Coreference Resolution

Slides are modified from Prof. Claire Cardie's

Plan for the Talk

- Linguistic background for coreference resolution
- supervised machine learning approach
- weakly supervised approaches

Reference resolution

- **Reference**: the process by which speakers use expressions like "John Simon" and "his" to denote a real-world entity
  - **Referring expressions**: NL expression used to perform reference
  - **Referent**: the entity that is referred to
  - **Shorthand form**: *his* refers to John Simon

?

John Simon, Chief Financial Officer of Prime Corp. since 1986, saw his pay jump 20%, to $1.3 million, as the 37-year-old also became the financial-services company's president...

Coreference

- **Coreference:** two referring expressions that are used to refer to the same entity are said to corefer
- *John Simon* is the **antecedent** of *his*.
- Reference to an entity that has been previously introduced into the discourse is called **anaphora**; and the referring expression used is said to be **anaphoric**.

John Simon, Chief Financial Officer of Prime Corp. since 1986, saw his pay jump 20%, to $1.3 million, as the 37-year-old also became the financial-services company's president...

Types of referring expressions

- Definite Noun Phrases
- Indefinite Noun Phrases
- Pronouns
- Demonstrative pronouns
- One-Anaphora

Indefinite noun phrases

- Introduce entities that are new to the hearer into the discourse context
  - I saw *a Subaru WRX* today.
  - I saw *this awesome Subaru WRX* today.

Definite noun phrases

- Refer to an entity that is identifiable to the hearer
- It has already been mentioned in the discourse
- It is contained in the hearer's set of beliefs about the world
- The uniqueness of the object is implied by the description itself
  - I saw a Subaru WRX today. *The WRX* was blue and needed a wash.
  - *The Indy 500* is the most popular car race in the US.
  - *The fastest car in the Indy 500* was a Subaru WRX.

<u>Pronouns</u>

- Another form of ***definite*** reference
- Also known as **Anaphora**
- Referent must have a high degree of activation or **salience** in the discourse model
  - John went to Bob's party, and parked next to a beautiful Subaru WRX. He went inside and talked to Bob for more than an hour. Bob told him that he recently got engaged.

    ➔ (a)?? He also said that he bought <u>*it*</u> yesterday.

    ➔ (a') He also said that he bought <u>*the WRX*</u> yesterday.

- **Cataphora**: referring expression is mentioned before its referent
  - Before <u>*he*</u> bought <u>*it*</u>, John checked over the WRX carefully.

Types of referring expressions

- Definite Noun Phrases
- Indefinite Noun Phrases
- Pronouns
- Demonstrative pronouns
- One-Anaphora

Demonstrative pronouns

- Behave somewhat differently than simple definite pronouns
- Can appear alone or as determiners
- Choice of *this* or *that* depends on some notion of spatial or temporal proximity
  - I bought a WRX yesterday. It's similar to the one I bought a year ago. *That one* was really nice, but I like *this one* even better.

One-anaphora

- Blends properties of definite and indefinite reference
  - I saw no fewer than 6 Subaru WRX's today. Now I want *one*.
- May introduce a new entity into the discourse, but it is dependent on an existing referent for the description of this new entity.

Noun Phrase Coreference Resolution

- Identify all phrases that refer to each real-world entity mentioned in the text

John Simon, Chief Financial Officer of Prime Corp. since 1986, saw his pay jump 20%, to $1.3 million, as the 37-year-old also became the financial-services company's president...

Why It's Hard

Many sources of information play a role

- head noun matches
  - IBM *executives* = the *executives*
  - Microsoft *executives*
- syntactic constraints
  - John helped himself to...
  - John helped him to...
- discourse focus, recency, syntactic parallelism, semantic class, agreement, world knowledge, …

Why It’s Hard

No single source is a completely reliable indicator

- semantic preferences
  - Mr. Callahan = president =? the carrier
- number and gender
  - assassination (of Jesuit priests) = these murders
  - the woman = she = Mary =? the chairman

Why It's Hard

Coreference strategies differ depending on the type of referring NP

- definiteness of NPs
  - … Then Mark saw the man walking down the street.
  - … Then Mark saw a man walking down the street.

- pronoun resolution alone is notoriously difficult
  - resolution strategies differ for each type of pronoun
  - some pronouns refer to nothing in the text

I went outside and it was snowing.

Types of referents: complications

- Inferable
  - A referring expression does not refer to an entity in the text, but to one that is inferentially related to it.
    - I almost bought a WRX today, but *a door* had a dent and *the engine* seemed noisy.
    - Mix the flour, butter, and water. Stir *the batter* until all lumps are gone.
- Discontinuous sets
  - Referents may have been evoked in discontinuous phrases
    - John has a Volvo, and Mary has a Mazda. *They* drive *them* all the time.
- Generics – refer to a class of entities
  - I saw no fewer than 6 WRX's today. *They* are the coolest cars.

Traditional Knowledge-Based Approaches

Lappin and Leass [1994]

- hand-crafted heuristics and filters
  - syntactic filters [Lappin and McCord 1990a]
  - morphological filter
  - pleonastic pronoun filter ("It was raining.")
  - procedure for identifying possible antecedents [Lappin and McCord 1990b]
  - salience assignment w.r.t. grammatical role, proximity, parallelism,etc.

- decision procedure

Problems with hand-written rules

- Portability
- Robustness
- Few large-scale evaluations
- Evaluations make a number of simplifying assumptions
  - perfect parse
  - omit many difficult cases, e.g. pleonastic pronouns
- **Impose coreference resolution strategies rather than learn them empirically**

Plan for the Talk

- Linguistic background for coreference resolution
- supervised machine learning approach
- weakly supervised approaches

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 the King overcome his speech impediment...

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Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into <u>a viable monarch</u>. Logue, a renowned speech therapist, was summoned to help the King overcome his <u>speech impediment</u>...

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Singletons!

Noun Phrase Coreference

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A Machine Learning Approach

Typical Steps:

- Step1: Noun Phrase Identification
- Step2: Pairwise Classification
- Step3: Clustering (Why?)

A Machine Learning Approach

- Step1: Find all noun phrases
  - Using "***partial parsers***" or "***chunkers***"

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

A Machine Learning Approach

- Step2: Pair-wise Classification (using machine learning)
  - given a description of two noun phrases, *NP_i* and *NP_j*, classify the pair as *coreferent* or *not coreferent*

coref ? *coref ?*

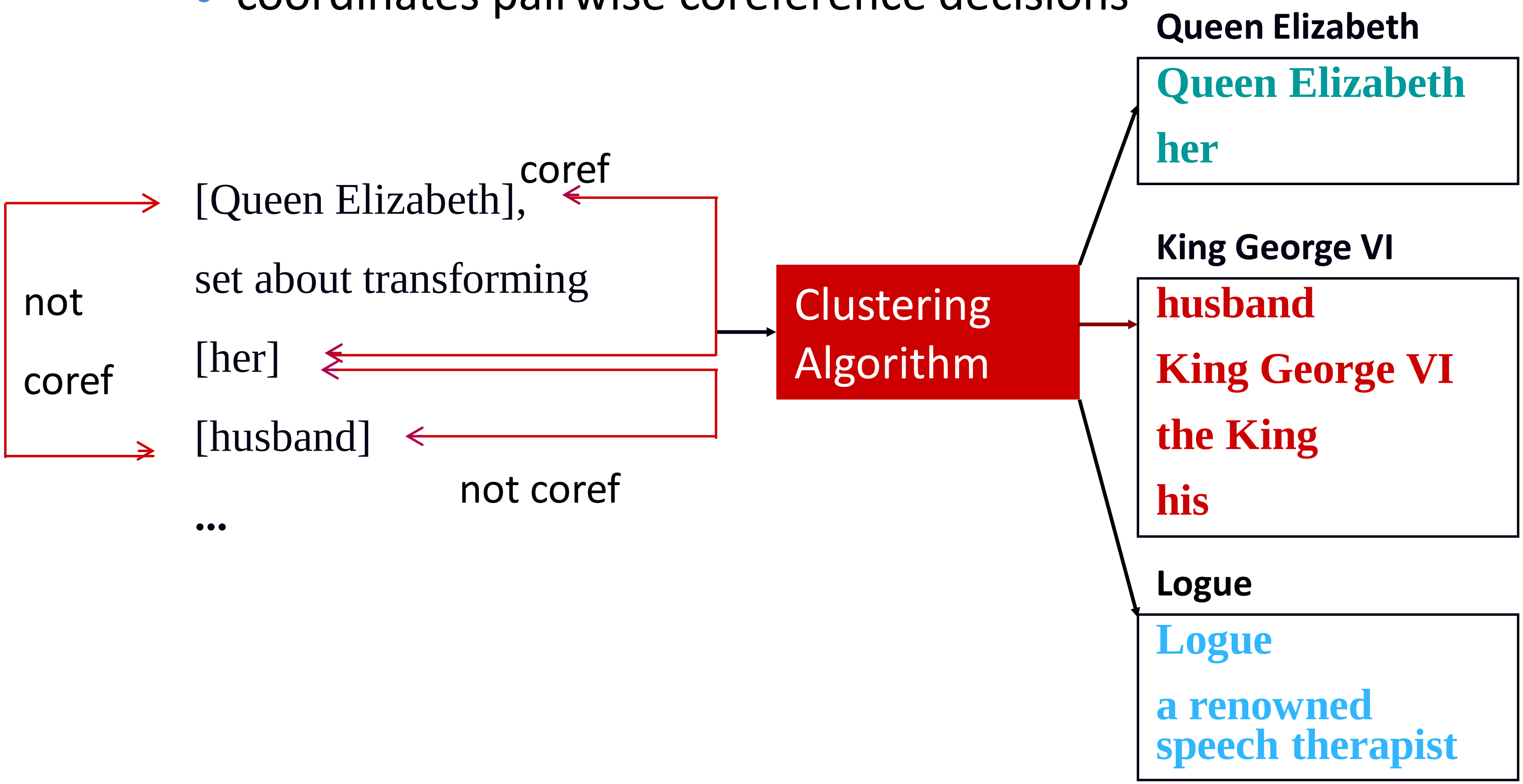
[Queen Elizabeth] set about transforming [her] [husband], ...

coref ?

Aone & Bennett [1995]; Connolly et al. [1994]; McCarthy & Lehnert [1995];
Soon et al. [2001]; Ng & Cardie [2002]; ...

A Machine Learning Approach

- Step3: Clustering
  - coordinates pairwise coreference decisions



Machine Learning Issues

- Training data creation
- Instance representation
- Learning algorithm for pair-wise decisions
- Clustering algorithm (to combine pair-wise decisions)

Supervised Inductive Learning

Examples of NP pairs (features + class)

ML Algorithm

Concept description

(novel) pair of NPs
(features)

(program)

class

Training Data Creation

- Creating training instances
  - texts annotated with coreference information

candidate antecedent anaphor

- one instance *inst*(NP_i, NP_j) for each *ordered* pair of NPs
  - NP_i precedes NP_j
  - feature vector: describes the two NPs and context
  - class value:

    coref pairs on the same coreference chain

    not coref otherwise

Instance Representation

- lexical
  - string matching for pronouns, proper names, common nouns
- grammatical
  - pronoun_1, pronoun_2, demonstrative_2, indefinite_2, …
  - number, gender, animacy
  - appositive, predicate nominative
  - binding constraints, simple contra-indexing constraints, …
  - span, maximalnp, …
- semantic
  - same WordNet class
  - alias
- positional
  - distance between the NPs in terms of # of sentences
- knowledge-based
  - naïve pronoun resolution algorithm

Why It's Hard

Many sources of information play a role

- string matching, syntactic constraints, semantic class,
- number agreement, gender agreement,
- discourse focus, recency,
- world knowledge…

- No single source is a completely reliable indicator
- Identifying each of these features automatically, accurately, and in context, is hard

Clustering Algorithm

- Best-first single-link clustering
  - 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, NP_j, create test instances, $inst(NP_i, NP_j)$, for all of its preceding NPs, NP_i.
    - Select as the antecedent for NP_j the highest-confidence coreferent NP, NP_i, according to the coreference classifier (or none if all have below .5 confidence);
    - Merge c_j and c_j .

➔ Pros?

➔ Cons?

Clustering Algorithm

- Best-first single-link clustering

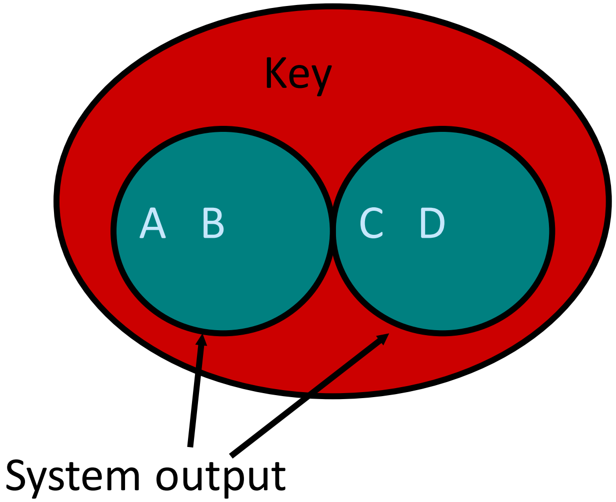
  → Pros: Simple but works surprisingly well!

  → Cons: Can’t go back and revise previous decisions

- Clustering algorithms that make collective decisions:
  - Corelational Clustering
  - Multi-cut
  - NP-hard, often hard to beat single-link clustering

Evaluation

- MUC-6 and MUC-7 coreference data sets
- documents annotated w.r.t. coreference
- 30 + 30 training texts (dry run)
- 30 + 20 test texts (formal evaluation)
- scoring program
  - recall
  - precision
  - F-measure: 2PR/(P+R)

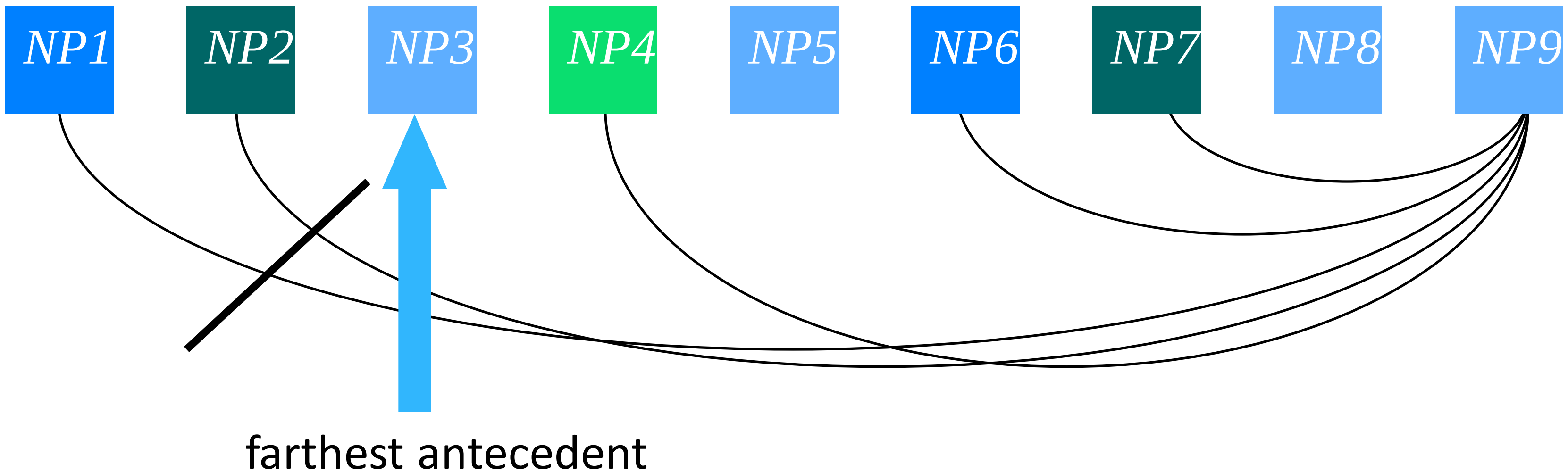


Baseline Results

	MUC-6			MUC-7		
	R	P	F	R	P	F
Baseline	40.7	73.5	**52.4**	27.2	86.3	**41.3**
Worst MUC System	36	44	40	52.5	21.4	30.4
Best MUC System	59	72	65	56.1	68.8	61.8

Problem 1

- Coreference is a rare relation
  - skewed class distributions (2% positive instances)
  - *remove some negative instances*



Problem 2

- Which pair do you think is harder for computers to learn/predict?

Queen Elizabeth set about transforming **her husband**,
King George VI, into a viable monarch. Logue,
the renowned speech therapist, was summoned to help
the King overcome his speech impediment...

Problem 2

- Order the following in the order of difficulties: (assuming best-first single-link clustering)
  - Pronouns
  - Proper Nouns
  - Common nouns

Queen Elizabeth set about transforming **her husband**, **King George VI**, into a viable monarch. Logue, the renowned speech therapist, was summoned to help **the King** overcome his speech impediment...

Problem 2

- Order the following in the order of difficulties

  → common nouns < pronouns < proper nouns

  (hardest) (easest)

Queen Elizabeth set about transforming **her husband**, **King George VI**, into a viable monarch. Logue, the renowned speech therapist, was summoned to help **the King** overcome his speech impediment...

Problem 2

- Coreference is a discourse-level problem with different solutions for different types of NPs
- positive example selection: selects easy positive training instances (cf. Harabagiu *et al.* (2001))

Queen Elizabeth set about transforming **her husband**, **King George VI**, into a viable monarch. Logue, the renowned speech therapist, was summoned to help **the King** overcome his speech impediment...

Problem 3

- Coreference is an ***equivalence relation***
  - loss of transitivity during pair-wise classification
  - need to tighten the connection between classification and clustering

coref ? *coref* ?

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

not coref ?

Results

	MUC-6			MUC-7		
	R	P	F	R	P	F
Baseline	40.7	73.5	52.4	27.2	86.3	41.3
NEG-SELECT	46.5	67.8	55.2	37.4	59.7	46.0
POS-SELECT	53.1	80.8	64.1	41.1	78.0	53.8
NEG-SELECT + POS-SELECT	63.4	76.3	69.3	59.5	55.1	57.2
NEG-SELECT + POS-SELECT + RULE-SELECT	63.3	76.9	**69.5**	54.2	76.3	**63.4**

- Ultimately: large increase in F-measure, due to gains in recall

Comparison with Best MUC Systems

	MUC-6			MUC-7		
	R	P	F	R	P	F
NEG-SELECT + POS-SELECT + RULE-SELECT	63.3	76.9	**69.5**	54.2	76.3	**63.4**
Best MUC System	59	72	**65**	56.1	68.8	**61.8**

Plan for the Talk

- noun phrase coreference resolution
- a (supervised) machine learning approach
- weakly supervised approaches
  - background
  - two techniques
  - evaluation

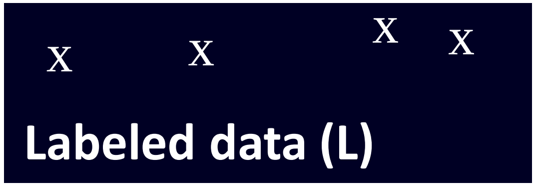
Weakly Supervised Approaches

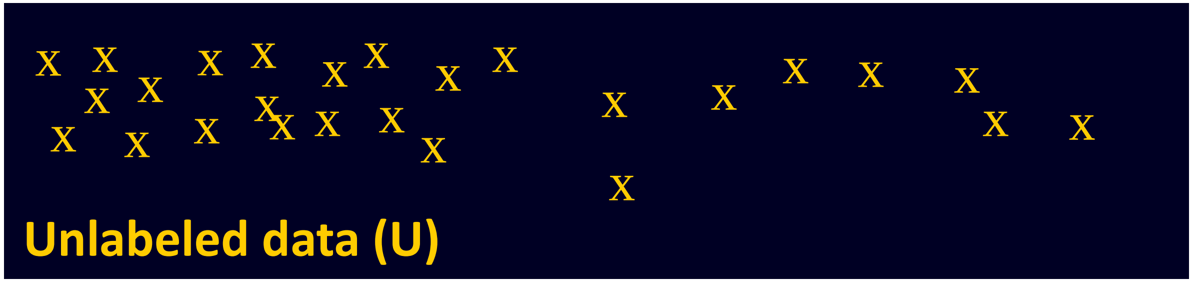
- Idea:

  bootstrap (NP coreference) classifiers using a *small amount of labeled data* (expensive) and a *large amount of unlabeled data* (cheap)

- Methods
  - Co-training
  - Self-training

Co-Training [Blum and Mitchell, 1998]





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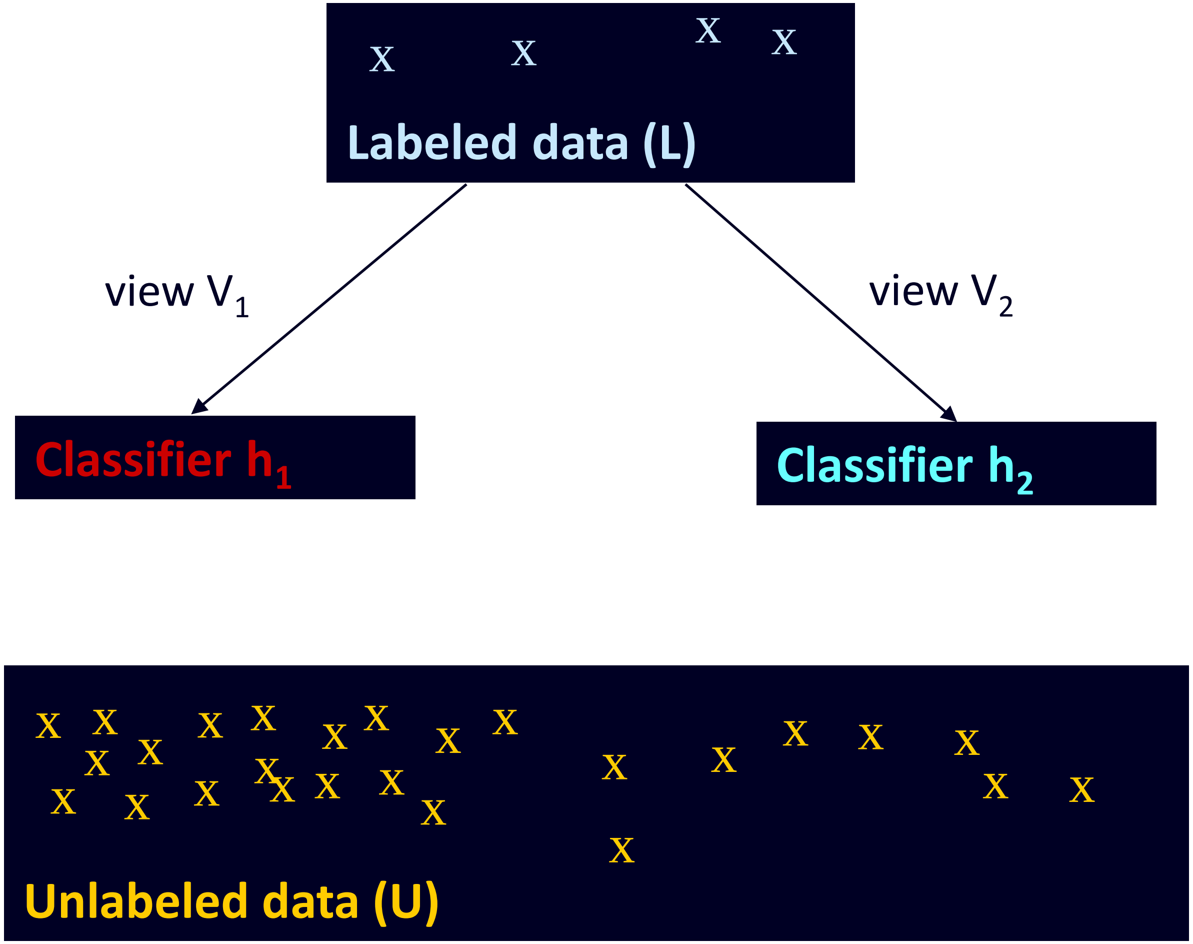

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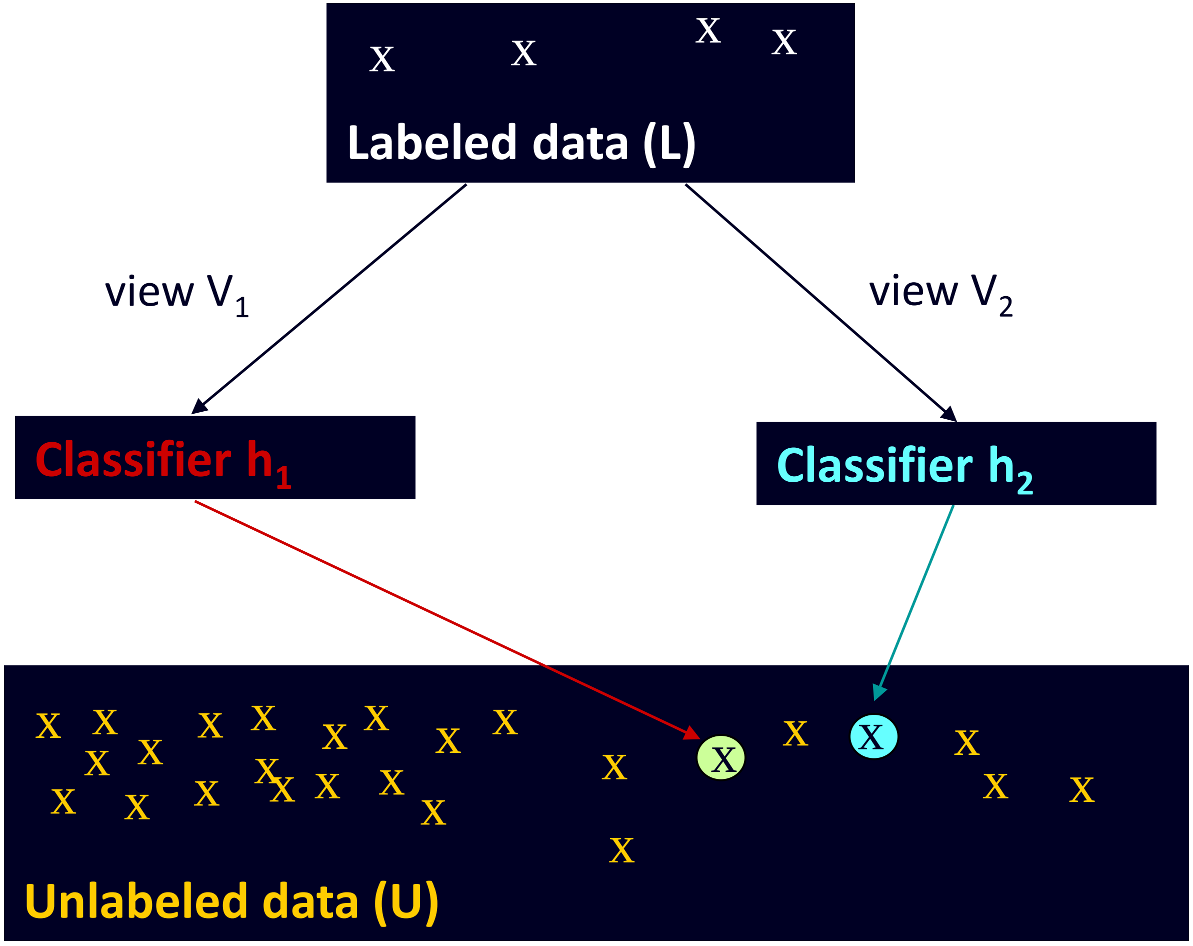

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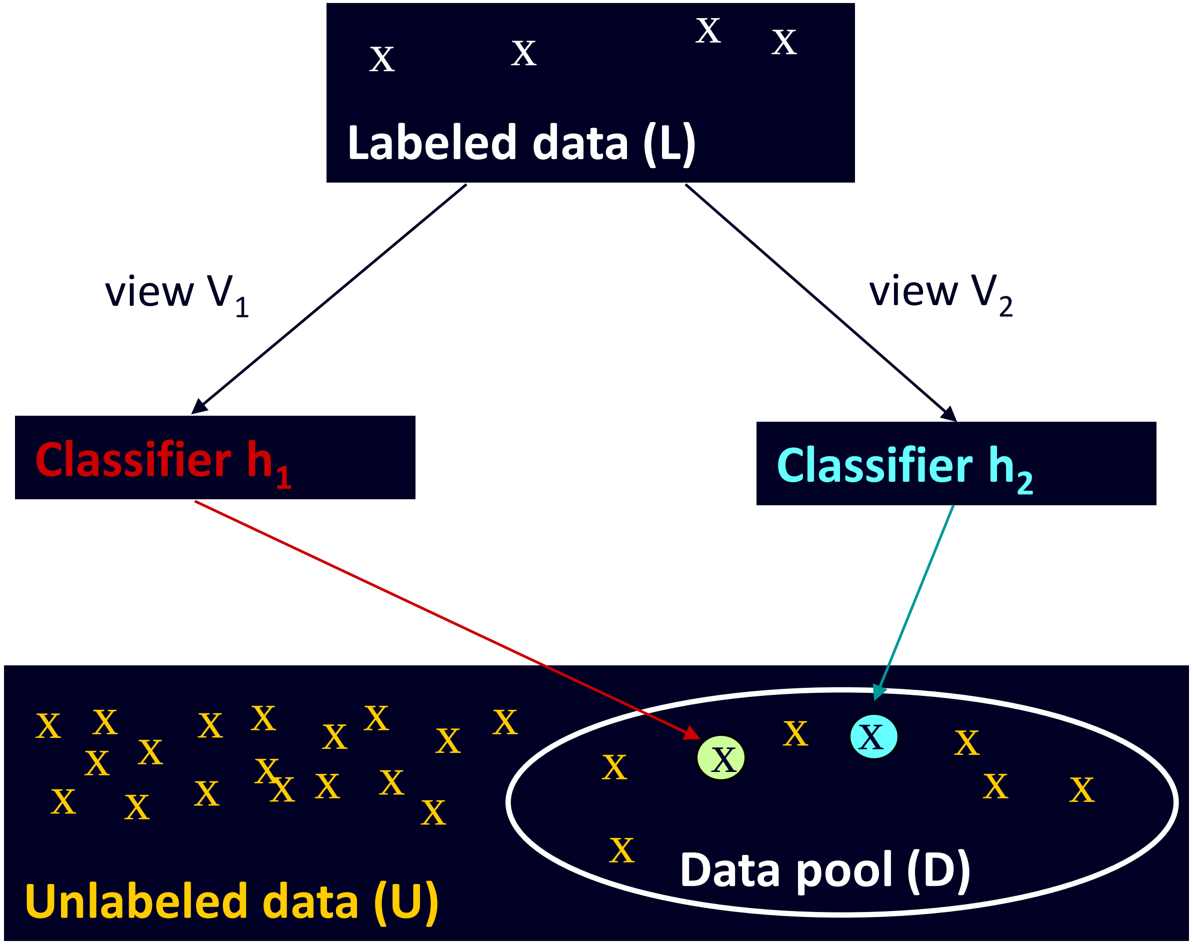

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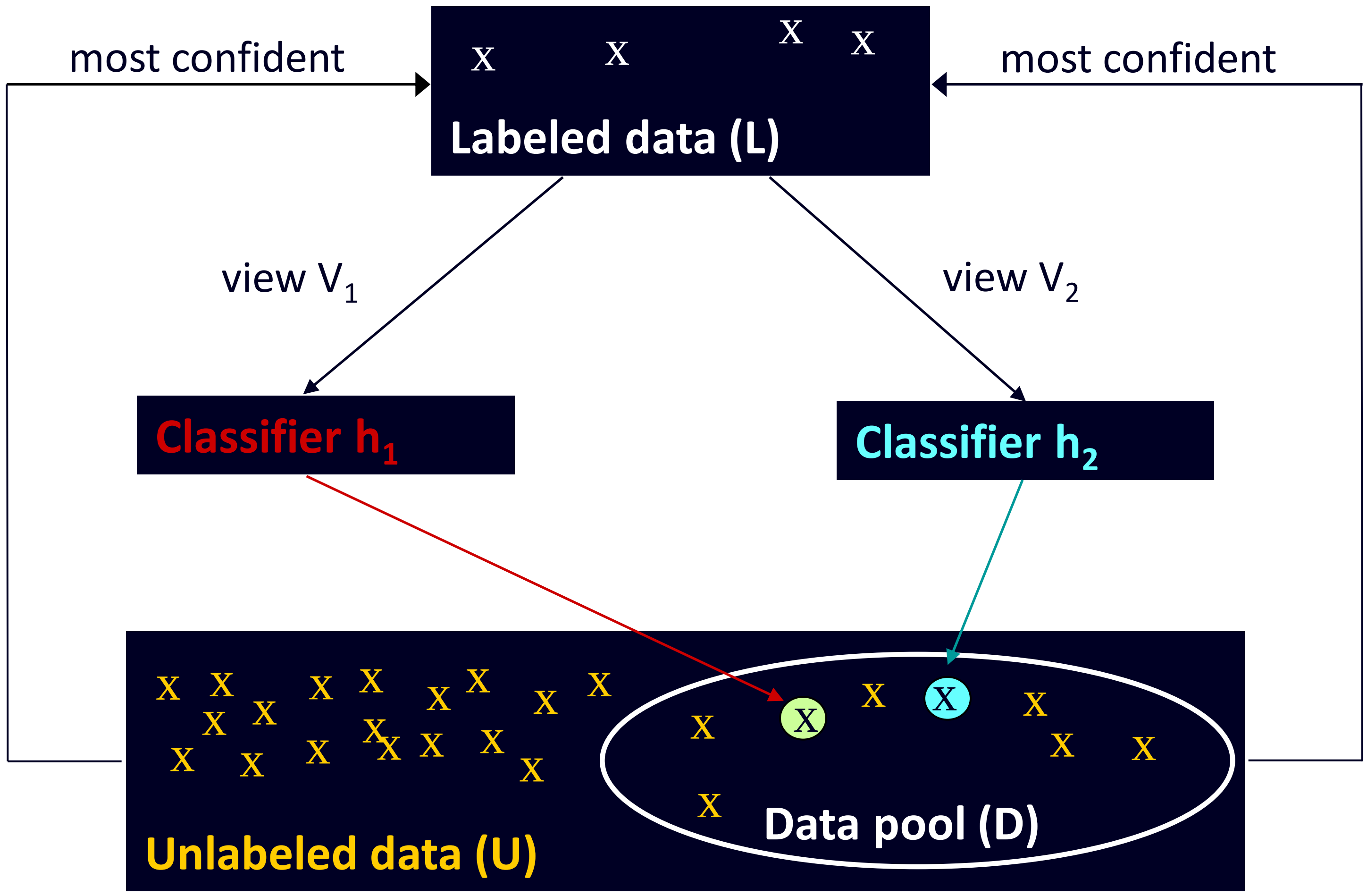


Potential Problems with Co-Training

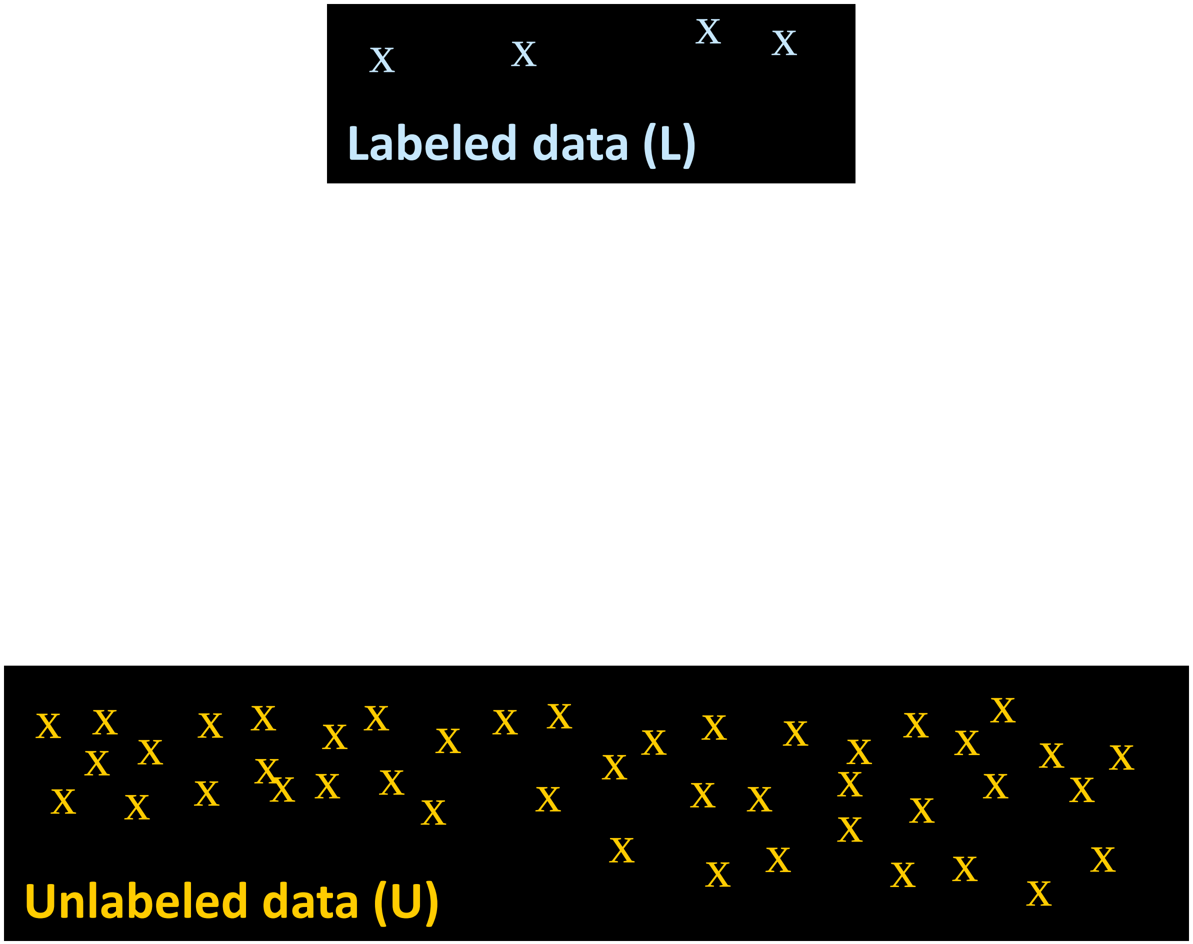
- Strong assumptions on the "views" (Blum and Mitchell, 1998)
  - each view must be sufficient for learning the target concept
  - the views must be conditionally independent given the class
  - empirically shown to be sensitive to these assumptions (Muslea *et al*., 2002)

- A number of parameters need to be tuned
  - views, data pool size, growth size, number of iterations, initial size of labeled data
  - algorithm is sensitive to its input parameters (Nigam and Ghani, 2000; Pierce and Cardie, 2001; Pierce 2003)

Potential Problems with Co-Training

- Multi-view algorithm
  - Is there any natural feature split for NP coreference?
    - view factorization is a non-trivial problem for coreference
      - Mueller *et al.*'s (2002) greedy method

Self-Training with Bagging [Banko and Brill, 2001]



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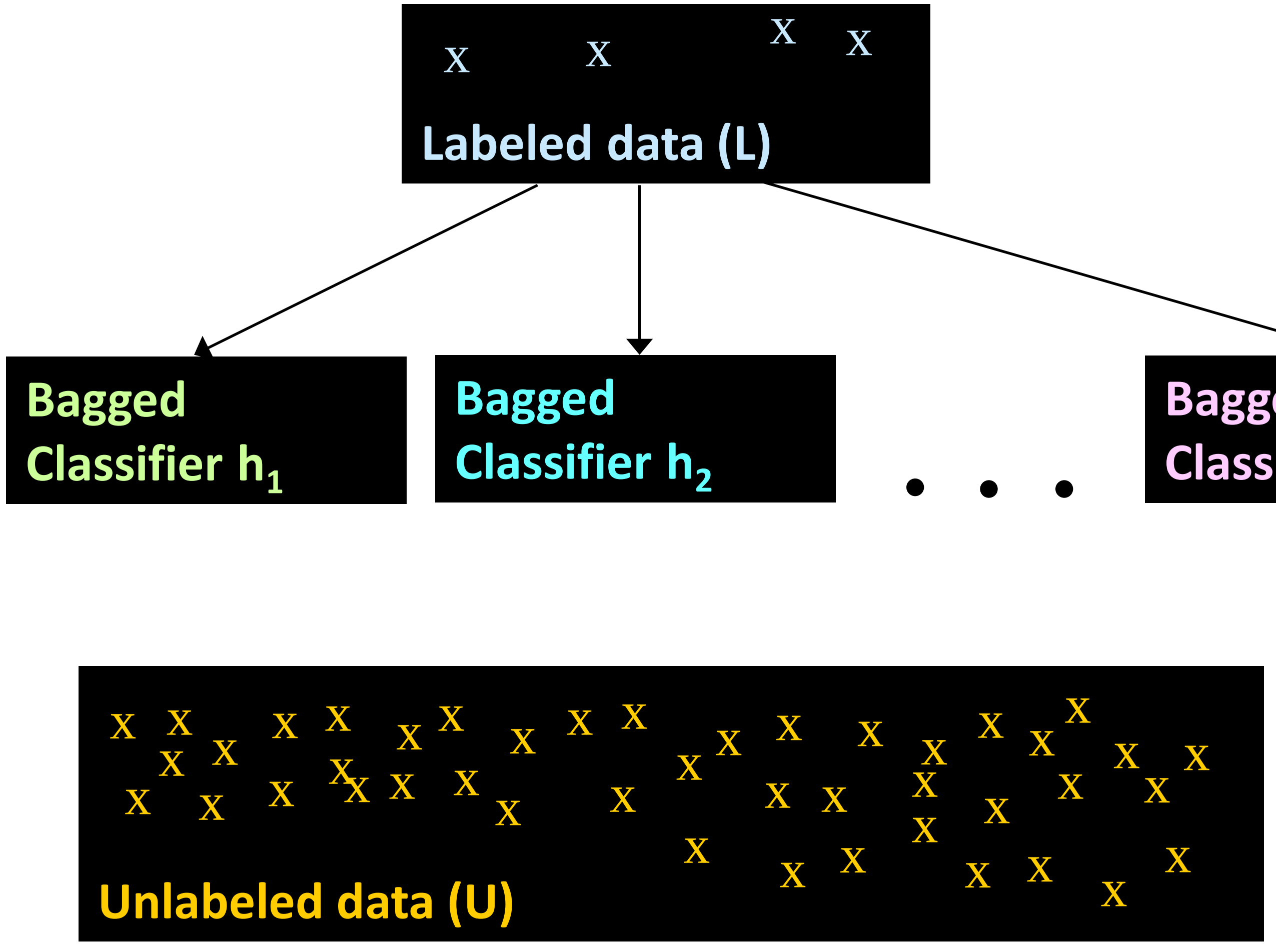

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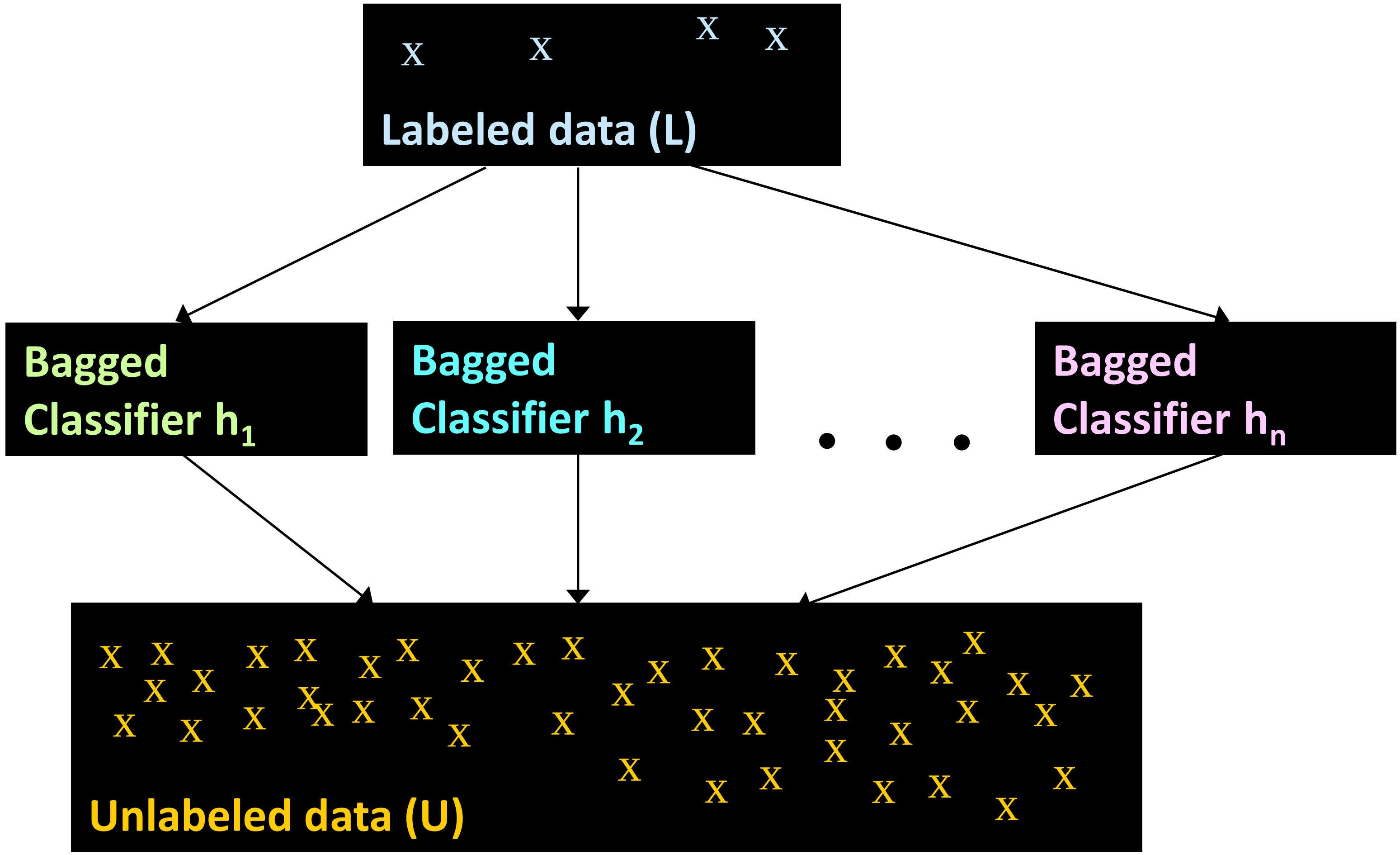

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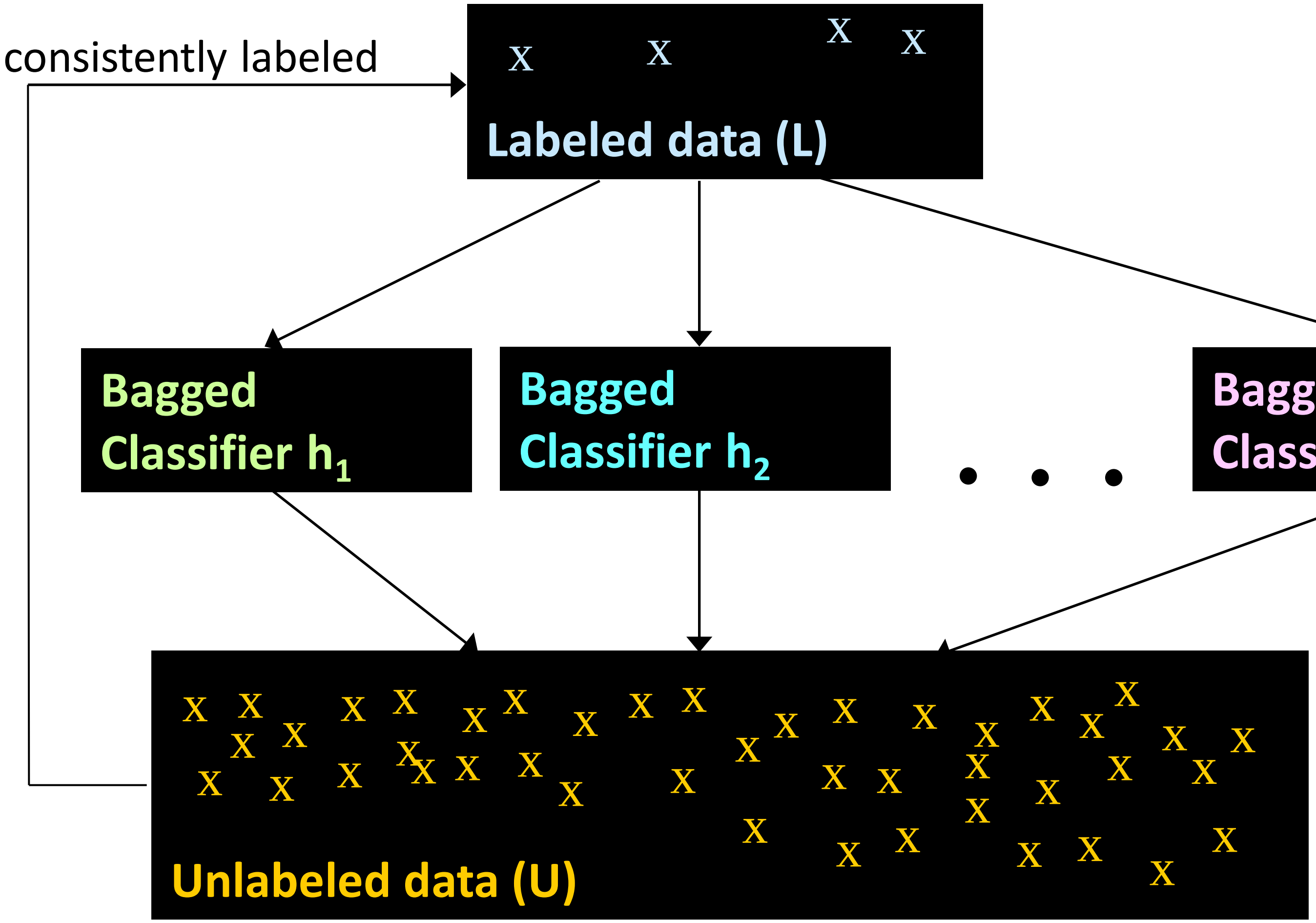
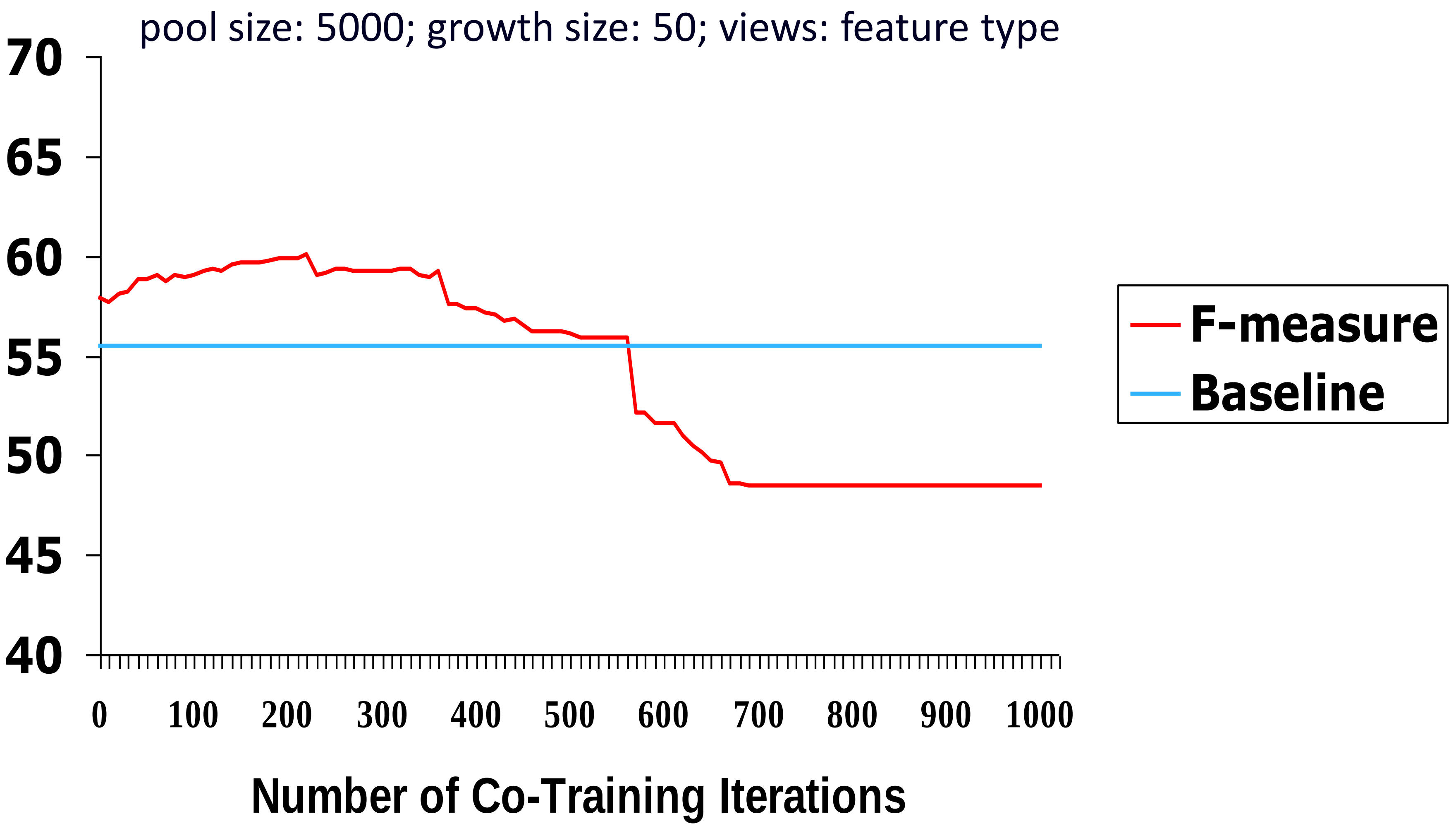


Evaluation

- MUC-6 and MUC-7 coreference data sets
- labeled data (L): one dryrun text
    - 3500-3700 instances
- unlabeled data (U): remaining 29 dryrun texts
- vs. fully supervised ML
    - ~500,000 instances (30 dryrun texts)

Learning Curve for Co-Training (MUC-6)



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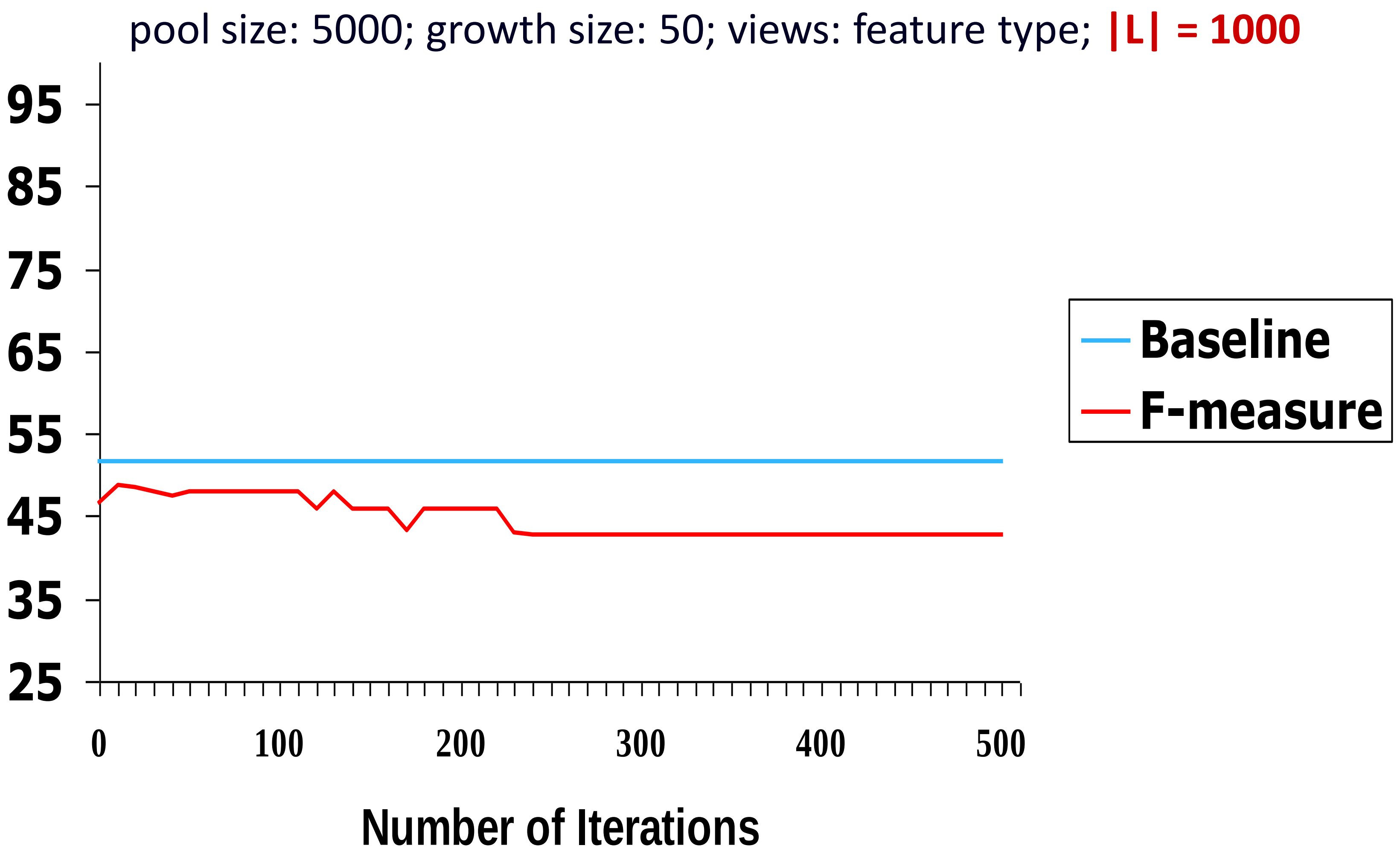

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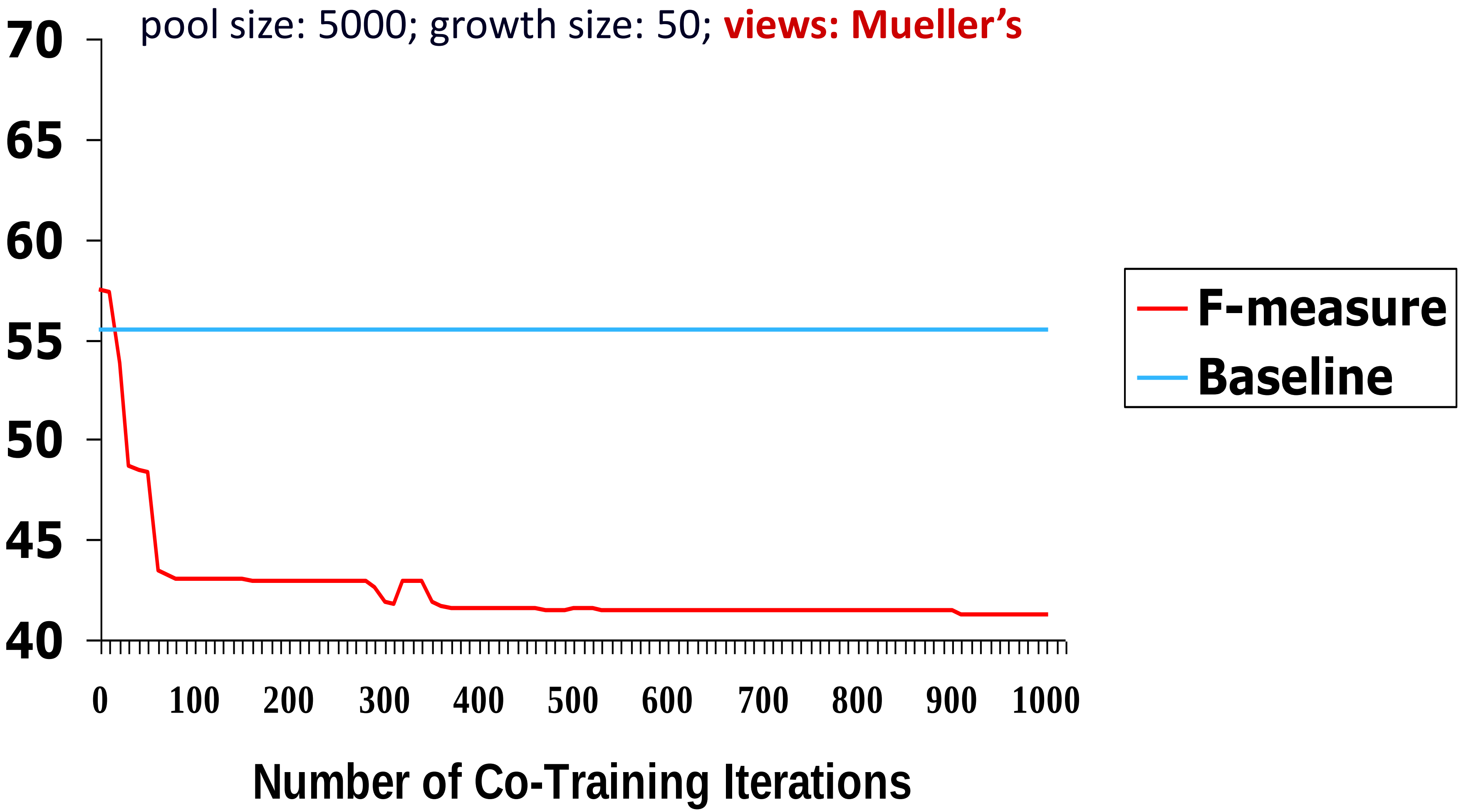


Self-Training Parameters

- Number of bags
  - tested all odd number of bags between 1 and 25

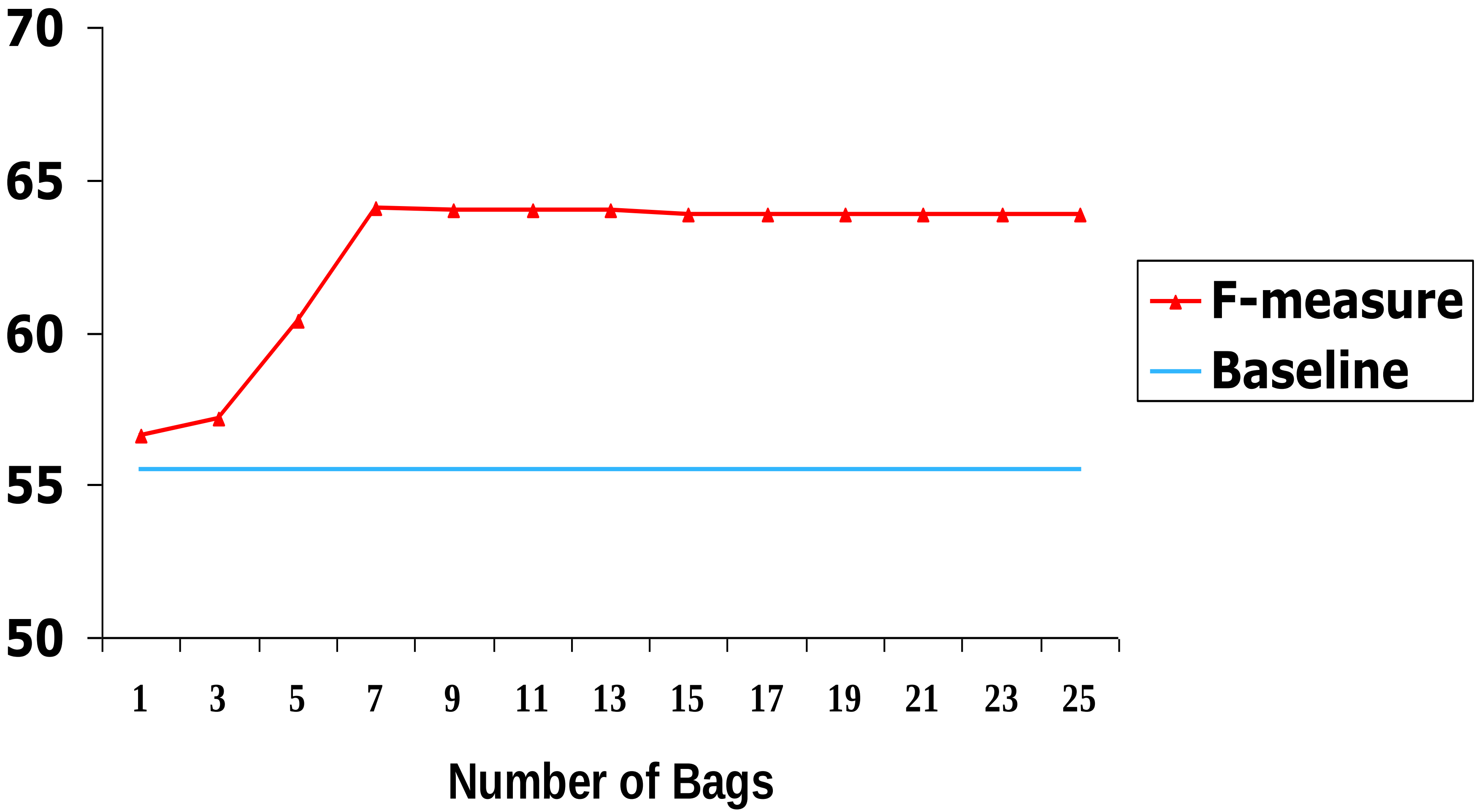
- 25 bags are sufficient for most learning tasks (Breiman, 1996)

Results (Self-Training with Bagging)

	MUC-6			MUC-7		
	R	P	F	R	P	F
Baseline	58.3	52.9	**55.5**	52.8	37.4	**43.8**
Co-Training	47.5	81.9	**60.1**	40.6	77.6	**53.3**
Self-Training with Bagging	54.1	78.6	**64.1**	54.6	62.6	**58.3**

- Self-training performs better than co-training

Self-Training: Effect of the Number of Bags (MUC-6)



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Self-Training with Bagging	54.1	78.6	**64.1**	54.6	62.6	**58.3**
Supervised ML* (~500,000 insts)	63.3	76.9	69.5	54.2	76.3	63.4

Summary

- Supervised ML approach to NP coreference resolution
  - Good performance relative to other approaches
  - Still lots of room for improvement
- Weakly supervised approaches are promising
  - Not as good performance as fully supervised, but use much less manually annotated training data
- For problems where no natural view factorization exists…
  - Single-view weakly supervised algorithms
    - Self-training with bagging