Frequentist Statistics and Bayesian Statistics

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Frequentist Statistics
Approach

- Natural science attempts to find regularities and rules in nature

\[ F = ma \]

- The laws are valid under idealized conditions. Example: Fall of a point object without air friction, with velocities much smaller than the speed of light

- There might be measurement errors, but there is an underlying true (simple) dependency

- This motivates the frequentist statistics: derivation of probabilistic statements under repeatable experiments under identical conditions
Repeated experiments with an underlying linear dependency
Basic Terms

• Thus a statistical analysis requires a precise description of the experiment. For example, the details on who gets which medication (randomized?)

• A **statistical unit** is an object, on which measurements are executed (attributes are registered). Could be a person. A statistical unit defines a row in the data matrix, the attributes define the columns

• The population is the conceptual set of all statistical units about which we want to perform statistical inference. Example: diabetics

• For the analysis, only a sample is available (training data). Often it is assumes that the sample is a random subset of the population
Population

- A population can be finite, infinite, or hypothetic
- Example: all people who vote in an election
Typical Assumption

- The sample is a random subset of the population
- For each statistical unit \( i \) in the sample, we determine the attributes (features) \( x_i \)
- Assuming a random sample, we can write (in a finite sample, we would assume sampling with replacement) with \( P(\cdot) \) known

\[
P(x_1, \ldots, x_N) = \prod_{i=1}^{N} P(x_i)
\]

- The probability that I sample \( N \) units with attributes \( x_1, \ldots, x_N \) is the product of the probabilities of observing individual units with their individual attributes
Modelling

- $P(x_i)$ is unknown

- Assumption in parametric modelling: The data has been generated by a probability distribution $P_w(x_i)$, which is parameterized by the parameter vector $w$. For example, we might assume a Gaussian distribution with unknown mean but known variance.

- Thus we assume that for at least one parameter vector $w$

  $$P_w(x_i) \approx P(x_i)$$

- The goal is to estimate the parameter vector
Example: a Person’s Height

- We assume that the height \( x_i \) is Gaussian distributed with unknown mean and variance

\[
P_w(x_i) = \mathcal{N}(x_i; \mu, \sigma^2) = \frac{1}{\sigma \sqrt{2\pi}} \exp \left( -\frac{1}{2\sigma^2} (x_i - \mu)^2 \right)
\]

with \( w = (\mu, \sigma)^T \)

- Thus we get

\[
P_w(x_1, \ldots, x_N) = \prod_{i=1}^{N} P_w(x_i) = \prod_{i=1}^{N} \mathcal{N}(x_i; \mu, \sigma^2)
\]

\[
= \frac{1}{(2\pi\sigma^2)^{N/2}} \exp \left( -\frac{1}{2\sigma^2} \sum_{i=1}^{N} (x_i - \mu)^2 \right)
\]
How can we define and find the best parameters?
Maximum Likelihood

• We consider the probability of the observed data as a function of the parameters. This is the likelihood-function, where we assume that data points where generated independently

\[ L(w) = P_w(x_1, ..., x_N) = \prod_{i=1}^{N} P_w(x_i) \]

• It is often more convenient to work with the log-likelihood,

\[ l(w) = \log L(w) = \sum_{i=1}^{N} \log P_w(x_i) \]

• The maximum likelihood (ML) estimator is given by

\[ \hat{w}_{ml} \doteq \text{arg max}(l(w)) \]

• This means: in the family of distributions under considerations, the ML estimator is the one which explains the data the best
ML-estimator for Person’s Height

• The ML estimators are

\[ \hat{\mu} = \frac{1}{N} \sum_{i=1}^{N} x_i \]

and

\[ \hat{\sigma}^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - \hat{\mu})^2 \]
ML-Estimator for a Linear Model

• Let’s assume that the true dependency is linear, but we only have available noisy target measurements

\[ y_i = x_i^T w + \epsilon_i \]

• Let’s further assume that the noise is Gaussian distributed

\[ P(\epsilon_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{1}{2\sigma^2} \epsilon_i^2 \right) \]

• It follows that

\[ P_w(y_i|x_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{1}{2\sigma^2} (y_i - x_i^T w)^2 \right) \]

• It is easier to deal with the log

\[ \log P_w(y_i|x_i) = -\frac{1}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} (y_i - x_i^T w)^2 \]
The log-likelihood function is then

\[ l = -\frac{N}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - x_i^T w)^2 \]

The first term does not depend on \( w \). Under the assumption of independent additive noise, the ML estimator is the same as the LS estimator

\[ \hat{w}_{ml} = \arg \max(l(w)) = \hat{w}_{LS} \]

Since, \( \hat{w}_{ml} = \arg \max[-\sum_i (y_i - x_i^T w)^2] \) and \( \hat{w}_{ls} = \arg \min[\sum_i (y_i - x_i^T w)^2] \)
Analysis of Estimators

- Certainly the ML estimator makes sense (best fit). But how certain are we about the estimates. Maybe there are parameter values that would give us almost the same likelihood?

- To analyse the ML estimate we do the following thought experiment (see next slide)

- Let $\mu$ be the unknown but fixed parameter

- In addition to the available sample we are able to generate additional samples $D_1, D_2, \ldots D_L$, $L \to \infty$, each of size $N$

- For each of these $D_i$, we estimate the parameter and obtain $\hat{\mu}_i$ (for example, using the ML-estimator)

- We analyse the distribution of the estimated parameter

- In the example, we get for the mean person height (with known $\sigma^2$)

\[
P_\mu(\hat{\mu} - \mu) = \mathcal{N}(\hat{\mu} - \mu; 0, \frac{\sigma^2}{N})
\]
• The interpretation of probability here is: averaged of all $D_1, D_2, \ldots D_L$

• We can calculate this distribution without knowing the particular data set (although I need $\sigma^2$)

• Assuming, we estimate $\hat{\mu}$ from the available sample, we can answer the question: how probable is it to measure $\hat{\mu}$ if the true value is $\mu = 175\, cm$?
The frequentist experiment

\[
P(D | \mu) \quad \mu \quad D_1 \quad \cdots \quad D_i \quad \cdots \quad D_L
\]

\[
\hat{\mu}_1 \quad \cdots \quad \hat{\mu}_i \quad \cdots \quad \hat{\mu}_L
\]

\[
P(\hat{\mu} | \mu) \propto N(\mu, \sigma^2 / N)
\]
Bias of an Estimator

• The difference between the true parameter and the expected value of the parameter estimate (averaged over many data sets of size $N$) is called the bias

$$Bias(\hat{w}) = E_D(\hat{w}) - w_{true}$$

Here,

$$E_D(\hat{w}) = \lim_{L \to \infty} \frac{1}{L} \sum_{i=1}^{L} \hat{w}_{D_i}$$

In the example, the bias is zero.
The ML-Estimator can be Biased with finite Data

- The ML-estimator can be biased with finite data

\[ \hat{\sigma}^2_{ml} = \frac{1}{N} \sum_{i=1}^{N} (x_i - \hat{\mu})^2 \]

\[ \hat{\sigma}^2_{unbiased} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \hat{\mu})^2 \]
Variance of an Estimator

- The variance indicates how much an estimator varies around its mean

\[ Var(\hat{w}) = E_D (\hat{w} - E_D(\hat{w}))^2 \]

\[ Var(\hat{w}) = \lim_{L \to \infty} \frac{1}{L} \sum_{i=1}^{L} (\hat{w}_{Di} - E_D(\hat{w}))^2 \]

- In the example: \( Var(\hat{w}) = \sigma^2 / N \)
For finite $N$

The ML estimator can have a finite bias

For $N \rightarrow \infty$

The ML estimator is unbiased

$0$ $E_D(\hat{w})$ $\sqrt{\text{Var}(\hat{w})}$

$P(\hat{w} | w)$

$0$ $E_D(\hat{w}) = w$ $\sqrt{\text{Var}(\hat{w})} \rightarrow 0$

$Bias(\hat{w}) \rightarrow 0$
Expected Error

• The expected mean squared error evaluates the deviation of the estimator from the true parameter

\[ MSE(\hat{w}) = E_D (\hat{w} - w_{true})^2 \]

\[ MSE(\hat{w}) = \lim_{L \to \infty} \frac{1}{L} \sum_{i=1}^{L} (\hat{w}_{D_i} - w_{true})^2 \]

• The expected mean squared error is the sum of the variance and the square of the bias

\[ MSE(\hat{w}) = Var_D(\hat{w}) + Bias_D^2(\hat{w}) \]
Expected Error (cont’d)

Proof:

\[ \text{MSE}(\hat{w}) = E_D (\hat{w} - w_{true})^2 = E_D [(\hat{w} - E_D(\hat{w})) - (w_{true} - E_D(\hat{w}))]^2 \]

\[ = E_D (\hat{w} - E_D(\hat{w}))^2 + E_D (w_{true} - E_D(\hat{w}))^2 \]

\[ -2E_D [(\hat{w} - E_D(\hat{w}))(w_{true} - E_D(\hat{w}))] = \text{Var}_D(\hat{w}) + \text{Bias}^2_D(\hat{w}) + 0 \]

The cross term is zero since

\[ E_D [(\hat{w} - E_D(\hat{w}))(w_{true} - E_D(\hat{w}))] = (w_{true} - E_D(\hat{w})) E_D(\hat{w} - E_D(\hat{w})) = 0 \]
Desirable Properties of Estimators

• An estimator is unbiased, if $\text{Bias}(\hat{w}) = 0$

• An estimator is asymptotically unbiased, if $\text{Bias}(\hat{w}) = 0$, for $N \to \infty$

• An estimator is MSE consistent, if we have

$$MSE(\hat{w})_{N \to \infty} \to 0$$

• An estimator $\hat{w}$ ist MSE-effective, if

$$MSE[\hat{w}] \leq MSE[\tilde{w}] \quad \forall \hat{w}$$
Properties of the ML-Estimator

The ML-estimator has many desirable properties:

- The ML-estimator is asymptotically \( N \to \infty \) unbiased (although with a finite sample size it might be biased).
- Maybe surprisingly, the ML estimator is asymptotically \( (N \to \infty) \) MSE-efficient among all unbiased estimators.
- Asymptotically, the estimator is Gaussian distributed, even when the noise is not!
Estimating the Variance via Bootstrap

- In particular for complex models it might be difficult to derive the sampling distribution, for example the distribution of the ML parameter estimate.
- Recall that ideally we would have many training sets of the same size available, fit the model, and observe the distribution of the parameter estimates.
- Proxies for the new data sets of the same size $N$ can be generated surprisingly simple: A new data set can be generated by sampling $N$ times from the original data with replacement.
Classical Statistical Inference

- For hypothesis testing and the derivation of error bounds, please consult your favorite statistics book.
Discussion: ML

- The likelihood can be calculated even for complex models (e.g., models with latent variables)

- With the assumption that the data have been generated independently, the log-likelihood is the sum over the log likelihoods of individual data points

\[
l(w) = \sum_{i=1}^{N} \log P(y_i | w)\]
Discussion: ML (cont’d)

• The necessity to emulate the data generating process leads to interesting problem specific models

• A certain problem: One needs to assume that the true model is (approximately) in the class of the models under considerations.

• With finite data, the ML estimator can lead to over fitting: more complex models will have a higher likelihood

• The frequentist statistics has a strong focus in the analysis of the properties of parameter estimates
Bayesian Statistics
The Bayesian Approach

- In a frequentist setting, the parameters are fixed but unknown and the data are generated by a random process.
- In a Bayesian approach, also the parameters have been generated by a random process.
- This means we need an *a priori* distribution:
  \[ P(w) \]
- The we obtain a complete probabilistic model:
  \[ P(w)P(D|w) \]
- ... and can calculate the posterior parameter distribution using Bayes’ formula as:
  \[ P(w|D) = \frac{P(D|w)P(w)}{P(D)} \]
An Example

• Let’s assume that the height $w$ of all German males of age 20 follows a Gaussian distribution

$$P(w) = N(w; \mu, \alpha^2)$$

• Now you measure the height of one male German person with some Gaussian measurement noise

$$P(x|w) = N(x; w, \sigma^2)$$

• An ML estimate of this person’s height, ignoring the prior, would be $\hat{w} = x$, $Var(\hat{w}) = \sigma^2$

• The Bayesian would say that

$$P(w|x) = \frac{P(x|w)P(w)}{P(x)} = N\left(w; \frac{x + \frac{\sigma^2}{\alpha^2}\mu}{1 + \frac{\sigma^2}{\alpha^2}}, \frac{\sigma^2}{1 + \frac{\sigma^2}{\alpha^2}}\right)$$
Prior Distribution

• In the previous example, even a frequentist might agree that the Bayesian solution makes sense

• The Bayesian approach goes further: Even if $P(w)$ was not available from prior measurements, the user must specify a $P(w)$ according to the user’s prior belief!

• As if your money (or life) would depend on it!
The Prior

- Does it make sense to assume a personal $P(w)$?

- Cox (1946): If one is willing to assign numbers to one's personal beliefs, then one arrives, under few consistent conditions, at the Bayesian formalism.
The Bayesian Experiment

- In contrast to the frequentist experiment, we only work with the actual data \( D \) and do not need to assume that additional hypothetical data sets can be generated.

- One assume that the true parameter \( \mu \) has been generated from the prior distribution \( P(\mu) \) in one experiment. In the example: \( P(\mu) = \mathcal{N}(\mu; 0, \alpha^2) \)

- The data are generated from \( P(D|\mu) \), in the example \( P(D|\mu) = \prod_i \mathcal{N}(x_i; \mu, \sigma^2) \)

- Applying Bayes’ formula I get the \textit{a posteriori} distribution

\[
P(\mu|D) = \frac{P(D|\mu)P(\mu)}{P(D)} = \mathcal{N} \left( \mu; \frac{\text{mean}}{1 + \frac{\sigma^2}{N\alpha^2}}, \frac{\sigma^2}{N + \sigma^2/\alpha^2} \right)
\]

with mean \( = \frac{1}{N} \sum_{i=1}^{N} x_i \)
The Bayesian experiment

\[ P(\mu) \propto N(0, \alpha^2) \]

\[ P(\mu | D) \propto N \left( \frac{\text{mean}}{\sigma^2}, \frac{\sigma^2}{N + \frac{\sigma^2}{\alpha^2}} \right) \]
Analysis

- The Bayesian approach gives you the complete a posteriori parameter distribution.
- One can derive a maximum a posteriori estimator as,

\[ \hat{w}_{map} = \arg \max (P(w|D)) \]

In the example,

\[ \hat{\mu}_{MAP} = \frac{\text{mean}}{1 + \frac{\sigma^2}{N\alpha^2}} \]

- Note, that the MAP estimator converges to the ML estimator, for \( N \to \infty \).
Our Favorite Example: Linear Regression

- Assume, that the true dependency is linear but that we only measure noisy target data

\[ y_i = x_i^T w + \epsilon_i \]

We get (same as in the frequentist approach)

\[
P(y_i|w) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(y_i - x_i^T w)^2\right)
\]
Linear Regression: a priori Assumption

- A convenient *a priori* assumption is that

\[ P(w) = (2\pi\alpha^2)^{-M/2} \exp \left( -\frac{1}{2\alpha^2} \sum_{i=0}^{M-1} w_i^2 \right) \]

- We give smaller parameters a higher *a priori* probability

- Ockham’s razor: simple explanations should be preferred

- We will assume that the hyperparameters \( \sigma^2 \) and \( \alpha^2 \) are known. If they are unknown, one can define prior distributions for those. The analysis becomes more involved
Linear Regression: the a posteriori Distribution

• Using the likelihood-function and the prior parameter distribution, we can apply Bayes’ formula and obtain the a posteriori distribution

\[ P(w|D) = \frac{P(w)P(D|w)}{P(D)} \]
Linear Regression: Calculating the a posteriori Distribution

\[ P(w|D) = \frac{P(w)P(D|w)}{P(D)} \propto \exp \left( -\frac{1}{2\alpha^2} \sum_{j=0}^{M-1} w_i^2 - \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - x_i^T w)^2 \right) \]

\[ P(w|D) = \mathcal{N}(w; w_{map}, \text{cov}(w|D)) \]

With

\[ w_{map} = \left( X^T X + \frac{\sigma^2}{\alpha^2} I \right)^{-1} X^T y \]

and covariance

\[ \text{cov}(w|D) = \sigma^2 \left( X^T X + \frac{\sigma^2}{\alpha^2} I \right)^{-1} \]
Linear Regression: the MAP estimate and the PLS-solution

• The most probable parameter value, after observing the data, is (the maximum a posteriori (MAP) estimate)

\[ \hat{w}_{map} \doteq \text{arg max} (P(w|D)) = \hat{w}_{Pen} \]

with \( \lambda = \frac{\sigma^2}{\alpha^2} \).

• One sees that despite different experimental assumptions the frequentist ML estimate and the Bayesian MAP estimate are very similar. The ML estimate corresponds to the LS-solution and the MAP estimate corresponds to the PLS solution.
Bayesian Prediction with Linear Regression

- An important difference between is prediction. In a frequentist solution one substitutes the parameter estimate \( \hat{y}_i = x_i^T w_{ml} \), and one can calculate the variance in the prediction. In a Bayesian approach one applies the rules of probability and marginalizes (integrates over) the parameters.

- With

\[
P(y, w|x, D) = P(w|D)P(y|w, x)
\]

it follows that

\[
P(y|x, D) = \int P(w|D)P(y|w, x)dw
\]
Predictive Distribution for a Linear Model

- The \textit{a posteriori} predictive distribution becomes

\[
P(y|x, D) = \int P(y|w, x)P(w|D)dw
\]

\[
= \mathcal{N}(y| x^T \hat{w}_{map}, x^T \text{cov}(w|D)x + \sigma^2)
\]

and is Gaussian distributed with mean \(x^T \hat{w}_{map}\) and variance \(x^T \text{cov}(w|D)x + \sigma^2\).

- The variance on the prediction considers both the noise on the prediction as well as the uncertainty in the parameters (by integrating over possible values).

- This is an essential advantage of the Bayesian approach: one considers all plausible parameter values and, e.g., one can also consider all local optima in the integral.

- This is also the main technical challenge: for the Bayesian solution complex integrals need to be solved or approximated.
$P(D \mid w)$

**frequentist**

$w_{ML}$

$P(w \mid D)$

**Bayesian**

$w_{MAP}$
Personal belief is formulated as a probability distribution; a mechanism for consistent approach for various kinds of modeling uncertainty. For basic distributions (Gaussian, Poisson, Dirichlet, ...) which belong to the exponential family of distributions, closed form solutions for the complete Bayesian approach are available! For more complex models, a predictive analysis leads to integrals which often cannot be solved analytically. Special approximations: Monte-Carlo integration, evidence framework. The simplest approximation is

\[ P(y|x, D) = \int P(y|w, x)P(w|D)dw \approx P(y|x, w_{map}) \]

which means that one uses a MAP point estimate.