Improving Machine Learning Approaches to Coreference Resolution

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Plan for the Talk

- noun phrase coreference resolution
- standard machine learning approach
  - an instantiation (W. M. Soon, H. T. Ng, and D. Lim [2001])
- two extensions
  - extra-linguistic modifications to the learning framework
  - large-scale expansion in linguistic knowledge sources

Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband,
King George VI, into a viable monarch. Logue,
a renowned speech therapist, was summoned to help
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A Machine Learning Approach

- Classification
  - given a description of two noun phrases, NP_i and NP_j, classify the pair as *coreferent* or *not coreferent*
  - create one training instance for each pair of noun phrases from texts annotated with coreference information
    - feature vector: describes the two NPs and context

coref ? *coref ?*

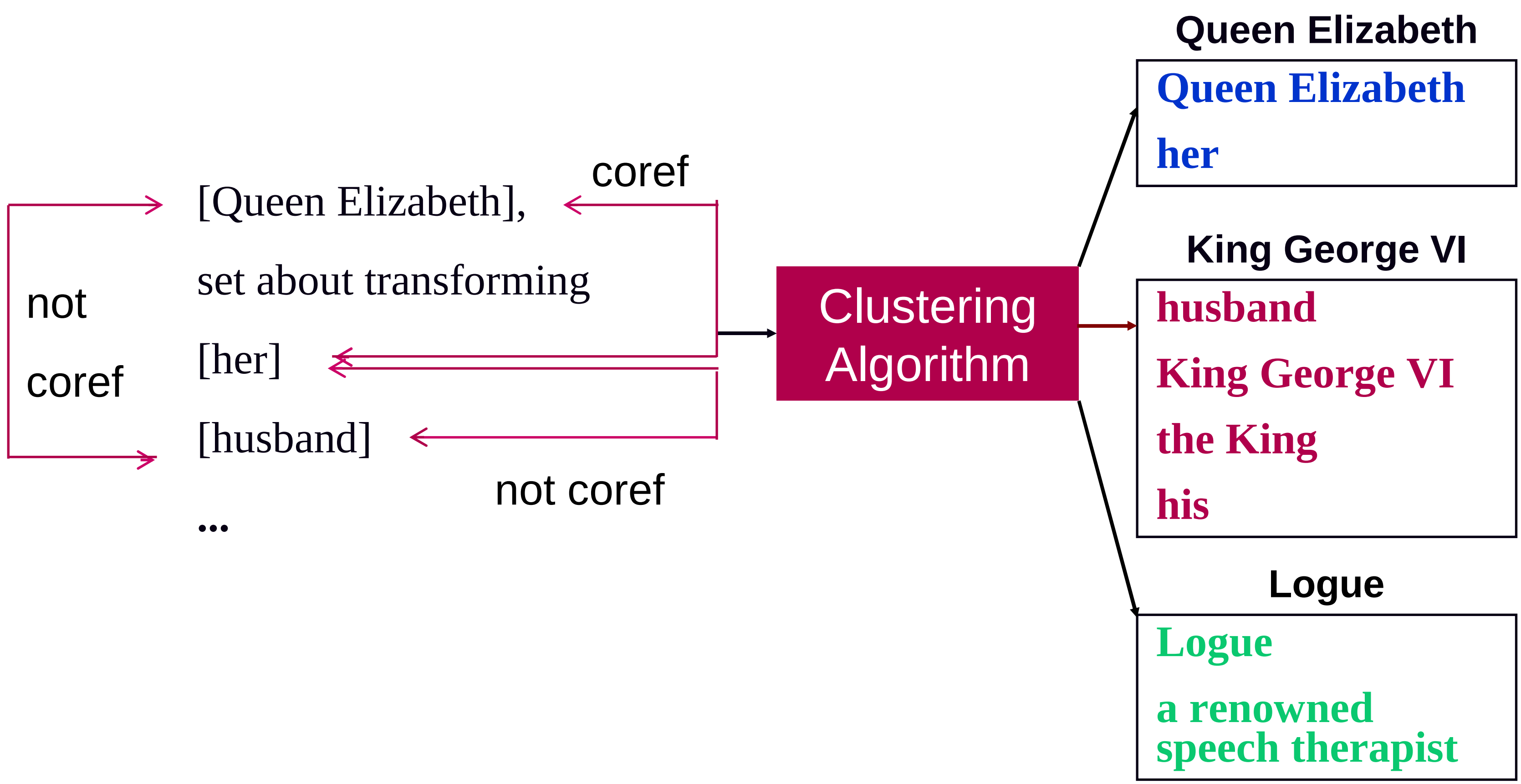
[Queen Elizabeth] set about transforming [her] [husband], ...

not coref ?

Aone & Bennett [1995]; Connolly et al. [1994]; McCarthy & Lehnert [1995]; Soon, Ng & Lim [2001]

A Machine Learning Approach

- Clustering
  - coordinates pairwise coreference decisions



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Soon *et al.* Training Instance Selection

- Creating training instances
  - Naïve method: one instance for each pair of noun phrases
  - Problem: all NP pairs produces highly skewed data set
  - Soon *et al.*'s solution: create
    - » *positive instance* for each anaphoric noun phrase, NP_j, and its closest preceding antecedent, NP_i
    - » *negative instance* for NP_j and each intervening noun phrase, NP_{i+1}, NP_{i+2} , … , NP_{j-1}

Soon Instance Representation

	Soon_str	Pronoun_1 Pronoun_2 Definite_2 Demonst_2	Number	Gender	Both_ proper_ nouns	Appos- itive	Semantic class	Alias	Sent_ dist	Class
NP1/ NP2	✗	No; Yes; No; No	✓	✓	✗	✗	✓	✗	0	Coref
NP2/ NP3	✗	Yes; No; No; No	✓	✗	✗	✗	✓	✗	0	Not coref

NP1 NP2 NP3

[Queen Elizabeth] set about transforming [her] [husband] ...

Soon *et al.* Clustering Algorithm

CREATE-COREF-CHAINS ($NP_1, NP_2, \ldots, NP_n; doc$)

Mark each NP_j as belonging to its own class: $NP_j \in c_j$

Proceed through the NPs in left-to-right order. For each NP_j encountered, consider each preceding NP_i:

Let c_i = class of NP_i and c_j = class of NP_j

Let *coref-likelihood* =

dtree (feat_vec (NP_i, NP_j, *doc*))

If *coref-likelihood* > *0.5* then $c_j = c_j \cup c_i$; break

- selects as antecedent the closest preceding coreferent NP

Soon *et al.* Evaluation

- MUC-6 and MUC-7 coreference data sets
- documents annotated w.r.t. coreference
- MUC-6: 30 training texts + 30 test texts
- MUC-7: 30 training texts + 20 test texts
- MUC scoring program
  - recall, precision, F-measure

Results (Soon *et al.* system)

	MUC-6			MUC-7		
	R	P	F	R	P	F
Soon	58.6	67.3	**62.6**	56.1	65.5	**60.4**
Best MUC System	59	72	**65**	56.1	68.8	**61.8**
Worst MUC System	36	44	**40**	52.5	21.4	**30.4**

- Soon's system is the first learning-based system that achieves performance comparable to the best MUC systems

Results (Baseline System)

	MUC-6			MUC-7		
	R	P	F	R	P	F
Original Soon	58.6	67.3	**62.6**	56.1	65.5	**60.4**
Duplicated Soon Baseline	62.4	70.7	**66.3**	55.2	68.5	**61.2**

- improvements over Soon:
  - MUC-6: better identification of NPs (93.8 vs. 89.9 max recall)
  - MUC-7: more accurate feature value computation

Results (Baseline System)

	MUC-6			MUC-7		
	R	P	F	R	P	F
Duplicated Soon Baseline	62.4	70.7	**66.3**	55.2	68.5	**61.2**
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Modification 1: Best-first Clustering

- Focus on improving precision

Modify create-coref-chain to select as the antecedent of NP_j the noun phrase with the

highest coref-likelihood score

from among preceding noun phrases with coref-likelihood scores > 0.5.

Assume non-anaphoric otherwise.

Modification 2: Training Instance Selection

- Focus on improving precision

Generate a positive training example for the

most confident antecedent

of each anaphoric NP_j. Negative examples are generated as in the Baseline system.

non-pronominal NP: closest preceding non-pronominal antecedent

pronouns: closest preceding antecedent

Modification 2: Training Instance Selection

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. The Queen was said to have acted as a buffer for the King's fierce temper during the process.

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Modification 3: String Match Feature

- Focus on improving precision

Split the SOON_STR feature into several primitive features:

PRONOUN_STR

PROPER_NAME_STR

WORDS_STR

These restrict string matching to pronouns, proper names, and non-pronominal noun phrases, respectively.

Results (Learning Framework Modifications)

	MUC-6			MUC-7		
	R	P	F	R	P	F
Duplicated Soon Baseline	62.4	70.7	**66.3**	55.2	68.5	**61.2**
Learning Framework Modifications	62.4	73.5	**67.5**	56.3	71.5	**63.0**
clustering	60.4	74.4	66.7	54.3	72.1	62.0
instance selection	61.9	70.3	65.8	55.2	68.3	61.1
string match	62.4	70.8	66.3	56.5	69.6	62.3

§ gain in precision without loss in recall

Results (Learning Framework Modifications)

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Duplicated Soon Baseline	62.4	70.7	66.3	55.2	68.5	61.2
Learning Framework Modifications	62.4	73.5	**67.5**	56.3	71.5	**63.0**
clustering	60.4	74.4	**66.7**	54.3	72.1	**62.0**
instance selection	61.9	70.3	**65.8**	55.2	68.3	**61.1**
string match	62.4	70.8	**66.3**	56.5	69.6	**62.3**

- F-measure increases in most cases with weaker effects

Can we stop here?

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Best MUC System	59	72	**65**	56.1	68.8	**61.8**

NP Coreference Using Many Features

Will incorporating additional knowledge further improve performance?

- propose 41 additional features
- similar features have been explored in the past [Lappin & Leass, 1994; Grishman, 1995; Lin, 1995]
  - » but not in a machine learning framework
  - » previous work generally treats linguistic constraints as *broadly and unconditionally applicable hard constraints*

Additional Features

Lexical (8)	More complex string matching
Semantic (4)	Finer-grained semantic compatibility tests
Positional (1)	Distance in terms of number of paragraphs
Knowledge-based (2)	Naïve pronoun resolution, rule-based coref resolution
Grammatical (26)	NP type Grammatical role Linguistic constraints Linguistic preferences Heuristics

Results (Expanded Feature Set)

	MUC-6			MUC-7		
	R	P	F	R	P	F
Duplicated Soon Baseline	62.4	70.7	66.3	55.2	68.5	61.2
Learning Framework Modifications	62.4	73.5	**67.5**	56.3	71.5	**63.0**
All Features	70.3	58.3	**63.8**	65.5	58.2	**61.6**
pronouns	-	66.3	-	-	62.1	-
proper nouns	-	84.2	-	-	77.7	-
common nouns	-	40.1	-	-	45.2	-

- with the expanded feature set performance drops!
- gain in recall but larger loss in precision

Results (Expanded Feature Set)

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All Features	70.3	58.3	63.8	65.5	58.2	61.6
pronouns	-	66.3	-	-	62.1	-
proper nouns	-	84.2	-	-	77.7	-
common nouns	-	**40.1**	-	-	**45.2**	-

- poor precision on common nouns

Fixing Low Precision Rules

- example:
  - NP_i and NP_j ($i < j$) are *coreferent* if
    - » NP_i is a proper name
    - » NP_j is a definite noun phrase in the subject position
    - » NP_i and NP_j have the same semantic class
    - » NP_i and NP_j are at most one sentence apart
  - covers 38 examples with 18 exceptions
- manually discard features used primarily to induce low-precision rules for common noun resolution
- re-train coreference classifier using the reduced feature set consisting of 22-26 features

Results (Manual Feature Selection)

	MUC-6			MUC-7		
	R	P	F	R	P	F
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Learning Framework Modifications	62.4	73.5	67.5	56.3	71.5	63.0
All Features	70.3	58.3	**63.8**	65.5	58.2	**61.6**
Hand-selected Features	64.1	74.9	**69.1**	57.4	70.8	**63.4**
pronouns	-	67.4	-	-	54.4	-
proper nouns	-	93.3	-	-	86.6	-
common nouns	-	63.0	-	-	64.8	-

- gain in precision and smaller loss in recall

Results (Manual Feature Selection)

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Hand-selected Features	64.1	74.9	69.1	57.4	70.8	63.4
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proper nouns	-	93.3	-	-	86.6	-
common nouns	-	**63.0**	-	-	**64.8**	-

- precision on common nouns rises from 40s to 60s.

Summary

- Investigated two methods to improve the best existing machine learning approach to noun phrase coreference resolution
  - Baseline: better NP identification -> gain in recall
  - Changes to ML framework: gain in precision (without loss in recall)
  - Expanded feature set: gain in recall but larger loss in precision
  - Manual feature selection: small loss in recall and larger gain in precision