

# Analytic Geometry

**DEF** (*Dot Product*) The dot product between two vectors  $u$  and  $v$  is defined as

$$u^\top v = u_1 v_1 + u_2 v_2 + \dots + u_n v_n = \sum_{i=1}^n u_i v_i$$

**DEF** (*Bilinearity*) The dot product is bilinear, i.e. for any vectors  $u, v, w$  and scalar  $a$ ,

$$\begin{aligned} au^\top v &= au^\top v = u^\top av \\ u + v^\top w &= u^\top w + v^\top w \\ w^\top u + v &= w^\top u + w^\top v \end{aligned}$$

**DEF** (*Commutativity*) The dot product is commutative, i.e.  $u^\top v = v^\top u$

**DEF** (*Inner Product*) The inner product between two vectors  $u$  and  $v$  is defined as

$$\langle u, v \rangle$$

Dot product is a special case of inner product.

**DEF** ( $\ell_2$  Norm) The  $\ell_2$  norm of a vector  $v$  is defined as

$$\|v\|_2 = \sqrt{v^\top v} = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}$$

Also called the Euclidean norm.

**DEF** ( $\ell_2$  properties) For all vectors  $u, v$  and scalar  $a$ ,

- The  $\ell_2$  norm is non-negative, i.e.  $\|v\|_2 \geq 0$ .
- $\|au\|_2 = |a| \|u\|_2$  for any scalar  $a$ .
- $\|u\|_2$  is zero if and only if  $u$  is the zero vector.
- The triangle inequality holds, i.e.  $\|u + v\|_2 \leq \|u\|_2 + \|v\|_2$ .
- $\|x - y\|_2 = \|y - x\|_2$ , also called symmetry.
- $\|u + v\|_2^2 = \|u\|_2^2 + 2u^\top v + \|v\|_2^2$
- $\cos \theta = \frac{u^\top v}{\|u\|_2 \|v\|_2}$  (can be proved using the law of cosines)

**THM** (*Cauchy-Schwarz Inequality*) For any vectors  $u, v$ , the following inequality holds:

$$|\langle u, v \rangle| \leq \|u\|_2 \|v\|_2$$

**DEF** (*Line*) A line is a set of points

$$\{x : x = u + tv \text{ for some } t \in \mathbb{R}\}$$

where  $u$  is a point on the line and  $v \neq 0$  is the direction vector.

**DEF** (*Plane*) A plane is a set of points

$$\{x : v^\top x - u = 0\}$$

where  $v$  is the normal vector to the plane and  $u$  is the shift from the origin.

**DEF** (*Projection*) The vector  $\|u\|_2 \cos \theta \frac{v}{\|v\|_2}$  is a projection of  $u$  onto  $v$ .

**DEF** (*Distance between a point and a plane*) The distance between a point  $z$  and a plane  $v^\top x - u = 0$  is given by

$$\frac{|v^\top z - u|}{\|v\|_2}$$

**DEF** (*Distance between a point and a line*) The distance between a point  $z$  and a line  $x = u + tv$  is given by

$$\left\| z - u - \frac{z - u^\top v}{\|v\|_2^2} v \right\|_2$$

**DEF** (*Singular Value Decomposition (SVD)*) The SVD of a matrix  $X$  is  $U\Sigma V^\top$ , where  $U^\top U = I, V^\top V = I$  and  $\Sigma$  is a diagonal matrix:

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_n \end{bmatrix}$$

and  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0$ .

**THM** (*Eckart-Young Theorem*) Let  $\Sigma_k = \text{diag}(\sigma_1, \dots, \sigma_k, 0, \dots, 0)$  where  $k \leq d$ . The matrix  $U\Sigma_k V^\top$  is the optimal solution to the following problem:

$$\min_{\hat{X}} \|X - \hat{X}\|_F \text{ s.t. } \text{rank}(\hat{X}) \leq k$$

The matrices  $Z = U\Sigma_k$  and  $W = V^\top$  are the optimal solution to

$$\min_{Z, W} \|X - ZW\|_F \text{ s.t. } Z \in \mathbb{R}^{n \times k}, W \in \mathbb{R}^{k \times d}$$

## Calculus

**DEF** (*Derivative*) The derivative of a function  $f : \mathbb{R} \rightarrow \mathbb{R}$  at  $x_0$  is defined as:

$$(D_x f)(x_0) = \left( \frac{d}{dx} f \right) (x_0) = \lim_{h \rightarrow 0} \frac{f(x_0 + h) - f(x_0)}{h}$$

**DEF** (*Directional Derivative*) The directional derivative of a function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  along the direction  $v$  at  $x_0 \in \mathbb{R}^d$  is defined as:

$$(D_v f)(x_0) = \lim_{h \rightarrow 0} \frac{f(x_0 + hv) - f(x_0)}{h}$$

**DEF** (*Partial Derivative*) The partial derivative is a directional derivative along the direction of coordinate axes. For a function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$ , the partial derivative with respect to the  $i$ -th coordinate is denoted as:

$$\frac{\partial f}{\partial x_i} = \lim_{h \rightarrow 0} \frac{f(x_1, \dots, x_i + h, \dots, x_d) - f(x_1, \dots, x_i, \dots, x_d)}{h}$$

**DEF** (*Gradient*) The gradient of a function is the vector consisting of all partial derivatives denoted by  $\nabla f$  or  $\frac{\partial f}{\partial x}$ . For a function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$ ,

**EX** (*Gradient Identities*)

- Given a function  $f(a) = b^\top a$ ,  $(\nabla f)(a) = b$
- Given a function  $f(a) = \|a\|_2^2$ ,  $(\nabla f)(a) = 2a$

**DEF (Hessian)** The Hessian of a function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  is the matrix of second partial derivatives:

$$\nabla^2 f = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_d} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2 \partial x_d} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_d \partial x_1} & \frac{\partial^2 f}{\partial x_d \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_d^2} \end{bmatrix}$$

**EX (Hessian Example)** Given a function  $f(x, y) = x^2 - y^2$ , the Hessian is:

$$\nabla^2 f = \begin{bmatrix} 2 & 0 \\ 0 & -2 \end{bmatrix}$$

The 2 indicates that it looks like a cup along the  $x$ -axis and the -2 indicates that it looks like an upside-down cup along the  $y$ -axis.

## Optimisation

**DEF (Minimum)** The minimum of a function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  is written as  $\min_x f(x)$ , and has the property that  $\min_x f(x) \leq f(y)$  for all  $y \in \mathbb{R}^d$ . The value  $x^*$  such that  $f(x^*) = \min_x f(x)$  is called the minimizer.

**DEF (Convexity)** A function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  is convex if for any  $0 \leq \alpha \leq 1$ , we have

$$f(\alpha x + (1 - \alpha)y) \leq \alpha f(x) + (1 - \alpha)f(y)$$

In general,

$$f\left(\sum_{i=1}^k \alpha_i x_i\right) \leq \sum_{i=1}^k \alpha_i f(x_i)$$

**DEF (Concavity)** A function  $f$  is concave if  $-f$  is convex.

**THM (First Order Condition (Convexity))** If  $f$  is convex then,

$$\bullet f(x) \geq f(y) + \nabla f(y)^\top (x - y)$$

**DEF (Positive Semidefinite)** A matrix  $A$  is positive semidefinite if for all vectors  $v \neq 0$  we have  $v^\top A v \geq 0$ . Also written as  $A \succeq 0$ .

**THM (Convex Function Implies Positive Semidefinite Hessian)** If  $f$  is convex, then  $\nabla^2 f(x) \succeq 0$ .

**DEF (Positive Definite)** A matrix  $A$  is positive definite if for all vectors  $v \neq 0$  we have  $v^\top A v > 0$ . Also written as  $A \succ 0$ .

**DEF (Affine)** A function  $f$  is affine if  $f(x) = Ax + b$  for some matrix  $A$  and vector  $b$ .

**THM (Affine Transform Preservation)** If  $f$  is convex, then  $g(x) = f(Ax + b)$  is also convex.

**THM (Non-negative Weighted Sum)** If  $f_1, f_2, \dots, f_k$  are convex functions, then  $f(x) = \sum_{i=1}^k \beta_i f_i(x)$  is convex for all  $\beta_i \geq 0$ .

**EX (Gradient of Quadratic Form)**  $\nabla_x (x^\top A x) = (A + A^\top)x$

**DEF (Strictly Convex)** A function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  is called strictly convex if for  $0 \leq \alpha \leq 1$  we have

$$f(\alpha x + (1 - \alpha)y) < \alpha f(x) + (1 - \alpha)f(y)$$

for any  $x \neq y$ .

**DEF (First Order Condition (Strict Convexity))** If  $f$  is strictly convex then,

$$\bullet f(x) > f(y) + \nabla f(y)^\top (x - y)$$

**THM (Unique Minimizer)** If  $f$  is strictly convex, then  $f$  has a unique minimizer.

**THM (Jensen's Inequality)** If a function  $f$  is convex,

$$f(\mathbb{E}_{x \sim p}[x]) \leq \mathbb{E}_{x \sim p}[f(x)]$$

**DEF (Subgradient)** A subgradient at  $x$  is a vector  $g$  that satisfies

$$f(y) \geq f(x) + g^\top (y - x)$$

for any  $y$ , and the set of subgradients at  $x$  is denoted as  $\partial f(x)$ .  $\nabla f(x) \in \partial f(x)$  if  $f$  is differentiable at  $x$ . In other words subgradients are tangents that are below the function.

**EX (Constrained Optimisation Problem)** An example of a constrained optimisation problem is

$$\min_x x^2 \text{ s.t. } -2.5 \leq x \leq -0.5$$

**DEF (Feasible Solution)** A feasible solution is a point that satisfies all the constraints.

**DEF (Lagrangian)** If you have an optimisation problem of the form

$$\min_x f(x) \text{ s.t. } h(x) \leq 0$$

the **Lagrangian** is defined as

$$f(x) + \lambda h(x)$$

for some  $\lambda \geq 0$  (Lagrange multiplier).

**ALG (Solving the Lagrangian)**

- Solve  $g(\lambda) = \min_x [f(x) + \lambda h(x)]$
- Find  $\hat{\lambda}$  such that  $\min_x [f(x) + \hat{\lambda} h(x)]$  gives a feasible solution
- Suppose  $\hat{x}$  is the solution to the above, and  $x^* = \arg \min_{x: h(x) \leq 0} f(x)$  (the optimal solution), then

$$f(\hat{x}) = f(\hat{x}) + \hat{\lambda} h(\hat{x}) \leq f(x^*) + \hat{\lambda} h(x^*) \leq f(x^*)$$

## Probability

**DEF (Gaussian Distribution)** We write  $x \sim \mathcal{N}(\mu, \Sigma)$  to denote that  $x$  is a random variable with mean  $\mu$  and covariance  $\Sigma$ . It means that the probability density function of  $x$  is given by

$$p(x) = \frac{1}{2\pi^{d/2} |\Sigma|^{1/2}} \exp \left( -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right)$$

**DEF (Statistical Independence)** Two variables  $x$  and  $y$  are independent if

$$p(x, y) = p(x)p(y)$$

Equivalently,

$$p(x|y) = p(x)$$

. The independence of  $x$  and  $y$  is denoted by  $x \perp y$ .

**DEF** (*Statistical Independence [general]*) If  $\{x_1, \dots, x_n\} \perp \{y_1, \dots, y_m\}$  then

$$p(x_1, \dots, x_n, y_1, \dots, y_m) = p(x_1, \dots, x_n)p(y_1, \dots, y_m)$$

**EX** (*Factorisation of a joint distribution*) Suppose  $x \in \mathcal{X}, y \in \mathcal{Y}, z \in \mathcal{Z}$ . If  $\{x, y\} \perp z$  then

$$p(x, y, z) = p(x, y)p(z)$$

The original joint distribution (of size  $|\mathcal{X}| \times |\mathcal{Y}| \times |\mathcal{Z}|$ ) can be factorised into two distributions of size  $|\mathcal{X}| \times |\mathcal{Y}|$  and  $|\mathcal{Z}|$ .

**DEF** (*Mutual Independence*) A set of variables  $\{x_1, \dots, x_n\}$  are mutually independent if

$$p(x_1, \dots, x_n) = \prod_{i=1}^n p(x_i)$$

**DEF** (*Pairwise Independence*) A set of variables  $\{x_1, \dots, x_n\}$  are pairwise independent if

$$p(x_i, x_j) = p(x_i)p(x_j)$$

for all  $i \neq j$ .

**THM** (*Mutual Independence implies Pairwise Independence*) If a set of variables  $\{x_1, \dots, x_n\}$  are mutually independent, then they are pairwise independent. Converse is not true!

**DEF** (*Conditional Independence*) The variables  $x$  and  $y$  are conditionally independent given  $z$  if

$$p(x, y|z) = p(x|z)p(y|z)$$

This is denoted by  $x \perp y|z$ .

**DEF** (*Marginilisation*) The marginal distribution of  $x$  is obtained by summing out all other variables.

$$p(x) = \sum_y p(x, y)$$

$$p(x|z) = \sum_y p(x, y|z)$$

$$p(x, y|z) = p(x|z)p(y|z)$$

**DEF** (*Bayes Rule*) Bayes rule is a way to invert conditional probabilities.

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$

**DEF** (*Chain Rule*) Any joint distribution can be factorised into a product of conditional distributions.

$$p(x_1, \dots, x_n) = p(x_1)p(x_2|x_1)p(x_3|x_1, x_2) \cdots p(x_n|x_1, \dots, x_{n-1})$$

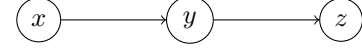
**DEF** (*(directed) Graph Representation*) A directed graph is a set of nodes connected by edges. Each vertex is a random

variable and each edge represents a direct dependency. It is directed and acyclic (DAG). A distribution factorises according to the graph if

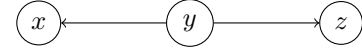
$$p(x_1, \dots, x_n) = \prod_{i=1}^n p(x_i | \text{parents}(x_i))$$

**DEF** (*Graph structures*)

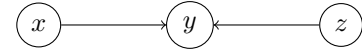
- Chain  $x \perp z|y$



- Common cause  $x \perp z|y$



- v-structure  $x \perp z$  but  $x \not\perp z|y$



## Training

**DEF** (*Loss Function*) Given a predicted output  $\hat{y}$  and observed output  $y$ , the loss function measures how close the model's prediction is

**DEF** (*Zero-One Loss*)  $L(y, \hat{y}) = \mathbb{I}_{\{y \neq \hat{y}\}}$

**DEF** (*Mean Squared Error (MSE)*)  $L(y, \hat{y}) = (y - \hat{y})^2$

**DEF** (*Hinge Loss*)  $L(y, \hat{y}) = \max(0, 1 - y \cdot \hat{y})$

**DEF** (*Gradient Descent*) The gradient descent algorithm is given by

$$x_{t+1} = x_t - \eta \nabla f(x_t)$$

where  $\eta$  is the learning rate/step size.

**DEF** (*Convergence*) Given  $\epsilon > 0$ , we say that an algorithm converges to a point  $x^*$  if

$$f(x_t) - f(x^*) \leq \epsilon$$

**DEF** (*Convergence Rate*) The convergence rate of an algorithm is the rate at which the algorithm converges to the optimal point. There are three types of convergence rates:

- Sublinear:  $f(x_t) - f(x^*) \leq \frac{c}{t^2}$  ( $\epsilon = O(\frac{1}{t^2}), t = O(\frac{1}{\sqrt{\epsilon}})$ )
- Linear:  $f(x_t) - f(x^*) \leq cr^t$  ( $\epsilon = O(r^t), t = O(\log \frac{1}{\epsilon})$ )
- Quadratic:  $f(x_t) - f(x^*) \leq cr^{2^t}$

**ALG** (*Stochastic Gradient Descent (SGD)*) Sample a random point  $x_t, y_t$  from the dataset and compute the gradient at that point. Repeat until solution is satisfactory.

**ALG** (*Mini-batch Gradient Descent*) Sample a mini-batch of points  $x_t, y_t$  from the dataset and compute the gradient at that point. Repeat until solution is satisfactory.

**DEF** (*Training*) The act of minimising the loss function by adjusting the model's parameters is known as training.

## Regression

**DEF** (*Regression*) The learning of relationships between input variables  $x$  and a numerical output  $y$

**DEF** (*Feature Transformation*) We call  $\phi$  a feature transformation. It transforms the input space  $X$  into a new space  $Z$ .

**DEF** (*Linear Regression*) Given a dataset  $S = \{(\phi(x_1), y_1), \dots, (\phi(x_n), y_n)\}$ , minimise the MSE loss function

$$L = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where  $\hat{y}_i = w^T \phi(x_i)$

**DEF (Closed-form Solution)** The closed-form solution to linear regression is given by

$$w = (\Phi \Phi^T)^{-1} \Phi y$$

**DEF (Probabilistic Interpretation)** The probabilistic interpretation of linear regression is that

$$y = w^T \phi(x) + \epsilon_i$$

where  $\epsilon_i \sim \mathcal{N}(0, 1)$  which implies  $y_i \sim \mathcal{N}(w^T \phi(x_i), 1)$ . So the log likelihood (L) of the data is

$$L = \sum_{i=1}^N \left[ \frac{1}{2} \log(2\pi) - \frac{1}{2} (y_i - w^T \phi(x_i))^2 \right]$$

## Classification

**DEF (Classification)** Given a dataset  $S$ , the goal is to learn a function  $h$  that maps input variables  $x$  to  $y$ , where  $y$  is a class label.

**DEF (Linear Separability)** A dataset is linearly separable if there exists a hyperplane that can separate the data points

**DEF (Training of Classification)** Find parameters  $\theta$  such that the zero-one loss is minimised

**DEF (Logistic Regression)** A linear classifier that models the probability of a class label. The model is given by

$$p(y|x, \theta) = \sigma(-y\theta^T x) = \frac{1}{1 + \exp(-y(w^T x + b))}$$

where  $\sigma$  is the sigmoid function.

**DEF (Maximum Likelihood Estimation (MLE))** The MLE of the parameters  $\theta$  is given by

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \prod_{i=1}^n p(y_i|x_i, \theta)$$

**DEF (Log Likelihood)** The log likelihood is applying log to the MLE to obtain a more numerically stable solution:

$$L = \sum_{i=1}^n \log p(y_i|x_i, \theta)$$

**ALG (Training of Logistic Regression)** The training of logistic regression is done by maximising the log likelihood  $L$  of  $w$  and  $b$ .

$$L = \sum_{i=1}^n \log p(y_i|x_i, \theta)$$

There are no closed-form solutions to this problem, so iterative methods like gradient ascent are used which is equivalent to minimising the negative log likelihood.

**DEF (Multiclass Classification)** Using the softmax function, we can extend logistic regression to multiclass classification. Softmax is defined as

$$\operatorname{softmax} \left( \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_k \end{bmatrix} \right) = \begin{bmatrix} \frac{e^{z_1}}{\sum_{i=1}^k e^{z_i}} \\ \frac{e^{z_2}}{\sum_{i=1}^k e^{z_i}} \\ \vdots \\ \frac{e^{z_k}}{\sum_{i=1}^k e^{z_i}} \end{bmatrix}$$

**DEF (Support Vector Machine (SVM))** A linear classifier that finds the hyperplane that maximises the margin between the classes. It does so by solving the following optimisation problem:

$$\min_w \frac{1}{2} \|w\|_2^2 \quad \text{s.t.} \quad y_i(w^T x_i + b) \geq 1$$

So the lagrangian is

$$L(\alpha, w) = \frac{1}{2} \|w\|_2^2 - \sum_{i=1}^n \alpha_i (y_i(w^T x_i + b) - 1)$$

**DEF (Kernel)** A kernel  $k : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$  is defined as

$$k(x, x') = \phi(x)^T \phi(x')$$

for some feature function  $\phi$ . It is a measure of similarity between two points in the input space.

**EX (Common Kernels)**

- Linear:  $k(x, x') = x^T x'$
- Polynomial:  $k(x, x') = (x^T x' + 1)^d$
- Gaussian:  $k(x, x') = \exp \left( -\frac{\|x - x'\|_2^2}{2\sigma^2} \right)$
- Hyperbolic Tangent:  $k(x, x') = \tanh(kx^T x' + c)$

**DEF (Making Kernels)** A kernel should satisfy

- $k(x, z) = \langle \phi(x), \phi(z) \rangle = \langle \phi(z), \phi(x) \rangle = k(z, x)$  (symmetric)
- $k(z, x)^2 = k(x, x)k(z, z)$
- 

$$K = \begin{bmatrix} k(x_1, x_1) & \cdots & k(x_1, x_n) \\ \vdots & \ddots & \vdots \\ k(x_n, x_1) & \cdots & k(x_n, x_n) \end{bmatrix}$$

is positive semi-definite

**THM (Mercer's Theorem)** Suppose  $k$  is a continuous symmetric non-negative definite kernel, then  $k$  can be expressed as

$$k(x, z) = \sum_{i=1}^{\infty} \lambda_i \phi_i(x) \phi_i(z)$$

where  $\{\phi\}$  are eigen-functions,  $\|\phi_i\|_2 = 1$  and  $\{\lambda_i\}$  are positive eigen values  $\lambda_i \geq 0$ .

**DEF (Kernel Trick)** The kernel trick is a method to transform the input space into a higher dimensional space without explicitly computing the transformation. This is done by using a kernel function

$$k(x, x') = \phi(x)^T \phi(x')$$

where  $\phi$  is the transformation function.

## Neural Networks

**DEF** (*Perceptron (Single-layer Neural Network)*) A simple linear classifier that learns a weight vector  $w$  to classify data points. The perceptron training algorithm can be used to learn the weights. Can model logical functions like AND, OR and NOT.

**THM** (*Universal Approximation Theorem*) A single-output node NN with a single hidden layer with finite neurons can app finite neurons can approximate continuous (and discontinuous) functions

**DEF** (*Multi-layer Perceptron (MLP) / Feedforward Neural Network (FNN)*) A neural network with multiple layers of perceptrons. The network is feedforward as there are no cycles in the network. It can model complex decision boundaries (piecewise linear) [XOR, etc] The perceptron training algorithm can not be used to learn the weights.

**DEF** (*Activation Function*) Allows for non-linear decision boundaries. They should be differentiable. Also controls the output range to a specific range. Common activation functions are:

- Sigmoid:  $\sigma(x) = \frac{1}{1+e^{-x}}$
- Hyperbolic Tangent (tanh):  $\tanh(x) = \frac{1-\exp(-2x)}{1+\exp(-2x)}$
- ReLU:  $f(x) = \max(0, x)$  (faster than tanh)
- Leaky ReLU solves the 'dying ReLU' problem

**DEF** (*Computation Graph*) Represents computation as a directed graph comprising of simple operations on vectors and

matrices which allows for automatic differentiation.

## Expectation Maximisation

**DEF** (*K-means Distortion*)

$$J = \sum_{n=1}^N \sum_{k=1}^K r_{nk} \|x_n - \mu_k\|^2$$

**DEF** (*K-means Steps*) Randomly initialise  $\mu_{k=1,\dots,K} \rightarrow$  Minimise  $J$  with respect to  $r_{nk} \rightarrow$  Minimise  $J$  with respect to  $\mu_k \rightarrow$  Repeat

**DEF** (*K-means Solutions*)

$$\mu_k = \frac{\sum_n r_{nk} x_n}{\sum_n r_{nk}}, r_{nk} = \mathbb{I}(k = \arg \min_j \|x_n - \mu_j\|^2)$$

**DEF** (*GMM Probabilities*)

$$p(z_k = 1) = \pi_k, p(\mathbf{z}) = \prod_{k=1}^K \pi_k^{z_k}, p(\mathbf{x}|\mathbf{z}) = \prod_{k=1}^K \mathcal{N}(x|\mu_k, \Sigma_k)^{z_k}$$

**DEF** (*Kullback-Leibler Divergence*)

$$KL(p||q) = \mathbb{E}_{x \sim p} \left[ \log \frac{p(x)}{q(x)} \right] = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)}$$