CMSC 723: Computational Linguistics I — Session #11

Word Sense Disambiguation

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Material drawn from slides by Saif Mohammad and Bonnie Dorr

Progression of the Course

- Words
  - Finite-state morphology
  - Part-of-speech tagging (TBL + HMM)
- Structure
  - CFGs + parsing (CKY, Earley)
  - N-gram language models
- Meaning!

Today's Agenda

- Word sense disambiguation
- Beyond lexical semantics
  - Semantic attachments to syntax
  - Shallow semantics: PropBank

Word Sense Disambiguation

Recap: Word Sense

From WordNet:

Noun
{pipe, tobacco pipe} (a tube with a small bowl at one end; used for smoking tobacco)
{pipe, pipage, piping} (a long tube made of metal or plastic that is used to carry water or oil or gas etc.)
{pipe, tube} (a hollow cylindrical shape)
{pipe} (a tubular wind instrument)
{organ pipe, pipe, pipework} (the flues and stops on a pipe organ)

Verb
{shriek, shrill, pipe up, pipe} (utter a shrill cry)
{pipe} (transport by pipeline) “pipe oil, water, and gas into the desert”
{pipe} (play on a pipe) “pipe a tune”
{pipe} (trim with piping) “pipe the skirt”

Word Sense Disambiguation

- Task: automatically select the correct sense of a word
  - Lexical sample
  - All-words
- Theoretically useful for many applications:
  - Semantic similarity (remember from last time?)
  - Information retrieval
  - Machine translation
  - …
- Solution in search of a problem? Why?

How big is the problem?

- Most words in English have only one sense
  - 62% in Longman's Dictionary of Contemporary English
  - 79% in WordNet
- But the others tend to have several senses
  - Average of 3.83 in LDOCE
  - Average of 2.96 in WordNet
- Ambiguous words are more frequently used
  - In the British National Corpus, 84% of instances have more than one sense
- Some senses are more frequent than others

Ground Truth

- Which sense inventory do we use?
- Issues there?
- Application specificity?

Corpora

- Lexical sample
  - *line-hard-serve* corpus (4k sense-tagged examples)
  - *interest corpus* (2,369 sense-tagged examples)
  - …
- All-words
  - SemCor (234k words, subset of Brown Corpus)
  - Senseval-3 (2081 tagged content words from 5k total words)
  - …
- Observations about the size?

Evaluation

- Intrinsic
  - Measure accuracy of sense selection wrt ground truth
- Extrinsic
  - Integrate WSD as part of a bigger end-to-end system, e.g., machine translation or information retrieval
  - Compare ±WSD

Baseline + Upper Bound

- Baseline: most frequent sense
  - Equivalent to “take first sense” in WordNet
  - Does surprisingly well!

62% accuracy in this case!

Freq	Synset	Gloss
338	plant^1, works, industrial plant	buildings for carrying on industrial labor
207	plant^2, flora, plant life	a living organism lacking the power of locomotion
2	plant^3	something planted secretly for discovery by another
0	plant^4	an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience

- Upper bound:
  - Fine-grained WordNet sense: 75-80% human agreement
  - Coarser-grained inventories: 90% human agreement possible
- What does this mean?

WSD Approaches

- Depending on use of manually created knowledge sources
  - Knowledge-lean
  - Knowledge-rich
- Depending on use of labeled data
  - Supervised
  - Semi- or minimally supervised
  - Unsupervised

Lesk's Algorithm

- Intuition: note word overlap between context and dictionary entries
  - Unsupervised, but knowledge rich

The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

WordNet

$bank^1$	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	"he cashed a check at the bank", "that bank holds the mortgage on my home"
$bank^2$	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	"they pulled the canoe up on the bank", "he sat on the bank of the river and watched the currents"

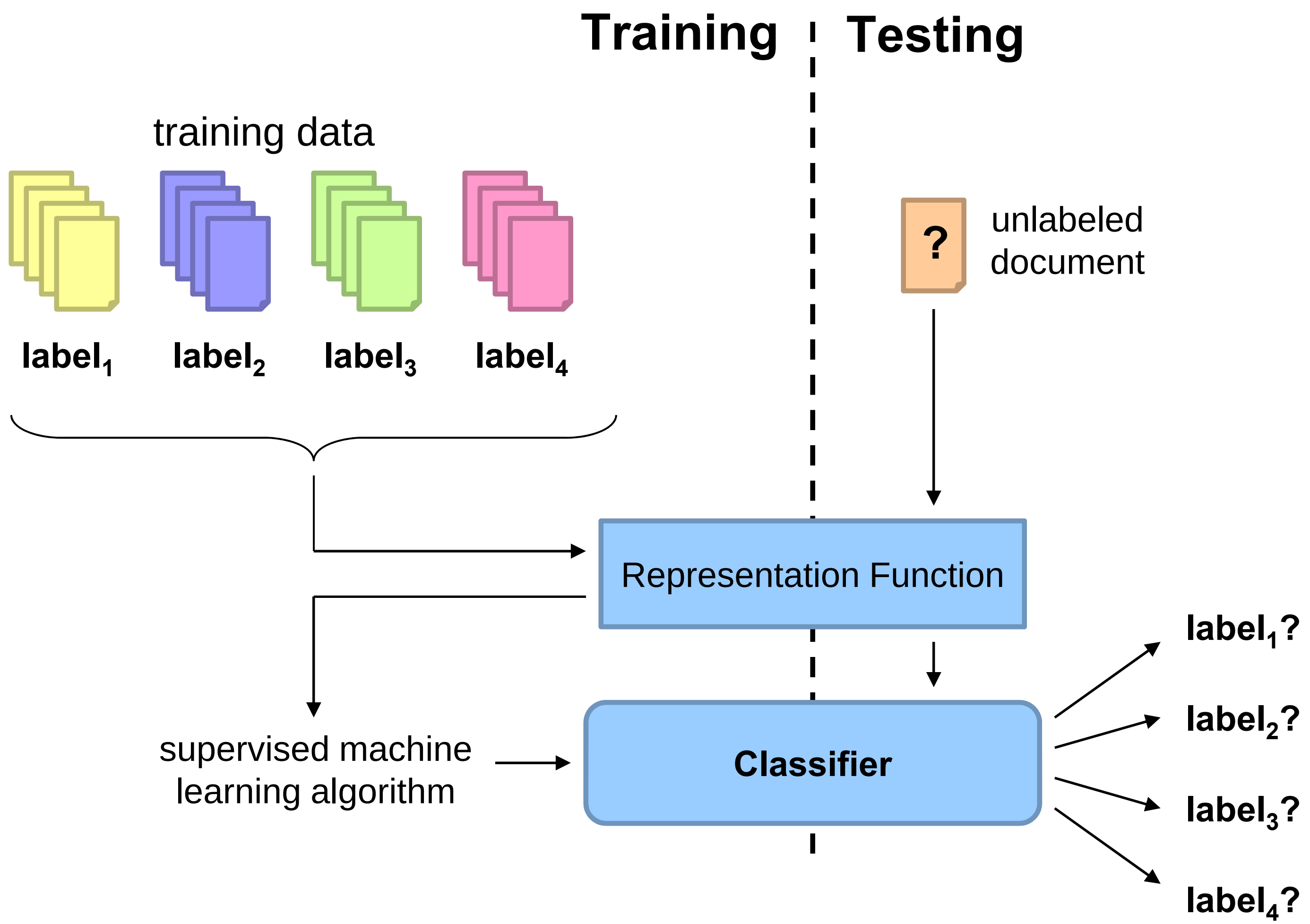
Lesk's Algorithm

- Simplest implementation:
  - Count overlapping content words between glosses and context
- Lots of variants:
  - Include the examples in dictionary definitions
  - Include hypernyms and hyponyms
  - Give more weight to larger overlaps (e.g., bigrams)
  - Give extra weight to infrequent words (e.g., *idf* weighting)
  - …
- Works reasonably well!

Supervised WSD: NLP meets ML

- WSD as a supervised classification task
  - Train a separate classifier for each word
- Three components of a machine learning problem:
  - Training data (corpora)
  - Representations (features)
  - Learning method (algorithm, model)

Supervised Classification



Three Laws of Machine Learning

- Thou shalt not mingle training data with test data
- Thou shalt not mingle training data with test data
- Thou shalt not mingle training data with test data

But what do you do if you need more test data?

Features

- Possible features
  - POS and surface form of the word itself
  - Surrounding words and POS tag
  - Positional information of surrounding words and POS tags
  - Same as above, but with *n*-grams
  - Grammatical information
  - …
- Richness of the features?
  - Richer features = ML algorithm does less of the work
  - More impoverished features = ML algorithm does more of the work

Classifiers

- Once we cast the WSD problem as supervised classification, many learning techniques are possible:
  - Naïve Bayes (the thing to try first)
  - Decision lists
  - Decision trees
  - MaxEnt
  - Support vector machines
  - Nearest neighbor methods
  - …

Classifiers Tradeoffs

- Which classifier should I use?
- It depends:
  - Number of features
  - Types of features
  - Number of possible values for a feature
  - Noise
  - …
- General advice:
  - Start with Naïve Bayes
  - Use decision trees/lists if you want to understand what the classifier is doing
  - SVMs often give state of the art performance
  - MaxEnt methods also work well

Naïve Bayes

- Pick the sense that is most probable given the context
  - Context represented by feature vector

$$\hat{s} = \arg\max_{s \in S} P(s|\vec{f})$$

  - By Bayes' Theorem:

$$\hat{s} = \arg\max_{s \in S} \frac{P(\vec{f} \mid s)P(s)}{\cancel{P(\vec{f})}}$$

We can ignore this term… why?

- Problem: data sparsity!

The “Naïve” Part

- Feature vectors are too sparse to estimate directly:

$$P(\vec{f} \mid s) \approx \prod_{j=1}^{n} P(f_j \mid s)$$

  - So… assume features are conditionally independent given the word sense
  - This is naïve because?

- Putting everything together:

$$\hat{s} = \arg\max_{s \in S} P(s) \prod_{j=1}^{n} P(f_j \mid s)$$

Naïve Bayes: Training

- How do we estimate the probability distributions?

$$\hat{s} = \arg\max_{s \in S} P(s) \prod_{j=1}^{n} P(f_j \mid s)$$

- Maximum-Likelihood Estimates (MLE):

$$P(s_i) = \frac{\text{count}(s_i, w_j)}{\text{count}(w_j)}$$

$$P(f_j \mid s) = \frac{\text{count}(f_j, s)}{\text{count}(s)}$$

- What else do we need to do?

Well, how well does it work? (later…)

Decision List

- Ordered list of tests (equivalent to “case” statement):
- Example decision list, discriminating between bass (fish) and bass (music) :

Context	Sense
fish in $\pm k$ words	FISH
striped bass	FISH
guitar in $\pm k$ words	MUSIC
bass player	MUSIC
piano in $\pm k$ words	MUSIC
sea bass	FISH
play bass	MUSIC
river in $\pm k$ words	FISH
on bass	MUSIC
bass are	FISH

Building Decision Lists

- Simple algorithm:
  - Compute how discriminative each feature is:

$$\left|\log\left(\frac{P(S_1 \mid f_i)}{P(S_2 \mid f_i)}\right)\right|$$

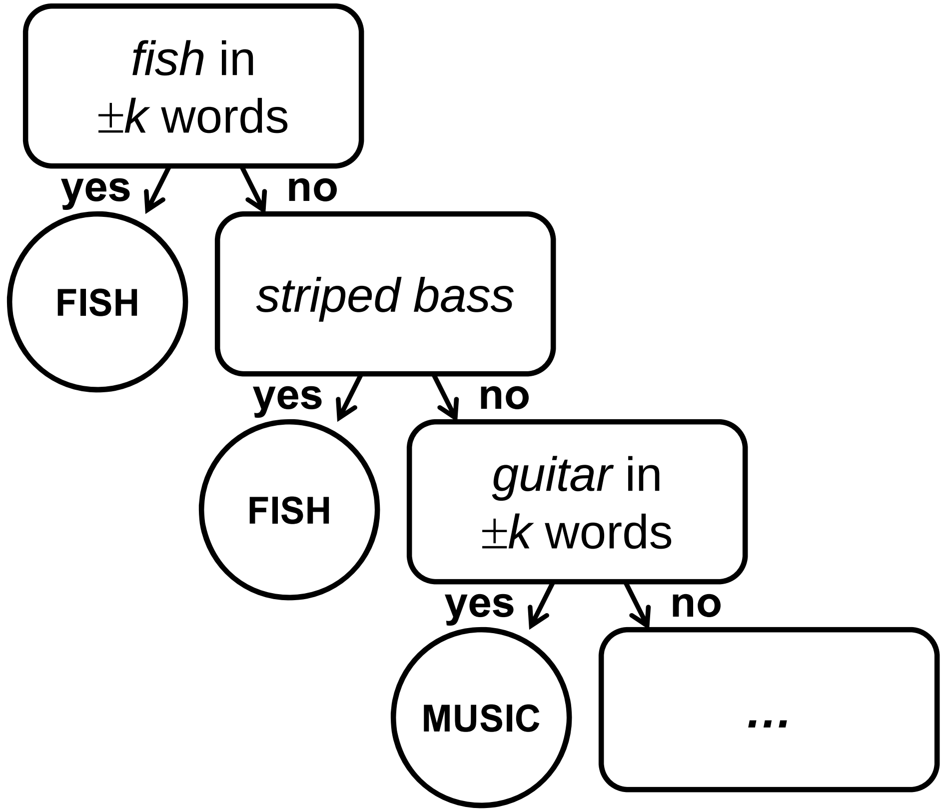
  - Create ordered list of tests from these values
- Limitation?
- How do you build *n*-way classifiers from binary classifiers?
  - One vs. rest (sequential vs. parallel)
  - Another learning problem

Well, how well does it work? (later…)

Decision Trees

- Instead of a list, imagine a tree…

Context	Sense
fish in ±*k* words	FISH
striped bass	FISH
guitar in ±*k* words	MUSIC
bass player	MUSIC
piano in ±*k* words	MUSIC
sea bass	FISH
play bass	MUSIC
river in ±*k* words	FISH
on bass	MUSIC
bass are	FISH



Using Decision Trees

- Given an instance (= list of feature values)
  - Start at the root
  - At each interior node, check feature value
  - Follow corresponding branch based on the test
  - When a leaf node is reached, return its category

Decision tree material drawn from slides by Ed Loper

Building Decision Trees

- Basic idea: build tree top down, recursively partitioning the training data at each step
  - At each node, try to split the training data on a feature (could be binary or otherwise)
- What features should we split on?
  - Small decision tree desired
  - Pick the feature that gives the most information about the category
- Example: 20 questions
  - I’m thinking of a number from 1 to 1,000
  - You can ask any yes no question
  - What question would you ask?

Evaluating Splits via Entropy

- Entropy of a set of events *E*:

$$H(E) = -\sum_{c \in C} P(c) \log_2 P(c)$$

  - Where *P(c)* is the probability that an event in *E* has category *c*
- How much information does a feature give us about the category (sense)?
  - *H(E)* = entropy of event set *E*
  - *H(E|f)* = expected entropy of event set *E* once we know the value of feature *f*
  - Information Gain: *G(E, f) = H(E) – H(E|f)* = amount of new information provided by feature *f*
- Split on feature that maximizes information gain

Well, how well does it work? (later…)

WSD Accuracy

- Generally:
  - Naïve Bayes provides a reasonable baseline: ~70%
  - Decision lists and decision trees slightly lower
  - State of the art is slightly higher
- However:
  - Accuracy depends on actual word, sense inventory, amount of training data, number of features, etc.
  - Remember caveat about baseline and upper bound

Minimally Supervised WSD

- But annotations are expensive!
- “Bootstrapping” or co-training (Yarowsky 1995)
  - Start with (small) seed, learn decision list
  - Use decision list to label rest of corpus
  - Retain “confident” labels, treat as annotated data to learn new decision list
  - Repeat…
- Heuristics (derived from observation):
  - One sense per discourse
  - One sense per collocation

One Sense per Discourse

- A word tends to preserve its meaning across all its occurrences in a given discourse
- Evaluation:
  - 8 words with two-way ambiguity, e.g. plant, crane, etc.
  - 98% of the two-word occurrences in the same discourse carry the same meaning
- The grain of salt: accuracy depends on granularity
  - Performance of “one sense per discourse” measured on SemCor is approximately 70%

Slide by Mihalcea and Pedersen

One Sense per Collocation

- A word tends to preserve its meaning when used in the same collocation
  - Strong for adjacent collocations
  - Weaker as the distance between words increases
- Evaluation:
  - 97% precision on words with two-way ambiguity
- Again, accuracy depends on granularity:
  - 70% precision on SemCor words

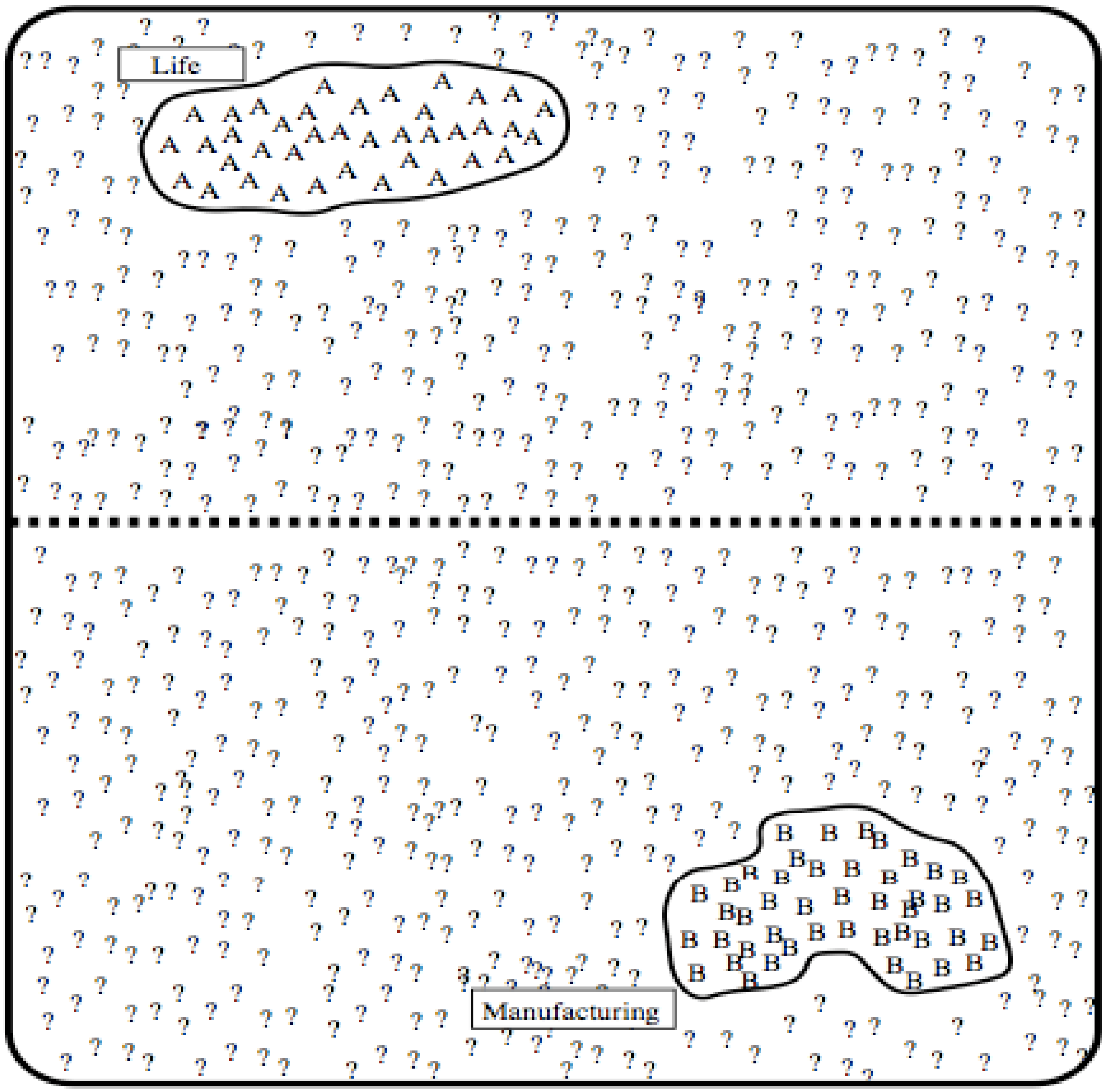
Yarowsky's Method: Example

- Disambiguating plant (industrial sense) vs. plant (living thing sense)
- Think of seed features for each sense
  - Industrial sense: co-occurring with "manufacturing"
  - Living thing sense: co-occurring with "life"
- Use "one sense per collocation" to build initial decision list classifier
- Treat results as annotated data, train new decision list classifier, iterate…

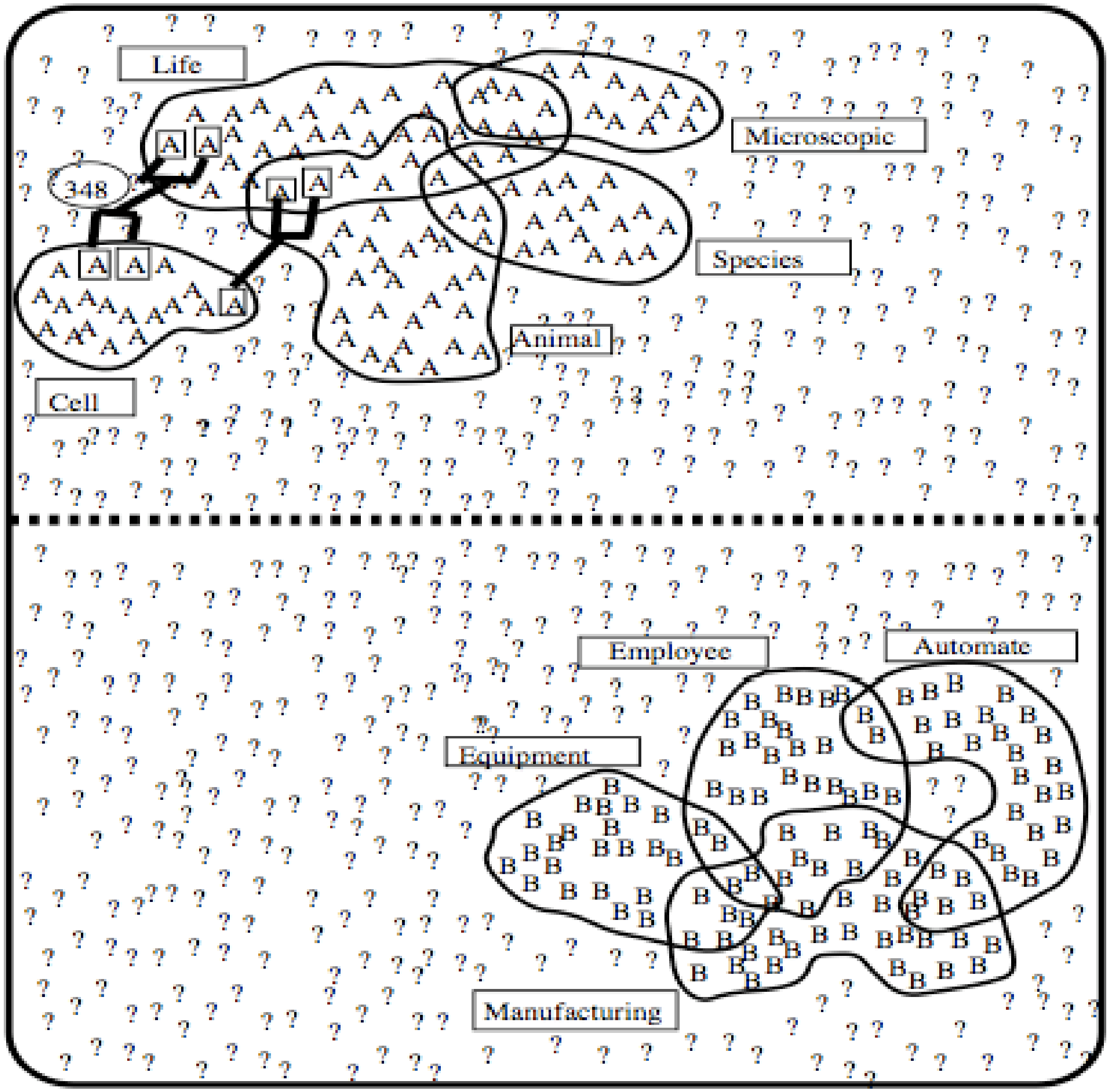
used to strain microscopic plant life from the
zonal distribution of plant life .
close-up studies of plant life and natural
too rapid growth of aquatic plant life in water
the proliferation of plant and animal life
establishment phase of the plant virus life cycle
that divide life into plant and animal kingdom
many dangers to plant and animal life
mammals . Animal and plant life are delicately

automated manufacturing plant in Fremont
vast manufacturing plant and distribution
chemical manufacturing plant , producing viscose
keep a manufacturing plant profitable without
computer manufacturing plant and adjacent
discovered at a St. Louis plant manufacturing
copper manufacturing plant found that they
copper wire manufacturing plant , for example
s cement manufacturing plant in Alpena

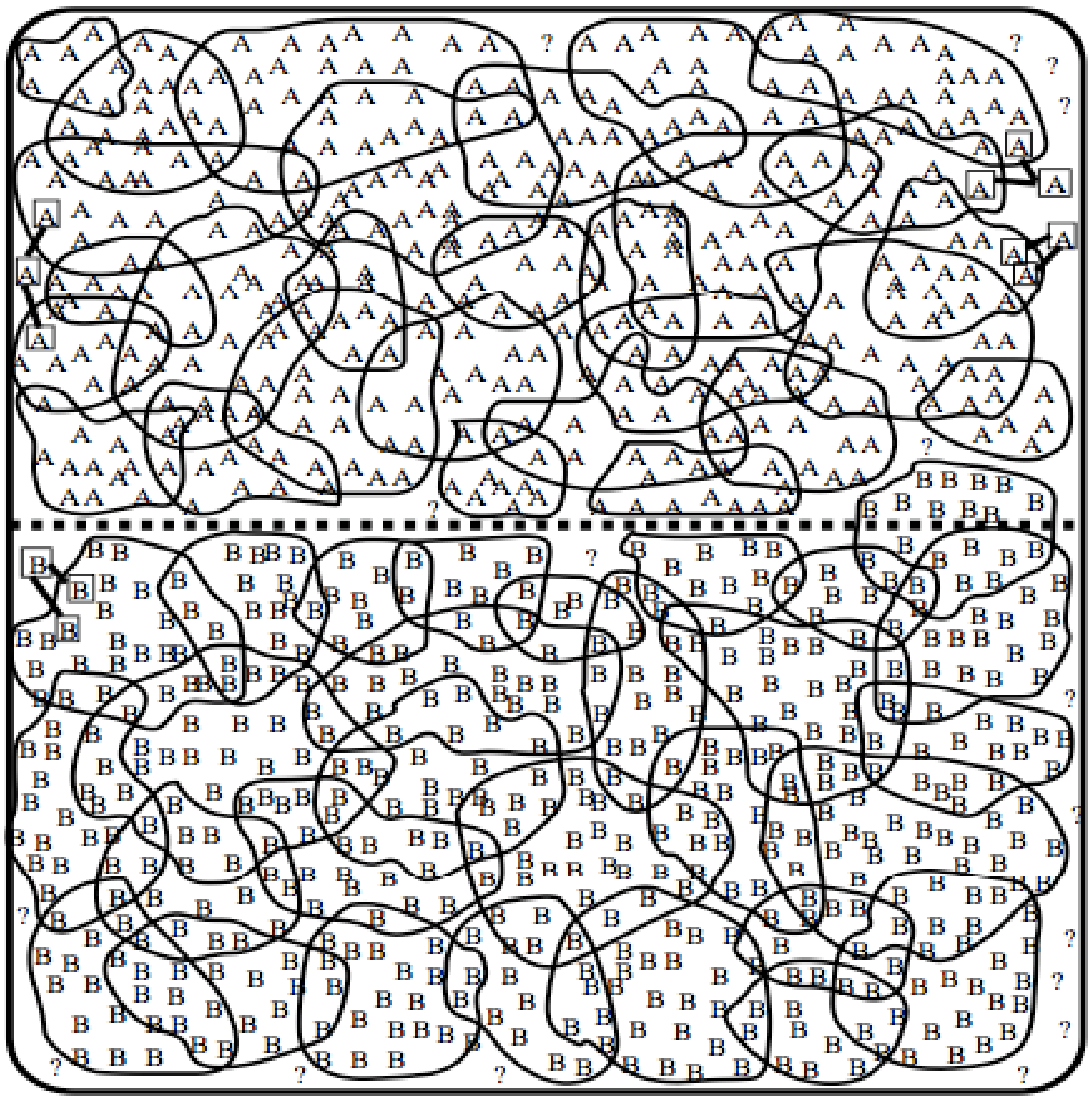
vinyl chloride monomer plant , which is
molecules found in plant and animal tissue
Nissan car and truck plant in Japan is
and Golgi apparatus of plant and animal cells
union responses to plant closures .
cell types found in the plant kingdom are
company said the plant is still operating
Although thousands of plant and animal species
animal rather than plant tissues can be



Initial state after use of seed rules



Intermediate state



Final state

Yarowsky's Method: Stopping

- Stop when:
  - Error on training data is less than a threshold
  - No more training data is covered
- Use final decision list for WSD

Yarowsky's Method: Discussion

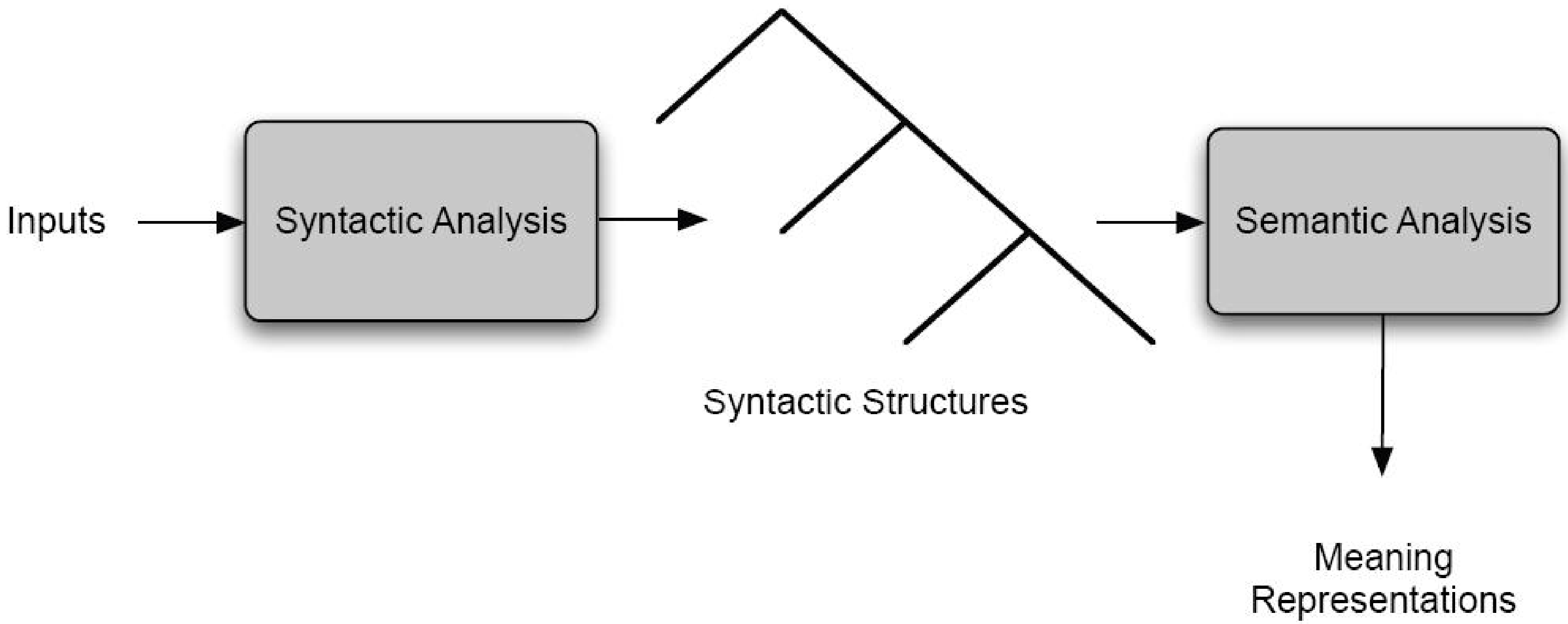
- Advantages:
  - Accuracy is about as good as a supervised algorithm
  - Bootstrapping: far less manual effort
- Disadvantages:
  - Seeds may be tricky to construct
  - Works only for coarse-grained sense distinctions
  - Snowballing error with co-training
- Recent extension: now apply this to the web!

WSD with Parallel Text

- But annotations are expensive!
- What's the "proper" sense inventory?
  - How fine or coarse grained?
  - Application specific?
- Observation: multiple senses translate to different words in other languages!
  - A "bill" in English may be a "pico" (bird jaw) in or a "cuenta" (invoice) in Spanish
  - Use the foreign language as the sense inventory!
  - Added bonus: annotations for free! (Byproduct of word-alignment process in machine translation)

Beyond Lexical Semantics

Syntax-Semantics Pipeline



Example: FOPL

Semantic Attachments

- Basic idea:
  - Associate λ-expressions with lexical items
  - At branching node, apply semantics of one child to another (based on synctatic rule)
- Refresher in λ-calculus…

Augmenting Syntactic Rules

Grammar Rule
$S \rightarrow NP\ VP$
$NP \rightarrow Det\ Nominal$
$NP \rightarrow ProperNoun$
$Nominal \rightarrow Noun$
$VP \rightarrow Verb$
$VP \rightarrow Verb\ NP$
$Det \rightarrow every$
$Det \rightarrow a$
$Noun \rightarrow restaurant$
$ProperNoun \rightarrow Matthew$
$ProperNoun \rightarrow Franco$
$ProperNoun \rightarrow Frasca$
$Verb \rightarrow closed$
$Verb \rightarrow opened$

Semantic Analysis: Example

$$\forall x\, Restaurant(x) \Rightarrow \exists e\, Closed(e) \wedge ClosedThing(e,x)$$

$$\lambda Q.\forall x\, Restaurant(x) \Rightarrow Q(x) \qquad \lambda x.\exists e\, Closed(e) \wedge ClosedThing(e,x)$$

closed

$$\lambda P.\lambda Q.\forall x P(x) \Rightarrow Q(x) \qquad \lambda x.Restaurant(x)$$

Every *restaurant*

NP $\rightarrow$ Det Nominal {Det.*sem*(Nominal.*sem*)}

$$\lambda P.\lambda Q.\forall x\, P(x) \Rightarrow Q(x)(\lambda x.\text{Restaurant}(x))$$

$$\lambda Q.\forall x \lambda x.\text{Restaurant}(x)(x) \Rightarrow Q(x)$$

$$\lambda Q.\forall x\, \text{Restaurant}(x) \Rightarrow Q(x)$$

Complexities

- Oh, there are many…
- Classic problem: quantifier scoping
  - Every restaurant has a menu
- Issues with this style of semantic analysis?

Semantics in NLP Today

- Can be characterized as "shallow semantics"
- Verbs denote events
  - Represent as "frames"
- Nouns (in general) participate in events
  - Types of event participants = "slots" or "roles"
  - Event participants themselves = "slot fillers"
  - Depending on the linguistic theory, roles may have special names: agent, theme, etc.
- Semantic analysis: semantic role labeling
  - Automatically identify the event type (i.e., frame)
  - Automatically identify event participants and the role that each plays (i.e., label the semantic role)

What works in NLP?

- POS-annotated corpora
- Tree-annotated corpora: Penn Treebank
- Role-annotated corpora: Proposition Bank (PropBank)

PropBank: Two Examples

- agree.01
  - Arg0: Agreer
  - Arg1: Proposition
  - Arg2: Other entity agreeing
  - Example: [$_{\text{Arg0}}$ John] *agrees* [$_{\text{Arg2}}$ with Mary] [$_{\text{Arg1}}$ on everything]
- fall.01
  - Arg1: Logical subject, patient, thing falling
  - Arg2: Extent, amount fallen
  - Arg3: Start point
  - Arg4: End point
  - Example: [$_{\text{Arg1}}$ Sales] fell [$_{\text{Arg4}}$ to $251.2 million] [$_{\text{Arg3}}$ from $278.7 million]

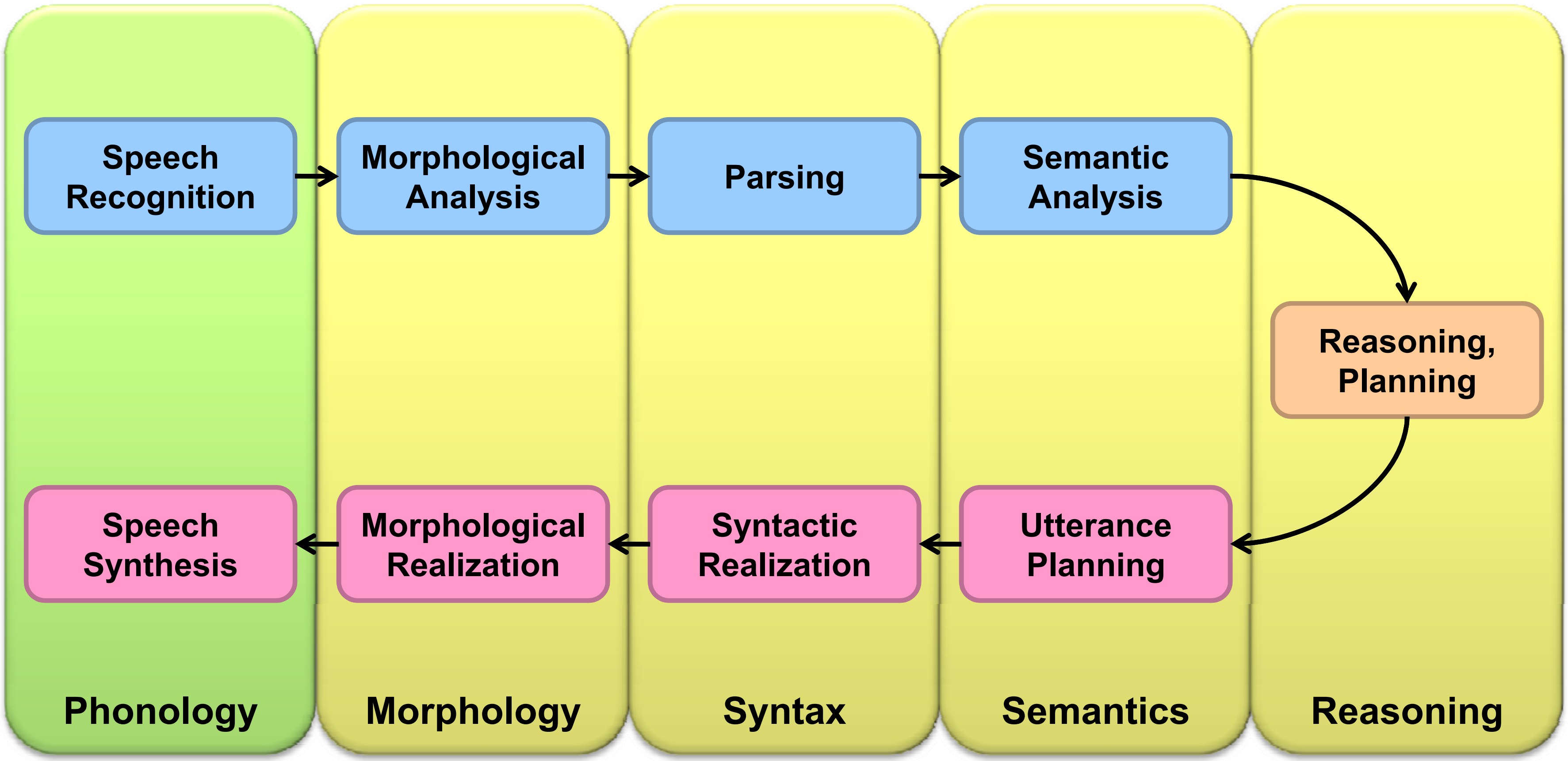
How do we do it?

- Short answer: supervised machine learning
- One approach: classification of each tree constituent
  - Features can be words, phrase type, linear position, tree position, etc.
  - Apply standard machine learning algorithms

Recap of Today’s Topics

- Word sense disambiguation
- Beyond lexical semantics
  - Semantic attachments to syntax
  - Shallow semantics: PropBank

The Complete Picture



The Home Stretch

- Next week: MapReduce and large-data processing
- No classes Thanksgiving week!
- December: two guest lectures by Ken Church