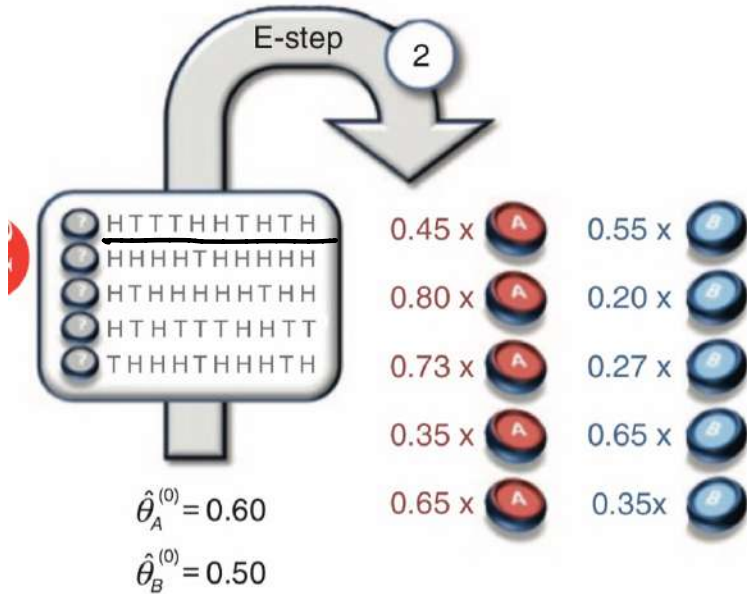


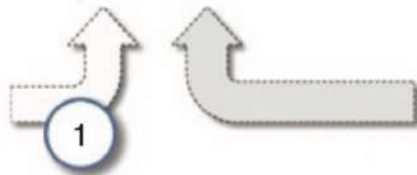
DMML, 20 Feb 2020

SHST: $P(\text{SHST} | \theta = 0.60) = P_1$
 $P(\text{SHST} | \theta = 0.50) = P_2$



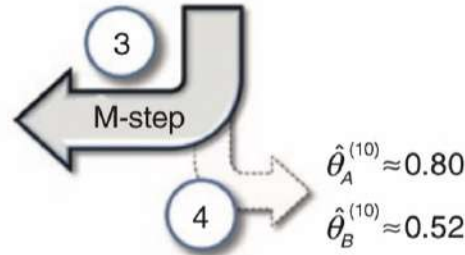
Coin A	Coin B
≈ 2.2 H, 2.2 T	≈ 2.8 H, 2.8 T
≈ 7.2 H, 0.8 T	≈ 1.8 H, 0.2 T
≈ 5.9 H, 1.5 T	≈ 2.1 H, 0.5 T
≈ 1.4 H, 2.1 T	≈ 2.6 H, 3.9 T
≈ 4.5 H, 1.9 T	≈ 2.5 H, 1.1 T
≈ 21.3 H, 8.6 T	≈ 11.7 H, 8.4 T

$\frac{P_1}{P_1+P_2}$ $\frac{P_2}{P_1+P_2}$
 0.45 0.55



$$\hat{\theta}_A^{(1)} \approx \frac{21.3}{21.3 + 8.6} \approx 0.71$$

$$\hat{\theta}_B^{(1)} \approx \frac{11.7}{11.7 + 8.4} \approx 0.58$$



Bottleneck of supervised learning - need for labelled training data

Volume + Timeliness

Bootstrapping — Semi Supervised Learning

1. EM - Expectation Maximization

Text Classification - Naive Bayes

$$P(w_i | c_j)$$

$$P(d_i | c_j)$$

$$P(w_i | c_j) = \frac{\text{Occ. of } w_i \text{ in } c_j}{\text{All words in } c_j}$$

$$= \frac{\sum_{d_k \in c_j} n_{ik}}{\sum_{w_l \in V} \sum_{d_k \in c_j} n_{lk}}$$

$$\sum_{w_l \in V} \sum_{d_k \in c_j} n_{lk}$$

n_{ik} = # of occurrences
of w_i in d_k

0 if $d_k \notin c_j$
1 if $d_k \in c_j$

Instead $\sum_{d_k} n_{ik} P(d_k | c_j)$

$$\sum_{w_l \in V} \sum_{d_k} n_{lk} P(d_k | c_j)$$

Semi Supervised Learning

Supervised case — compute $P(w_i | c_j)$, $P(d_k | c_j)$

Given a new d

Compute $P(c_i | d)$ for all c_i

$$\arg \max_i P(c_i | d)$$

Fractional assignments
of categories that
we discard after
 $\arg \max$

Semi supervised

label, say, 10% of document "randomly selected"

↓
Naive Bayes model

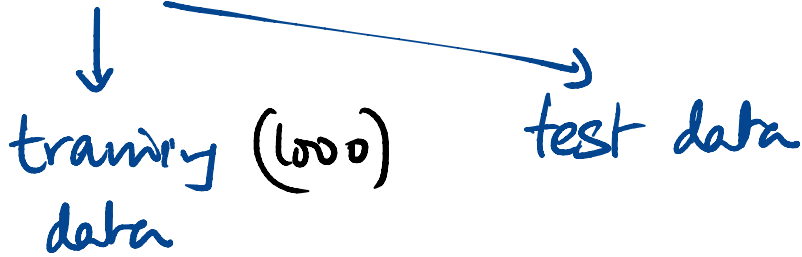
↓
Fractional topic allocation per document
class

↓
New estimates of $P(w_i | c_j)$, $P(d_n | G_i)$
Now $P(d_n | c_i)$ makes sense!



Another example

MNIST digit images



label only 50

Cluster remaining 950 using these 50 as centroids
- labels are inherited from centroid

Use distance from centroid for logistic regression

