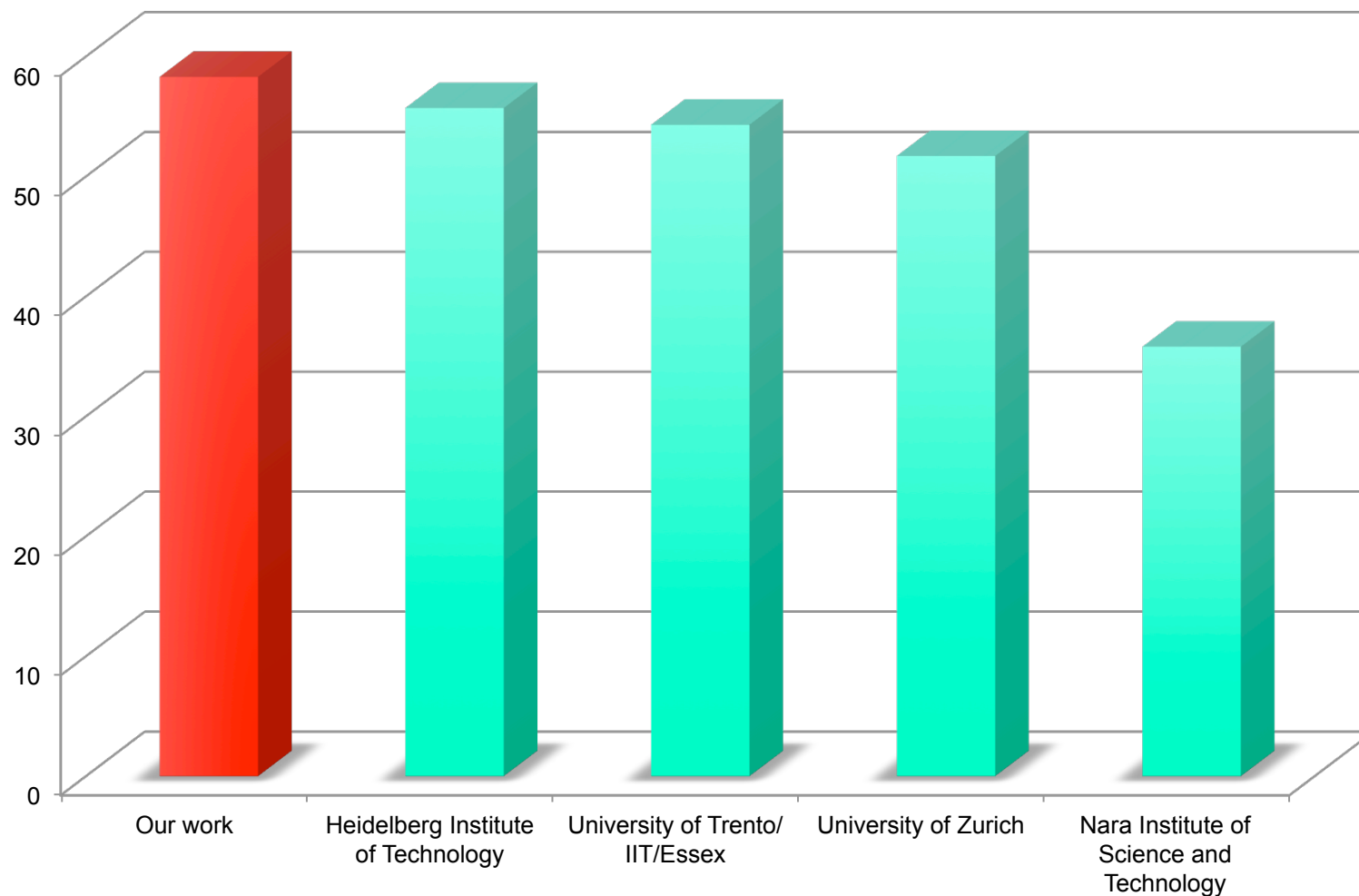
B³ F1 scores of different systems on standard corpora

Results: CoNLL-2011 closed track



$$\text{CoNLL score} = (\text{MUC F1} + \text{B}^3 \text{ F1} + \text{CEAF F1}) / 3$$

Results: CoNLL-2011 open track



$$\text{CoNLL score} = (\text{MUC F1} + \text{B}^3 \text{ F1} + \text{CEAF F1}) / 3$$

CoNLL-2012 shared task



- **Multilingual** unrestricted coreference resolution in OntoNotes
 - English, Chinese, Arabic
 - Higher barrier of entry
 - 16 submissions vs. 23 submissions in 2011
 - But there was significant progress
 - Best score for English increased from 58.3 to 63.4
-

CoNLL-2012 shared task

- Two out of the top three systems used our system
 - Fernandes et al., PUC/IBM Brazil
 - Adapted our system to Chinese and Arabic
 - Reranked the output of our system
 - **Best system overall**
 - Chen and Ng, UT Dallas
 - Adapted our system to Chinese and Arabic
 - Added two ML-based sieves to our system
 - **Best for Chinese**, top 3 overall
 - Proof that our approach is multilingual
-

Analysis: Importance of sharing features

Entity-centric model	59.3
Mention-pair model	55.9

CoNLL F1 in OntoNotes Dev

Analysis: Importance of multiple sieves

Multi-pass model	59.3
Single-pass model	53

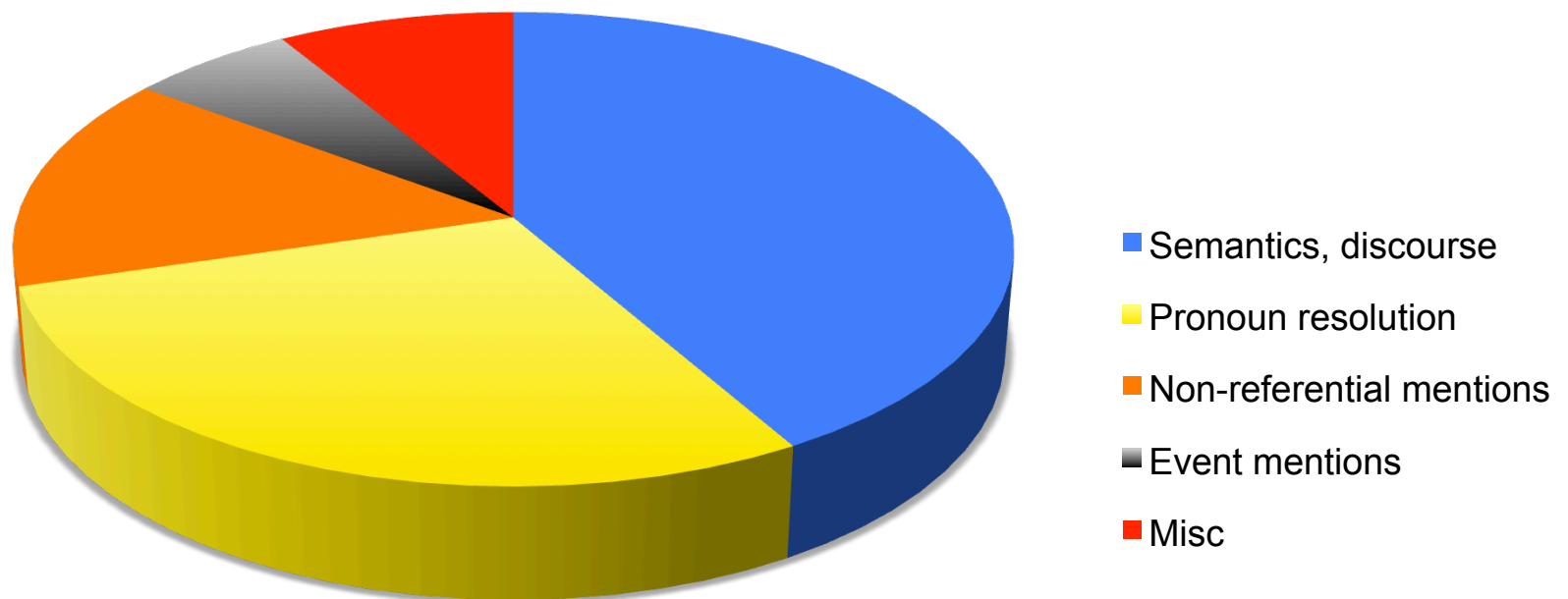
CoNLL F1 in OntoNotes Dev

Analysis: Importance of features

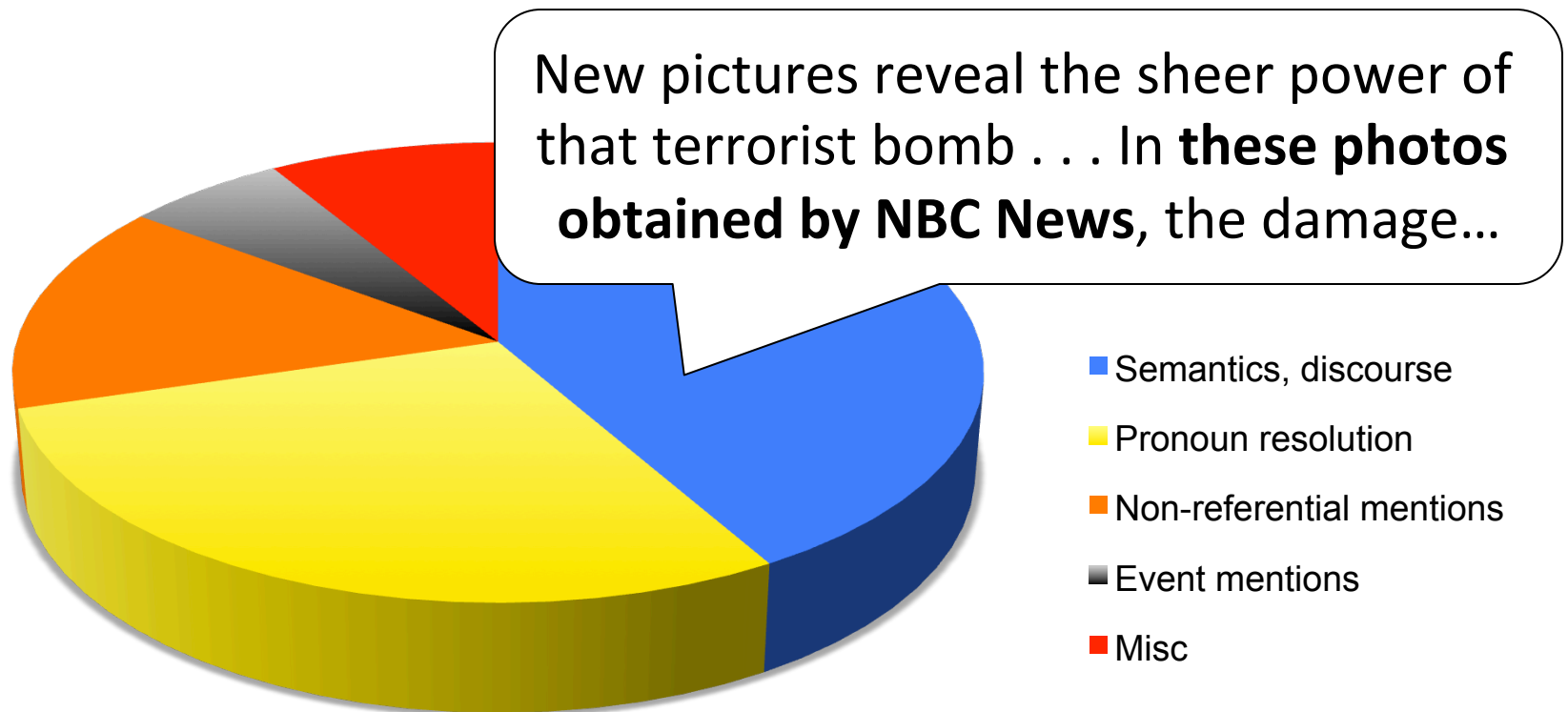
Complete	59.3	
wo/ Number	56.7	- 2.6
wo/ Gender	58.9	- 0.4
wo/ Animacy	58.3	- 1.0
wo/ NE	58.8	- 0.5

CoNLL F1 in OntoNotes Dev

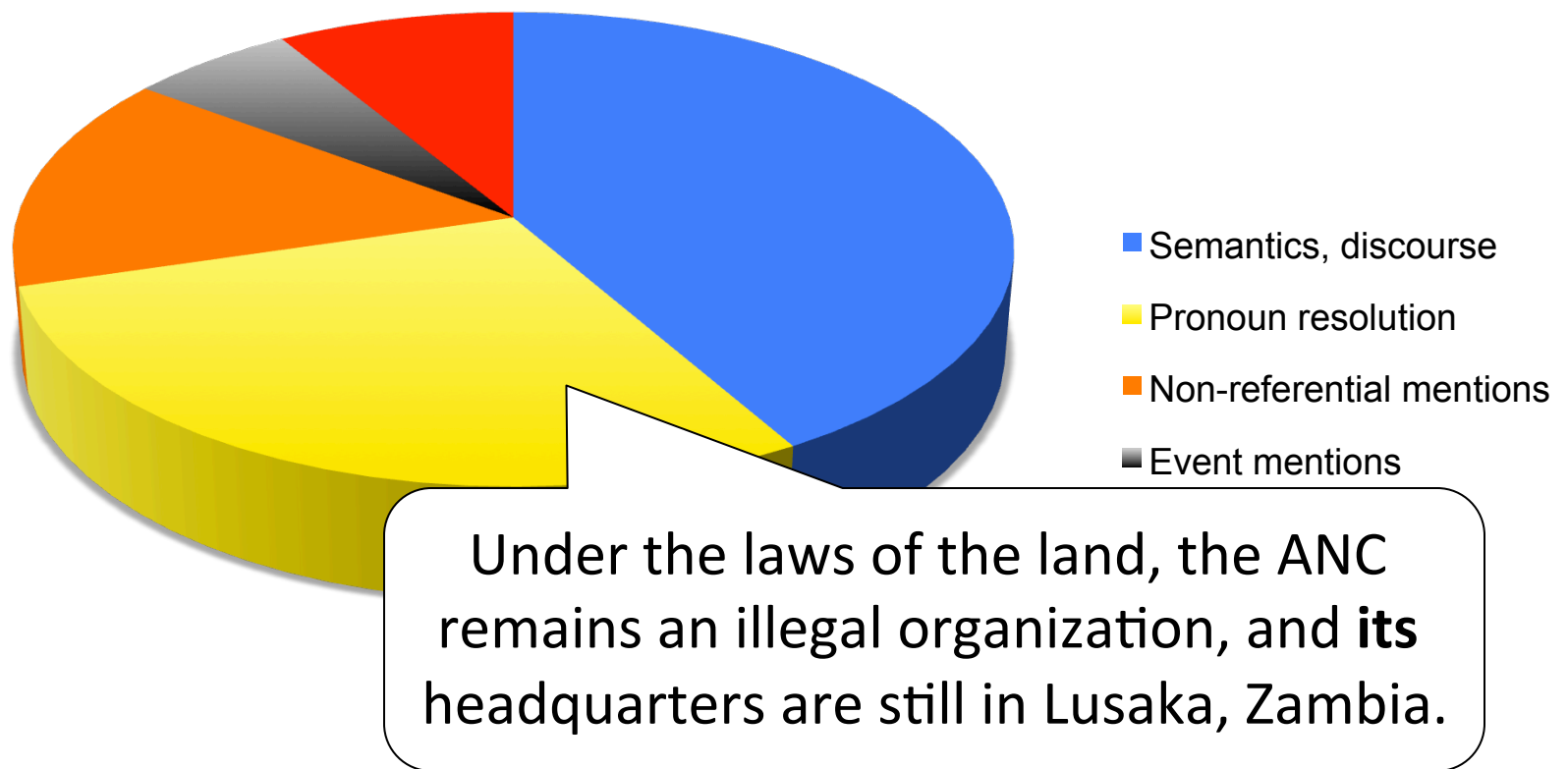
Error analysis



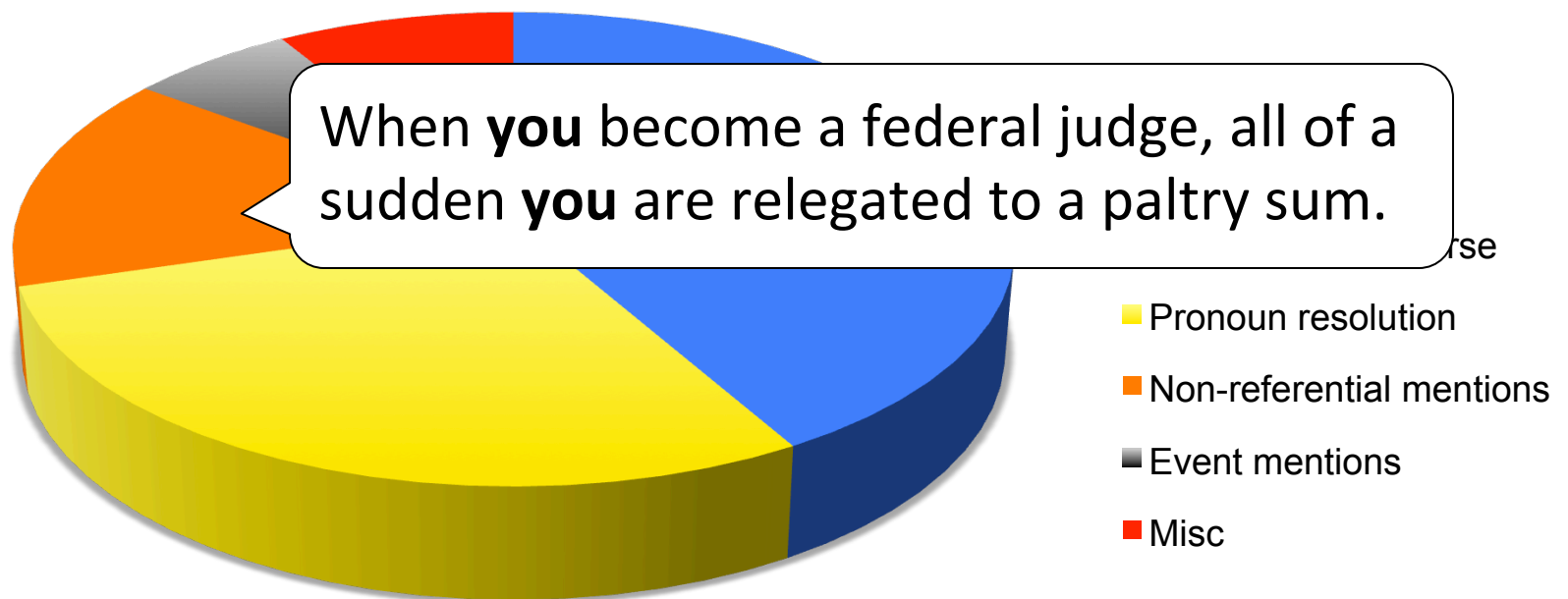
Error analysis



Error analysis

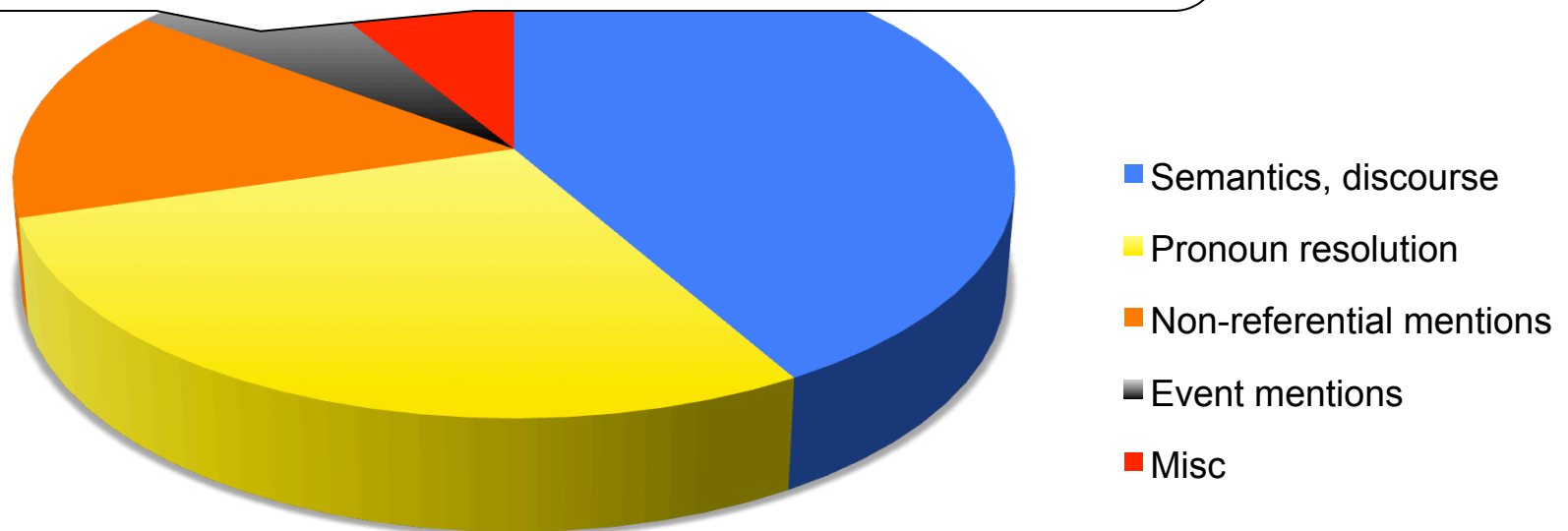


Error analysis



Error analysis

“Support the troops, not the regime” **That** ’s a noble idea until you’re supporting the weight of an armoured vehicle on your chest.



Idea I: Conclusions

- Novel architecture for coreference resolution
 - “Baby steps”
 - Global
 - Deterministic
 - State of the art results (in multiple languages)
 - Best at CoNLL-2011
 - Two of the top 3 systems at CoNLL-2012 used it
-

Overview



- Idea I – rule-based, global entity coreference resolution model
- Idea II – joint entity/event coreference resolution model

Cross-document event coreference

Doc 1

AMD announced the largest acquisition on Monday, paying about \$5.4 billion to acquire ATI Technologies.

Doc 2

Advanced Micro Devices announced its intention to buy ATI Technologies for \$5.4 billion on Monday.

Entities help event resolution



Doc 1

The New Orleans Saints placed Reggie Bush on the injured list or Wednesday.

Doc 2

Saints put Bush on I.R.

Events help entity resolution

Doc 1

*One of the key suspected Mafia bosses arrested yesterday **has hanged** himself.*

Doc 2

*Police said **Lo Presti** **had hanged** himself.*

Coreferent events have
coreferent arguments!

Objectives

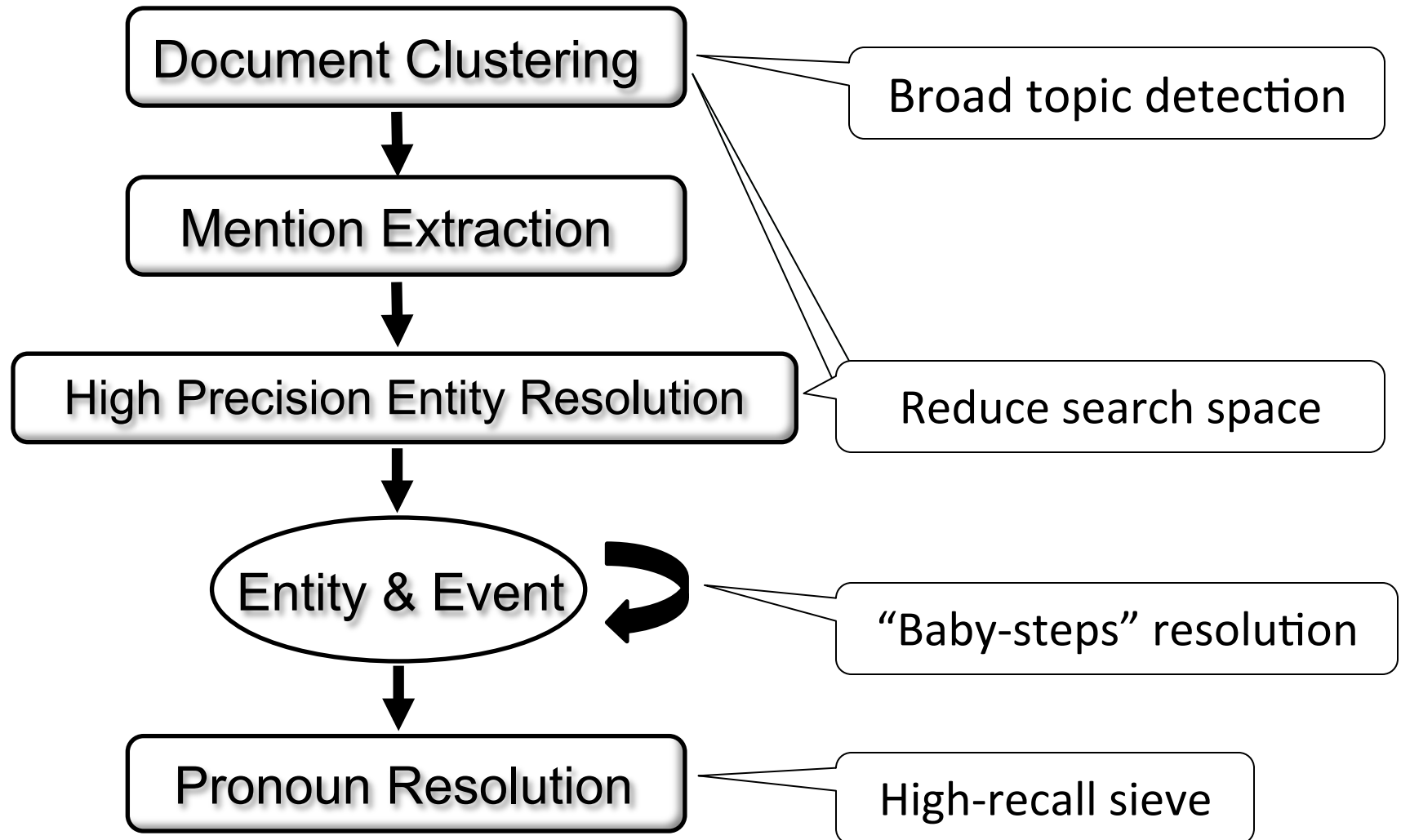


- Goal
 - Holistic approach to coreference resolution: entities and events should be resolved *jointly* and *transparently*
 - Cross document
 - Research questions
 - Does entity coreference help event coreference and vice versa?
 - Which features/model are best for this task?
-

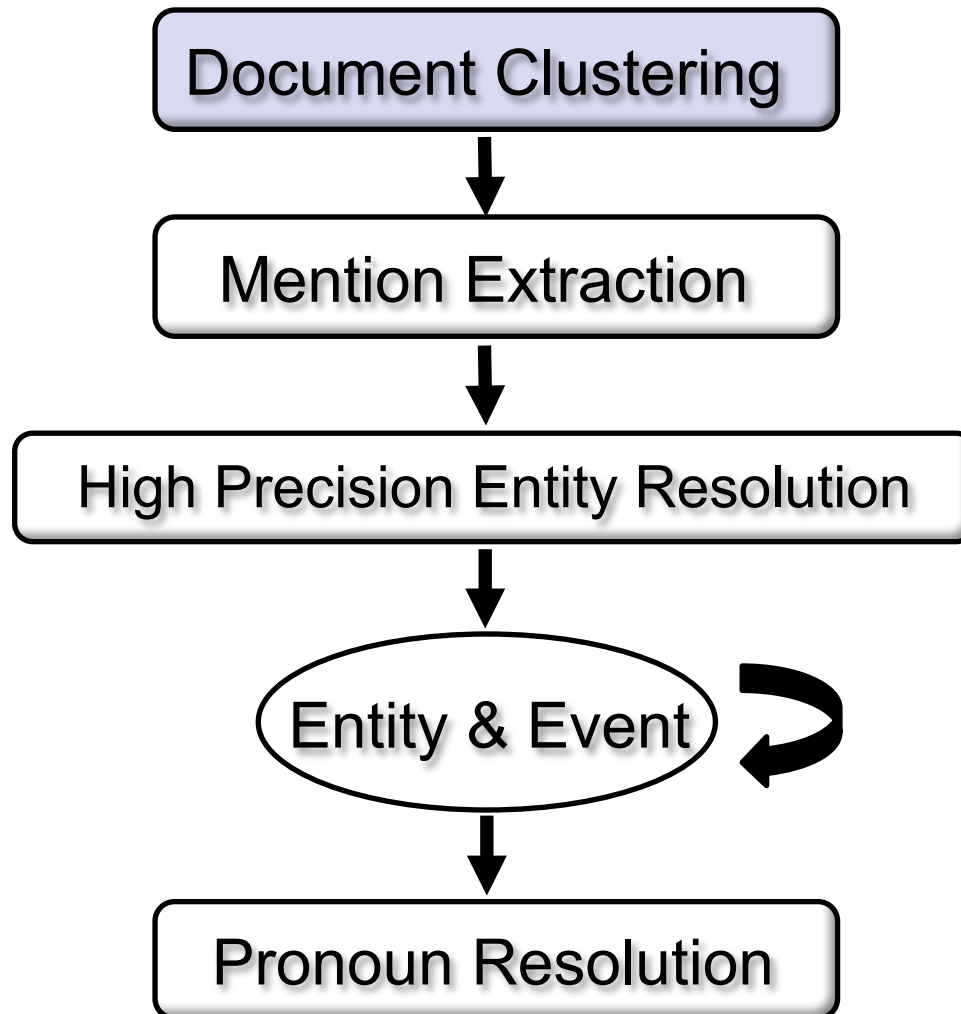
Previous work

- Mostly about entity coreference
 - Ponzetto and Strube, 2006; Haghighi and Klein, 2009; Stoyanov et al., 2009; Haghighi and Klein, 2010; Raghunathan et al., 2010; Rahman and Ng, 2011
- A few about event coreference
 - Humphreys et al., 1997; Bagga and Baldwin, 1999; Chen and Ji, 2009; Bejan and Harabagiu, 2010
- Almost none on joint entity and event coreference
 - He 2007 – medical domain, focused on five semantic categories

Architecture



Document clustering



Document clustering

- Reduces search space
 - Subsequent steps only work within a given cluster
- It provides a word sense disambiguation based on corpus-wide topics
 - *hit* in *earthquake reports* vs. *criminal reports*
- Non-parametric clustering model (Surdeanu et al., 2005)
 - EM variant
 - Initial points and number of clusters chosen using geometric heuristics

Example of document clustering

Doc 1

AMD announced the largest acquisition on Monday, paying about \$5.4 billion to **acquire** **ATI Technologies**.

Doc 2

Advanced Micro Devices announced its intention to **buy** **ATI Technologies** for \$5.4 billion on Monday.

Topic 1

Doc 3

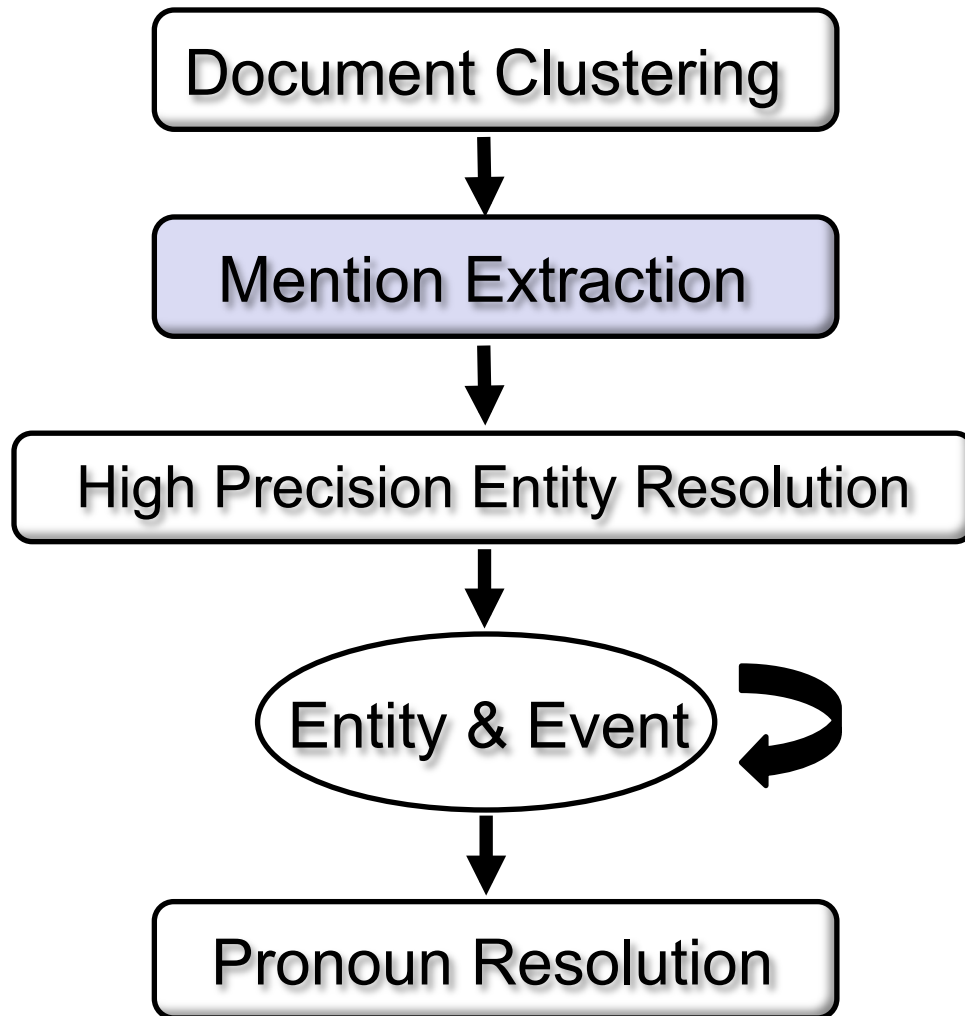
... **at least 40 people** were **injured** in the earthquakes ...

Doc 4

A series of powerful earthquakes ... **injuring dozens** and destroying ...

Topic 2

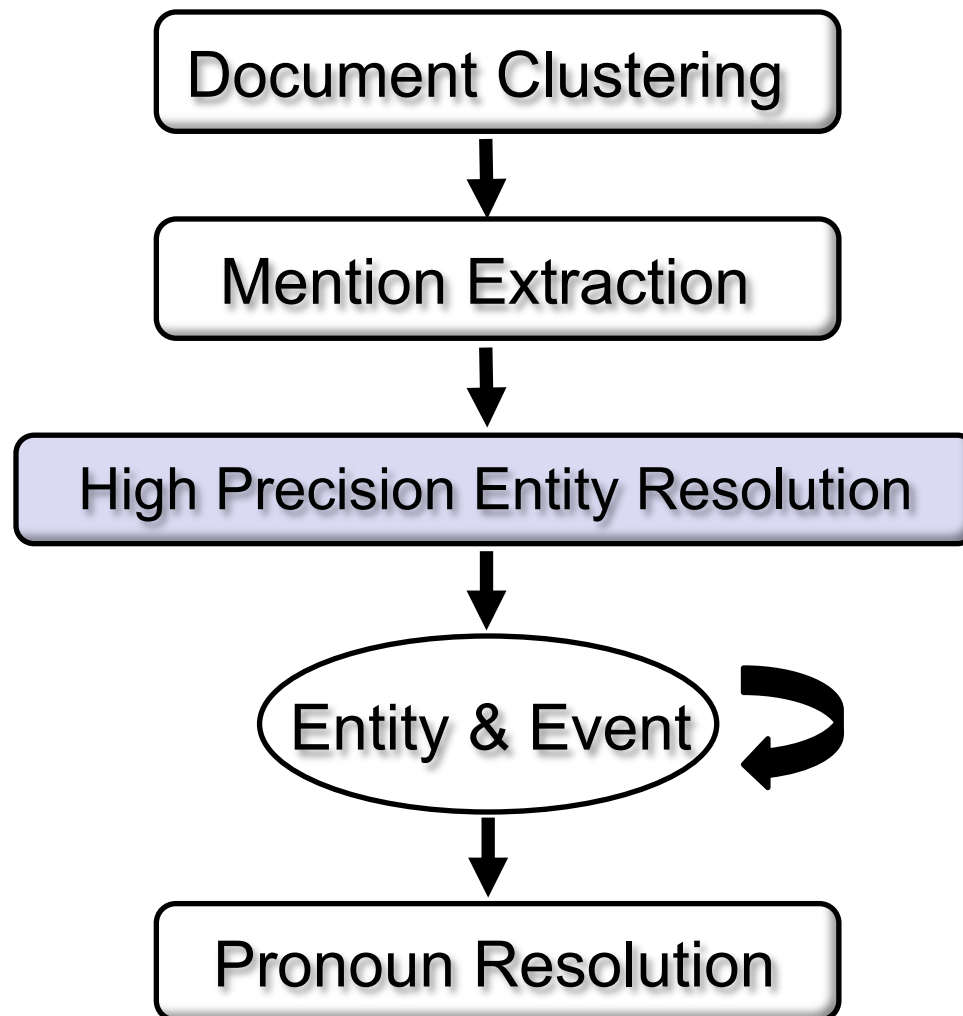
Mention extraction



Mention extraction

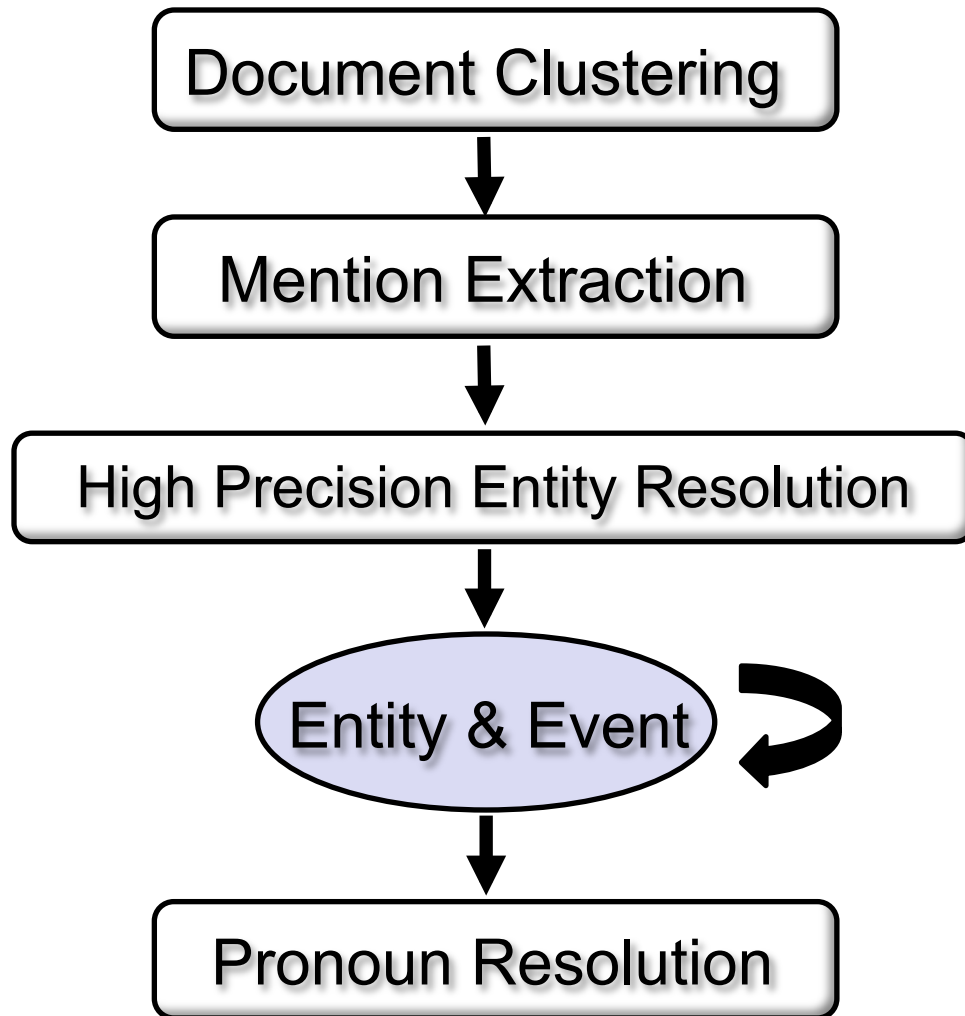
- Nominal: same as the previous system
- Verbal: all VB* - some auxiliary/copulative verbs (e.g., “have”, “be”, “seem”)
- Note: events do appear as nominal mentions!
 - Hard to distinguish between nominal entity and event mentions
 - Our system transparently handles entity and event mentions

High-precision entity resolution

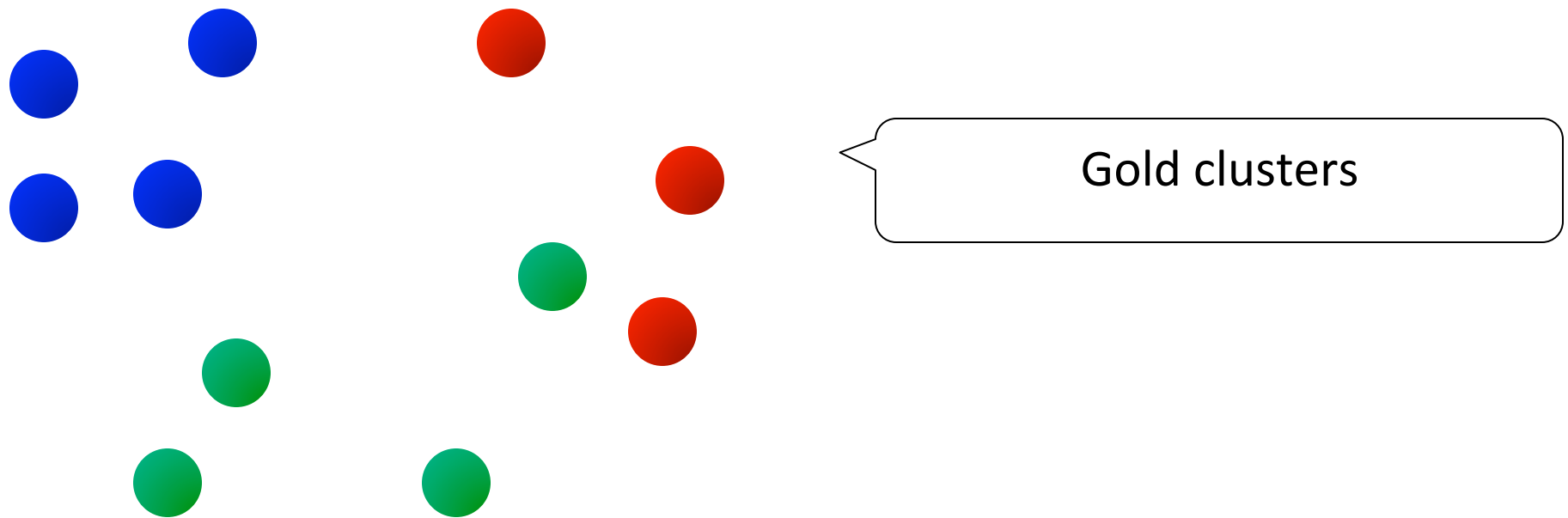


- All sieves minus the pronoun resolution sieve from previous system
- Further reduces search space

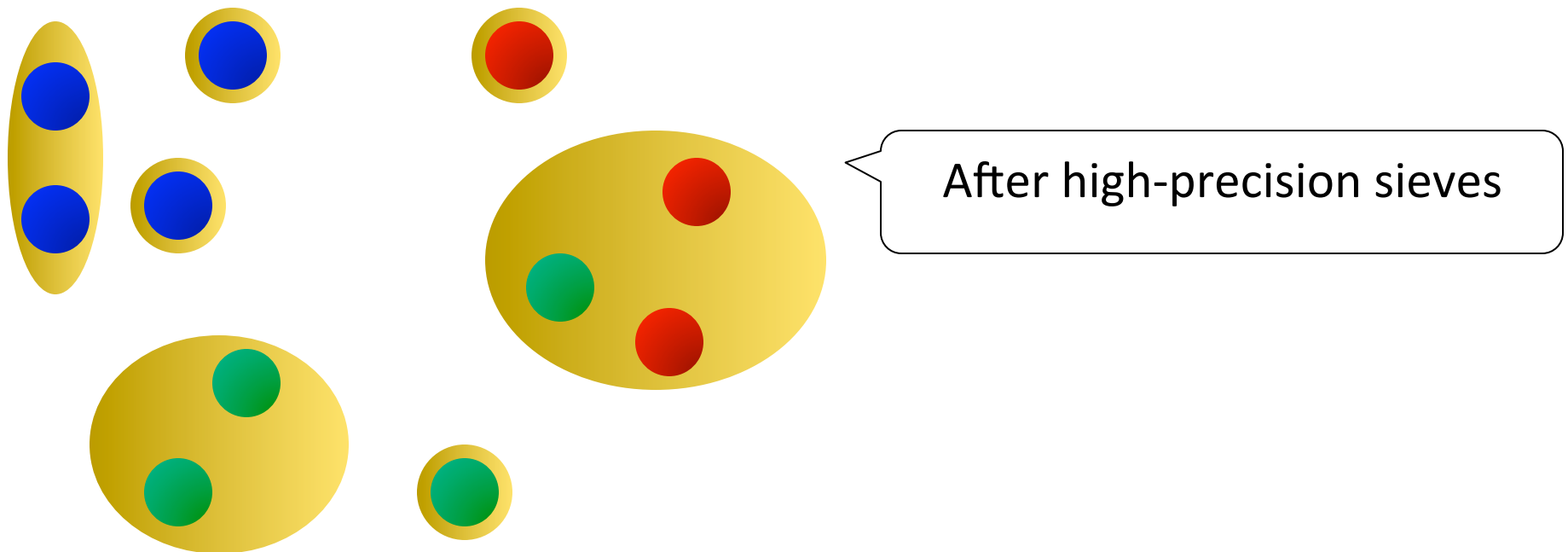
Iterative entity/event resolution



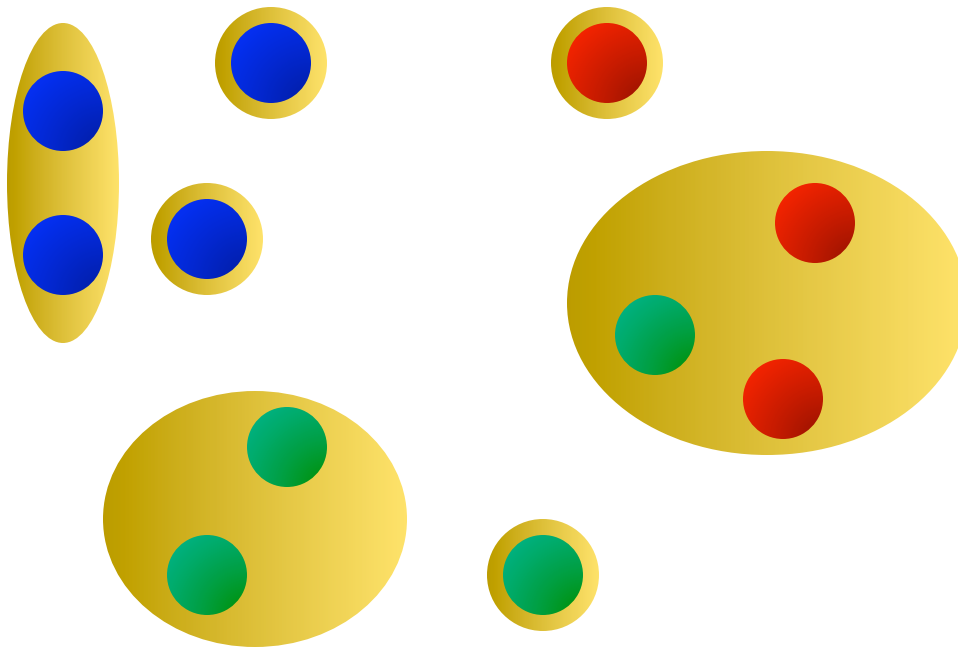
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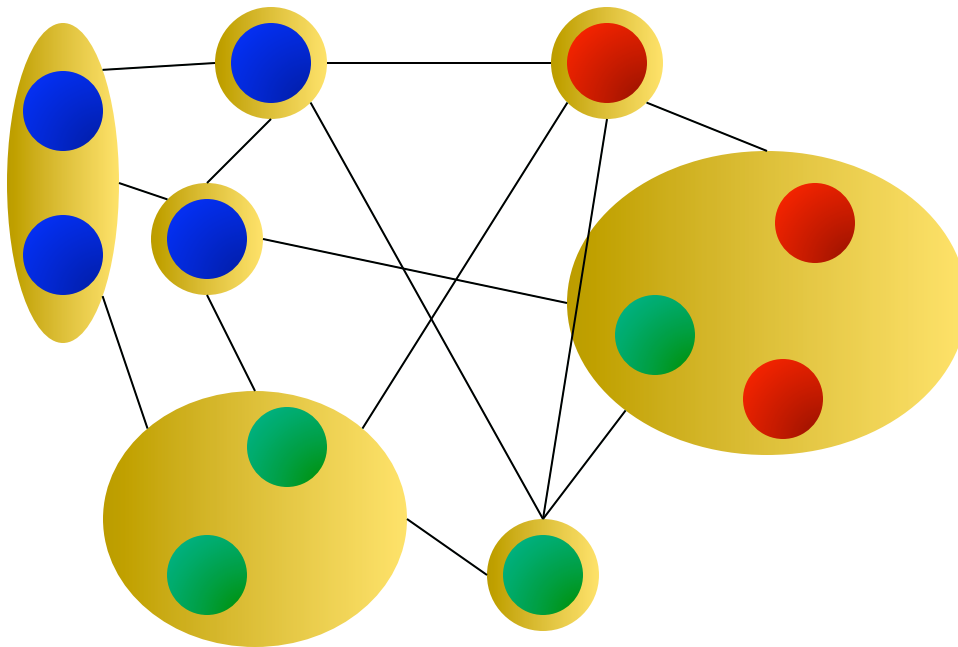


- Calculate pairwise scores and merge best:

$$(e_1, e_2) = \arg \max_{e_1, e_2 \in \mathcal{E}'} \text{score}(e_1, e_2, \Theta)$$
$$\mathcal{E}' = \text{merge}(e_1, e_2, \mathcal{E}')$$

- Regenerate features in modified clusters
- Transparently merges nominal and verbal mentions

Iterative entity/event resolution

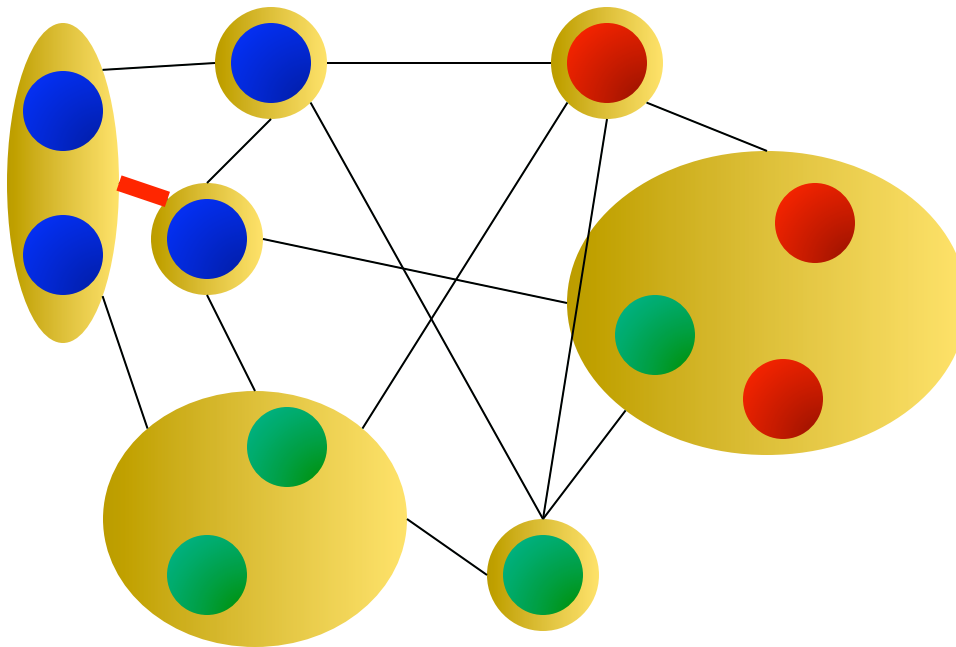


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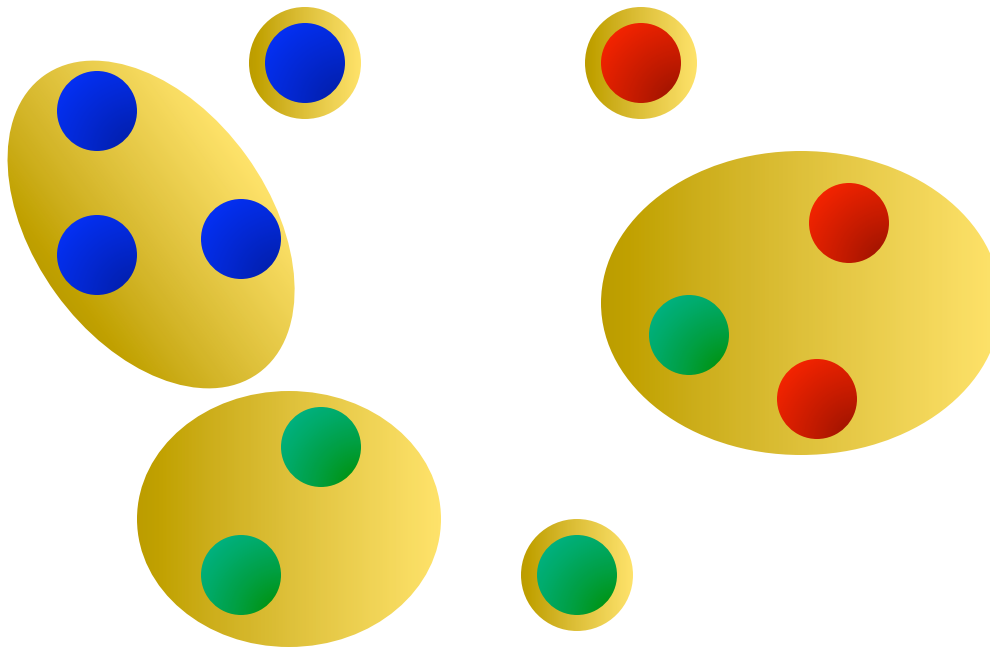


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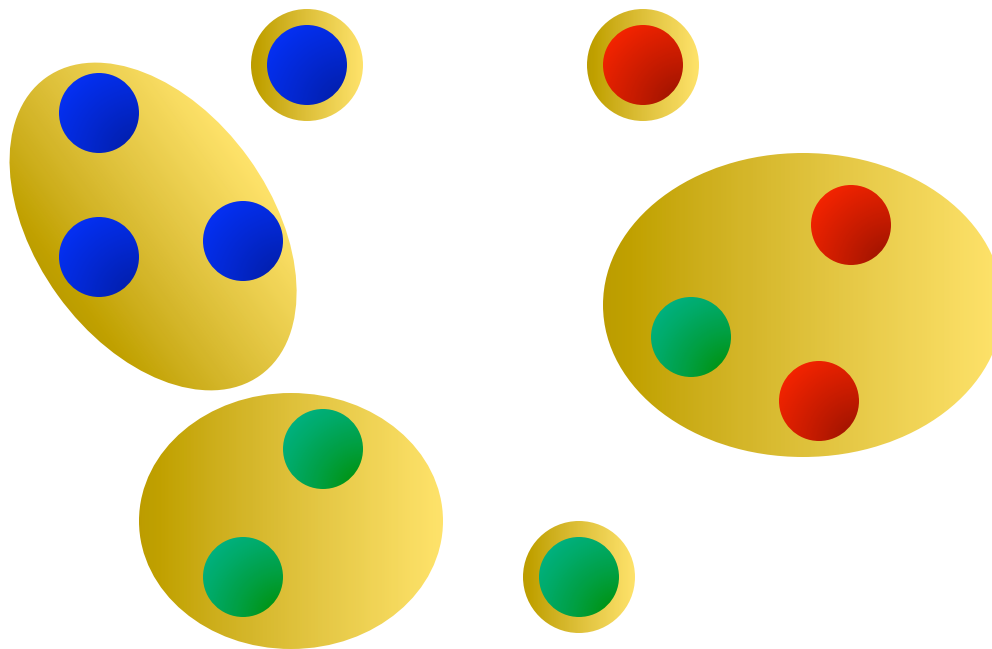


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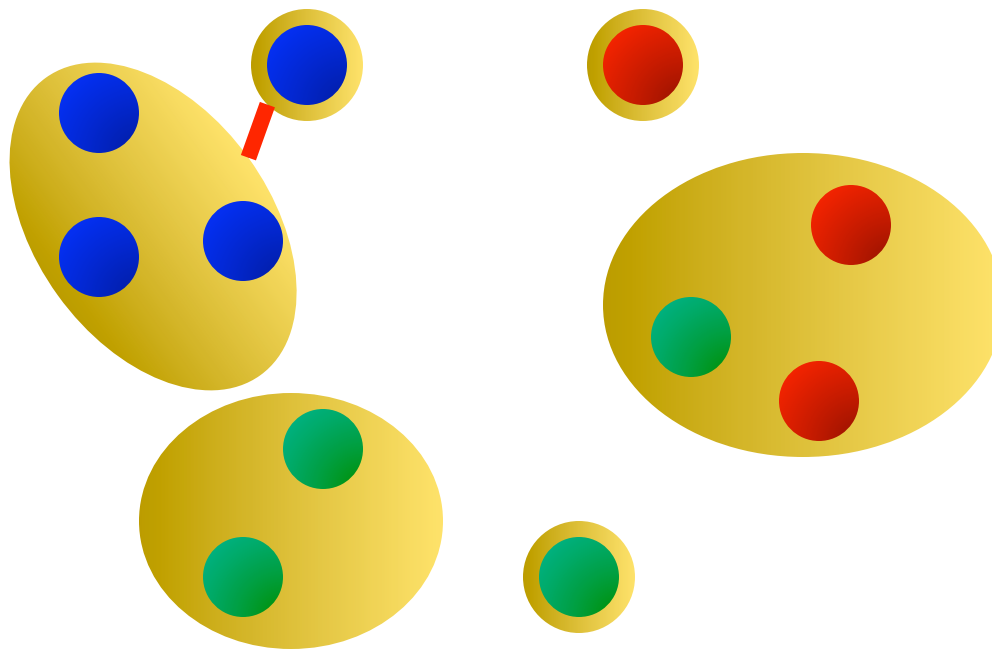
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Repeat

Iterative entity/event resolution



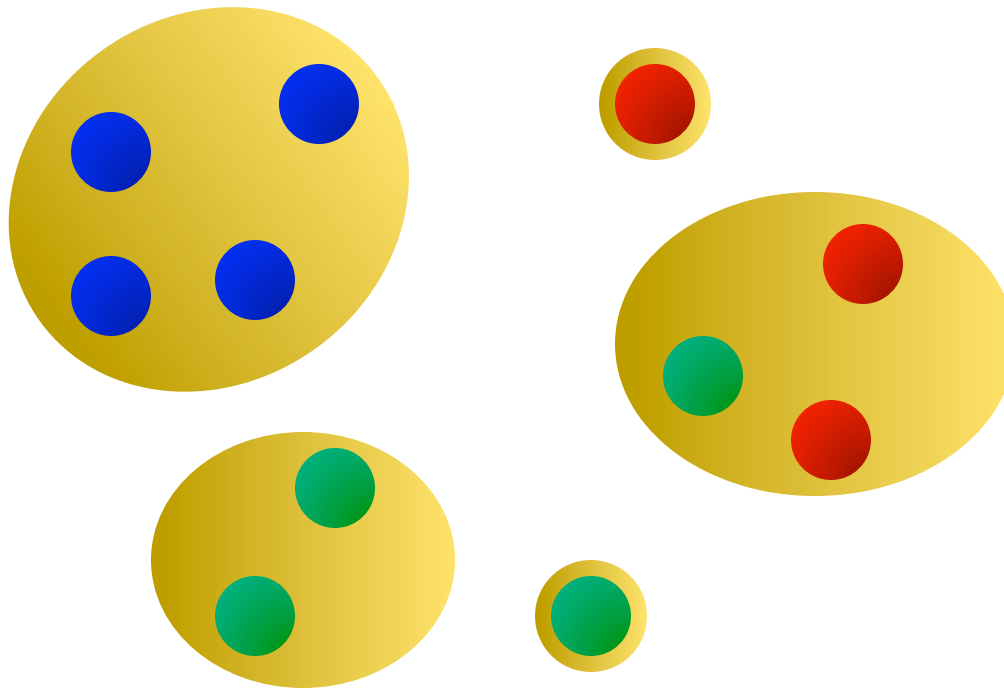
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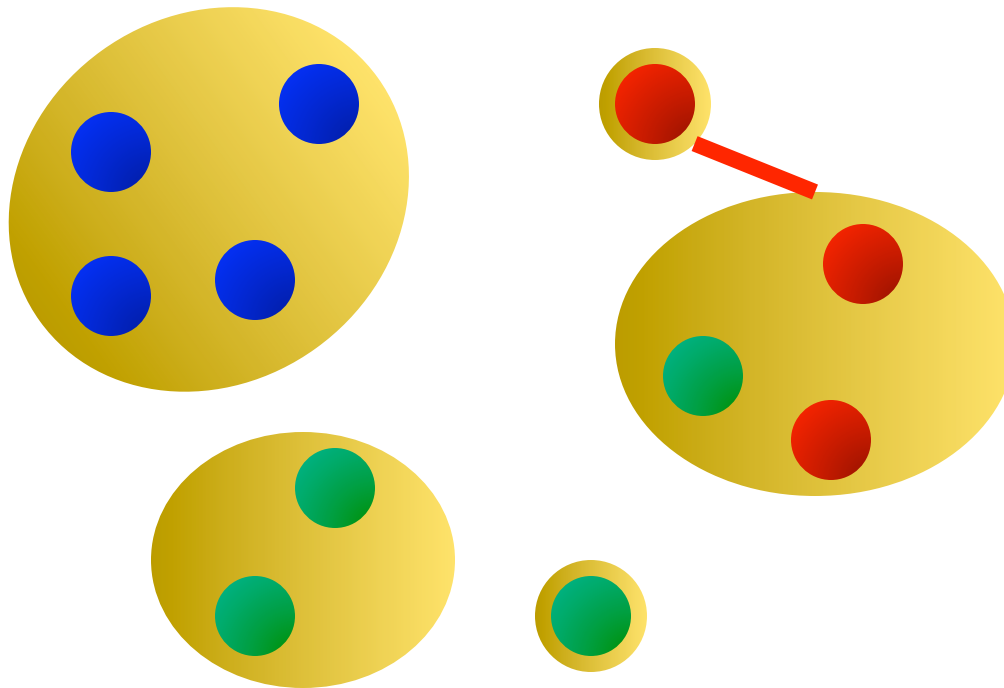
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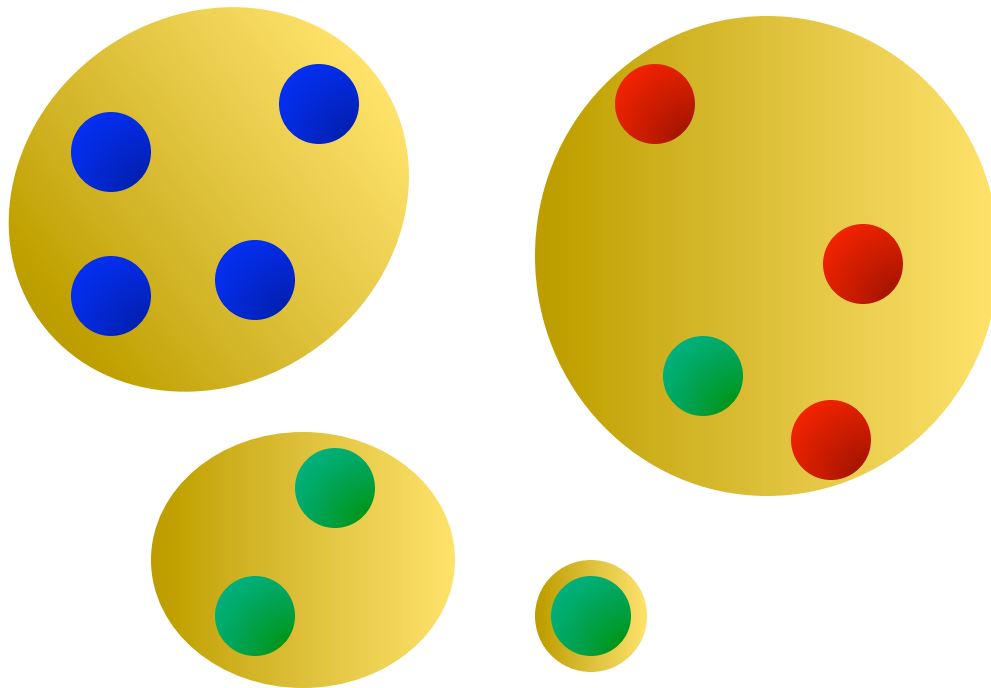
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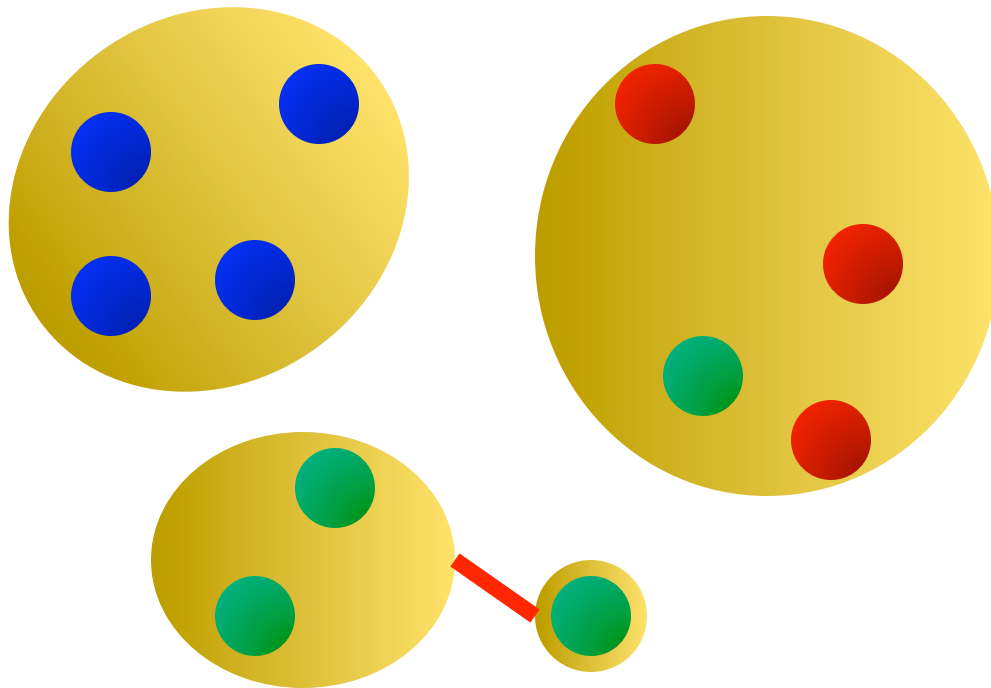
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Repeat

Iterative entity/event resolution



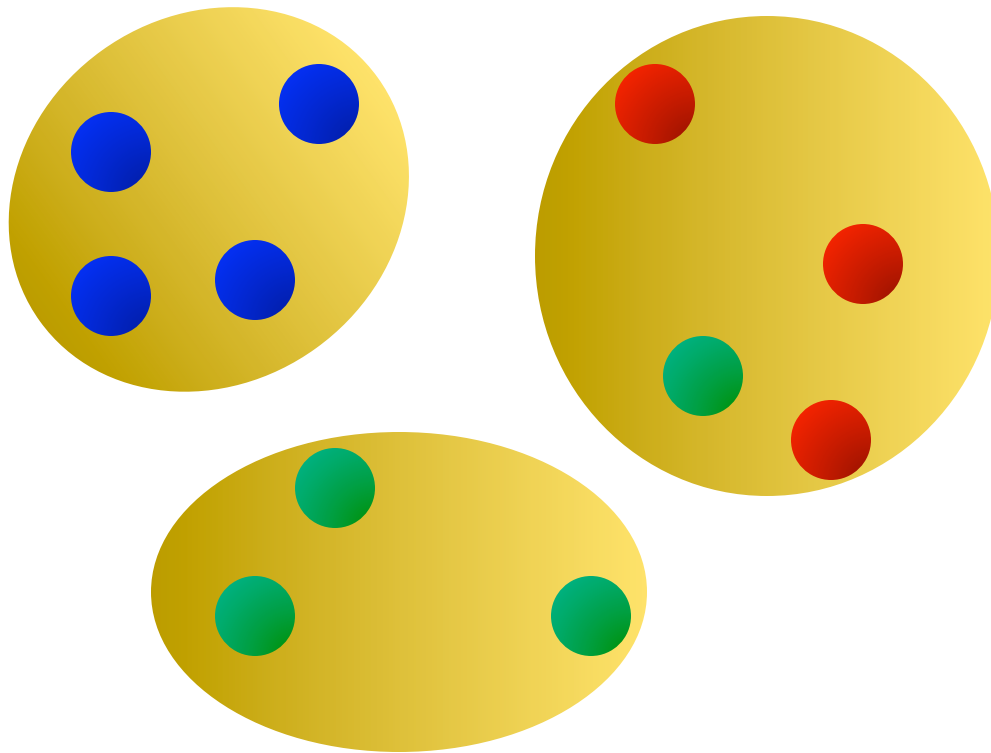
- Calculate pairwise scores and merge best:

$$(e_1, e_2) = \arg \max_{e_1, e_2 \in \mathcal{E}'} \text{score}(e_1, e_2, \Theta)$$
$$\mathcal{E}' = \text{merge}(e_1, e_2, \mathcal{E}')$$

- Regenerate features in modified clusters
- Transparently merges nominal and verbal mentions

Repeat

Iterative entity/event resolution



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Repeat

Training the model

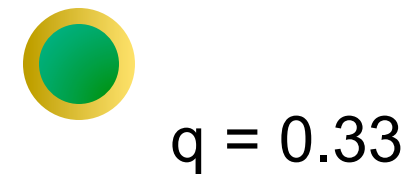
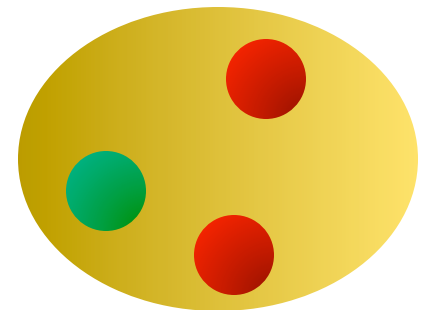
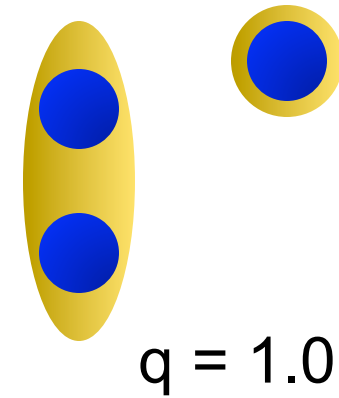
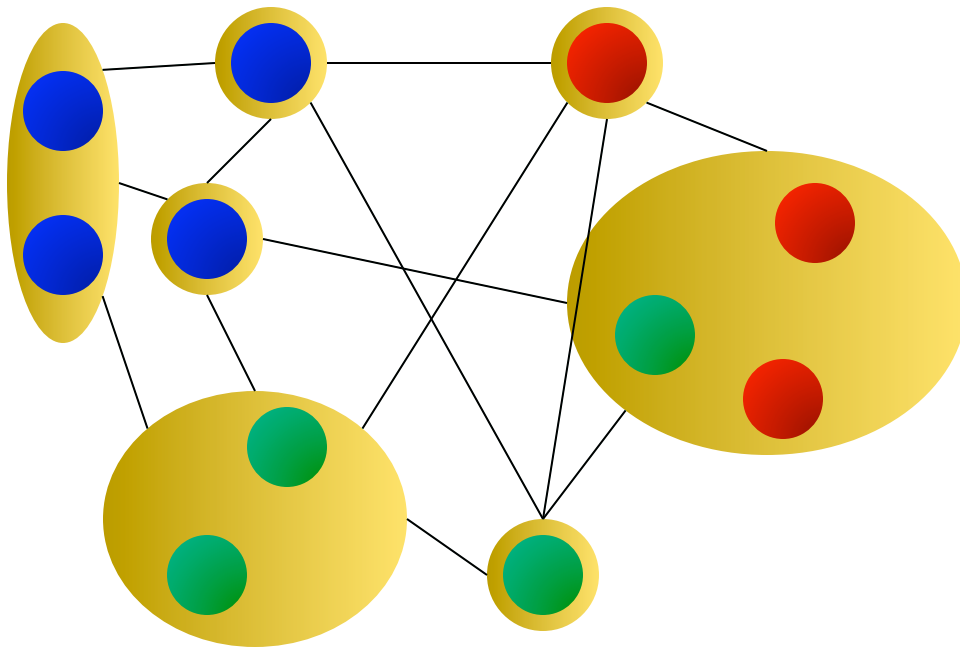
Driven by two observations



1. Need regression because almost no generated cluster is perfectly correct or perfectly incorrect

$$q = \frac{links_{correct}}{links_{correct} + links_{incorrect}}$$

Training the model



Training the model

Driven by two observations



2. Need an online learning setup because a brute force training approach generates an exponential number of candidates
 - Training after applying the high-precision sieves
 - Repeatedly applies the current model over training to generate candidates
 - Model retrained after each epoch
 - L2-regularized linear regression, 10 epochs
-

Features (1/3)

- Cosine similarity of vectors of head words (for nominal mentions) or head lemmas (for verbal mentions)
 - {Barack Obama, President Obama, US president} → {Obama:2, president:1}
- The percentage of newly-introduced mention links after the merge that are WordNet synonyms
 - E.g., 2/6 for the merge of {hit, strike} and {strike, join, say}

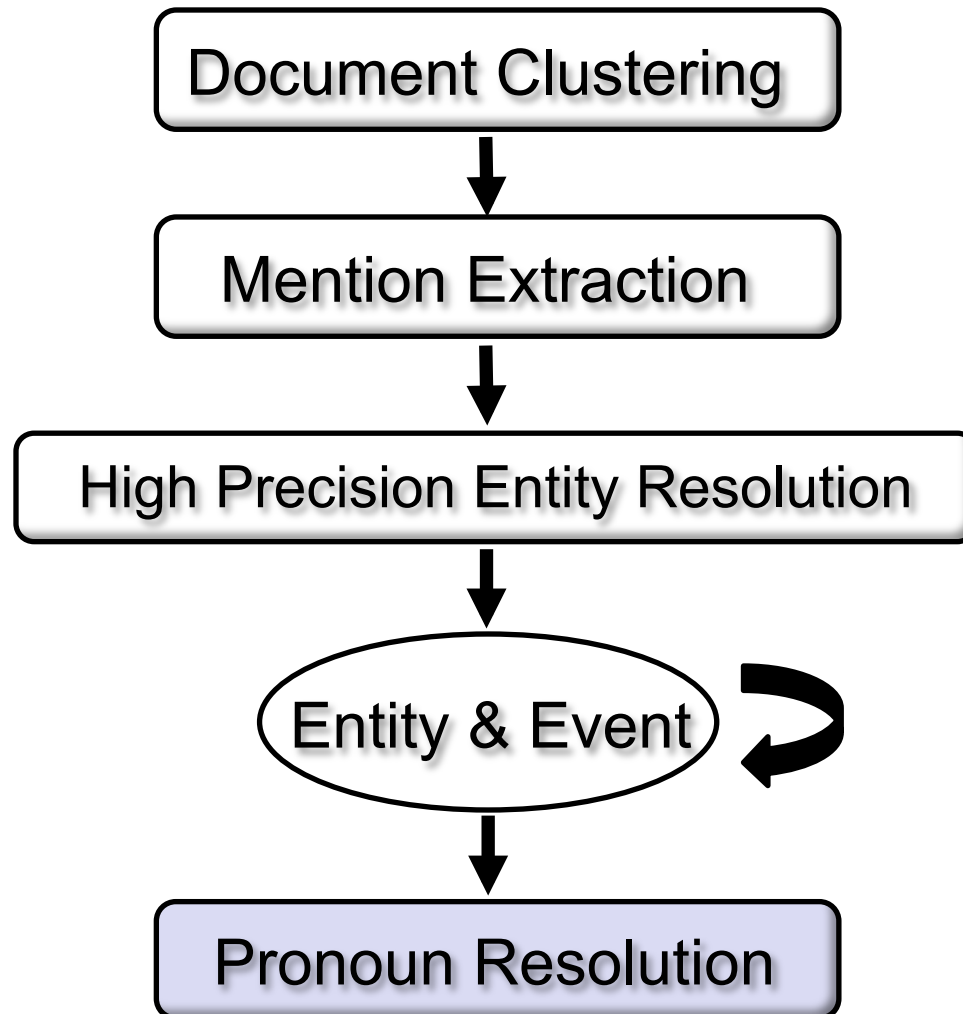
Features (2/3)

- Number of coreferent arguments/predicates
 - E.g., 2 for **AMD**_{Arg0} **bought** **ATI**_{Arg1} and **AMD**_{Arg0} **acquired** **ATI**_{Arg1}
- Number of coreferent arguments/predicates with a specific role (Arg0, Arg1, etc.)
 - E.g., 1 for Arg0 in the previous example

Features (3/3)

- 2nd order distributional similarity of mention words
 - E.g., the singleton cluster {a new home} becomes: {new:1, original:1, old:1, existing:1, current:1, unique:1, modern:1, different:1, special:1, major:1, small:1, home:1, house:1, apartment:1, building:1, hotel:1, residence:1, office:1, mansion:1, school:1, restaurant:1, hospital:1}
- Cosine similarity of number, gender, animacy, and NE label vectors
 - E.g., the vector for the cluster {systems, a pen} is: {number:singular:1, number:plural:1, gender:neutral:2}

Pronoun resolution



- From CoNLL-2011
- Needed because the previous components focus on nominal and verbal mentions

EXPERIMENTS

Corpus

- 43 topics, 482 documents from (Bejan, 2010)
- Annotated by 4 experts
- 5447 entity mentions, 2533 event mentions
 - Event mentions extend Bejan's annotations; corrections made to align them to Onto Notes spec
 - Entity mentions annotated from scratch in house
- Example:

A publicist says Tara Reid has checked herself into rehab ...

The beautiful party girl Tara Reid is taking the time this season and checking herself into rehab.

Baselines

- Baseline 1 – wo/ SRL
 - CoNLL-2011 model (for nominal and pronominal)
 - Lemma matching (for verbal)
- Baseline 2 – with SRL
 - Baseline 1 + two sieves
 - Merges two nominal clusters if head words match and predicates have same lemma
 - {Obama_{Arg0} attended, the president_{Arg1} was elected},
 {Obama_{Arg1} was elected}
 - Merges two verbal clusters if same lemma and arguments with same head word
 - Shows how much simple usage of argument info helps

Results – All mentions

Baseline 1 wo/ SRL	49.8
Baseline 2 with SRL	52.6
Complete model	55.9

CoNLL F1 on the test partition

Results – Only entity mentions

Baseline 1 wo/ SRL	47.9
Baseline 2 with SRL	50.8
Complete model	54.2

CoNLL F1 on the test partition

Results – Only event mentions

Baseline 1 wo/ SRL	51.2
Baseline 2 with SRL	52.2
Complete model	54.8

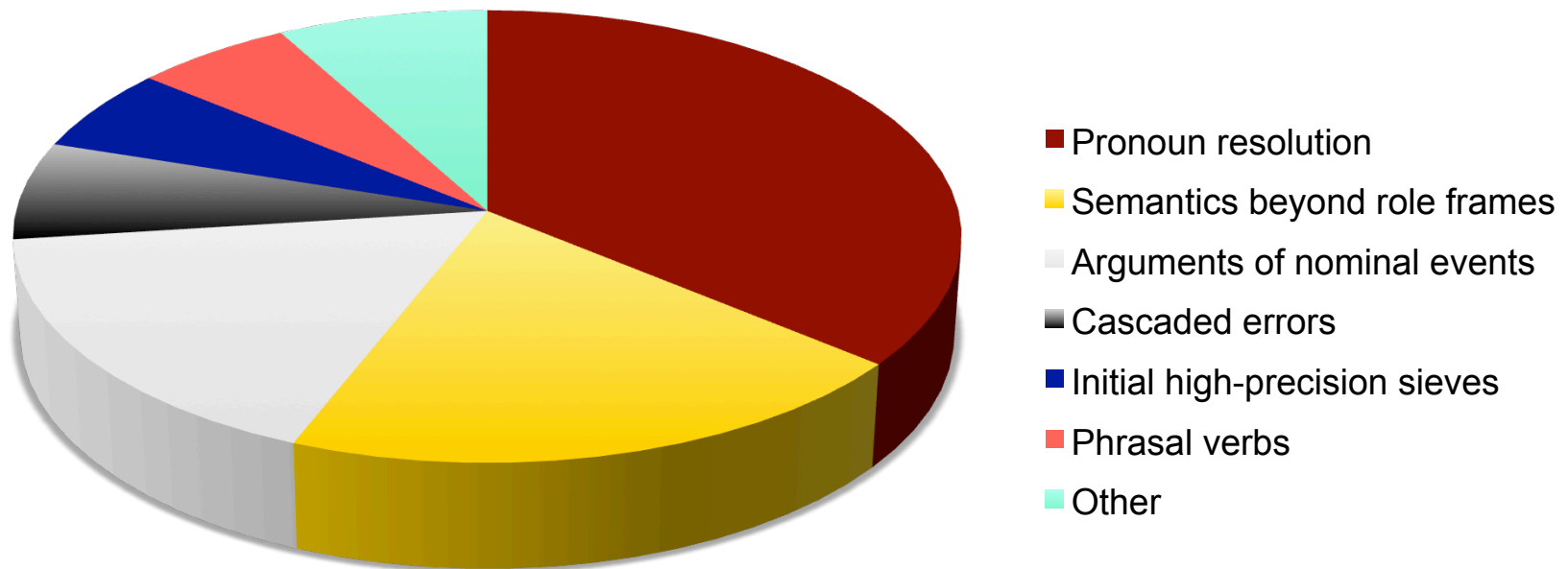
CoNLL F1 on the test partition

Discussion

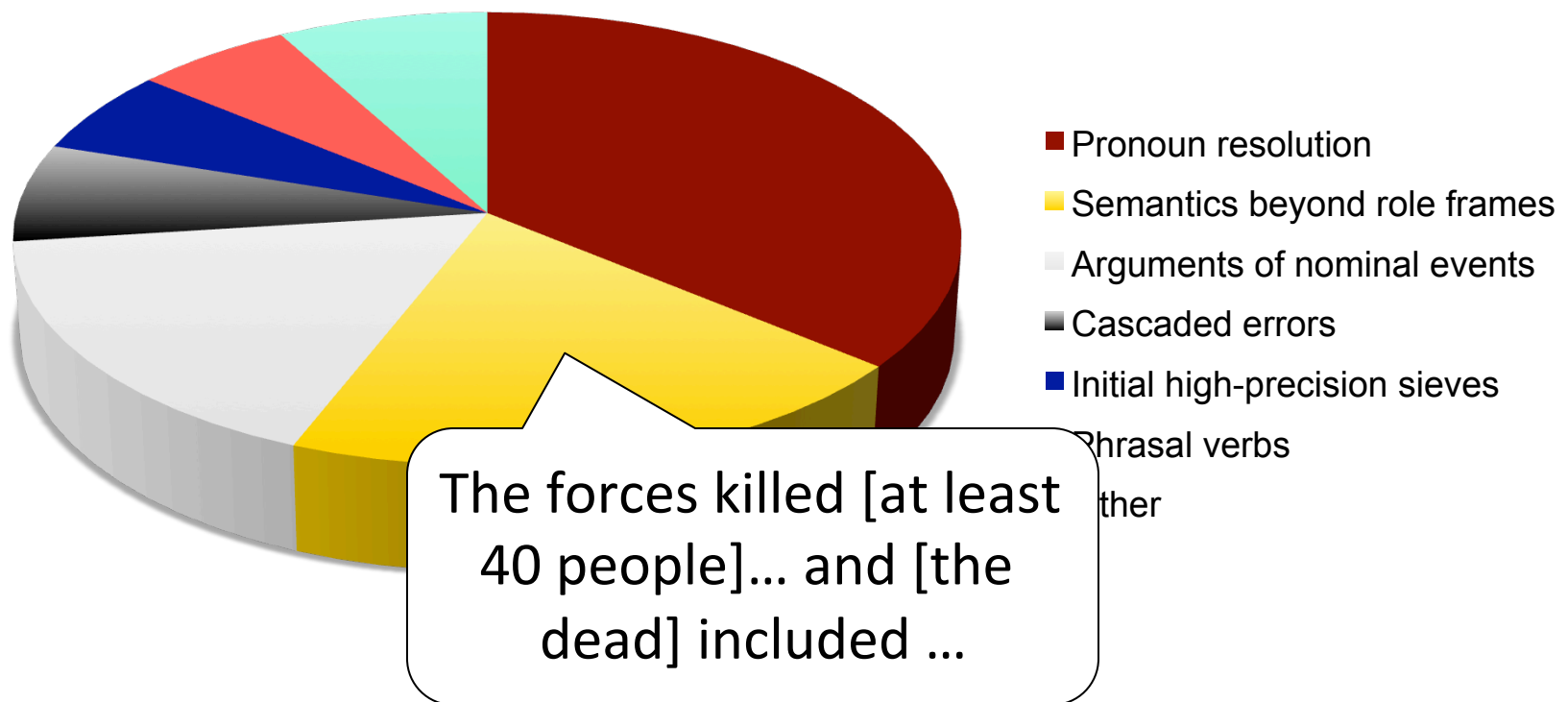
- Many SRL features get high weights (6 out of 10)

Entity Feature		Weight
	Entity Heads – Proper	1.10
➡	Coreferent Predicate for ArgM-LOC – Common	0.45
	Entity Heads – Common	0.36
➡	Coreferent Predicate for Arg0 – Proper	0.29
➡	Coreferent Predicate for Arg2 – Common	0.28
Event Feature		Weight
	Event Lemmas	0.45
➡	Coreferent Argument for Arg1	0.19
	Links between Synonym	0.16
➡	Coreferent Argument for Arg2	0.13
➡	Number of Coreferent Arguments	0.07

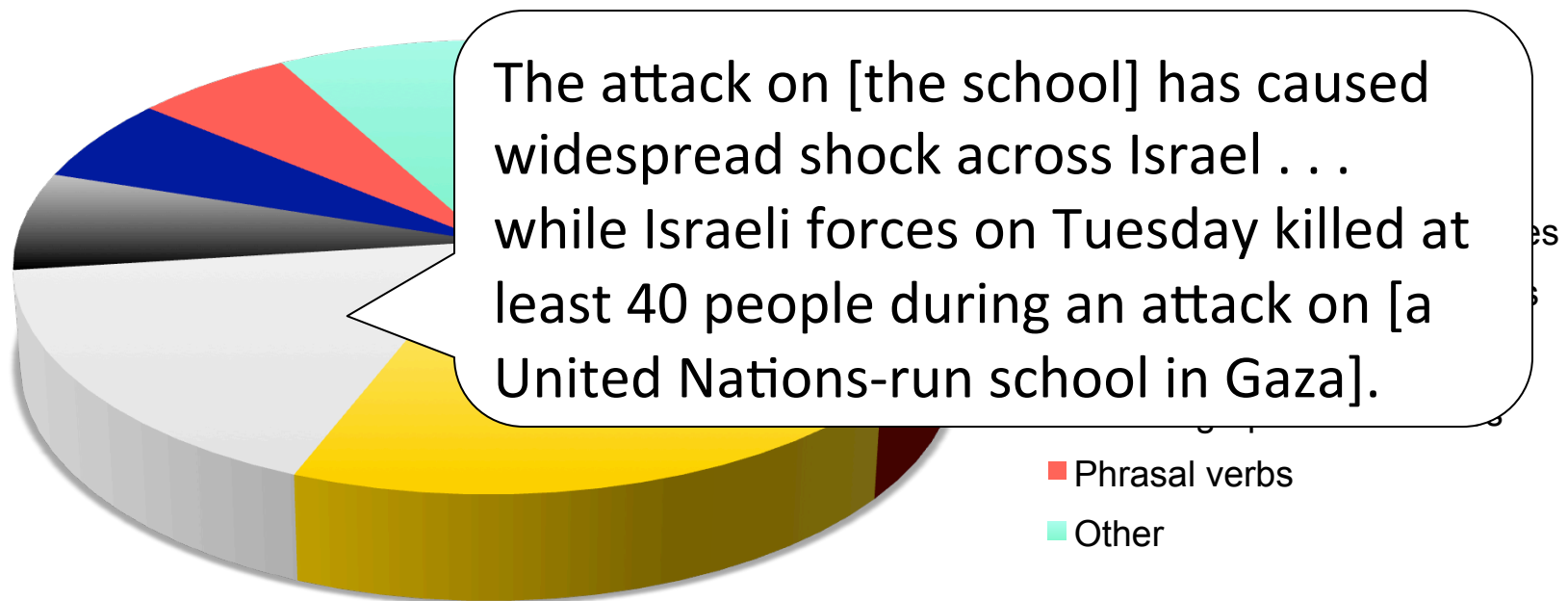
Error analysis



Error analysis



Error analysis



Idea II: Conclusions

- Holistic model for cross-document coreference resolution
 - Jointly solves references to events and entities by handling both nominal and verbal mentions
- Model/features
 - Yet another “baby-steps” model
 - Events and entities linked through semantic role frames
- Joint modeling beneficial for both entities and events

Big-picture conclusions

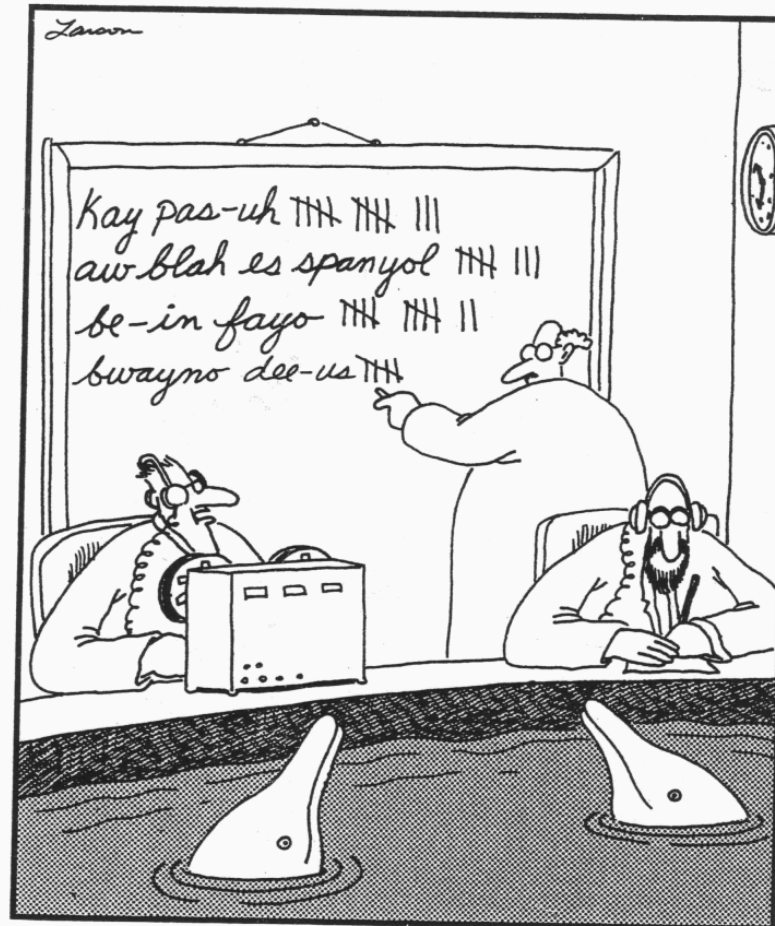


- Understanding the problem is more important than machine learning
- Model things jointly when you can

Acknowledgements

- Joint work with Heeyoung Lee, Karthik Raghunathan, Marta Recasens, Nathanael Chambers, Yves Peirsman, Angel Chang, Sudarshan Rangarajan, and Dan Jurafsky.

© Gary Larson



"Matthews ... we're getting another one of those strange 'aw blah es span yol' sounds."

THANK YOU! QUESTIONS?
