CMPT-413
Computational Linguistics

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Lexical Semantics

- So far, we have listed **words** in our **lexicon** or **vocabulary** assuming a single meaning per word:
  Consider *n*-grams $P(w_i \mid w_{i-2}, w_{i-1}) =$ *P(Bank | on, Commerce)* or
  prepositional phrase attachment *if p=on and n2=bank then change N to V*
- Consider … *withdraw twenty dollars on the bank* (correct = *V*) vs.
  … *withdraw the troops on the bank* (correct = *N*)
- The same word *bank* means two different things but we cannot distinguish between them using the traditional definition of word.

Lexical Semantics

- To deal with this issue, we combine the *spelling* or *pronunciation* of a word and the *meaning*.
  In the *lexicon* we now store **lexemes** instead of words. A lexeme pairs a particular spelling or pronunciation with a particular meaning.
- The meaning part of a lexeme is called a **sense**. For CL, our interest is in relations between lexemes or disambiguating different senses of a word.
  word: bank → lexeme: **bank**^{1} *OR* word: bank → lexeme: **bank**^{2}
- Note that meanings are often not definitions, but often are simple listings of compatible lexemes.
  cf. dictionary defns: *red, n.* the color of blood or ruby; *blood, n.* red liquid circulating in animals

Homonyms

- Homonyms: *words that have the same form but different meanings*
  1. *Instead, the chemical* plant *was found in violation of several environmental laws*
  2. *Stanley formed an expedition to find a rare* plant *found along the Amazon river*
- Same *orthographic* form: *plant* but two senses: **plant**^{1} and **plant**^{2}

Homonyms

- Text vs. speech: fly-casting for *bass* vs. rhythmic *bass* chords
  These cases are homonyms in text, but not in speech.
  Referred to as **homographs**
- Speech vs. text: *would* vs. *wood*
  These cases are not homonyms in text, but easily confused in speech. Referred to as **homophones**
- Note that this problem in some cases can be solved using *part of speech tagging*
  Can you think of a case which cannot be solved using POS tagging?

Applications

- Spelling correction: homophones: *weather* vs. *whether*
- Speech recognition: homophones: *to*, *two*, *too*. Also homonyms (see *n*-gram e.g.)
- Text to speech: homographs: *bass* vs. *bass*
- Information retrieval: homonyms: *latex*

Polysemy

- Consider the homonym: *bank* → commercial **bank**^{1} vs. river **bank**^{2}
- Now consider
  1. *A PCFG can be trained using derivation trees from a tree* bank *annotated by human experts*
- Is this a new sense of *bank*?

Polysemy

- Senses can be derived from a particular lexeme. This process is known as **polysemy**
  In previous case we would say that the use of *bank* is a sense derived from commercial **bank**^{1}
- In some cases, splitting into different lexemes has other supporting evidence: **bank**^{1} has Italian origin vs. **bank**^{2} has Scandinavian origin
  1. *A PCFG can be trained using a* bank *of derivation trees called a tree-bank annotated by human experts*
- How can we tell between homonyms and polysemous uses of a word?

Word sense and conjunction: zeugma

- Consider the case for a verb like *serve*
    1. *Does United serve breakfast?*
    2. *Does United serve Philadelphia?*
    3. *Does United serve breakfast and dinner?*
    4. *#Does United serve breakfast and Philadelphia?*

Word Sense Disambiguation

- Consider a noun like *bank*
    1. *How many senses does it have?*
    2. *How are these senses related?*
    3. *How can they be reliably distinguished?*
- For NLP software, among these three questions, typically at runtime we need to automatically find the answer to the last question: given a word in context, map it to the correct lexeme: **word-sense disambiguation**

Word Sense Disambiguation: data

```
            new_JJ Ukrainian_JJ  plant _NN operators_NNS to_TO re
       are_VBP leaving_VBG the_DT  plant s_NNS in_IN Ukraine_NNP an
 safety_NN procedures_NNS at_IN  plant s_NNS in_IN both_DT countr
   the_DT Orange_NNP County_NNP  plant _NN ._.
            three_CD missile_NN  plant s_NNS in_IN southern_JJ Ca
  the_DT whole_JJ Chernobyl_NNP  plant _NN in_IN 1991_CD ,_, five
 a_DT hill_NN ,_, gardeners_NNS  plant _NN begonias_NNS ,_, makin
  200_CD million_CD printing_NN  plant _NN in_IN Brooklyn_NNP ,_,
    incompletely_JJ oxidated_JJ  plant _NN and_CC animal_NN sedim
             you_PRP eat_VBP a_DT  plant _NN ._.
    return_NN for_IN a_DT new_JJ  plant _NN near_IN Tuscaloosa_NNP
            could_MD finance_VB  plant _NN construction_NN with_I
    return_NN for_IN a_DT new_JJ  plant _NN near_IN Tuscaloosa_NNP
```

- Keyword in context listing for *plant* as a noun.
- Two senses of *plant*: *living* or *factory*.
- Part of speech tagging is essential: ignore *plant* as a verb.

Word Sense Disambiguation: features

- Consider the input:

  ```
  that_WDT also_RB is_VBZ a_DT preserve_VB for_IN
  plant_NN ,_, animal_NN and_CC bird_NN life_NN
  ```
- Features that can help us determine the word sense:

  ```
  'W+1=,_,',
  'W-1=for_IN',
  'W-2,W-1=preserve_VB,for_IN',
  'W+1,W+2=,_,,animal_NN',
  'W-1,W+1=for_IN,,_,',
  'W+-K=that_WDT',
  'W+-K=also_RB',
  'W+-K=is_VBZ',
  'W+-K=a_DT',
  'W+-K=preserve_VB',
  'W+-K=animal_NN',
  'W+-K=and_CC',
  'W+-K=bird_NN',
  'W+-K=life_NN'
  ```

Word Sense Disambiguation: methods

- Several options for creating a system that does word-sense disambiguation
- Supervised learning:
  - Label training data.
  - Learn a classifier Pr(*sense* | *features*)
- Unsupervised learning
  - Cluster sentences into two (or more) classes.
  - Label each class manually with the sense information.
- Bootstrapping
  - Use *seed rules* to identify some examples of almost sure cases of each sense.
  - Train a classifier on this data.
  - Use classifier to identify the sense for new examples, and iterate.

Word Sense Disambiguation: Decision Lists

- A *Decision List* is a simple classifier that is effective for word-sense disambiguation
- For each feature, we get an estimate for the probability of the word sense
- For example, consider factory sense (TECH) or living sense (BIO) for the word plant:
  - Consider the feature 'W+1=life'
  - We might get the following counts from training data:

$$\begin{aligned} \mathit{Count}(\texttt{TECH}, \texttt{'W+1=life'}) &= 1 \\ \mathit{Count}(\texttt{BIO}, \texttt{'W+1=life'}) &= 100 \end{aligned}$$

  - Using these counts we derive an estimate for:

$$P(\texttt{BIO} \mid \texttt{'W+1=life'}) = \frac{100 + \alpha}{101 + 2\alpha}$$

  - Interpret this probability as a rule: if *feature* is observed, label as *sense* with confidence $P(\mathit{sense} \mid \mathit{feature})$
  - Set $\alpha = 0.1$ (smoothing is essential in the next step)

Word Sense Disambiguation: Decision Lists

- A *Decision List* is a list of such rules sorted by strength
- The strength of a rule is derived using the log odds of picking one sense over another:

$$strength(feature) = \text{abs}\left(\log\left(\frac{P(sense\ 1 \mid feature)}{P(sense\ 2 \mid feature)}\right)\right)$$

- For example,

strength	feature f	sense s	$P(s \mid f)$
5.6	'W-1=manufacturing_NN'	'TECH'	0.99
4.7	'W-1,W+1=manufacturing_NN,in_IN'	'TECH'	0.99
4.5	'W+-K=animal_NN'	'BIO'	0.99
4.5	'W+1=life_NN'	'BIO'	0.99
⋮			

- To apply the decision list, use the strongest (first) rule that can be applied (the feature appears in the input).

Word Sense Disambiguation: Decision Lists

- Decision lists can be trained on labeled data
- Yarowsky (1994) applies decision lists to accent restoration in French and Spanish:

De-accented form	Accented form	Percent
cesse	cesse	53%
	cessé	47%
coute	coûte	53%
	coûté	47%
cote	côté	69%
	côte	28%
	cote	3%
	coté	$< 1\%$

- Task is to convert the de-accented form to the appropriate accented form.
- Very similar to word-sense disambiguation. (labeled data is easily constructed)
- Useful for automatic generation of accents while typing.

Word Sense Disambiguation: Decision Lists

- Yarowsky (1995) describes a bootstrapping approach for WSD for the following words:

Word	Senses
plant	living/factory
tank	vehicle/container
poach	steal/boil
palm	tree/hand
axes	grind/tools
sake	benefit/drink
bass	fish/music
space	volume/outer
motion	legal/physical
crane	bird/machine

Word Sense Disambiguation: Bootstrapping

- Expert picks a few seed rules (they should be *strong* rules)

$$\begin{aligned} \textit{manufacturing plant} &\Rightarrow \texttt{TECH} \\ \textit{plant life} &\Rightarrow \texttt{BIO} \end{aligned}$$

- Apply seed rules on the unlabeled data.
- Bootstrapping Algorithm (Yarowsky 1995)
  - Train a decision list using the (partially labeled) data.
  - Use the original unlabeled data, and apply the decision list classifier only if the probability of prediction is greater than some threshold, say 0.97
  - Re-train a new decision list, and repeat this procedure until the labels for the data do not change.

Word Sense Disambiguation: Bootstrapping

- Another useful property: "One Sense Per Discourse".
- Yarowksy (1995) observes that if the same word occurs multiple times in a document, then it is very likely to have the same word sense.
- After the decision list is applied, this "one sense per discourse" property is applied to label all the target words in a document.
- With just two seed rules, Yarowsky (1995) obtains 90.6% accuracy (average across all the words in previous slide).
- With better seed rules, accuracy goes up to 95.5% accuracy.

Word Sense Disambiguation: Bootstrapping

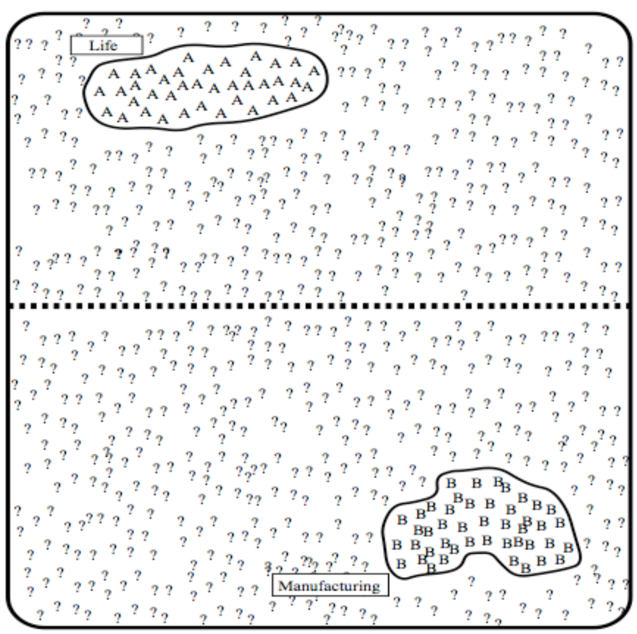
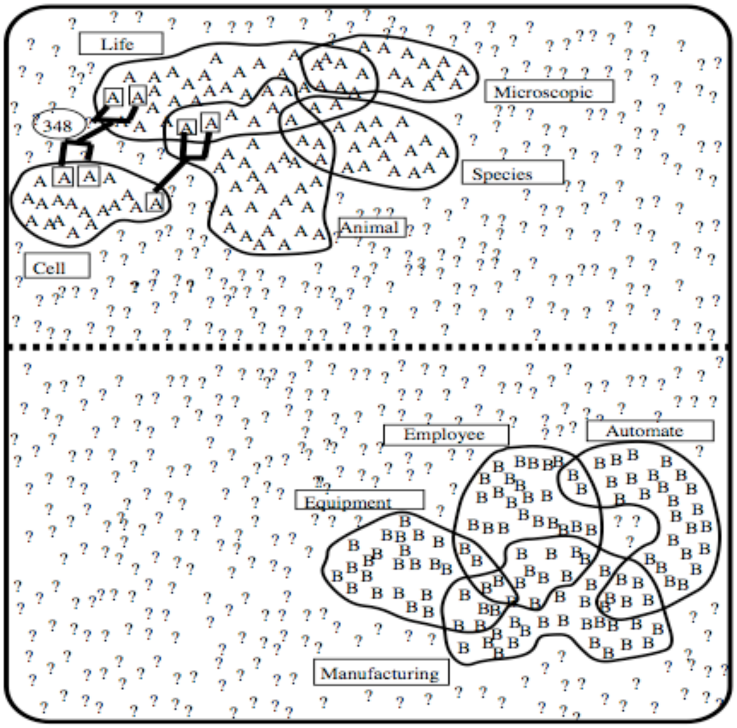


Figure 1: Sample Initial State

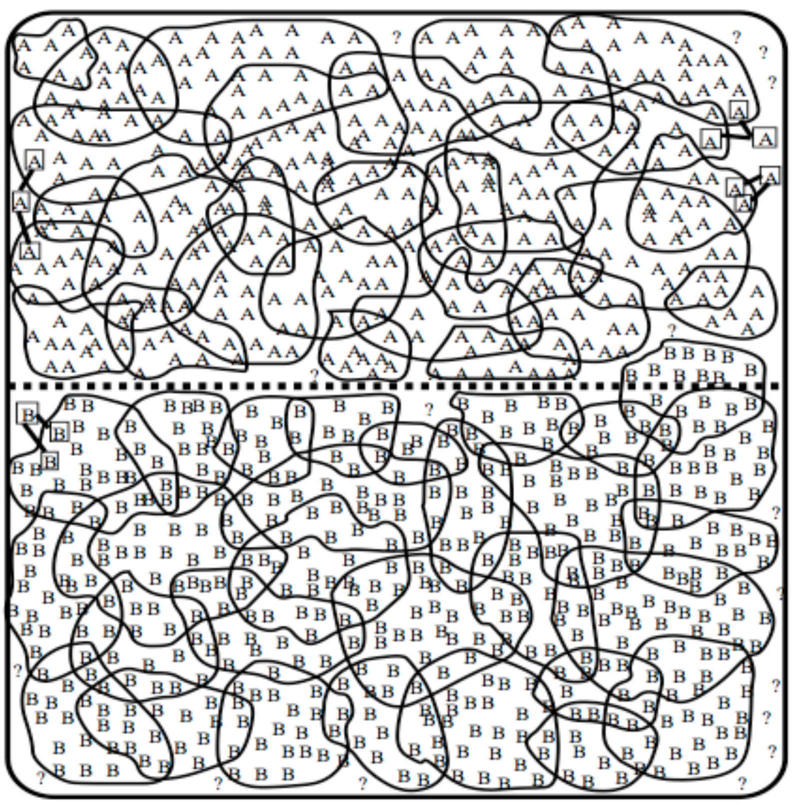
A = SENSE-A training example
B = SENSE-B training example
? = currently unclassified training example
$\boxed{\text{Life}}$ = Set of training examples containing the collocation "life".

Word Sense Disambiguation: Bootstrapping



“One Sense Per Discourse” applied to Document 348

Word Sense Disambiguation: Bootstrapping



Synonyms

- Synonyms: Different lexemes with the same meaning
  1. *How big/large is that plane?*
  2. *Would I be flying on a big/large or small plane?*
- Synonyms clash with polysemous meanings
  1. *Seema is my big sister*
  2. *#Seema is my large sister*

WordNet

- `WordNet` is an electronic database of word relationships, handcrafted from scratch by researchers at Princeton University (George Miller, Christine Fellbaum, et al.)
- WordNet contains 3 databases: for verbs, nouns and one for adjectives and adverbs

Category	Unique Forms	Number of Senses
Noun	94474	116317
Verb	10319	22066
Adjective	20170	29881
Adverb	4546	5677

WordNet

- Ask the question: how many senses per noun or verb? The distribution of senses follows Zipf's (2nd) Law.
- WordNet provides multiple lexeme entries for each word and for each part of speech,
  e.g. *plant* as noun has 3 senses; *plant* as verb has 2 senses
- WordNet also provides *domain-independent* lexical relations such as IS-A, HasMember, MemberOf, . . .

WordNet: noun relations

Relation	Definition	Example
Hypernym	this is a kind of	*breakfast* → *meal*
Hyponym	this has a specific instance	*meal* → *lunch*
Has-Member	this has a member	*faculty* → *professor*
Member-Of	this is member of a group	*copilot* → *crew*
Has-Part	this has a part	*table* → *leg*
Part-Of	this is part of	*course* → *meal*
Antonym	this is an opposite of	*leader* → *follower*

WordNet: verb relations

Relation	Definition	Example
Hypernym	this event is a kind of	*fly* → *travel*
Tropynym	this event has a subtype	*walk* → *stroll*
Entails	this event entails	*snore* → *sleep*
Antonym	this event is opposite of	*increase* → *decrease*

WordNet: example from ver1.7.1

Sense1: Canada
- ⇒North American country,North American nation
  - ⇒country, state, land
    - ⇒administrative district,administrative division,territorial division
      - ⇒district, territory
        - ⇒region
          - ⇒location
            - ⇒entity, physical thing

WordNet: example from ver1.7.1

Sense 3: Vancouver
- ⇒city, metropolis, urban center
  - ⇒municipality
    - ⇒urban area
      - ⇒geographical area
        - ⇒region
          - ⇒location
            - ⇒entity, physical thing
    - ⇒administrative district, territorial division
      - ⇒district, territory
        - ⇒region
          - ⇒location
            - ⇒entity, physical thing
- ⇒port
  - ⇒geographic point
    - ⇒point
      - ⇒location
        - ⇒entity, physical thing

WordNet

- A **synset** in WordNet is a list of synonyms (interchangeable words)
- { `chump, fish, fool, gull, mark, patsy, fall guy, sucker, schlemiel, shlemiel, soft touch, mug` }
- How can we use this information like synsets, hypernyms, etc. from WordNet to benefit NLP applications?
- Consider one example: PP attachment, words plus word classes extracted from the hypernym hierarchy increase accuracy from 84% to 88% (Stetina and Nagao, 1998)

WordNet

- Another example of WordNet used in NLP applications: **selectional restrictions**
- We have considered subcategorization:
  VP-with-NP-complement → *V(eat) NP* "eat six bowls of rice "
  But not selectional restrictions of the verb itself: *" eat tomorrow "*
  Consider *what do you want to eat tomorrow*
- We can use the **synset** { `food, nutrient` } to describe the NP argument of *eat* – then the 60K lexemes under these nodes in the WordNet hierarchy will be acceptable.
  (however, what about *" eat my shorts "*)
  → several other applications have been explored