

→ Supervised Learning for WSD.
 ↳ Parametric Model (Naive Bayes)

$$s^1 = \operatorname{argmax}_{s \in S} P(s|f)$$

$$= \operatorname{argmax}_{s \in S} \frac{P(f|s) \cdot P(s)}{P(f)}$$

$$= \operatorname{argmax}_{s \in S} P(s) \cdot P(f|s)$$

$$= \operatorname{argmax}_{s \in S} P(s) \prod_{i=1}^n P(f_i|s)$$

$[f_1, \dots, f_n]$
 ↳ context

→ Collocation Vector (Set of words around it)

→ Setting parameters of Naive Bayes using
 MLE from training data:

$$n_i = \sum_{j=1}^n (s_i = w_j)$$

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

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

→ Non-Parametric Method (Decision List)

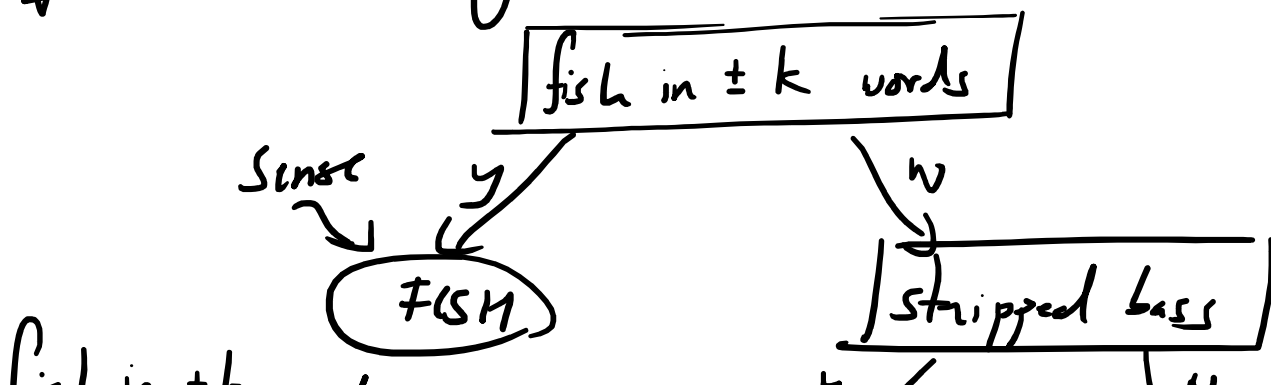
↳ One sense per Collocation.

↳ log-likelihood Ratio:

$$\log \left\{ \frac{P(\text{Sense-A} | \text{Collocation}_i)}{P(\text{Sense-B} | \text{Collocation}_i)} \right\}$$

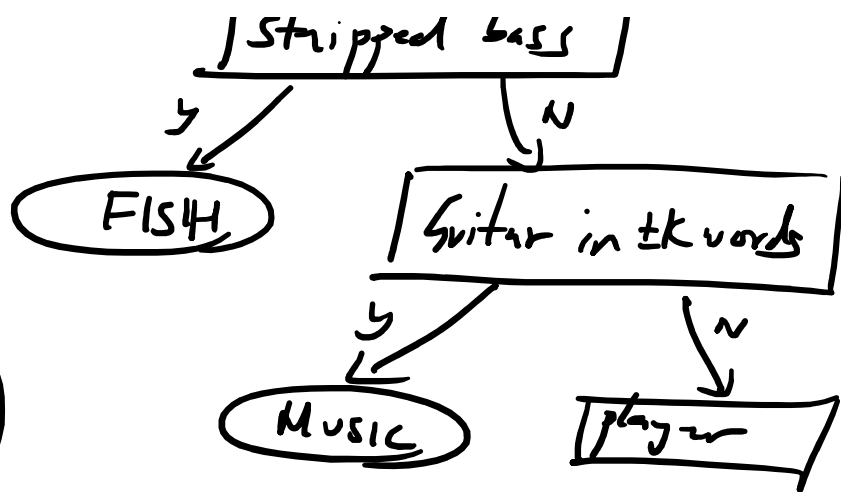
→ Higher log-likelihood = More Predictive Evidence.

Eg: Discriminating blu bass (fish sense)



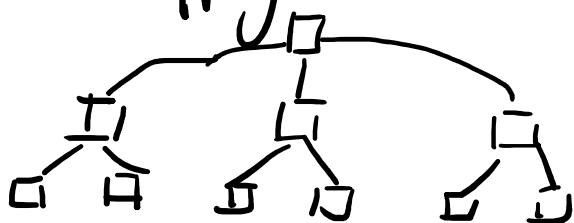
fish in $\pm k$ words
 stripped bass
 guitar in $\pm k$ words
 player

$O(\log n)$



→ Minimally Supervised WSD ~ Jowersky.

↳ Bootstrapping or Co-training.



Random Forest

↳ Start with small seed, decision list.

↳ Use decision list to label corpus.

↳ Retain confident labels as annotated data to learn new decision list.

⇒ Heuristics (Derived from observations)

↳ One sense per discourse

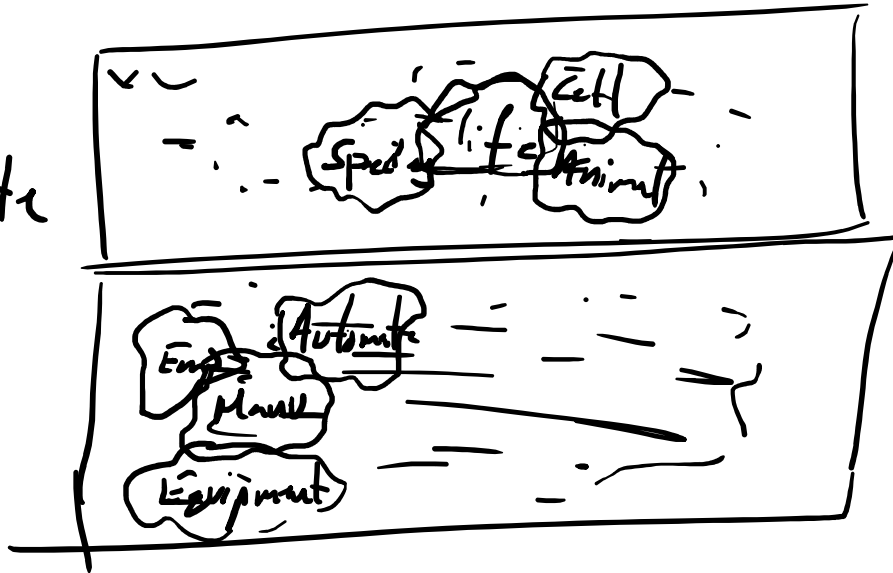
↳ One sense per collocation.

E.g.

Ej:

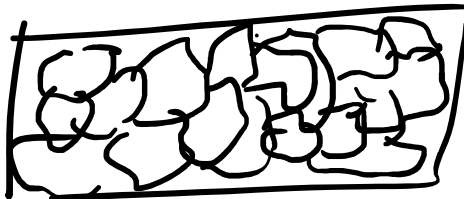
-> Disambiguate plant (living thing) vs plant (industrial)

Intermediate
State

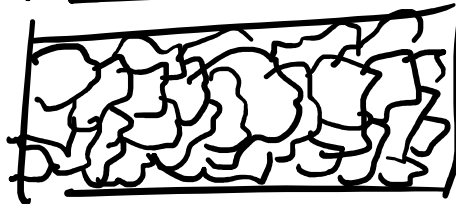


life

Manufacturing



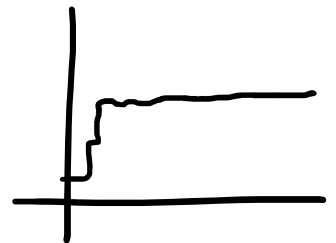
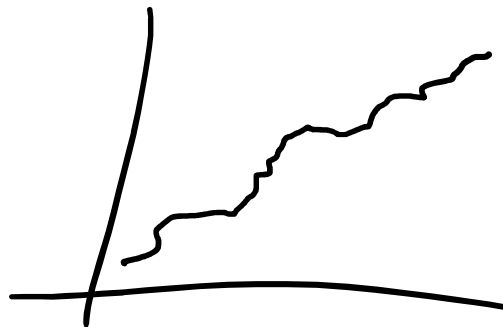
life



Manufacturing

Termination :

-> Stop when?

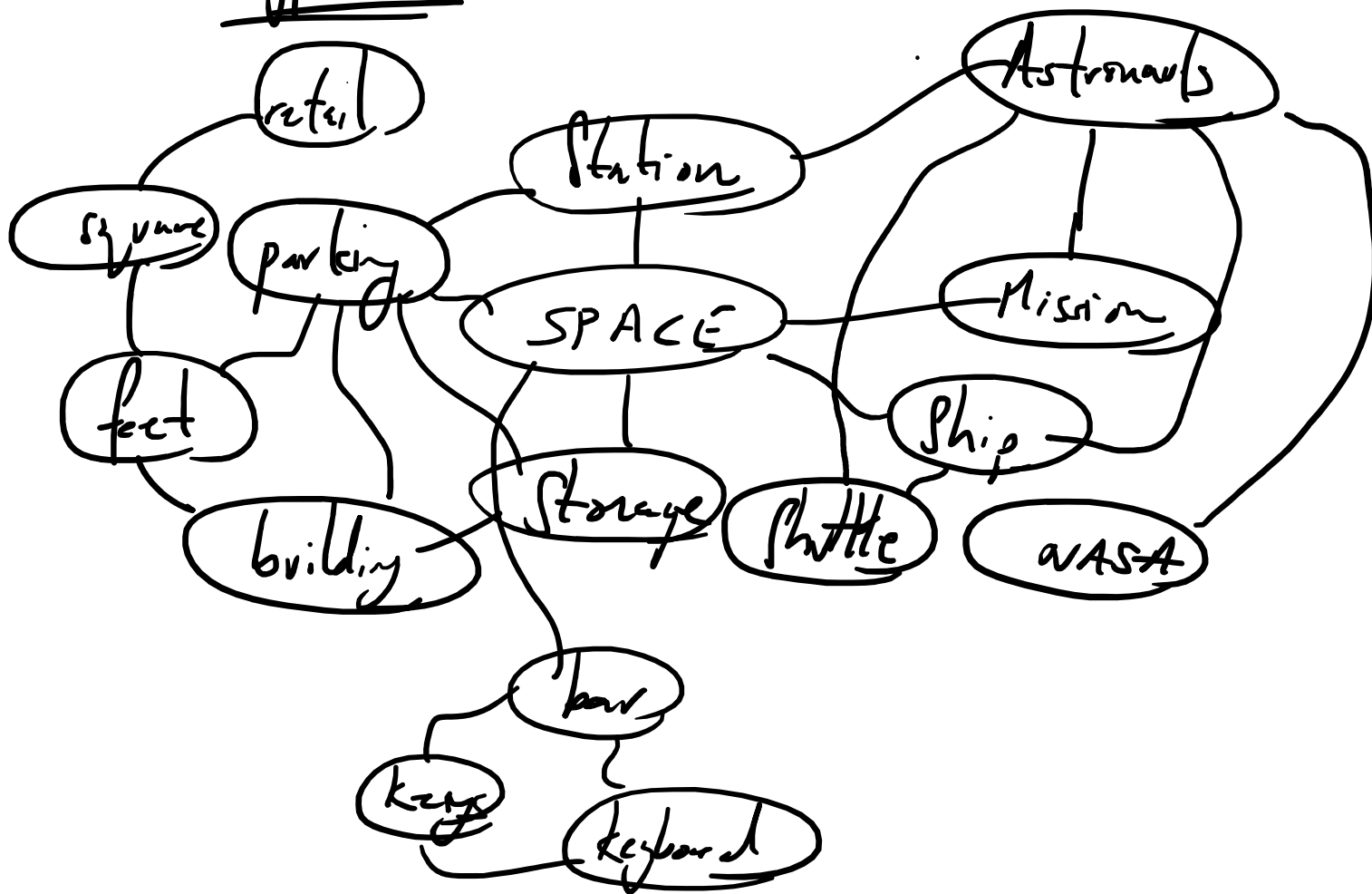


Advantages :

Summary

-> Unsupervised:

-> Hyperlex: Word Sense Induction

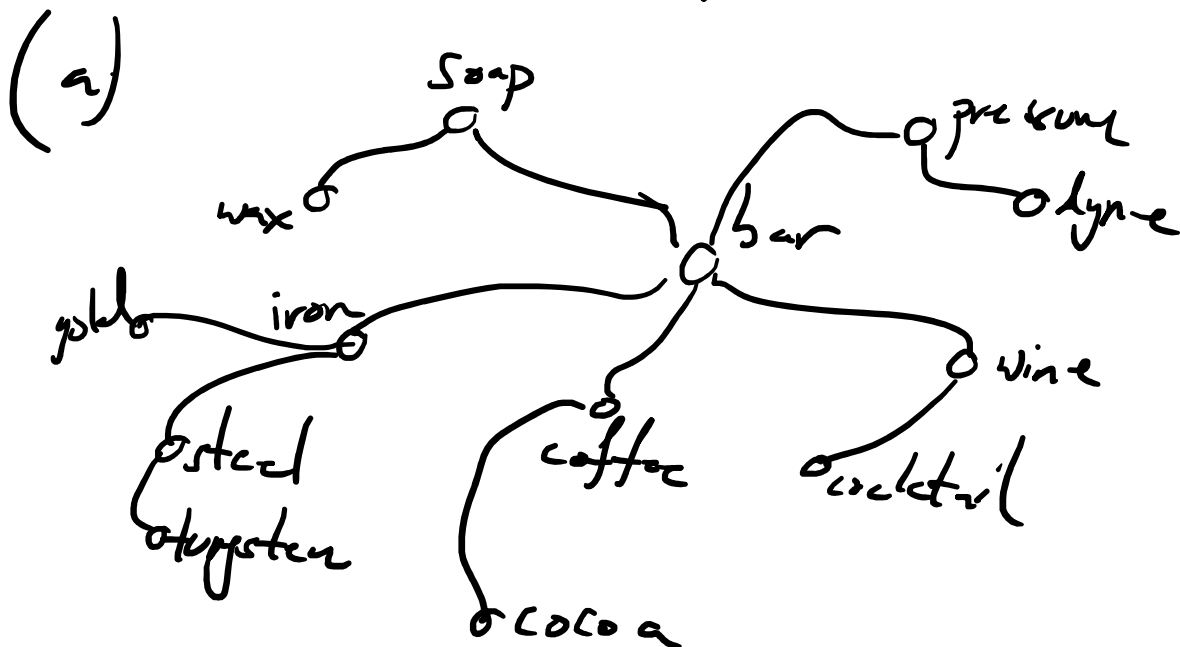


-> Detecting Lost Hubs:

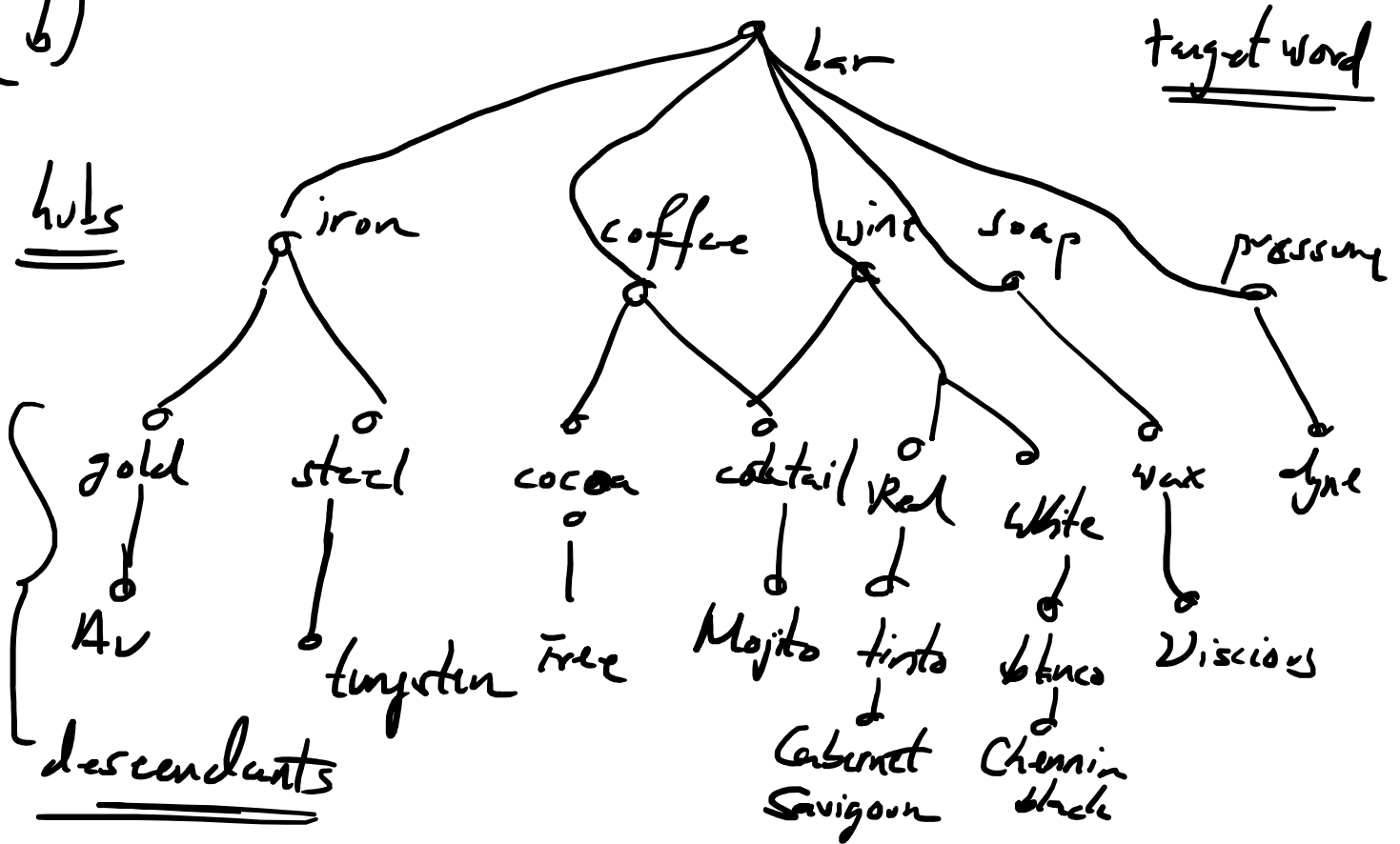
-> Co-occurrence graph:

↳ Arrange nodes in decreasing order
n n

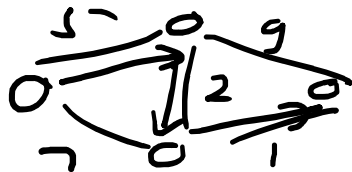
- ↳ Arrange nodes in decreasing order of degree.
- ↳ Select the nodes from graph which has the highest degree. This node will be the hub of the first high density component.
- ↳ Delete the hub & all its neighbors from graph.
- ↳ Repeat steps -b to detect hubs of other high degree components.



(b)



→ Delimiting Components:



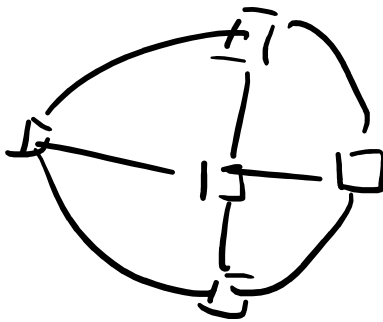
Computing distance b/w 2 nodes
 w_i & w_j

$$w_{ij} = 1 - \max \{P(w_i|w_j), P(w_j|w_i)\}$$

... $P(\dots)$... P /

where $P(w_i | w_j) = \frac{\text{freq}_{ij}}{\text{freq}_j}$

→ Disambiguation : Minimum Spanning Tree



- let $w = (w_1, \dots, w_i, \dots, w_n)$ be a context in which w_i is an instance of over target word.
- let w_i has k hubs in its MST.
- A score vector \underline{s} is associated with each $w_j \in W(j \neq i)$, such that S_k represents the contribution of the k^{th} hub. as :

$$s_k = \frac{1}{n_k}$$

$$s_k = \frac{1}{1 + d(h_k, w_j)}$$

if h_k is an ancestor of w_j

= 0 otherwise