Bayesian Learning

- Bayes Theorem
- MAP, ML hypotheses
- MAP learners
- Minimum description length principle
- Bayes optimal classifier
- Naive Bayes learner
- Example: Learning over text data
- Bayesian belief networks
- Expectation Maximization algorithm
Two Roles for Bayesian Methods

Provides practical learning algorithms:

- Naive Bayes learning
- Bayesian belief network learning
- Combine prior knowledge (prior probabilities) with observed data
- Requires prior probabilities

Provides useful conceptual framework

- Provides “gold standard” for evaluating other learning algorithms
- Additional insight into Occam’s razor
Bayes Theorem

\[ P(h|D) = \frac{P(D|h)P(h)}{P(D)} \]

- \( P(h) \) = prior probability of hypothesis \( h \)
- \( P(D) \) = prior probability of training data \( D \)
- \( P(h|D) \) = probability of \( h \) given \( D \)
- \( P(D|h) \) = probability of \( D \) given \( h \)
Choosing Hypotheses

\[ P(h|D) = \frac{P(D|h)P(h)}{P(D)} \]

Generally want the most probable hypothesis given the training data
Maximum a posteriori hypothesis \( h_{MAP} \):

\[
\begin{align*}
h_{MAP} &= \arg \max_{h \in H} P(h|D) \\
&= \arg \max_{h \in H} \frac{P(D|h)P(h)}{P(D)} \\
&= \arg \max_{h \in H} P(D|h)P(h)
\end{align*}
\]

If assume \( P(h_i) = P(h_j) \) then can further simplify, and choose the Maximum likelihood (ML) hypothesis

\[
h_{ML} = \arg \max_{h_i \in H} P(D|h_i)
\]
Bayes Theorem

Does patient have cancer or not?

A patient takes a lab test and the result comes back positive. The test returns a correct positive result in only 98% of the cases in which the disease is actually present, and a correct negative result in only 97% of the cases in which the disease is not present. Furthermore, .008 of the entire population have this cancer.

\[
\begin{align*}
P(cancer) &= \quad P(\neg cancer) = \\
P(+|cancer) &= \quad P(-|cancer) = \\
P(+|\neg cancer) &= \quad P(-|\neg cancer) = 
\end{align*}
\]
Basic Formulas for Probabilities

- **Product Rule**: probability $P(A \land B)$ of a conjunction of two events $A$ and $B$:

$$P(A \land B) = P(A|B)P(B) = P(B|A)P(A)$$

- **Sum Rule**: probability of a disjunction of two events $A$ and $B$:

$$P(A \lor B) = P(A) + P(B) - P(A \land B)$$

- **Theorem of total probability**: if events $A_1, \ldots, A_n$ are mutually exclusive with $\sum_{i=1}^{n} P(A_i) = 1$, then

$$P(B) = \sum_{i=1}^{n} P(B|A_i)P(A_i)$$
Brute Force MAP Hypothesis Learner

1. For each hypothesis $h$ in $H$, calculate the posterior probability

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)}$$

2. Output the hypothesis $h_{MAP}$ with the highest posterior probability

$$h_{MAP} = \arg\max_{h \in H} P(h|D)$$
Relation to Concept Learning

Consider our usual concept learning task

- instance space $X$, hypothesis space $H$, training examples $D$
- consider the FINDS learning algorithm (outputs most specific hypothesis from the version space $VS_{H,D}$)

What would Bayes rule produce as the MAP hypothesis?

Does $FindS$ output a MAP hypothesis??
Relation to Concept Learning

Assume fixed set of instances $\langle x_1, \ldots, x_m \rangle$
Assume $D$ is the set of classifications

$D = \langle c(x_1), \ldots, c(x_m) \rangle$

Choose $P(D|h)$:
Relation to Concept Learning

Assume fixed set of instances $\langle x_1, \ldots, x_m \rangle$
Assume $D$ is the set of classifications $D = \langle c(x_1), \ldots, c(x_m) \rangle$
Choose $P(D|h)$
  - $P(D|h) = 1$ if $h$ consistent with $D$
  - $P(D|h) = 0$ otherwise
Choose $P(h)$ to be uniform distribution
  - $P(h) = \frac{1}{|H|}$ for all $h$ in $H$
Then,

$$P(h|D) = \begin{cases} 
\frac{1}{|VS_{H,D}|} & \text{if } h \text{ is consistent with } D \\
0 & \text{otherwise}
\end{cases}$$
Evolution of Posterior Probabilities
Characterizing Learning Algorithms by Equivalent MAP Learners

Inductive system

Candidate Elimination Algorithm

Training examples D
Hypothesis space H

Output hypotheses

Equivalent Bayesian inference system

Brute force MAP learner

Training examples D
Hypothesis space H

Prior assumptions made explicit

$P(h)$ uniform
$P(D|h) = 0$ if inconsistent,
$= 1$ if consistent
Learning A Real Valued Function

Consider any real-valued target function \( f \)
Training examples \( \langle x_i, d_i \rangle \), where \( d_i \) is noisy training value

- \( d_i = f(x_i) + e_i \)
- \( e_i \) is random variable (noise) drawn independently for each \( x_i \) according to some Gaussian distribution with mean=0

Then the maximum likelihood hypothesis \( h_{ML} \) is the one that minimizes the sum of squared errors:

\[
h_{ML} = \arg\min_{h \in H} \sum_{i=1}^{m} (d_i - h(x_i))^2
\]
Learning A Real Valued Function

\[
h_{ML} = \arg\max_{h \in H} p(D|h)
\]

\[
= \arg\max_{h \in H} \prod_{i=1}^{m} p(d_i|h)
\]

\[
= \arg\max_{h \in H} \prod_{i=1}^{m} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2} \left( \frac{d_i - h(x_i)}{\sigma} \right)^2}
\]

Maximize natural log of this instead...

\[
h_{ML} = \arg\max_{h \in H} \sum_{i=1}^{m} \ln \left( \frac{1}{\sqrt{2\pi\sigma^2}} - \frac{1}{2} \left( \frac{d_i - h(x_i)}{\sigma} \right)^2 \right)
\]

\[
= \arg\max_{h \in H} \sum_{i=1}^{m} -\frac{1}{2} \left( \frac{d_i - h(x_i)}{\sigma} \right)^2
\]

\[
= \arg\max_{h \in H} \sum_{i=1}^{m} -(d_i - h(x_i))^2
\]

\[
= \arg\min_{h \in H} \sum_{i=1}^{m} (d_i - h(x_i))^2
\]
Learning to Predict Probabilities

Consider predicting survival probability from patient data

Training examples $\langle x_i, d_i \rangle$, where $d_i$ is 1 or 0

Want to train neural network to output a probability given $x_i$ (not a 0 or 1)

In this case can show

$$h_{ML} = \arg\max_{h \in H} \sum_{i=1}^{m} d_i \ln h(x_i) + (1 - d_i) \ln (1 - h(x_i))$$

Weight update rule for a sigmoid unit:

$$w_{jk} \leftarrow w_{jk} + \Delta w_{jk}$$

where

$$\Delta w_{jk} = \eta \sum_{i=1}^{m} (d_i - h(x_i)) x_{ijk}$$
Minimum Description Length Principle

Occam’s razor: prefer the shortest hypothesis

MDL: prefer the hypothesis \( h \) that minimizes

\[
h_{MDL} = \arg\min_{h \in H} L_{C_1}(h) + L_{C_2}(D|h)
\]

where \( L_C(x) \) is the description length of \( x \) under encoding \( C \)

Example: \( H = \) decision trees, \( D = \) training data labels

- \( L_{C_1}(h) \) is \# bits to describe tree \( h \)
- \( L_{C_2}(D|h) \) is \# bits to describe \( D \) given \( h \)
  - Note \( L_{C_2}(D|h) = 0 \) if examples classified perfectly by \( h \). Need only describe exceptions
- Hence \( h_{MDL} \) trades off tree size for training errors
Minimum Description Length Principle

\[ h_{MAP} = \arg \max_{h \in H} P(D|h) P(h) \]
\[ = \arg \max_{h \in H} \log_2 P(D|h) + \log_2 P(h) \]
\[ = \arg \min_{h \in H} - \log_2 P(D|h) - \log_2 P(h) \quad (1) \]

Interesting fact from information theory:

The optimal (shortest expected coding length) code for an event with probability \( p \) is \( -\log_2 p \) bits.

So interpret (1):

- \( -\log_2 P(h) \) is length of \( h \) under optimal code
- \( -\log_2 P(D|h) \) is length of \( D \) given \( h \) under optimal code

\[ \rightarrow \text{prefer the hypothesis that minimizes} \]

\[ \text{length}(h) + \text{length}(\text{misclassifications}) \]
Most Probable Classification of New Instances

So far we’ve sought the most probable hypothesis given the data $D$ (i.e., $h_{MAP}$)

Given new instance $x$, what is its most probable classification?

• $h_{MAP}(x)$ is not the most probable classification!

Consider:

• Three possible hypotheses:
  \[ P(h_1|D) = .4, \ P(h_2|D) = .3, \ P(h_3|D) = .3 \]

• Given new instance $x$,
  \[ h_1(x) = +, \ h_2(x) = -, \ h_3(x) = - \]

• What’s most probable classification of $x$?
Bayes Optimal Classifier

Bayes optimal classification:

$$\arg\max_{v_j \in V} \sum_{h_i \in H} P(v_j|h_i)P(h_i|D)$$

Example:

\[ P(h_1|D) = .4, \quad P(-|h_1) = 0, \quad P(+/h_1) = 1 \]
\[ P(h_2|D) = .3, \quad P(-|h_2) = 1, \quad P(+/h_2) = 0 \]
\[ P(h_3|D) = .3, \quad P(-|h_3) = 1, \quad P(+/h_3) = 0 \]

therefore

\[ \sum_{h_i \in H} P(+|h_i)P(h_i|D) = .4 \]
\[ \sum_{h_i \in H} P(-|h_i)P(h_i|D) = .6 \]

and

\[ \arg\max_{v_j \in V} \sum_{h_i \in H} P(v_j|h_i)P(h_i|D) = - \]
Gibbs Classifier

Bayes optimal classifier provides best result, but can be expensive if many hypotheses.

Gibbs algorithm:

1. Choose one hypothesis at random, according to $P(h|D)$
2. Use this to classify new instance

Surprising fact: Assume target concepts are drawn at random from $H$ according to priors on $H$. Then:

$$E[error_{Gibbs}] \leq 2E[error_{BayesOptimal}]$$

Suppose correct, uniform prior distribution over $H$, then

- Pick any hypothesis from VS, with uniform probability
- Its expected error no worse than twice Bayes optimal
Naive Bayes Classifier

Along with decision trees, neural networks, nearest nbr, one of the most practical learning methods.

When to use

• Moderate or large training set available
• Attributes that describe instances are conditionally independent given classification

Successful applications:

• Diagnosis
• Classifying text documents
Naive Bayes Classifier

Assume target function $f : X \rightarrow V$, where each instance $x$ described by attributes $\langle a_1, a_2 \ldots a_n \rangle$. Most probable value of $f(x)$ is:

$$v_{MAP} = \arg\max_{v_j \in V} P(v_j|a_1, a_2 \ldots a_n)$$

$$v_{MAP} = \arg\max_{v_j \in V} \frac{P(a_1, a_2 \ldots a_n|v_j)P(v_j)}{P(a_1, a_2 \ldots a_n)}$$

$$= \arg\max_{v_j \in V} P(a_1, a_2 \ldots a_n|v_j)P(v_j)$$

Naive Bayes assumption:

$$P(a_1, a_2 \ldots a_n|v_j) = \prod_i P(a_i|v_j)$$

which gives

**Naive Bayes classifier:** $v_{NB} = \arg\max_{v_j \in V} P(v_j) \prod_i P(a_i|v_j)$
Naive Bayes Algorithm

Naive\_Bayes\_Learn(\textit{examples})

For each target value $v_j$

\[ \hat{P}(v_j) \leftarrow \text{estimate } P(v_j) \]

For each attribute value $a_i$ of each attribute $a$

\[ \hat{P}(a_i|v_j) \leftarrow \text{estimate } P(a_i|v_j) \]

Classify\_New\_Instance(\textit{x})

\[ v_{NB} = \argmax_{v_j \in V} \hat{P}(v_j) \prod_{a_i \in x} \hat{P}(a_i|v_j) \]
Naive Bayes: Example

Consider *PlayTennis* again, and new instance

\( \langle \text{Outlk} = \text{sun}, \text{Temp} = \text{cool}, \text{Humid} = \text{high}, \text{Wind} = \text{strong} \rangle \)

Want to compute:

\[
v_{NB} = \arg\max_{v_j \in V} P(v_j) \prod_i P(a_i | v_j)
\]

\[
P(y) P(\text{sun}|y) P(\text{cool}|y) P(\text{high}|y) P(\text{strong}|y) = .005
\]

\[
P(n) P(\text{sun}|n) P(\text{cool}|n) P(\text{high}|n) P(\text{strong}|n) = .021
\]

\[\rightarrow v_{NB} = n\]
Naive Bayes: Subtleties

1. Conditional independence assumption is often violated

\[ P(a_1, a_2 \ldots a_n | v_j) = \prod_i P(a_i | v_j) \]

• ...but it works surprisingly well anyway. Note don’t need estimated posteriors \( \hat{P}(v_j | x) \) to be correct; need only that

\[
\arg\max_{v_j \in V} \hat{P}(v_j) \prod_i \hat{P}(a_i | v_j) = \arg\max_{v_j \in V} P(v_j) P(a_1 \ldots, a_n | v_j)
\]

• see [Domingos & Pazzani, 1996] for analysis

• Naive Bayes posteriors often unrealistically close to 1 or 0
2. what if none of the training instances with target value \( v_j \) have attribute value \( a_i \)? Then

\[
\hat{P}(a_i|v_j) = 0, \text{ and...}
\]

\[
\hat{P}(v_j) \prod_i \hat{P}(a_i|v_j) = 0
\]

Typical solution is Bayesian estimate for \( \hat{P}(a_i|v_j) \)

\[
\hat{P}(a_i|v_j) \leftarrow \frac{n_c + mp}{n + m}
\]

where

- \( n \) is number of training examples for which \( v = v_j \),
- \( n_c \) number of examples for which \( v = v_j \) and \( a = a_i \)
- \( p \) is prior estimate for \( \hat{P}(a_i|v_j) \)
- \( m \) is weight given to prior (i.e. number of “virtual” examples)
Learning to Classify Text

Why?

• Learn which news articles are of interest
• Learn to classify web pages by topic

Naive Bayes is among most effective algorithms

What attributes shall we use to represent text documents??
Learning to Classify Text

Target concept $Interesting? : Document \rightarrow \{+, -\}$

1. Represent each document by vector of words
   - one attribute per word position in document

2. Learning: Use training examples to estimate
   - $P(+)$
   - $P(-)$
   - $P(doc|+)$
   - $P(doc|-)$

Naive Bayes conditional independence assumption

$$P(doc|v_j) = \prod_{i=1}^{\text{length}(doc)} P(a_i = w_k|v_j)$$

where $P(a_i = w_k|v_j)$ is probability that word in position $i$ is $w_k$, given $v_j$

one more assumption:

$$P(a_i = w_k|v_j) = P(a_m = w_k|v_j), \forall i, m$$
Learn_naive_Bayes_text(Examples, V)

1. collect all words and other tokens that occur in Examples

- Vocabulary ← all distinct words and other tokens in Examples

2. calculate the required $P(v_j)$ and $P(w_k|v_j)$ probability terms

- For each target value $v_j$ in $V$ do
  
  - $docs_j$ ← subset of Examples for which the target value is $v_j$
  
  - $P(v_j) ← \frac{|docs_j|}{|Examples|}$

  - $Text_j$ ← a single document created by concatenating all members of $docs_j$

  - $n ←$ total number of words in $Text_j$ (counting duplicate words multiple times)

  - for each word $w_k$ in Vocabulary
    
    * $n_k ←$ number of times word $w_k$ occurs in $Text_j$

    * $P(w_k|v_j) ← \frac{n_k+1}{n+|Vocabulary|}$
\textbf{CLASSIFY\_NAIVE\_BAYES\_TEXT}(\textit{Doc})

- \textit{positions} $\leftarrow$ all word positions in \textit{Doc} that contain tokens found in \textit{Vocabulary}
- Return $v_{NB}$, where

$$v_{NB} = \arg\max_{v_j \in V} P(v_j) \prod_{i \in \text{positions}} P(a_i | v_j)$$
Twenty NewsGroups

Given 1000 training documents from each group
Learn to classify new documents according to which
newsgroup it came from

comp.graphics  misc.forsale
comp.os.ms-windows.misc rec.autos
comp.sys.ibm.pc.hardware rec.motorcycles
comp.sys.mac.hardware rec.sport.baseball
comp.windows.x rec.sport.hockey

alt.atheism    sci.space
soc.religion.christian sci.crypt
talk.religion.misc sci.electronics
talk.politics.mideast sci.med
talk.politics.misc
talk.politics.guns

Naive Bayes: 89% classification accuracy
Article from rec.sport.hockey

I can only comment on the Kings, but the most obvious candidate for pleasant surprise is Alex Zhitnik. He came highly touted as a defensive defenseman, but he’s clearly much more than that. Great skater and hard shot (though wish he were more accurate). In fact, he pretty much allowed the Kings to trade away that huge defensive liability Paul Coffey. Kelly Hrudey is only the biggest disappointment if you thought he was any good to begin with. But, at best, he’s only a mediocre goaltender. A better choice would be Tomas Sandstrom, though not through any fault of his own, but because some thugs in Toronto decided
Learning Curve for 20 Newsgroups

Accuracy vs. Training set size (1/3 withheld for test)
Bayesian Belief Networks

Interesting because:

• Naive Bayes assumption of conditional independence too restrictive

• But it’s intractable without some such assumptions...

• Bayesian Belief networks describe conditional independence among *subsets* of variables

→ allows combining prior knowledge about (in)dependencies among variables with observed training data

(also called Bayes Nets)
Conditional Independence

**Definition:** $X$ is *conditionally independent* of $Y$ given $Z$ if the probability distribution governing $X$ is independent of the value of $Y$ given the value of $Z$; that is, if

$$(\forall x_i, y_j, z_k) \ P(X = x_i | Y = y_j, Z = z_k) = P(X = x_i | Z = z_k)$$

more compactly, we write

$$P(X|Y, Z) = P(X|Z)$$

Example: *Thunder* is conditionally independent of *Rain*, given *Lightning*

$$P(Thunder|Rain, Lightning) = P(Thunder|Lightning)$$

Naive Bayes uses cond. indep. to justify

$$P(X, Y | Z) = P(X|Y, Z)P(Y | Z) = P(X|Z)P(Y | Z)$$
Bayesian Belief Network

Network represents a set of conditional independence assertions:

- Each node is asserted to be conditionally independent of its nondescendants, given its immediate predecessors.
- Directed acyclic graph

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<tr>
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<td>¬C</td>
<td>0.6</td>
<td>0.9</td>
<td>0.2</td>
<td>0.8</td>
</tr>
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</table>
Bayesian Belief Network

Represents joint probability distribution over all variables

- e.g., $P(\text{Storm}, \text{BusTourGroup}, \ldots, \text{ForestFire})$
- in general,
  \[ P(y_1, \ldots, y_n) = \prod_{i=1}^{n} P(y_i | \text{Parents}(Y_i)) \]
  where $\text{Parents}(Y_i)$ denotes immediate predecessors of $Y_i$ in graph
- so, joint distribution is fully defined by graph, plus the $P(y_i | \text{Parents}(Y_i))$
Inference in Bayesian Networks

How can one infer the (probabilities of) values of one or more network variables, given observed values of others?

- Bayes net contains all information needed for this inference
- If only one variable with unknown value, easy to infer it
- In general case, problem is NP hard

In practice, can succeed in many cases

- Exact inference methods work well for some network structures
- Monte Carlo methods “simulate” the network randomly to calculate approximate solutions
Learning of Bayesian Networks

Several variants of this learning task

- Network structure might be *known* or *unknown*
- Training examples might provide values of *all* network variables, or just *some*

If structure known and observe all variables

- Then it’s easy as training a Naive Bayes classifier
Learning Bayes Nets

Suppose structure known, variables partially observable
e.g., observe ForestFire, Storm, BusTourGroup, Thunder, but not Lightning, Campfire...

• Similar to training neural network with hidden units

• In fact, can learn network conditional probability tables using gradient ascent!

• Converge to network $h$ that (locally) maximizes $P(D|h)$
Gradient Ascent for Bayes Nets

Let $w_{ijk}$ denote one entry in the conditional probability table for variable $Y_i$ in the network

$$w_{ijk} = P(Y_i = y_{ij} | \text{Parents}(Y_i) = \text{the list } u_{ik} \text{ of values})$$

e.g., if $Y_i = Campfire$, then $u_{ik}$ might be $\langle Storm = T, BusTourGroup = F \rangle$

Perform gradient ascent by repeatedly

1. update all $w_{ijk}$ using training data $D$

   $$w_{ijk} \leftarrow w_{ijk} + \eta \sum_{d \in D} \frac{P_h(y_{ij}, u_{ik} | d)}{w_{ijk}}$$

2. then, renormalize the $w_{ijk}$ to assure

   $\bullet \Sigma_j w_{ijk} = 1$

   $\bullet 0 \leq w_{ijk} \leq 1$
More on Learning Bayes Nets

EM algorithm can also be used. Repeatedly:

1. Calculate probabilities of unobserved variables, assuming $h$

2. Calculate new $w_{ijk}$ to maximize $E[\ln P(D|h)]$ where
   $D$ now includes both observed and (calculated probabilities of) unobserved variables

When structure unknown...

- Algorithms use greedy search to add/subtract edges and nodes
- Active research topic
Summary: Bayesian Belief Networks

- Combine prior knowledge with observed data
- Impact of prior knowledge (when correct!) is to lower the sample complexity
- Active research area
  - Extend from boolean to real-valued variables
  - Parameterized distributions instead of tables
  - Extend to first-order instead of propositional systems
  - More effective inference methods
  - ...
Expectation Maximization (EM)

When to use:

- Data is only partially observable
- Unsupervised clustering (target value unobservable)
- Supervised learning (some instance attributes unobservable)

Some uses:

- Train Bayesian Belief Networks
- Unsupervised clustering (AUTOCLASS)
- Learning Hidden Markov Models
Generating Data from Mixture of $k$ Gaussians

Each instance $x$ generated by

1. Choosing one of the $k$ Gaussians with uniform probability
2. Generating an instance at random according to that Gaussian
EM for Estimating $k$ Means

Given:
- Instances from $X$ generated by mixture of $k$ Gaussian distributions
- Unknown means $\langle \mu_1, \ldots, \mu_k \rangle$ of the $k$ Gaussians
- Don’t know which instance $x_i$ was generated by which Gaussian

Determine:
- Maximum likelihood estimates of $\langle \mu_1, \ldots, \mu_k \rangle$

Think of full description of each instance as $y_i = \langle x_i, z_{i1}, z_{i2} \rangle$, where
- $z_{ij}$ is 1 if $x_i$ generated by $j$th Gaussian
- $x_i$ observable
- $z_{ij}$ unobservable
EM for Estimating $k$ Means

EM Algorithm: Pick random initial $h = \langle \mu_1, \mu_2 \rangle$, then iterate

E step: Calculate the expected value $E[z_{ij}]$ of each hidden variable $z_{ij}$, assuming the current hypothesis $h = \langle \mu_1, \mu_2 \rangle$ holds.

$$E[z_{ij}] = \frac{p(x = x_i | \mu = \mu_j)}{\sum_{n=1}^{2} p(x = x_i | \mu = \mu_n)} e^{-\frac{1}{2\sigma^2}(x_i - \mu_j)^2}$$

$$= \frac{\sum_{n=1}^{2} e^{-\frac{1}{2\sigma^2}(x_i - \mu_n)^2}}{\sum_{n=1}^{2} e^{-\frac{1}{2\sigma^2}(x_i - \mu_n)^2}}$$

M step: Calculate a new maximum likelihood hypothesis $h' = \langle \mu'_1, \mu'_2 \rangle$, assuming the value taken on by each hidden variable $z_{ij}$ is its expected value $E[z_{ij}]$ calculated above. Replace $h = \langle \mu_1, \mu_2 \rangle$ by $h' = \langle \mu'_1, \mu'_2 \rangle$.

$$\mu_j \leftarrow \frac{\sum_{i=1}^{m} E[z_{ij}] x_i}{\sum_{i=1}^{m} E[z_{ij}]}$$
EM Algorithm

Converges to local maximum likelihood $h$
and provides estimates of hidden variables $z_{ij}$

In fact, local maximum in $E[\ln P(Y|h)]$

- $Y$ is complete (observable plus unobservable variables) data
- Expected value is taken over possible values of unobserved variables in $Y$
General EM Problem

Given:
- Observed data $X = \{x_1, \ldots, x_m\}$
- Unobserved data $Z = \{z_1, \ldots, z_m\}$
- Parameterized probability distribution $P(Y|h)$, where

  \[-Y = \{y_1, \ldots, y_m\} \text{ is the full data } y_i = x_i \cup z_i\]

  \[-h \text{ are the parameters}\]

Determine:
- $h$ that (locally) maximizes $E[\ln P(Y|h)]$

Many uses:
- Train Bayesian belief networks
- Unsupervised clustering (e.g., $k$ means)
- Hidden Markov Models
General EM Method

Define likelihood function $Q(h'|h)$ which calculates $Y = X \cup Z$ using observed $X$ and current parameters $h$ to estimate $Z$

$$Q(h'|h) \leftarrow E[\ln P(Y|h')|h, X]$$

EM Algorithm:

**Estimation (E) step:** Calculate $Q(h'|h)$ using the current hypothesis $h$ and the observed data $X$ to estimate the probability distribution over $Y$.

$$Q(h'|h) \leftarrow E[\ln P(Y|h')|h, X]$$

**Maximization (M) step:** Replace hypothesis $h$ by the hypothesis $h'$ that maximizes this $Q$ function.

$$h \leftarrow \arg\max_{h'} Q(h'|h)$$
Bayesian Learning: Summary

- Bayes Theorem
- MAP, ML hypotheses
- MAP learners
- Minimum description length principle
- Bayes optimal classifier
- Naive Bayes learner
- Example: Learning over text data
- Bayesian belief networks
- Expectation Maximization algorithm