Machine Learning for Signal Processing

Expectation Maximization Mixture Models

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Class 10. 3 Oct 2013

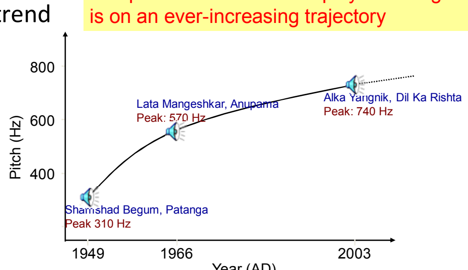
Administrivia

- HW2 is up
  - A final problem will be added
  - You have four weeks
  - It's a loooooong homework
  - About 12-24 hours of work
- Does everyone have teams/project proposals
- Begin working on your projects immediately..

A Strange Observation

- A trend

The pitch of female Indian playback singers is on an ever-increasing trajectory



- Mean pitch values: 278Hz, 410Hz, 580Hz

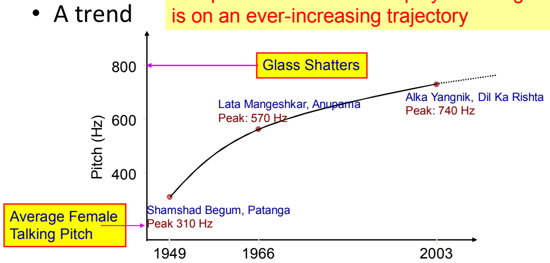
I'm not the only one to find the high-pitched stuff annoying

- Sarah McDonald (Holy Cow): ".. shrieking…"
- Khazana.com: ".. female Indian movie playback singers who can produce ultra high frequncies which only dogs can hear clearly.."
- www.roadjunky.com: ".. High pitched female singers doing their best to sound like they were seven years old .."

A Disturbing Observation

- A trend

The pitch of female Indian playback singers is on an ever-increasing trajectory



- Mean pitch values: 278Hz, 410Hz, 580Hz

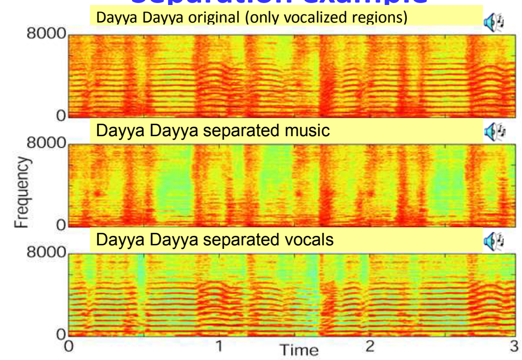
Lets Fix the Song

- The pitch is unpleasant
- The melody isn't bad
- Modify the pitch, but retain melody
- Problem:
  - Cannot just shift the pitch: will destroy the music
    - The music is fine, leave it alone
  - Modify the singing pitch without affecting the music

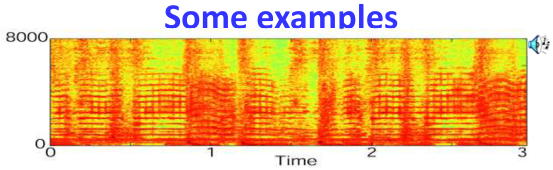
"Personalizing" the Song

- Separate the vocals from the background music
  - Modify the separated vocals, keep music unchanged
- Separation need not be perfect
  - Must only be sufficient to enable pitch modification of vocals
  - Pitch modification is tolerant of low-level artifacts
    - For octave level pitch modification artifacts can be undetectable.

Separation example

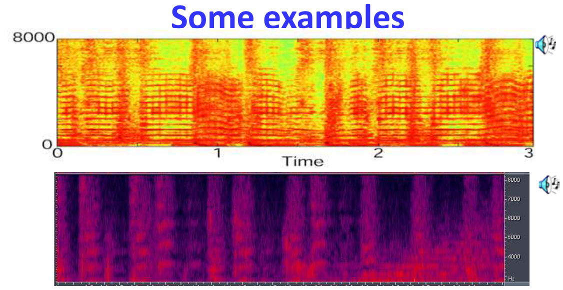


Some examples



- Example 1: Vocals shifted down by 4 semitones

Some examples



- Example 1: Vocals shifted down by 4 semitones
- Example 2: Gender of singer partially modified

Techniques Employed

- Signal separation
  - Employed a simple latent-variable based separation method
- Voice modification
  - Equally simple techniques
- Separation: Extensive use of Expectation Maximization

Learning Distributions for Data

- Problem: Given a collection of examples from some data, estimate its distribution
- Solution: Assign a model to the distribution
  - Learn parameters of model from data
- Models can be arbitrarily complex
  - Mixture densities, Hierarchical models.
- Learning must be done using Expectation Maximization
- Following slides: An intuitive explanation using a simple example of multinomials

A Thought Experiment

6 3 1 5 4 1 2 4 …

- A person shoots a loaded dice repeatedly
- You observe the series of outcomes
- **You can form a good idea of how the dice is loaded**
  - Figure out what the probabilities of the various numbers are for dice
- P(number) = count(number)/sum(rolls)
- This is a *maximum likelihood* estimate
  - Estimate that makes the observed sequence of numbers most probable

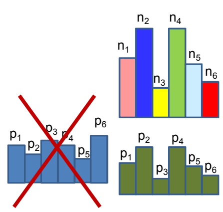
The Multinomial Distribution

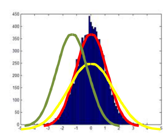
- A probability distribution over a discrete collection of items is a *Multinomial*

$$P(X : X \text{ belongs to a discrete set}) = P(X)$$

- E.g. the roll of dice
  - X : X in (1,2,3,4,5,6)
- Or the toss of a coin
  - X : X in (head, tails)

Maximum Likelihood Estimation





- Basic principle: Assign a form to the distribution
  - E.g. a multinomial
  - Or a Gaussian
- Find the *distribution* that best fits the histogram of the data

Defining "Best Fit"

- The data are generated by draws from the distribution
  - I.e. the generating process draws from the distribution
- Assumption: The world is a boring place
  - The data you have observed are very typical of the process
- Consequent assumption: The distribution has a high probability of generating the observed data
  - Not necessarily true
- Select the distribution that has the *highest* probability of generating the data
  - Should assign lower probability to less frequent observations and vice versa

Maximum Likelihood Estimation: Multinomial

- Probability of generating (n_1, n_2, n_3, n_4, n_5, n_6)

$$P(n_1,n_2,n_3,n_4,n_5,n_6) = Const\prod_i p_i^{n_i}$$

- Find p_1,p_2,p_3,p_4,p_5,p_6 so that the above is maximized
- Alternately maximize

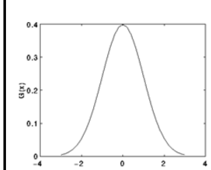
$$\log\left(P(n_1,n_2,n_3,n_4,n_5,n_6)\right) = \log(Const) + \sum_i n_i \log(p_i)$$

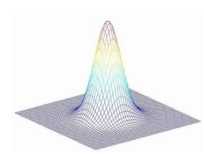
  - Log() is a monotonic function
  - $\text{argmax}_x f(x) = \text{argmax}_x \log(f(x))$
- Solving for the probabilities gives us
  - Requires constrained optimization to ensure probabilities sum to 1

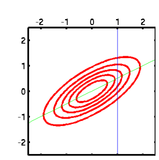
$$p_i = \frac{n_i}{\sum_j n_j}$$

EVENTUALLY ITS JUST COUNTING!

Segue: Gaussians







$$P(X) = N(X;\mu,\Theta) = \frac{1}{\sqrt{(2\pi)^d |\Theta|}} \exp\left(-0.5(X-\mu)^T \Theta^{-1}(X-\mu)\right)$$

- Parameters of a Gaussian:
  - Mean μ, Covariance Θ

Maximum Likelihood: Gaussian

- Given a collection of observations $(X_1, X_2, \ldots)$, estimate mean μ and covariance Θ

$$P(X_1, X_2, \ldots) = \prod_i \frac{1}{\sqrt{(2\pi)^d |\Theta|}} \exp\left(-0.5 (X_i - \mu)^T \Theta^{-1} (X_i - \mu)\right)$$

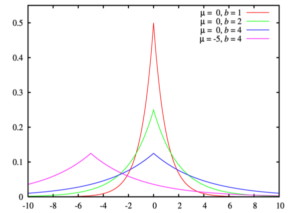
$$\log\left(P(X_1, X_2, \ldots)\right) = C - 0.5 \sum_i \left(\log(|\Theta|) + (X_i - \mu)^T \Theta^{-1} (X_i - \mu)\right)$$

- Maximizing w.r.t μ and Θ gives us

$$\mu = \frac{1}{N} \sum_i X_i \qquad \Theta = \frac{1}{N} \sum_i (X_i - \mu)(X_i - \mu)^T$$

ITS STILL JUST COUNTING!

Laplacian



$$P(x) = L(x; \mu, b) = \frac{1}{2b} \exp\left(-\frac{|x - \mu|}{b}\right)$$

- Parameters: Mean μ, scale b ($b > 0$)

Maximum Likelihood: Laplacian

- Given a collection of observations $(x_1, x_2, \ldots)$, estimate mean μ and scale b

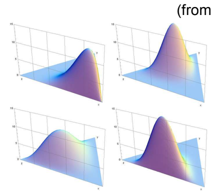
$$\log\left(P(x_1, x_2, \ldots)\right) = C - N\log(b) - \sum_i \frac{|x_i - \mu|}{b}$$

- Maximizing w.r.t μ and b gives us

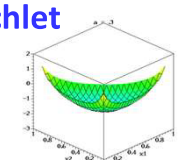
$$\mu = \frac{1}{N} \sum_i x_i \qquad b = \frac{1}{N} \sum_i |x_i - \mu|$$

Dirichlet

(from wikipedia)



K=3. Clockwise from top left: α=(6, 2, 2), (3, 7, 5), (6, 2, 6), (2, 3, 4)



log of the density as we change α from α=(0.3, 0.3, 0.3) to (2.0, 2.0, 2.0), keeping all the individual αi's equal to each other.

$$P(X) = D(X; \alpha) = \frac{\prod_i \Gamma(\alpha_i)}{\Gamma\left(\sum_i \alpha_i\right)} \prod_i x_i^{\alpha_i - 1}$$

- Parameters are αs
  - Determine mode and curvature
- Defined only of probability vectors
  - $X = [x_1\ x_2\ ..\ x_K]$, $\Sigma_i x_i = 1$, $x_i >= 0$ for all i

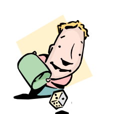
Maximum Likelihood: Dirichlet

- Given a collection of observations $(X_1, X_2, \ldots)$, estimate α

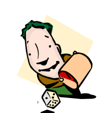
$$\log\left(P(X_1, X_2, \ldots)\right) = \sum_j \sum_i (\alpha_i - 1)\log(X_{j,i}) + N\sum_i \log(\Gamma(\alpha_i)) - N\log\left(\Gamma\left(\sum_i \alpha_i\right)\right)$$

- No closed form solution for αs.
  - Needs gradient ascent
- Several distributions have this property: the ML estimate of their parameters have no closed form solution

Continuing the Thought Experiment



6 3 1 5 4 1 2 4 …



4 4 1 6 3 2 1 2 …

- Two persons shoot loaded dice repeatedly
  - The dice are differently loaded for the two of them
- We observe the series of outcomes for both persons
- **How to determine the probability distributions of the two dice?**

Estimating Probabilities

- Observation: The sequence of numbers from the two dice
  - As indicated by the colors, we know who rolled what number

6 4 5 1 2 3 4 5 2 2 1 4 3 4 6 2 1 6…

Estimating Probabilities

- Observation: The sequence of numbers from the two dice
  - As indicated by the colors, we know who rolled what number
- Segregation: Separate the blue observations from the red

6 4 5 1 2 3 4 5 2 2 1 4 3 4 6 2 1 6…

6 5 2 4 2 1 3 6 1..
Collection of "blue" numbers

4 1 3 5 2 4 4 2 6..
Collection of "red" numbers

Estimating Probabilities

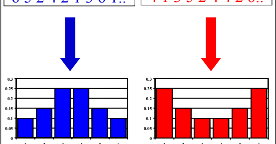
- Observation: The sequence of numbers from the two dice
  - As indicated by the colors, we know who rolled what number
- Segregation: Separate the blue observations from the red
- From each set compute probabilities for each of the 6 possible outcomes

$$P(number) = \frac{\text{no. of times number was rolled}}{\text{total number of observed rolls}}$$

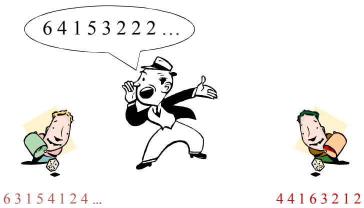
6 4 5 1 2 3 4 5 2 2 1 4 3 4 6 2 1 6…

6 5 2 4 2 1 3 6 1..

4 1 3 5 2 4 4 2 6..

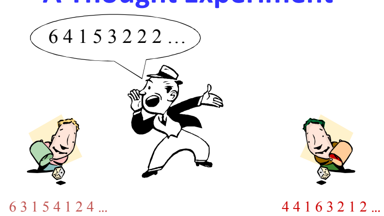


A Thought Experiment



- Now imagine that you cannot observe the dice yourself
- Instead there is a "caller" who randomly calls out the outcomes
  - 40% of the time he calls out the number from the left shooter, and 60% of the time, the one from the right (and you know this)
- At any time, you do not know which of the two he is calling out
- How do you determine the probability distributions for the two dice?

A Thought Experiment



- How do you now determine the probability distributions for the two sets of dice …
- .. If you do not even know what fraction of time the blue numbers are called, and what fraction are red?

A Mixture Multinomial

- The caller will call out a number X in any given callout IF
  - He selects "RED", and the Red die rolls the number X
  - OR
  - He selects "BLUE" and the Blue die rolls the number X
- P(X) = P(Red)P(X|Red) + P(Blue)P(X|Blue)
  - E.g. P(6) = P(Red)P(6|Red) + P(Blue)P(6|Blue)
- A distribution that *combines* (or *mixes*) multiple multinomials is a *mixture* multinomial

$$P(X) = \sum_Z P(Z)P(X|Z)$$

Mixture weights   Component multinomials

Mixture Distributions

Mixture Gaussian

$$P(X) = \sum_Z P(Z)P(X \mid Z) \qquad P(X) = \sum_Z P(Z)N(X; \mu_z, \Theta_z)$$

Mixture weights Component distributions

Mixture of Gaussians and Laplacians

$$P(X) = \sum_Z P(Z)N(X; \mu_z, \Theta_z) + \sum_Z P(Z)\prod_i L(X_i; \mu_{z,i}, b_{z,i})$$

- Mixture distributions mix several component distributions
  - Component distributions may be of varied type
- Mixing weights must sum to 1.0
- Component distributions integrate to 1.0
- Mixture distribution integrates to 1.0

Maximum Likelihood Estimation

- For our problem: $P(X) = \sum_Z P(Z)P(X \mid Z)$
  - Z = color of dice

$$P(n_1, n_2, n_3, n_4, n_5, n_6) = Const\prod_X P(X)^{n_X} = Const\prod_X \left(\sum_Z P(Z)P(X \mid Z)\right)^{n_X}$$

- Maximum likelihood solution: Maximize

$$\log(P(n_1, n_2, n_3, n_4, n_5, n_6)) = \log(Const) + \sum_X n_X \log\left(\sum_Z P(Z)P(X \mid Z)\right)$$

- No closed form solution (summation inside log)!
  - In general ML estimates for mixtures do not have a closed form
  - USE EM!

Expectation Maximization

- It is possible to estimate all parameters in this setup using the Expectation Maximization (or EM) algorithm
- First described in a landmark paper by Dempster, Laird and Rubin
  - Maximum Likelihood Estimation from incomplete data, via the EM Algorithm, Journal of the Royal Statistical Society, Series B, 1977
- Much work on the algorithm since then
- The principles behind the algorithm existed for several years prior to the landmark paper, however.

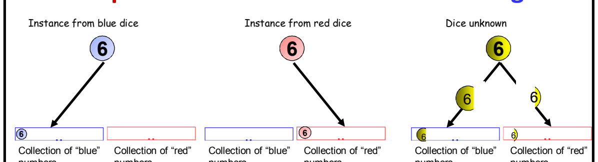
Expectation Maximization

- Iterative solution
- Get some initial estimates for all parameters
  - Dice shooter example: This includes probability distributions for dice AND the probability with which the caller selects the dice
- Two steps that are iterated:
  - ***Expectation Step:*** Estimate statistically, the values of ***unseen*** variables
  - ***Maximization Step:*** Using the estimated values of the unseen variables as truth, estimates of the model parameters

EM: The auxiliary function

- EM iteratively optimizes the following auxiliary function
- $Q(\theta, \theta') = \Sigma_Z P(Z|X,\theta') \log(P(Z,X \mid \theta))$
  - Z are the unseen variables
  - Assuming Z is discrete (may not be)
- θ' are the parameter estimates from the previous iteration
- θ are the estimates to be obtained in the current iteration

Expectation Maximization as counting



- Hidden variable: *Z*
  - Dice: The identity of the dice whose number has been called out
- If we knew *Z* for every observation, we could estimate all terms
  - By adding the observation to the right bin
- Unfortunately, we do not know *Z* – it is hidden from us!
- Solution: FRAGMENT THE OBSERVATION

Fragmenting the Observation

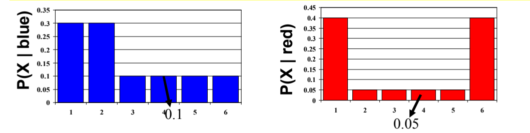
- EM is an iterative algorithm
  - At each time there is a *current* estimate of parameters
- The "size" of the fragments is proportional to the *a posteriori probability* of the component distributions
  - The *a posteriori* probabilities of the various values of *Z* are computed using Bayes' rule:

$$P(Z \mid X) = \frac{P(X \mid Z)P(Z)}{P(X)} = CP(X \mid Z)P(Z)$$

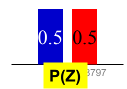
- Every dice gets a fragment of size P(dice | number)

Expectation Maximization

- Hypothetical Dice Shooter Example:
- We obtain an initial estimate for the probability distribution of the two sets of dice (somehow):



- We obtain an initial estimate for the probability with which the caller calls out the two shooters (somehow)



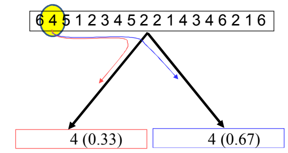
Expectation Maximization

- Hypothetical Dice Shooter Example:
- Initial estimate:
  - P(blue) = P(red) = 0.5
  - P(4 | blue) = 0.1, for P(4 | red) = 0.05
- Caller has just called out 4
- Posterior probability of colors:

$$P(red \mid X=4) = CP(X=4 \mid Z=red)P(Z=red) = C \times 0.05 \times 0.5 = C0.025$$
$$P(blue \mid X=4) = CP(X=4 \mid Z=blue)P(Z=blue) = C \times 0.1 \times 0.5 = C0.05$$

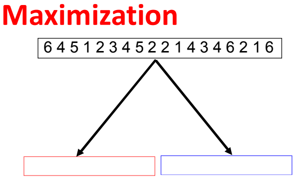
$$\text{Normalizing}: P(red \mid X=4) = 0.33; \quad P(blue \mid X=4) = 0.67$$

Expectation Maximization



Expectation Maximization

- Every observed roll of the dice contributes to both "Red" and "Blue"



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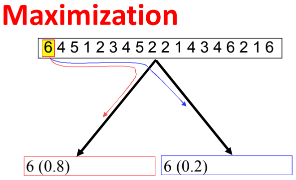

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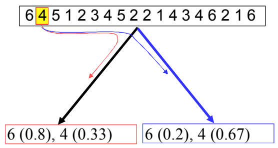

Expectation Maximization

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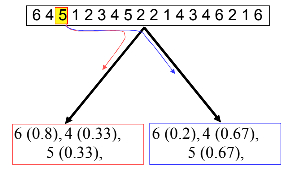
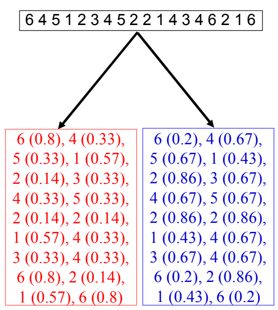


Expectation Maximization

- Every observed roll of the dice contributes to both “Red” and “Blue”



Expectation Maximization

- Every observed roll of the dice contributes to both “Red” and “Blue”
- Total count for “Red” is the sum of all the posterior probabilities in the red column
  - 7.31
- Total count for “Blue” is the sum of all the posterior probabilities in the blue column
  - 10.69
  - Note: 10.69 + 7.31 = 18 = the total number of instances

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Red” : 7.31
- Red:
  - Total count for 1: 1.71

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
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2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Red” : 7.31
- Red:
  - Total count for 1: 1.71
  - Total count for 2: 0.56

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Red” : 7.31
- Red:
  - Total count for 1: 1.71
  - Total count for 2: 0.56
  - Total count for 3: 0.66

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Red” : 7.31
- Red:
  - Total count for 1: 1.71
  - Total count for 2: 0.56
  - Total count for 3: 0.66
  - Total count for 4: 1.32

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Red” : 7.31
- Red:
  - Total count for 1: 1.71
  - Total count for 2: 0.56
  - Total count for 3: 0.66
  - Total count for 4: 1.32
  - Total count for 5: 0.66

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Red” : 7.31
- Red:
  - Total count for 1: 1.71
  - Total count for 2: 0.56
  - Total count for 3: 0.66
  - Total count for 4: 1.32
  - Total count for 5: 0.66
  - Total count for 6: 2.4

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Red” : 7.31
- Red:
  - Total count for 1: 1.71
  - Total count for 2: 0.56
  - Total count for 3: 0.66
  - Total count for 4: 1.32
  - Total count for 5: 0.66
  - Total count for 6: 2.4
- **Updated probability of Red dice:**
  - **P(1 | Red) = 1.71/7.31 = 0.234**
  - **P(2 | Red) = 0.56/7.31 = 0.077**
  - **P(3 | Red) = 0.66/7.31 = 0.090**
  - **P(4 | Red) = 1.32/7.31 = 0.181**
  - **P(5 | Red) = 0.66/7.31 = 0.090**
  - **P(6 | Red) = 2.40/7.31 = 0.328**

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for “Blue” : 10.69
- Blue:
  - Total count for 1: 1.29

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for "Blue" : 10.69
- Blue:
  - Total count for 1: 1.29
  - Total count for 2: 3.44

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for "Blue" : 10.69
- Blue:
  - Total count for 1: 1.29
  - Total count for 2: 3.44
  - Total count for 3: 1.34

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for "Blue" : 10.69
- Blue:
  - Total count for 1: 1.29
  - Total count for 2: 3.44
  - Total count for 3: 1.34
  - Total count for 4: 2.68

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for "Blue" : 10.69
- Blue:
  - Total count for 1: 1.29
  - Total count for 2: 3.44
  - Total count for 3: 1.34
  - Total count for 4: 2.68
  - Total count for 5: 1.34

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for "Blue" : 10.69
- Blue:
  - Total count for 1: 1.29
  - Total count for 2: 3.44
  - Total count for 3: 1.34
  - Total count for 4: 2.68
  - Total count for 5: 1.34
  - Total count for 6: 0.6

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation Maximization

- Total count for "Blue" : 10.69
- Blue:
  - Total count for 1: 1.29
  - Total count for 2: 3.44
  - Total count for 3: 1.34
  - Total count for 4: 2.68
  - Total count for 5: 1.34
  - Total count for 6: 0.6
- **Updated probability of Blue dice:**
  - **P(1 | Blue) = 1.29/11.69 = 0.122**
  - **P(2 | Blue) = 0.56/11.69 = 0.322**
  - **P(3 | Blue) = 0.66/11.69 = 0.125**
  - **P(4 | Blue) = 1.32/11.69 = 0.250**
  - **P(5 | Blue) = 0.66/11.69 = 0.125**
  - **P(6 | Blue) = 2.40/11.69 = 0.056**

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

Expectation **Maximization**

- Total count for "Red" : 7.31
- Total count for "Blue" : 10.69
- Total instances = 18
  - Note 7.31+10.69 = 18
- We also revise our estimate for the probability that the caller calls out Red or Blue
  - i.e the fraction of times that he calls Red and the fraction of times he calls Blue
- P(Z=Red) = 7.31/18 = 0.41
- P(Z=Blue) = 10.69/18 = 0.59

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2
	7.31	10.69

The updated values

- Probability of Red dice:
  - P(1 | Red) = 1.71/7.31 = 0.234
  - P(2 | Red) = 0.56/7.31 = 0.077
  - P(3 | Red) = 0.66/7.31 = 0.090
  - P(4 | Red) = 1.32/7.31 = 0.181
  - P(5 | Red) = 0.66/7.31 = 0.090
  - P(6 | Red) = 2.40/7.31 = 0.328
- Probability of Blue dice:
  - P(1 | Blue) = 1.29/11.69 = 0.122
  - P(2 | Blue) = 0.56/11.69 = 0.322
  - P(3 | Blue) = 0.66/11.69 = 0.125
  - P(4 | Blue) = 1.32/11.69 = 0.250
  - P(5 | Blue) = 0.66/11.69 = 0.125
  - P(6 | Blue) = 2.40/11.69 = 0.056
- P(Z=Red) = 7.31/18 = 0.41
- P(Z=Blue) = 10.69/18 = 0.59

Called	P(red|X)	P(blue|X)
6	.8	.2
4	.33	.67
5	.33	.67
1	.57	.43
2	.14	.86
3	.33	.67
4	.33	.67
5	.33	.67
2	.14	.86
2	.14	.86
1	.57	.43
4	.33	.67
3	.33	.67
4	.33	.67
6	.8	.2
2	.14	.86
1	.57	.43
6	.8	.2

THE UPDATED VALUES CAN BE USED TO REPEAT THE PROCESS. ESTIMATION IS AN ITERATIVE PROCESS

The Dice Shooter Example

6 3 1 5 4 1 2 4 … 4 4 1 6 3 2 1 2 …

1. Initialize *P*(*Z*), *P*(*X* | *Z*)
2. Estimate *P*(*Z* | *X*) for each *Z*, for each called out number
   - Associate *X* with each value of *Z*, with weight *P*(*Z* | *X*)
3. Re-estimate *P*(*X* | *Z*) for every value of *X* and *Z*
4. Re-estimate *P*(*Z*)
5. If not converged, return to 2

In Squiggles

- Given a sequence of observations O_1, O_2, ..
  - N_X is the number of observations of number X
- Initialize P(Z), P(X|Z) for dice Z and numbers X
- Iterate:
  - For each number X: $$P(Z \mid X) = \frac{P(X \mid Z)P(Z)}{\sum_{Z'} P(Z')P(X \mid Z')}$$
  - Update:

$$P(X \mid Z) = \frac{\sum_{O \text{ such that } O==X} P(Z \mid X)}{\sum_{O} P(Z \mid O)} = \frac{N_X P(Z \mid X)}{\sum_X N_X P(Z \mid X)}$$

$$P(Z) = \frac{\sum_X N_X P(Z \mid X)}{\sum_{Z'} \sum_X N_X P(Z' \mid X)}$$

Solutions may not be unique

- The EM algorithm will give us one of many solutions, all equally valid!
  - The probability of 6 being called out:

$$P(6) = \alpha P(6 \mid red) + \beta P(6 \mid blue) = \alpha P_r + \beta P_b$$

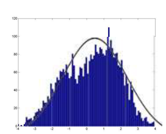
    - Assigns P_r as the probability of 6 for the red die
    - Assigns P_b as the probability of 6 for the blue die
  - The following too is a valid solution [FIX]

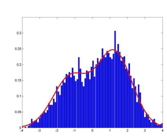
$$P(6) = 1.0(\alpha P_r + \beta P_b) + 0.0 anything$$

    - Assigns 1.0 as the a priori probability of the red die
    - Assigns 0.0 as the probability of the blue die
- The solution is NOT unique

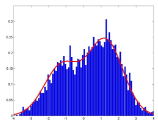
A more complex model: Gaussian mixtures

- A Gaussian mixture can represent data distributions far better than a simple Gaussian
- The two panels show the histogram of an unknown random variable
- The first panel shows how it is modeled by a simple Gaussian
- The second panel models the histogram by a mixture of two Gaussians
- Caveat: It is hard to know the optimal number of Gaussians in a mixture





A More Complex Model

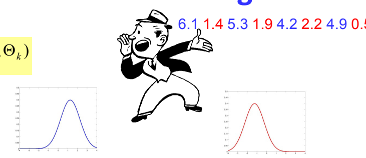


$$P(X) = \sum_k P(k) N(X;\mu_k,\Theta_k) = \sum_k \frac{P(k)}{\sqrt{(2\pi)^d |\Theta_k|}} \exp\left(-0.5(X-\mu_k)^T \Theta_k^{-1}(X-\mu_k)\right)$$

- Gaussian mixtures are often good models for the distribution of multivariate data
- Problem: Estimating the parameters, given a collection of data

Gaussian Mixtures: Generating model

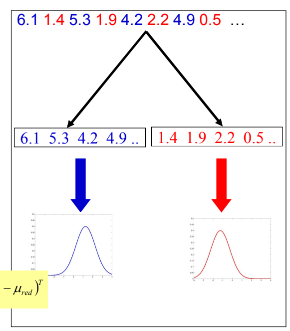
$$P(X) = \sum_k P(k) N(X;\mu_k,\Theta_k)$$



- The caller now has two Gaussians
  - At each draw he randomly selects a Gaussian, by the mixture weight distribution
  - He then draws an observation from that Gaussian
  - Much like the dice problem (only the outcomes are now real numbers and can be anything)

Estimating GMM with complete information

- Observation: A collection of numbers drawn from a mixture of 2 Gaussians
  - As indicated by the colors, we know which Gaussian generated what number
- Segregation: Separate the blue observations from the red
- From each set compute parameters for that Gaussian

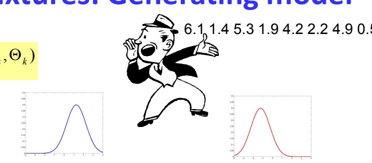


$$\mu_{red} = \frac{1}{N_{red}} \sum_{i \in red} X_i \qquad \Theta_{red} = \frac{1}{N_{red}} \sum_{i \in red} (X_i - \mu_{red})(X_i - \mu_{red})^T$$

$$P(red) = \frac{N_{red}}{N}$$

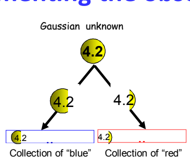
Gaussian Mixtures: Generating model

$$P(X) = \sum_k P(k) N(X;\mu_k,\Theta_k)$$



- Problem: In reality we will not know which Gaussian any observation was drawn from..
  - The color information is missing

Fragmenting the observation



- The identity of the Gaussian is not known!
- Solution: **Fragment the observation**
- Fragment size proportional to *a posteriori* probability

$$P(k|X) = \frac{P(X|k)P(k)}{\sum_{k'} P(k')P(X|k')} = \frac{P(k)N(X;\mu_k,\Theta_k)}{\sum_{k'} P(k')N(X;\mu_{k'},\Theta_{k'})}$$

Expectation Maximization

- Initialize P(k), μ_k and Θ_k for both Gaussians
  - Important how we do this
  - Typical solution: Initialize means randomly, Θ_k as the global covariance of the data and P(k) uniformly
- Compute fragment sizes for each Gaussian, for each observation

Number	P(red|X)	P(blue|X)
6.1	.81	.19
1.4	.33	.67
5.3	.75	.25
1.9	.41	.59
4.2	.64	.36
2.2	.43	.57
4.9	.66	.34
0.5	.05	.95

$$P(k|X) = \frac{P(k)N(X;\mu_k,\Theta_k)}{\sum_{k'} P(k')N(X;\mu_{k'},\Theta_{k'})}$$

Expectation Maximization

- ***Each observation contributes only as much as its fragment size to each statistic***
- Mean(red) = (6.1*0.81 + 1.4*0.33 + 5.3*0.75 + 1.9*0.41 + 4.2*0.64 + 2.2*0.43 + 4.9*0.66 + 0.5*0.05) / (0.81 + 0.33 + 0.75 + 0.41 + 0.64 + 0.43 + 0.66 + 0.05) = 17.05 / 4.08 = 4.18

Number	P(red|X)	P(blue|X)
6.1	.81	.19
1.4	.33	.67
5.3	.75	.25
1.9	.41	.59
4.2	.64	.36
2.2	.43	.57
4.9	.66	.34
0.5	.05	.95
	4.08	3.92

- Var(red) = ((6.1-4.18)^2*0.81 + (1.4-4.18)^2*0.33 + (5.3-4.18)^2*0.75 + (1.9-4.18)^2*0.41 + (4.2-4.18)^2*0.64 + (2.2-4.18)^2*0.43 + (4.9-4.18)^2*0.66 + (0.5-4.18)^2*0.05) / (0.81 + 0.33 + 0.75 + 0.41 + 0.64 + 0.43 + 0.66 + 0.05)

$$P(red) = \frac{4.08}{8}$$

EM for Gaussian Mixtures

1. Initialize P(k), μ_k and Θ_k for all Gaussians
2. For each observation X compute *a posteriori* probabilities for all Gaussian

$$P(k \mid X) = \frac{P(k)N(X;\mu_k,\Theta_k)}{\sum_{k'} P(k')N(X;\mu_{k'},\Theta_{k'})}$$

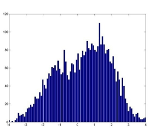
3. Update mixture weights, means and variances for all Gaussians

$$P(k) = \frac{\sum_X P(k|X)}{N} \qquad \mu_k = \frac{\sum_X P(k|X)\,X}{\sum_X P(k|X)} \qquad \Theta_k = \frac{\sum_X P(k|X)(X-\mu_k)^2}{\sum_X P(k|X)}$$

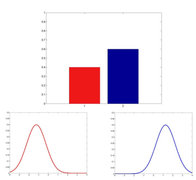
4. If not converged, return to 2

EM estimation of Gaussian Mixtures

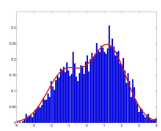
- An Example



Histogram of 4000 instances of a randomly generated data



Individual parameters of a two-Gaussian mixture estimated by EM



Two-Gaussian mixture estimated by EM

Expectation Maximization

- The same principle can be extended to mixtures of other distributions.
- E.g. Mixture of Laplacians: Laplacian parameters become

$$\mu_k = \frac{1}{\sum_x P(k \mid x)} \sum_x P(k \mid x)x \qquad b_k = \frac{1}{\sum_x P(k \mid x)} \sum_x P(k \mid x)\,|x - \mu_k|$$

- In a mixture of Gaussians and Laplacians, Gaussians use the Gaussian update rules, Laplacians use the Laplacian rule

Expectation Maximization

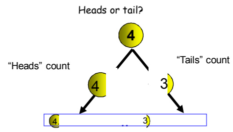
- The EM algorithm is used whenever proper statistical analysis of a phenomenon requires the knowledge of a hidden or missing variable (or a set of hidden/missing variables)
  - The hidden variable is often called a "latent" variable
- Some examples:
  - Estimating mixtures of distributions
    - Only data are observed. The individual distributions and mixing proportions must both be learnt.
  - Estimating the distribution of data, when some attributes are missing
  - Estimating the dynamics of a system, based only on observations that may be a complex function of system state

Solve this problem:

- Problem 1:
  - Caller rolls a dice and flips a coin
  - He calls out the number rolled if the coin shows head
  - Otherwise he calls the number+1
  - Determine p(heads) and p(number) for the dice from a collection of outputs

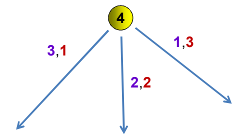
- Problem 2:
  - Caller rolls two dice
  - He calls out the sum
  - Determine P(dice) from a collection of ouputs

The dice and the coin



- Unknown: Whether it was head or tails

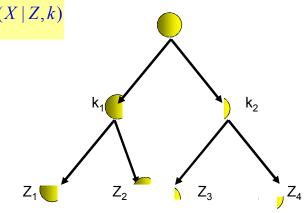
The two dice



- Unknown: How to partition the number
- $\text{Count}_{\text{blue}}(3)$ += P(3,1 | 4)
- $\text{Count}_{\text{blue}}(2)$ += P(2,2 | 4)
- $\text{Count}_{\text{blue}}(1)$ += P(1,3 | 4)

Fragmentation can be hierarchical

$$P(X) = \sum_k P(k) \sum_Z P(Z \mid k) P(X \mid Z, k)$$



- E.g. mixture of mixtures
- Fragments are further fragmented..
  - Work this out

More later

- Will see a couple of other instances of the use of EM
- EM for signal representation: PCA and factor analysis
- EM for signal separation
- EM for parameter estimation
- EM for homework..