Classification Logistic regression

Tech Lead Data Science

Master en Data Science 2022-2023



ÍNDICE

Introduction to classification problems

- **2** Logistic regression
- **3** Evaluation metrics

- Classification problems have an independent categorical variable Y.
- They are processes that consist on identifying to which category or class belongs a determined object, according to their dependent variables.
- Examples:
 - Fraud detection
 - Definition of a target in a marketing campaign
 - Medical diagnosis
 - Image classification



STEPS

1. Training:

We build a classifier (model) learning from a labeled train set.

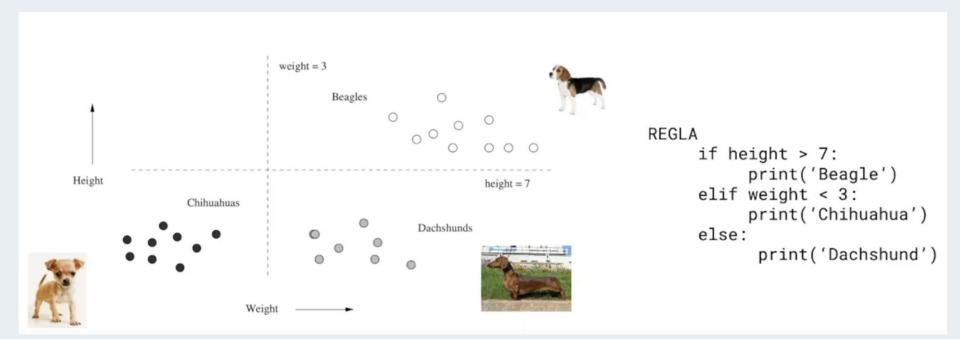
2. Classification:

We use the model to classify.

3. Evaluation:

We evaluate the model. This step can be included in the previous one.







Life is not so easy: we cannot always develop clear rules 🙁

To solve this kind of problem, we have machine learning models that **predict** the probability of a given observation to belong to a particular class:

- Bayesian models
- Logistic regression
- Decision Trees Random forests
- Neural networks
- And more!!



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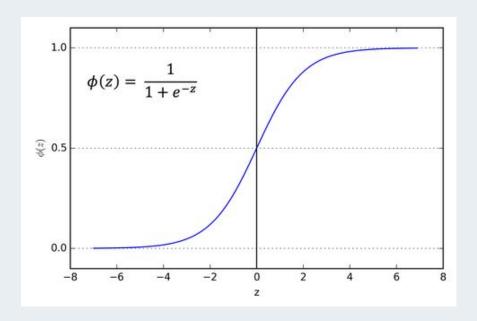
- Logistic Regression is a classification model, which is very easy to realize and achieves very good performance with linearly separable classes.
- Assumption about y:

$$y \sim binomial(1, p) \longrightarrow y \begin{cases} 1 & p \\ 0 & 1-p \end{cases}$$

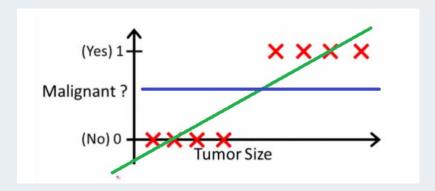
- The predictor variables must be linearly independent.
- It is necessary to standardize the variables.
- It is a very sensitive model to atypical values or outliers.
- Logistic regression can be generalized to problems of more than two classes.



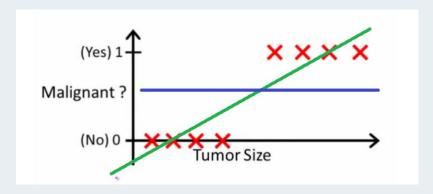
It uses a logistic function

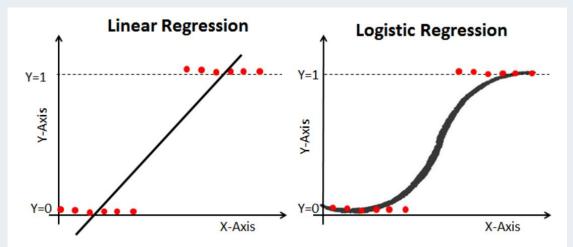














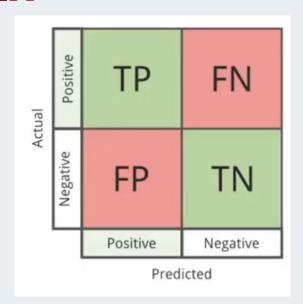
$$\hat{y}^{(i)}=eta_0+eta_1x_1^{(i)}+\ldots+eta_px_p^{(i)}$$

$$\phi(z) = \frac{1}{1 + e^{-z}} = \frac{1}{1 + exp(-(\beta_0 + \beta_1 x_1^{(i)} + \ldots + \beta_p x_p^{(i)}))}$$

CONFUSION MATRIX

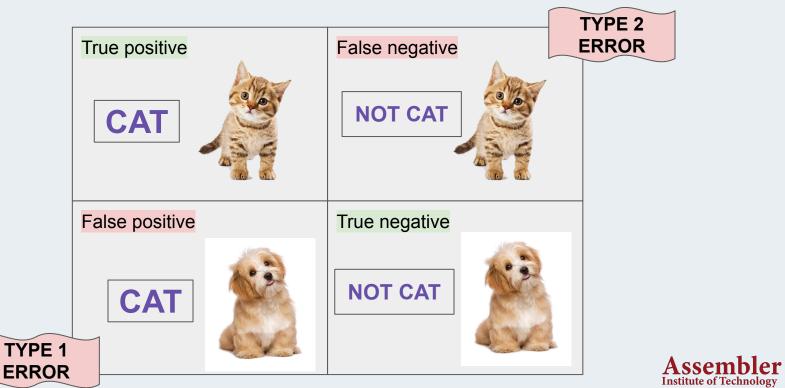
There are 4 possible values:

- True Positives (TP)
- True Negatives (TN)
- False Positives (FP)
- False Negatives (FN)





CONFUSION MATRIX



METRICS

- Accuracy: Percentage of cases in which our model was correct
- Precision: Percentage of values that have been classified as positive are actually positive
- Recall: Percentage of positive values that are identified
- **F1 Score :** Combines accuracy and comprehensiveness

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$



ROC CURVE

- Represents the percentage of **true positives** (TPR or Recall) **against the false positives** ratio (FPR).
- Its values range from 0 to 1.

