

# Probabilistic tools

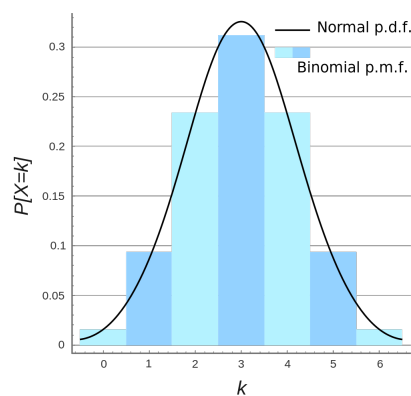
## Mass function

The probability mass function (p.m.f.) is the histogram of the distribution, that is:

- x-axis: values
- y-axis: frequency

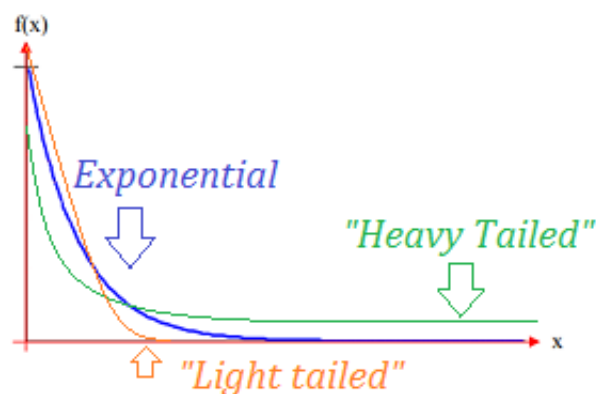
## Density function

The probability density function (p.d.f.) is the "smooth histogram" of the distribution.



## Heavy-Tailed Distribution

A distribution is heavy-tailed when there are more chances to get large values. Consequently, the variance is higher and will make the mean misleading as many outliers have high values. Below are p.d.f. (light-tailed and heavy-tailed)



An real-life example of heavy-tailed distribution is the income in the US.

## Central Limit Theorem

Let  $(X_n)_{n \geq 1}$  be a real and independent sequence with same law such that  $\mu = \mathbb{E}[X_1]$  and  $\mathbb{V}[X_1] = \sigma^2$  are defined ( $\mathbb{V}[X_1] \leq +\infty$ ). Noting  $\bar{X}_n = \frac{1}{n}(X_1 + \dots + X_n)$ , we have:

$$\sqrt{n} \frac{(\bar{X}_n - \mu)}{\sigma} \sim_{n \rightarrow \infty} \mathcal{N}(0, 1)$$

Spectral Theorem

Let  $M$  be a symmetric matrix with real coefficients. Then it exists  $U$  orthogonal and  $D$  diagonal with real coefficients such that  $M = UDU^T$ .

## Inferential statistics

### Parametric Tests

Procedure:

- 1) find the test to perform
- 2) find the right estimator to use
- 3) deduce the reject region
- 4) compute the test statistic
- 5) retrieve quantiles of known distributions

Example 1:

(*inspired from example in Saporta p.325*)

$$X_1, \dots, X_n \text{ (iid)} \sim \mathbb{P}_\theta$$

We want to analyze the mean.  $m = a$ ?

- 1) find the test to perform

$$\begin{cases} \mathcal{H}_0 : \theta = a \\ \mathcal{H}_1 : \theta > a \end{cases}$$

- 2) find the right estimator to use

Since we are testing the mean, we choose the empirical mean as **estimator**  $\hat{\theta} = \frac{1}{n} \sum X_i$

- 3) deduce the reject region

We fix  $k$  for a rejection level  $\alpha$ . The rejection region is:

$$Z = \{\hat{\theta} \geq k\}$$

We look for  $k$  defined as such:

$$\mathbb{P}_{\theta \in \Theta_0}(\hat{\theta} \geq k) = \alpha \Rightarrow \text{under } \mathcal{H}_0, \text{ we reject the hypothesis when our estimator } \hat{\theta} \text{ is above } k$$

*Intuitively, we want to keep our hypothesis if it's verified in most of the cases  $\Rightarrow$  under our hypothesis, there is a low probability that we are in the rejection region.*

Thus, if in real life we have a result that makes the hypothesis unverified, we reject the hypothesis. However, we have a risk of  $\alpha$  that our hypothesis was correct and that we ended up in the rejection region by mistake.

4) compute the test statistic

We center and reduce the estimator in order to get the Gaussian law and thus end up with known quantiles:

$$\mathbb{P}_{\theta=a}(T \geq \frac{\sqrt{n}(k-a)}{\sqrt{\sigma^2}}) = \alpha \text{ with } T \sim_{n \rightarrow \infty} \mathcal{N}(0,1)$$

$T$  is the test statistic (a test statistic is a random variable for which we know the law under  $\mathcal{H}_0$ )

5) retrieve quantiles of known distributions

Finally,  $\frac{\sqrt{n}(k-a)}{\sqrt{\sigma^2}} = q_\alpha \Rightarrow$  we can find  $k$  telling us when rejecting  $\mathcal{H}_0$

Why not looking at the average directly?

$\Rightarrow$  the average can be influenced by the outliers and thus doesn't take into consideration extreme events.

How about the median?

$\Rightarrow$  the median doesn't take into account the distribution / tendency of the values.

$\alpha$  is also called the p-value. The lower the p-value is, the less error we make in rejecting our hypothesis so the more significant the rejection is.

p-value is the lowest error probability we want to make when rejecting our hypothesis.

When performing OLS, our hypothesis is  $\theta_{x1} = 0$  so we reject it if the pvalue column is higher than our threshold. In the below OLS result, pvalues are displayed in column  $P > |t|$ . All variables are significant.

Dep. Variable:	y	R-squared:	0.106			
Model:	OLS	Adj. R-squared:	0.104			
Method:	Least Squares	F-statistic:	62.11			
Date:	Thu, 12 Mar 2020	Prob (F-statistic):	1.89e-14			
Time:	11:18:36	Log-Likelihood:	-383.98			
No. Observations:	526	AIC:	772.0			
Df Residuals:	524	BIC:	780.5			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	1.5010	0.027	55.870	0.000	1.448	1.554
x1	0.0240	0.003	7.881	0.000	0.018	0.030
=====						
Omnibus:	8.882	Durbin-Watson:	1.776			
Prob(Omnibus):	0.012	Jarque-Bera (JB):	11.058			
Skew:	0.185	Prob(JB):	0.00397			
Kurtosis:	3.606	Cond. No.	10.9			
=====						

Example 2: when the variance is not known.

Say we want to test whether a coefficient is zero:

1) find the test to perform

$$\begin{cases} \mathcal{H}_0 : \theta_j = 0 \\ \mathcal{H}_1 : \theta_j \neq 0 \end{cases}$$

2) find the right estimator to use

$$\hat{\theta}_j = (X^T X)^{-1} X^T Y$$

3) deduce the reject region

$$Z = \{k_1 \leq \hat{\theta}_j \leq k_2\}$$

4) compute the test statistic

$$T_j = \frac{\hat{\theta}_j - \theta_j}{\sigma_{\theta_j}} = \frac{\hat{\theta}_j}{\sigma_{\theta_j}} \sim \mathcal{N}(0, 1) \text{ with } \sigma_{\theta_j} = \sigma \sqrt{(X^T X)^{-1}} \text{ (recall that } \sigma = \sigma_\epsilon \text{)}$$

Since we don't know  $\sigma$ , we can use the Cochran theorem to remove this value:

$$T_j = \frac{\frac{\hat{\theta}_j}{\sigma \sqrt{(X^T X)^{-1}}} \sim \mathcal{N}(0, 1)}{\sqrt{\frac{\hat{\sigma}^2 (n-p-1)}{\sigma^2} \sim \chi_{n-p-1}}} \sim \mathcal{T}(n-p-1) \text{ with } \hat{\sigma}^2 = \frac{1}{n-p-1} \Sigma \epsilon^2$$

$$T_j = \frac{\hat{\theta}_j}{\Sigma \epsilon^2 \sqrt{(X^T X)^{-1}}}$$

5) retrieve quantiles of known distributions

Finally,

$$\mathcal{P}_{\theta_j=0} \left( \frac{k_1}{\Sigma \epsilon^2 \sqrt{(X^T X)^{-1}}} \leq T_j \leq \frac{k_2}{\Sigma \epsilon^2 \sqrt{(X^T X)^{-1}}} \right) = \alpha$$

$$\text{Thus, } \frac{k_1}{\Sigma \epsilon^2 \sqrt{(X^T X)^{-1}}} = t_{\frac{\alpha}{2}} \text{ (same for } k_2 \text{)}$$

Example 3 (forward selection):

Concept:

Regress all variables one by one on the most significant variable's residual, remove the most significant variable after each full round

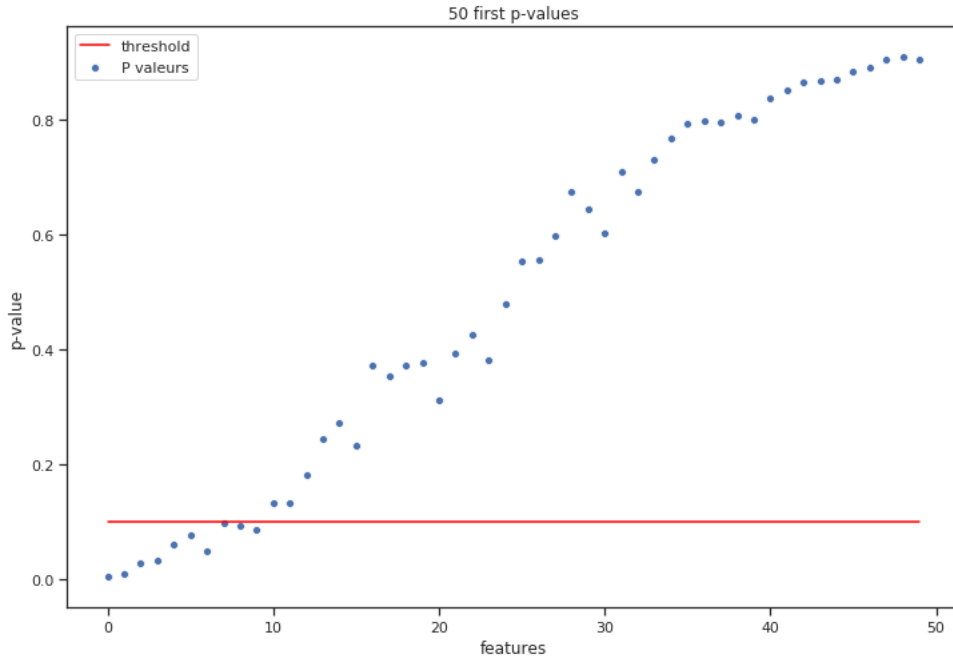
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**Algorithm 1** Forward selection

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```
sel_variables  $\leftarrow \emptyset$ 
for  $i = 1$  to nb_variables do
  resid_mem  $\leftarrow \emptyset$ 
  T_stats  $\leftarrow \emptyset$ 
  for  $j = 1$  to rem_variables do
     $Y = X_j \theta$ 
    resid_mem  $\leftarrow$  resid_mem + {res} // adding residuals from previous regression
    T_stats  $\leftarrow$  T_stats + { $T_j$ } //  $T_j$  is computed as seen in example 2
  end for
   $k \leftarrow \text{argmax}(T\_stats)$ 
   $Y = \text{resid\_mem}(k)$ 
  rem_variable  $\leftarrow$  rem_variable -  $k$ 
  sel_variables  $\leftarrow$  sel_variables + { $k$ }
end for
```

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(x-axis is the order in which we selected variables; see notebook *ACP\_ForwardSelection\_Ridge\_Lasso.ipynb*)

We can then select only the most significant variables based on p-values on variables from list *sel\_variables*

*Note*: since  $pval = 2 * (1 - cdf(T)) = 2 * \frac{1-(1-\alpha)}{2}$ , choosing the biggest T-stat is equivalent to choose the smallest p-value

## Likelihood method

This method consists on finding the parameter that maximizes the likelihood:

$L(x_1, \dots, x_n; \theta) = f(X|\theta) = \prod_{i=1}^n f_{\theta}(x_i; \theta)$  which is the product of densities across all samples.

Intuitively, we want to find the  $\theta$  that maximizes a certain event, that is, obtaining some data  $X$  (which is why we have  $X|\theta$ ).

We often use the log in order to get rid of power coefficients appearing with the product.

*likelihood equation:*  $\frac{d}{d\theta} \ln(L(x_1, \dots, x_n; \theta)) = 0$

## Exploratory statistics

Mahalanobis distance

Mahalanobis distance is a good alternative to Euclidean distance. For any given point  $x$  in a set  $X$ , the squared Mahalanobis distance is:

$$D^2 = (x - \mu_X)^T \Sigma^{-1} (x - \mu_X)$$

Advantage : it takes into account the data standard deviation and correlation. The more the data is dispersed, the lower the distance is. Indeed, using the inverse matrix is like if we divided the distance from the mean  $(x - \mu_X)$  by the standard deviation.

*Note:* Euclidean distance is when  $\Sigma = Id$ .

## Predictive models

### ROC curve

ROC curve is used essentially for binary classification.

ROC = Receiver Operating Curve

Use of the ROC curve

One model:

We use ROC curve to evaluate the performance of one classifying model that we can obtain when varying a threshold.

Several models:

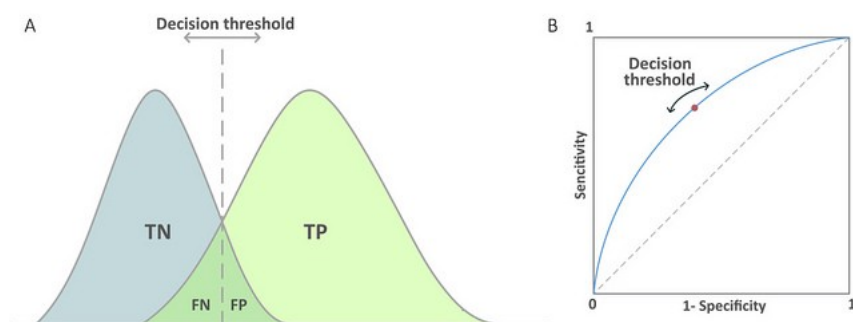
We use ROC curve to compare several classifying models in evaluating the area under the curve (AUC) for a range of threshold.

Intuition

After running the prediction of a specific model, we draw the confusion matrix (actual vs predicted) with a certain threshold.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

We then modify the threshold and draw another confusion matrix. The ROC graph summarizes all of the confusion matrices that each threshold produced.



On the left picture we see the ability of a model to give a clear distinction between the two classes. The curves are drawn from the predictions and the actual results (**how?**)

### Implementation

1. Get probability predictions
2. Sort the probabilities (prediction)
3. Sort the validation (actual) according to previous sort
4. Loop on the sorted validation. At each iteration:
  - increment TP or FP
  - compute the TPR and FPR.
5. Plot (FPR, TPR)

See <https://docs.eyesopen.com/toolkits/cookbook/python/plotting/roc.html> for an implementation example, or data challenge Face\_Recognition.