

LTAT.02.004 MACHINE LEARNING II

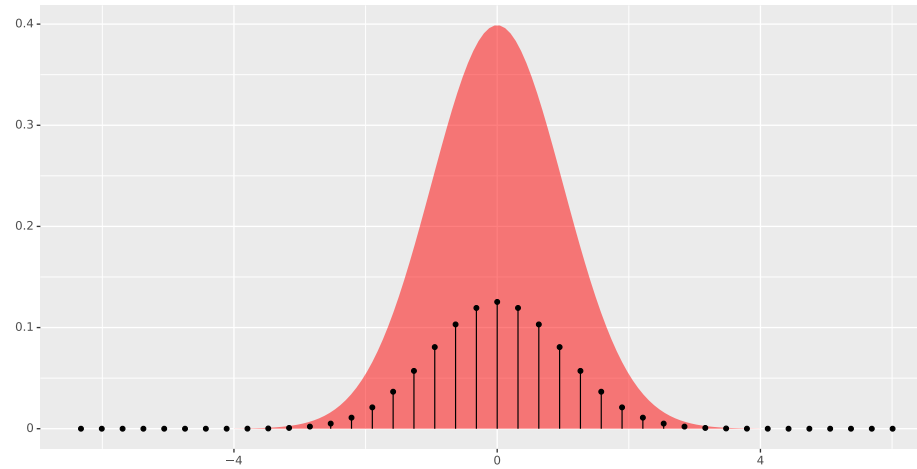
Multivariate normal distribution

Direct applications

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Univariate normal distribution

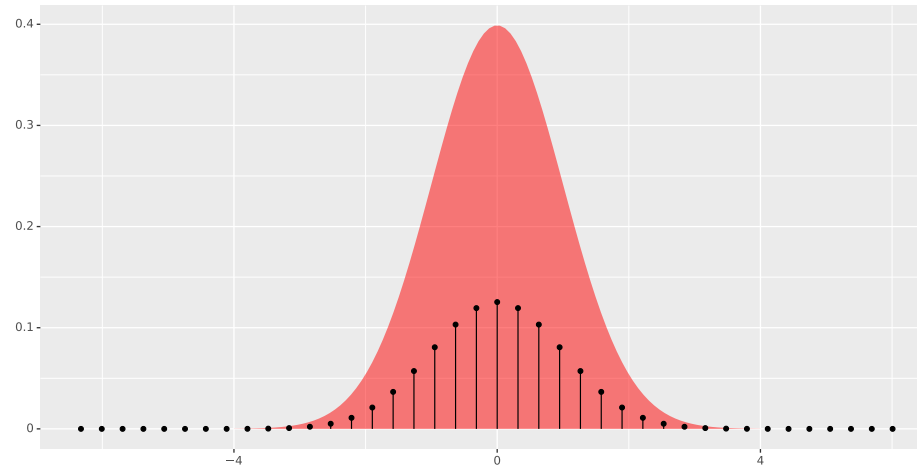
Probability density function



Definition. A real-valued random variable X comes from a continuous distribution with *a probability density function* $p : \mathbb{R} \rightarrow \mathbb{R}^+ \cup \{0\}$ if the following limit exists for any $x \in \mathbb{R}$:

$$p(x) = \lim_{\Delta x \rightarrow 0^+} \frac{\Pr[x - \Delta x \leq X \leq x + \Delta x]}{2 \cdot \Delta x} .$$

Probability mass function

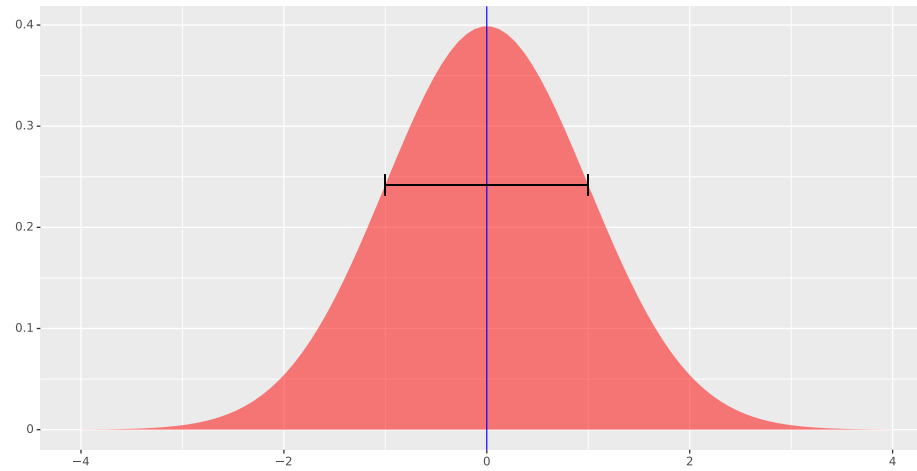


Definition. A real-valued random variable X comes from a discrete distribution with *a probability mass function* $p : \mathbb{R} \rightarrow \mathbb{R}^+ \cup \{0\}$ defined as

$$p(x) = \Pr[X = x] = \lim_{\Delta x \rightarrow 0^+} \Pr[x - \Delta x \leq X \leq x + \Delta x]$$

if there exist a sequence $(x_i)_{i=1}^{\infty}$ such that $p(x_1) + \dots + p(x_i) + \dots = 1$.

Standard normal distribution



Standard normal distribution $\mathcal{N}(\mu = 0, \sigma = 1)$ is a continuous distribution with a probability density function

$$p(x) = \frac{1}{\sqrt{2\pi}} \cdot \exp\left(-\frac{x^2}{2}\right)$$

The mean value $\mu = 0$ and variance $\sigma^2 = 1$ for this distribution.

Univariate normal distribution

Definition. A random variable y is distributed according to a normal distribution $\mathcal{N}(\mu = a, \sigma = b)$ if it can be expressed

$$y = bx + a$$

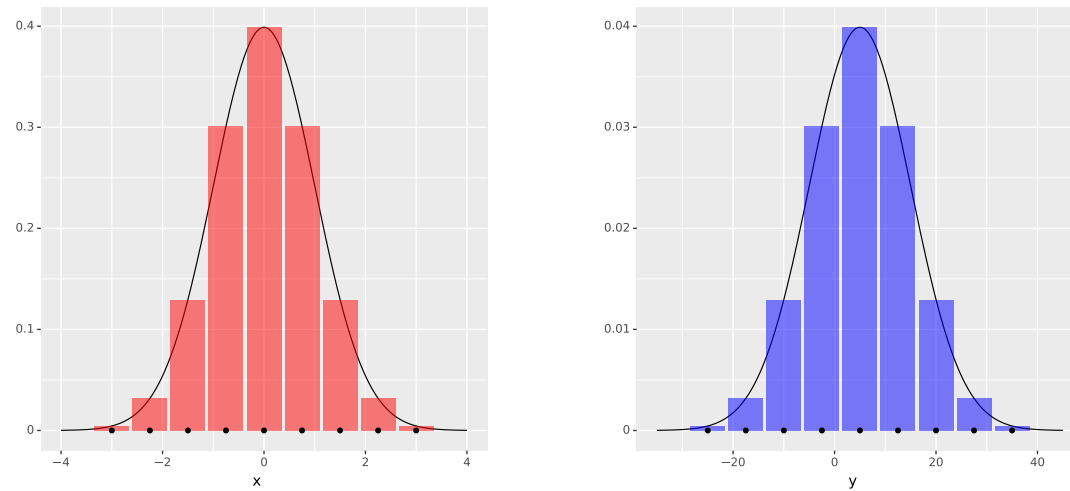
where x is distributed according to standardised normal distribution $\mathcal{N}(0, 1)$.

The corresponding probability density functions is

$$p[y|\mu, \sigma] = \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right)$$

and the mean value μ and variance σ^2 for this distribution.

Density derivation



Let $y = ax + b$ the the relation between densities

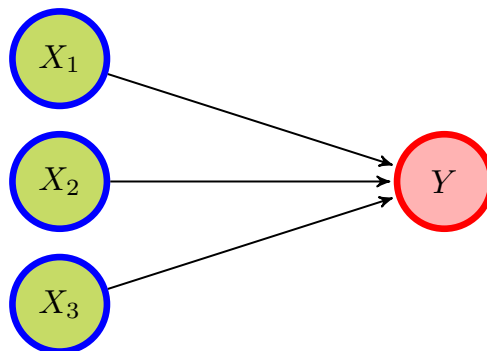
$$p_x(x) = \sigma \cdot p_y(y)$$

follows form the fact that areas of red and blue columns must be the same.

Motivating examples

Supervised learning

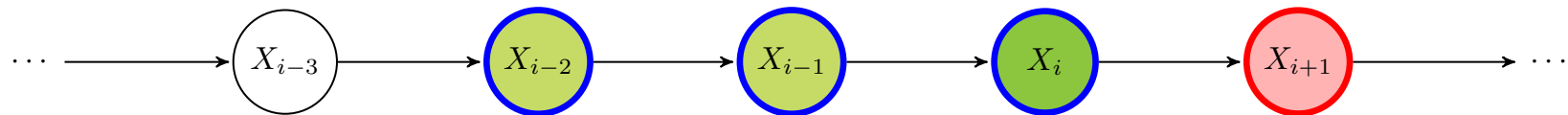
Repeated experiments with external controls



Linear regression models

- ▷ We assume that y_i depends only on the values of $x_{i1}, \dots, x_{i\ell}$
- ▷ A linear model assumes $y_i = w_1 x_{i1} + \dots + w_\ell x_{i\ell} + w_0 + \varepsilon_i$.
- ▷ All error terms ε_i are assumed to be independent.
- ▷ All error terms ε_i are drawn from a normal distribution $\mathcal{N}(0, \sigma)$.

Higher-order Markov chains



Time-series models

- ▷ We assume that x_{i+1} depends only on the values of $x_i, \dots, x_{i-\ell}$
- ▷ A linear model assumes $x_{i+1} = w_0 + w_1 x_i + \dots + w_{\ell+1} x_{i-\ell} + \varepsilon_i$.
- ▷ All error terms ε_i are assumed to be independent.
- ▷ All error terms ε_i are drawn from a normal distribution $\mathcal{N}(0, \sigma)$.

Univariate linear regression

- ▷ Fix a set of inputs $x_1, \dots, x_n \in \mathbb{R}$.
- ▷ A probabilistic model is defined by three coefficients $a, b, \sigma \in \mathbb{R}$.
- ▷ The model assigns a probability to outcomes y_1, \dots, y_n through the following observation generation mechanism

$$y_i = ax_i + b + \varepsilon_i, \quad \varepsilon_i \sim \mathcal{N}(0, \sigma)$$

- ▷ Consequently

$$p[\mathbf{y}|\mathbf{x}, a, b] = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left(-\frac{(y_i - ax_i - b)^2}{2\sigma^2}\right)$$

Maximum likelihood estimate

As usual we can find $a, b, \sigma \in \mathbb{R}$ that maximise the log-likelihood

$$\log p[\mathbf{y}|\mathbf{x}, a, b, \sigma] = \text{const} - n \log \sigma - \sum_{i=1}^n \frac{(y_i - ax_i - b)^2}{2\sigma^2}$$

and thus we can find a and b by minimising

$$\text{MSE} = \frac{1}{n} \cdot \sum_{i=1}^n (y_i - ax_i - b)^2 \ .$$

Residuals and the variance parameter

For fixed $a, b \in \mathbb{R}$ we can define predictions and residuals

$$\hat{y}_i = ax_i - b$$

$$r_i = y_i - \hat{y}_i$$

To find the optimal variance σ^2 we need to maximise

$$\log p[\mathbf{y}|\mathbf{x}, a, b, \sigma] = \text{const} - n \log \sigma - \sum_{i=1}^n \frac{r_i^2}{2\sigma^2}$$

The resulting solution is

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

Linear time-series model

- ▷ Fix a set of initial inputs $x_{-\ell}, \dots, x_0 \in \mathbb{R}$. Denote them by \mathbf{x}_\circ .
- ▷ Think of x_1, x_2, \dots, x_n as observations. Denote them by \mathbf{x} .
- ▷ A probabilistic model for state transitions is defined as follows

$$x_{i+1} = \underbrace{w_0 + w_1 x_i + \dots + w_{\ell+1} x_{i-\ell}}_{\hat{x}_{i+1}} + \varepsilon_i, \quad \varepsilon_i \sim \mathcal{N}(0, \sigma)$$

- ▷ Consequently

$$p[\mathbf{x} | \mathbf{x}_\circ, \mathbf{w}, \sigma] = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left(-\frac{(x_i - \hat{x}_i)^2}{2\sigma^2}\right)$$

Maximum likelihood estimate

As usual we can find $\mathbf{w} \in \mathbb{R}^{\ell+2}$ and $\sigma \in \mathbb{R}$ that maximise the log-likelihood

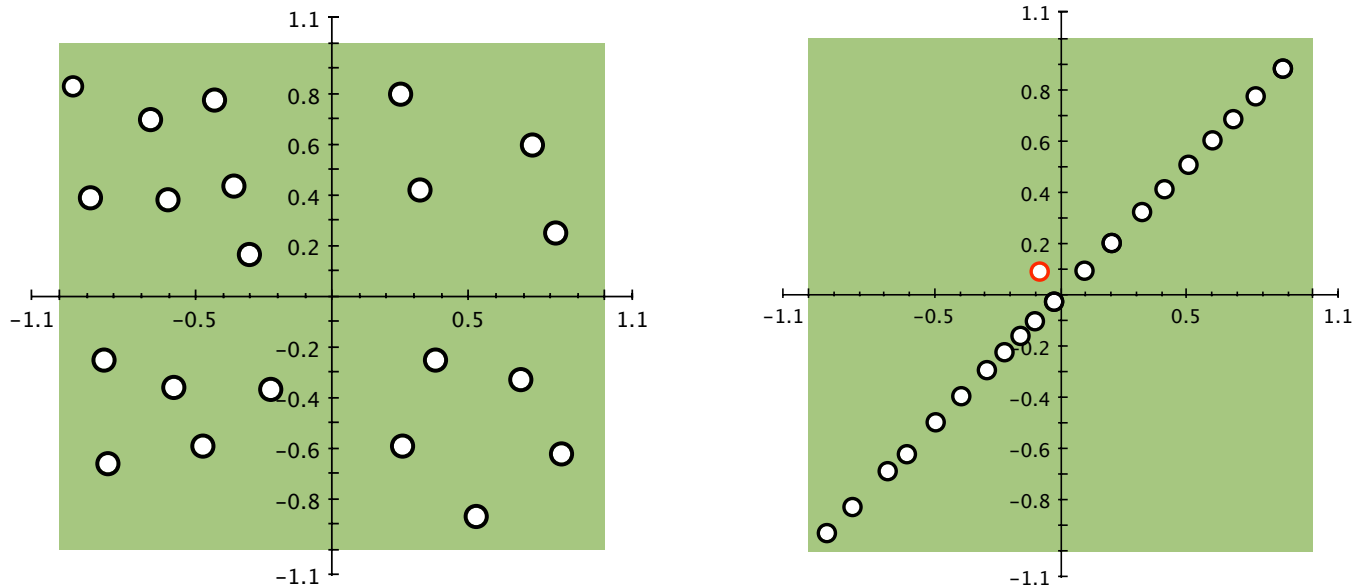
$$\log p[\mathbf{x}|\mathbf{x}_o, \boldsymbol{\beta}, \sigma] = \text{const} - n \log \sigma - \sum_{i=1}^n \frac{(x_i - \hat{x}_i)^2}{2\sigma^2}$$

and thus we can find \mathbf{w} by minimising

$$\text{MSE} = \frac{1}{n} \cdot \sum_{i=1}^n (x_i - w_0 - w_1 x_{i-1} - \dots - w_{\ell+1} x_{i-1-\ell})^2 .$$

The latter is the standard multivariate linear regression setup. The variance of the model σ^2 can be found by the same formula as for linear regression.

Input values and numerical stability

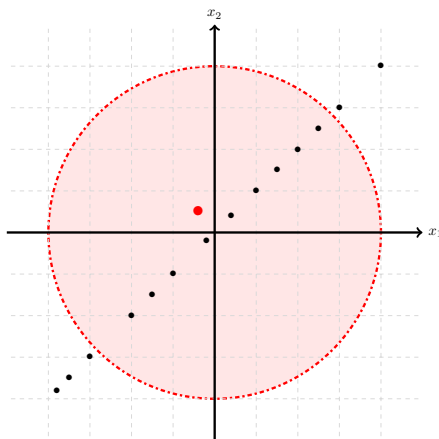


A small error in a point with big leverage can make linear regression function arbitrary large, which can lead to large test errors.

▷ In many case we know that the final output must be in fixed range.

Ridge regression

Let us seek the prediction as a function $f(\mathbf{x}) = w_1x_1 + \dots + w_kx_k$ with restriction $f(\mathbf{x}) \leq c$ inside a unit ball $\|\mathbf{x}\|_2^2 = x_1^2 + x_2^2 + \dots + x_k^2 \leq 1$.

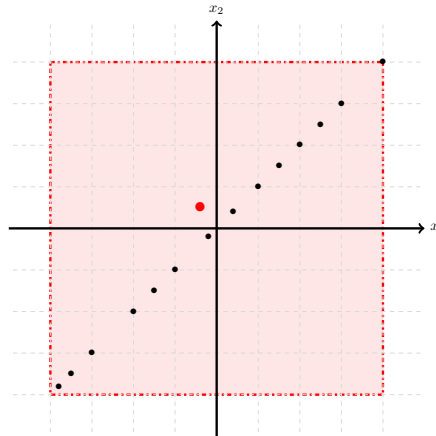


Then we should solve the following task instead:

$$\begin{aligned} \frac{1}{N} \cdot \sum_{i=1}^N (y_i - f(\mathbf{x}_i))^2 &\rightarrow \min \\ \text{s.t. } w_1^2 + \dots + w_k^2 &\leq c^2 \end{aligned}$$

LASSO regression

Let us seek the prediction as a function $f(\mathbf{x}) = w_1x_1 + \dots + w_kx_k$ with restriction $f(\mathbf{x}) \leq c$ inside a unit ball $\|\mathbf{x}\|_\infty = \max \{|x_1|, \dots, |x_k|\} \leq 1$.



Then we should solve the following task instead:

$$\begin{aligned} \frac{1}{N} \cdot \sum_{i=1}^N (y_i - f(\mathbf{x}_i))^2 &\rightarrow \min \\ \text{s.t. } |w_1| + \dots + |w_k| &\leq c \end{aligned}$$

Lagrange' trick

If we want to minimise $f(\mathbf{x})$ such that $g(\mathbf{x}) \leq c$ for a non-negative function $g(\cdot)$, then there exists $\lambda \geq 0$ such that the solution of the original problem is a minimum for a modified function

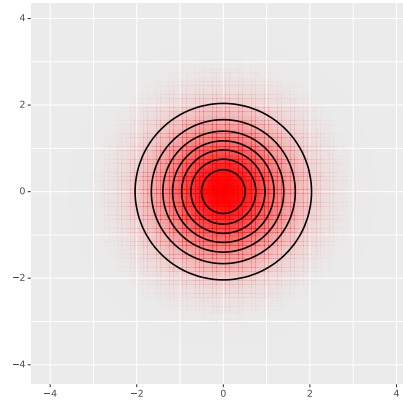
$$f_*(\mathbf{x}) = f(\mathbf{x}) + \lambda g(\mathbf{x})$$

Consequences

- ▷ We can use a penalty term $\lambda \|\mathbf{w}\|_1$ for rectangular area
- ▷ We can use a penalty term $\lambda \|\mathbf{w}\|_2^2$ for circular area

Multivariate normal distribution

White Gaussian noise



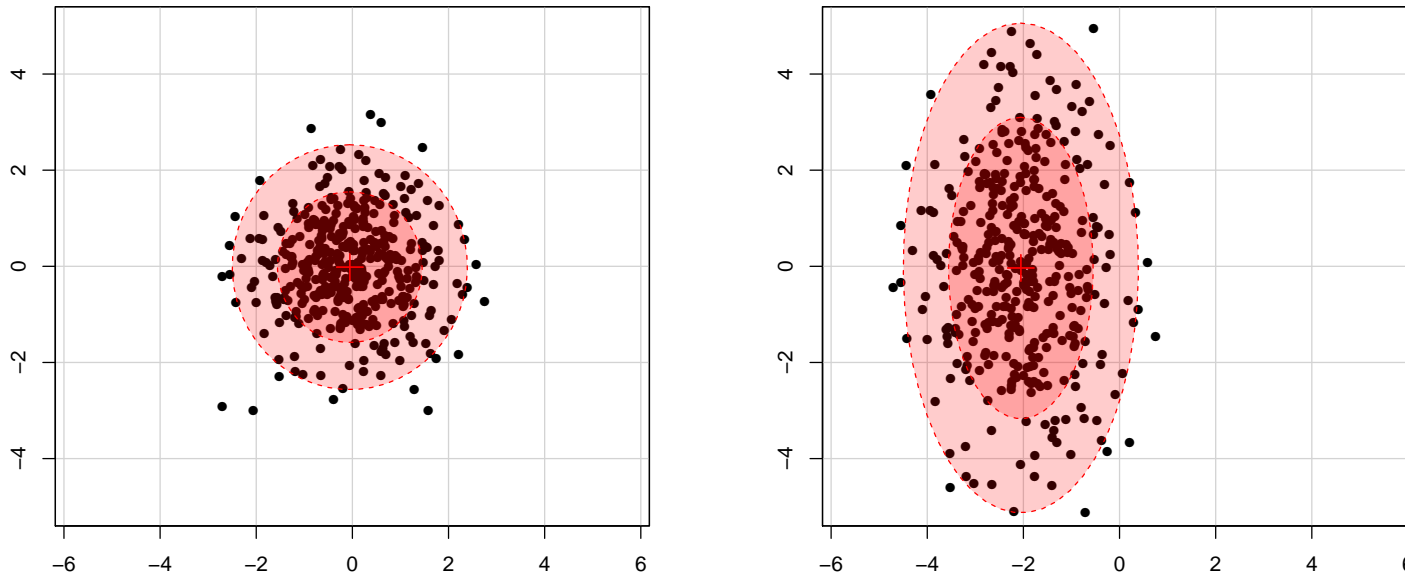
Definition. A random vector X_1, \dots, X_n is a standard normal random vector if all of its components are independent and $X_i \sim \mathcal{N}(0, 1)$.

▷ The density can be computed based on independence:

$$p(x_1, \dots, x_n) = p(x_1) \cdots p(x_n) = \frac{1}{(2\pi)^{n/2}} \cdot \exp\left(-\frac{x_1^2 + \cdots + x_n^2}{2}\right) .$$

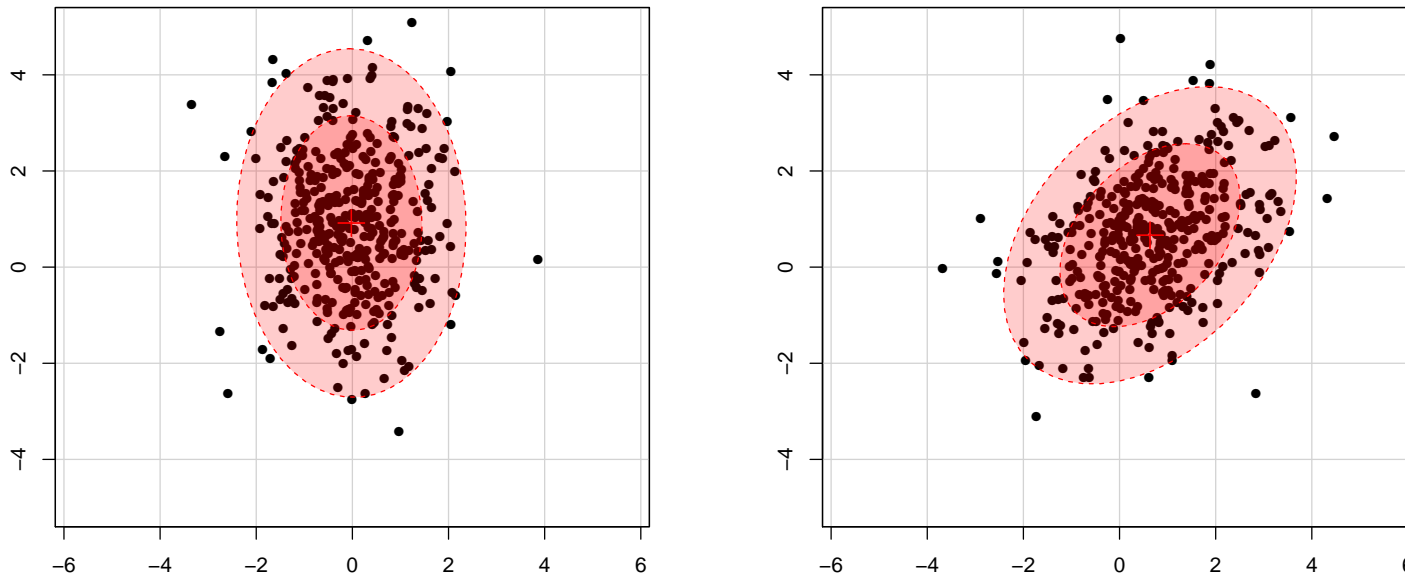
Scaling and shifting

By shifting and scaling the source distribution $\mathcal{N}(\mathbf{0}, I)$ we can obtain some other instances of multivariate normal distribution.



Necessity of rotations

As the choice of coordinate axis is sometimes arbitrary, there must be other ways to form a normal distribution – rotations of coordinate axis.



Any affine transformation can be expressed as scaling, rotating and shifting.

Affine transformations

Let \mathbf{x} be standard normal random vector and let \mathbf{y} be obtained the scaling, translation and rotation of the coordinate plane.

Then we can express \mathbf{x} and \mathbf{y} in terms of an affine transformation

$$\begin{aligned}\mathbf{y} &= A\mathbf{x} + \boldsymbol{\mu} \ , \\ \mathbf{x} &= A^{-1}(\mathbf{y} - \boldsymbol{\mu}) \ .\end{aligned}$$

Observation. Affine transformations are closed with respect to composition, i.e., applying two affine transformations yields a new affine transformation.

Remark. Not all affine transformations are invertible.

What is density in 2D?

Recall that density assigns probability to small enough regions \mathcal{R} :

$$\Pr_{x_1^*, x_2^*} \left[\begin{array}{l} x_1 \leq x_1^* \leq x_1 + \Delta x_1 \\ x_2 \leq x_2^* \leq x_2 + \Delta x_2 \end{array} \right] = p(x_1, x_2) \cdot \underbrace{\Delta x_1 \Delta x_2}_S + \varepsilon$$

where $\varepsilon = o(\Delta x_1 \cdot \Delta x_2)$ in the process $\Delta x_1 \rightarrow 0$ and $\Delta x_2 \rightarrow 0$.

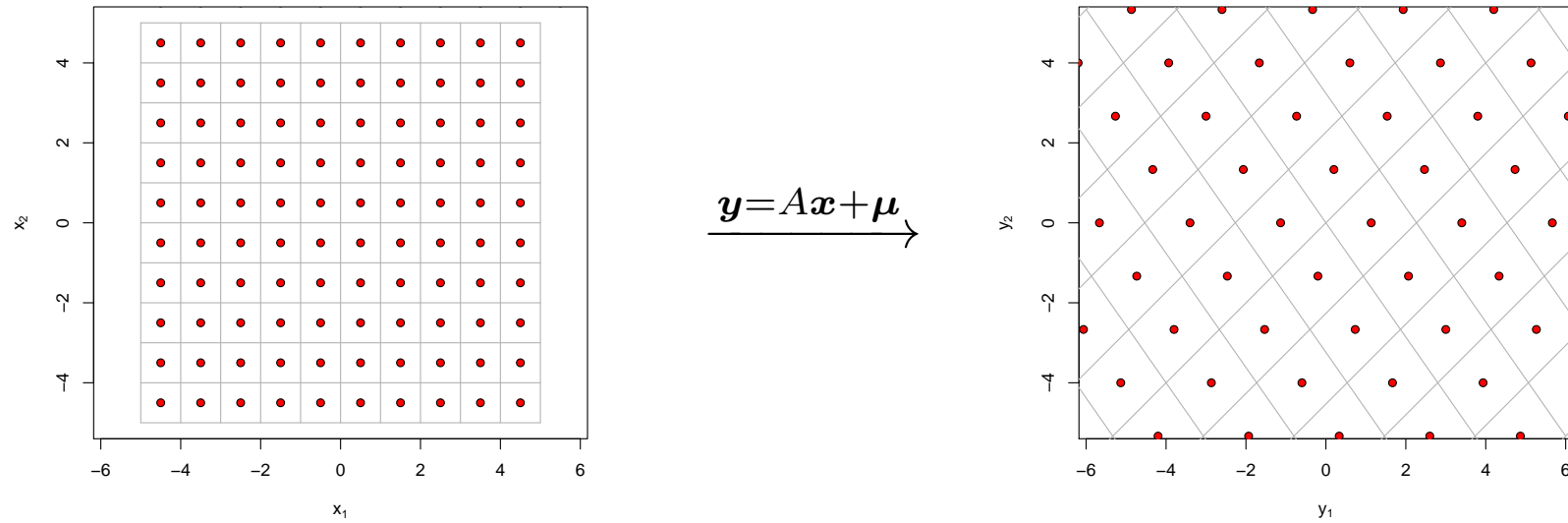
Remark. Regions \mathcal{R} do not have to be rectangular as long as:

- ▷ The area $S(\mathcal{R})$ of a region can be computed.
- ▷ Probability can be assigned to the region \mathcal{R} and its scalings.

Then $\varepsilon = o(S)$ when we rescale the region \mathcal{R} around the point (x_1, x_2) .

Density recalibration

Any affine transformation changes a square grid into parallelograms.



As a result, the area of the regions is different on the left and on the right:

$$p(x_1, x_2) \cdot S_1 \approx q(y_1, y_2) \cdot S_2 \quad \implies \quad q(y_1, y_2) = \frac{S_1}{S_2} \cdot p(x_1, x_2)$$

Fortunately, the ratio between areas are constant over the entire plane!

Density of two-variate normal distribution

The density of (x_1, x_2) pairs can be computed based on independence:

$$p(x_1, x_2) = p(x_1) \cdot p(x_2) = \frac{1}{2\pi} \cdot \exp\left(-\frac{x_1^2 + x_2^2}{2}\right) .$$

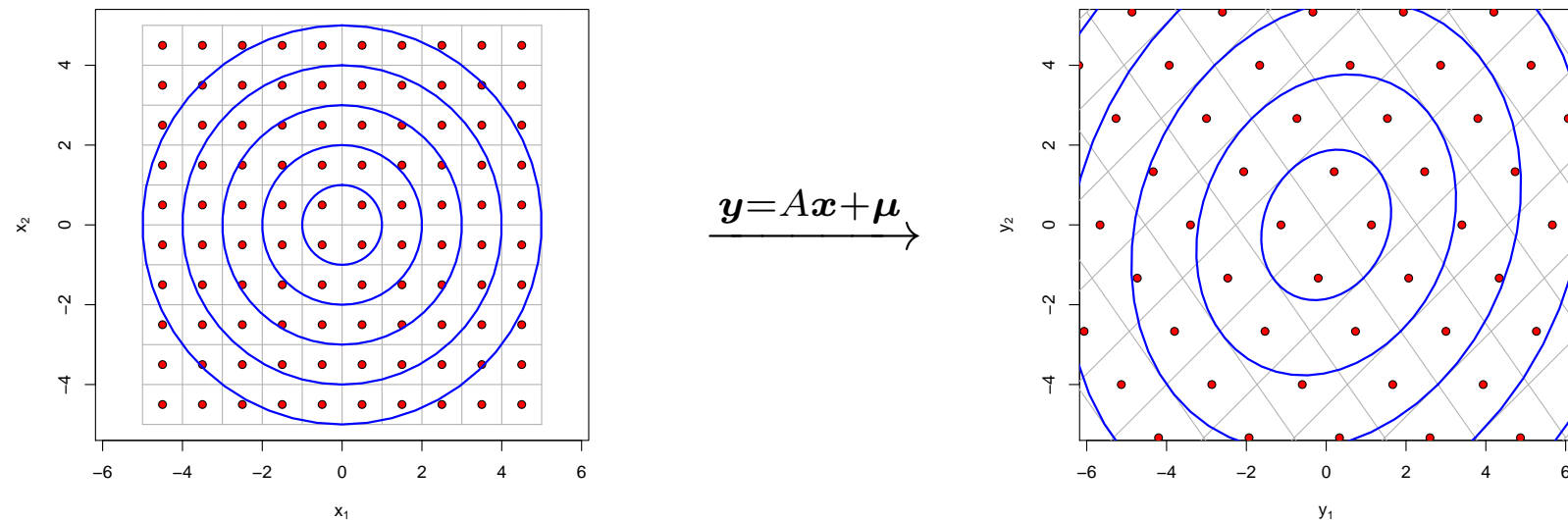
To estimate density $q(y_1, y_2)$, we must find the corresponding (x_1, x_2) :

$$\mathbf{y} = A\mathbf{x} + \boldsymbol{\mu} \quad \Leftrightarrow \quad \mathbf{x} = A^{-1}(\mathbf{y} - \boldsymbol{\mu}) .$$

Thus we get

$$\begin{aligned} q(y_1, y_2) &= \frac{S_1}{S_2} \cdot \frac{1}{2\pi} \cdot \exp\left(-\frac{(\mathbf{y} - \boldsymbol{\mu})^T A^{-T} A^{-1}(\mathbf{y} - \boldsymbol{\mu})}{2}\right) \\ &= \frac{1}{\sqrt{\det(\Sigma)}} \cdot \frac{1}{2\pi} \cdot \exp\left(-\frac{(\mathbf{y} - \boldsymbol{\mu})^T \Sigma^{-1}(\mathbf{y} - \boldsymbol{\mu})}{2}\right) . \end{aligned}$$

Illustrative example



- ▷ Affine transformation changes the square grid into parallelograms.
- ▷ Affine transformation changes circular equiprobability lines into ellipses.
- ▷ The axes of the ellipses may intersect with the sides of parallelograms.

Generalisation to multivariate case

If observed quantities \mathbf{y} are generated by applying the affine transformation

$$\mathbf{y} = A\mathbf{x} + \boldsymbol{\mu} \quad \Leftrightarrow \quad \mathbf{x} = A^{-1}(\mathbf{y} - \boldsymbol{\mu})$$

to the *independent source signals* $x_1, \dots, x_n \sim \mathcal{N}(0, 1)$, then the resulting distribution is *a multivariate normal distribution* with the density:

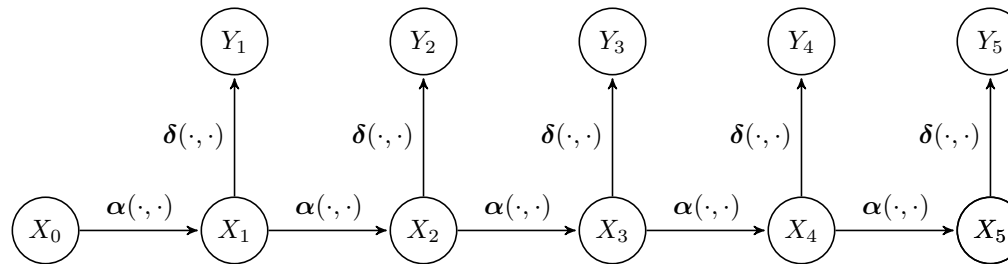
$$p(\mathbf{y}) = \frac{1}{(2\pi)^{n/2}} \cdot \frac{1}{\sqrt{\det(\Sigma)}} \cdot \exp\left(-\frac{(\mathbf{y} - \boldsymbol{\mu})^T \Sigma^{-1}(\mathbf{y} - \boldsymbol{\mu})}{2}\right)$$

where $\Sigma^{-1} = A^{-T}A^{-1}$ is *a positively definite symmetric matrix*.

Motivating examples

Unsupervised learning

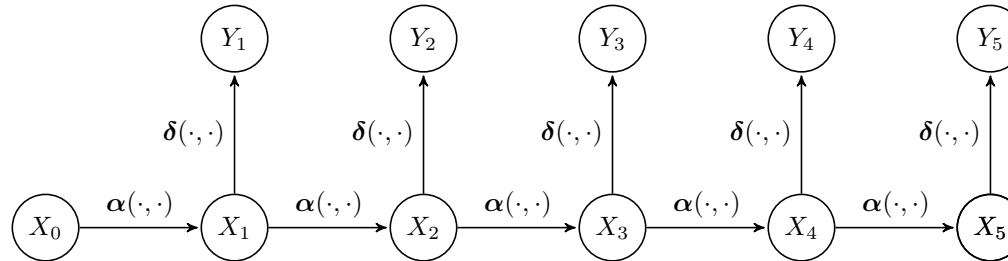
Hidden Markov Model



Sensor fusion problem

- ▷ Several sensors measure a physical system
- ▷ Measurements are observable as $\mathbf{y} \in \mathbb{R}^p$.
- ▷ Physical system has an hidden state $\mathbf{x} \in \mathbb{R}^n$.
- ▷ Physical system evolves linearly $\mathbf{x}_{i+1} = A\mathbf{x}_i + \mathbf{w}_i$.
- ▷ Measurements are linear from the state $\mathbf{y}_i = C\mathbf{x}_i + \mathbf{v}_i$.
- ▷ Distribution of error terms \mathbf{v}_i and \mathbf{w}_i is known.
- ▷ Error terms \mathbf{v}_i and \mathbf{w}_i are independently drawn.

Belief propagation for continuous distributions



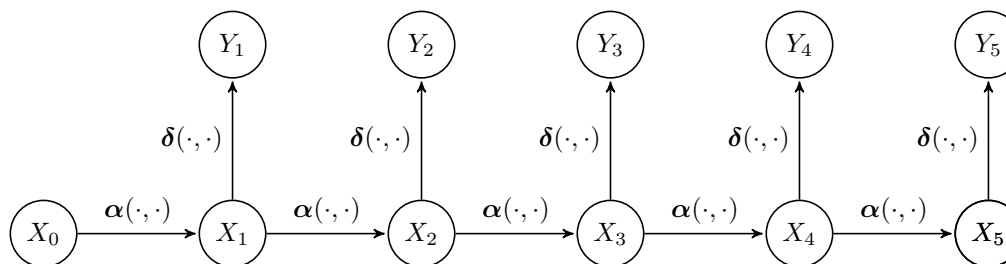
Continuous distributions are rarely compatible with belief propagation

$$\pi_{X_i}(\mathbf{x}_i) \propto \int_{\mathbf{x}_{i-1}} \alpha[\mathbf{x}_{i-1}, \mathbf{x}_i] \cdot \lambda_{i-1}^*(\mathbf{x}_{i-1}) \cdot \pi_{X_{i-1}}(\mathbf{x}_{i-1}) d\mathbf{x}_{i-1}$$

$$\lambda_{X_i}(x_i) \propto \int_{\mathbf{x}_{i+1}} \alpha[\mathbf{x}_i, \mathbf{x}_{i+1}] \cdot \lambda_i^*(\mathbf{x}_i) \cdot \lambda_{X_{i+1}}(\mathbf{x}_{i+1}) d\mathbf{x}_{i+1}$$

but normal distributions form a rare exception.

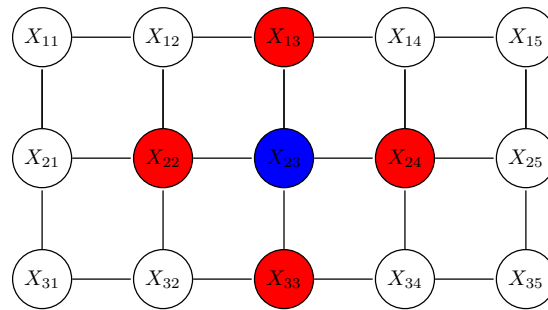
Kalman filter



Belief propagation becomes tractable under following assumptions:

- ▷ Measurement noise \mathbf{v}_t is modelled with a normal distribution.
- ▷ Unknown control signal \mathbf{w}_i is modelled with a normal distribution.
- ▷ Unknown initial state \mathbf{x}_0 is modelled with a normal distribution.
- ▷ Quantities $\mathbf{x}_0, \mathbf{v}_i, \mathbf{w}_i$ are assumed to be independent.
- ▷ All normal distributions can have complex correlation structure.

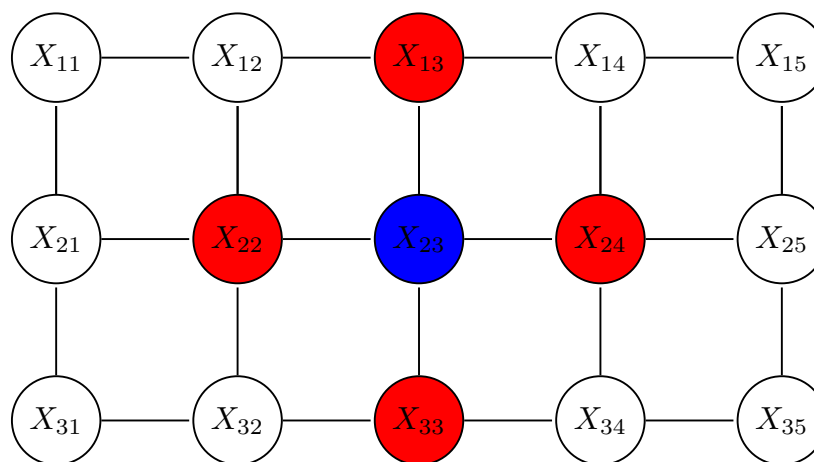
Background model for digital images



In most images intensity of pixel is influenced only by its neighbours:

- ▷ For simple textures the neighbourhood consist of four adjacent pixels.
- ▷ For complex textures the the neighbourhood contains much more pixels.
- ▷ For homogenous textures the conditional probabilities are universal.
 - ◇ Generative repetitive patterns for textile and grass
- ▷ For complex patterns conditional probabilities can be location dependent.
 - ◇ Generative patterns for human faces and fashion accessories

Random Markov Fields



Definition. Markov random field is specified by undirected graph connecting random variables X_1, X_2, \dots such that for any node X_i

$$\Pr [x_i | (x_j)_{j \neq i}] = \Pr [x_i | (x_j)_{j \in \mathcal{N}(X_i)}]$$

where the set of neighbours $\mathcal{N}(X_i)$ is also known as *Markov blanket* for X_i .

Hammersley-Clifford theorem

The probability of an observation $\mathbf{x} = (x_1, x_2, \dots)$ generated by a Markov random field can be expressed in the form

$$\Pr[\mathbf{x}] = \frac{1}{Z(\omega)} \cdot \exp \left(- \sum_{c \in \text{MaxClique}} \Psi_c(\mathbf{x}_c, \omega) \right)$$

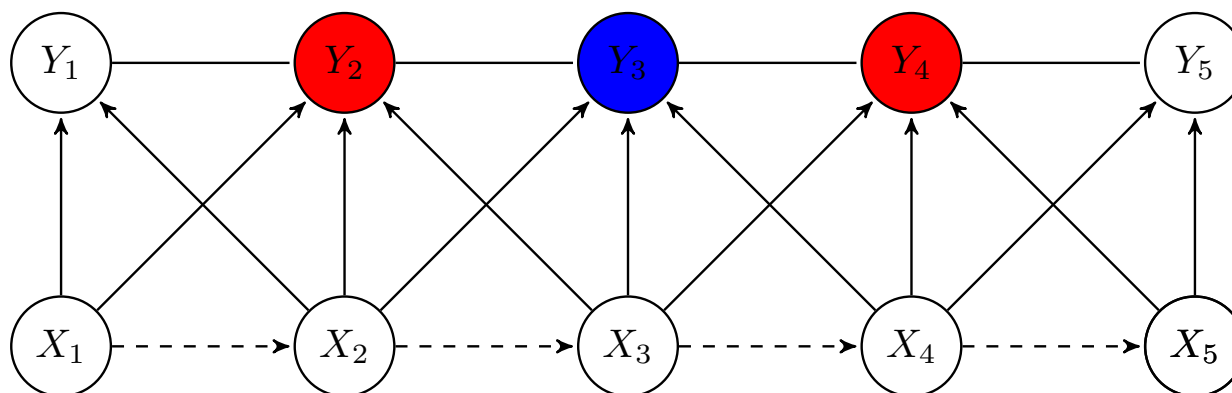
where

- ▷ $Z(\omega)$ is a normalising constant
- ▷ MaxClique is the set of maximal cliques in the Markov random field
- ▷ Ψ_c is defined on the variables in the clique c

The formula implies that the distribution belongs to the exponential family.

- ▷ Multivariate normal distribution belongs to the exponential family

Conditional Random Fields

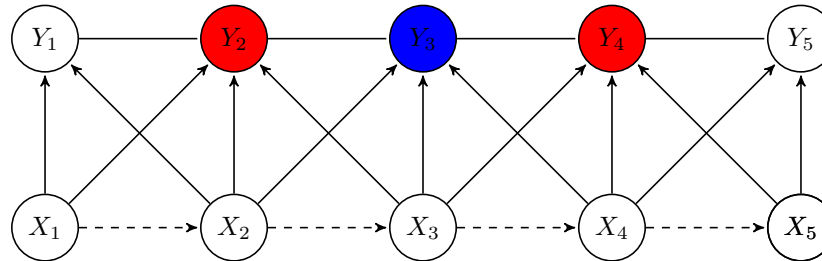


Definition. Let X_1, X_2, \dots and Y_1, Y_2, \dots be random variables. The entire process is conditional random field if random variables Y_1, Y_2, \dots conditioned for any sequence of observations x_1, x_2, \dots form a Markov random field

$$\Pr [y_i | (x_k)_{k=1}^{\infty}, (y_j)_{j \neq i}] = \Pr [y_i | (x_k)_{k=1}^{\infty}, (y_j)_{j \in \mathcal{N}(Y_i)}]$$

where the set of neighbours $\mathcal{N}(Y_i)$ is a *conditional Markov blanket* for Y_i .

Image segmentation and sequence labelling



- ▷ The input x is used to predict labels y_1, y_2, \dots
- ▷ A correct label sequence must satisfy possibly unknown restrictions.
- ▷ These restrictions are captured by conditional random random field.

Consequences of Hammersley-Clifford theorem

- ▷ Clique features Ψ_c can depend on $(y_i)_{i \in c}, (x_i)_{i=1}^{\infty}$
- ▷ Features can be defined as linear combination of vertex and edge features.
- ▷ A vertex feature looks only variable y_i associated with the vertex.
- ▷ An edge feature looks only variables y_i, y_j associated with the edge.

Markov fields
with
multivariate normal distributions

General form of the likelihood function

The celebrated Hammersley-Clifford theorem fixes the format in which the corresponding probability distribution must be sought:

$$p[\mathbf{x}|\omega] = \frac{1}{Z(\omega)} \cdot \exp \left(- \sum_{c \in \text{MaxClique}} \Psi_c(\mathbf{x}_c, \omega) \right)$$

where

- ▷ ω is a set of model parameters
- ▷ $Z(\omega)$ is a normalising constant
- ▷ MaxClique is the set of maximal cliques in the Markov random field
- ▷ Ψ_c is defined on the variables x_i in the clique c .

Multivariate normal distribution as likelihood

If individual sub-potentials $\Psi_c(\mathbf{x}_c, \omega)$ are quadratic forms then the energy

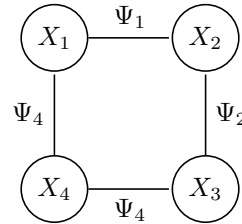
$$\Psi(\mathbf{x}) = \sum_{c \in \text{MaxClique}} \Psi_c(\mathbf{x}_c, \omega)$$

is also a quadratic form and thus $p[\mathbf{x}|\omega]$ is a multivariate normal distribution.

Sub-potentials are often fixed directly based on smoothness constraints

- ▷ Intensities have bounded variance: $\Psi_e = \delta^2 x_{ij}^2$.
- ▷ Intensity changes smoothly vertically: $\Psi_e = \beta(x_{i,j} - x_{i+1,j})^2$.
- ▷ Intensity changes smoothly horizontally: $\Psi_e = \alpha(x_{i,j} - x_{i,j+1})^2$.

Toy example



Sub-potentials corresponding four edges are:

$$\Psi_1(x_1, x_2) = \alpha_1(x_1 - x_2)^2 = \alpha_1 x_1^2 - 2\alpha_1 x_1 x_2 + \alpha_1 x_2^2$$

$$\Psi_2(x_2, x_3) = \alpha_2(x_2 - x_3)^2 = \alpha_2 x_2^2 - 2\alpha_2 x_2 x_3 + \alpha_2 x_3^2$$

$$\Psi_3(x_3, x_4) = \alpha_3(x_3 - x_4)^2 = \alpha_3 x_3^2 - 2\alpha_3 x_3 x_4 + \alpha_3 x_4^2$$

$$\Psi_4(x_4, x_1) = \alpha_4(x_4 - x_1)^2 = \alpha_4 x_4^2 - 2\alpha_4 x_4 x_1 + \alpha_4 x_1^2$$

Sub-potentials corresponding to four vertices are $\Psi_i^*(x_i) = \delta_i^2 x_i^2$

Resulting potential function

$$\Psi(\mathbf{x}) = \mathbf{x}^T \begin{pmatrix} \alpha_1 + \alpha_4 + \delta_1^2 & -\alpha_1 & 0 & -\alpha_4 \\ -\alpha_1 & \alpha_1 + \alpha_2 + \delta_2^2 & -\alpha_2 & 0 \\ 0 & -\alpha_2 & \alpha_2 + \alpha_3 + \delta_3^2 & -\alpha_3 \\ -\alpha_4 & 0 & -\alpha_3 & \alpha_3 + \alpha_4 + \delta_4^2 \end{pmatrix} \mathbf{x}$$

and thus the covariance matrix Σ and mean $\boldsymbol{\mu}$ can be computed by matching the shape of the multivariate normal density

$$p[\mathbf{x}|\boldsymbol{\mu}, \Sigma] \propto \frac{1}{\sqrt{\det \Sigma}} \cdot \exp \left(-\frac{1}{2} \cdot (\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right)$$

Important properties of normal distributions

Closeness under marginalisation

Let $\mathbf{x}_{\mathcal{I}} = (x_i)_{i \in \mathcal{I}}$ be a subvector determined by the coordinate set \mathcal{I} . Then $\mathbf{x}_{\mathcal{I}}$ is distributed according to a multivariate normal distribution as long as the vector \mathbf{x} comes from a multivariate normal distribution $\mathcal{N}(\boldsymbol{\mu}, \Sigma)$.

▷ Moment matching gives the parameters of the resulting distribution

$$\begin{aligned}\mathbf{E}(\mathbf{x}_{\mathcal{I}}) &= \mathbf{E}(\mathbf{x})_{\mathcal{I}} = \boldsymbol{\mu}_{\mathcal{I}} \\ \mathbf{Cov}(\mathbf{x}_{\mathcal{I}}) &= \mathbf{Cov}(\mathbf{x})_{\mathcal{I} \times \mathcal{I}} = \Sigma[\mathcal{I}, \mathcal{I}]\end{aligned}$$

Closeness under linear combinations

Linear combination $y = \alpha_1^T x_1 + \alpha_2^T x_2$ of independent multivariate normal distributions $x_1 \sim \mathcal{N}(\mu_1, \Sigma_1)$ and $x_2 \sim \mathcal{N}(\mu_2, \Sigma_2)$ is also a multivariate normal distribution.

▷ Moment matching gives the parameters of the resulting distribution

$$\begin{aligned}\mathbf{E}(y) &= \alpha_1^T \mathbf{E}(x_1) + \alpha_2^T \mathbf{E}(x_2) = \alpha_1^T \mu_1 + \alpha_2^T \mu_2 \\ \mathbf{Var}(y) &= \mathbf{Cov}(\alpha_1^T x_1) + \mathbf{Cov}(\alpha_2^T x_2) \\ &= \alpha_1^T \mathbf{Cov}(x_1) \alpha_1 + \alpha_2^T \mathbf{Cov}(x_2) \alpha_2 \\ &= \alpha_1^T \Sigma_1 \alpha_1 + \alpha_2^T \Sigma_2 \alpha_2\end{aligned}$$

▷ Closeness under linear combinations holds also for matrix combinations.

Closeness under conditioning

Let \mathbf{x} and \mathbf{y} be related random variables. Let $\mathbf{x}|\mathbf{y}_*$ denote the conditional distribution of \mathbf{x} given that a random variable \mathbf{y} has a fixed value \mathbf{y}_* . Then $\mathbf{x}|\mathbf{y}_*$ is distributed according to a multivariate normal distribution provided that (\mathbf{x}, \mathbf{y}) comes from a multivariate normal distribution $\mathcal{N}((\boldsymbol{\mu}_i), (\Sigma_{ij}))$

▷ Moment matching gives the parameters of the resulting distribution

$$\mathbf{E}(\mathbf{x}|\mathbf{y}_*) = \boldsymbol{\mu}_1 + \Sigma_{1,2}\Sigma_{2,2}^{-1}(\mathbf{y} - \boldsymbol{\mu}_2)$$

$$\mathbf{Cov}(\mathbf{x}|\mathbf{y}_*) = \Sigma_{1,1} - \Sigma_{1,2}\Sigma_{2,2}^{-1}\Sigma_{2,1}$$

Closeness under conditioning

Kalman filter

To be completed next year