Latent variable models

Explain correlations in $x$ by assuming dependence on latent variables $y$

$$y \sim P[\theta_y]$$

$$x | y \sim P[\theta_x]$$

$$p(x, y; \theta_x, \theta_y) = p(x | y; \theta_x)p(y; \theta_y)$$

$$p(x; \theta_x, \theta_y) = \int dy \; p(x | y; \theta_x)p(y; \theta_y)$$

Exponential family models

- Simple, ‘single-stage’ generative models.
- Easy, often closed-form expressions for learning and model comparison.
- . . . but limited in expressiveness.

What about distributions like these?

In each case, data may be generated by **combining** and **transforming** latent exponential family variates.

Latent variable models

- Describe structured distributions.
  - Correlations in high-dimensional $x$ may be captured by fewer parameters.

- Capture an underlying generative process.
  - $y$ may describe **causes** of $x$.
  - Help to separate signal from noise.

- Combine exponential family distributions into richer, more flexible forms.
  - $P(y)$, $P(x|y)$ and even $P(x, y)$ may be in the exponential family
  - $P(x)$ rarely is. (Exception: Linear Gaussian models).
Latent variables and Gaussians
Gaussian correlation can be composed from latent components and uncorrelated noise.

\[
x \sim \mathcal{N}\left(0, \begin{bmatrix} 3 & 2 \\ 2 & 3 \end{bmatrix}\right) \quad \Leftrightarrow \quad y \sim \mathcal{N}\left(0, 1\right) \quad x \sim \mathcal{N}\left(\sqrt{2} \begin{bmatrix} 1 \\ 1 \end{bmatrix}, y, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right)
\]

Probabilistic Principal Components Analysis (PPCA)
If the uncorrelated noise is assumed to be isotropic, this model is called PPCA.

Data: \( D = \{x_1, x_2, \ldots, x_N\}; x_i \in \mathbb{R}^D \)

Latents: \( Y = \{y_1, y_2, \ldots, y_N\}; y_i \in \mathbb{R}^K \)

Linear generative model: \( x_d = \sum_{k=1}^{K} \Lambda_{dk} y_k + \epsilon_d \)

\( y_k \) are independent \( \mathcal{N}(0, 1) \) Gaussian factors

\( \epsilon_d \) are independent \( \mathcal{N}(0, \psi) \) Gaussian noise

\( K < D \)

Model for observations \( x \) is a correlated Gaussian:

\[
p(y) = \mathcal{N}(0, I) \\
p(x|y) = \mathcal{N}(\Lambda y, \psi I) \\
p(x) = \int p(y)p(x|y)dy = \mathcal{N}\left(\mathbb{E}_y [\Lambda y], \mathbb{E}_y [\Lambda yy^T \Lambda^T + \psi I]\right) = \mathcal{N}\left(0, \Lambda^T + \psi I\right)
\]

where \( \Lambda \) is a \( D \times K \) matrix.

The \( \psi \to 0 \) limit
As \( \psi \to 0 \), the latent model can only capture \( K \) dimensions of variance.

PPCA likelihood
The marginal distribution on \( x \) gives us the PPCA likelihood:

\[
\log p(x|\Lambda, \psi) = -\frac{N}{2} \log |2\pi(\Lambda \Lambda^T + \psi I)| - \frac{1}{2} \text{Tr}\left((\Lambda \Lambda^T + \psi I)^{-1} \sum_n x_n x_n^T\right)
\]

To find the ML values of \( (\Lambda, \psi) \) we could optimise numerically (gradient ascent / Newton’s method), or we could use a different iterative algorithm called EM which we’ll introduce soon.

In fact, however, ML for PPCA is more straightforward in principle, as we will see by first considering the limit \( \psi \to 0 \).

[Note: We may also add a constant mean \( \mu \) to the output, so as to model data that are not distributed around 0. In this case, the ML estimate \( \hat{\mu} = \frac{1}{N} \sum_n x_n \), and we can define \( S = \frac{1}{N} \sum_n (x - \hat{\mu})(x - \hat{\mu})^T \) in the likelihood above.]
Principal Components Analysis

This leads us to an (old) algorithm called Principal Components Analysis (PCA).

Assume data \(D = \{x_i\}\) have zero mean (if not, subtract it).

- Find direction of greatest variance – \(\lambda_{(1)}\).
  \[
  \lambda_{(1)} = \operatorname{argmax}_{v} \sum_{i} (x_i^T v)^2
  \]

- Find direction orthogonal to \(\lambda_{(1)}\) with greatest variance – \(\lambda_{(2)}\).

- Find direction orthogonal to \(\{\lambda_{(1)}, \lambda_{(2)}, \ldots, \lambda_{(n-1)}\}\) with greatest variance – \(\lambda_{(n)}\).

- Terminate when remaining variance drops below a threshold.

PCA and eigenvectors

- The variance in direction \(u_{(i)}\) is
  \[
  \left< x^T u_{(i)} \right>^2 = u_{(i)}^T x x^T u_{(i)} = u_{(i)}^T S u_{(i)} = u_{(i)}^T \omega_{(i)} u_{(i)} = \omega_{(i)}
  \]

- The variance in an arbitrary direction \(v\) is
  \[
  \left< x^T v \right>^2 = \left< \left( x^T \left( \sum_{i} v_{(i)} u_{(i)} \right) \right) \right>^2 = \sum_{i} v_{(i)}^2 u_{(i)}^T S u_{(i)} v_{(i)} = \sum_{i} v_{(i)}^2 \omega_{(i)}
  \]

- If \(v^T v = 1\), then \(\sum_{i} v_{(i)}^2 = 1\) and so \(\operatorname{argmax}_{|v| = 1} \left< x^T v \right>^2 = u_{(\text{max})}\)

- In general, the PCs are exactly the eigenvectors of the empirical covariance matrix, ordered by decreasing eigenvalue.

- The eigenspectrum shows how the variance is distributed across dimensions; can identify transitions that might separate signal from noise, or the number of PCs that capture a predetermined fraction of variance.

Eigendecomposition of a covariance matrix

The eigendecomposition of a covariance matrix makes finding the PCs easy. Recall that \(u\) is an eigenvector, with scalar eigenvalue \(\omega\), of a matrix \(S\) if

\[
Su = \omega u
\]

\(u\) can have any norm, but we will define it to be unity (i.e., \(u^T u = 1\)). For a covariance matrix \(S = (xx^T)\) (which is \(D \times D\), symmetric, positive semi-definite):

- In general there are \(D\) eigenvector-eigenvalue pairs \((u_{(i)}, \omega_{(i)})\), except if two or more eigenvectors share the same eigenvalue (in which case the eigenvectors are degenerate — any linear combination is also an eigenvector).

- The \(D\) eigenvectors are orthogonal (or orthogonalisable, if \(\omega_{(i)} = \omega_{(j)}\)). Thus, they form an orthonormal basis, \(\sum_{i} u_{(i)} u_{(i)^T} = I\).

- Any vector \(v\) can be written as
  \[
  v = \left( \sum_{i} u_{(i)} u_{(i)^T} \right) v = \sum_{i} (u_{(i)^T} v) u_{(i)} = \sum_{i} v_{(i)} u_{(i)}
  \]

- The original matrix \(S\) can be written:
  \[
  S = \sum_{i} \omega_{(i)} u_{(i)^T} u_{(i)} = U \Lambda U^T
  \]

where \(U = [u_{(1)}, u_{(2)}, \ldots, u_{(D)}]\) collects the eigenvectors and

\[
W = \text{diag}\left([\omega_{(1)}, \omega_{(2)}, \ldots, \omega_{(D)}]\right).
\]

PCA subspace

The \(K\) principle components define the \(K\)-dimensional subspace of greatest variance.

- Each data point \(x_i\) is associated with a projection \(\hat{x}_i\) into the principle subspace.

  \[
  \hat{x}_i = \sum_{k=1}^{K} x_{(i)(k)} \lambda_{(k)}
  \]

- This can be used for lossy compression, denoising, recognition, …
Example of PCA: Eigenfaces

Example of PCA: Genetic variation within Europe


Example of PCA: Genetic variation within Europe

Equivalent definitions of PCA

- Find $K$ directions of greatest variance in data.
- Find $K$-dimensional orthogonal projection that preserves greatest variance.
- Find $K$-dimensional vectors $y_i$ and matrix $\Lambda$ so that $\hat{x}_i = \Lambda y_i$ is as close as possible (in squared distance) to $x_i$.
- ... (many others)
Another view of PCA: Mutual information

Problem: Given \( x \), find \( y = Ax \) with columns of \( A \) unit vectors, s.t. \( I(y; x) \) is maximised (assuming that \( P(x) \) is Gaussian).

\[
I(y; x) = H(y) + H(x) - H(y, x) = H(y)
\]

So we want to maximise the entropy of \( y \). What is the entropy of a Gaussian?

\[
H(z) = -\int dz \, p(z) \ln p(z) = \frac{1}{2} \ln |\Sigma| + \frac{D}{2} (1 + \ln 2\pi)
\]

Therefore we want the distribution of \( y \) to have largest volume (i.e. det of covariance matrix).

\[
\Sigma_y = A \Sigma A^T = AUW, U^T A^T
\]

So, \( A \) should be aligned with the columns of \( U \) which are associated with the largest eigenvalues (variances).

Projection to the principal component subspace preserves the most information about the (Gaussian) data.

ML learning for PPCA

\[
\ell = -\frac{N}{2} \log |2\pi \Sigma| - \frac{N}{2} \text{Tr}[\Sigma^{-1} S] \quad \text{where } C = \Lambda \Lambda^T + \psi I
\]

\[
\frac{\partial \ell}{\partial \Lambda} = -N \left( \psi - \frac{\text{Tr}[C^{-1} S]}{\text{Tr}[C^{-1}]} \right) = \frac{N}{2} \left( C^{-1} - C^{-1} \Lambda - \Lambda C^{-1} \right)
\]

So at the stationary points we have \( SC^{-1} \Lambda = \Lambda \). This implies either:

\( \Lambda = 0 \), which turns out to be a minimum.

\( C = S \Rightarrow \Lambda \Lambda = S - \psi I. \) Now \( \text{rank}(\Lambda \Lambda) \leq K \Rightarrow \text{rank}(S - \psi I) \leq K \)

\( \Rightarrow S \) has \( D - K \) eigenvalues as \( \psi \) and \( \Lambda \) aligns with space of remaining eigenvectors.

or, taking the SVD: \( \Lambda = ULV^T \):

\[
S(UL^2V^T + \psi I)^{-1}ULV^T = (UL^2 + \psi I)^{-1}UL = U(L^2 + \psi I)^{-1}UL
\]

\[
\Rightarrow SU(L^2 + \psi I)^{-1}U = U(L^2 + \psi I)
\]

\[
\Rightarrow S = U(L^2 + \psi I)
\]

\( \Rightarrow \) columns of \( U \) are eigenvectors of \( S \) with eigenvalues given by \( L^2 + \psi \).

Thus, \( \Lambda = ULV^T \) spans a space defined by \( K \) eigenvectors of \( S \); and the lengths of the column vectors of \( L \) are given by the eigenvalues \( -\psi \) (\( V \) selects an arbitrary basis in the latent space).

Remains to show (we won’t), but it’s intuitively reasonable) that the global ML solution is attained when \( \Lambda \) aligns with the \( K \) leading eigenvectors.

PPCA latents

\( \bullet \) In PCA the “noise” is orthogonal to the subspace, and we can project \( x_n \to \hat{x}_n \) trivially.

\( \bullet \) In PPCA, the noise is more sensible (equal in all directions). But what is the projection? Find the expected value of \( y_n | x_n \) and then take \( \hat{x}_n = \Lambda y_n \).

\( \bullet \) Tactic: write \( p(y_n | x_n | \theta) \), consider \( x_n \) to be fixed. What is this as a function of \( y_n \)?

\[
p(y_n | x_n | \theta) = p(y_n | x_n) = (2\pi)^{-\frac{D}{2}} \exp \left\{ -\frac{1}{2} (y_n - \Lambda y_n)^T \psi^{-1} (y_n - \Lambda y_n) \right\}
\]

\[
= c \times \exp \left\{ -\frac{1}{2} y_n^T (I + \Lambda^T \psi^{-1} \Lambda)^{-1} y_n - 2 \psi^{-1} \Lambda^T y_n (\Lambda y_n - \psi_{-1} x_n) \right\}
\]

\[
= c' \times \exp \left\{ -\frac{1}{2} y_n^T (I + \Lambda^T \psi^{-1} \Lambda)^{-1} y_n - 2 \psi^{-1} \Lambda^T y_n (\Lambda y_n - \psi_{-1} x_n) \right\}
\]

So \( \Sigma = (I + \Lambda^T \psi^{-1} \Lambda)^{-1} \) and \( \mu = \Sigma \Lambda^T \psi^{-1} x_n = \beta x_n \). Where \( \beta = \Sigma \Lambda^T \psi^{-1} \).

\( \bullet \) Thus, \( \hat{x}_n = \Lambda (I + \Lambda^T \psi^{-1} \Lambda)^{-1} \Lambda^T \psi_{-1} x_n = x_n - \psi(\Lambda \Lambda^T + \psi)^{-1} x_n \)

\( \bullet \) This is not the same projection. PPCA takes into account noise in the principal subspace.

\( \bullet \) As \( \psi \to 0 \), the PPCA estimate \( \to \) the PCA value.
Factor Analysis

If dimensions are not equivalent, equal variance assumption is inappropriate.

Data: \( D = \{ x_1, x_2, \ldots, x_N \}; x_i \in \mathbb{R}^D \)

Latents: \( Y = \{ y_1, y_2, \ldots, y_N \}; y_i \in \mathbb{R}^K \)

Linear generative model: \( x_d = \sum_{k=1}^{K} \Lambda_{dk} y_k + \epsilon_d \)

- \( y_k \) are independent \( \mathcal{N}(0,1) \) Gaussian factors
- \( \epsilon_d \) are independent \( \mathcal{N}(0, \Psi_{dd}) \) Gaussian noise
- \( K < D \)

Model for observations \( x \) is still a correlated Gaussian:

\[
\begin{align*}
    p(y) &= \mathcal{N}(0, I) \\
    p(x|y) &= \mathcal{N}(\Lambda y, \Psi) \\
    p(x) &= \int p(y) p(x|y) dy = \mathcal{N}(0, \Lambda \Lambda^T + \Psi)
\end{align*}
\]

where \( \Lambda \) is a \( D \times K \), and \( \Psi \) is \( K \times K \) and diagonal.

**Dimensionality Reduction:** Finds a low-dimensional projection of high dimensional data that captures the correlation structure of the data.

Factor Analysis projections

Our analysis for PPCA still applies:

\[
\tilde{x}_n = \Lambda (I + \Lambda^T \Psi^{-1} \Lambda)^{-1} \Lambda^T x_n = x_n - \Psi (\Lambda \Lambda^T + \Psi)^{-1} x_n
\]

but now \( \Psi \) is diagonal but not spherical.

Note, though, that \( \Lambda \) is generally different from that found by PPCA.

And \( \Lambda \) is not unique: the latent space may be transformed by an arbitrary orthogonal transform \( U (U^T U = UU^T = I) \) without changing the likelihood.

\[
\begin{align*}
    \bar{y} &= U y & \bar{\Lambda} &= \Lambda U^T \\
    -\ell &= \frac{1}{2} \log 2\pi |(\Lambda \Lambda^T + \Psi)| + \frac{1}{2} x^T (\Lambda \Lambda^T + \Psi)^{-1} x \\
    &= \frac{1}{2} \log 2\pi |(\bar{\Lambda} \bar{\Lambda}^T + \Psi)| + \frac{1}{2} x^T (\bar{\Lambda} \bar{\Lambda}^T + \Psi)^{-1} x
\end{align*}
\]
Gradient methods for learning FA

Optimise negative log-likelihood:
\[-\ell = \frac{1}{2} \log |2\pi(\Lambda \Lambda^T + \Psi)| + \frac{1}{2} x^T(\Lambda \Lambda^T + \Psi)^{-1} x\]

w.r.t. $\Lambda$ and $\Psi$ (need matrix calculus) subject to constraints.

- No spectral short-cut exists.
- Likelihood can have more than one (local) optimum, making it difficult to find the global value.
- For some data (“Heywood cases”) likelihood may grow unboundedly by taking one or more $\Psi_{dd} \to 0$. Can eliminate by assuming a prior on $\Psi$ with zero density at $\Psi_{dd} = 0$, but results sensitive to precise choice of prior.

Expectation maximisation (next week) provides an alternative approach to maximisation, but doesn’t solve these issues.

Canonical Correlations Analysis

Data vector pairs: $D = \{(u_1, v_1), (u_2, v_2), \ldots\}$ in spaces $U$ and $V$.

Classic CCA
- Find unit vectors $\upsilon_1 \in U, \phi_1 \in V$ such that the correlation of $u_1^T \upsilon_1$ and $v_1^T \phi_1$ is maximised.
- As with PCA, repeat in orthogonal subspaces.

Probabilistic CCA
- Generative model with latent $y_i \in \mathbb{R}^K$:
  \[
  y \sim \mathcal{N}(0, I) \\
  u \sim \mathcal{N}(\Upsilon y, \Psi_u) \quad \Psi_u > 0 \\
  v \sim \mathcal{N}(\Phi y, \Psi_v) \quad \Psi_v > 0
  \]
- Block diagonal noise.

FA vs PCA

- PCA and PPCA are rotationally invariant; FA is not
  \[
  \text{If } x \rightarrow Ux \text{ for unitary } U, \quad \text{then } \lambda_{i(i)}^{\text{PCA}} \rightarrow U \lambda_{i(i)}^{\text{PCA}}
  \]
- FA is measurement scale invariant; PCA and PPCA are not
  \[
  \text{If } x \rightarrow Sx \text{ for diagonal } S, \quad \text{then } \lambda_{i(i)}^{\text{FA}} \rightarrow S \lambda_{i(i)}^{\text{FA}}
  \]
- FA and PPCA define a probabilistic model; PCA does not

Limitations of Gaussian, FA and PCA models

- Gaussian, FA and PCA models are easy to understand and use in practice.
- They are a convenient way to find interesting directions in very high dimensional data sets, eg as preprocessing.
- Their problem is that they make very strong assumptions about the distribution of the data, only the mean and variance of the data are taken into account.

The class of densities which can be modelled is too restrictive.

By using mixtures of simple distributions, such as Gaussians, we can expand the class of densities greatly.
A mixture distribution has a single discrete latent variable:

\[ s_i \sim \text{Discrete}[\pi] \]
\[ x_i \mid s_i \sim P_{s_i}[\theta_{s_i}] \]

Mixtures arise naturally when observations from different sources have been collated. They can also be used to approximate arbitrary distributions.

### The Mixture Likelihood

The mixture model is

\[ s_i \sim \text{Discrete}[\pi] \]
\[ x_i \mid s_i \sim P_{s_i}[\theta_{s_i}] \]

Under the discrete distribution

\[ P(s_i = m) = \pi_m; \quad \pi_m \geq 0, \quad \sum_{m=1}^{k} \pi_m = 1 \]

Thus, the probability (density) at a single data point \( x_i \) is

\[ P(x_i) = \sum_{m=1}^{k} P(x_i \mid s_i = m)P(s_i = m) \]
\[ = \sum_{m=1}^{k} \pi_m P_m(x_i; \theta_m) \]

The mixture distribution (density) is a convex combination (or weighted average) of the component distributions (densities).

### Approximation with a Mixture of Gaussians (MoG)

The component densities may be viewed as elements of a basis which can be combined to approximate arbitrary distributions.

Here are examples where non-Gaussian densities are modelled (approximated) as a mixture of Gaussians. The red curves show the (weighted) Gaussians, and the blue curve the resulting density.

Given enough mixture components we can model (almost) any density (as accurately as desired), but still only need to work with the well-known Gaussian form.
Maximum Likelihood for a Mixture Model

The log likelihood is:

\[ \mathcal{L} = \sum_{i=1}^{n} \log \sum_{m=1}^{k} \pi_m P_m(x_i; \theta_m) \]

Its partial derivative wrt \( \theta_m \) is

\[
\frac{\partial \mathcal{L}}{\partial \theta_m} = \sum_{i=1}^{n} \frac{\pi_m}{\sum_{m=1}^{k} \pi_m P_m(x_i; \theta_m)} \frac{\partial P_m(x_i; \theta_m)}{\partial \theta_m}
\]

or, using \( \partial P / \partial \theta = P \times \partial \log P / \partial \theta \),

\[
= \sum_{i=1}^{n} \frac{\pi_m P_m(x_i; \theta_m)}{\sum_{m=1}^{k} \pi_m P_m(x_i; \theta_m)} \frac{\partial \log P_m(x_i; \theta_m)}{\partial \theta_m}
\]

\[
= \sum_{i=1}^{n} \frac{\pi_m}{\sum_{m=1}^{k} \pi_m} \frac{\partial \log P_m(x_i; \theta_m)}{\partial \theta_m}
\]

And its partial derivative wrt \( \pi_m \) is

\[
\frac{\partial \mathcal{L}}{\partial \pi_m} = \sum_{i=1}^{n} \frac{P_m(x_i; \theta_m)}{\sum_{m=1}^{k} \pi_m P_m(x_i; \theta_m)} = \sum_{i=1}^{n} \frac{r_m}{\pi_m}
\]

The MoG likelihood

Each component of a MoG is a Gaussian, with mean \( \mu_m \) and covariance matrix \( \Sigma_m \). Thus, the probability density evaluated at a set of \( n \) iid observations, \( D = \{x_1, \ldots, x_n\} \) (i.e. the likelihood) is

\[
p(D \mid \{\mu_m\}, \{\Sigma_m\}, \pi) = \prod_{i=1}^{n} \sum_{m=1}^{k} \pi_m \mathcal{N}(x_i \mid \mu_m, \Sigma_m)
\]

\[
= \prod_{i=1}^{n} \sum_{m=1}^{k} \pi_m \frac{1}{\sqrt{2\pi\Sigma_m}} e^{-\frac{1}{2}(x_i - \mu_m)^T \Sigma_m^{-1} (x_i - \mu_m)}
\]

The log of the likelihood is

\[
\log p(D \mid \{\mu_m\}, \{\Sigma_m\}, \pi) = \sum_{i=1}^{n} \log \sum_{m=1}^{k} \pi_m \frac{1}{\sqrt{2\pi\Sigma_m}} e^{-\frac{1}{2}(x_i - \mu_m)^T \Sigma_m^{-1} (x_i - \mu_m)}
\]

Note that the logarithm fails to simplify the component density terms. A mixture distribution does not lie in the exponential family. Direct optimisation is not easy.

MoG Derivatives

For a MoG, with \( \theta_m = \{\mu_m, \Sigma_m\} \) we get

\[
\frac{\partial \mathcal{L}}{\partial \mu_m} = \sum_{i=1}^{n} r_m \Sigma_m^{-1} (x_i - \mu_m)
\]

\[
\frac{\partial \mathcal{L}}{\partial \Sigma_m} = \frac{1}{2} \sum_{i=1}^{n} r_m \left( \Sigma_m - (x_i - \mu_m)(x_i - \mu_m)^T \right)
\]

These equations can be used (along with the derivatives wrt \( \pi_m \)) for gradient based learning; e.g., taking small steps in the direction of the gradient (or using conjugate gradients).
The K-means Algorithm

The K-means algorithm is a limiting case of the mixture of Gaussians (c.f. PCA and Factor Analysis).

Take \( \pi_m = \frac{1}{k} \) and \( \Sigma_m = \sigma^2 I \), with \( \sigma^2 \to 0 \). Then the responsibilities become binary

\[ r_{im} \to \delta(m, \arg\min_l \|x_i - \mu_l\|^2) \]

with 1 for the component with the closest mean and 0 for all other components. We can then solve directly for the means by setting the gradient to 0.

The \textit{k-means algorithm} iterates these two steps:

- assign each point to its closest mean \( r_{im} = \delta(m, \arg\min_l \|x_i - \mu_l\|^2) \)
- update the means to the average of their assigned points \( \mu_m = \frac{\sum_i r_{im} x_i}{\sum_i r_{im}} \)

This usually converges within a few iterations, although the fixed point depends on the initial values chosen for \( \mu_m \). The algorithm has no learning rate, but the assumptions are quite limiting.

Issues

There are several problems with these algorithms:

- slow convergence for the gradient based method
- gradient based method may develop invalid covariance matrices
- local minima; the end configuration may depend on the starting state
- how do you adjust \( k \)? Using the likelihood alone is no good.
- singularities; components with a single data point will have their covariance going to zero and the likelihood will tend to infinity.

We will attempt to address many of these as the course goes on.

A preview of the EM algorithm

We wrote the k-means algorithm in terms of binary responsibilities. Suppose, instead, we used the fractional responsibilities from the full (non-limiting) MoG, but still neglected the dependence of the responsibilities on the parameters. We could then solve for both \( \mu_m \) and \( \Sigma_m \).

The \textit{EM algorithm} for MoGs iterates these two steps:

- Evaluate the responsibilities for each point given the current parameters.
- Optimise the parameters assuming the responsibilities stay fixed:

\[ \mu_m = \frac{\sum_i r_{im} x_i}{\sum_i r_{im}} \quad \text{and} \quad \Sigma_m = \frac{\sum_i r_{im} (x_i - \mu_m) (x_i - \mu_m)^T}{\sum_i r_{im}} \]

Although this appears \textit{ad hoc}, we will see (later) that it is a special case of a general algorithm, and is actually guaranteed to increase the likelihood at each iteration.