

Linear Models for Classification and Regression

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TUM

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Table of Contents

Introduction

Multiple Linear Regression

Binary Logistic Regression for Classification

Summary and Outlook

Why use Linear Models?

METHODS AND ALGORITHMS USAGE

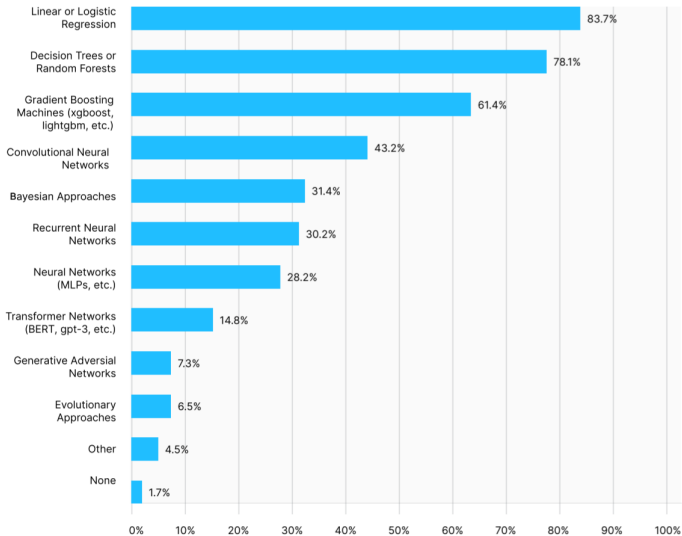
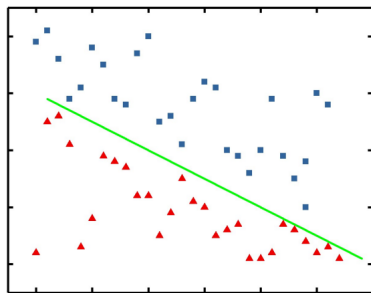
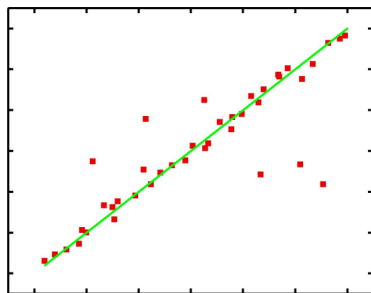


Figure: adapted from <https://www.kaggle.com/kaggle-survey-2020>

Regression vs Classification



(a) Logistic Regression



(b) Linear Regression

Figure: left: Classification, right: Regression (adapted from [1])

Idea of Linear Models:

$$a_1 v_1 + a_2 v_2 + \cdots + a_n v_n$$

Table of Contents

Introduction

Multiple Linear Regression

Binary Logistic Regression for Classification

Summary and Outlook

Table of Contents

Introduction

Multiple Linear Regression

Binary Logistic Regression for Classification

Summary and Outlook

Model

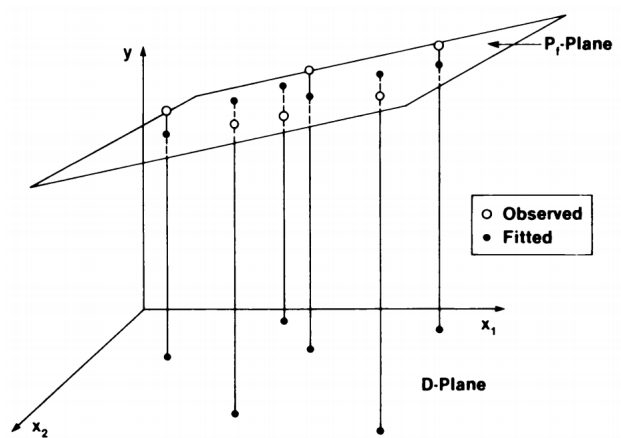


Figure: geometric representation of a regression plane (adapted from [2])

Mathematical Description

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1p} \\ 1 & x_{21} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{np} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix} + \begin{pmatrix} \epsilon_0 \\ \epsilon_1 \\ \vdots \\ \epsilon_n \end{pmatrix}$$

minimize error via Least Squares

$$\arg \min_{\beta} \left[(\mathbf{y} - X\beta)^T (\mathbf{y} - X\beta) \right]$$

Assumptions and Goodness of Fit

Assumption:

- input parameters are (linearly) **independent** from each other [3]
- errors ϵ_i have **Normal Distribution** with zero mean and constant variance

Goodness of Fit:

- Mean Squared Error
- R^2
- F-Test (Hypothesis Test)

Case Study with Linear Regression

show Python-Notebook!

Library: Statsmodels with Python

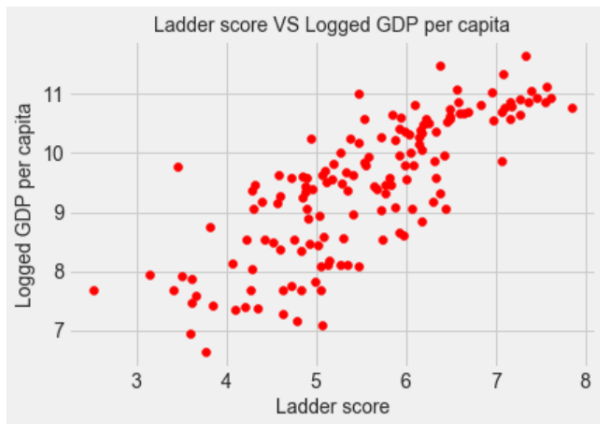
<https://worldhappiness.report/faq/>

Case Study with Linear Regression

| | Country name | Ladder score | Logged GDP per capita | Social support | Healthy life expectancy |
|---|--------------|--------------|-----------------------|----------------|-------------------------|
| 0 | Finland | 7.842 | 10.775 | 0.954 | 72.0 |
| 1 | Denmark | 7.620 | 10.933 | 0.954 | 72.7 |
| 2 | Switzerland | 7.571 | 11.117 | 0.942 | 74.4 |
| 3 | Iceland | 7.554 | 10.878 | 0.983 | 73.0 |
| 4 | Netherlands | 7.464 | 10.932 | 0.942 | 72.4 |

Figure: excerpt of happines-dataset

Case Study with Linear Regression



Case Study with Linear Regression

| OLS Regression Results | | | | | | |
|------------------------------|------------------|---------------------|----------|-------|--------|--------|
| ===== | | | | | | |
| Dep. Variable: | Ladder score | R-squared: | 0.756 | | | |
| Model: | OLS | Adj. R-squared: | 0.746 | | | |
| Method: | Least Squares | F-statistic: | 73.27 | | | |
| Date: | Thu, 03 Jun 2021 | Prob (F-statistic): | 5.06e-41 | | | |
| Time: | 12:31:21 | Log-Likelihood: | -116.50 | | | |
| No. Observations: | 149 | AIC: | 247.0 | | | |
| Df Residuals: | 142 | BIC: | 268.0 | | | |
| Df Model: | 6 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | -2.2372 | 0.630 | -3.548 | 0.001 | -3.484 | -0.991 |
| Logged GDP per capita | 0.2795 | 0.087 | 3.219 | 0.002 | 0.108 | 0.451 |
| Social support | 2.4762 | 0.668 | 3.706 | 0.000 | 1.155 | 3.797 |
| Healthy life expectancy | 0.0303 | 0.013 | 2.274 | 0.024 | 0.004 | 0.057 |
| Freedom to make life choices | 2.0105 | 0.495 | 4.063 | 0.000 | 1.032 | 2.989 |
| Generosity | 0.3644 | 0.321 | 1.134 | 0.259 | -0.271 | 0.999 |
| Perceptions of corruption | -0.6051 | 0.291 | -2.083 | 0.039 | -1.179 | -0.031 |
| ===== | | | | | | |
| Omnibus: | 12.908 | Durbin-Watson: | 1.614 | | | |
| Prob(Omnibus): | 0.002 | Jarque-Bera (JB): | 13.688 | | | |
| Skew: | -0.667 | Prob(JB): | 0.00107 | | | |
| Kurtosis: | 3.650 | Cond. No. | 1.15e+03 | | | |
| ===== | | | | | | |

Table of Contents

Introduction

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Summary and Outlook

Reuse

- Can we somehow reuse/reframe previously presented Linear Regression Methods to solve a Classification problem?
- Reason why it's called Logistic **Regression**

Model

$$\log\left(\frac{1}{1-p}\right) = X\beta$$

$$\Rightarrow P(y = 1|\mathbf{x}) = \frac{1}{1 + e^{-(\beta^T \mathbf{x})}}$$

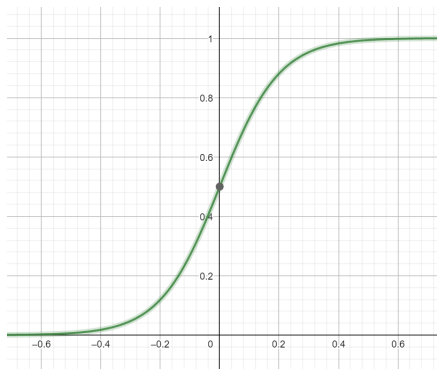


Figure: logistic function

Case Study with Logistic Regression

show Python-Notebook!

Library: Scikit-Learn with Python

<https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+%28Diagnostic%29>

Case Study with Logistic Regression

| | diagnosis | texture_mean | perimeter_mean | smoothness_mean | compactness_mean | symmetry_mean |
|------------|-----------|--------------|----------------|-----------------|------------------|---------------|
| 564 | M | 22.39 | 142.00 | 0.11100 | 0.11590 | 0.1726 |
| 565 | M | 28.25 | 131.20 | 0.09780 | 0.10340 | 0.1752 |
| 566 | M | 28.08 | 108.30 | 0.08455 | 0.10230 | 0.1590 |
| 567 | M | 29.33 | 140.10 | 0.11780 | 0.27700 | 0.2397 |
| 568 | B | 24.54 | 47.92 | 0.05263 | 0.04362 | 0.1587 |

Figure: excerpt of cancer-dataset

Case Study with Logistic Regression

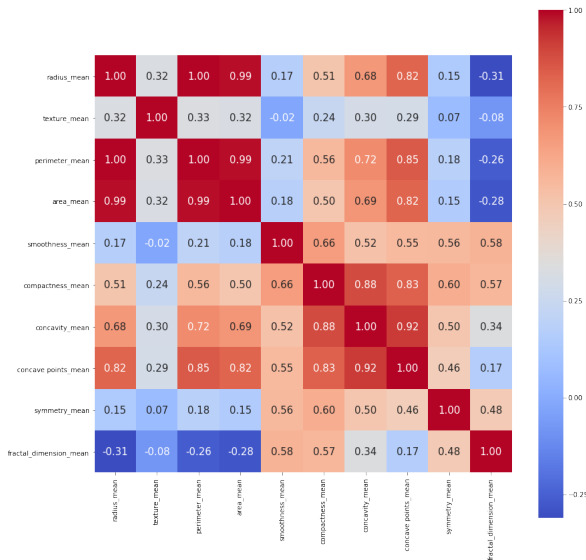


Figure: correlation-matrix

Case Study with Logistic Regression

| Metrics | Values |
|-------------------------|--------|
| Classification Accuracy | 91.2% |
| MSE | 0.0877 |

Table: Metrics for Logistic Regression Model

Table of Contents

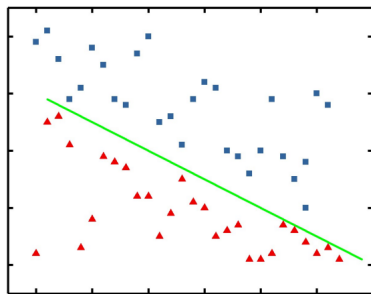
Introduction

Multiple Linear Regression

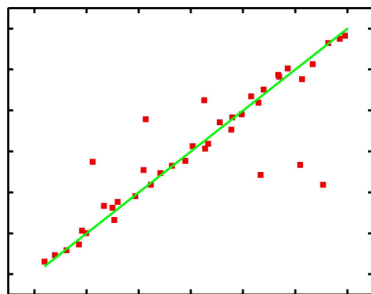
Binary Logistic Regression for Classification

Summary and Outlook

Drawback of Linear Models



(a) Logistic Regression



(b) Linear Regression

Figure: left: Classification, right: Regression (adapted from [1])

Summary

- Linear Models are the most often used Data Analysis Algorithms (in Kaggle)
- should be used before applying more complex Algorithms

Questions

Any Questions? :)



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Everything below here are just extra slides

[4] [5] [3] [6] [7] [1] [8] [9] [10] [2]

Computation via Singular Value Decomposition

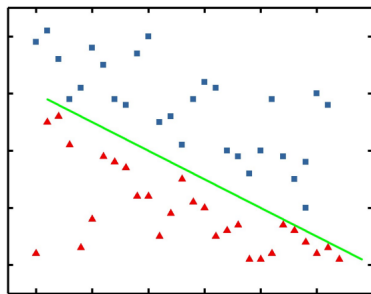
$$\mathbf{y} = X\boldsymbol{\beta} + \boldsymbol{\epsilon} = U\Sigma V^T\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

$$\Rightarrow \boldsymbol{\beta} = V\Sigma^{-1}U^T\mathbf{y}$$

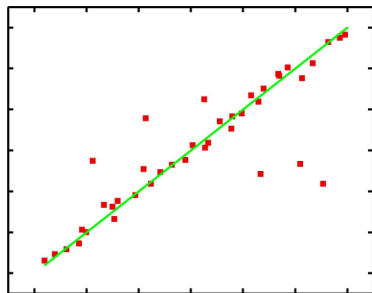
$O(n_{\text{samples}} \cdot n_{\text{features}}^2)$ Scikit-Learn [8]

- analogon of Eigendecomposition
- U ($n \times n$) and V ($p \times p$) as orthogonal matrices
- Σ ($p \times p$) consists only of diagonal entries known as the singular values of X
- check colinearities with singular values

Problem Setting



(a) Logistic Regression



(b) Linear Regression

Figure: left: Classification, right: Regression (adapted from [1])

Linear Regression

$$y = X\beta$$

Transformation Function

$$y = \log\left(\frac{1}{1-p}\right)$$

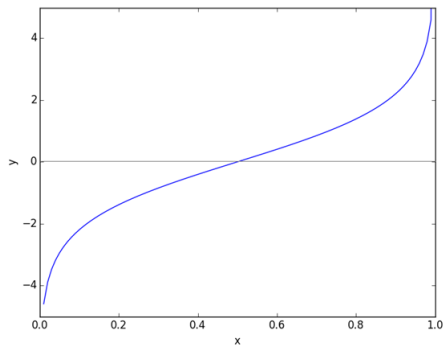


Figure: transformation function from $(0, 1)$ to \mathbb{R}

Computation

minimization problem:

$$\arg \min_{\beta} \frac{1}{m} \sum_{i=1}^m e(f(\mathbf{x}^{(i)}; \beta),$$

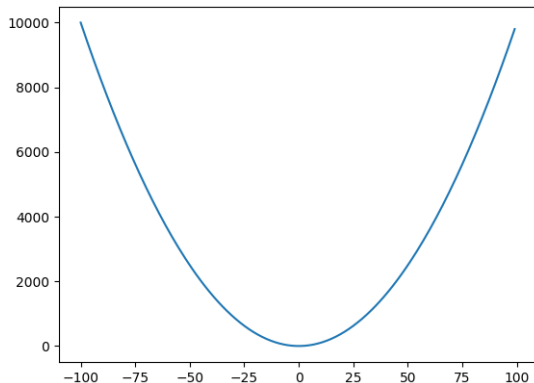
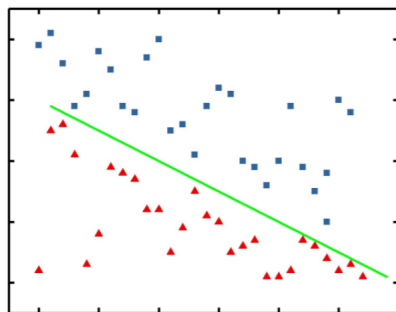


Figure: convex error function

Goodness of Fit

- split dataset into training and testing dataset
- **Classification Accuracy**



(a) Logistic Regression

Figure: Logistic Regression

Polynomial Regression

$$X = \begin{pmatrix} 1 & x_1 & \cdots & x_1^p \\ 1 & x_2 & \cdots & x_2^p \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & \cdots & x_n^p \end{pmatrix}$$

Logistic Regression as "Mini"-Neural-Network

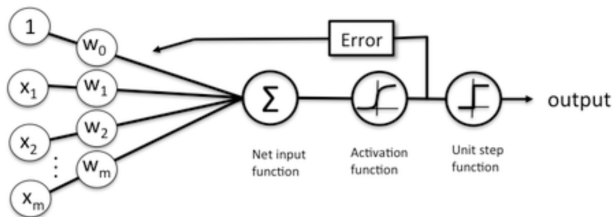


Figure: Logistic Regression as a Neural Net (adapted from [6])