

Search with Partial Information: Data-Driven Word Sense Disambiguation

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- Goal: we’d like to assign a *sense tag* to words in a sentence
 - A classic labeling problem

Terminology

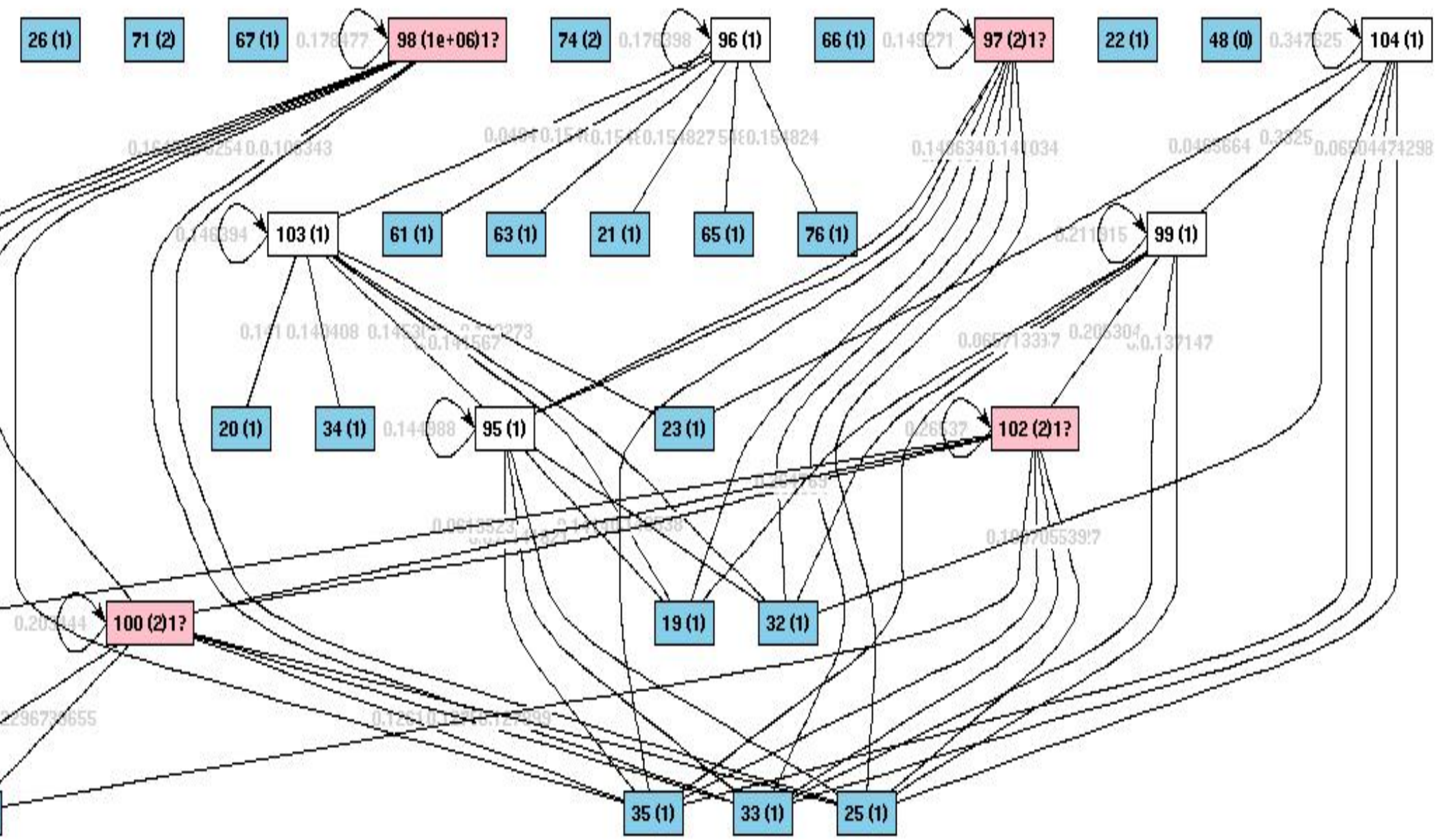
- ***Features:*** Any visible input that can help a decision – e.g. “cats”, “fileserver” etc.
- ***Soft prediction:*** “Sample has label X with probability 0.6, Y with probability 0.3, Z with 0.1”
- ***Supervised learning:*** Train on known data, then test on unseen data
- ***Semi-supervised learning:*** Test features are visible during training on known data

Label Propagation (Zhu, 2005)

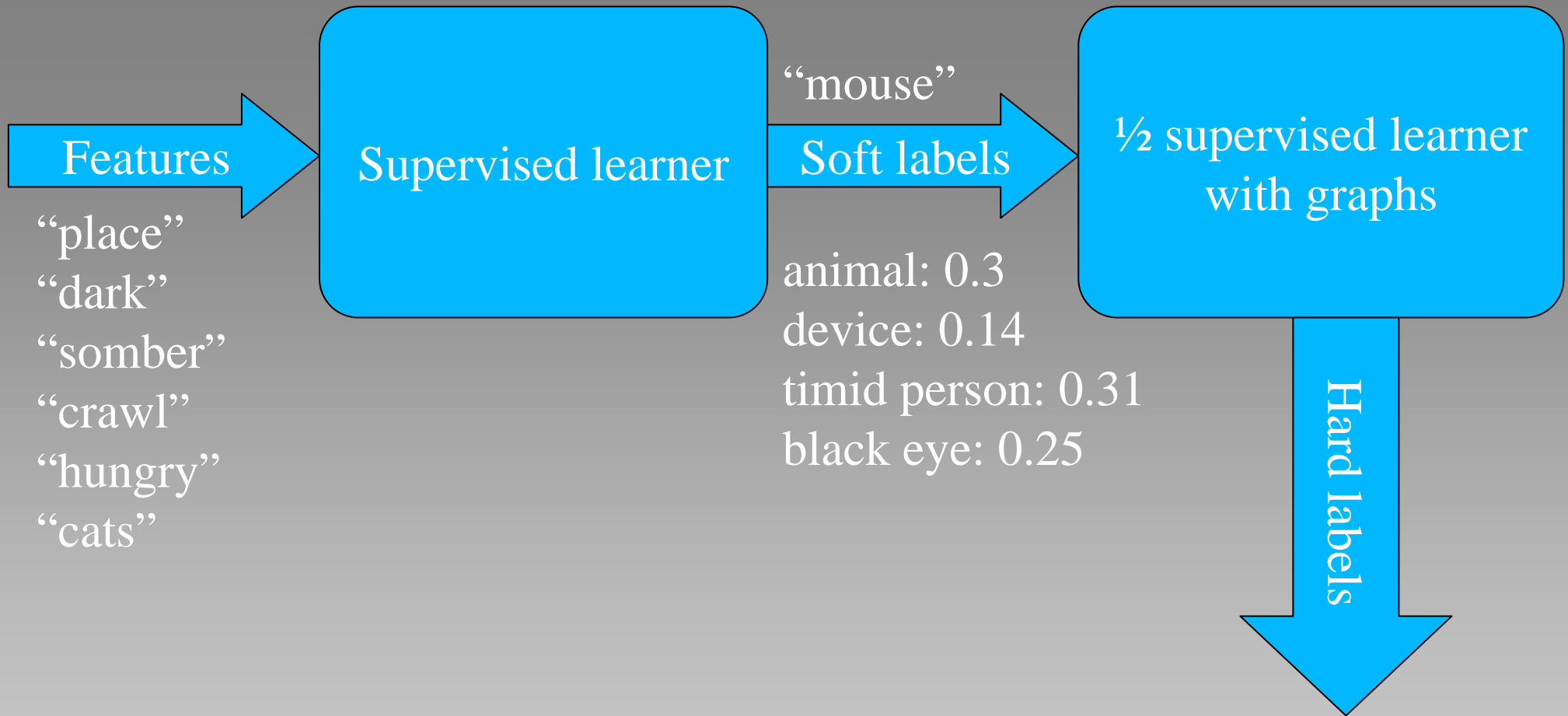
- Construct a graph from all features (train + test)
 - Each sample is a vertex in the graph
 - Edges reflect similarity among samples
- Assign labels to known data
- Propagate labels using a random walk

- Problems:
 - graph construction process is very domain-specific
 - critically depends on the chosen similarity measure
 - NLP features are often discrete or mixed

Example



Our idea: Data-driven graph construction

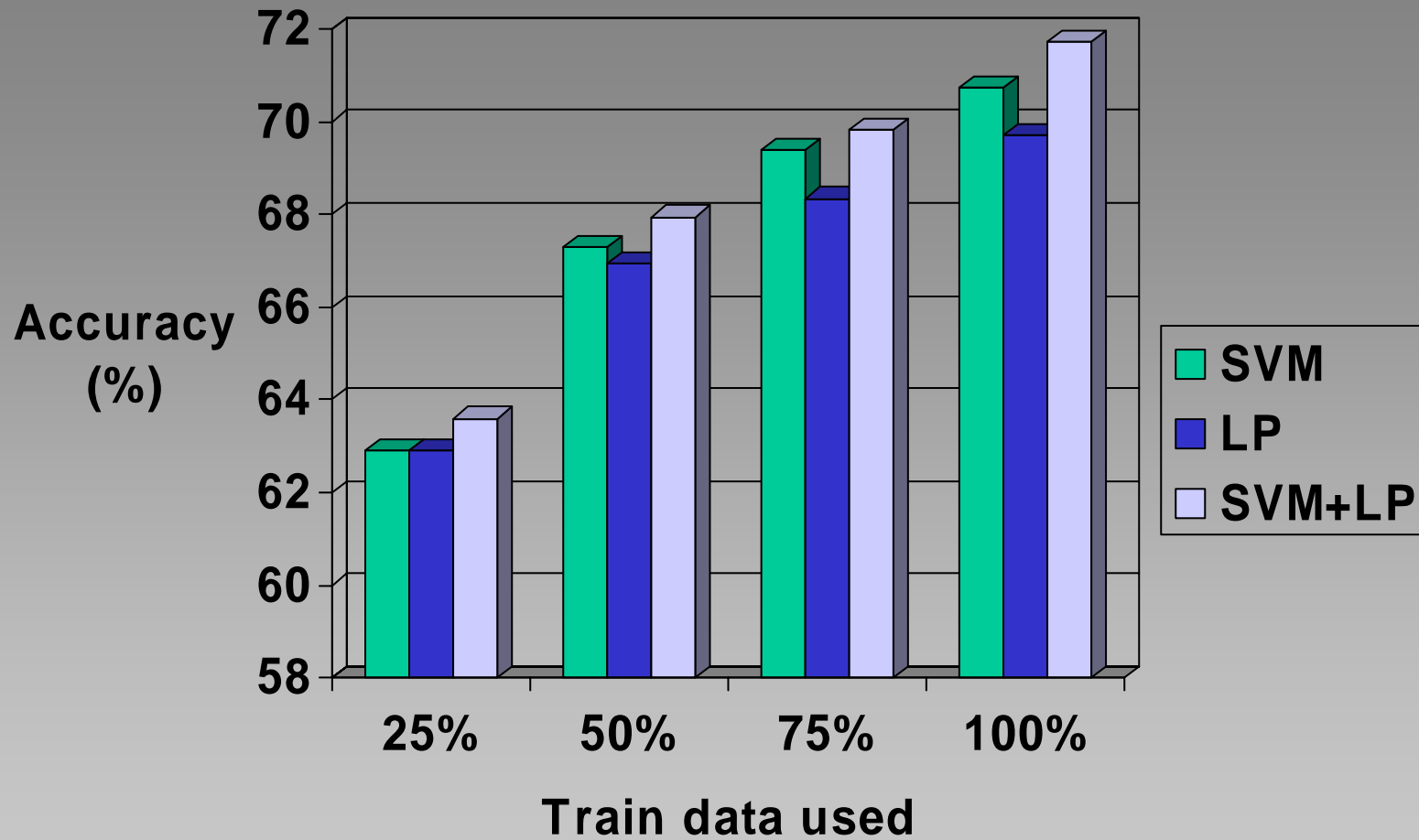


✓ They meant “mouse” as “animal”

Characteristics

- Particularities
 - Special training for supervised classifier
- Advantages
 - Uniform range and type of features
 - Facile feature postprocessing
 - Optimized class separation
- Risks
 - Overspecialization of first-pass classifier
 - Confident but wrong predictions

Results



Conclusions

- Better graphs
 - Closer to optimal features by using a separate learner
 - Non-uniform \rightarrow uniform features
- Better performance
 - Significantly better than label propagation using the initial features
- Simplified graph construction step
 - Domain-specific knowledge not needed