

Clustering and Latent Variable Models

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K-means Clustering

Unsupervised learning

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Formulation Density estimation: $p(x; \theta)$ (often with *latent* variables).

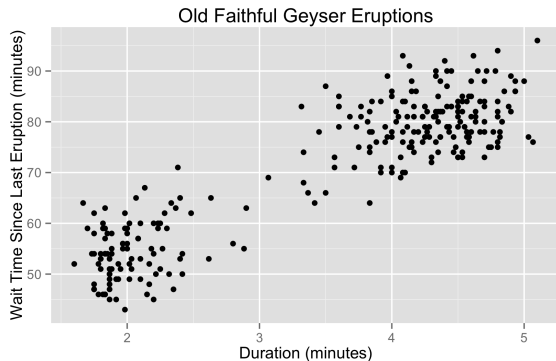
Unsupervised learning

Goal Discover interesting *structure* in the data.

Formulation Density estimation: $p(x; \theta)$ (often with *latent* variables).

- Examples**
- Discover *clusters*: cluster data into groups.
 - Discover *factors*: project high-dimensional data to a small number of “meaningful” dimensions, i.e. dimensionality reduction.
 - Discover *graph structures*: learn joint distribution of correlated variables, i.e. graphical models.

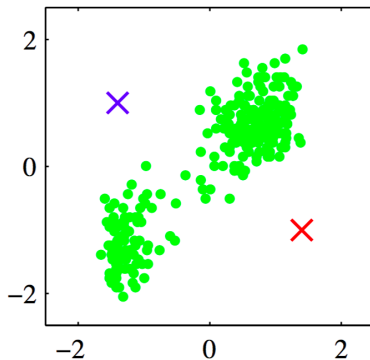
Example: Old Faithful Geyser



- Looks like two clusters.
- How to find these clusters algorithmically?

k-Means: By Example

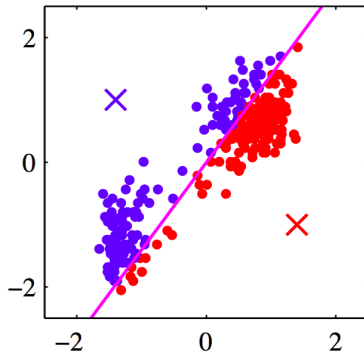
- Standardize the data.
- Choose two cluster centers.



From Bishop's *Pattern recognition and machine learning*, Figure 9.1(a).

k-means: by example

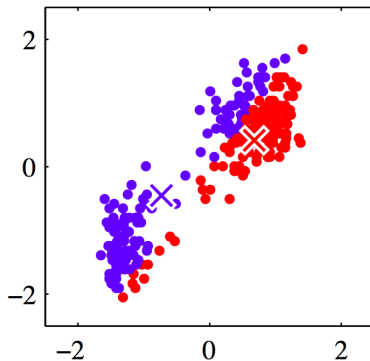
- Assign each point to closest center.



From Bishop's *Pattern recognition and machine learning*, Figure 9.1(b).

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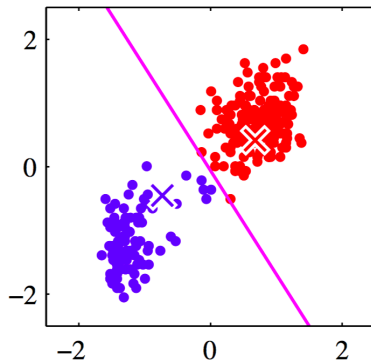
- Compute new cluster centers.



From Bishop's *Pattern recognition and machine learning*, Figure 9.1(c).

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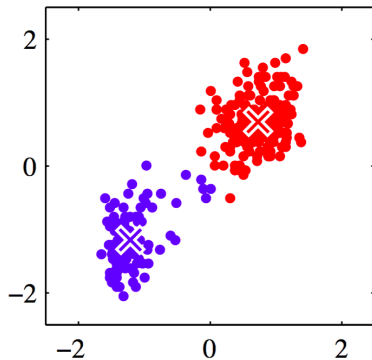
- Assign points to closest center.



From Bishop's *Pattern recognition and machine learning*, Figure 9.1(d).

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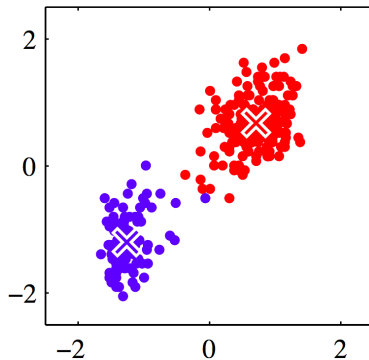
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From Bishop's *Pattern recognition and machine learning*, Figure 9.1(e).

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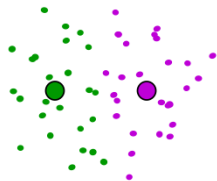
- Iterate until convergence.



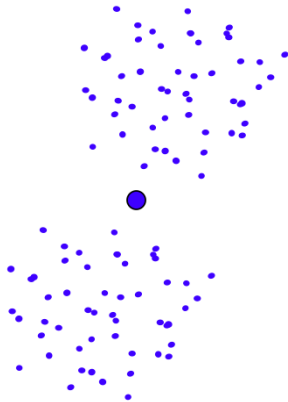
From Bishop's *Pattern recognition and machine learning*, Figure 9.1(i).

Suboptimal Local Minimum

- The clustering for $k = 3$ below is a local minimum, but suboptimal:



Would be better to have
one cluster here



... and two clusters here

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- Dataset $\mathcal{D} = \{x_1, \dots, x_n\} \subset \mathcal{X}$ where $\mathcal{X} = \mathbb{R}^d$.

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- The k -means objective is to minimize the distance between each example and its cluster centroid:

$$J(c, \mu) = \sum_{i=1}^n \|x_i - \mu_{c_i}\|^2. \quad (2)$$

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 - Compute distance between each x_i and the closest already chosen centroids.
 - Randomly choose next centroid with probability proportional to the computed distance squared.

Summary

We've seen

- Clustering—an unsupervised learning problem that aims to discover group assignments.
- k -means:
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 - Objective: minimizing some loss function by coordinate descent.
 - Converge to a local minimum.

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We've seen

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Next, probabilistic model of clustering.

- A generative model of x .
- Maximum likelihood estimation.

Gaussian Mixture Models

Probabilistic Model for Clustering

- Problem setup:
 - There are k clusters (or **mixture components**).
 - We have a probability distribution for each cluster.

Probabilistic Model for Clustering

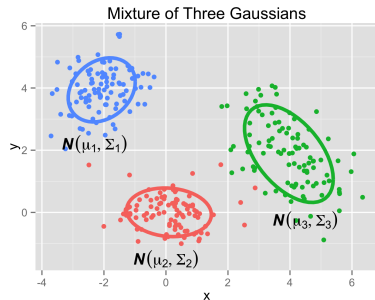
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Example:

- 1 Choose $z \in \{1, 2, 3\}$ with $p(1) = p(2) = p(3) = \frac{1}{3}$.
- 2 Choose $x \mid z \sim \mathcal{N}(X \mid \mu_z, \Sigma_z)$.



Gaussian mixture model (GMM)

Generative story of GMM with k mixture components:

- 1 Choose cluster $z \sim \text{Categorical}(\pi_1, \dots, \pi_k)$.
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Probability density of x :

- Sum over (marginalize) the **latent variable** z .

$$p(x) = \sum_z p(x, z) \tag{5}$$

$$= \sum_z p(x | z) p(z) \tag{6}$$

$$= \sum_k \pi_k \mathcal{N}(\mu_k, \Sigma_k) \tag{7}$$

Identifiability Issues for GMM

- Suppose we have found parameters

Cluster probabilities: $\pi = (\pi_1, \dots, \pi_k)$

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- We'll get the same likelihood. How many such equivalent settings are there?
- Assuming all clusters are distinct, there are $k!$ equivalent solutions.
- Not a problem *per se*, but something to be aware of.

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- MLE (also called maximize marginal likelihood).
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$$L(\theta) = \sum_{i=1}^n \log p(x_i; \theta) \quad (8)$$

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- Cannot push log into the sum... z and x are coupled.
- No closed-form solution for GMM—try to compute the gradient yourself!

Gradient Descent / SGD for GMM

- What about running gradient descent or SGD on

$$J(\pi, \mu, \Sigma) = - \sum_{i=1}^n \log \left\{ \sum_{z=1}^k \pi_z \mathcal{N}(x_i \mid \mu_z, \Sigma_z) \right\}?$$

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 - Rewrite $\Sigma_i = M_i M_i^T$, where M_i is an unconstrained matrix.
 - Then Σ_i is positive semidefinite.
- Even then, pure gradient-based methods have trouble.¹

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Learning GMMs: observable case

Suppose we observe cluster assignments z . Then MLE is easy:

$$n_z = \sum_{i=1}^n \mathbb{1}[z_i = z] \quad \# \text{ examples in each cluster} \quad (10)$$

$$\hat{\pi}(z) = \frac{n_z}{n} \quad \text{fraction of examples in each cluster} \quad (11)$$

$$\hat{\mu}_z = \frac{1}{n_z} \sum_{i: z_i = z} x_i \quad \text{empirical cluster mean} \quad (12)$$

$$\hat{\Sigma}_z = \frac{1}{n_z} \sum_{i: z_i = z} (x_i - \hat{\mu}_z)(x_i - \hat{\mu}_z)^T. \quad \text{empirical cluster covariance} \quad (13)$$

The inference problem: observe x , want to know z .

(16)

Learning GMMs: inference

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- $p(z | x)$ is a *soft assignment*.
- If we know the parameters μ, Σ, π , this would be easy to compute.

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The expectation-minimization (EM) algorithm:

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The expectation-minimization (EM) algorithm:

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- ② Run until convergence:
 - ① E-step: fill in latent variables by inference.
 - compute soft assignments $p(z | x_i)$ for all i .
 - ② M-step: standard MLE for μ, Σ, π given “observed” variables.
 - Equivalent to MLE in the observable case on data weighted by $p(z | x_i)$.

M-step for GMM

- Let $p(z | x)$ be the soft assignments:

$$\gamma_i^j = \frac{\pi_j^{\text{old}} \mathcal{N}(x_i | \mu_j^{\text{old}}, \Sigma_j^{\text{old}})}{\sum_{c=1}^k \pi_c^{\text{old}} \mathcal{N}(x_i | \mu_c^{\text{old}}, \Sigma_c^{\text{old}})}.$$

- Exercise: show that

$$n_z = \sum_{i=1}^n \gamma_i^z$$

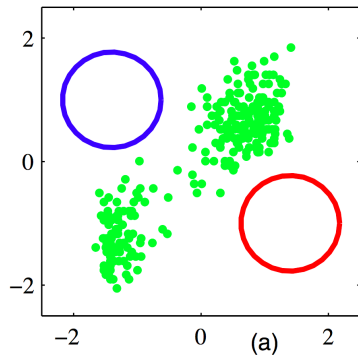
$$\mu_z^{\text{new}} = \frac{1}{n_z} \sum_{i=1}^n \gamma_i^z x_i$$

$$\Sigma_z^{\text{new}} = \frac{1}{n_z} \sum_{i=1}^n \gamma_i^z (x_i - \mu_z^{\text{new}}) (x_i - \mu_z^{\text{new}})^T$$

$$\pi_z^{\text{new}} = \frac{n_z}{n}.$$

EM for GMM

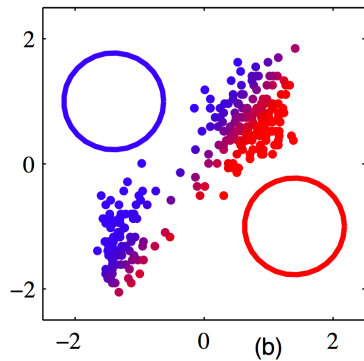
• Initialization



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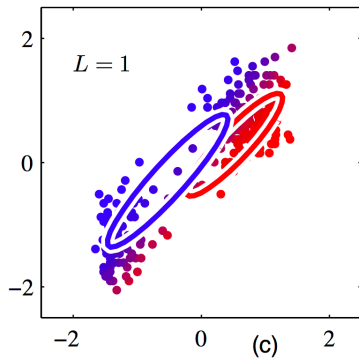
- First soft assignment:



From Bishop's *Pattern recognition and machine learning*, Figure 9.8.

EM for GMM

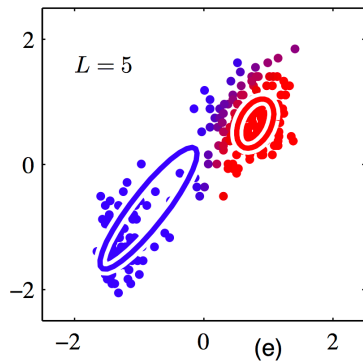
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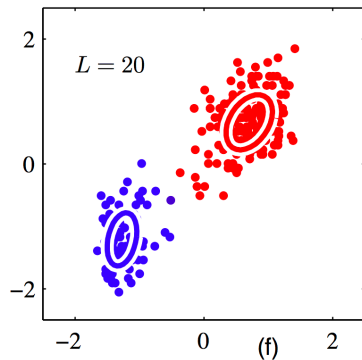
- After 5 rounds of EM:



From Bishop's *Pattern recognition and machine learning*, Figure 9.8.

EM for GMM

- After 20 rounds of EM:



From Bishop's *Pattern recognition and machine learning*, Figure 9.8.

EM for GMM: Summary

- EM is a general algorithm for learning latent variable models.
- *Key idea*: if data was fully observed, then MLE is easy.
 - E-step: fill in latent variables by computing $p(z \mid x, \theta)$.
 - M-step: standard MLE given fully observed data.
- Simpler and more efficient than gradient methods.
- Can prove that EM monotonically improves the likelihood and converges to a local minimum.
- k -means is a special case of EM for GMM with *hard assignments*, also called hard-EM.

Latent Variable Models

General Latent Variable Model

- Two sets of random variables: z and x .
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e.g. The Gaussian mixture model is a latent variable model.

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Complete and Incomplete Data

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- To simplify notation, take x to represent the entire dataset

$$x = (x_1, \dots, x_n),$$

and z to represent the corresponding unobserved variables

$$z = (z_1, \dots, z_n).$$

- An observation of x is called an **incomplete data set**.
- An observation (x, z) is called a **complete data set**.

Our Objectives

- **Learning problem:** Given incomplete dataset x , find MLE

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- For Gaussian mixture model, learning is hard, inference is easy.
- For more complicated models, inference can also be hard. (See DSGA-1005)

Log-Likelihood and Terminology

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- We often call $p(x, z)$ the **joint**. (for “joint distribution”)
- Similarly, $\log p(x)$ is the **marginal log-likelihood**.

EM Algorithm

Intuition

Problem: marginal log-likelihood $\log p(x; \theta)$ is hard to optimize (observing only x)

Observation: complete data log-likelihood $\log p(x, z; \theta)$ is easy to optimize (observing both x and z)

Idea: guess a distribution of the latent variables $q(z)$ (soft assignments)

Maximize the **expected complete data log-likelihood**:

$$\max_{\theta} \sum_{z \in \mathcal{Z}} q(z) \log p(x, z; \theta)$$

EM assumption: the expected complete data log-likelihood is easy to optimize

Why should this work?

Math Prerequisites

Jensen's Inequality

Theorem (Jensen's Inequality)

If $f : \mathbb{R} \rightarrow \mathbb{R}$ is a **convex** function, and x is a random variable, then

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- e.g. $f(x) = x^2$ is convex. So $\mathbb{E}x^2 \geq (\mathbb{E}x)^2$. Thus

$$\text{Var}(x) = \mathbb{E}x^2 - (\mathbb{E}x)^2 \geq 0.$$

Kullback-Leibler Divergence

- Let $p(x)$ and $q(x)$ be probability mass functions (PMFs) on \mathcal{X} .
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- Can also write this as

$$\text{KL}(p\|q) = \mathbb{E}_{x \sim p} \log \frac{p(x)}{q(x)}.$$

Gibbs Inequality ($\text{KL}(p\|q) \geq 0$ and $\text{KL}(p\|p) = 0$)

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- KL divergence measures the “distance” between distributions.
- Note:
 - KL divergence **not a metric**.
 - KL divergence is **not symmetric**.

Gibbs Inequality: Proof

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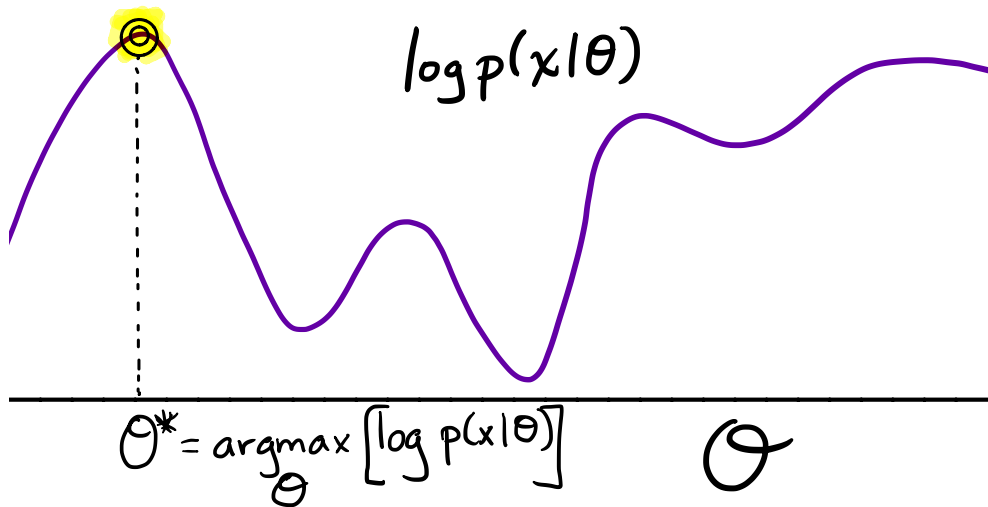
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- Since $-\log$ is strictly convex, we have strict equality iff $q(x)/p(x)$ is a constant, which implies $q = p$.

The ELBO: Family of Lower Bounds on $\log p(x | \theta)$

The Maximum Likelihood Estimator



Lower bound of the marginal log-likelihood

$$\log p(x; \theta) = \log \sum_{z \in \mathcal{Z}} p(x, z; \theta)$$

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- **Evidence:** $\log p(x; \theta)$
- **Evidence lower bound (ELBO):** $\mathcal{L}(q, \theta)$
- q : chosen to be a family of tractable distributions
- Idea: *maximize the ELBO* instead of $\log p(x; \theta)$

MLE, EM, and the ELBO

- The MLE is defined as a maximum over θ :

$$\hat{\theta}_{\text{MLE}} = \arg \max_{\theta} [\log p(x | \theta)].$$

- For any PMF $q(z)$, we have a lower bound on the marginal log-likelihood

$$\log p(x | \theta) \geq \mathcal{L}(q, \theta).$$

- In EM algorithm, we maximize the lower bound (ELBO) over θ and q :

$$\hat{\theta}_{\text{EM}} \approx \arg \max_{\theta} \left[\max_q \mathcal{L}(q, \theta) \right]$$

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- In EM algorithm, q ranges over all distributions on z .

EM: Coordinate Ascent on Lower Bound

- Choose sequence of q 's and θ 's by “**coordinate ascent**” on $\mathcal{L}(q, \theta)$.

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 - ① Choose initial θ^{old} .
 - ② Let $q^* = \arg \max_q \mathcal{L}(q, \theta^{\text{old}})$

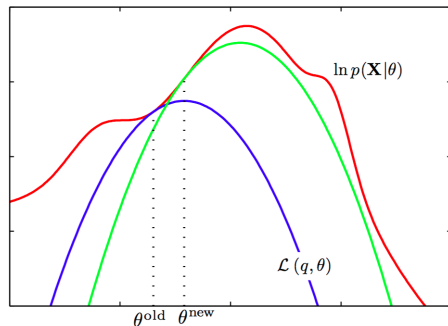
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 - ③ Let $\theta^{\text{new}} = \arg \max_{\theta} \mathcal{L}(q^*, \theta)$.
 - ④ Go to step 2, until converged.
- Will show: $p(x | \theta^{\text{new}}) \geq p(x | \theta^{\text{old}})$
- **Get sequence of θ 's with monotonically increasing likelihood.**

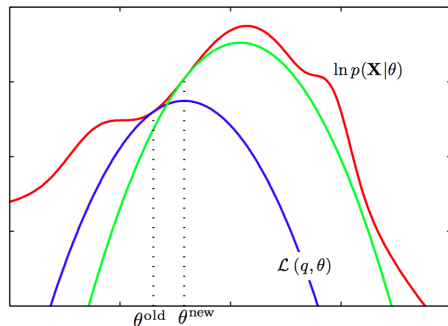
EM: Coordinate Ascent on Lower Bound



- 1 Start at θ^{old} .

From Bishop's *Pattern recognition and machine learning*, Figure 9.14.

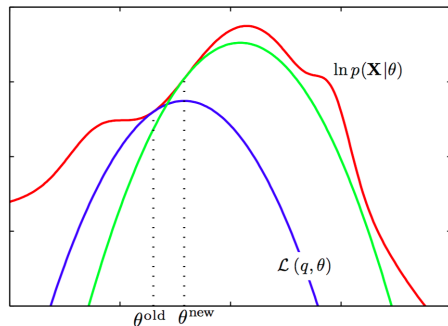
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EM: Coordinate Ascent on Lower Bound



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Is ELBO a "good" lowerbound?

$$\begin{aligned}\mathcal{L}(q, \theta) &= \sum_{z \in \mathcal{Z}} q(z) \log \frac{p(x, z | \theta)}{q(z)} \\&= \sum_{z \in \mathcal{Z}} q(z) \log \frac{p(z | x, \theta) p(x | \theta)}{q(z)} \\&= - \sum_{z \in \mathcal{Z}} q(z) \log \frac{q(z)}{p(z | x, \theta)} + \sum_{z \in \mathcal{Z}} q(z) \log p(x | \theta) \\&= -\text{KL}(q(z) \| p(z | x, \theta)) + \underbrace{\log p(x | \theta)}_{\text{evidence}}\end{aligned}$$

- **KL divergence:** measures "distance" between two distributions (not symmetric!)
- $\text{KL}(q \| p) \geq 0$ with equality iff $q(z) = p(z | x)$.
- $\text{ELBO} = \text{evidence} - \text{KL} \leq \text{evidence}$

Maximizing over q for fixed θ .

- Find q maximizing

$$\mathcal{L}(q, \theta) = -\text{KL}[q(z), p(z | x, \theta)] + \log p(x | \theta)$$

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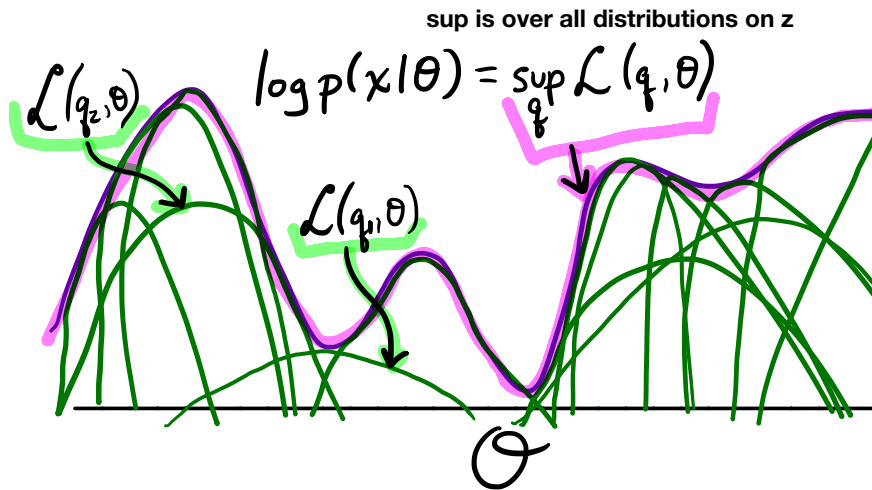
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- Summary:

$$\log p(x | \theta) = \sup_q \mathcal{L}(q, \theta) \quad \forall \theta$$

- For any θ , **sup is attained** at $q(z) = p(z | x, \theta)$.

Marginal Log-Likelihood **IS** the Supremum over Lower Bounds



Summary

Latent variable models: clustering, latent structure, missing labels etc.

Parameter estimation: maximum marginal log-likelihood

Challenge: directly maximize the **evidence** $\log p(x; \theta)$ is hard

Solution: maximize the **evidence lower bound**:

$$\text{ELBO} = \mathcal{L}(q, \theta) = -\text{KL}(q(z) \| p(z | x; \theta)) + \log p(x; \theta)$$

Why does it work?

$$q^*(z) = p(z | x; \theta) \quad \forall \theta \in \Theta$$
$$\mathcal{L}(q^*, \theta^*) = \max_{\theta} \log p(x; \theta)$$

EM algorithm

Coordinate ascent on $\mathcal{L}(q, \theta)$

- 1 Random initialization: $\theta^{\text{old}} \leftarrow \theta_0$
- 2 Repeat until convergence
 - i $q(z) \leftarrow \arg \max_q \mathcal{L}(q, \theta^{\text{old}})$

Expectation (the E-step): $q^*(z) = p(z | x; \theta^{\text{old}})$

$$J(\theta) = \mathcal{L}(q^*, \theta)$$

ii $\theta^{\text{new}} \leftarrow \arg \max_{\theta} \mathcal{L}(q^*, \theta)$

Maximization (the M-step): $\theta^{\text{new}} \leftarrow \arg \max_{\theta} J(\theta)$

① Expectation Step

- Let $q^*(z) = p(z \mid x, \theta^{\text{old}})$. [q^* gives best lower bound at θ^{old}]

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[Equivalent to maximizing expected complete log-likelihood.]

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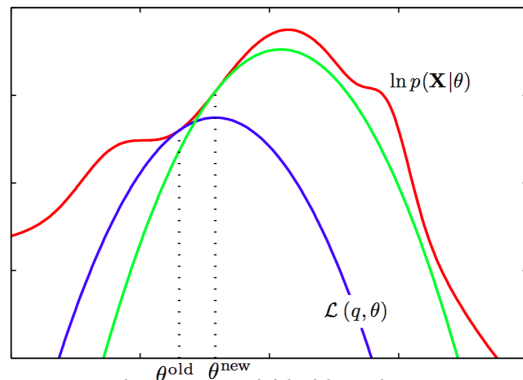
2 Maximization Step

$$\theta^{\text{new}} = \arg \max_{\theta} J(\theta).$$

[Equivalent to maximizing expected complete log-likelihood.]

EM puts no constraint on q in the E-step and assumes the M-step is easy. In general, both steps can be hard.

Monotonically increasing likelihood



Exercise: prove that EM increases the marginal likelihood monotonically

$$\log p(x; \theta^{\text{new}}) \geq \log p(x; \theta^{\text{old}}).$$

Does EM converge to a global maximum?

Variations on EM

EM Gives Us Two New Problems

- The “E” Step: Computing

$$J(\theta) := \mathcal{L}(q^*, \theta) = \sum_z q^*(z) \log \left(\frac{p(x, z | \theta)}{q^*(z)} \right)$$

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EM Gives Us Two New Problems

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- Either of these can be too hard to do in practice.

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 - e.g. take a gradient step on J .
- We still get monotonically increasing likelihood.

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- Suppose “E” step is difficult:
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 - Hard to take expectation w.r.t. $q^*(z) = p(z | x, \theta^{\text{old}})$.
- Solution: Restrict to distributions \mathcal{Q} that are easy to work with.
- Lower bound now looser:

$$q^* = \arg \min_{q \in \mathcal{Q}} \text{KL}[q(z), p(z | x, \theta^{\text{old}})]$$

Deep Latent Variable Models

Variational Autoencoders

Vector Quantization (VQ)

Other Divergence Metrics

Diffusion Models

Today's Summary

- Motivation: Unsupervised learning
- K-means: A simple algorithm for discovering clusters
- Making k-means probabilistic: Gaussian mixture models
- More generally: Latent variable models
- Learning of latent variable models: EM
- Underlying principle: Maximizing ELBO

Conclusion and Outlook

End of the course

- Congrats, you are almost done.
- Originally developed by Prof. David Rosenberg (now at Bloomberg).
- Later adapted by Prof. He He and other colleagues.
- Added my twists on the topics.
- A very challenging course.

Next Lecture: Project Presentation

- Dec 12.
- 24 groups, 120mins.
- Aim for 3 mins per group, hard stop at 4 mins, and 1 min Q&A.
- Send me your slides in PDF with your group number by Dec 14 11:59pm.

Models

Linear Perceptron, conditional probability models, SVMs

Non-linear Kernelized models, trees, basis function models, neural nets

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Non-linear Kernelized models, trees, basis function models, neural nets

How to choose the model family?

- Trade-offs:
 - approximation error and estimation error (bias and variance),
 - accuracy and efficiency (during both training and inference).
- Start from the task requirements, e.g. amount of data, computation resource

Objectives

Loss functions How far off a prediction is from the target, e.g. 0-1 loss, margin-based loss, squared loss.

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Risk Expected loss - but expectation over what?

- Frequentist approach: expectation over data.
 - Empirical risk minimization, i.e. average loss on the training data.
 - Regularization: balance estimation error and generalization error.
- Bayesian approach: expectation over parameters.
 - Posterior: prior belief updated by observed data.
 - Bayes action minimizes the posterior risk.

Learning Find model parameters—often an optimization problem.

- (Stochastic) (sub)gradient descent
- Functional gradient descent (gradient boosting)
- Convex vs non-convex objectives

Inference Answer questions given a learned model.

- Bayesian inference: compute various quantities given the posterior.
- Dynamic programming: compute $\arg \max$ in structured prediction.

Do we still need ML?

- DL is not necessarily good for all types of data (availability, data quality, data modality etc.).
- Classic methods also have their sweet spots.
- Classic ML lays down foundation when building innovative DL algorithm.
- Classic ML sheds new insight into understand DL.

Other ML Related Advanced Courses in CS

- Computer Vision (Prof. Rob Fergus)
- Deep Learning (Prof. Yann LeCun)
- Deep Reinforcement Learning (Prof. Lerrel Pinto)
- Foundations of Deep Learning Theory (Prof. Matus Telgarsky)
- Learning with Large Language and Vision Models (Prof. Saining Xie)
- Mathematics of Deep Learning (Prof. Joan Bruna)
- Natural Language Processing (Prof. He He)