Translation-Based Projection for Multilingual Coreference Resolution

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Noun Phrase Coreference

- Identify the noun phrases (mentions) that refer to the same real-world entity

- Lots of work on English coreference, but there has also been work on coreference in other languages

Multilingual Coreference Resolution

- A natural next step
- An important next step
  - Coreference resolvers do not exist for many languages

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- An important next step
  - Coreference resolvers do not exist for many languages
- Surge of interest in multilingual coreference resolution
  - ACE 2004/2005
    - English, Chinese, Arabic
  - SemEval 2010 Task 1
    - English, Spanish, Catalan, Italian, Dutch, German
  - CoNLL 2012 shared task
    - English, Chinese, Arabic

Multilingual Coreference Resolution: How?

- We have coreference-annotated data for multiple languages
  - Employ a supervised approach
    - Train a coreference resolver for each language

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- **Weakness**: corpus annotation bottleneck
  - For each new language of interest, need to coreference-annotate a potentially large number of documents

How about a Rule-Based Approach?

- Revived interest in rule-based approaches owing to the Stanford resolver’s competitive performance

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- **Strength**: no need to coreference-annotate any data

- **Weakness**: we are replacing the corpus annotation bottleneck with the knowledge acquisition bottleneck
  - Need knowledge of the target language to design rules

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- Unsupervised coreference models are not models that can be designed without knowledge of the target language

But … we still need to pick an approach

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  - Designing coreference rules and generative models may not be as time-consuming as coreference-annotating data

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- Argument for a heuristic/unsupervised approach:
    - Designing coreference rules and generative models may not be as time-consuming as coreference-annotating data
- This may be true for English
    - can easily write a rule to enforce gender/number agreement
- But .. computing these features may not be simple for …
    - Chinese
        - No morphology
            - difficult to determine number
        - Many first names used by both gender
            - difficult to determine gender

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Translation-based projection

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Source language

Target language

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Source language

- coreference resolver available

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- Goal
  - coreference-annotate documents in target language using resolver in source language

Translation-Based Projection

Source language	**Target language**
coreference resolver available	coreference resolver not available

- Goal
  - coreference-annotate documents in target language using resolver in source language
- Idea
  - project annotations produced by resolver from source to target

Translation-Based Projection Algorithm

- Input: document in target language
- Output: document coreference-annotated

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- 3 steps:
  1. Machine-translate document from target to source
  2. Run resolver on the translated document
  3. Project annotations from source back to target

Translation-Based Projection: Example

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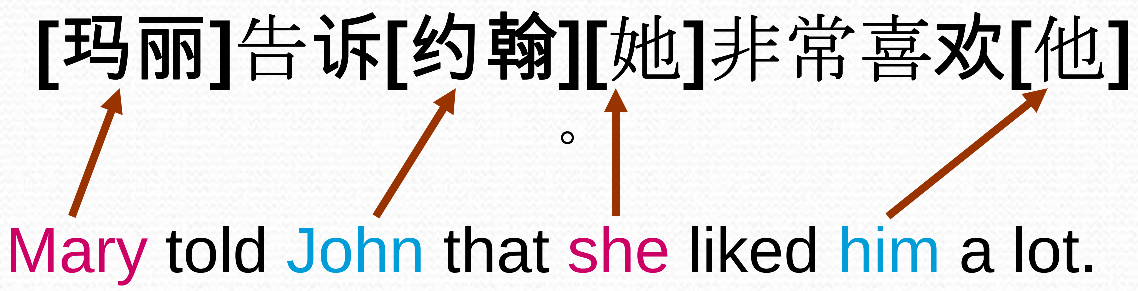

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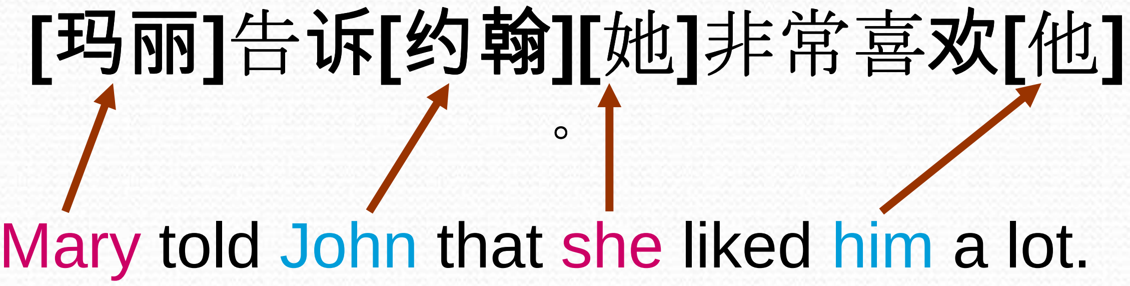

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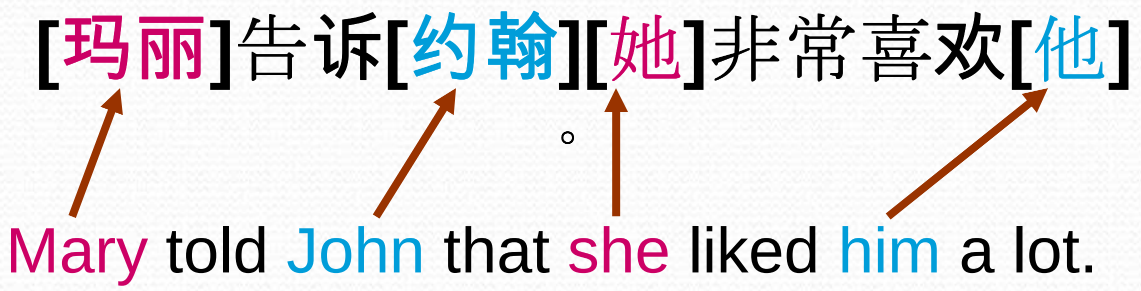

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Translation-Based Projection

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- Problem solved?
  - Not really
  - Projection is not a solution to multilingual coreference problem
    - Every language has its own idiosyncrasies
    - Projection cannot produce annotations capturing language-specific properties
      - E.g., zero pronouns

Goal

- Explore the extent to which projection can push the limits of multilingual coreference resolution
  - projection is not meant to and cannot replace corpus annotation

Caveat

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- True, but …
  - Number of language pairs for which MT services are available is increasing
  - Parallel corpus may be used, if available

Plan for the Talk

- Translation-based projection
  - Related work
  - Implementation details
  - Evaluation

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Related Work

- Projecting annotations from a resource-rich language to a resource-poor language
  - proposed by Yarowsky and Ngai (2001)
  - assumes a parallel corpus for the source and target languages
  - more recent work uses an MT engine instead

Related Work

- Applying projection to coreference resolution
  - Idea formulated in a declined EU proposal circa 2005
  - Postolache et al. (2006)
    - English-Romanian parallel corpus: Orwell's "1984"
    - Manually create coreference annotations on English side
    - Automatically project English annotations to Romanian
    - Manually fix projection errors
  - Harabagiu and Maiorano (2000)
    - English-Romanian parallel corpus: manually translating MUC-6
    - Manually project MUC-6 coreference annotations to Romanian

Related Work

- So … their goal is different from ours
  - They create clean coreference corpus by employing significant knowledge of the target language
  - We create a coreference corpus via an entirely automatic process without using knowledge of the target language

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Translation-Based Projection

Source language **Target language**

Translation-Based Projection

(resource-rich)

Source language

(resource-poor)

Target language

Translation-Based Projection

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Source language

- coreference resolver available

(resource-poor)

Target language

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Translation-Based Projection

(resource-rich)

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- coreference resolver available

(resource-poor)

Target language

- coreference resolver not available
- not necessarily resource-poor
  - we may have many linguistic taggers at the morphological, syntactic and semantic levels

Translation-Based Projection

(resource-rich)

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- coreference resolver available

(resource-poor)

Target language

- coreference resolver not available
- not necessarily resource-poor
  - we may have many linguistic taggers at the morphological, syntactic and semantic levels

- Goal
  - Examine whether the linguistic taggers for the target language, if available, can be exploited to improve projection approach

Translation-Based Projection

- Evaluate the projection approach in 3 settings
  - Differ in terms of the extent to which linguistic taggers for the target language are available

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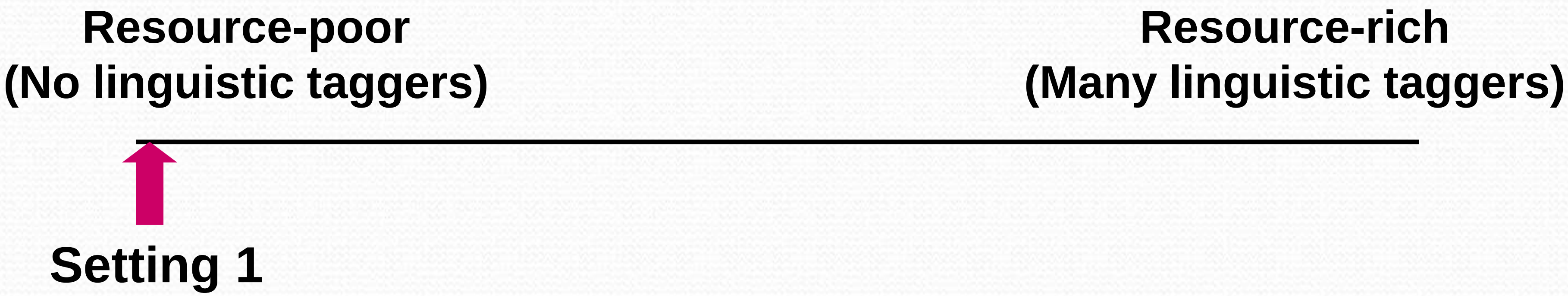

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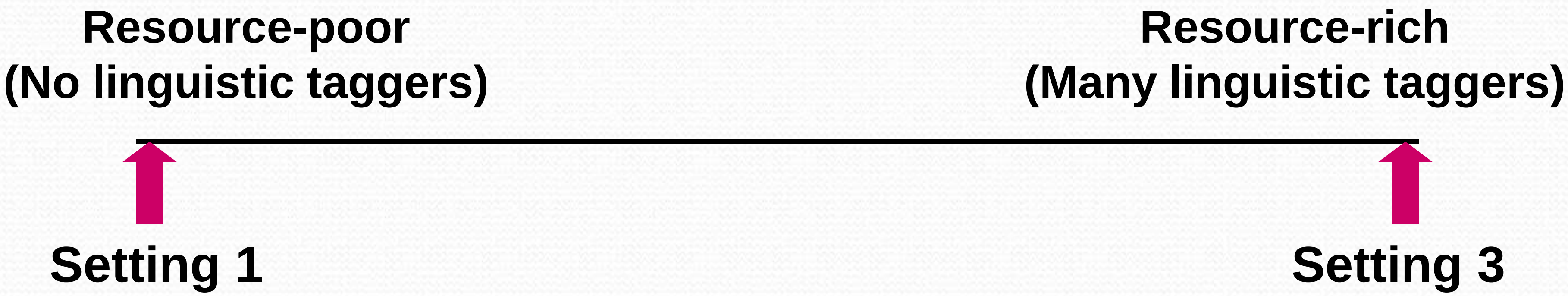

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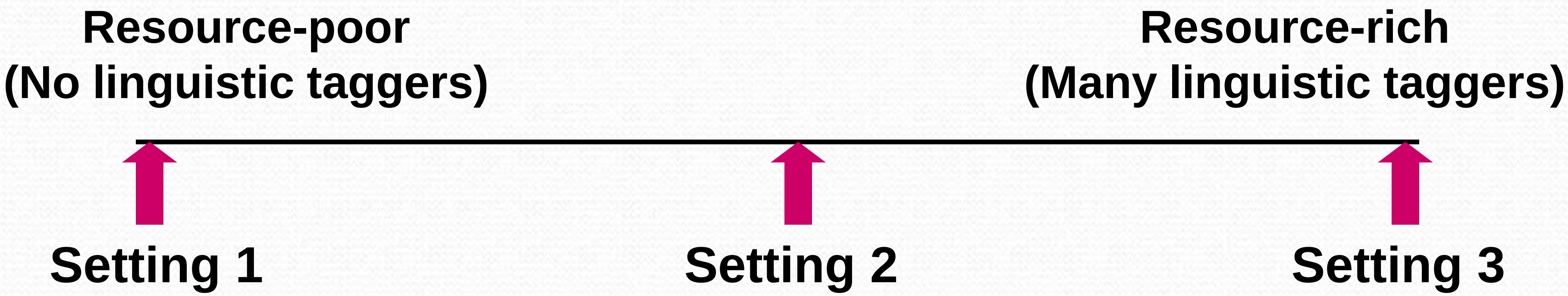

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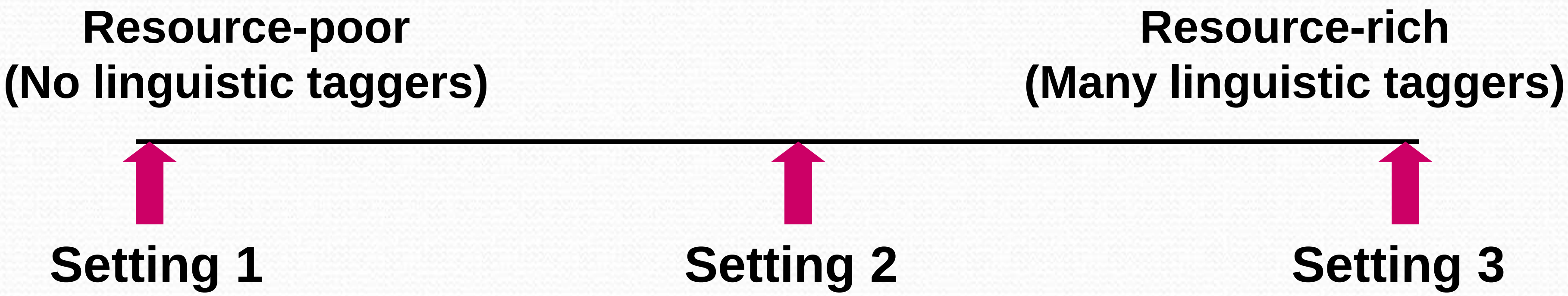

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Setting 1

Setting 2

Setting 3

  - Assume **English** is source language
    Chinese is target language

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- No Chinese taggers available
- Simply apply the 3 steps involved in MT-based projection

1. Machine-translate text from Chinese to English

2. Run resolver on the translated English text

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     - Heuristically create Chinese mentions from Reconcile mentions

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       - Improve alignment via a bilingual dictionary from web sources
     - Heuristically create Chinese mentions from Reconcile mentions
       - Use Yarowsky and Ngai's (2001) NP projection method

Setting 2

- A Chinese mention detector available

- How can we profitably exploit this mention detector?

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3. Use Reconcile to detect mentions and perform coreference

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   [Mary] told [John] that [she] liked [him] a lot.

4. Project chains back to Chinese (using word alignment)

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Chinese mention boundaries are sensitive to word alignment errors.

Setting 2's mention detection method more robust to word alignment errors

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- How can we profitably exploit these Chinese taggers?
  - Use them to generate features to train a Chinese coreference resolver in a supervised manner
    - But we don’t have any manual coreference annotations to train a supervised resolver
    - Idea (Kobdani et al., 2011):
      - use pseudo coreference annotations
      - Setting 2 can be used to produce these pseudo annotations

Setting 3

- In our experiments, we didn’t run any linguistic taggers for the target language
  - Took a shared task dataset for the target language
    - Features have been computed for each word in the dataset
    - Partition the dataset into a training set and a test set
    - Train a coreference resolver on training set by replacing correct coreference labels with pseudo labels generated via Setting 2

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- Setting 3
    - exploits information provided by additional taggers
        - but no manual coreference annotations are needed

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Data Sets

- Italian and Spanish datasets from SemEval-2010 shared task on Coreference Resolution in Multiple Languages
  - Each dataset is composed of a training set and a test set
  - Statistics:

	Italian		Spanish	
	Training	**Test**	**Training**	**Test**
Number of mentions	24853	13394	78779	14133
Number of non-singleton clusters	18376	9520	48681	8789
Number of singleton clusters	15984	8288	37336	6737

Scoring Programs

- 4 scoring programs used in the shared task
  - MUC (Vilain et al., 1995)
  - B^3 (Bagga and Baldwin, 1998)
  - ϕ_3-CEAF (Luo, 1995)
  - BLANC (Recasens and Hovy, 2011)

Gold vs. Regular Settings

- refer to what information in a dataset can be used
- format of dataset follows that of a CoNLL shared task dataset
  - each row corresponds to a word
  - each column corresponds to a feature
    - some correspond to manually computed features
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Gold setting

- Use gold mentions and manually computed features

Regular setting

- Use automatically computed mentions and features

Results for Italian

	Regular (CEAF)			Gold (CEAF)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	74.5	74.5	**74.5**

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- obtained via a resolver trained on all training data using all features made available by the shared task organizers
- upper bound on performance of our projection approach

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- Sanity check on whether upper bounds established by our supervised resolver are reasonable

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- Results worse than those of our supervised resolver

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- No gold results
  - No gold mentions or manually computed features are used
  - Mentions are projected from the Reconcile mentions

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- F-score significantly worse than its supervised counterparts ($p < 0.05$, paired t-test)

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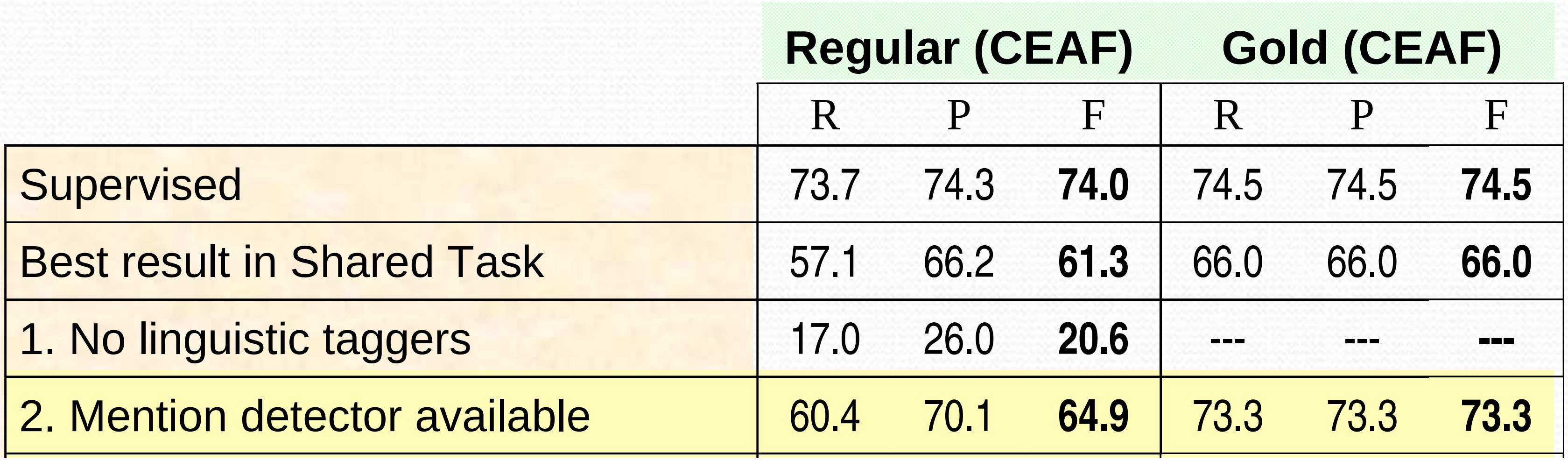

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2. Mention detector available	60.4	70.1	**64.9**	73.3	73.3	**73.3**

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Supervised	73.7	74.3	**74.0**	74.5	74.5	**74.5**
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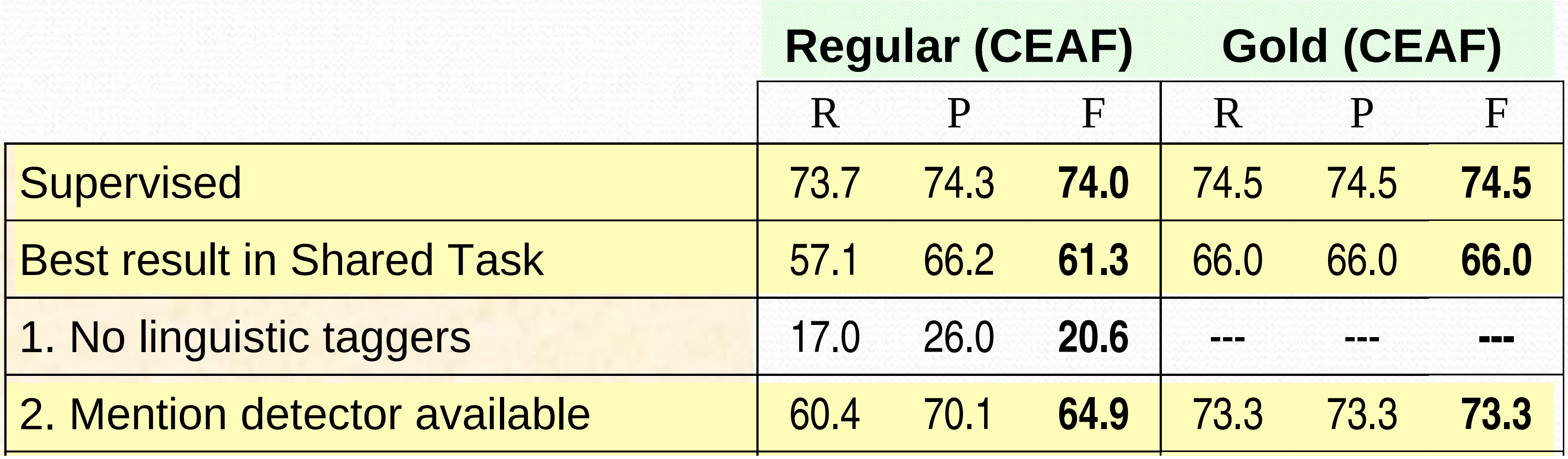
1. No linguistic taggers	17.0	26.0	**20.6**	---	---	**---**
2. Mention detector available	60.4	70.1	**64.9**	73.3	73.3	**73.3**

- In comparison to Setting 1
  - Setting 2 yields significantly better results

Results for Italian



	Regular (CEAF)			Gold (CEAF)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	74.5	74.5	**74.5**
Best result in Shared Task	57.1	66.2	**61.3**	66.0	66.0	**66.0**
1. No linguistic taggers	17.0	26.0	**20.6**	---	---	**---**
2. Mention detector available	60.4	70.1	**64.9**	73.3	73.3	**73.3**

- In comparison to supervised results:
  - beats best shared task resolver
  - lags behind our supervised resolver

Results for Italian

	Regular (CEAF)			Gold (CEAF)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	74.5	74.5	**74.5**
Best result in Shared Task	57.1	66.2	**61.3**	66.0	66.0	**66.0**
1. No linguistic taggers	17.0	26.0	**20.6**	---	---	**---**
2. Mention detector available	60.4	70.1	**64.9**	73.3	73.3	**73.3**
3. Additional taggers available	61.1	62.9	**61.9**	64.3	64.3	**64.3**

Results for Italian

	Regular (CEAF)			**Gold (CEAF)**		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	74.5	74.5	**74.5**
Best result in Shared Task	57.1	66.2	**61.3**	66.0	66.0	**66.0**
1. No linguistic taggers	17.0	26.0	**20.6**	---	---	**---**
2. Mention detector available	60.4	70.1	**64.9**	73.3	73.3	**73.3**
3. Additional taggers available	61.1	62.9	**61.9**	64.3	64.3	**64.3**

- In comparison to Setting 2
  - Performance drops for both Regular and Gold settings

Italian Results

	Regular (CEAF)			Regular (MUC)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	31.9	68.0	**43.4**
Best result in Shared Task	57.1	66.2	**61.3**	50.1	50.7	**50.4**
1. No linguistic taggers	17.0	26.0	**20.6**	8.1	28.5	**12.6**
2. Mention detector available	60.4	70.1	**64.9**	17.2	68.2	**27.5**
3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

Italian Results

	Regular (CEAF)			Regular (MUC)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	31.9	68.0	**43.4**
Best result in Shared Task	57.1	66.2	**61.3**	50.1	50.7	**50.4**
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	Regular (CEAF)			Regular (MUC)		
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3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

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3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

- CEAF: Setting 3 is worse than Setting 2 (poorer precision)
- MUC: Setting 3 is better than Setting 2 (better recall)

Italian Results

	Regular (CEAF)			Regular (MUC)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	31.9	68.0	**43.4**
Best result in Shared Task	57.1	66.2	**61.3**	50.1	50.7	**50.4**
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3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

- Setting 3 has higher recall according to both scoring programs
  - More coreference links are discovered
  - The additional taggers have enabled us to discover new links

Italian Results

	Regular (CEAF)			Regular (MUC)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	31.9	68.0	**43.4**
Best result in Shared Task	57.1	66.2	**61.3**	50.1	50.7	**50.4**
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3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

- Setting 3 has higher recall according to both scoring programs
  - More coreference links are discovered
  - The additional taggers have enabled us to discover new links
- Setting 3 has lower precision according to both scoring programs
  - Some of these new links are spurious

Italian Results

	Regular (CEAF)			Regular (MUC)		
	R	P	F	R	P	F
Supervised	73.7	74.3	**74.0**	31.9	68.0	**43.4**
Best result in Shared Task	57.1	66.2	**61.3**	50.1	50.7	**50.4**
1. No linguistic taggers	17.0	26.0	**20.6**	8.1	28.5	**12.6**
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3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

- MUC gives a much higher recall to Setting 3 than to Setting 2
- CEAF gives only a slightly higher recall to Setting 3

Italian Results

	Regular (CEAF)			Regular (MUC)		
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Best result in Shared Task	57.1	66.2	**61.3**	50.1	50.7	**50.4**
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3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

- MUC gives a much higher recall to Setting 3 than to Setting 2
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  - MUC scores only coreference links, not singleton clusters
  - CEAF scores both coreference links and singleton clusters

Italian Results

	Regular (CEAF)			Regular (MUC)		
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Supervised	73.7	74.3	**74.0**	31.9	68.0	**43.4**
Best result in Shared Task	57.1	66.2	**61.3**	50.1	50.7	**50.4**
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2. Mention detector available	60.4	70.1	**64.9**	17.2	68.2	**27.5**
3. Additional taggers available	61.1	62.9	**61.9**	29.5	63.2	**40.2**

- MUC gives a much higher recall to Setting 3 than to Setting 2
- CEAF gives only a slightly higher recall to Setting 3
  - MUC scores only coreference links, not singleton clusters
  - CEAF scores both coreference links and singleton clusters
    - overwhelmed by the large number singleton clusters

Results (Averaged over all Scoring Programs)

	Italian		Spanish	
	Regular	Gold	Regular	Gold
	F	F	F	F
Supervised	63.4	65.9	54.6	66.1
Best result in Shared Task	60.0	61.2	49.6	66.8
Setting 1	21.4	---	37.6	---
Setting 2	54.9	58.2	46.8	56.1
Setting 3	57.7	58.9	51.7	61.4

Results (Averaged over all Scoring Programs)

	Italian		Spanish	
	Regular	**Gold**	**Regular**	**Gold**
	F	F	F	F
Supervised	63.4	65.9	54.6	66.1
Best result in Shared Task	60.0	61.2	49.6	66.8
Setting 1	21.4	---	37.6	---
Setting 2	54.9	58.2	46.8	56.1
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Results (Averaged over all Scoring Programs)

	Italian		Spanish	
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	F	F	F	F
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Results (Averaged over all Scoring Programs)

	Italian		Spanish	
	Regular	Gold	Regular	Gold
	F	F	F	F
Supervised	63.4	65.9	54.6	66.1
Best result in Shared Task	60.0	61.2	49.6	66.8
Setting 1	21.4	---	37.6	---
Setting 2	54.9	58.2	46.8	56.1
Setting 3	57.7	58.9	51.7	61.4

- Supervised results comparable to/better than shared task result

Results (Averaged over all Scoring Programs)

	Italian		Spanish	
	Regular	Gold	Regular	Gold
	F	F	F	F
Supervised	63.4	65.9	54.6	66.1
Best result in Shared Task	60.0	61.2	49.6	66.8
Setting 1	21.4	---	37.6	---
Setting 2	54.9	58.2	46.8	56.1
Setting 3	57.7	58.9	51.7	61.4

- Setting 2 results are better than Setting 1 results

Results (Averaged over all Scoring Programs)

	Italian		Spanish	
	Regular	Gold	Regular	Gold
	F	F	F	F
Supervised	63.4	65.9	54.6	66.1
Best result in Shared Task	60.0	61.2	49.6	66.8
Setting 1	21.4	---	37.6	---
Setting 2	54.9	58.2	46.8	56.1
Setting 3	57.7	58.9	51.7	61.4

- Setting 3 results are
  - slightly better than Setting 2 results for Italian
  - significantly better than Setting 2 results for Spanish

Results (Averaged over all Scoring Programs)

	Italian		Spanish	
	Regular	Gold	Regular	Gold
	F	F	F	F
Supervised	63.4	65.9	54.6	66.1
Best result in Shared Task	60.0	61.2	49.6	66.8
Setting 1	21.4	---	37.6	---
Setting 2	54.9	58.2	46.8	56.1
Setting 3	57.7	58.9	51.7	61.4

- Setting 3 results are around 89-94% of the supervised results

Results (Averaged over all Scoring Programs)

	Italian		Spanish	
	Regular	Gold	Regular	Gold
	F	F	F	F
Supervised	63.4	65.9	54.6	66.1
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Setting 2	54.9	58.2	46.8	56.1
Setting 3	57.7	58.9	51.7	61.4

- Setting 3 results are around 89-94% of the supervised results
  - obtained without any manual coreference annotations

Summary

- Investigated MT-based projection approach to coreference
  - can perform coreference resolution for a language
    - without coreference-annotated data
    - without linguistic knowledge of the language
  - can exploit any available knowledge about the target language

- Obtained promising results for Italian and Spanish
  - achieved ~90% of the performance of a supervised resolver when only a mention detector for the target language is available

- Has the potential to allow coreference technologies to be deployed across a larger number of languages

Future Work

- Isolate the impact of each factor that harms performance
  - Errors in MT, coreference in source language, projection

- Explore alternatives
  - Translate all coreference-annotated data from source to target, then train a coreference model on the translated data

- Use our approach to alleviate corpus annotation bottleneck
  - Use the annotated data it produces to augment the manual coreference annotations capturing language-specific properties