Learning by Bootstrapping

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Supervised & Unsupervised Machine Learning

Supervised Learning

Word sense disambiguation:

- … company said the plant is still operating.
  factory sense +
- …and divide life into plant and animal kingdom.
  living organism sense -

Supervised Learning

Word sense disambiguation:

- … company said the plant is still operating.

sense +

- …and divide life into plant and animal kingdom.

sense -

Supervised Learning

Word sense disambiguation:

- … company said the plant is still operating.

Features (company , operating) sense +

- …and divide life into plant and animal kingdom.

Features (life , animal) sense -

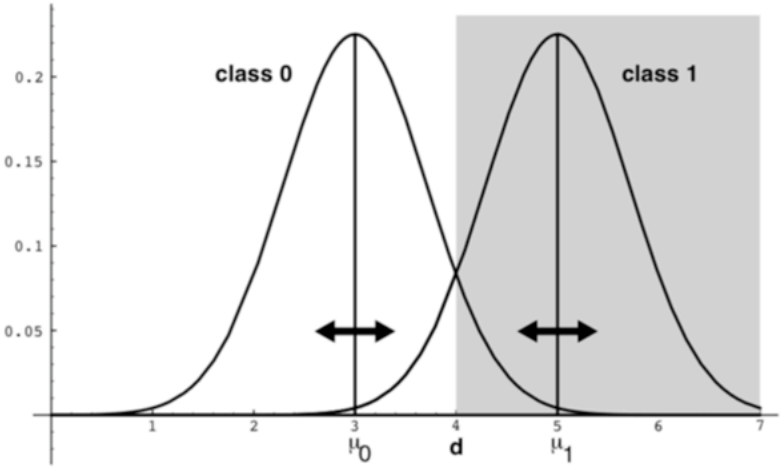
Supervised Word Sense Disambiguation:

1. Label a large number of sentences with the correct sense y
2. Each sentence x is mapped to predictive features $f_k(x,y)$
3. Using labeled data, learn a weight w_k for each f_k
4. Weighted features active in x provide *score*(x,y) for any given x
5. Label any new input x using *score*(x,y): output y with best score

Unsupervised Learning

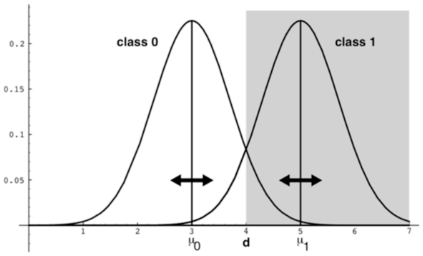
- Can we learn the labels without any supervision?
- Assumptions about unsupervised learning
  - Clustering (group by similarity)
  - Maximum Likelihood (generative models)
  - Co-training (learn from agreement with others)
  - Self-training (learn from agreement between features)

Clustering



(Castelli and Cover, 1995)

Problem with Clustering



- Having similar elements grouped is not enough
- Which class corresponds to which cluster?
- **Identifiable problem** = a problem in which a small number of labeled examples help identify the class of a cluster
- Problem: natural language learning tasks are not easily identifiable

(DLR, 1977)

Maximum Likelihood (EM)

Word sense disambiguation:

x ▪ … company said the plant is still operating. y

f_{20} f_{12}

(company , operating) sense +/-

x ▪ …and divide life into plant and animal kingdom. y

f_{64} f_2 f_{35}

(life , animal, kingdom) sense +/-

Construct a probabilistic model P(y,x):

1. $P(y_i, x_i) = P(y_i, f_1(x_i), \ldots, f_m(x_i)) = P(y_i) \times P(f_1 | y_i) \times \ldots \times P(f_m | y_i)$
2. Some examples are labeled (y is known) others are not
3. Likelihood of the data $L = P(y_1,x_1) \times \ldots \times P(y_m,x_m) \times [\, P(+,x_{m+1}) + P(-, x_{m+1}) \,] \times \ldots \times [\, P(+,x_n) + P(-,x_n) \,]$ labeled & unlabeled
4. The EM algorithm: searches for values of P(y) and $P(f_k | y)$ to give the maximum value for L

(Blum and Mitchell, 1998)

Co-training

…, says [$_{NE}$ Maury Cooper] , a vice [$_{CONTEXT}$ president] at S. & P.

- Is *Maury Cooper* a PERSON name?
- Assume a feature in the context (*president*) predicts that *Maury Cooper* is a PERSON name
- This creates a newly labeled item, the feature *Cooper* can now be associated with PERSON
- In another example, the feature *Cooper* can now be sufficient to label *Mr. Cooper* as a PERSON
- More importantly, this new example indicates that the feature *old* is now likely to modify a PERSON
- The feature *old* modifying other noun phrases can then be used to label them as PERSON, and so on …

… hired [$_{NE}$ Mr. Cooper] , 61 years [$_{CONTEXT}$ old] , as director .

(Yarowsky, 1995)

Self-Training / Yarowsky Algorithm

- Example: disambiguate 2 senses of sentence
- Seed rules:
  - If context contains *served*, label +1, conf = 1.0
  - If context contains *reads*, label -1, conf = 1.0
- Seed rules label 8 out of 303 unlabeled examples
- Create new rules from these 8 pseudo-labeled examples
  - If feature f co-occurs with served, label +1, conf = Pr(+1|f)
  - If feature f co-occurs with reads, label -1, conf = Pr(-1|f)
  - Feature f could co-occur with both served & reads
- These 8 pseudo-labeled examples provide 6 rules above 0.95 conf threshold (including the original seed rules) e.g.
  - If context contains *read*, label -1, conf = 0.953
- These 6 rules label 151 out of 303 unlabeled examples

Example: disambiguate 2 senses of sentence

- These 151 pseudo-labeled examples provide 60 rules above the threshold, e.g.
  - If context contains *prison*, label +1, conf = 0.989
  - If prev word is *life*, label +1, conf = 0.986
  - If prev word is *his*, label +1, conf = 0.983
  - If next word is *from*, label -1, conf = 0.982
  - If context contains *relevant*, label -1, conf = 0.953
  - If context contains *page*, label -1, conf = 0.953
- After 5 iterations, 297/303 unlabeled examples are permanently labeled (no changes possible)
- Building final classifier gives 67% accuracy on test set of 515 sentences. With some "tricks" we can get 76% accuracy.

Semi-supervised Learning

- Use few supervised examples to start the learning process
- These labeled examples provide the desired class labels for the categories we will discover
- Four methods to compare:
  - Baseline (knowledge-free)
  - Maximum Likelihood using EM
  - Co-training (requires two views to bootstrap)
  - Self-training (Yarowsky algorithm)

Experiments

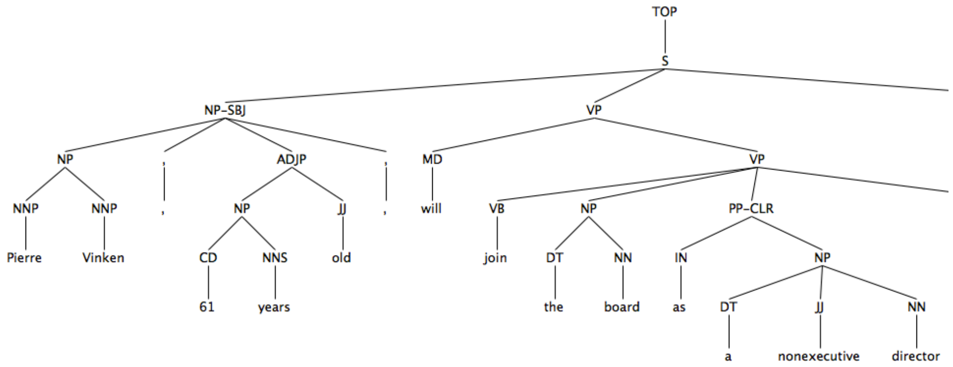
Named Entity Classification

(Collins and Singer, 1999)

- 971,476 sentences from the NYT were provided a full syntactic parse
  - – Using a statistical parser (Collins parser)
- The task is to identify three types of named entities:
  1. Location (LOC)
  2. Person (PER)
  3. Organization (ORG)

  −1. not a NE or “don’t know”

Syntax -> Lexical Semantics



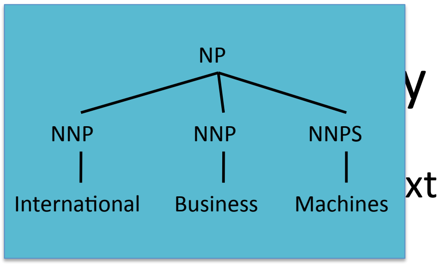
Pierre Vinken , 61 years old , will join the board as a nonexecutive director Nov. 29 .

Appositive

Prepositional Phrase attachment

Named Entity Classification

- Noun phrases were extracted that met the following conditions
  1. The NP contained only words tagged as proper nouns
  2. The NP appeared in the following two syntactic contexts:
     - Modified by an appositive whose head is a singular noun
     - In a prepositional phrase modifying an NP whose head is a singular noun



y Classification

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1. The NP contained only words tagged as proper nouns

…, fraud related to work on a federally funded sewage $[_{\text{CONTEXT}}$ plant in] $[_{\text{NE}}$ Georgia]

…, says $[_{\text{NE}}$ Maury Cooper] , a vice $[_{\text{CONTEXT}}$ president] at S. & P.

Named Entity Classification

(Collins and Singer, 1999)

- The task: classify NPs into LOC, PER, ORG
- 89,305 training examples with 68,475 distinct feature types
  - 88,962 was used in CS99 experiments
- 1000 test data examples (includes NPs that are not LOC, PER or ORG)
  - Month names are easily identifiable as not named entities: leaves 962 examples
  - Still 85 NPs that are not LOC, PER, ORG.
  - Clean accuracy over 877; Noisy over 962

Yarowsky Variants

(Abney 2004, Collins and Singer, 1999)

- A trick from Co-training (Blum and Mitchell 1998) is to be **cautious**. Don’t add all rules above the 0.95 threshold
- Add only n rules *per label* (say 5) and increase this amount by n in each iteration
- Changes the dynamics of learning in the algorithm but not the objective fn
- Two variants: Yarowsky (basic), Yarowsky (cautious)
- Without a threshold: Yarowsky (no threshold)

Results

Learning Algorithm	Accuracy (Clean)	Accuracy (Noisy)
Baseline (all organization)	45.8	41.8
EM	83.1	75.8
Yarowsky (basic)	80.7	73.5
Yarowsky (no threshold)	80.3	73.2
Yarowsky (cautious)	**91**	**83**
Co-Training	**91**	**83**

Word Sense Disambiguation

- Data from (Eisner and Karakos 2005)
- Disambiguate two senses each for drug, duty, land, language, position, sentence (Gale et. al. 1992)
- Source of unlabeled data: 14M word Canadian Hansards (English only)
- Two seed rules for each disambiguation task from (Eisner and Karakos 2005)

Word Sense Disambiguation

- Just as people become addicted to **drug**s and alcohol , they become addicted to gambling .
- Why are the socialists and their spouse , the Liberals , acting like intoxicated **drug** addicts ?
- The NDP is the only group in this House which does not need **drugs** to suffer from fantasies .
- Our young Canadians are not all a bunch of **drug** addicts , alcoholics and suicidal people .

- **Drug** information to physicians is being distributed exclusively by the **drug** companies themselves
- Does the Minister think that the people of Canada are being hosed by these **drug** companies ?

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Results

Learning Algorithm	**drug**		**land**		**sentence**	
Seeds ➔	*alcohol*	*medical*	*acres*	*courts*	*served*	*reads*
Train / Test size ➔	134 / 386		1604 / 1488		303 / 515	
Yarowsky (basic)	53.3		79.3		67.7	
Yarowsky (no threshold)	52		**79**		64.8	
Yarowsky (cautious)	**55.9**		**79**		**76.1**	
DL-CoTrain (2 views = long distance v.s. immediate context)	53.1		77.7		75.9	

Summary

- Start from a small set of seed rules.
- Bootstrapping works by trading precision for recall – very cautiously.
  - Precision: number of correct predictions (be conservative = make fewer predictions)
  - Recall: how many correct examples were recovered (be rash = make lots of predictions)
- Effective in learning diverse natural language tasks (finding names, identifying word senses, etc.)
- Questions that I did not address (yet):
  - Does the choice of seed rules matter in bootstrapping?
  - Can bootstrapping be used for complex tasks like translation?
  - Is there a theoretical analysis of bootstrapping?

Seed Rules

Seeds

(Eisner and Karakos 2005, Zagibalov and Carroll 2008)

- Selecting seed rules: what is a good strategy?
  - Frequency: sort by frequency of feature occurrence
  - Contexts: sort by number of other features a feature was observed with
  - Weighted: sort by a weighted count of other features observed with feature.

    $\text{Weight}(f) = \text{count}(f) / \Sigma_{f'} \text{count}(f')$

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Seeds

- In each case the frequencies were taken from the unlabeled training data
- Seeds were extracted from the sorted list of features by manual inspection and assigned a label (the entire example was used)
- Location (LOC) features appear infrequently in all three orderings
- It is possible that some good LOC seeds were missed

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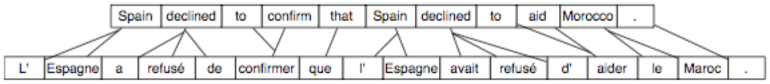
Seeds

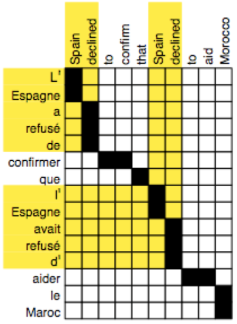
Number of Rules	Frequency		Contexts		Weighted	
(n/3) rules/label	Clean	Noisy	Clean	Noisy	Clean	Noisy
3	84	77	84	77	88	80
9	**91**	**83**	90	82	82	74
15	**91**	**83**	**91**	**83**	85	77
7 (CS99)	Clean: **91**			Noisy: **83**		

Self-Training for Machine Translation

Statistical Machine Translation



Learn to translate from previously translated text.
Align words in a parallel text.
Extract phrases based on the word alignment.
Translate by using a probabilistic model to combine and then reorder phrases.



L' Espagne	Spain
L' Espagne a refusé de	Spain declined
L' Espagne a refusé de confirmer	Spain declined to confirm
a refusé de	declined
a refusé de confirmer	declined to confirm
a refusé de confirmer que	declined to confirm that
confirmer	to confirm
confirmer que	to confirm that
que	that
que l' Espagne	that Spain
que l' Espagne avait refusé d'	that Spain declined
l' Espagne	Spain
l' Espagne avait refusé d'	Spain declined
l' Espagne avait refusé d' aider	Spain declined to aid
...	...

Self-training for MT

- Can a machine translation system learn by translating twice?
- Translate a second time by observing its own output translation.
- Why does it work? Reinforces parts of the phrase translation model which are relevant for test corpus
- Glue phrases from test data used to compose new phrases (most phrases still from original phrase table)

eval-04	editorials	newswire	speeches
sentences	449	901	438
selected translations	101	187	113
size of adapted phrase table	1,981	3,591	2,321
adapted phrases used	707	1,314	815
new phrases	679	1,359	657
new phrases used	23	47	25

Self-training for MT

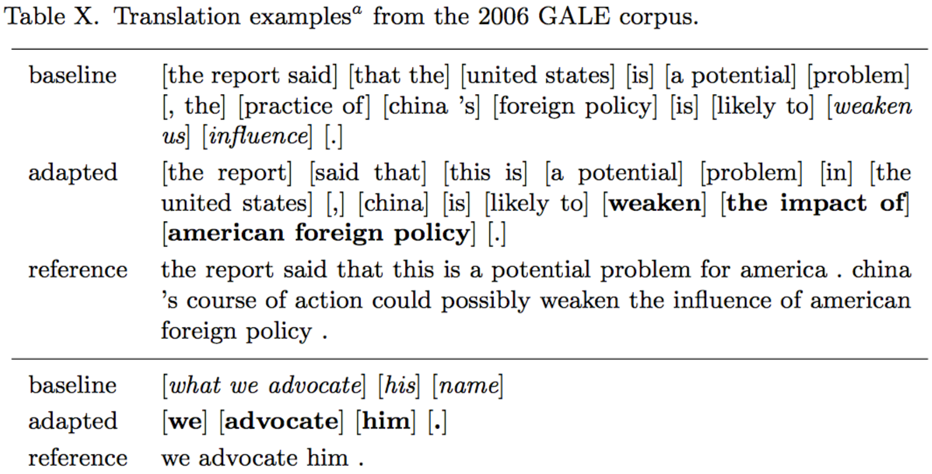


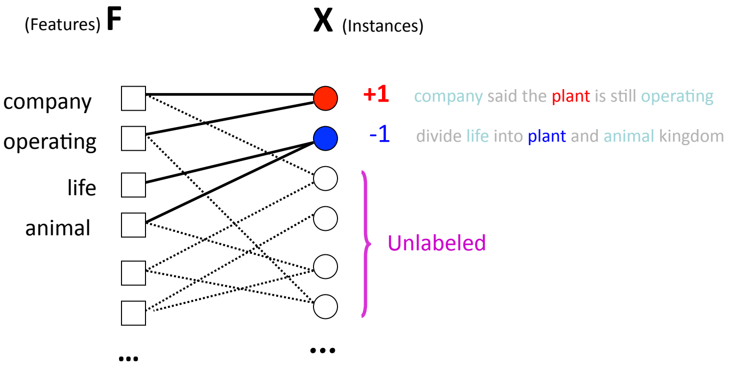
Table X. Translation examples^a from the 2006 GALE corpus.

baseline	[the report said] [that the] [united states] [is] [a potential] [problem] [, the] [practice of] [china 's] [foreign policy] [is] [likely to] [*weaken us*] [*influence*] [.]
adapted	[the report] [said that] [this is] [a potential] [problem] [in] [the united states] [,] [china] [is] [likely to] [**weaken**] [**the impact of**] [**american foreign policy**] [.]
reference	the report said that this is a potential problem for america . china 's course of action could possibly weaken the influence of american foreign policy .
baseline	[*what we advocate*] [*his*] [*name*]
adapted	[**we**] [**advocate**] [**him**] [**.**]
reference	we advocate him .

Analysis

(Abney 2004, Haffari & Sarkar 2007)

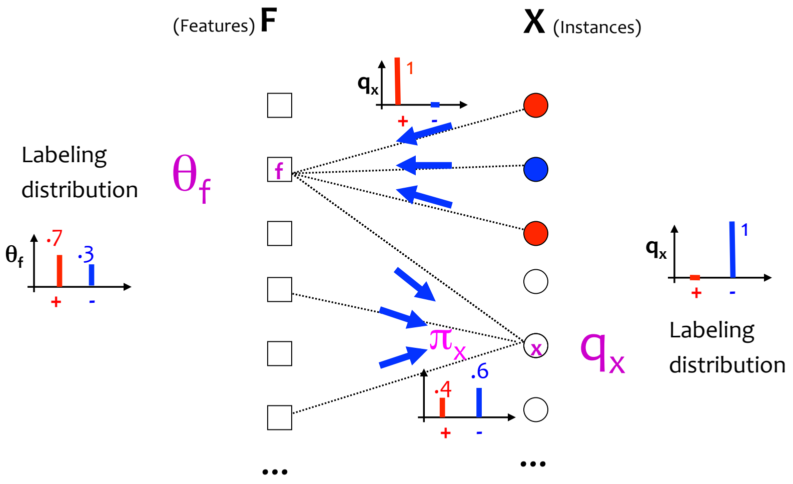
Analysis of Self-Training

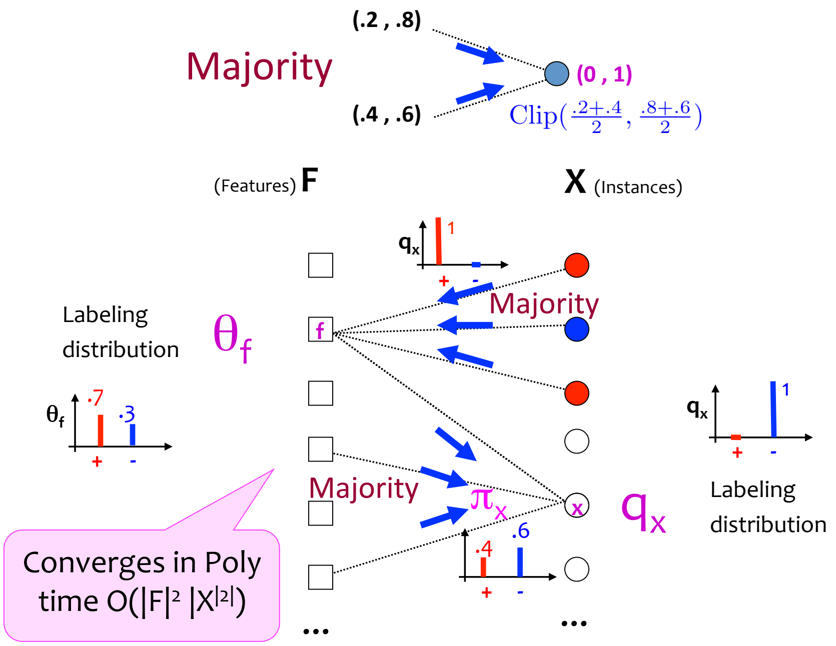

(Features) F
X (Instances)
company
operating
life
animal
...
...
+1
company said the plant is still operating
-1
divide life into plant and animal kingdom
Unlabeled

We propose to view bootstrapping as propagating the labels of initially labeled nodes to the rest of the graph nodes.

Analysis of Self-Training

(Haffari & Sarkar 2007)





Converges in Poly time $O(|F|^2 |X^{|2|})$

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