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Machine Learning

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1 Introduction

A first definition of machine learning by T. Mitchell is the following one:

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

That is, machine learning builds a model that allows the computer to learn from experience, but does not solve the problem directly (as it's not always possible).

For a well-posed learning problem there a few key components:

- **Task:** For example recognising characters;
- **Performance measure:** to evaluate the learned system, that is the way the success of the predictors is measured (for example the number of misclassified characters).
- **Training experience:** to train the learning system, that is what is given to the system as experience E so that the algorithm can improve. The easiest way to do so is to give a training set made of couples.

1.1 Designing a machine learning system

The following steps should be followed when designing a machine learning system:

- Formalize the learning task;
- Collect data;
- Extract features;
- Choose class of learning models;
- Train model;
- Evaluate model.

1.1.1 Formalize the learning task

As a first step, it's important to define the task that the learning system should address, for example recognizing handwritten characters.

Often the main task can be divided in smaller tasks such that the problem gets easier to be solved. Considering the example before, it could be split in:

- Segment the image into words and then each word into characters.
- Identify the language of the writing.

- Classify each character into the language alphabet.

At last to define the task, one should also choose an appropriate performance number for evaluating such system, for example the number of misclassified characters could be a good performance measure.

1.1.2 Collect data

Since the machine learning system needs to learn from something, we need a so called training set, that is a set of example written in a *machine readable format*.

For such reason, often the data require some manual intervention, for example in labelling, in order to have a so called supervised learning, that is the training set is formed of a couple containing the initial data and also the correct result that the system should get. This, though, could be quite expansive to be achieved so a much cheaper learning mode is being used, the so called semi-supervised learning, where supervised data is mixed to data which does not have the expected result nor it's labeled.

1.1.3 Extract features

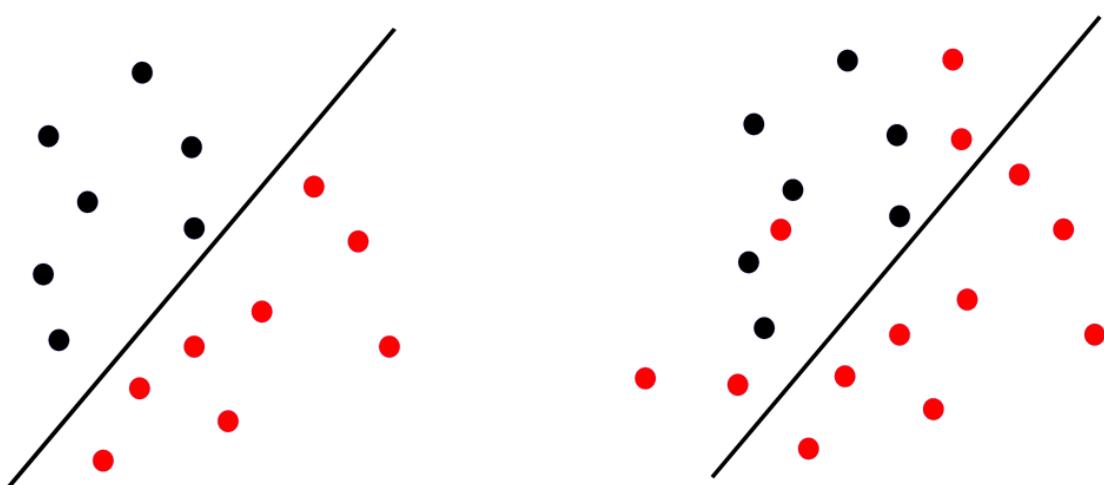
Not all the data that is given is really useful and instead sometime is harmful. For this reason a relevant set of feature should be extracted from all the data, that is fundamental information for the input in order for the algorithm to give the correct solution. To do this the best way possible, some prior knowledge is usually necessary.

Mind that:

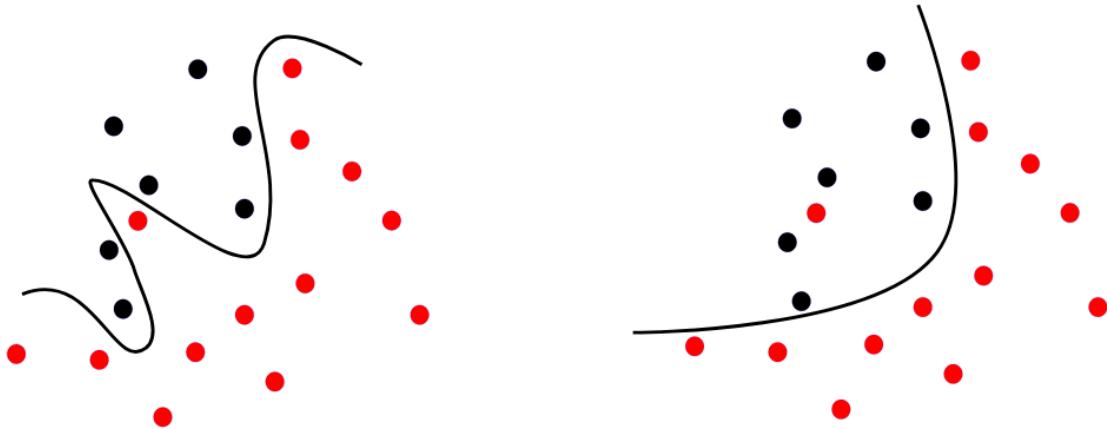
- Too few features could miss some relevant information preventing the system from learning in a correct way.
- Too many feature could heavy the system too much and the training phase could take a lot of time.
- Including noisy features complicates the training phase as the algorithm needs to learn to avoid these.

1.1.4 Model class

Many model classes are available and choosing the best one is important. For example a binary classification, that is a simple linear model that separates data in to two classes.



We call features all the points, that is the example given, and classes the colors, that is the supposed result of the algorithm. It's easy to notice that a binary classifier works as a separator that is a feature can have a class or another. Not always is possible to define a linear function that separates the features, so in some cases a more complex model can be used.



It's possible to notice that in this case the red feature in the middle of all the black ones introduce a lot of noise. Mind that we still are in a training phase and we do not mind for some false positive or negatives, we want our system to be good in real life not in the training set. If now a complex model is designed, such as the one on the left, the system doesn't learn how to recognize noise and to get rid of it. This problem is called overfitting and should be avoided.

Quindi non vogliamo che il nostro sistema semplicemente memorizzi i dati del training, ma che riesca a generalizzarli.

1.1.5 Learning settings

We have already talked about possible types of learning, such as supervised or semi-supervised learning, but they are not all that there is.

- **Supervised learning:** the learner is given a series of pairs where one element is input and one is the correct output. What the algorithm should do is to learn a function f that maps each input to output. Formally given a set of inputs \mathcal{X} and outputs \mathcal{Y} , the learner is provided with couples $(x_i, y_i) \in \mathcal{X} \times \mathcal{Y}$ in order to create a *model* $f : \mathcal{X} \mapsto \mathcal{Y}$. Since each example needs to have a correct output, usually a domain expert is involved in *labelling* the couples.
- **Unsupervised learning:** the learner is provided with a set of input examples \mathcal{X} but without any labelling information, that is no output. In this case the learner models training examples, for instance grouping examples into clusters according to their similarity.
- **Semi-supervised learning:** this stays in the middle of the former. As in supervised learning, the learner is provided with a set of input/output pairs: $(x_i, y_i) \in \mathcal{X} \times \mathcal{Y}$. The difference is that the set of inputs is usually much larger than the outputs one providing additional unlabelled examples. As in supervised learning the goal is to find a model f that maps input into outputs: $f : \mathcal{X} \mapsto \mathcal{Y}$. The unlabelled data is exploited in order to improve performance, for example by forcing the model to produce similar outputs for similar inputs.

- **Reinforcement learning:** in this type of learning, the actor is not provided anymore with inputs and outputs, but is given a set of possible states \mathcal{S} and a set of possible actions \mathcal{A} that allows it to move to the next state. When the learner performs an action a from a state s , it is given a reward $r(s, a)$. The task is to learn a policy allowing to choose for each state s the action a maximizing the overall reward. One problem is that the reward may not always be immediate but instead might be delayed. If this is the case, the learner needs to find the right trade-off between exploitation and exploration. An example of delayed reward is chess where the learner knows its reward only at the end.

1.1.5.1 Choice of learning algorithm

The choice of the algorithm to use is based on the knowledge we have of the data:

- Full knowledge of probability distribution of data: Bayesian decision theory.
- Form of probabilities known, parameters unknown: parameter estimation from training data.
- Form of probabilities unknown, training examples available: do not model input data (generative methods), learn a function predicting the desired output given the input.
- Form of probabilities unknown, training examples unavailable (only inputs): unsupervised methods, cluster examples by similarity.

1.1.5.2 Learning tasks

For what concerns the supervised learning, possible tasks are:

- *Binary:* it's the easiest task, or the element belongs to a class, or to the other.
- *Multiclass:* an element can belong to one of the set of the class.
- *Multilabel:* given n possible classes, the example can be assigned to a subset of $m \leq n$ classes.
- *Regression:* in this case a real value is predicted, for example the biodegradation rate of a molecular compound.
- *Ordinal regression* (ranking): a set of examples is ordered according to their relative importance with respect to the task, for example ordering email according to their urgency.

For what concerns unsupervised learning:

- *Clustering:* data is divided into groups in order to have homogeneous elements in each group and so that each group is enough different from the others.
- *Dimensionality reduction:* in this case there are many features and the aim is to reduce their dimensionality maintaining as much information as possible.
- *Novelty detection:* given a certain distribution of data, the aim of this task is to find all the elements that are novel, that is don't respect the distribution. This approach is used for example in network traffic analysis in order to detect anomalous traffic that indicates a possible attack.

1.1.6 Train Model

Training a model implies searching through the space of possible models (aka hypotheses) given the chosen model class.

Such search typically aims at fitting the available training examples well according to the chosen performance measure.

However, the learned model should perform well on unseen data, **generalization**, and not simply memorize training examples, **overfitting**.

Different techniques can be used to improve generalization, usually by trading off model complexity with training set fitting.

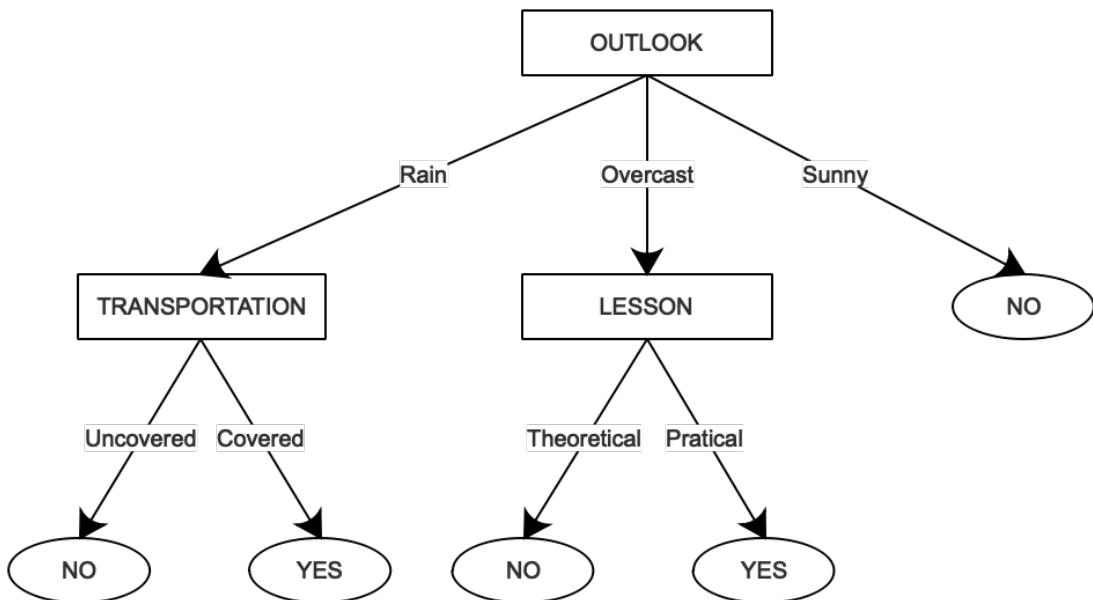
1.1.7 Evaluate Model

Once a fitting model is found, it needs to be evaluated on its ability to generalize to unseen examples.

For this reason there is the need to have a set of data that is different from the training one. Usually from a unique dataset, two are derived, one for training and one for evaluation.

2 Decision tree learning

From data is sometime possible to build a tree of features that allows to find an item's target value: given an example, with respect to the values the example assumes for each feature, it's possible to build a path which will lead to a leaf, that is a label.



A tree is a disjunction of conjunctions of constraints over attribute values, that is it express a disjunction normal form. Each path from the root to a leaf is a conjunction of the constraints specified in the nodes along it, e.g., if it's cloudy and the lesson is theoretical, then a student is not going to go to the lesson.

$$\text{OUTLOOK} = \text{Overcast} \wedge \text{LESSON} = \text{Theoretical}$$

One of the strongest advantages of this model is its explainability: it's easy to know what the model does and what the outcome may be.

Such representation works best with binary and multiclass classification tasks, even though some extensions to regression also exists, for example exploiting means properties. Another field in which it works fine is with missing attribute, that is for example when some feature don't have any value.

2.1 Algorithm

The learning algorithm in this case is simply a greedy approach proposed by Quinlan: for each node, starting from the root:

1. Choose the best attribute to be evaluated;
2. Add a child for each attribute value;
3. Split node training set into children according to value of chosen attribute;
4. Stop splitting a node if it contains examples from a single class, or there are no more attribute to test.

The idea is to start with a whole training set and then choose the feature so that the set will become as parted as possible. We stop when the example in the training set are all of the same class or there are no more features to be tested.

2.1.1 Choosing the best attribute

The best strategy to choose the best attribute on which to split, is to use sets' **homogeneity**, which is based on the concept of **entropy**.

Definition 2.1: Entropy

Entropy is a measure of the amount of information contained in a collection of instances S which can take a number c of possible values:

$$H(S) = - \sum_{i=1}^c p_i \log_2(p_i)$$

Where p_i is the fraction of S taking value i .

Entropy is the way in which the increment of homogeneity is measured since it's based on the information contained in a set: if all the values inside the set are the same, then there is no information, otherwise if two values are one the opposite of the other, then there is maximum entropy since the probability of taking one or the other becomes 5%.

Given the entropy then it's possible to compute the **information** gain:

Definition 2.2: Information Gain

The information gain IG is the expected reduction in entropy obtained by partitioning a set S according to the value of a certain attribute A :

$$IG(S, A) = H(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} H(S_v)$$

The greater the difference (IG), the better it is.

2.1.2 Overfitting

With decision tree it's possible to end up with overfitting for example when from each set of n elements, only one element is selected at the time. In this way the leaves would just contain one example creating a complex tree and leading to overfitting.

So the goal is not to obtain pure leaves, but instead to have also leaves that can contains example not strictly from that class.

There are two ways to avoid this possibility in decision trees:

- **Pre-pruning:** decide whether to stop splitting a node even if it contains training example with different labels.
- **Post-pruning:** learn a full tree, risking overfitting, and then in case prune to remove subtrees. Usually this strategy is the one used.

Let's focus on the post-pruning strategy: for this we shall introduce a validation set, that is a set against which to test the trained model. Let's consider a full tree, then:

1. For each node in the tree: evaluate the performance on the validation set when removing the subtree rooted at it;
2. If all node removals worsen performance, then stop;
3. Choose the node whose removal has the best performance improvement;
4. Replace the subtree rooted at it with a leaf;
5. Assign to the leaf the majority label of all examples in the subtree;
6. Return to 1.

When no more improvements are obtained through pruning, then the pruning is finished. Obviously validation, training and test set must all have the same statistics.

2.2 Problem with decision tree

2.2.1 Discretization

A first problem with decision trees are continuous-valued attributes. One easy solution is to discretize the variable in order to be used in the internal nodes tests.

Discretization implies the usage of thresholds, which can be set in order to maximize the attribute quality criterion, e.g. information gain.

The procedure to achieve this is:

- Examples are sorted according to their continuous attribute values;
- For each pair of successive examples having different labels, a *candidate threshold* is placed at the average of the two attribute values.
- For each candidate threshold, the information gain is achieved splitting examples according to how it is computed;
- The threshold producing the higher information gain is used to discretize the attribute.

2.2.1.1 Example

Let's suppose that we want to accept a work based on the age via the following table:

age	class
23	y
27	y
34	n
38	n
35	y
32	n

As a first thing, ordering data can be a great deal:

age	class
23	y
27	y
32	n
34	n
35	y
38	n

Then a threshold can be chosen, for example in the point where the class changes, even if some other examples are present afterwards, so for example age=32 can be a threshold.

2.2.2 Alternative attributes test measures

Information gain has a problem: if for example the set contained people with an id, it would place each person into a leaf, because this would make the information gain as big as possible. Information gain works fine, but in some cases it divides too much.

In order to avoid the tree from becoming too much spread, it's possible to measure the entropy with respect to the attribute value instead of the class value:

$$H_A(S) = - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} \log_2 \frac{|S_v|}{|S|}$$

Bigger the entropy, bigger is the division the attribute is making of the tree.

Now instead of using the information gain, we could downweight it with respect to the new entropy and compute the **gain ratio**:

$$IGR(S, A) = \frac{IG(S, A)}{H_A(S)}$$

2.2.3 Missing values

At the beginning we said that decision trees could deal also with missing values. Let's suppose that at a certain node n we'd like to split on attribute A , but the example x of class $c(x)$ is missing its value for attribute A . Two solutions are possible:

- Simple: assign to x the most common attribute values among examples in n , or the most common of examples in n with class $c(x)$. This works in every condition, but it's not very performing.
- Complex: propagate x to each of the children of n with a fractional value equal to the proportion of example with the corresponding attribute value. This implies that at test time, for each candidate class, all fractions of the test example which reached a leaf with that class are summed, and the example is assigned the class with the highest overall value.

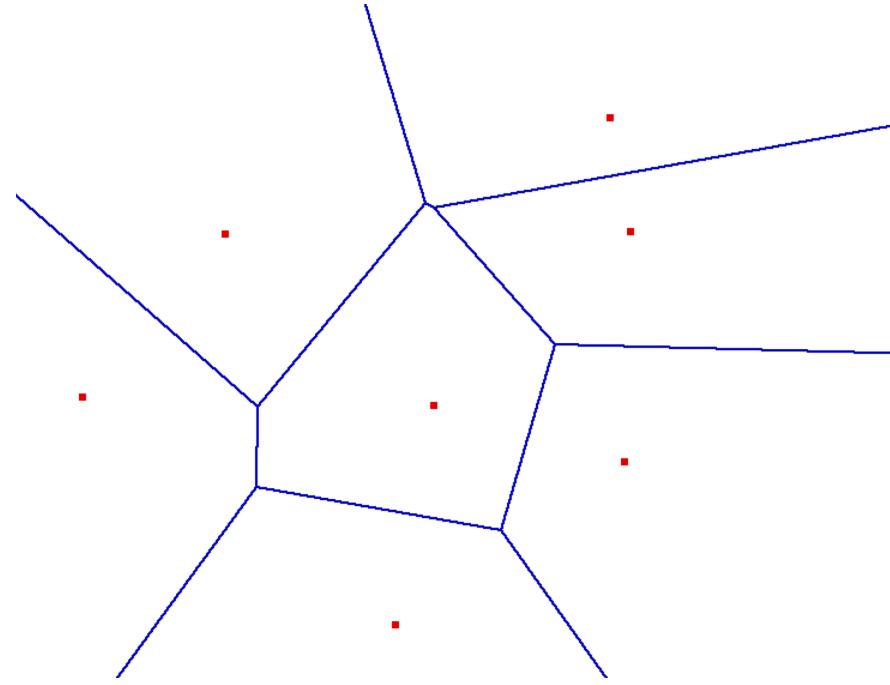
2.3 Random Forests

The decision trees are easy to be used, but not really great in terms of accuracy. An extension of the decision trees is random forests.

Given a set of N examples, sample N examples with replacement, that is the same example can be selected multiple times. Then train a decision tree on the sample, selecting at each node m features at random among which to choose the best one. Repeat this procedure multiple times to generate a forest with multiple trees.

As for the testing, each example is tested against each tree in the forest, and the majority class among the predictions is returned.

3 k-Nearest Neighbour Learning



Definition 3.1: Metrics

Given a set \mathcal{X} , a function $d : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}_0^+$ is a *metric* for \mathcal{X} if for any $x, y, z \in \mathcal{X}$ the following properties are satisfied:

1. **Reflexivity:** $d(x, y) = 0 \iff x = y;$
2. **Symmetry:** $d(x, y) = d(y, x);$
3. **Triangle inequality:** $d(x, y) + d(y, z) \geq d(x, z)$

A frequently used, and well-known, function d is the Euclidean distance defined in \mathbb{R}^n :

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

3.1 The algorithm

3.1.1 Classification problem

```

for all test examples x do
    for all training examples  $(x_i, y_i)$  do
        compute distance  $d(x, x_i)$ 
    end for
    select the k-nearest neighbours of x
    return class of x as majority class among neighbours:
         $\operatorname{argmax}_y \sum_{i=1}^k \delta(y, y_i)$ 
end for

```

Where

$$\delta(x, y) = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{otherwise} \end{cases}$$

3.1.2 Regression problem

```

for all test examples x do
    for all training examples  $(x_i, y_i)$  do
        compute distance  $d(x, x_i)$ 
    end for
    select the k-nearest neighbours of x
    return the average output value among neighbours:
         $\frac{1}{k} \sum_{i=1}^k y_i$ 
end for

```

3.2 Characteristics

- **Instance-based learning:** the model used for prediction is calibrated for the test example to be processed;
- **Lazy learning:** computation is mostly deferred to the classification phase;
- **Local learner:** assumes prediction should be mainly influenced by nearby instances;
- **Uniform feature weighting:** all features are uniformly weighted in computing distances.

4 Linear Algebra

Definition 4.1: Vector Space

A set \mathcal{X} is called a vector space over \mathbb{R} if addition and scalar multiplication are defined and, for all $\mathbf{x}, \mathbf{y}, \mathbf{z} \in \mathbb{X}$ and $\lambda, \mu \in \mathbb{R}$, satisfy the following properties:

- Addition:
 - *Associative*: $\mathbf{x} + (\mathbf{y} + \mathbf{z}) = (\mathbf{x} + \mathbf{y}) + \mathbf{z}$
 - *Commutative*: $\mathbf{x} + \mathbf{y} = \mathbf{y} + \mathbf{x}$
 - *Identity element*: $\exists 0 \in \mathcal{X} : \mathbf{x} + 0 = \mathbf{x}$
 - *Inverse element*: $\forall \mathbf{x} \in \mathcal{X} \exists \mathbf{x}' \in \mathcal{X} : \mathbf{x} + \mathbf{x}' = 0$
- Scalar multiplication:
 - *Distributive over elements*: $\lambda(\mathbf{x} + \mathbf{y}) = \lambda\mathbf{x} + \lambda\mathbf{y}$
 - *Distributive over scalars*: $(\lambda + \mu)\mathbf{x} = \lambda\mathbf{x} + \mu\mathbf{x}$
 - *Associative over scalars*: $\lambda(\mu\mathbf{x}) = (\lambda\mu)\mathbf{x}$
 - *Identity element*: $\exists 1 \in \mathbb{R} : 1\mathbf{x} = \mathbf{x}$

Definition 4.2: Subspace

A subspace is any non-empty subset of \mathcal{X} being itself a vector space.

Definition 4.3: Linear Combination

Given n scalars $\lambda_i \in \mathbb{R}$ and n vectors $\mathbf{x}_i \in \mathcal{X}$, their linear combination is:

$$\sum_{i=1}^n \lambda_i \mathbf{x}_i$$

Definition 4.4: Span

The span of vectors $\mathbf{x}_1, \dots, \mathbf{x}_n$ is defined as the set of their linear combinations:

$$\left\{ \sum_{i=1}^n \lambda_i \mathbf{x}_i, \lambda_i \in \mathbb{R} \right\}$$

Definition 4.5: Linear independency

A set of vectors \mathbf{x}_i is linearly independent if none of them can be written as a linear combination of the others.

Definition 4.6: Basis

A set of vectors \mathbf{x}_i is a basis for \mathcal{X} if any element in \mathcal{X} can be uniquely written as a linear combination of vectors \mathbf{x}_i .

A necessary condition for this to be true is that vectors \mathbf{x}_i are linearly independent. All bases of \mathcal{X} have the same number of elements, called the *dimension* of the vector space.

Definition 4.7: Linear Map

Given two vector spaces \mathcal{X}, \mathcal{Z} , a function $f : \mathcal{X} \rightarrow \mathcal{Z}$ is a linear map if all $\mathbf{x}, \mathbf{y} \in \mathcal{X}, \lambda \in \mathbb{R}$:

- $f(\mathbf{x} + \mathbf{y}) = f(\mathbf{x}) + f(\mathbf{y})$
- $f(\lambda \mathbf{x}) = \lambda f(\mathbf{x})$

A linear map between two finite-dimensional spaces \mathcal{X}, \mathcal{Z} , $\mathcal{X} \xrightarrow{f} \mathcal{Z}$ of dimensions n, m can always be written as a matrix of basis transformation:

$$M \in \mathbb{R}^{m \times n} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix}$$

Let $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ and $\{\mathbf{z}_1, \dots, \mathbf{z}_m\}$ be some bases for \mathcal{X} and \mathcal{Z} respectively. For any $\mathbf{x} \in \mathcal{X}$ we have that it can be written as the linear combination of vectors in the basis, hence:

$$f(\mathbf{x}) = f\left(\sum_{i=1}^n \lambda_i \mathbf{x}_i\right) = \sum_{i=1}^n \lambda_i f(\mathbf{x}_i)$$

Since there is a function f that maps values from \mathcal{X} to \mathcal{Z} , then:

$$f(\mathbf{x}_i) = \sum_{j=1}^m a_{ji} \mathbf{z}_j$$

Which leads to:

$$f(\mathbf{x}) = \sum_{i=1}^n \sum_{j=1}^m \lambda_i a_{ji} \mathbf{z}_j = \sum_{j=1}^m \left(\sum_{i=1}^n \lambda_i a_{ji} \right) \mathbf{z}_j = \sum_{j=1}^m \mu_j \mathbf{z}_j$$

In short:

$$M\lambda = \mu$$

Definition 4.8: Matrix Properties Transpose

Given a matrix M , the transposed matrix M^T is the matrix obtained by exchanging rows and columns. The transpose of the product of two matrixes M, N , is the product of the two transposed:

$$(MN)^T = N^T M^T$$

Definition 4.9: Matrix Properties Trace

The trace of a matrix M is the sum of the diagonal elements of the matrix:

$$tr(M) = \sum_{i=1}^n M_{ii}$$

Definition 4.10: Matrix Properties Inverse

The inverse matrix is a matrix that multiplies with the original matrix gives the identity:

$$MM^{-1} = I$$

Definition 4.11

Matrix Properties Rank The rank of a $n \times m$ matrix is the dimension of the space spanned by its columns.

The following properties for matrix derivation hold:

$$\begin{aligned}\frac{\partial M\mathbf{x}}{\partial \mathbf{x}} &= M \\ \frac{\partial \mathbf{y}^T M\mathbf{x}}{\partial \mathbf{x}} &= M^T \mathbf{y} \\ \frac{\partial \mathbf{x}^T M\mathbf{x}}{\partial \mathbf{x}} &= (M^T + M)\mathbf{x} \\ \frac{\partial \mathbf{x}^T M\mathbf{x}}{\partial \mathbf{x}} &= 2M\mathbf{x} \quad \text{if } M \text{ is symmetric} \\ \frac{\partial \mathbf{x}^T \mathbf{x}}{\partial \mathbf{x}} &= 2\mathbf{x}\end{aligned}$$

Definition 4.12: Norm

A function $\|\cdot\| : \mathcal{X} \rightarrow \mathbb{R}_0^+$ is a norm if for all $\mathbf{x}, \mathbf{y} \in \mathcal{X}, \lambda \in \mathbb{R}$:

- $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$
- $\|\lambda\mathbf{x}\| = |\lambda| \|\mathbf{x}\|$
- $\|\mathbf{x}\| > 0$ if $\mathbf{x} \neq 0$

A norm defines a metric $d : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}_0^+$:

$$d(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|$$

Definition 4.13: Bilinear Form

A function $Q : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ is a bilinear form if for all $\mathbf{x}, \mathbf{y}, \mathbf{z} \in \mathcal{X}, \lambda, \mu \in \mathbb{R}$:

- $Q(\lambda\mathbf{x} + \mu\mathbf{y}, \mathbf{z}) = \lambda Q(\mathbf{x}, \mathbf{z}) + \mu Q(\mathbf{y}, \mathbf{z})$
- $Q(\mathbf{x}, \lambda\mathbf{y} + \mu\mathbf{z}) = \lambda Q(\mathbf{x}, \mathbf{y}) + \mu Q(\mathbf{x}, \mathbf{z})$

Definition 4.14: Bilinear Form Symmetry

A bilinear form is said to be *symmetric* if $\forall \mathbf{x}, \mathbf{y} \in \mathcal{X}$:

$$Q(\mathbf{x}, \mathbf{y}) = Q(\mathbf{y}, \mathbf{x})$$

Definition 4.15: Dot Product

A dot product $\langle \cdot, \cdot \rangle : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ is a symmetric bilinear form which is positive semi-definite:

$$\langle \mathbf{x}, \mathbf{x} \rangle \geq 0 \quad \forall \mathbf{x} \in \mathcal{X}$$

A positive definite dot product defines a corresponding norm via:

$$\|\mathbf{x}\| = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle}$$

One main property of the dot product is:

$$\cos \theta = \frac{\langle \mathbf{x}, \mathbf{z} \rangle}{\|\mathbf{x}\| \|\mathbf{z}\|}$$

From which follow that if two vectors are **orthogonal**, that is $\theta = \frac{\pi}{2} + k\pi, k \in \mathbb{N}$, then, $\langle \mathbf{x}, \mathbf{z} \rangle = 0$. Moreover a set of vectors $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ is said to be **orthonormal** if, for all vectors $\mathbf{x}_i, \mathbf{x}_j$ in the set:

$$\langle \mathbf{x}_i, \mathbf{x}_j \rangle = \begin{cases} 1 & \text{if } i = j, \\ 0 & \text{otherwise.} \end{cases}$$

Definition 4.16: Eigenvalue and Eigenvector

Given an $n \times n$ matrix M , the real value λ and (non-zero) vector \mathbf{x} are an eigenvalue and corresponding eigenvector of M if:

$$M\mathbf{x} = \lambda\mathbf{x}$$

Definition 4.17: Singular Matrix

A matrix is singular if it has a zero eigenvalue:

$$M\mathbf{x} = 0\mathbf{x} = 0$$

A singular matrix has linearly dependent columns:

$$\begin{bmatrix} M_1 & \dots & M_{n-1} & M_n \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_{n_1} \\ x_n \end{bmatrix} = 0$$

$$M_1 x_1 + \dots + M_{n-1} x_{n-1} + M_n x_n = 0$$

$$M_n = M_1 \frac{-x_1}{x_n} + \dots + M_{n-1} \frac{-x_{n-1}}{x_n}$$

The determinant $|M|$ of a $n \times n$ matrix M is the product of its eigenvalues.

Since a matrix is invertible if its determinant is not zero, then it must not be singular.

We said that the eigenvalue and eigenvector of a matrix are a value and a vector such that:

$$A\mathbf{x} = \lambda \mathbf{x}$$

Trying to solve for λ we obtain:

$$\frac{\mathbf{x}^T A \mathbf{x}}{\mathbf{x}^T \mathbf{x}} = \lambda \frac{\mathbf{x}^T \mathbf{x}}{\mathbf{x}^T \mathbf{x}}$$

Definition 4.18: Raleigh quotient

$$\lambda = \frac{\mathbf{x}^T A \mathbf{x}}{\mathbf{x}^T \mathbf{x}}$$

5 Probability

5.1 Discrete

Definition 5.1: Probability Mass Function

Given a discrete random variable X taking values in $\mathcal{X} = \{v_1, \dots, v_m\}$, its probability mass function $P : \mathcal{X} \rightarrow [0, 1]$ is defined as:

$$P(v_i) = \Pr[X = v_i]$$

And satisfies the following conditions:

- $P(x) \geq 0$
- $\sum_{x \in \mathcal{X}} P(x) = 1$

So a variable is said to be discrete if it can assume m possible values $\{v_1, \dots, v_m\}$ which are mutual exclusive and if all probability of the values to happen are non-negative and the sum of probabilities of the events must be 1.

Definition 5.2: Expected Value

The expected value of a random variable x , also known as *mean* or *average*, is:

$$\mathbb{E}[x] = \mu = \sum_{x \in \mathcal{X}} xP(x) = \sum_{i=1}^m v_i P(v_i)$$

The expected value is linear:

$$\mathbb{E}[\lambda x + \lambda' y] = \lambda \mathbb{E}[x] + \lambda' \mathbb{E}[y] \quad (5.1)$$

Definition 5.3: Variance

The variance of a random variable is the moment of inertia of its probability mass function:

$$\text{Var}[x] = \sigma^2 = \mathbb{E}[(x - \mu)^2] = \sum_{x \in \mathcal{X}} (x - \mu)^2 P(x)$$

Another important value is the standard deviation σ which indicates the typical amount of deviation from the mean.

The followings are properties of mean and variance:

- **Second moment:** it's similar to the expected value:

$$\mathbb{E}[x^2] = \sum_{x \in \mathcal{X}} x^2 P(x)$$

- It's possible to write the variance in term via the mean:

$$\text{Var}[x] = \mathbb{E}[x^2] - \mathbb{E}[x]^2$$

- The variance is *not* always linear, for example when the variable is multiplied by a scalar:

$$\text{Var}[\lambda x] = \lambda^2 \text{Var}[x] \quad (5.2)$$

- The variance of the sum of two variables corresponds to the sum of the variance *only* if the two variables are not *correlated*:

$$\text{Var}[x + y] = \text{Var}[x] + \text{Var}[y] \quad (5.3)$$

5.2 Discrete Probability Distribution

5.2.1 Bernoulli

This probabilistic distribution is used to model a binary event, that is an event that can only result in success or failure.

The probability p of an event x is the probability of success ($x = 1$), while the probability of failure ($x = 0$) is $1 - p$. The probability mass function is:

$$P(x, p) = \begin{cases} p & \text{if } x = 1 \\ 1 - p & \text{if } x = 0 \end{cases}$$

A scenarios that can be modelled using this distribution is for example the toss of a coin where head is success and tail is failure (or viceversa).

Theorem 5.1: Estimated Value – Bernoulli

$$\mathbb{E}[x] = p$$

Proof.

$$\begin{aligned} \mathbb{E}[x] &= \sum_{x \in X} x P(x) \\ \mathbb{E}[x] &= \sum_{x \in \{1, 0\}} x P(x) \\ \mathbb{E}[x] &= 0 \times (1 - p) + 1 \times p = p \end{aligned}$$

□

Theorem 5.2: Variance – Bernoulli

$$\text{Var}[x] = p(1 - p)$$

Proof.

$$\begin{aligned}\text{Var}[x] &= \mathbb{E}[(x - \mu)^2] = \\ &= \sum_{x \in X} (x - \mathbb{E}[x])^2 P(x) = \\ &= \sum_{x \in X} (x - p)^2 P(x) = \\ &= (0 - p)^2(1 - p) + (1 - p)^2 p = \\ &= p^2 - p^3 + (1 + p^2 - 2p)p = \\ &= p^3 - p^3 + p^2 + p - 2p^2 \\ &= \text{Var}[x] = p(1 - p)\end{aligned}$$

□

The Bernoulli probability can be expressed also via an analytic function which is often used in if-then-else cases:

$$p(x, p) = p^x(1 - p)^{1-x}$$

If $x = 1$ then only the first term remains, resulting in $p(x, p) = p$, while if $x = 0$, then what remains is: $p(x, p) = 1 - p$

5.2.2 Binomial

Bernoulli distribution can be generalized with more than two events: this distribution models the probability of having a certain number of successes in n independent Bernoulli trials.

The parameter of this distribution are p has the probability of a success, and n as the number of trials.

The probability mass function is:

$$P(x; p, n) = \binom{n}{x} p^x (1 - p)^{n-x}$$

Which represents the probability of success for x trials and can be seen as the Bernoulli distribution applied to all trials.

An example of event that can be modelled with this distribution is the toss of a coin for n times and trying to guess the probability of having x heads.

Mean and variation are:

$$\mathbb{E}[x] = np \quad \text{Var}[x] = np(1 - p)$$

That is the same as the Bernoulli distribution but multiplied for the n tests.

5.2.3 Joint Probability

If two random variables are given instead of one, then the model must be different since they may not be independent.

Definition 5.4: Joint Probability

Given a pair of discrete random variables X, Y taking values $\mathcal{X} = \{v_1, \dots, v_m\}, \mathcal{Y} = \{w_1, \dots, w_n\}$, the joint probability mass function is defined as:

$$P(v_i, w_i) = \Pr[X = v_i, Y = w_i]$$

With properties:

- $P(x, y) \geq 0$
- $\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} P(x, y) = 1$

The characteristics of this function are:

- *Expected value*: since there are multiple random variables, then there will be one estimated value for each variable. Mind though that the mean for each variable is not simply the mean for that variable without considering the other variables, but is given by the sum of the value multiplied by the joint probability:

$$\mu_x = \mathbb{E}[x] = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} x P(x, y)$$

$$\mu_y = \mathbb{E}[y] = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} y P(x, y)$$

- *Variance*: as for the expected value, there will be one variance for each variable, and they will be computed based on the joint probability:

$$\sigma_x^2 = \text{Var}[(x - \mu_x)^2] = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} (x - \mu_x)^2 P(x, y)$$

$$\sigma_y^2 = \text{Var}[(y - \mu_y)^2] = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} (y - \mu_y)^2 P(x, y)$$

- *Covariance*: this is a statistics of how the random variables change at the change of another variable:

$$\sigma_{xy} = \mathbb{E}[(x - \mu_x)(y - \mu_y)] = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} (x - \mu_x)(y - \mu_y) P(x, y)$$

- *Correlation coefficient*: it is the normalization of the covariance with respect to the product of the variance:

$$\rho = \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$

5.2.3.1 Multinomial Distribution – One sample

Models the probability of a certain outcome for an event with $m > 2$ possible outcomes¹. With a multinomial distribution, there are m parameters p_1, \dots, p_m that indicate the probability

¹If $m = 2$, then it's simply a Bernoulli distribution.

of the j outcome to happen.

For example this model represents the tossing of a dice one time, where m is the number of faces of the dice and p_i is the probability of face i to exit.

Since only one sample is considered, then the mass function of this distribution becomes the probability of that event to happen:

$$P(x_1, \dots, x_m; p_1, \dots, p_m) = \prod_{i=1}^m p_i^{x_i} \quad (5.4)$$

Where if $x_i = 1$, then all other outcomes must be 0: $x_j = 0, j \neq i$. The expected value, the variance are the same as the Bernoulli's while the covariance is:

$$\mathbb{E}[x_i] = p_i \quad \text{Var}[x_i] = p_i(1 - p_i) \quad \text{Cov}[x_i, x_j] = -p_i p_j$$

5.2.3.2 Multinomial Distribution – General

As for the Bernoulli distribution, also for the multinomial there exists a general version with more samples.

Given n samples of an event with m possible outcomes, the general version models the probability of a certain distribution of outcomes.

For example the following scenario is modelled by a general multinomial distribution: the toss of a coin with m faces, each with p_i probability, n times.

The mass function of this distribution is:

$$P(x_1, \dots, x_m; p_1, \dots, p_m) = \frac{n!}{\prod_{i=1}^m x_i!} \prod_{i=1}^m p_i^{x_i}$$

As for the Bernoulli distribution and the binomial distribution, also in this case the statistics of the general distribution are the same as the one for one sample, just multiplied by n . The expected value, variance and covariance are:

$$\mathbb{E}[x_i] = np_i \quad \text{Var}[x_i] = np_i(1 - p_i) \quad \text{Cov}[x_i, x_j] = -np_i p_j$$

5.3 Conditional probabilities

In some cases we want to know the probability of an event to happen given that another event has happened. This is called *conditional probability*:

Definition 5.5: Conditional probability

The probability of x once y is observed:

$$P(x|y) = \frac{P(x, y)}{P(y)}$$

This implies the **product rule**:

Definition 5.6: Product rule

$$P(x, y) = P(x|y)P(y) = P(y|x)P(x)$$

This rule is useful because it allows to break down a joint probability into a combination of conditional probabilities.

Definition 5.7: Statistically independence

Two variable X and Y are said to be statistically independent if and only if:

$$P(x, y) = P(x)P(y) \quad (5.5)$$

This implies that if two variables X and Y are statistically independent, then:

$$P(x|y) = P(x) \quad P(y|x) = P(y)$$

Definition 5.8: Law of Total Probability

The *marginal distribution* of a variable is obtained from a joint distribution summing over all possible values of the other variable (*sum rule*):

$$P(x) = \sum_{y \in \mathcal{Y}} P(x, y) \quad P(y) = \sum_{x \in \mathcal{X}} P(x, y)$$

This means for example that considering a multinomial variable, it's possible to obtain its probability by removing it from the product and multiplying over the other values.

Definition 5.9: Bayes' Rule

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

Bayes' rule comes from the product rule and allows us to invert the dependency between two probabilities. In particular it allows to invert statistical connections between *effect(x)* and *cause(y)*:

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$

Mind that evidence can be obtained using the sum rule from likelihood and prior:

$$P(x) = \sum_y P(x, y) = \sum_y P(x|y)P(y)$$

These rules can be applied to more variables:

- **Sum rule:** $P(y) = \sum_x \sum_z P(x, y, z)$
- **Product rule:** apply the first rule more times, for example $P(x, y, z) = P(x|y, z)P(y|z)P(z) = P(x|y, z)P(y|z)P(z) = P(x, y, z) = P(x, y|z)p(z)$
- **Bayes' rule:** $P(y|x, z) = \frac{P(x|y, z)P(y|z)}{P(x|z)}$

Let's compute the probability of y applying these rules:

For the sum rule (aka law of total), we know that:

$$P(y) = \sum_x \sum_z P(x, y, z)$$

And for the product rule we know that:

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

Hence:

$$P(y) = \sum_x \sum_z P(y|x, z)P(x, z)$$

At last applying Bayes' rule to $P(y|x, z)$ we obtain:

$$P(y) = \sum_x \sum_z \frac{P(x|y, z)P(y|z)P(x, z)}{P(x|z)}$$

5.3.1 Example of style

Let's start from the following expression and apply the rules:

$$P(y|x, z)$$

First of all let's apply Bayes' rule:

$$P(y|x, z) = \frac{P(x, z|y)P(y)}{P(x, z)}$$

Consider the discriminator $P(x, z)$, it's possible to apply the product rule:

$$P(y|x, z) = \frac{P(x, z|y)P(y)}{P(x|z)P(z)}$$

Now let's focus on the term $P(x, z|y)$. We can imagine it to come from $P(x, z, y)$ to which was applied the product rule: $P(x, z, y) = P(x, z|y)P(y)$, but it's also true that $P(x, z, y) = P(x|z, y)P(z|y)P(y)$, and hence $P(x, z|y) = P(x|z, y)P(z|y)$. It's possible then to rewrite the before as:

$$P(y|x, z) = \frac{P(x|z, y)P(z|y)P(y)}{P(x|z)P(z)}$$

Now focus on $P(z|y)P(y)$, it's obvious that by reversing the product rule, it equals $P(z, y)$, which can be written also as $P(y|z)P(z)$ since $P(z, y) = p(y, z)$:

$$P(y|x, z) = \frac{P(x|z, y)P(y|z)P(z)}{P(x|z)P(z)}$$

At last it's possible to simplify $P(z)$:

$$P(y|x, z) = \frac{P(x|z, y)P(y|z)}{P(x|z)}$$

5.4 Continuos variable

It's not possible to represent continuous variables with mass function since even if it had a small value, for as small it can be, we are summing it infinite times making it infinite.

Let's consider a continuous variable X and let's consider some intervals: $W = (a < X \leq b)$, $A = (x \leq a)$, $B(X \leq b)$. It's possible to notice that W and A are mutually esclusive, hence it's possible to write:

$$P(B) = P(A) + P(W) \quad P(W) = P(B) - P(A)$$

Definition 5.10: Cumulative Distribution Function

A function $F(q)$ that models the probability of a continuous variable of having a value less or equal to q is called cumulative distributed function:

$$F(q) = P(X \leq q)$$

Mind that this is a monotonic function non decreasing: if the interval is enlarged, or it stays the same or it increases.

It's possible to get the probability of intervals by computing the difference between the cumulative distribution functions of the extremities:

$$P(a < X \leq b) = F(b) - F(a)$$

Definition 5.11: Probability Density Function

The derivative of the cumulative distribution function is called probability density function and it represents the probability in a single point:

$$p(x) = \frac{d}{dx} F(x)$$

The cumulative distribution can also be computed from the density function integrating:

$$F(q) = P(X \leq q) = \int_{-\infty}^q p(x) dx$$

The following are properties of the density function:

- $p(x) \geq 0$: which implies that the density probability can also be greater than 1;
- $\int_{-\infty}^{\infty} p(x) dx = 1$: even if the density function can be grater than 1, the total integral over the possible values is 1.

Let's consider the following density distribution, the uniform distribution over $[a, b]$:

$$p(x) = Unif(x; a, b) = \frac{1}{b-a}$$

For $a = 0, b = 1/2$, then $\forall x \in [0, 1/2], p(x) = 2$. Let's now check the value of the integral:

$$F(0 < x \leq 1/2) = \int_{-\infty}^{1/2} p(x) dx = \int_a^b p(x) dx = \int_0^{1/2} 2 dx = [2x]_0^{1/2} = 2 * \frac{1}{2} - 2 * 0 = 1$$

The expected value of a continuous variable, is computed as the integral of the product of the variable value by its probability:

$$E[x] = \mu = \int_{-\infty}^{\infty} xp(x)dx$$

Notice the similarity with the discrete value, only instead of the sum, an integral is used, as can be expected. It should come as no surprise then, the expression for the variance:

$$\text{Var}[x] = \sigma^2 = \int_{-\infty}^{\infty} (x - \mu)^2 p(x)dx$$

5.4.1 Gaussian – Normal

It is described in terms of μ and σ^2 which are its parameters.

Its density function is:

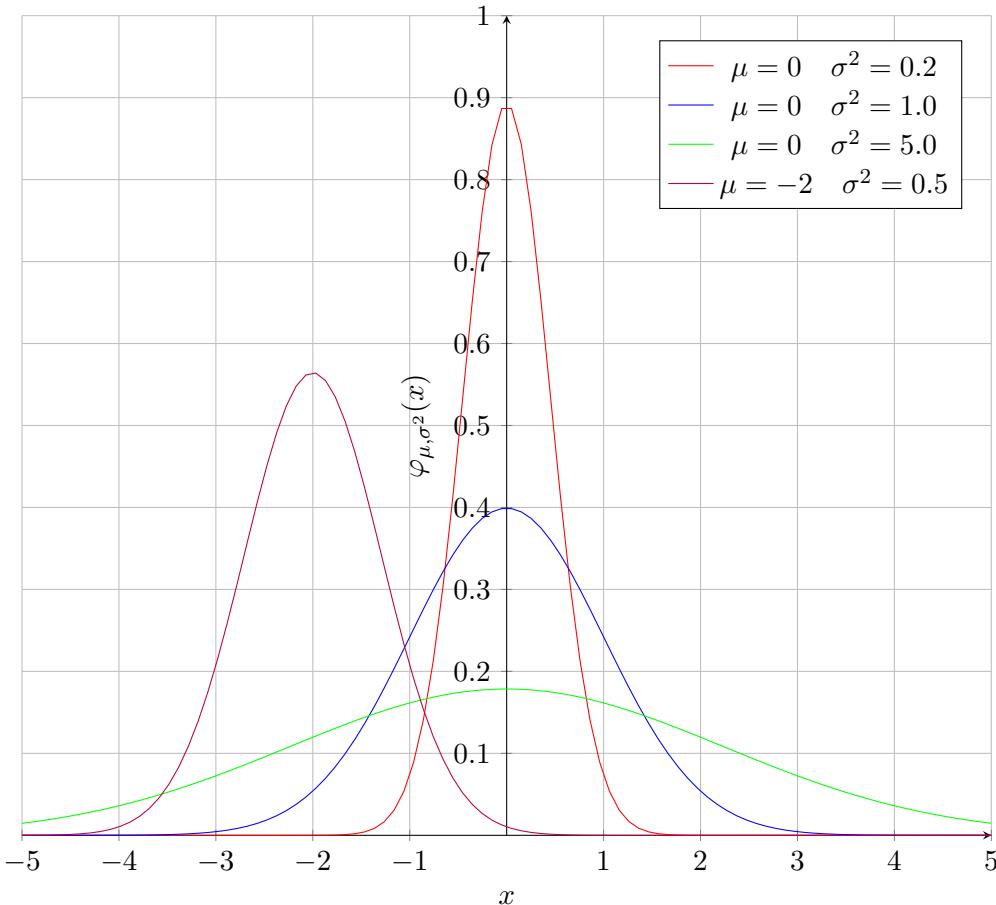
$$p(x; \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right) \quad (5.6)$$

Where the term $\frac{(x - \mu)^2}{2\sigma^2}$ is called standardisation of a normal distribution: $N(\mu, \sigma^2)$, and what it does is basically translate the bell shape and normalize it.

The standard normal distribution is a Gaussian distribution with mean 0 and variance 1.

As it can be expected, the expected value and the variance of the gaussian are μ and σ^2 respectively:

$$E[x] = \mu \quad \text{Var}[x] = \sigma^2$$



5.4.2 Beta Distribution

The Beta² distribution is defined inside the interval $[0, 1]$.

It is based on parameters α, β which let the density function vary as follows:

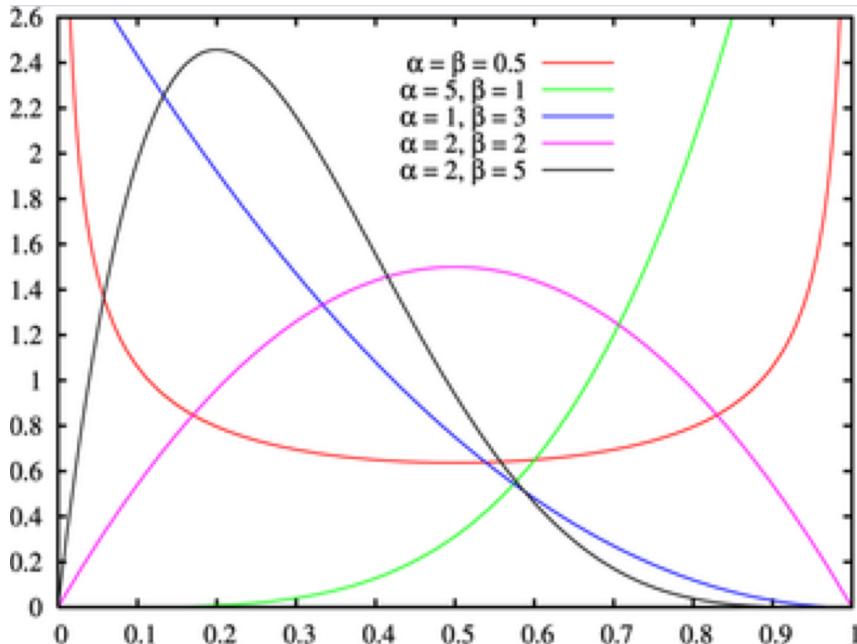
$$p(x; \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} \quad (5.7)$$

This distribution can model for example the following scenario: we have a Bernoulli distribution, but no probability distribution for the event to happen is given. Such distribution can be modelled via a Beta distribution, making this a probability of the second order.

Notice that the terms $x^{\alpha-1}, (1-x)^{\beta-1}$ reminds of the binomial one, the beta distribution models the posterior distribution of parameter p of a binomial distribution after observing $\alpha - 1$ independent events with probability p and $\beta - 1$ events with probability $1 - p$.

The expected value and variation are:

$$\mathbb{E}[x] = \frac{\alpha}{\alpha + \beta} \quad \text{Var}[x] = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} \quad (5.8)$$



5.4.3 Multivariate Normal Distribution

This is a normal distribution for d -dimensional vectorial data. For this reason the parameters are μ , a vector containing the means, Σ a covariance matrix.

It's possible to rewrite the gaussian distribution with the new data by exploiting matrices:

$$p(\mathbf{x}; \mu, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} e^{-\frac{1}{2} (\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu)} \quad (5.9)$$

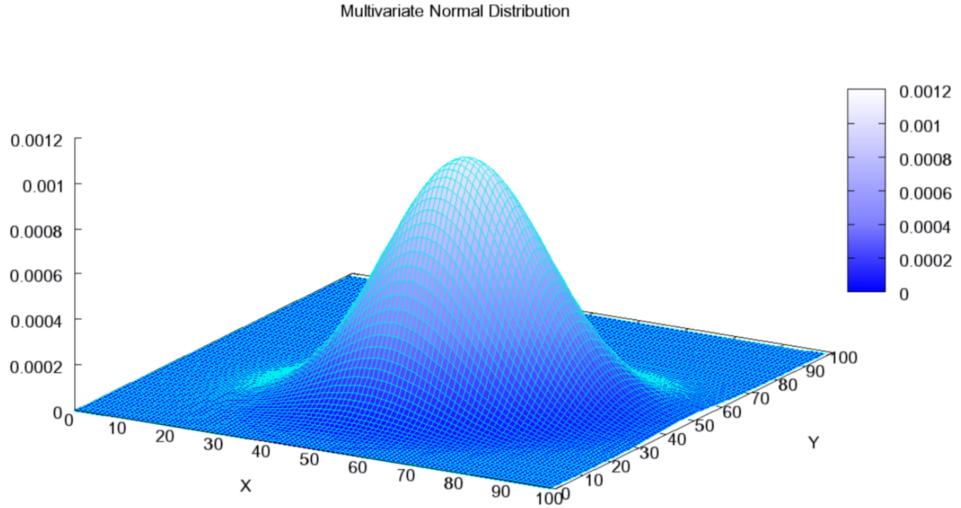
The term

$$r^2 = (\mathbf{x} - \mu)^T \Sigma^{-1} (\mathbf{x} - \mu) \quad (5.10)$$

is called Mahalanobis distance and is the generalization of the euclidean distance with respect to the covariance of data. r^2 measures the distance from the mean μ .

²Pronounced /bit/.

The expected value is actually the expected one: $E[x] = \mu$, while the variance is actually the covariance parameters: $\text{Var}[x] = \Sigma$.



5.4.4 Dirichlet Distribution

The beta distribution is used to model for example the probability of a binary event. Obviously it can be generalized to the Dirichlet distribution, which is nothing less the continuous version of the multinomial distribution. The Dirichlet distribution allows to model the probability of an event with more than two possible results.

The Dirichlet distribution is defined for $\mathbf{x} \in [0, 1]^m$, $\sum_{i=1}^m x_i = 1$, that is, given m possible outcomes, x_1, \dots, x_m , the sum of all the outcomes must be 1.

It is parametrized over $\boldsymbol{\alpha} = \alpha_1, \dots, \alpha_m$.

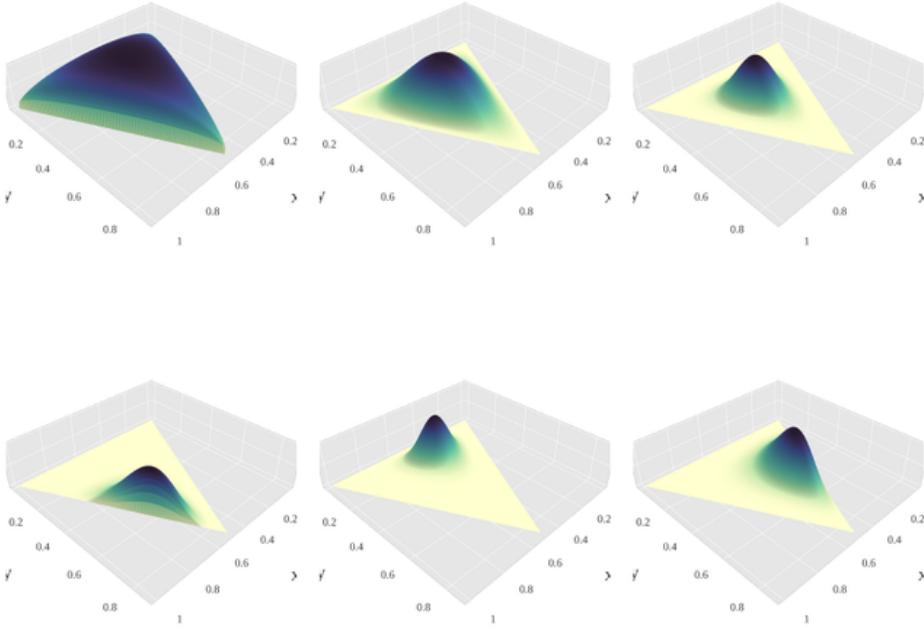
The probability density function is:

$$p(x_1, \dots, x_m; \boldsymbol{\alpha}) = \frac{\Gamma(\alpha_0)}{\prod_{i=1}^m \Gamma(\alpha_i)} \prod_{i=1}^m x_i^{\alpha_i - 1} \quad (5.11)$$

Where $\alpha_0 = \sum_{j=1}^m \alpha_j$. The expected value and variance are the followings:

$$E[x_i] = \frac{\alpha_i}{\alpha_0} \quad \text{Var}[x_i] = \frac{\alpha_i(\alpha_0 - \alpha_i)}{\alpha_0^2(\alpha_0 + 1)} \quad \text{Cov}[x_i, x_j] = \frac{-\alpha_i \alpha_j}{\alpha_0^2(\alpha_0 + 1)} \quad (5.12)$$

This distribution models the posterior distribution of parameters \mathbf{p} of a multinomial distribution after observing $\alpha_i - 1$ times each mutually exclusive event.



5.5 Probability Laws

5.5.1 Expectation and Variance of an Average

Consider a sample of X_1, \dots, X_n *independent and identical distributed* (iid) instances drawn from a distribution with mean μ and variance σ^2 .

Consider the random variable \bar{X}_n measuring the sample average:

$$\bar{X}_n = \frac{X_1 + \dots + X_n}{n}$$

Its expectation is computed as:

$$E[\bar{X}_n] = E\left[\frac{1}{n}(X_1 + \dots + X_n)\right]$$

Now recall that the expected value is linear (Equation 5.1), hence it can be rewritten as:

$$E[\bar{X}_n] = \frac{1}{n}(E[X_1] + \dots + E[X_n])$$

Since $E[X_i] = \mu$, then we have:

$$E[\bar{X}_n] = \frac{1}{n}(\mu + \dots + \mu) = \frac{1}{n} * n\mu = \mu$$

That is the expectation of an average is the true mean of the distribution.

Now let's consider the variance which though is not linear with respect to scalars (Equation ??), while it behaves linear when summing variances (Equation 5.3). It's possible to write the variance of \bar{X}_n as:

$$\text{Var}[\bar{X}_n] = \frac{1}{n^2}(\text{Var}[X_1] + \dots + \text{Var}[X_n]) = \frac{\sigma^2}{n}$$

From this is possible to notice that the variance of the average decreases with the number of observation: the more examples are taken into consideration, the more likely estimating the correct average is.

5.5.2 Chebyshev's Inequality

Consider a random variable X with mean μ and variance σ^2 . The Chebyshev's inequality states that for all $a > 0$:

$$\Pr[|X - \mu| \geq a] \leq \frac{\sigma^2}{a^2}$$

Replacing a with $k\sigma$, $k > 0$ we obtain:

$$\Pr[|X - \mu| \geq k\sigma] \leq \frac{1}{k^2}$$

Chebyshev's inequality shows that most of the probability mass of a random variable stays within few standard deviations from its mean.

5.6 The Law of Large Numbers

Let's suppose to have some phenomenon to model and the distribution was not observed in its entirety, but only n events, for example we register only if rains for some days. Let's suppose also that the events are *identically distributed* since they come from the same phenomenon and that they are also independent which implies that the outcome of an event does not affect other events.

Our goal is to evaluate the average and the variance observing the data at our disposal.

Consider a sample of X_1, \dots, X_n iid instances drawn from a distribution with mean μ and variance σ^2 .

We have already shown in the previous sections that the expected value of iid samples of mean μ is actually μ , now it's possible to show through the Chebyshev's inequality that the probability that the sample-mean drifts away from the actual mean of a little value

epsilon decreases at the increasing of the number of samples. This implies that the accuracy of an empirical statistic increases with the number of samples.

$$\Pr[|\bar{X}_n - \mathbb{E}[\bar{X}_n]| \geq \epsilon] \leq \frac{\sigma^2}{n\epsilon^2}$$

$$\lim_{n \rightarrow \infty} \Pr[|\bar{X}_n - \mu| \geq \epsilon] = 0$$

5.6.1 Central Limit Theorem

Definition 5.12: Central Limit Theorem

The sum of a sufficiently large sample of iid random measurement is approximately normally distributed.

This means that if we have a number n of samples sufficiently large, with mean μ and variance σ^2 , we don't need to know the form of their distribution, because they can be modelled through a normal gaussian.

Questo significa che se abbiamo molti dati, se non conosciamo la distribuzione dei dati, allora la possiamo considerare questa distribuzione come una normale.

5.7 Information theory

5.7.1 Entropy

Consider a set of symbols $\mathcal{V} = \{v_1, \dots, v_n\}$ with mutually exclusive probabilities $P(v_i)$. The goal is to design a binary code for each symbol minimizing the average length of messages. In 1949 Shannon and Weaver proved that the optimal code assigns to each symbol v_i a number of bits equal to:

$$-\log P(v_i)$$

Definition 5.13: Entropy

The entropy of a set of symbols is the **expected value** length of a message encoding a symbol assuming such optimal coding:

$$H[\mathcal{V}] = E[-\log P(v)] = - \sum_{i=1}^n P(v_i) \log P(v_i)$$

If all symbols have the same probability, then the entropy is maximized, while if the symbols have very much different probabilities, then the entropy becomes 0.

5.7.2 Cross entropy

Definition 5.14: Cross Entropy

Given two distributions P and Q over a variable X , the cross entropy between P and Q measures the expected number of bits needed to code a symbol sampled from P using Q instead:

$$H(P; Q) = E_P[-\log Q(v)] = - \sum_{i=1}^n P(v_i) \log Q(v_i)$$

This is often used as a loss function for binary classification, with P (empirical) true distribution and Q (empirical) predicted distribution.

5.7.3 Relative Entropy

Definition 5.15: Relative Entropy

Given two distribution P, Q over a variable X , the relative entropy (or *Kullback-Leibler divergence*) measures the expected length difference when coding instances samples from P using Q instead:

$$D_{KL}(p\|q) = \sum_{i=1}^n P(v_i) \log \frac{P(v_i)}{Q(v_i)}$$

This can be derived as follows:

$$\begin{aligned}
D_{KL}(p\|Q) &= H(P; Q) - H(P) \\
&= \mathbb{E}_P[-\log Q(v)] - \mathbb{E}[-\log P(v)] \\
&= -\sum_{i=1}^n P(v_i) \log Q(v_i) + \sum_{i=1}^n P(v_i) \log P(v_i) \\
&= \sum_{i=1}^n [P(v_i) \log P(v_i) - P(v_i) \log Q(v_i)] \\
&= \sum_{i=1}^n P(v_i) (\log P(v_i) - \log Q(v_i)) \\
&= \sum_{i=1}^n P(v_i) \log \frac{P(v_i)}{Q(v_i)}
\end{aligned}$$

5.7.4 Conditional entropy

Definition 5.16: Conditional Entropy

Given two variables V, W with possibly different distributions P , the conditional entropy is the entropy remaining for variable W once V is known:

$$\begin{aligned}
H(W|V) &= \sum_v P(v) H(W|V=v) \\
&= -\sum_v P(v) \sum_w P(w|v) \log P(w|v)
\end{aligned}$$

This says that, the more we know about V , the more is the entropy of W , and viceversa.

5.7.5 Mutual Information – Information Gain

Definition 5.17: Information Gain

Given two variables V, W with (possibly different) distributions P , the mutual information, or information gain, is the reduction in entropy for W once V is known:

$$\begin{aligned}
I(W; V) &= H(W) - H(W|V) \\
&= -\sum_w p(w) \log p(w) + \sum_v P(v) \sum_w P(w|v) \log P(w|v)
\end{aligned}$$

The information gain is the reduction of entropy on W once V is known. This can be used, for example, when deciding which attribute is best to select when building a decision tree, where V is the attribute and W is the label.

6 Bayesian Decision Theory

We are not yet to the point of taking decision. Bayesian decision *theory* allows to take optimal decisions in a fully probabilistic way.

It allows to provide an upper bounds on achievable errors and evaluate classifiers accordingly. Moreover bayesian reasoning can be generalized to cases when the probabilistic structure is not entirely known.

From now on we will be using $P(x)$ for mass functions and $p(x)$ for distribution functions or unknowns.

6.1 Bayes decision Rule

Let's consider a binary classification. Assume of having examples $(x, y) \in \mathcal{X} \times \{-1, 1\}$ drawn from a known distribution $p(x, y)$. The task is predicting the class y of examples given the input x , which can be done via Bayes' rule (Definition 5.9):

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

Bayes rule allows to compute the posterior probability given likelihood, prior and evidence:

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{evidence}}$$

Where:

- **posterior** $P(y|x)$ is the probability that the class is y given that x was observed;
- **Likelihood** $p(x|y)$ is the probability of observing x given that its class is y ;
- **Prior**: $P(y)$: is the prior probability of the class, without any evidence;
- **Evidence**: $p(x)$ is the probability of the observation, and by the law of total probability -sum rule (Definition 5.8), and the product rule (Definition 5.6), it can be computed as:

$$p(x) = \sum_{i=1}^2 p(x|y_i)P(y_i)$$

When taking decision it's possible to commit mistake, for this reason we want to know the probability of making mistakes.

The probability of an error can be expressed as the probability of the error given x on all possible values of y . For example when considering the binomial, then

$$P(\text{error}|x) = \begin{cases} P(y_2|x) & \text{if we decide } y_1 \\ P(y_1|x) & \text{if we decide } y_2 \end{cases}$$

For the sum rule (Definition 5.8), the average error can be expressed as:

$$P(\text{error}) = \sum_x P(\text{error}, x)$$

And by the product rule (Definition 5.6), it can be expanded to:

$$P(\text{error}) = \sum_x P(\text{error}|x)p(x)$$

This is for the discrete case, if the variable were to be continuous, then the formula would be:

$$P(\text{error}) = \int_{-\infty}^{\infty} P(\text{error}|x)p(x)dx$$

Based on the error probability value, a decision can be made in order to minimize the error maximize the probability of success. This rule is called Bayes Decision Rule and is divided in two cases; the first one is for binary classification:

$$y_B = \operatorname{argmax}_{y_i \in \{-1,1\}} P(y_i|x) = \operatorname{argmax}_{y_i \in \{-1,1\}} p(x|y_i)P(y_i) \quad (6.1)$$

Mind that by the Bayes Rule (Definition 5.9) the last expression should have $p(x)$ at the denominator, but this doesn't change with the changing of y_i , hence it can be removed.

A second case is the multiclass case:

$$y_B = \operatorname{argmax}_{y_i \in \{1, \dots, c\}} P(y_i|x) = \operatorname{argmax}_{y_i \in \{1, \dots, c\}} p(x|y_i)P(y_i) \quad (6.2)$$

The **optimal rule** says that the probability of error given x :

$$P(\text{error}|x) = 1 - P(y_B|x)$$

Hence, the Bayes Decision Rule *minimizes* the probability of error.

6.2 Representing Classifiers

So when we are making a decision, that is trying to classify an input, we are trying to maximize the probability a posteriori. To execute the classification, a *classifier* is used, that is a function, or more that we hope are as similar to the reality as they can be.

A classifier can be represented as a set of **discriminant functions** $g_i(\mathbf{x})$, $i \in \{1, \dots, c\}$, where c is the number of classes. For such reason, the Bayes optimal rule can be rewritten as:

$$y = \operatorname{argmax}_{i \in \{1, \dots, c\}} g_i(\mathbf{x})$$

By comparison with Equation 5.3, we have:

$$\begin{aligned} g_i(\mathbf{x}) &= P(y_i|\mathbf{x}) = \frac{p(\mathbf{x}|y_i)P(y_i)}{p(\mathbf{x})} \\ &= p(\mathbf{x}|y_i)P(y_i) \end{aligned}$$

Which by the rule of logarithms can be rewritten as:

$$g_i(\mathbf{x}) = \ln p(\mathbf{x}|y_i) + \ln P(y_i)$$

With these discriminant functions, the features space is divided into decisions regions $\mathcal{R}_1, \dots, \mathcal{R}_c$ such that:

$$\mathbf{x} \in \mathcal{R}_i \quad \text{if } g_i(\mathbf{x}) > g_j(\mathbf{x}) \quad \forall j \neq i$$

Decision regions are separated by **decision boundaries**, that is regions in which ties occur among the the discriminant functions and hence the classifier is ambiguous.

Let's suppose to have two features (ω_1 and ω_2) and to divide the space via two discriminant functions, hence binary. The most common choice to model likelihood is using gaussians which allows to have a multivariate normal distribution. From Figure 6.1 it's possible to notice the gaussians functions which has two peaks which represents the values for which the class will be chosen. For some values of x , the value of g will be the same, hence the decision boundaries. Let's first recall the equation for the multivariate normal density:

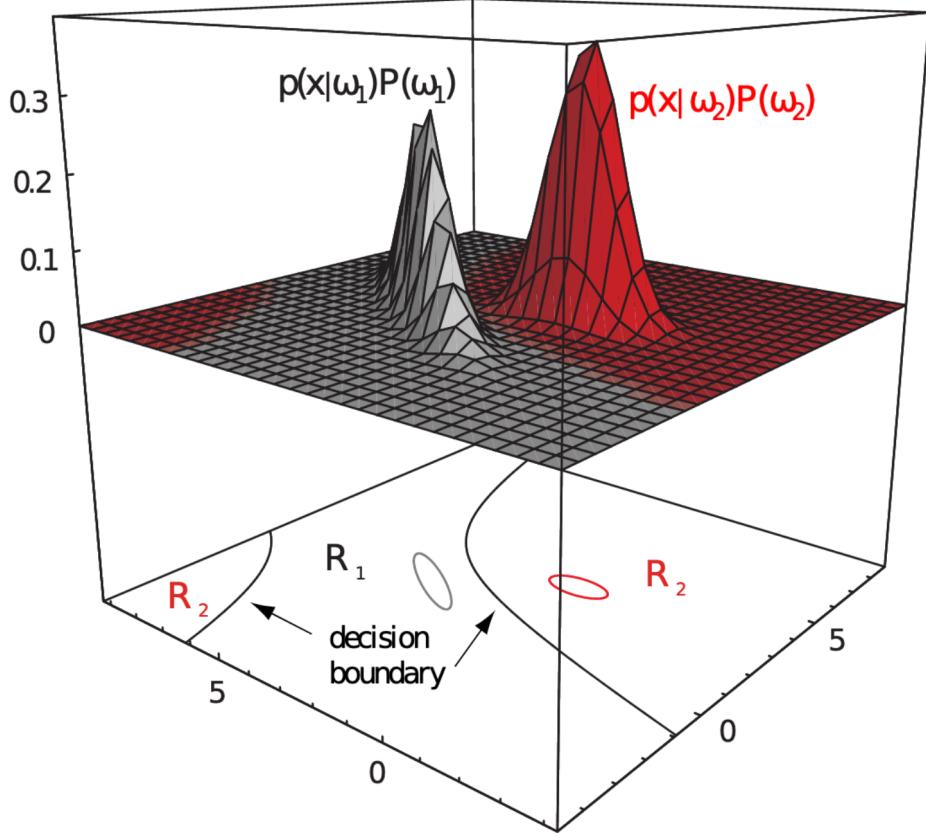


Figure 6.1: Example of classifiers.

$$p(\mathbf{x}; \boldsymbol{\mu}, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} e^{-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu})}$$

And let's remember that the covariance matrix Σ is always symmetric and positive semi-definite, and becomes strictly positive if the dimension of the feature space is f .

This distribution can map the probability of \mathbf{x} given y_i :

$$p(\mathbf{x}|y_i) = \frac{1}{(2\pi)^{d/2} |\Sigma_i|^{1/2}} e^{-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\mathbf{x} - \boldsymbol{\mu}_i)}$$

Given a multivariate normal distribution, the location of points of constant density are hyper-ellipsoids of constant Mahalanobis distance (Equation 5.10) from \mathbf{x} to $\boldsymbol{\mu}$.

6.2.1 Discriminant function

Let's know take expression from before describing discriminant functions:

$$g(x) = \ln P(x|y_i) + \ln P(y_i)$$

And substitute the multivariate normal distribution inside:

$$\begin{aligned} g_i(\mathbf{x}) &= \ln \frac{1}{(2\pi)^{\frac{d}{2}} |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\mathbf{x}-\boldsymbol{\mu}_i)} + \ln P(y_i) \\ g_i(\mathbf{x}) &= \ln \left[\frac{1}{(2\pi)^{\frac{d}{2}} |\Sigma|^{\frac{1}{2}}} \right] + \left[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\mathbf{x}-\boldsymbol{\mu}_i) \right] + \ln P(y_i) \\ g_i(\mathbf{x}) &= -\frac{d}{2} \ln 2\pi - \frac{1}{2} \ln |\Sigma_i| - \frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\mathbf{x}-\boldsymbol{\mu}_i) + \ln P(y_i) \end{aligned}$$

Since $\frac{-d}{2} \ln 2\pi$ does not depend on i then we can erase it:

$$g_i(\mathbf{x}) = -\frac{1}{2} \ln |\Sigma_i| - \frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \Sigma_i^{-1} (\mathbf{x}-\boldsymbol{\mu}_i) + \ln P(y_i) \quad (6.3)$$

6.2.1.1 $\Sigma_i = \sigma^2 I$

All features are statistically independent which means that they have the same variance σ^2 . Now the covariance determinant $|\Sigma_i| = \sigma^{2d}$ is independent of i and can hence be ignored from the Equation 6.3.

The inverse of the covariance is $\Sigma_i^{-1} = (1/\sigma^2)I$ and even though is not dependent of i , it cannot be cancelled because part of another term. The new discriminant functions become:

$$g_i(\mathbf{x}) = -\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T \frac{I}{\sigma^2} (\mathbf{x}-\boldsymbol{\mu}_i) + \ln P(y_i)$$

Which equals to:

$$g_i(\mathbf{x}) = -\frac{\|\mathbf{x}-\boldsymbol{\mu}_i\|^2}{2\sigma^2} + \ln P(y_i)$$

Expanding the quadratic term, we obtain:

$$g_i(\mathbf{x}) = -\frac{1}{2\sigma^2} [\mathbf{x}^T \mathbf{x} - 2\boldsymbol{\mu}_i^T \mathbf{x} + \boldsymbol{\mu}_i^T \boldsymbol{\mu}_i] + \ln P(y_i)$$

Discarding terms which are independent of i we obtain *linear discriminant functions*:

$$g_i(\mathbf{x}) = \underbrace{\frac{1}{\sigma^2} \boldsymbol{\mu}_i^T \mathbf{x}}_{\mathbf{w}_i^T} - \underbrace{\frac{1}{2\sigma^2} \boldsymbol{\mu}_i^T \boldsymbol{\mu}_i + \ln P(y_i)}_{w_{i0}} \quad (6.4)$$

This is in fact linear: said $\mathbf{w}_i^T = 1/\sigma^2 \boldsymbol{\mu}_i^T \mathbf{x}$ and $w_{i0} = -1/(2\sigma^2) \boldsymbol{\mu}_i^T \boldsymbol{\mu}_i + \ln P(y_i)$, none of them depend on \mathbf{x} , hence $g_i(\mathbf{x})$ can be rewritten has:

$$g_i(\mathbf{x}) = \mathbf{w}_i^T \mathbf{x} + w_{i0}$$

which is indeed a line.

We have said that the boundaries are the region where the discriminant functions intersect, that is when they are equal $g_i(\mathbf{x}) = g_j(\mathbf{x})$. It's possible to find the equation of the decision boundaries:

$$\begin{aligned}
g_i(\mathbf{x}) &= g_j(\mathbf{x}) \\
\frac{\boldsymbol{\mu}_i^T \mathbf{x}}{\sigma^2} - \frac{\boldsymbol{\mu}_i^T \boldsymbol{\mu}_i}{2\sigma^2} + \ln P(y_i) &= \frac{\boldsymbol{\mu}_j^T \mathbf{x}}{\sigma^2} - \frac{\boldsymbol{\mu}_j^T \boldsymbol{\mu}_j}{2\sigma^2} + \ln P(y_j) \\
\underbrace{\frac{(\boldsymbol{\mu}_i - \boldsymbol{\mu}_j)^T}{\sigma^2} \mathbf{x}}_{\mathbf{w}^T} - \underbrace{\frac{\boldsymbol{\mu}_i \boldsymbol{\mu}_j}{\sigma^2}}_{\mathbf{x}_0} + \frac{\boldsymbol{\mu}_j^T \boldsymbol{\mu}_j}{\sigma^2} + \ln \frac{P(y_i)}{P(y_j)} &= 0
\end{aligned} \tag{6.5}$$

Which do not depend on \mathbf{x} again hence making it linear again:

$$\mathbf{w}^T \mathbf{x} + x_0$$

This line (which is an hyperplane btw) is orthogonal to the vector \mathbf{w} , that is to the distance between $\boldsymbol{\mu}_i$ and $\boldsymbol{\mu}_j$ since \mathbf{w} is transposed with respect to \mathbf{x} .

Moreover the hyperplane passes through \mathbf{x}_0 which is based on the prior probabilities of classed being equal. If they are, then \mathbf{x}_0 is halfway between the means, while if they are not, \mathbf{x}_0 shifts away from the more likely mean. This can be seen in the logarithm: if $y_i = y_j$, then it would be $\ln 1 = 0$.

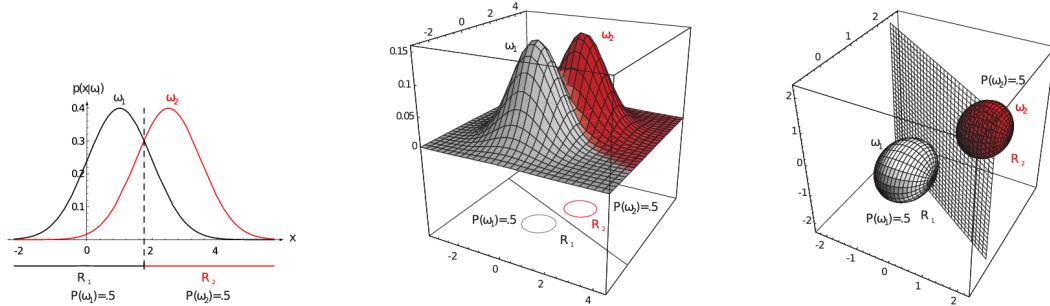


Figure 6.2: Case in which $P(y_i) = P(y_j)$. The discriminant function is a line which pass right through the middle of the distance of the two regions.

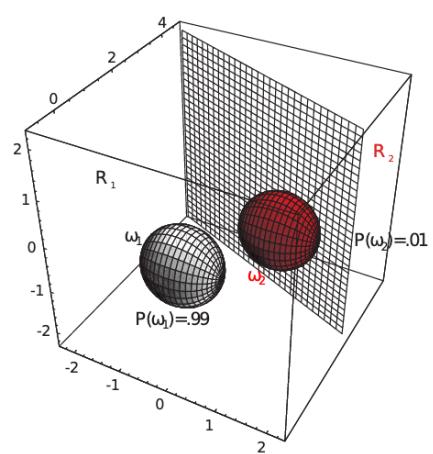
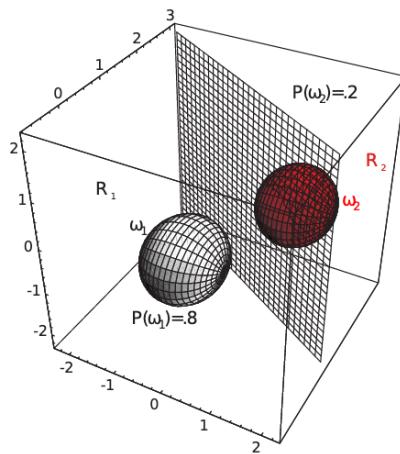
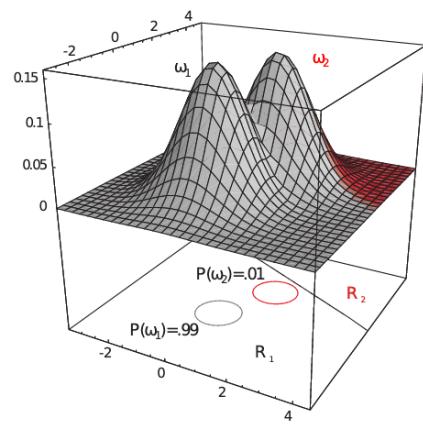
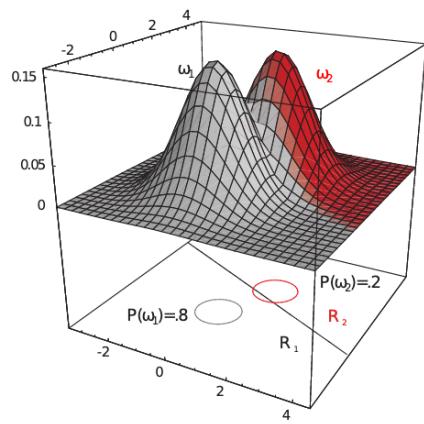
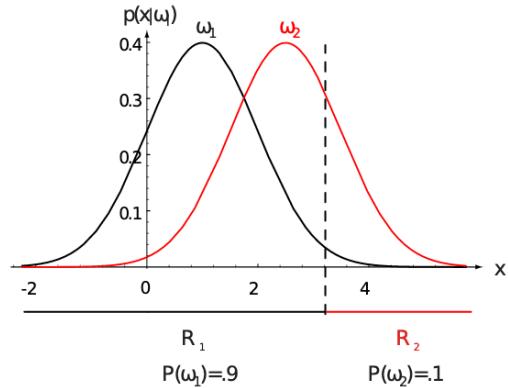
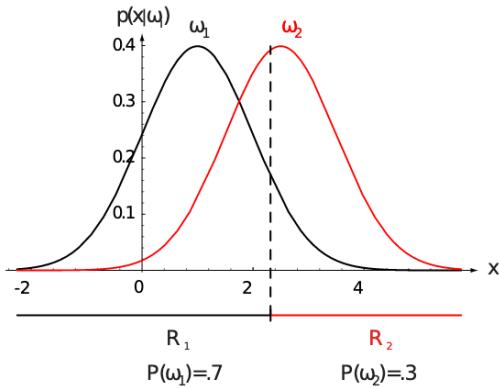


Figure 6.3: Case in which $P(y_i) \neq P(y_j)$. It's possible to notice that the more the probability difference increases, the more the line drifts away from that probability.

7 Maximum-Likelihood and Bayesian Parameter Estimation

Until now we have seen cases in which the parameters of the distributions were known. Now we'll look on how to estimate also this data.

Let's suppose to have data sampled from a probability distribution $p(x, y)$, but while the form of the distribution is known, the parameters of such are not. Let's suppose also to have a training set $\mathcal{D} = \{(x_1, y_1), \dots, (x_m, y_m)\}$ of examples sampled independently and identically distributed¹ according to $p(x, y)$. The goal is to estimate the unknown parameters of p from the training data \mathcal{D} .

Let's consider a multiclass classification problem: the training set can be divided into $\mathcal{D}_1, \dots, \mathcal{D}_c$ subsets, one for each class. Mind that each subset contains iid examples for target class y_i : $\mathcal{D}_i = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$.

If the goal is to compute the probability of a class for a new example \mathbf{x} , then we can compute the probability of a class given the new example and all the dataset as described by Bayes rule, Definition 5.9:

$$P(y_i|\mathbf{x}, \mathcal{D}) = \frac{p(\mathbf{x}|y_i, \mathcal{D})p(y_i|\mathcal{D})}{p(\mathbf{x}|\mathcal{D})}$$

To really get the class of the new example we are going to compute the probability for all possible classes and then maximize over it.

Since \mathbf{x} will be in a class y_i , it's safe to assume that it will be independent of $D_j, i \neq j$. It's possible to notice that the term $p(y_i|\mathcal{D})$ is the probability of finding a class inside the dataset, for example if the dataset contained students, and the class were to be Italian students, so it simply is:

$$p(y_i|\mathcal{D}) = \frac{|D_i|}{|\mathcal{D}|}$$

As for the denominator, it's possible to marginalize (Sum rule 5.8) $p(\mathbf{x}|y_i, \mathcal{D}_i)p(y_i|\mathcal{D})$ over all possible classes:

$$p(\mathbf{x}|\mathcal{D}) = \sum_{y_i} p(\mathbf{x}|y_i, \mathcal{D}_i)p(y_i|\mathcal{D})$$

The idea of this step is that y_i does not depend on all \mathcal{D} , but only on \mathcal{D}_i .

The goal is to estimate *class-dependent* parameters θ_i for $p(\mathbf{x}|y_i, \mathcal{D}_i)$. There are two ways to solve this problem:

- **Bayesian estimation:** assumes that parameters θ_i are random variables with some known prior distribution. Once the example has been observed, the probability becomes a posterior distribution. Predictions for new examples are obtained integrating over all possible values for the parameters:

¹ *Independent*: each example is sampled independently from the others; *identically distributed*: all examples are sampled from the same distribution.

$$p(\mathbf{x}|y_i, \mathcal{D}_i) = \int_{\theta_i} p(\mathbf{x}, \theta_i | y_i, \mathcal{D}_i) d\theta_i$$

- **Maximum likelihood:** The parameters are computed as those maximizing the probability of the observed examples \mathcal{D}_i , that is the training set for the class. For such reason they can be used to compute the probability for the new examples:

$$p(\mathbf{x}|y_i, \mathcal{D}_i) \approx p(\mathbf{x}|\theta_i)$$

7.1 Maximum likelihood

maximum likelihood Maximum likelihood If we can assume a prior distribution for the parameters $p(\theta_i)$, then maximum likelihood becomes maximum a-posteriori estimation and can be summarized as:

$$\theta_i^* = \operatorname{argmax}_{\theta_i} p(\theta_i | \mathcal{D}_i, y_i) = \operatorname{argmax}_{\theta_i} p(\mathcal{D}_i, y_i | \theta_i) p(\theta_i)$$

If a priori distribution is not available, then the solution is indeed maximum likelihood, that is maximizing the likelihood of the parameters with respect to the training samples:

$$\theta_i^* = \operatorname{argmax}_{\theta_i} p(\mathcal{D}_i, y_i | \theta_i)$$

From now on, for simplicity, since each class y_i is treated independently, we'll write y_i, \mathcal{D}_i as simply \mathcal{D} .

Given a training dataset $\mathcal{D} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ of iid examples for the target class y , assumed that the parameter vector $\boldsymbol{\theta}$ has a fixed but unknown value, we estimate such value by maximizing its likelihood with respect to the training data:

$$\theta^* = \operatorname{argmax}_{\boldsymbol{\theta}} p(\mathcal{D} | \boldsymbol{\theta})$$

Since the examples are iid, the joint probability over \mathcal{D} can be decomposed into a product:

$$\theta^* = \operatorname{argmax}_{\boldsymbol{\theta}} \prod_{j=1}^n p(\mathbf{x}_j | \boldsymbol{\theta})$$

Moreover we don't generally like products, and since the goal is to maximize, it is possible to maximize over the logarithm of the product which equals to the sum of the logarithms. This is possible because the logarithm function is monotonic:

$$\theta^* = \operatorname{argmax}_{\boldsymbol{\theta}} \ln p(\mathcal{D} | \boldsymbol{\theta}) = \operatorname{argmax}_{\boldsymbol{\theta}} \ln \prod_{j=1}^n p(\mathbf{x}_j | \boldsymbol{\theta})$$

$$\theta^* = \operatorname{argmax}_{\boldsymbol{\theta}} \sum_{j=1}^n \ln p(\mathbf{x}_j | \boldsymbol{\theta})$$

This is also called *maximizing the log-likelihood*.

The maxima can be obtained zeroing the gradient with respect to $\boldsymbol{\theta}$:

$$\nabla_{\boldsymbol{\theta}} = \sum_{j=1}^n \ln p(\mathbf{x}_j | \boldsymbol{\theta}) = \mathbf{0}$$

Since points zeroing the gradient can be local or global maxima.

7.1.1 Example – Univariate Gaussian

Let's consider a Gaussian distribution (Equation 5.6) with unknown μ and σ^2 , then the log-likelihood \mathcal{L} is:

$$\begin{aligned}\mathcal{L} &= \sum_{j=1}^n \ln \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x_j - \mu)^2}{2\sigma^2}} \\ &= \sum_{j=1}^n -\frac{1}{2\sigma^2}(x_j - \mu)^2 - \frac{1}{2} \ln 2\pi\sigma^2\end{aligned}$$

Now let's do the gradient with respect to θ , that is derive first for μ and then for σ^2 :

$$\nabla_\theta = \begin{cases} \frac{\partial \mathcal{L}}{\partial \mu} \\ \frac{\partial \mathcal{L}}{\partial \sigma^2} \end{cases}$$

Let's do the one respect to μ first:

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mu} &= -\sum_{j=1}^n \frac{1}{2\sigma^2}(2\mu - 2x_j) + 0 \\ &= \sum_{j=1}^n \frac{1}{\sigma^2}(x_j - \mu)\end{aligned}$$

Let's then do the one respect to σ^2 :

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \sigma^2} &= -\sum_{j=1}^n \frac{1}{2\sigma^2}(2\mu - 2x_j) - \frac{1}{2} \ln 2\pi\sigma^2 \\ &= -\sum_{j=1}^n \left[\frac{1}{2}(x_j - \mu)^2 \frac{\partial}{\partial \sigma^2} \frac{1}{\sigma^2} \right] - \frac{n}{2} \frac{\partial}{\partial \sigma^2} \ln 2\pi\sigma^2 \\ &= -\frac{n}{2} 2\pi \frac{1}{2\pi\sigma^2} - \sum_{j=1}^n \frac{(x_j - \mu)^2}{2} (-1) \frac{1}{\sigma^4} \\ &= -\frac{n}{2\sigma^2} + \sum_{j=1}^n \frac{(x_j - \mu)^2}{2\sigma^4}\end{aligned}$$

The gradient with respect to the parameters is:

$$\nabla_\theta = \begin{cases} \frac{\partial \mathcal{L}}{\partial \mu} = \sum_{j=1}^n \frac{1}{\sigma^2}(x_j - \mu) \\ \frac{\partial \mathcal{L}}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \sum_{j=1}^n \frac{(x_j - \mu)^2}{2\sigma^4} \end{cases}$$

Now we need to zero the gradient. First for μ :

$$\begin{aligned}\sum_{j=1}^n \frac{1}{\sigma^2}(x_j - \mu) &= 0 \\ \sum_{j=1}^n (x_j - \mu) &= 0\end{aligned}$$

$$\begin{aligned}
\sum_{j=1}^n x_j - \sum_{j=1}^n \mu &= 0 \\
\sum_{j=1}^n x_j &= \sum_{j=1}^n \mu \\
\sum_{j=1}^n x_j &= n\mu \\
\mu &= \frac{1}{n} \sum_{j=1}^n x_j
\end{aligned}$$

Now let's do the one for σ^2 :

$$\begin{aligned}
-\frac{n}{2\sigma^2} + \sum_{j=1}^n \frac{(x_j - \mu)^2}{2\sigma^4} &= 0 \\
\sum_{j=1}^n \frac{(x_j - \mu)^2}{2\sigma^4} &= \frac{n}{2\sigma^2} \\
\frac{1}{2\sigma^4} \sum_{j=1}^n (x_j - \mu)^2 &= \frac{n}{2\sigma^2} \\
\frac{1}{\sigma^2} \sum_{j=1}^n (x_j - \mu)^2 &= n \\
\sigma^2 &= \frac{1}{n} \sum_{j=1}^n (x_j - \mu)^2
\end{aligned}$$

So the maximum-likelihood estimates are:

$$\begin{aligned}
\mu &= \frac{1}{n} \sum_{j=1}^n x_j \\
\sigma^2 &= \frac{1}{n} \sum_{j=1}^n (x_j - \mu)^2
\end{aligned}$$

7.1.2 Example – Multivariate Gaussian

Let's recall the multivariate distribution (Equation 5.9):

$$p(\mathbf{x}; \boldsymbol{\mu}, \Sigma) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} e^{-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu})}$$

The log-likelihood is:

$$\sum_{j=1}^n -\frac{1}{2} (\mathbf{x}_j - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x}_j - \boldsymbol{\mu}) - \frac{1}{2} \ln (2\pi)^d |\Sigma|$$

And the maximum -likelihood estimates are:

$$\begin{aligned}
\boldsymbol{\mu} &= \frac{1}{n} \sum_{j=1}^n \mathbf{x}_j \\
\Sigma &= \frac{1}{n} \sum_{j=1}^n (\mathbf{x}_j \boldsymbol{\mu})(\mathbf{x}_j - \boldsymbol{\mu})^T
\end{aligned}$$

It's possible to notice then, that for Gaussian distributions, the parameters are simply their empirical estimates over the sample:

- Gaussian mean is the sample mean;
- Gaussian covariance matrix is the mean of the sample covariances.

7.2 Bayesian estimation

Let's assume that parameters θ_i are *random variables* with some known *prior* distribution. Predictions for new examples are obtained integrating over all possible values for the parameters:

$$p(\mathbf{x}|y_i, \mathcal{D}_i) = \int_{\boldsymbol{\theta}_i} p(\mathbf{x}, \boldsymbol{\theta}_i | y_i, \mathcal{D}_i) d\boldsymbol{\theta}_i$$

Probability of \mathbf{x} given each class y_i is independent of the other classes y_i , for simplicity we can again write:

$$p(\mathbf{x}|y_i, \mathcal{D}_i) \rightarrow p(\mathbf{x}|\mathcal{D}) = \int_{\boldsymbol{\theta}} p(\mathbf{x}, \boldsymbol{\theta}|\mathcal{D}) d\boldsymbol{\theta}$$

Where \mathcal{D} is a dataset for a certain class y , and $\boldsymbol{\theta}$ the parameters of the distribution.

$$p(\mathbf{x}|\mathcal{D}) = \int_{\boldsymbol{\theta}} p(\mathbf{x}, \boldsymbol{\theta}|\mathcal{D}) d\boldsymbol{\theta} = \int_{\boldsymbol{\theta}} p(\mathbf{x}|\boldsymbol{\theta}, \mathcal{D}) p(\boldsymbol{\theta}|\mathcal{D}) d\boldsymbol{\theta} = \int_{\boldsymbol{\theta}} p(\mathbf{x}|\boldsymbol{\theta}) p(\boldsymbol{\theta}|\mathcal{D}) d\boldsymbol{\theta} \quad (7.1)$$

Where $p(\mathbf{x}|\mathcal{D})$ can be easily computed since we have both form and parameters of the distribution, e.g., if it were a gaussian the form is Equation 5.6, while the parameters are μ and σ^2 . Since our goal is to estimate the parameters' posterior density given a training set $p(\boldsymbol{\theta}|\mathcal{D})$ by using Bayes rule (Definition 5.9), then we can write:

$$p(\boldsymbol{\theta}|\mathcal{D}) = \frac{p(\mathcal{D}|\boldsymbol{\theta})p(\boldsymbol{\theta})}{p(\mathcal{D})} = \frac{\left(\prod_{j=i}^n P(\mathbf{x}_i|\boldsymbol{\theta}) \right) P(\boldsymbol{\theta})}{P(\mathcal{D})}$$

$P(\mathcal{D}|\boldsymbol{\theta})$ is the likelihood probability that has been used also in the maximum likelihood method. In this case though, the parameters are weighted with respect to their probability avoiding overfitting which is a problem of maximum likelihood.

Mind that $P(\mathcal{D})$ is a constant independent of $\boldsymbol{\theta}$, hence it will have no influence in the final Bayesian decision, therefore it can be neglected.

At last, if final probability is needed, then $P(\mathcal{D})$ is computable via:

$$p(\mathcal{D}) = \int_{\boldsymbol{\theta}} p(\mathcal{D}|\boldsymbol{\theta})p(\boldsymbol{\theta}) d\boldsymbol{\theta}$$

7.2.1 Example – Univariate Normal, unknown μ , known σ^2

Example are drawn from a normal distribution, hence:

$$p(\mathbf{x}|\boldsymbol{\theta}) = p(x|\mu) \sim N(\mu, \sigma^2)$$

Moreover the Gaussian mean distribution is itself a normal distribution:

$$P(\mu) \sim N(\mu_0, \sigma_0^2)$$

So the distribution of the parameter's posterior distribution can be computed as:

$$p(\mu|\mathcal{D}) = \frac{p(\mathcal{D}|\mu)p(\mu)}{p(\mathcal{D})} = \frac{1}{p(\mathcal{D})} \left(\prod_{j=1}^n p(x_j|\mu) \right) p(\mu)$$

Where we said that $p(x_j|\mu) \sim N(\mu, \sigma^2)$ and $p(\mu) \sim N(\mu_0, \sigma_0^2)$:

$$p(\mu|\mathcal{D}) = \frac{1}{p(\mathcal{D})} \left(\prod_{j=1}^n \underbrace{\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_j - \mu)^2}{2\sigma^2}}}_{p(x_j|\mu)} \right) \underbrace{\frac{1}{\sigma_0\sqrt{2\pi}} e^{-\frac{(\mu - \mu_0)^2}{2\sigma_0^2}}}_{p(\mu)}$$

Since $p(\mathcal{D})$ is constant, it can be moved out of the product, and we'll call it $\alpha = 1/p(\mathcal{D})$:

$$p(\mu|\mathcal{D}) = \alpha \prod_{j=1}^n \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_j - \mu)^2}{2\sigma^2}} \frac{1}{\sigma_0\sqrt{2\pi}} e^{-\frac{(\mu - \mu_0)^2}{2\sigma_0^2}}$$

Now we could use the exponentiation's properties:

$$e^x \times e^y = e^{x+y}$$

$$\prod_i e^{x_i} = e^{\sum_i x_i}$$

Before though, the constant parts could be moved outside the product and we'll call the new constant part outside the product as α' :

$$\begin{aligned} p(\mu|\mathcal{D}) &= \alpha \left(\frac{1}{2\sigma\sigma_0\pi} \right)^n \left(\prod_{j=1}^n \exp \left\{ -\frac{(x_j - \mu)^2}{2\sigma^2} \right\} \right) \exp \left\{ -\frac{(\mu - \mu_0)^2}{2\sigma_0^2} \right\} \\ p(\mu|\mathcal{D}) &= \alpha' \exp \left\{ \sum_{j=1}^n -\frac{(x_j - \mu)^2}{2\sigma^2} \right\} \exp \left\{ -\frac{(\mu - \mu_0)^2}{2\sigma_0^2} \right\} \\ p(\mu|\mathcal{D}) &= \alpha' \exp \left\{ \frac{1}{2} \left(\sum_{j=1}^n \frac{(x_j - \mu)^2}{\sigma^2} + \frac{(\mu - \mu_0)^2}{\sigma_0^2} \right) \right\} \end{aligned}$$

Let's now focus only on the exponent²:

$$-\frac{1}{2} \left(\sum_{j=1}^n \frac{(\mu - x_j)^2}{\sigma^2} + \frac{(\mu - \mu_0)^2}{\sigma_0^2} \right)$$

Now it's possible to expand the exponentials:

$$-\frac{1}{2} \left(\sum_{j=1}^n \frac{\mu^2 + x_j^2 - 2\mu x_j}{\sigma^2} + \frac{\mu^2 + \mu_0^2 - 2\mu\mu_0}{\sigma_0^2} \right)$$

And move the constant term wrt to the sum outside the sum:

$$-\frac{1}{2} \left(\frac{n\mu^2}{\sigma^2} + \frac{1}{\sigma^2} \sum_{j=1}^n x_j^2 - \frac{1}{\sigma^2} \sum_{j=1}^n 2\mu x_j + \frac{\mu^2}{\sigma^2} + \frac{\mu_0^2}{\sigma_0^2} - \frac{2\mu\mu_0}{\sigma_0^2} \right)$$

² $(x_j - \mu)^2 = (\mu - x_j)^2$.

First of all let's group the common terms:

$$-\frac{1}{2} \left(\mu^2 \left(\frac{n}{\sigma^2} + \frac{1}{\sigma^2} \right) + \frac{\mu_0^2}{\sigma^2} + \frac{1}{\sigma^2} \sum_{j=1}^n x_j^2 - 2\mu \left(\frac{1}{\sigma^2} \sum_{j=1}^n x_j - \frac{\mu_0}{\sigma^2} \right) \right)$$

Let's now consider all the equation obtained:

$$p(\mu|\mathcal{D}) = \alpha' \exp \left\{ -\frac{1}{2} \left(\mu^2 \left(\frac{n}{\sigma^2} + \frac{1}{\sigma^2} \right) + \frac{\mu_0^2}{\sigma^2} + \frac{1}{\sigma^2} \sum_{j=1}^n x_j^2 - 2\mu \left(\frac{1}{\sigma^2} \sum_{j=1}^n x_j - \frac{\mu_0}{\sigma^2} \right) \right) \right\}$$

Mind now that this is, by the exponentials properties, the same as:

$$p(\mu|\mathcal{D}) = \alpha' \exp \left\{ -\frac{1}{2} \left(\mu^2 \left(\frac{n}{\sigma^2} + \frac{1}{\sigma^2} \right) - 2\mu \left(\frac{1}{\sigma^2} \sum_{j=1}^n x_j - \frac{\mu_0}{\sigma^2} \right) \right) \right\} \exp \left\{ +\frac{\mu_0^2}{\sigma^2} + \frac{1}{\sigma^2} \sum_{j=1}^n x_j^2 \right\}$$

Where the second exponential is actually not dependent on μ , hence it can be moved insider α' which then becomes $\alpha'' = \alpha' \times \exp \left\{ +\frac{\mu_0^2}{\sigma^2} + \frac{1}{\sigma^2} \sum_{j=1}^n x_j^2 \right\}$:

$$p(\mu|\mathcal{D}) = \alpha'' \exp \left\{ -\frac{1}{2} \left(\mu^2 \left(\frac{n}{\sigma^2} + \frac{1}{\sigma^2} \right) - 2\mu \left(\frac{1}{\sigma^2} \sum_{j=1}^n x_j - \frac{\mu_0}{\sigma^2} \right) \right) \right\}$$

It's possible to notice that this posterior probability is quite similar with a normal, let's describe it as:

$$p(\mu|\mathcal{D}) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp \left\{ -\frac{1}{2} \left(\frac{\mu - \mu_n}{\sigma_n} \right)^2 \right\} \quad (7.2)$$

$$p(\mu|\mathcal{D}) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp \left\{ -\frac{1}{2} \left(\frac{\mu^2}{\sigma_n^2} + \frac{\mu_n^2}{\sigma_n^2} - \frac{2\mu\mu_n}{\sigma_n^2} \right) \right\}$$

$$p(\mu|\mathcal{D}) = \frac{1}{\sqrt{2\pi}\sigma_n} \exp \left\{ \frac{\mu_n^2}{\sigma_n^2} \right\} \exp \left\{ -\frac{1}{2} \left(\frac{\mu^2}{\sigma_n^2} - \frac{2\mu\mu_n}{\sigma_n^2} \right) \right\} = \alpha''' \exp \left\{ -\frac{1}{2} \left(\frac{\mu^2}{\sigma_n^2} - \frac{2\mu\mu_n}{\sigma_n^2} \right) \right\}$$

By comparison with the equation obtained before it's possible to notice that:

$$\frac{1}{\sigma_n^2} = \frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \quad \frac{\mu_n}{\sigma_n^2} = \frac{\mu_0}{\sigma_0^2} + \sum_{j=1}^n x_j$$

Let's first focus on the second equation. By multiplying and dividing for n the sum, it's possible to obtain the sample mean $\hat{\mu}_n$:

$$\frac{\mu_n}{\sigma_n^2} = \frac{\mu_0}{\sigma_0^2} + n \frac{1}{n} \sum_{j=1}^n x_j = \frac{\mu_0}{\sigma_0^2} + n \hat{\mu}_n$$

Now let's solve for σ_n first since μ_n depends on σ_n :

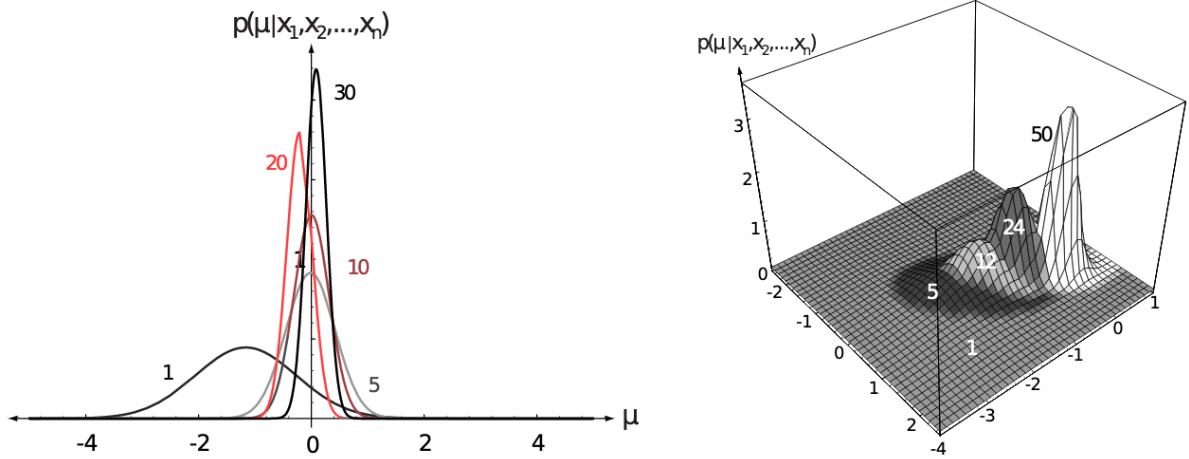
$$\frac{1}{\sigma_n^2} = \frac{n\sigma_0^2 + \sigma^2}{\sigma^2\sigma_0^2}$$

$$\sigma_n^2 = \frac{\sigma^2\sigma_0^2}{n\sigma_0^2 + \sigma^2}$$

It's now possible to solve for μ_n :

$$\begin{aligned}\mu_n &= n\hat{\mu}_n\sigma_n^2 + \frac{\mu_0\sigma_n^2}{\sigma_0} \\ \mu_n &= n\hat{\mu}_n \frac{\sigma^2\sigma_0^2}{n\sigma_0^2 + \sigma^2} + \mu_0 \frac{\sigma^2}{n\sigma_0^2 + \sigma^2}\end{aligned}$$

Notice that the mean μ_n is a linear combination of the prior μ_0 and the sample mean $\hat{\mu}_n$. If the number of samples increases, the sample mean starts to dominate over the prior mean and the variance decreases, making the distribution sharply peaked over its mean.



We still haven't computed the class conditional density $p(x|\mathcal{D})$. Remember Equation 7.1:

$$P(x|\mathcal{D}) = \int_{\mu} P(x|\mu)P(\mu|\mathcal{D})d\mu$$

Since we said that $p(x|\mu) \sim N(\mu, \sigma^2)$, and from what was achieved in Equation 7.2, it's possible to write:

$$\begin{aligned}p(x|\mathcal{D}) &= \int_{\mu} N(\mu, \sigma^2)N(\mu_n, \sigma_n^2)d\mu \\ p(x|\mathcal{D}) &= \int_{\mu} \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right\} \frac{1}{\sqrt{2\pi}\sigma_n} \exp\left\{-\frac{1}{2}\left(\frac{\mu-\mu_n}{\sigma_n}\right)^2\right\} d\mu\end{aligned}$$

Let's now define $f(\sigma, \sigma_n)$:

$$f(\sigma, \sigma_n) = \int_{\mu} \exp\left\{-\frac{1}{2}\frac{\sigma^2 + \sigma_n^2}{\sigma^2\sigma_n^2} \left(\mu - \frac{\sigma_n^2 x + \sigma^2 \mu_n}{\sigma^2 + \sigma_n^2}\right)^2\right\} d\mu$$

Then we could rewrite the previous probability as:

$$p(x|\mathcal{D}) = \int_{\mu} \underbrace{\frac{1}{2\pi\sigma\sigma_n} \exp\left\{-\frac{1}{2}\frac{(x-\mu_n)^2}{\sigma^2 + \sigma_n^2}\right\}}_{\beta} f(\sigma, \sigma_n) d\mu$$

If we consider $p(x|\mathcal{D})$ as a function of x , then it is proportional to β in the previous equation and hence $p(x|\mathcal{D})$ is normally distributed with mean μ_n and variance $\sigma^2 + \sigma_n^2$:

$$p(x|\mathcal{D}) \sim N(\mu_n, \sigma^2 + \sigma_n^2)$$

This means that the probability of x given the dataset for the class is a Gaussian with mean equal to the posterior mean, and the variance equal to the sum of the known variance (σ^2) and the additional variance (σ^2) due to the uncertainty of the mean.

The same thing happens with the multivariate. Known that the examples are drawn from a multivariate and that also distribution of the mean for the multivariate is still a multivariate:

$$p(\mathbf{x}|\boldsymbol{\mu}) \sim N(\boldsymbol{\mu}, \Sigma)$$

$$p(\boldsymbol{\mu}) \sim N(\boldsymbol{\mu}_0, \Sigma_0)$$

It's possible to obtain the posterior and the class-conditional distributions:

$$p(\boldsymbol{\mu}|\mathcal{D}) \sim N(\boldsymbol{\mu}_n, \Sigma_n)$$

$$p(\mathbf{x}|\mathcal{D}) \sim N(\boldsymbol{\mu}_n, \Sigma + \Sigma_n)$$

7.3 Sufficient statistics

Definition 7.1: Statistic

A function on a set of samples \mathcal{D} is called statistic.

One example of statistics is the mean. We'll use statistics to evaluate the forecast.

Definition 7.2: Sufficient Statistic

A statistic $\phi(\mathcal{D})$ is said to be *sufficient* for some parameters $\boldsymbol{\theta}$ if all we need to estimate the parameter is the statistic:

$$P(\mathcal{D}|\mathbf{s}, \boldsymbol{\theta}) = P(\mathcal{D}|\mathbf{s})$$

If $\boldsymbol{\theta}$ is a random variable, a sufficient statistic contains all relevant information \mathcal{D} has for estimating it:

$$p(\boldsymbol{\theta}|\mathcal{D}, \mathbf{s}) = \frac{p(\mathcal{D}|\boldsymbol{\theta}, \mathbf{s})p(\boldsymbol{\theta}|\mathbf{s})}{p(\mathcal{D}|\mathbf{s})} = p(\boldsymbol{\theta}|\mathbf{s})$$

For example if we consider the Gaussian, the sample mean was all one would need from the dataset, the exact values are meaningless.

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8.1 Conjugate

Definition 8.1: Conjugate priors

Given a likelihood function $p(x|\theta)$, given a prior distribution $p(\theta)$, $p(\theta)$ is said to be a conjugate prior for $p(x|\theta)$ if the posterior distribution $p(\theta|x)$ is the same family as the prior $p(\theta)$.

Over what was seen before about the univariate normal case, other examples are described in Table 8.1. For example if we are trying to estimate samples taken from a Normal distribution ($p(x|\theta) \sim N(\mu, \sigma^2)$), and the modelled parameter is the mean, then the conjugate prior will still be a normal distribution.

Likelihood	Parameters	Conjugate Prior
Binomial	p (probability)	Beta
Multinomial	\mathbf{p} (probability vector)	Dirichlet
Normal	μ (mean)	Normal
Multivariate Normal	$\boldsymbol{\mu}$ (mean vector)	Normal

Table 8.1: Table showing the conjugate prior of a likelihood depending on the parameter.

8.1.1 Bernoulli Distribution

This distribution models boolean events, either they are "success", or they are "failure". The parameter θ of the Bernoulli is simply the probability of success. The mass function (which will be used in the likelihood) is:

$$P(x|\theta) = \theta^x(1-\theta)^{1-x}$$

The conjugate prior is a Beta distribution:

$$P(\theta|\psi) = P(\theta|\alpha_h, \alpha_t) = \frac{\Gamma(\alpha)}{\Gamma(\alpha_h)\Gamma(\alpha_t)} \theta^{\alpha_h-1} (1-\theta)^{\alpha_t-1}$$

8.1.1.1 Example

Let's consider a dataset made out of the results of tossing a coin:

$$\mathcal{D} = \{H, H, T, T, T, H, H\}$$

The parameter θ indicates the probability of tossing head. The likelihood function becomes:

$$p(\mathcal{D}|\theta) = \theta \cdot \theta \cdot (1-\theta) \cdot (1-\theta) \cdot (1-\theta) \cdot \theta \cdot \theta = \theta^h (1-\theta)^t$$

First let's try to estimate θ via the maximum likelihood method seen in Section 7.1, that is basically deriving the log likelihood and seeing for what values it goes to zero.

$$\begin{aligned}\frac{\partial}{\partial \theta} \ln p(\mathcal{D}|\theta) &= 0 \\ \frac{\partial}{\partial \theta} \ln \theta^h (1-\theta)^t &= 0 \\ \frac{\partial}{\partial \theta} h \ln \theta + t \ln (1-\theta) &= 0 \\ h \frac{1}{\theta} + t \frac{1}{1-\theta} (-1) &= 0 \\ \frac{h}{\theta} &= \frac{t}{1-\theta} \\ h - \theta h &= t \theta \\ \theta &= \frac{h}{h+t}\end{aligned}$$

This tells us that h, t , that is the number of heads and tails in the dataset \mathcal{D} respectively, are the sufficient parameters. This implies that for example we don't care about the order of the outcomes.

Let's now try to estimate the value of the parameter θ by using the Bayesian estimation. We have seen in Section 7.2 that the parameter posterior is proportional to:

$$P(\theta|\mathcal{D}, \psi) \propto P(\mathcal{D}|\theta)P(\theta|\psi) \propto \theta^h (1-\theta)^{t-\alpha_h-1} (1-\theta)^{\alpha_t-1} = \theta^{h+\alpha_h-1} (1-\theta)^{t+\alpha_t-1}$$

That is the posterior is proportional to a Beta distribution with parameters $h + \alpha_h, t + \alpha_t$.

The prediction for a new event it's basically the expected value of the posterior Beta:

$$P(x|\mathcal{D}) = \int P(x|\theta)P(\theta|\mathcal{D}, \psi)d\theta$$

The probability $P(x|\theta)$ is actually θ since the parameter represents the probability of success for an event.

$$P(x|\mathcal{D}) = \int \theta P(\theta|\mathcal{D}, \psi)d\theta$$

Such integral is just the expected value of the Beta (Equation 5.8):

$$P(x|\mathcal{D}) = E_{P(\theta|\mathcal{D}, \psi)}[\theta] = \frac{h + \alpha_h}{h + t + \alpha_h + \alpha_t}$$

Our prior knowledge is encoded as a number $\alpha = \alpha_h + \alpha_t$ of imaginary experiments. α is called equivalent sample size. Notice that if $\alpha \rightarrow 0$, then the estimation is reduced to the classical maximum likelihood approach.

8.1.2 Multinomial distribution

Let's now consider an event with r states, that is r outcomes: $x \in \{x^1, \dots, x^r\}$. For example tossing a six face dice is such an event with $r = 6$ states.

Such event can be modelled via a Multinomial distribution. To represent the outcomes we could use the one-hot encoding:

$$\mathbf{z}(x) = [z_1(x), \dots, z_r(x)], z_k(x) = \begin{cases} 1 & \text{if } x = x^k \\ 0 & \text{otherwise} \end{cases}$$

For example if the outcome of rolling a dice was a 2, then $\mathbf{z}(x) = [0, 1, 0, 0, 0, 0]$.

The parameter is the vector $\boldsymbol{\theta} = [\theta_1, \dots, \theta_r]$ which contains the probability for each outcome. Finally the probability mass function can be written as (Equation 5.4):

$$P(x|\boldsymbol{\theta}) = \prod_{k=1}^r \theta_k^{z_k(x)}$$

As from Table 8.1, the conjugate prior is a Dirichlet distribution (Equation 5.11):

$$P(\boldsymbol{\theta}|\psi) = P(\boldsymbol{\theta}|\alpha_1, \dots, \alpha_r) = \frac{\Gamma(\alpha)}{\prod_{k=1}^r \Gamma(\alpha_k)} \prod_{k=1}^r \theta_k^{\alpha_k - 1}$$

Given a dataset \mathcal{D} of N realizations, e.g., results of tossing a dice N times, then the likelihood function is:

$$P(\mathcal{D}|\boldsymbol{\theta}) = \prod_{j=1}^N \prod_{k=1}^r \theta_k^{z_k(x_j)} = \prod_{k=1}^r \theta_k^{N_k}$$

For example let's consider instead a dataset containing RGB values: $\mathcal{D} = \{R, R, R, G, B, G, B, R, B, G\}$. The likelihood can be written as:

$$P(\mathcal{D}|\boldsymbol{\theta}) = \theta_R^4 \theta_G^3 \theta_B^3$$

Let's first apply maximum likelihood estimation:

$$\frac{\partial}{\partial \theta_k} \ln \prod_{k=1}^r \theta_k^{N_k} = 0$$

From which we obtain that:

$$\theta_k = \frac{N_k}{N}$$

Let's then apply Bayesian estimation. The parameter posterior is proportional to:

$$P(\boldsymbol{\theta}|\mathcal{D}, \psi) \propto P(\mathcal{D}|\boldsymbol{\theta})P(\boldsymbol{\theta}|\psi) \propto \prod_{k=1}^r \theta_k^{N_k + \alpha_k - 1}$$

From this is possible to observe that the posterior has a Dirichlet as expected from Table 8.1. Finally let's compute the probability of a new event via Bayesian estimation:

$$P(x_k|\mathcal{D}) = \int \theta_k P(\boldsymbol{\theta}|\mathcal{D}, \psi) d\boldsymbol{\theta}$$

Which is exactly as the expected value for the Dirichlet distribution (Equation 5.12):

$$P(x_k|\mathcal{D}) = E_{P(\boldsymbol{\theta}|\mathcal{D}, \psi)}[\theta_k] = \frac{\alpha_k + N_k}{\sum_{i=0}^r (\alpha_i + N_i)} = \frac{N_k + \alpha_k}{N + \alpha}$$

9 Bayesian Networks

Bayesian Networks are a fast and easy way to create graphical models to represent more variables and their relations.

In general *probabilistic graphical models* are graphical representation of the *qualitative*¹ aspects of probability distributions allowing to:

- Visualize the structure of a probabilistic model in a simple and intuitive way, in particular the relations between the variables.
- Detect dependency or independency between variables without having to apply derivation rules.
- Express complex computations for inference and learning in terms of graphical manipulations.
- Represent multiple probability distributions with the same graph, abstracting from their quantitative aspects (e.g. discrete vs continuous distributions).

9.1 Structure

A Bayesian Network structure \mathcal{G} is directed graph (graphical model).

Each node represents a random variable and each edge represents direct dependency between two random variables, that is one variable that is influenced by the other. This implies also that the father depends on the child, while the second does not depend on the first.

The structure hence can be described as encoding the independences assumptions:

$$\mathcal{I}_\ell(\mathcal{G}) = \{\forall i \ x_i \perp NonDescendants_{x_i} | Parents_{x_i}\}$$

NonDescendants are all those nodes that are not directly reachable from a node, that is the parents plus all the nodes that are not in its subtree. Let's consider node x_4 in Figure 9.1, its *NonDescendants* are its parents $\{x_1, x_2, x_3\}$ plus x_5 which is a non reachable node from x_4 . In total the *NonDescendants* nodes are: $\{x_1, x_2, x_3, x_5\}$ The \mathcal{I}_ℓ dependency is said to be local (ℓ) since it's defined only wrt to a single variable.

A part from the structure, we need also to have a probability distribution. Let's consider a dataset \mathcal{D} in which all variables are tied with the other by a distribution p which is a joint distribution. We'd like to represent qualitatively with a graph such distribution.

Since the Bayesian Network depends on the independences, it's possible to create a set $\mathcal{I}(p)$ of these by looking at the distribution p .

\mathcal{G} is an *independency map (I-map)* for p if p satisfies the local independencies in \mathcal{G} :

$$\mathcal{I}_\ell(\mathcal{G}) \subseteq \mathcal{I}(p)$$

¹The quantitative aspect is represented by the probabilistic distributions.

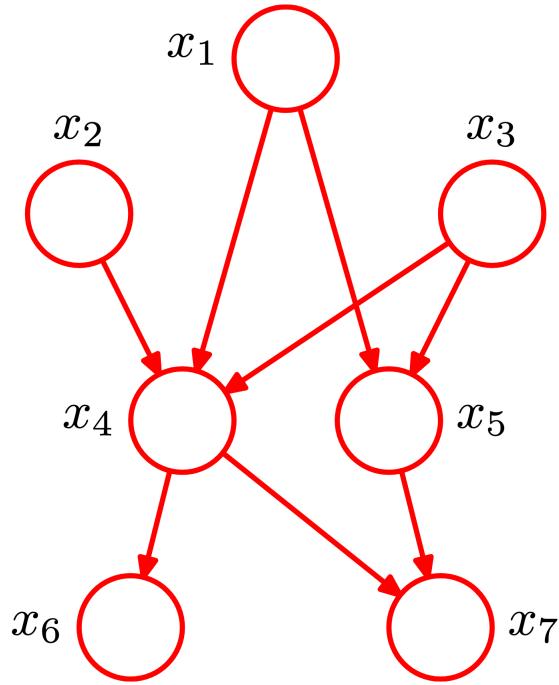


Figure 9.1: Example of Bayes Network.

The sufficient condition for \mathcal{G} to be valid is that all the independences are also in p , while the opposite is not always true. Indeed, if some independence from p cannot be modelled into \mathcal{G} via qualitative definition, then they must be modelled quantitatively.

Now we can describe p in terms of the graphical model, that is we can **factorize** the distribution based on the structure of the model.

Theorem 9.1

p is said to factorize according to \mathcal{G} if:

$$p(x_1, \dots, x_m) = \prod_{i=1}^m p(x_i | Parents_{x_i}) \quad (9.1)$$

Mind that this is a double implication: if \mathcal{G} is an I-map for p , then p factorizes according to \mathcal{G} , then it's true also that if p factorizes according to \mathcal{G} , then \mathcal{G} is an I-map for p . This can be proven as follows.

Proof. I-map \Rightarrow factorization

If \mathcal{G} is an I-map for p , then p satisfies at least these local independences:

$$\{\forall i \ x_i \perp NonDescendants_{x_i} | Parents_{x_i}\}$$

It's possible to order the variable in a topological order relative to \mathcal{G} , i.e.:

$$x_i \rightarrow x_j \Rightarrow i < j$$

That is the parents have a lower id than the children. Let us now decompose the joint probability using the chain rule as:

$$p(x_1, \dots, x_m) = \prod_{i=1}^m p(x_i | x_1, \dots, x_{i-1})$$

Finally local independences imply that for each x_i :

$$p(x_i|x_1, \dots, x_{i-1}) = p(x_i|Parents_{x_i})$$

Which by substitution:

$$p(x_1, \dots, x_m) = \prod_{i=1}^m p(x_i|Parents_{x_i})$$

□

Now we need to prove the inverse:

Proof. Factorization \Rightarrow I-map

If p factorizes according to \mathcal{G} , the joint probability can be written as

$$p(x_1, \dots, x_m) = \prod_{i=1}^m p(x_i|Parents_{x_i})$$

Said \mathcal{X} the set of all variables x_i : $\mathcal{X} = \{x_1, \dots, x_m\}$, let's consider variable x_m (repeat the following steps for the other variable), it's possible to write by the product and sum rules:

$$p(x_i|x_1, \dots, x_{m-1}) = \frac{p(x_1, \dots, x_m)}{p(x_1, \dots, x_{m-1})} = \frac{p(x_1, \dots, x_m)}{\sum_{x_m} p(x_1, \dots, x_m)}$$

Applying factorisation and isolating the only term containing x_m we get:

$$\begin{aligned} p(x_i|x_1, \dots, x_{m-1}) &= \frac{\prod_{i=1}^m p(x_i|Parents_{x_i})}{\sum_{x_m} \prod_{i=1}^m p(x_i|Parents_{x_i})} = \\ &= \frac{p(x_m|Parents_{x_m}) \prod_{i=1}^{m-1} p(x_i|Parents_{x_i})}{\prod_{i=1}^{m-1} p(x_i|Parents_{x_i}) \sum_{x_m} p(x_m|Parents_{x_m})} \end{aligned}$$

The sum cancels out because summing all the value of a variable equals to 1.

Hence:

$$p(x_i|x_1, \dots, x_{m-1}) = p(x_m|Parents_{x_m})$$

□

For example consider Figure 9.1. It's possible to write:

$$p(x_1, \dots, x_7) = p(x_1)p(x_2)p(x_3)p(x_4|x_1, x_2, x_3)p(x_5|x_2, x_3)p(x_6|x_4)p(x_7|x_4, x_5)$$

Mind that the joint probability $p(x_1, \dots, x_7)$ is largely influenced by the probability of node 4: $p(x_4|x_1, x_2, x_3)$. Now let's suppose that each variable defined a simple binary value, then the total number of possibility would be 2^7 , against the 2^4 we found right now. This allows to be able to work with a lot of variables.

Definition 9.1: Bayesian Network

A Bayesian Network is a pair (\mathcal{G}, p) where p factorizes over \mathcal{G} and its represents as a set of conditional probability distribution associated with the nodes of \mathcal{G}

9.1.1 Example

Let's consider another example: genes A and B have independent prior probabilities and gene C can be enhanced by both A and B, with the following probability tables:

Gene	Value	$P(\text{value})$	Gene	Value	$P(\text{value})$
A	Active	0.3	B	Active	0.3
A	Inactive	0.7	B	Inactive	0.7

		A			
		Active		Inactive	
		B			
		Active	Inactive	Active	Inactive
C	Active	0.9	0.6	0.7	0.1
C	Inactive	0.1	0.4	0.3	0.9

Table 9.1: Table showing $p(A, B, |C)$.

9.1.2 Conditional Independence

First of let's recall Definition 5.7: two variables a, b are said to be independent written $a \perp b | \emptyset$ if:

$$p(a, b) = p(a)p(b)$$

Definition 9.2: Conditional Independence

Two variables a, b are conditionally independent given c , written $a \perp b | c$ if:

$$p(a, b | c) = p(a | c)p(b | c)$$

Graphical models allow to directly verify them through the **d-separation** criterion.

9.2 D-separation

Looking at some simpler graphs, some dependency rules can be inferred and then used on larger graphs by applying them to subgraphs.

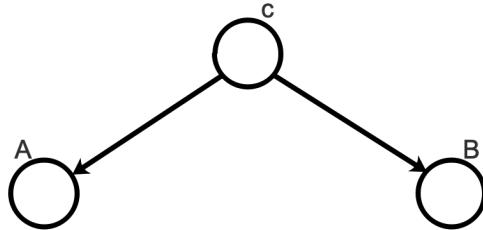
9.2.1 Two Nodes

Given two nodes, or they are independent, hence they are not connected, or they are dependent, hence they are connected.

9.2.2 Three Nodes

9.2.2.1 Tail-To-Tail

Also known as *common cause*.



As for the factorization Equation 9.1, the joint distribution can be expressed as:

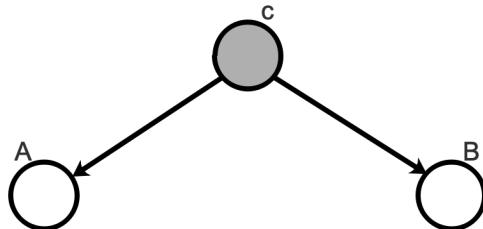
$$p(a, b, c) = p(a|c)p(b|c)p(c)$$

The tail-to-tail case says that a and b are *not independent*, written $a \not\perp\!\!\!\perp b$. If c is not given then we have that:

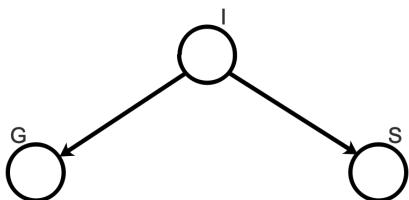
$$p(a, b) = \sum_c p(a|c)p(b|c)p(c) \neq p(a)p(b)$$

On the contrary, if c is given, then they are *conditionally independent*:

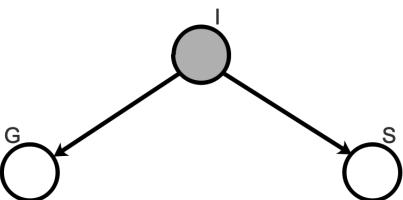
$$p(a, b|c) = \frac{p(a, b, c)}{p(c)} = p(a|c)p(b|c)$$



Let's consider an example: a company needs to choose the most intelligent (I) student between more students. For each student the variables grade (G) and score (S) are given. The following graph can be drawn since if the student is intelligent, then it should be seen in both grades and scores.



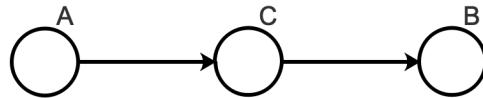
G and S are directly correlated, for example observing high scores could be indication of having a higher intelligence and hence also higher grades.



G and S are not directly dependent since once intelligence has been observed, the correlation disappear and nor G gives more information S , nor S gives more information about G than the what we already know.

9.2.2.2 Head-To-Tail

Also known as *indirect causal effect*.



The joint distribution can be expressed as:

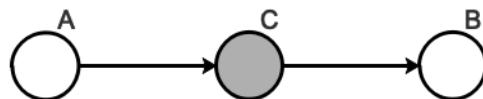
$$p(a, b, c) = p(b|c)p(c|a)p(a) = p(b|c)p(a|c)p(c)$$

If c is not given, then a and b are *not independent*:

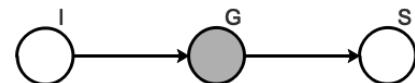
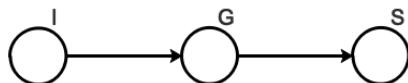
$$p(a, b) = p(a) \sum_c p(b|c)p(c|a) \neq p(a)p(b)$$

If instead c is given, then a and b are conditionally independent:

$$p(a, b|c) = \frac{p(b|c)p(a|c)p(c)}{p(c)} = p(b|c)p(a|c)$$



As before, let's consider the example of the intelligence of a student.

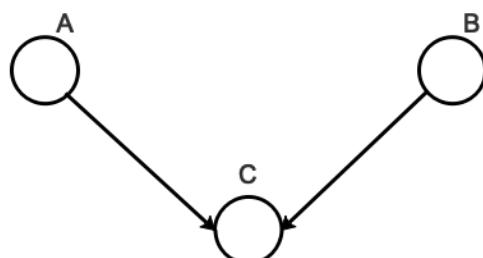


Intuitively, if we observe that the student is intelligent, then we are more inclined to believe that its grades G are good and that they will have a better score at the interview S , that is the probability of these latter events is higher conditioned on the observation that the student is intelligent.

Instead if we assume that G is observed, then it's intelligence no longer influences the score of the interview.

9.2.2.3 Head-To-Head

Also known as *common effect*.



The joint distribution can be expressed as:

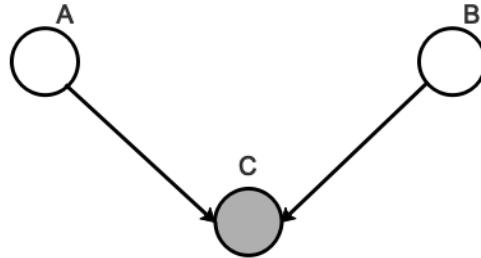
$$p(a, b, c) = p(c|a, b)p(a)p(b)$$

If c is not given, then a and b are *independent*:

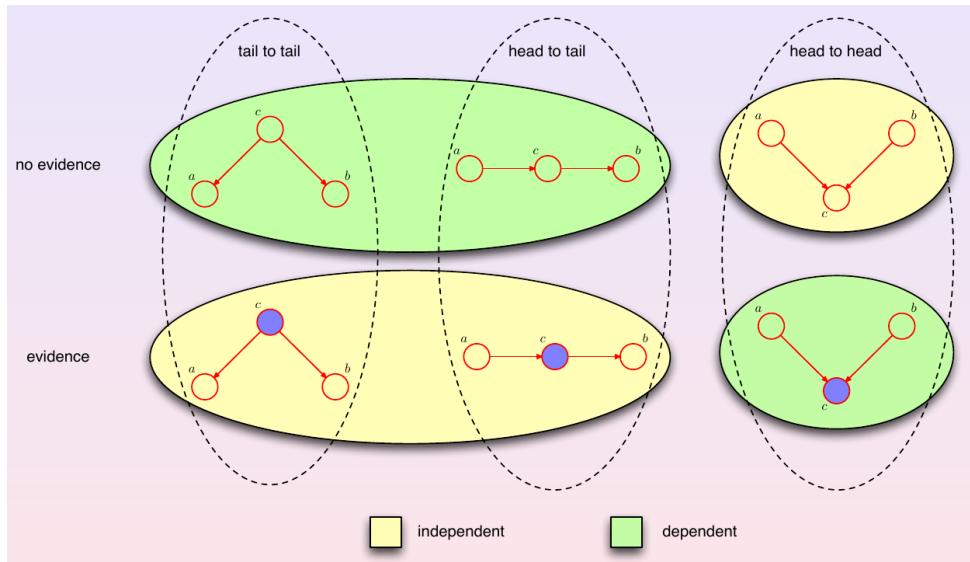
$$p(a, b) = \sum_c p(c|a, b)p(a)p(b) = p(a)p(b)$$

If instead c is given, then a and b are not conditionally independent, hence they are conditionally dependent:

$$p(a, b|c) = \frac{p(c|a, b)p(a)p(b)}{p(c)} \neq p(a|c)p(b|c)$$



Let's consider one last time the example of the student that is to be hired from a company. We have said that if c is not given, then a and b are independent, while if c is given they are dependent. Indeed, if c was the score of a test, then the student (G) and it was low, we could think that they are actually not that smart, but then if we were to observe that the test was difficult, then we could think that actually they are not *not* intelligent. Hence, a and b are actually correlated if c is given.



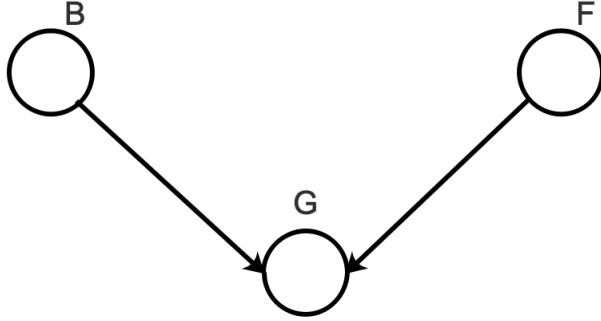
9.2.2.3.1 Example Head-To-Head Example

Let's consider a fuel system of a car. The fuel system is made of:

- Battery B : can either be charged ($B = 1$) or flat ($B = 0$);
- Fuel tank F : can either be full ($F = 1$) or empty ($F = 0$);
- Electric fuel gauge G : either full ($G = 1$) or empty ($G = 0$).

Let's now say that the probability of the battery to be charged is $P(B = 1) = 0.9$ and the probability for the fuel tank to be full is $P(F = 1) = 0.9$.

The electric fuel gauge is conditioned on both:



$$\begin{aligned} P(G = 1|B = 1, F = 1) &= 0.8 & P(G = 1|B = 1, F = 0) &= 0.2 \\ P(G = 1|B = 0, F = 1) &= 0.2 & P(G = 1|B = 0, F = 0) &= 0.1 \end{aligned}$$

We want to compute the probability of having an empty tank:

$$P(F = 0) = 1 - P(F = 1) = 0.1$$

What would happen to the probability if we were to notice that the fuel gauge was empty? In particular let's compute the probability of the fuel tank to be empty given the fact that the fuel gauge is empty $P(F = 0|G = 0)$. Such probability is not given, hence we need to find it. To compute $P(F = 0|G = 0)$ we could use Bayes:

$$P(F = 0|G = 0) = \frac{P(G = 0|F = 0)P(F = 0)}{P(G = 0)}$$

We need to compute $P(G = 0|F = 0)$ and $P(G = 0)$ but they are easier to compute by the product rule:

$$\begin{aligned} P(G = 0|F = 0) &= \sum_{B \in \{0,1\}} P(G = 0, B|F = 0) \\ &= \sum_{B \in \{0,1\}} P(G = 0|B, F = 0)P(B|F = 0) \\ &= \sum_{B \in \{0,1\}} P(G = 0|B, F = 0)P(B) \\ &= P(G = 0|B = 0, F = 0)P(B = 0) + P(G = 0|B = 1, F = 0)P(B = 1) \\ &= 0.9 \cdot 0.1 + 0.8 \cdot 0.9 = 0.81 \end{aligned}$$

Notice that the passage from the second to the third equation it's possible since B and F are independent, hence $P(B|F = 0) = P(B)$.

Similarly $P(G = 0)$ is given by:

$$\begin{aligned} P(G = 0) &= \sum_{B \in \{0,1\}} \sum_{F \in \{0,1\}} P(G = 0, B, F) \\ &= \sum_{B \in \{0,1\}} \sum_{F \in \{0,1\}} P(G = 0|B, F)P(B)P(F) = 0.315 \end{aligned}$$

In the end it's possible to see that by observing the fact that the fuel gauge is empty, then the probability of the fuel tank of being actually empty increases:

$$P(F = 0|G = 0) = \frac{P(G = 0|F = 0)P(F = 0)}{P(G = 0)} \simeq 0.257$$

Not as much as one would expect, but this is due to strong prior and an unreliable gauge. Now let's consider the case in which we knew that also the battery is flat. How does the

probability $P(F = 0|G = 0, B = 0)$ change knowing this information?

It's possible to apply again Bayes Theorem and have:

$$P(F = 0|G = 0, B = 0) = \frac{P(G = 0|F = 0, B = 0)P(F = 0|B = 0)}{P(G = 0|B = 0)}$$

Definition 9.3: Active Trail

Let's consider a graph with three node X, Y, Z connected as in one of the cases before. The trail $X \Rightarrow Y \Rightarrow Z$ is said to be *active* if information can flow from X to Y via Z .

- Head-to-Tail $X \rightarrow Z \rightarrow Y$ is active if and only if Z **is not** observed;
- Tail-to-Tail $X \leftarrow Z \rightarrow Y$ is active if and only if Z **is not** observed;
- Head-to-Head $X \rightarrow Z \leftarrow Y$ is active if and only if Z **is** observed;

9.2.3 d-Separation – General Case

Obviously the majority of the graphs is not made of three nodes, but has many nodes. Suppose that we want to find a path that allows to go from one group nodes holding evidence to another. We can say whether this is possible or not by applying the before rules and by adding the following rule: a head-to-head node c unblocks the dependency path between its parents if either itself or *any of its descendants* receives evidence.

Definition 9.4: Descendant

A descendant of a node x is any node which can be reached from x with a path following the direction of the arrows.

Theorem 9.2: d-Separation General Case

Let \mathcal{G} be a Bayesian Network structure and $X_1 \Rightarrow \dots \Rightarrow X_n$ a trail in \mathcal{G} . Let Z be a subset of observed variables. The trail $X_1 \Rightarrow \dots \Rightarrow X_n$ is active given Z if:

- Whenever we have a head-to-head structure $X_{i-1} \rightarrow X_i \leftarrow X_{i+1}$, then X_i or one of its descendants are in Z ;
- No other node along the trail is in Z .

Note that if X_1 or X_n are in Z , then the trail is not active.

Definition 9.5: Path Blocked

A path is said to be blocked if it includes at least one node such that either:

- The arrows on the path meet tail-to-tail or head-to-tail at the node and it is in C , or
- The arrows on the path meet head-to-head at the node and neither it nor any of its descendants is in C .

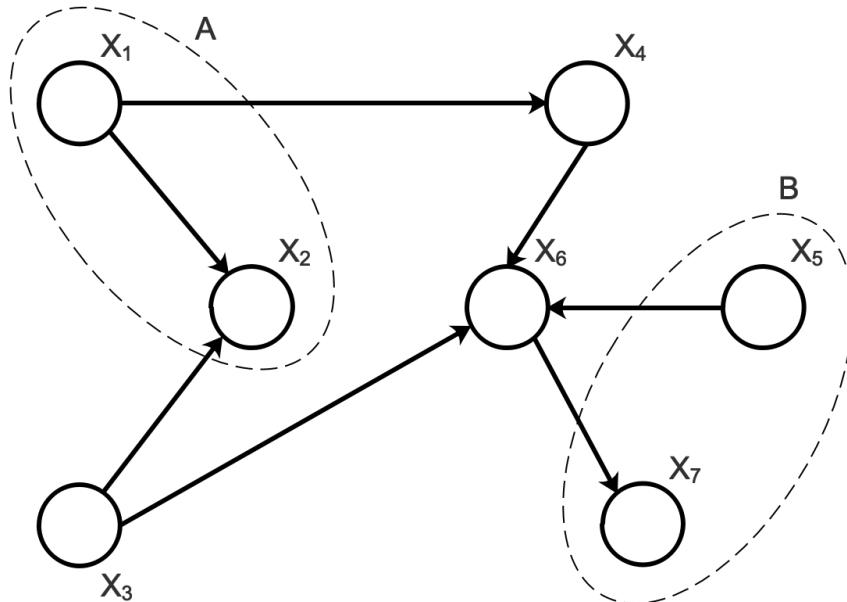
Definition 9.6: General d-separation Criterion

Given a generic Bayesian Network and nonintersecting arbitrary sets of nodes A, B, C , the sets A and B are d-separated by C , written $dsep(A; B|C)$ if all paths from any node in A to any node in B are blocked.

Note that d-separation *implies conditional independence*: the sets A and B are independent given C , written $A \perp B|C$ if they are d-separated by C .

9.2.3.1 Example 1

Let's consider the following graph:



and three independent sets: $A = \{X_1, X_2\}$, $B = \{X_5, X_7\}$, $C = \emptyset$. By applying the rules we need to find a possible path from one set to another. For example let's consider a first possibility made of the path $X_1 \rightarrow X_4 \rightarrow X_6 \leftarrow X_5$: the first three nodes are in a head-to-tail structure, we do not have any information regarding X_4 , hence the path is active till this point. $X_4 \rightarrow X_6 \leftarrow X_5$ is a head-to-head structure and there is no evidence on X_6 , hence the path is blocked.

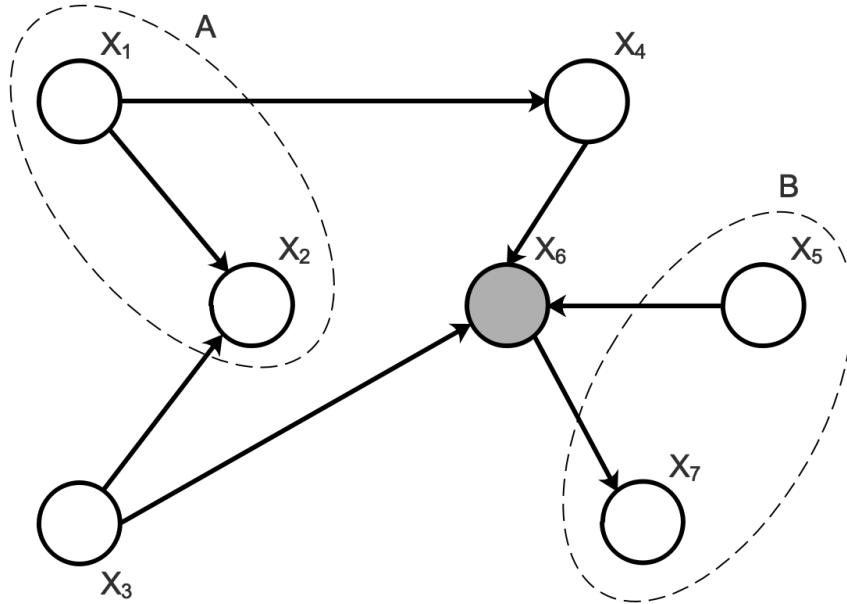
Let's instead consider the path: $X_1 \rightarrow X_4 \rightarrow X_6 \rightarrow X_7$. We saw that the first three nodes are in a head-to-tail structure and there is no evidence, so the trail is active. Let's then look at the last three nodes: $X_4 \rightarrow X_6 \rightarrow X_7$: this is head-to-tail structure and there is no evidence on X_6 , hence the trail is active and an actual path from the set A to the set B could be found.

It's possible to find also a path starting from X_2 : $X_2 \leftarrow X_3 \rightarrow X_6 \rightarrow X_7$ which actually works because the first three nodes are in a tail-to-tail structure and there is no evidence on X_3 , hence the trail is active, and the last three nodes are in a head-to-tail structure with no evidence on X_6 .

Similarly to before, the path $X_2 \leftarrow X_3 \rightarrow X_6 \rightarrow X_5$ does not work because the last three nodes are in a head-to-head structure and there is no evidence on X_6 .

9.2.3.2 Example 2

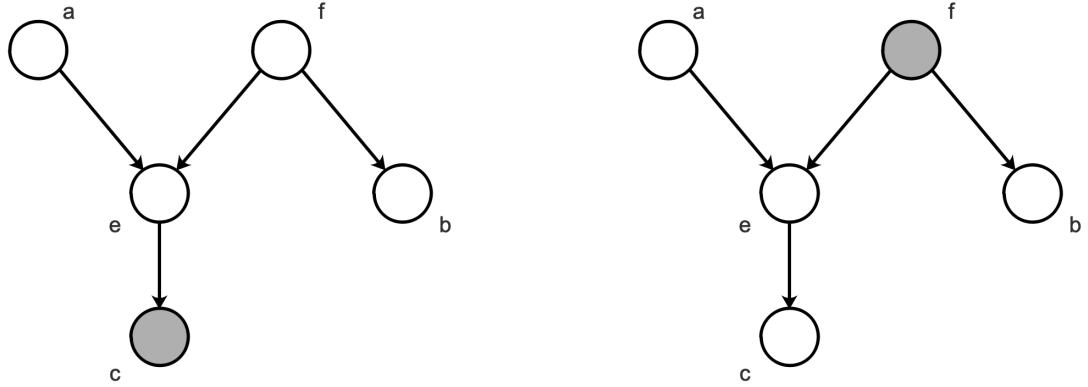
Let's consider the case in which X_6 is given evidence:



In this case the path $X_1 \rightarrow X_4 \rightarrow X_6 \leftarrow X_5$ is a correct path since X_4 holds no evidence hence the trail $X_1 \rightarrow X_4 \rightarrow X_6$ is active and X_6 holds evidence, so the structure $X_4 \rightarrow X_6 \leftarrow X_5$ is active too.

9.2.3.3 Example 3

Let's consider the following cases and decide whether a and b are d-separated:



In this case, the first three nodes meet a head-to-head structure and we have that c , which is a descendant of e , has evidence, hence the trail is active. The last three nodes are in a tail-to-tail structure, f does not have any evidence, hence the path is valid and a and b are not d-separated since there exists a path from a to b .

It's immediate to see that f is observed, hence the trail $e \leftarrow f \rightarrow b$ is not active, and also there is no evidence for e or any of its descendants. By Definition 9.6, a and b are d-separated given f : $a \perp b | f$.

9.3 Bayesian Networks independences

We saw how local independencies work, that is independencies between nodes, now we are going to define also global dependencies.

Definition 9.7: Local Independence

A Bayesian Networks structure \mathcal{G} encodes a set of local independence assumptions:

$$\mathcal{I}_l(\mathcal{G}) = \{\forall i \ x_i \perp \text{nondescendants}_{x_i} | \text{parents}_{x_i}\}$$

Definition 9.8: Global Independence

A Bayesian Network structure \mathcal{G} encodes a set of global (Markov) independence assumptions:

$$\mathcal{I}(\mathcal{G}) = \{(A \perp B | C) : \text{dsep}(A; B | C)\}$$

Notice that the global independences contain the local independences.

9.4 l -Equivalence

We can notice that different structures actually encode the same set of independences assumptions. Let's consider for example head-to-head in one direction or in the other: if the intermediate node does not present evidence, then the two structures encode the same independence. In Figure 9.2 are shown two equivalence classes.

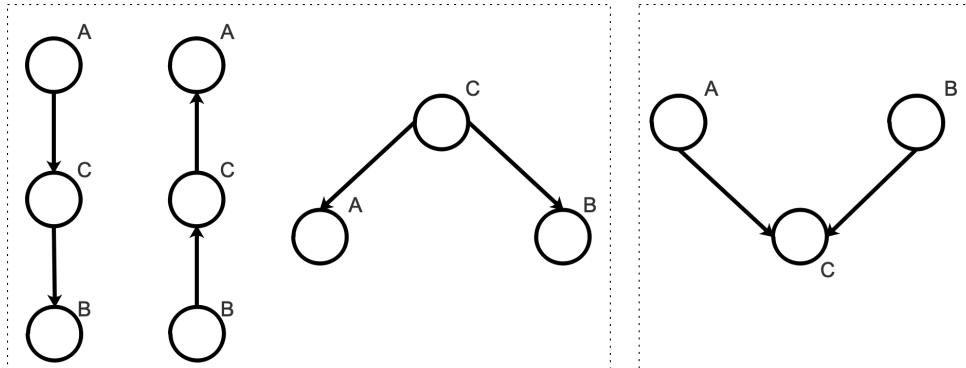


Figure 9.2: Two equivalence classes.

Definition 9.9: l -Equivalence

Two Bayesian Networks structures \mathcal{G} and \mathcal{G}' are l equivalent if $\mathcal{I}(\mathcal{G}) = \mathcal{I}(\mathcal{G}')$.

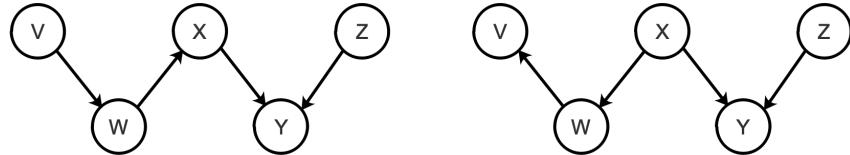
The space of Bayesian Network structures over the set of nodes \mathcal{X} is partitioned into a set of mutually exclusive and exhaustive l -equivalence classes.

Note that l -equivalence of two graphs implies that any distribution P that can be factorized over one of these graphs can be factorized over the other too. Furthermore, there is no intrinsic property P that would allow us to associate it with one graph rather than an equivalent one. In other words, although we can determine, for a distribution $P(X, Y)$, whether X and Y are correlated, there is nothing in the distribution that can help us determine whether the correct structure is $X \rightarrow Y$ or $Y \rightarrow X$.

Definition 9.10: Skeleton

The skeleton of a Bayesian network graph \mathcal{G} over a set of nodes \mathcal{X} is an undirected graph over \mathcal{X} that contains an edge $\{X, Y\}$ for every edge (X, Y) in \mathcal{G} .

It's possible to prove that if two structures \mathcal{G} and \mathcal{G}' have the same skeleton and the same set of v-structures, then they are l -equivalent.

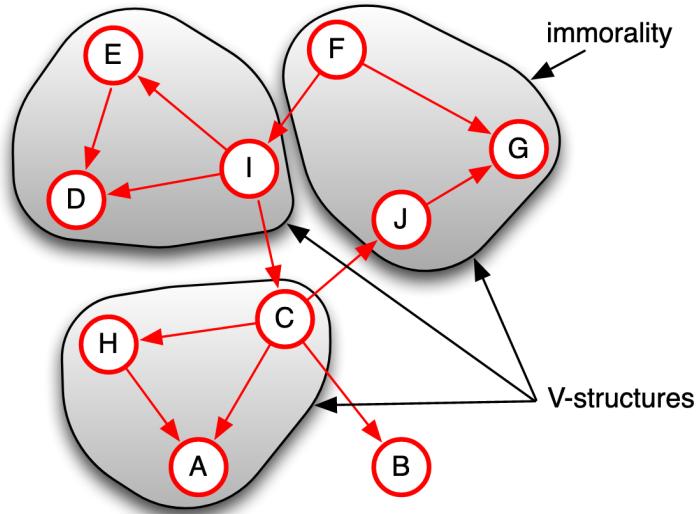


Considering the above structures, they are l -equivalent since they have the same skeleton and the same v-structure $(X \rightarrow Y \leftarrow Z)$.

This is actually a *sufficient condition*. Instead it's possible to have a *necessary and sufficient condition* by considering also **immoralities**.

Definition 9.11: Immorality

A v-structure $X \rightarrow Z \leftarrow Y$ is an **immorality** if there is no direct edge between X and Y . If there is such an edge, it is called a **covering edge** for the v-structure.



It's possible to notice that the v-structure $F \rightarrow G \leftarrow J$ is different from the other two since there is no edge between F and J . This implies that such v-structure is an **immorality**, while the others are not immoralities.

The following necessary and sufficient condition can be expressed and proven:

Theorem 9.3

Let \mathcal{G}_1 and \mathcal{G}_2 be two graphs over a set of nodes \mathcal{X} . Then \mathcal{G}_1 and \mathcal{G}_2 have the same skeleton and the same set of immoralities if and only if they are l -equivalent.

9.4.1 l -Maps

There can be two types of maps: *minimal l -maps* and *P -maps*, that is perfect maps.

Notice that for a structure \mathcal{G} to be an l -map for a distribution p , it does not need to encode all its independences, e.g., a fully connected graph is an l -map of any p defined over its variables.

Definition 9.12: Minimal l -Map

A minimal l -map for a distribution p is an l -map \mathcal{G} which can't be reduced into a $\mathcal{G}' \subset \mathcal{G}$ that is also an l -map for p .

To reduce an l -map to another l -map means that by removing some edges we obtain again a valid l -map.

Note that by this definition, a minimal l -map for p does not necessarily capture all the independences in p . On the contrary a perfect P -map does:

Definition 9.13: P -Map

A structure \mathcal{G} is a perfect map P -map for a distribution p if it captures all (and only) its independences:

$$\mathcal{I}(\mathcal{G}) = \mathcal{I}(p)$$

Notice that a P -map is also a minimal l -map, while the opposite is not valid.

There exists an algorithm that allows one to find a P -map for a distribution p , but it's exponential w.r.t. the *in-degree* of the P -map, that is the maximum number of connections of the nodes. Moreover the algorithms returns an equivalence class rather than a single structure.

Moreover there are some distributions for which is not possible to find P -maps. In these cases, indirect graphs called Markov Networks are used.

9.5 Making Bayesian Networks

The first step is to find a field-expert who can tell us the variables that we may need. For example, if we are trying to develop an algorithm to predict a disease, we need to know all the possible symptoms.

The next step is to actually define the variables that can be observed or that you can be interested in predicting, also latent variables can be useful.

By following *causality* considerations, we try to add edges to the variables. This would allow us to have a more interpretable network and also a sparser one.

Lastly we start to add the probabilities for the configurations and its best to (almost) never assign zero probabilities. If any data are available, we should use them to help in learning parameters, and also the structure.

9.6 Inference in Graphical Models

Bayesian Networks, as all the graphical models, actually models a joint probability.

Assume we have evidence e on the state of a subset of variables E in the model. Inference amounts at computing the posterior probability of a subset X of the non-observed variables given the observations:

$$P(X|E = e) = \frac{P(X, E)}{P(E = e)}$$

The problem consists in estimating such joint probabilities when dealing with a large number of variables: directly working on the full joint probabilities would require time exponential in the number of variables. For instance, if all N variables are discrete and take one of K possible values, a joint probability table has K^N entries.

$$P(\mathbf{X}|\mathbf{E} = \mathbf{e}) = \frac{P(\mathbf{X}, \mathbf{E})}{P(\mathbf{E} = \mathbf{e})} = \sum_{Y_1, \dots, Y_n} P(\mathbf{X}, Y_1, \dots, Y_n, \mathbf{E} = \mathbf{e})$$

Our goal is to exploit the structure in graphical models to do inference more efficiently.

9.6.1 Inference – Chain

The most simple structure we have seen is a chain of nodes where each variable has a connection to the following one.



In this way the probability of all variables in the chain becomes:

$$P(X) = P(X_1) \cdot P(X_2|X_1) \cdot \dots \cdot P(X_N|X_{N-1})$$

The marginal probability of an arbitrary variable X_i is:

$$P(X_i) = \sum_{X_1} \sum_{X_2} \dots \sum_{X_{i-1}} \sum_{X_{i+1}} \dots \sum_{X_n} P(\mathbf{X})$$

Suppose that $i = N$, then it's possible to see that only $P(X_N|X_{N-1})$ is involved in the last summation which can be computed first giving a function of X_{N-1} :

$$\mu_\beta(X_{N-1}) = \sum_{X_N} P(X_N|X_{N-1})$$

Now let's suppose that $i = N - 1$, then the marginalization can be iterated as:

$$\mu_\beta(X_{N-1}) = \sum_{X_{N-1}} P(X_{N-1}|X_{N-2})\mu_\beta(X_{N-1})$$

One could decrease the value of i and obtain the general function:

$$\mu_\beta(X_i) = \sum_{X_{i+1}} P(X_{i+1}|X_i)\mu_\beta(X_{i+1})$$

Now let's try to do the opposite and start from the front:

$$\mu_\alpha(X_2) = \sum_{X_1} P(X_1)P(X_2|X_1)$$

$$\mu_\alpha(x_3) = \sum_{x_2} P(x_3|x_2)\mu_\alpha(x_2)$$

It's possible to see the marginalization of the chain as a product of μ_α and μ_β . Indeed, we could write:

$$P(X_i) = \mu_\alpha(X_i)\mu_\beta(X_i)$$

We could think of $\mu_\alpha(X_i)$ and $\mu_\beta(X_i)$ as messages passing from X_{i-1} to X_i and from X_{i+1} to X_i respectively²:

$$\mu_\alpha = \sum_{X_{i-1}} P(X_i|X_{i-1})\mu_\alpha(X_{i-1})$$

$$\mu_\beta = \sum_{X_{i+1}} P(X_{i+1}|X_i)\mu_\beta(X_{i+1})$$

Each outgoing message is obtained by multiplying the incoming message by the local probability and summing over the node values. Suppose we want to compute the marginal probabilities for a number of different variables \mathbf{X}_i . For each variable we should send a message from the beginning to the variable and from the variable to the end of the chain. Since the probabilities at each node is not going to change, then one could simply send a message from the beginning to the end and one from the end to the beginning. If all nodes store messages, we can compute any marginal probability as:

$$P(\mathbf{X}_i) = \mu_\alpha(\mathbf{X}_i)\mu_\beta(\mathbf{X}_i)$$

This does not count for evidence. If we were to consider also the case in which some nodes \mathbf{X}_e are observed, then the formula would change and instead of summing over all possible values, we'd just use the observed values. For instance, let's consider the case in which we have 4 variables: $\mathbf{X} = \{X_1, X_2, X_3, X_4\}$, we could compute the probability of \mathbf{X} as:

$$P(\mathbf{X}) = P(X_1)P(X_2|X_1)P(X_3|X_2)P(X_4|X_3)$$

The marginal probability of X_2 and observations $X_1 = x_{e_1}, X_3 = x_{e_3}$ is:

$$P(X_2, X_1 = x_{e_1}, X_3 = x_{e_3}) = \sum_{X_1} \sum_{X_3} \sum_{X_4} P(\mathbf{X})$$

$$P(X_2, X_1 = x_{e_1}, X_3 = x_{e_3}) = \sum_{X_1} \sum_{X_3} \sum_{X_4} P(X_1)P(X_2|X_1)P(X_3|X_2)P(X_4|X_3)$$

Since $X_1 = x_{e_1}$ and $X_3 = x_{e_3}$, we have:

$$P(X_2, X_1 = x_{e_1}, X_3 = x_{e_3}) = P(X_1 = x_{e_1})P(X_2|X_1 = x_{e_1})P(X_3 = x_{e_3}|X_2) \sum_{X_4} P(X_4|X_3 = x_{e_3})$$

Whne adding evidence, the message passing procedure computes the joint probability of the variable and the evidence, hence it has to be normalized to obtain the conditional probability given the evidence:

$$P(X_n|\mathbf{X}_e = \mathbf{x}_e) = \frac{P(X_n, \mathbf{X}_e = \mathbf{x}_e)}{\sum_{X_n} P(X_n, \mathbf{X}_e = \mathbf{x}_e)}$$

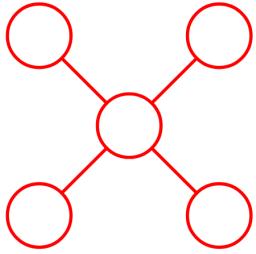
9.6.2 Inference – Trees

Obviously chains are not the only existing structure, but trees are another type of structure. In this case we can consider three cases:

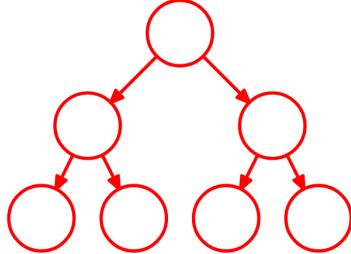
- **Undirected trees:** undirected graphs with a single path for each pair of nodes.
- **Directed trees:** directed graphs with a single node with no parentes (root) and all the other nodes with a single parent.

² α is passing the message forward, β is passing the message backwards.

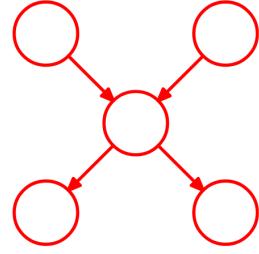
- **Directed polytrees:** directed graphs with multiple parents for node and multiple roots, but still a single (undirected) path between each pair of nodes.



Undirected trees.



Directed trees.



Directed polytrees.

Since explaining these structures per se is quite troublesome, we are introducing **facto graphs**.

9.6.3 Inference – Factor Graph

Factor graphs are an alternative graphical representation which is useful to better explain inference algorithms.

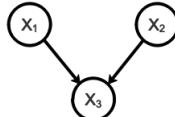
A factor graph is a graphical representation of a graphical model highlighting its factorization, i.e., its conditional probabilities. A factor graph has one node for each node in the original graph, one additional node for each factor (evidence) and undirected links to each of the node variables in the factor.

Mind that each node factor needs to be linked to all the nodes from which the decomposition comes from.

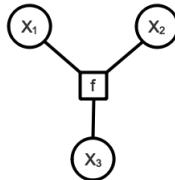
Let's consider for example the following probability distribution:

$$P(X_3|X_1, X_2)P(X_1)P(X_2)$$

We know that a Bayesian Network representation can be:



We could notice that actually X_3 is conditioned on X_1 and X_2 and hence we could create a factor node f as follows:



Actually f can be thought as a function:

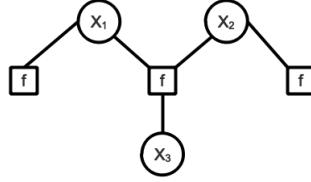
$$f(X_1, X_2, X_3) = P(X_3|X_1, X_2)P(X_1)P(X_2)$$

Now then it's possible to add also other two factor nodes which would express the probability of the nodes X_1 and X_2 .

$$f_c(X_1, X_2, X_3) = P(X_3|X_1, X_2)$$

$$f_a(X_1) = P(X_1)$$

$$f_b(X_2) = P(X_2)$$



9.6.4 Sum-Product Algorithm

The sum-product algorithm is an efficient algorithm for exact inference on tree-structured graphs. As the version for the chains, also this is a message passing algorithm.

This algorithm is applicable to undirected models, i.e., Markov Networks, as well as directed ones, i.e., Bayesian Networks. We will now present it on factor graphs assuming a tree-structured graph giving rise to a factor graph which is a tree.

9.6.4.1 Computing Marginals

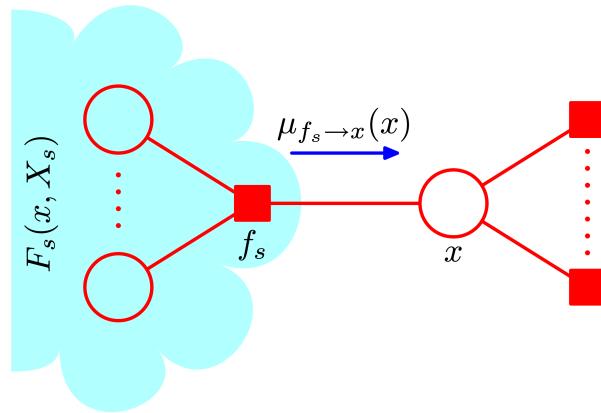
To compute the probability of a single variable, one sums over the probabilities of all variables except the one for which they wish to compute the marginal.

$$P(X) = \sum_{X \setminus X} P(\mathbf{X})$$

Since X is a node, then the probability $P(X)$ of an event is the product of all the incoming messages from the neighbouring factors f_s :

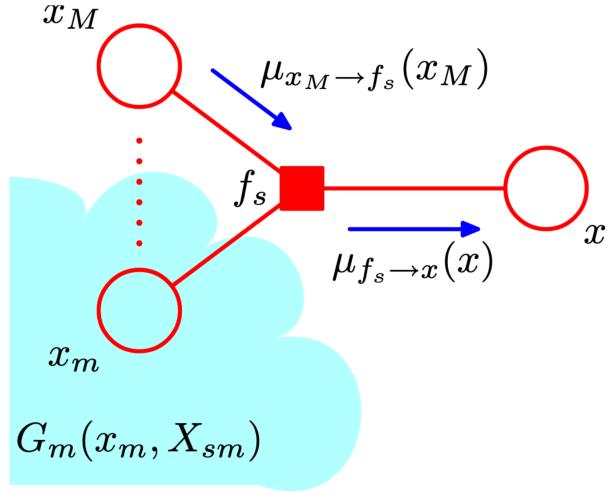
$$P(X) = \prod_{f_s \in \text{ne}(X)} \mu_{f_s \rightarrow X}(X)$$

where $\text{ne}(X)$ are the neighbours of X .



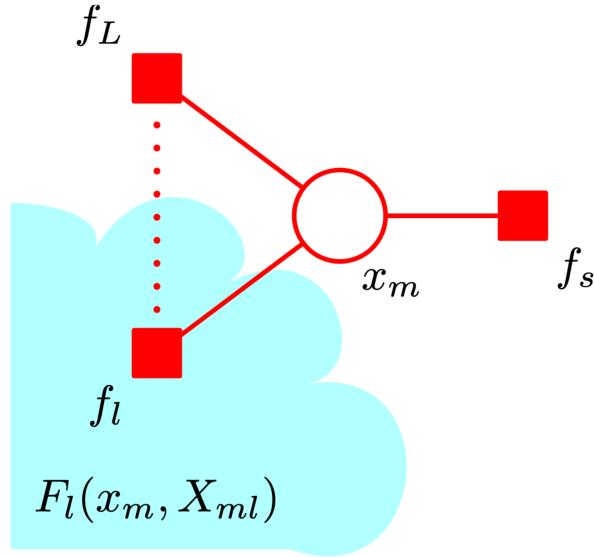
Each factor message is the product of messages coming from nodes other than X , times the factor, summed over all possible values of the factor variables other than X :

$$\mu_{f_s \rightarrow X}(X) = \sum_{X_1} \dots \sum_{X_M} f_s(X, X_1, \dots, X_M) \prod_{X_m \in \text{ne}(f_s) \setminus X} \mu_{X_m \rightarrow f_s}(X_m)$$



Now it's possible to notice that each message from node X_m to factor f_s is the product of the factor message to X_m coming from factors other than f_s :

$$\mu_{X_m \rightarrow f_s}(X_m) = \prod_{f_l \in \text{ne}(X_m) \setminus f_s} \mu_{f_l \rightarrow X_m}(X_m)$$



Knowing these informations, we can move to the algorithm. First of all the message passing starts from the leaves, either factors or nodes.

If the leaf is a factor, the message is initialized to the factor itself, indeed there would be no X_m different from the destination on which to sum over:

$$\mu_{f \rightarrow x}(x) = f(x)$$

If the leaf is a node, the message is initialized to 1:

$$\mu_{x \rightarrow f}(x) = 1$$

Now the node X whose marginal has to be computed is designed as root. Messages are sent from all leaves to their neighbours. Each internal node sends its message towards the root as soon as it has received the messages from all the other neighbours. Once the root has collected all messages, the marginal can be computed as the product of them.



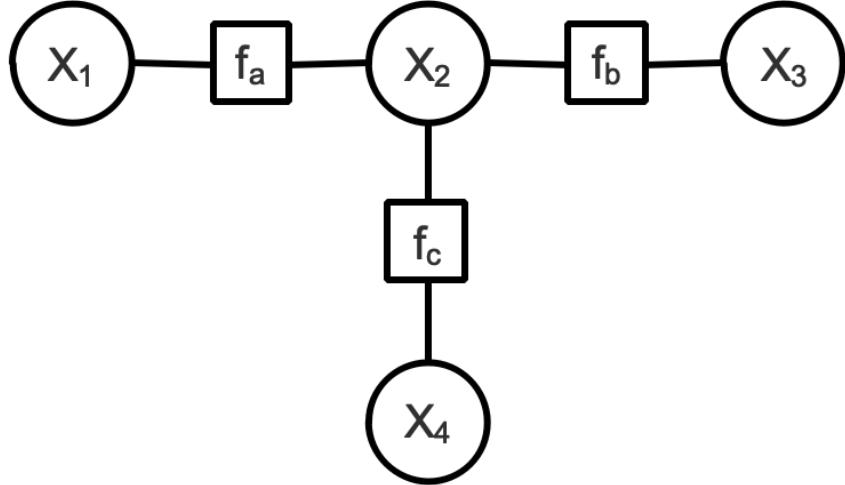
If the leaf is a factor, then the message is initialized to the factor itself.

If the leaf is a node, then the message is initialized to 1.

One should remember that for the chain structure the best approach was to send a message from one end to the other and another one on the opposite direction. Similarly, this can be done also for a tree structure: once the root has computed the marginal, send the value back to all the leaves. This allows to pass all messages in all directions using only twice the number of computations used for a single marginal.

9.6.4.2 Example

Let's consider the following factor graph:



Which has the following joint distribution:

$$P(\mathbf{X}) = f_a(X_1, X_2) f_b(X_2, X_3) f_c(X_2, X_4)$$

Let's consider the case in which we choose X_3 has the root of the tree, hence X_1 and X_4 are the leafs. Since they are nodes, then the messages are initialized to 1:

$$\mu_{X_1 \rightarrow f_a}(X_1) = 1$$

$$\mu_{X_4 \rightarrow f_c}(X_4) = 1$$

By definition, the message from factors to nodes is the product of the messages coming from nodes other than X_i , times the factor, summed over all possible values of the factor variables other than X_i . Since for both factors f_a and f_c there is only one node before, hence one single message which value is 1, then it's possible to write:

$$\mu_{f_a \rightarrow X_2}(X_2) = \sum_{X_1} f_a(X_1, X_2)$$

$$\mu_{f_c \rightarrow X_2}(X_2) = \sum_{X_4} f_c(X_2, X_4)$$

Now we need to send a message from the node X_2 to the factor f_b , and by definition, such message is the product of the message arriving to X_2 :

$$\mu_{X_2 \rightarrow f_b}(X_2) = \mu_{f_a \rightarrow X_2}(X_2)\mu_{f_c \rightarrow X_2}(X_2)$$

Then the message from f_b to X_3 can be written as:

$$\mu_{f_b \rightarrow X_3}(X_3) = \sum_{X_2} f_b(X_2, X_3)\mu_{X_2 \rightarrow f_b}(X_2)$$

Now we need to do the opposite, that is, start from X_3 and go towards the leaves. Since X_3 is a node, then the message is initialized to 1:

$$\mu_{X_3 \rightarrow f_b}(X_3) = 1$$

From factor f_b to factor node X_2 we have:

$$\mu_{f_b \rightarrow X_2}(X_2) = \sum_{X_3} f_b(X_2, X_3)$$

From X_2 to factors f_a and f_c :

$$\mu_{X_2 \rightarrow f_a}(X_2) = \mu_{f_b \rightarrow X_2}(X_2)\mu_{f_c \rightarrow X_2}(X_2)$$

$$\mu_{X_2 \rightarrow f_c}(X_2) = \mu_{f_b \rightarrow X_2}(X_2)\mu_{f_a \rightarrow X_2}(X_2)$$

Finally the message to the leaves are:

$$\mu_{f_a \rightarrow X_1}(X_1) = \sum_{X_2} f_a(X_1, X_2)\mu_{X_2 \rightarrow f_a}(X_2)$$

$$\mu_{f_c \rightarrow X_4}(X_4) = \sum_{X_2} f_c(X_2, X_4)\mu_{X_2 \rightarrow f_c}(X_2)$$

Now that we have all the information that we need, we could for example decide to compute the marginal probability of X_2 . We know that the marginal can be computed as the product of all the incoming messages:

$$P(\mathbf{X}) = \mu_{f_a \rightarrow X_2}(X_2)\mu_{f_b \rightarrow X_2}(X_2)\mu_{f_c \rightarrow X_2}(X_2)$$

By expanding each message as written before, we obtain:

$$\begin{aligned} &= \left[\sum_{X_1} f_a(X_1, X_2) \right] \left[\sum_{X_3} f_b(X_2, X_3) \right] \left[\sum_{X_4} f_c(X_2, X_4) \right] \\ &= \sum_{X_1} \sum_{X_3} \sum_{X_4} f_a(X_1, X_2)f_b(X_2, X_3)f_c(X_2, X_4) \end{aligned}$$

But the product of all factors is nothing but the initial distribution:

$$= \sum_{X_1} \sum_{X_3} \sum_{X_4} P(\mathbf{X})$$

This "proves" that we could use just two passing of messages to compute the marginal probabilities.

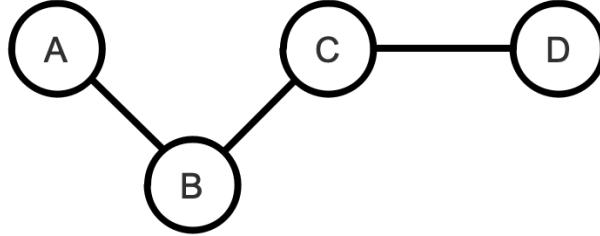
9.6.4.3 Example – Adding Evidence

As said before, if any node is observed, then we simply use their observed values instead of summing over all possible values when computing their messages. After normalization this gives the conditional probability given the evidence.

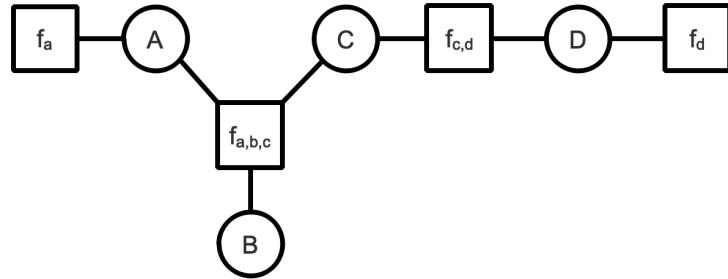
Consider for example the following probability distribution:

$$P(B|A, C)P(A)P(C|D)P(D)$$

Let's now represent this via a Bayesian Network:



We could convert it to a factor graph by looking at its probability distribution and adding a function for each probability:



Let's consider the case in which we'd like to compute the marginal of B . Notice that when we know which node we want to compute the probability of, then we can just use one passage of messages. So let's make B the root of the tree and start from f_a and f_d which are the leaves. Since the leaves are factors, then we can use directly their probability:

$$\mu_{f_A \rightarrow A} = P(A)$$

$$\mu_{f_D \rightarrow D} = P(D)$$

This are the incoming messages to A and D respectively. Now let's compute the outgoing messages; since both A and B do not have any factor except for f_A and f_D respectively, then their messages are:

$$\mu_{A \rightarrow f_{A,B,C}}(A) = \mu_{f_A \rightarrow A} = P(A)$$

$$\mu_{D \rightarrow f_{C,D}}(D) = \mu_{f_D \rightarrow D} = P(D)$$

Now let's wait for the branch of A and focus on the branch of C and D . We'll send a message from factor $f_{C,D}$ to node C . In this case we'll have to sum over all possible values of D :

$$\mu_{f_{C,D} \rightarrow C}(C) = \sum_D P(C|D)\mu_{D \rightarrow f_{C,D}}(D) = \sum_D P(C|D)P(D)$$

We can now also send the message from C to factor $f_{A,B,C}$:

$$\mu_{C \rightarrow f_{A,B,C}}(C) = \mu_{f_{C,D} \rightarrow C}(C) = \sum_D P(C|D)P(D)$$

At last the factor $f_{A,B,C}$ sends a message to the node B :

$$\begin{aligned}\mu_{f_{A,B,C} \rightarrow B}(B) &= \sum_A \sum_C P(B|A, C) \mu_{C \rightarrow f_{A,B,C}}(C) \mu_{A \rightarrow f_{A,B,C}}(A) \\ &= \sum_A \sum_C P(B|A, C) P(A) \sum_D P(C|D) P(D)\end{aligned}$$

Since the marginal probability of a node is the product of all incoming messages to the node, we have:

$$\begin{aligned}P(B) = \mu_{f_{A,B,C} \rightarrow B}(B) &= \sum_A \sum_C P(B|A, C) P(A) \sum_D P(C|D) P(D) \\ &= \sum_A \sum_C \sum_D P(B|A, C) P(A) P(C|D) P(D) \\ &= \sum_A \sum_C \sum_D P(A, B, C, D)\end{aligned}$$

9.6.5 Most Probable Configuration

Consider the following case: we are given a joint probability distribution $p(\mathbf{X})$ and our goal is to find the configuration for variables \mathbf{X} having the highest probability:

$$\mathbf{X}^{\max} = \operatorname{argmax}_{\mathbf{X}} P(\mathbf{X})$$

for which the probability is:

$$P(\mathbf{X}^{\max}) = \max_{\mathbf{X}} P(\mathbf{X})$$

For instance, we are not interested in computing the probability that in the next days it'll rain, but in knowing which is the most probable weather during the next week.

Notice that we are trying to find the configuration which is jointly maximal for all variables, that is if the variables are not independent, we cannot simply compute $P(X_i)$ for each i and then maximize.

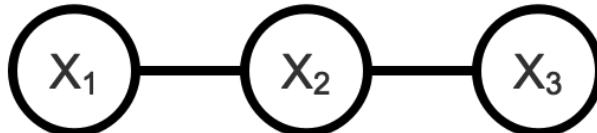
As for the sum-product algorithm, we can exploit the distribution factorization to efficiently compute the maximum:

$$P(\mathbf{X}^{\max}) = \max_{\mathbf{X}} P(\mathbf{X}) = \max_{X_1} \dots \max_{X_M} P(\mathbf{X})$$

All we have done is to replace the sum from the sum-product algorithm with a max function. When doing these maximizations, we are actually ignoring all the variables that are not the variable we are trying to maximize.

9.6.5.1 Chain Example

Let's consider a simple chain:



And let's say that the variables can take the following values: $X_1 = \{\text{Rainy, Cloudy, Sunny}\}$, $X_2 = \{T, F\}$, $X_3 = \{T, F\}$. The probability for X_1 and the conditional probabilities are the following:

X_1	X_1			X_2	
	R	C	S	T	F
X_2	T	0.2	0.4	0.8	
	F	0.8	0.6	0.2	
X_3	T	0.8	0.4		
	F	0.2	0.6		

The joint probability of a chain is:

$$P(\mathbf{X}) = P(X_3|X_2)P(X_2|X_1)P(X_1)$$

Our goal is to find the values for X_1, X_2, X_3 that maximize the joint probability.

Each maximization can be seen as an outgoing message (μ_β) where instead of having a sum we are actually maximizing. For instance:

$$\mu_\beta(X_2) = \max_{X_3} P(X_3|X_2) = \begin{cases} 0.8 & \text{if } X_2 = T \\ 0.6 & \text{if } X_2 = F \end{cases}$$

The result is due to the fact that, looking at the rightmost table, fixating a value for X_2 , it's possible to find the maximum probability, for instance, if X_2 is T , then the $P(X_3 = T|X_2 = T) > P(X_3 = F|X_2 = T)$.

The same can be done to compute the value for X_2 :

$$\mu_\beta(X_1) = \max_{X_2} P(X_2|X_1)\mu_\beta(X_2) = \begin{cases} 0.48 & \text{if } X_1 = R \\ 0.36 & \text{if } X_1 = C \\ 0.64 & \text{if } X_1 = S \end{cases}$$

In order to compute this we have to look at the center table above. First let's consider the case in which $X_1 = R$, then we could have $P(X_1 = R|X_2 = T) = 0.2$, or $P(X_1 = R|X_2 = F) = 0.8$. We want to check both of these possibilities and take the highest value:

$$P(X_1 = R|X_2 = T)\mu_\beta(X_2 = T) = 0.2 \cdot 0.8 = 0.16$$

$$P(X_1 = R|X_2 = F)\mu_\beta(X_2 = F) = 0.8 \cdot 0.6 = 0.48$$

Then we choose the highest value, that is 0.48. The same reasoning is applied for $P(X_1 = C|X_2)$ and $P(X_1 = S|X_2)$

$$P(X_1 = C|X_2 = T)\mu_\beta(X_2 = T) = 0.4 \cdot 0.8 = 0.48$$

$$P(X_1 = C|X_2 = F)\mu_\beta(X_2 = F) = 0.6 \cdot 0.6 = 0.36$$

$$P(X_1 = S|X_2 = T)\mu_\beta(X_2 = T) = 0.8 \cdot 0.8 = 0.64$$

$$P(X_1 = S|X_2 = F)\mu_\beta(X_2 = F) = 0.2 \cdot 0.6 = 0.12$$

At last we can compute the maximum configuration probability:

$$P(\mathbf{X}^{\max}) = \max_{X_1} P(X_1)\mu_\beta(X_1) = \max_{X_1} \begin{bmatrix} 0.48 \cdot 0.2 \\ 0.36 \cdot 0.2 \\ 0.64 \cdot 0.6 \end{bmatrix} = 0.64 \cdot 0.6 = 0.384$$

The most likely configuration for X_1 is:

$$\operatorname{argmax}_{X_1} P(X_1)\mu_\beta(X_1) = S$$

Then to know the most likely configuration for X_2 all we need to do is to go back to the computation of $\mu_\beta(X_1)$ and look to which value gave the highest probability when $X_1 = S$, that is when $X_2 = T$, $P(X_1 = S|X_2 = T)\mu_\beta(X_2) = 0.64$.

The same is done for X_3 keeping in mind that now we know that $X_2 = T$: given such information, the highest probability is obtained for $X_3 = T$, $P(X_3 = T|X_2 = T) = 0.8$.

This action of retrieving the correct configuration going backwards is called **backpropagation**.

9.6.5.2 Tree

As we saw in the example before, the max-product algorithm can be seen as a message passing over the graph. The algorithm is thus easily applied to tree-structured graphs via their factor trees: all one needs to do is to change the sum with a maximization:

$$\begin{aligned}\mu_{f \rightarrow X}(X) &= \max_{X_1, \dots, X_M} \left[f(X, X_1, \dots, X_M) \prod_{X_m \in \text{ne}(f) \setminus X} \mu_{X_m \rightarrow f}(X_m) \right] \\ \mu_{X \rightarrow f}(X) &= \prod_{f_l \in \text{ne}(X) \setminus f} \mu_{f_l \rightarrow X}(X)\end{aligned}$$

As the sum-product algorithm, once a root X_r is chosen, the leaves send messages towards the root. The probability of the maximal configuration is readily obtained as:

$$P(\mathbf{X}^{\max}) = \max_{X_r} \left[\prod_{f_l \in \text{ne}(X_r)} \mu_{f_l \rightarrow X_r}(X_r) \right]$$

The maximal configuration for the root is obtained as:

$$X_r^{\max} = \operatorname{argmax}_{X_r} \left[\prod_{f_l \in \text{ne}(X_r)} \mu_{f_l \rightarrow X_r}(X_r) \right]$$

We now need to recover the maximal configuration for the other variables. When sending a message towards x , each factor node should store the configuration of the other variables which gave the maximum:

$$\phi_{f \rightarrow X}(X) = \operatorname{argmax}_{X_1, \dots, X_M} \left[f(X, X_1, \dots, X_M) \prod_{X_m \in \text{ne}(f) \setminus X} \mu_{X_m \rightarrow f}(X_m) \right]$$

When the maximal configuration for the root node X_r has been obtained, it can be used to retrieve the maximal configuration for the variables in neighbouring factors from:

$$X_1^{\max}, \dots, X_M^{\max} = \phi_{f \rightarrow X_r}(X_r^{\max})$$

The procedure can be repeated *back-tracking* to the leaves, retrieving maximal values for all variables.

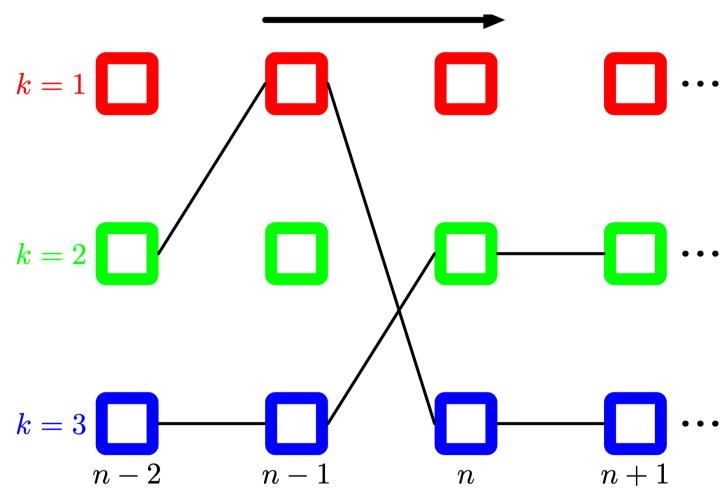
For the chain we saw before, back-tracking resolves in:

$$\begin{aligned}X_N^{\max} &= \operatorname{argmax}_{X_N} \mu_{f_{N-1,N} \rightarrow X_N}(X_N) \\ X_{N-1}^{\max} &= \phi_{f_{N-1,N} \rightarrow X_N}(X_N^{\max}) \\ X_{N-2}^{\max} &= \phi_{f_{N-2,N-1} \rightarrow X_{N-1}}(X_{N-1}^{\max}) \\ &\vdots \\ X_1^{\max} &= \phi_{f_{1,2} \rightarrow X_2}(X_2^{\max})\end{aligned}$$

9.6.5.3 Trellis

It's possible to visualize the best configuration by using a trellis diagram which shows the K possible states of each variable X_n one per row. For each state k of a variable X_n , $\phi_{f_{n-1,n} \rightarrow X_n}(X_n)$ defines a unique (maximal) previous state, linked by an edge in the diagram.

Once the maximal state for the last variable X_N is chosen, the maximal states for other variables are recovered following the edges backwards.



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10.0.0.1 Underflow

The max-product algorithm relies on products, but the multiplication of small numbers (probabilities) can lead to underflow problems. This can be solved by considering $\log(\max(P(\mathbf{X})))$ instead of simply $\max(P(\mathbf{X}))$.

Since the logarithm is monotonic, we have that the proper maximal configuration is recovered:

$$\log \left(\max_{\mathbf{X}} P(\mathbf{X}) \right) = \max_{\mathbf{X}} \log(P(\mathbf{X}))$$

Moreover we know that, by the properties of logarithms, the multiplication of logarithms can be converted into a sum, giving the *max-sum* algorithm.

10.0.1 Exact Inference – Junction Tree Algorithm

Let's see how to deal with inference when the network structure is not as nice as the ones we have seen until now. Indeed many applications require graphs with (undirected loops), so we actually need an extension of the max-product algorithm to generic graphs.

Such new algorithm is called **junction tree** algorithm. As the name suggests, this algorithm does not work on factor graphs, but on junction trees, i.e., tree-structured graphs with nodes containing clusters of variables of the original graph. Then a message passing scheme similar to the sum-product and max-product algorithms is run on the junction tree.

Notice though that such an algorithm is exponential on the maximal number of variables in a cluster, making it intractable for large complex graphs.

10.0.2 Approximate Inference

If the graph is too large or complex and the junction tree algorithm is not usable, then we can resort to *approximate* techniques such as:

- *Loopy belief propagation*: message passing on the original graph even if it contains loops;
- *Variational methods*: deterministic approximations, assuming the posterior probability (given the evidence) factorizes in a particular way;
- *Sampling methods*: approximate posterior is obtained sampling from the network.

10.0.2.1 Loopy Belief Propagation

The idea is simply to apply the sum-product algorithm even if it is not guaranteed to provide an exact solution.

We assume all nodes are in condition of sending messages, i.e., they already received a constant

1 message from all neighbours.

A message passing schedule is chosen in order to decide which nodes start sending messages, e.g., flooding.

The information then flows many times around the graph (because of loops), each message on a link replaces the previous one and is only based on the most recent messages received from the other neighbours.

The algorithm can eventually converge depending on the specific model over which it is applied.

10.0.2.2 Sampling Methods

Given the joint probability distribution $P(\mathbf{X})$, we want to compute $P(\mathbf{Y} = \mathbf{y} | \mathbf{E} = \mathbf{e})$. A sample from the distribution is an instantiation of all the variables \mathbf{X} according to the probability P , that is the "output" of the distribution probability P applied to some input \mathbf{X} .

Samples can be used to approximate the probability of a certain assignment $\mathbf{Y} = \mathbf{y}$ for a subset $\mathbf{Y} \subset \mathbf{X}$ of the variables: we simply count the fraction of samples which are consistent with the desired assignment.

We usually need to sample from a posterior distribution given some evidence $\mathbf{E} = \mathbf{e}$. The problem is that sampling from a distribution is difficult. We need to build to a process that allows us to do this and this is, for example the *Markov Chain Monte Carlo*.

10.0.2.2.1 Markov Chain Monte Carlo

We usually cannot directly sample from the posterior distribution since this would be too expensive. What we can do instead is to build a random process which gradually samples from distribution closer and closer to the posterior.

The state of the process is an instantiation of all the variables.

The process can be seen as randomly traversing the graph of states moving from one state to another with a certain probability. After enough time, the probability of being in any particular state is the desired posterior.

In this specific case, the random process is a Markov Chain.

10.0.2.3 Sampling Methods – Markov Chain

The state graph is very different from the graphical model of the joint distribution:

- Nodes in the graphical model are variables;
- Nodes in the state graph are instantiations of all the variables.

Definition 10.1: Markov Chain

A Markov Chain consists of:

- A space $Val(\mathbf{X})$ of possible states, one for each possible instantiation of all variables \mathbf{X} ;
- A *transition probability model* defining for each state $\mathbf{x} \in Val(\mathbf{X})$ a *next-state* distribution over $Val(\mathbf{X})$:

$$\mathcal{T}(\mathbf{x} \rightarrow \mathbf{x}')$$

A Markov chain *defines a stochastic process that evolves from state to state*.

Definition 10.2: Homogeneous Chains

A Markov chain is said to be homogeneous if its transition probability model does not change over time.

Transition probabilities between states do not depend on the particular time instant in the process: such are the chains we'll use for sampling.

Consider a sequence of states $\mathbf{x}^{(0)}, \mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots$ of the random process.

Being random, the state of the process at time t can be seen as a random variable $\mathbf{X}^{(t)}$. Assume the initial state $\mathbf{X}^{(0)}$ is distributed according to some initial probability $p^{(0)}(\mathbf{X}^{(0)})$. The distribution over subsequent states can be defined using the chain dynamics as:

$$p^{(t+1)}(\mathbf{X}^{(t+1)} = \mathbf{x}') = \sum_{\mathbf{x} \in Val(\mathbf{X})} p^{(t)}(\mathbf{X}^{(t)} = \mathbf{x}) \mathcal{T}(\mathbf{x} \rightarrow \mathbf{x}')$$

The probability of being in a certain state \mathbf{x} at time t is the sum of the probabilities of being in any possible state \mathbf{x}' at time $t - 1$ times the probability of a transition from \mathbf{x}' to \mathbf{x} .

As the process converges, we expect that $p^{(t+1)}$ becomes close to $p^{(t)}$:

$$p^{(t)}(\mathbf{x}') \approx p^{(t+1)}(\mathbf{x}') = \sum_{\mathbf{x} \in Val(\mathbf{X})} p^{(t)}(\mathbf{x}) \mathcal{T}(\mathbf{x} \rightarrow \mathbf{x}')$$

At convergence, we expect to have reached an equilibrium distribution $\pi(\mathbf{X})$: the probability of being in a state is the same as that of transitioning into it from a random predecessor.

Definition 10.3: Stationary Distribution

A distribution $\pi(\mathbf{X})$ is said to be a stationary distribution for a Markov chain \mathcal{T} if:

$$\pi(\mathbf{X} = \mathbf{x}') = \sum_{\mathbf{x} \in Val(\mathbf{X})} \pi(\mathbf{X} = \mathbf{x}) \mathcal{T}(\mathbf{x} \rightarrow \mathbf{x}')$$

We are interested only in Markov Chains with a unique stationary distribution which is reachable from any starting distribution $p^{(0)}$. This can be guaranteed via various conditions, for example ergodicity. Notice that for a Markov Chain with a finite state space $Val(\mathbf{X})$, **regularity** is a sufficient and necessary condition.

Definition 10.4: Regularity

A Markov chain is regular if there exists a number k such that for all state pairs $\mathbf{x}, \mathbf{x}' \in Val(\mathbf{X})$, the probability of getting from \mathbf{x} to \mathbf{x}' in exactly k steps is greater than zero.

This can be proven via 2 conditions:

- It is possible to get from any state to any other state using a positive probability path in the state graph;
- For every state \mathbf{x} there is a positive probability of transitioning from \mathbf{x} to \mathbf{x} in one step (self loop).

10.0.2.3.1 Markov Chains for Graphical Models

The typical use is estimating the probability of a certain instantiation of \mathbf{x} of the variables \mathbf{X} given some evidence $\mathbf{E} = \mathbf{e}$. This requires sampling from the posterior distribution $P(\mathbf{X}|\mathbf{E} = \mathbf{e})$. We wish to define a chain for which $P(\mathbf{X}|\mathbf{E} = \mathbf{e})$ is the stationary distribution.

States in the chain should be the subset of all possible instantiations which is consistent with the evidence \mathbf{e} :

$$\mathbf{x} \in Val(\mathbf{X}) : \mathbf{x}_{\mathbf{E}} = \mathbf{e}$$

A simple transition model that we can think consists in updating variables in $\widehat{\mathbf{X}} = \mathbf{X} - \mathbf{E}$ one at a time. Such model can be seen as made of a set of $k = |\widehat{\mathbf{X}}|$ local transition model \mathcal{T}_i , one for each variable $X_i \in \widehat{\mathbf{X}}$. Let $\mathbf{U}_i = \mathbf{X} - X_i$ and let \mathbf{u}_i be a possible instantiation of \mathbf{U}_i ; then the local transition model \mathcal{T}_i defines transitions between states (\mathbf{u}_i, x_i) and (\mathbf{u}_i, x'_i) :

$$\mathcal{T}_i : (\mathbf{u}_i, x_i) \mapsto (\mathbf{u}_i, x'_i)$$

By defining a transition as a sequence of k local transitions, one for each variable X_i , we obtain a homogeneous, i.e., not time-dependent, global transition model.

10.0.2.3.2 Gibbs Sampling

Gibbs sampling is an efficient and effective simple Markov chain for factored state spaces (like the ones in graphical models).

Local transitions \mathcal{T}_i are defined "forgetting" about the value of X_i in the current state: this allows to sample a new value according to the posterior probability of X_i given the rest of the current state:

$$\mathcal{T}_i((\mathbf{u}_i, x_i) \mapsto (\mathbf{u}_i, x'_i)) = P(x'_i | \mathbf{u}_i)$$

The Gibbs chain samples a new state performing k subsequent local moves and we only take samples after a full round of local moves.

Gibbs chains are ensured to be regular if the distribution is strictly positive: every value of X_i given any instantiation of \mathbf{U}_i has non-zero probability. If this is the case, then we can get from any state to any state in at most $k = |\widehat{\mathbf{X}}|$ local steps.

Gibbs chains have the desired posterior $P(\mathbf{X}|\mathbf{E} = \mathbf{e})$ as stationary distribution.

To generate samples from the correct posterior distribution, we need to wait until the Markov chain has converged to the stationary distribution. Once at convergence, all subsequent samples could be used to estimate the desired probability.

Mind though that consecutive samples are definitely not independent: a possible approach consists of letting an interval of d samples before collecting the next sample.

10.1 Learning in Graphical Models

We'll see how to apply what we have seen for parameters learning to Bayesian networks.

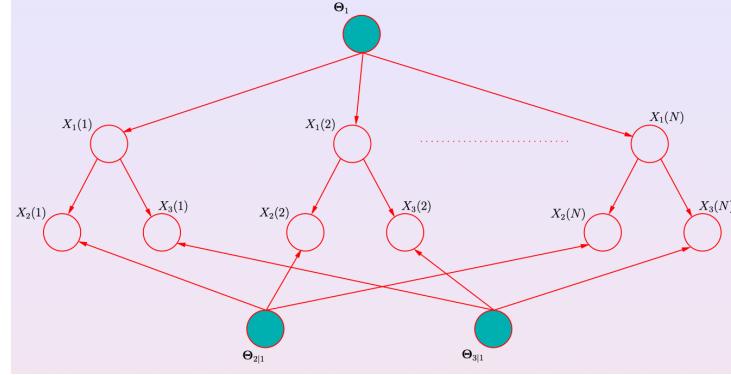
We are going to assume that the structure of the model is given and that we are also given a dataset of examples $\mathcal{D} = \{\mathbf{x}(1), \dots, \mathbf{x}(N)\}$. Each example $\mathbf{x}(i)$ is a configuration for all *complete data* or some *incomplete data* variables in the model.

As said, our goal is to estimate the parameters of the model, in form of conditional probability distributions (CPD), from the data. The simplest approach is to learn the parameters by maximizing the *likelihood* of the data:

$$\boldsymbol{\theta}^{\max} = \operatorname{argmax}_{\boldsymbol{\theta}} P(\mathcal{D} | \boldsymbol{\theta}) = \operatorname{argmax}_{\boldsymbol{\theta}} \mathcal{L}(\mathcal{D}, \boldsymbol{\theta})$$

Bayesian Network can be used not only to represent configuration of variables, but also to reason about what we want to learn. Suppose we have a simple graph with tail to tail connections and

a dataset of N examples, which can be specified by representing the network N times, where each copy refers to the network for a certain example:



The parameters $\boldsymbol{\theta}$ of the network are the ones in blue, and they are connected to the nodes that depend on the parameters. Now we can compute the likelihood as follows since the examples are independent given $\boldsymbol{\theta}$:

$$P(\mathcal{D}|\boldsymbol{\theta}) = \prod_{i=1}^N P(\mathbf{x}(i)|\boldsymbol{\theta})$$

Then if we consider the factorization of the Bayesian Network we have

$$P(\mathcal{D}|\boldsymbol{\theta}) = \prod_{i=1}^N \prod_{j=1}^m P(\mathbf{x}_j(i)|\text{pa}_j(i), \boldsymbol{\theta})$$

As it's possible to see from the previous graph, if, for instance, we'd want to compute the distribution of $\boldsymbol{\theta}_{3|1}$, there is no reason for which we should also keep in consideration $x_2(2)$ since they are not connected:

$$P(\mathcal{D}\boldsymbol{\theta}) = \prod_{i=1}^N \prod_{j=1}^m P(\mathbf{x}_j(i)|\text{pa}_j(i), \boldsymbol{\theta}_{X_j|\text{pa}_j})$$

Giving the disjoint conditional probability distribution.

The parameters of CPD can be estimated independently, the estimate of the parameter X_j by the maximum likelihood method is its maximum value:

$$\boldsymbol{\theta}_{X_j|\text{Pa}_j}^{\max} = \operatorname{argmax}_{\boldsymbol{\theta}_{X_j|\text{Pa}_j}} \prod_{i=1}^N P(\mathbf{x}_j(i)|\text{Pa}_j(i), \boldsymbol{\theta}_{X_j|\text{Pa}_j})$$

The second part is nothing but the likelihood of the parameters and the dataset:

$$\boldsymbol{\theta}_{X_j|\text{Pa}_j}^{\max} = \operatorname{argmax}_{\boldsymbol{\theta}_{X_j|\text{Pa}_j}} \prod_{i=1}^N P(\mathbf{x}_j(i)|\text{Pa}_j(i), \boldsymbol{\theta}_{X_j|\text{Pa}_j}) = \mathcal{L}(\boldsymbol{\theta}_{X_j|\text{Pa}_j}, \mathcal{D})$$

A discrete CPD $P(X|\mathbf{U})$ can be represented as a table with:

- A number of rows equal to the number X of configurations for X ;
- A number of columns equal to the number \mathbf{U} of configurations for its parents \mathbf{U} ;
- Each table entry $\theta_{x|\mathbf{u}}$ indicating the probability of a specific configuration $X = x$ and its parents $\mathbf{U} = \mathbf{u}$

Let's say we have this table sui fogli. allora possiamo massimizzare per ogni colonna quindi

E poi l'altra per l'altra colonna...

Il numero di colonne è il prodotto di tutti i possibili padri per il numero di possibili valori che assume. Vedi quaderno