

# Machine Learning

## Regression

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# Regression – Forecasting continuous values

- Supervised task
- The **target** variable is numeric
- **Minimize** the **error** of the prediction with respect to the target

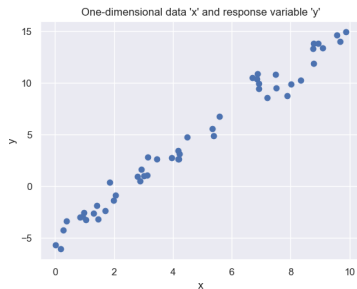
# Linear Regression

- data set  $\mathcal{X}$  with  $N$  rows and  $D$  columns
  - $x_i$  is a  $D$  dimensional **data element**
- response vector  $\bar{y}$  with  $N$  values  $y_i$
- $w$  is a  $D$ -dimensional vector of coefficients that needs to be learned
- we model the dependence of each response value  $y_i$  from the corresponding independent variables  $x_i$  as

$$y_i \approx w^T \cdot x_i \quad \forall i \in [1 \dots N]$$

- such that the **error of modelling** is minimised
- Classical statistic method (1805)

# Data and regression line



One-dimensional data and response variable



Regression and score - Score range ( $-\infty : 1$ )

# Objective function and minimisation I

$$\begin{aligned}\mathcal{O} &= \sum_{i=1}^N (w^T \cdot x_i - y_i)^2 = \|Xw^T - y\|^2 \\ &= (Xw^T - y)^T \cdot (Xw^T - y)\end{aligned}$$

Gradient of  $\mathcal{O}$  with respect to  $w$

$$2X^T(Xw^T - y)$$

Constraining the gradient to 0 we obtain the optimisation condition

$$X^T X w^T = X^T y$$

# Objective function and minimisation II

If the symmetric matrix  $X^T X$  is *invertible* the solution can be derived as

$$w = (X^T X)^{-1} X^T y$$

and the forecast is given by

$$y^f = X \cdot w^T$$

# Matrix calculus

- Issues related to matrix calculus if  $\bar{x}^T \bar{x}$  is not invertible
- *Moore–Penrose pseudoinverse*
- *Tikonov regularisation* (also known as *ridge regression*)
- *Lasso regularisation*

# Quality of the fitting - $R^2$

Mean of the observed data

$$y^{avg} = \frac{1}{N} \sum_i y_i$$

Sum of squared residuals

$$SS_{res} = \sum_i (y_i - y_i^f)^2$$

Total sum of squares

$$SS_{tot} = \sum_i (y_i - y^{avg})^2$$

**Coefficient of determination**  $R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$



# Intuition about $R^2$

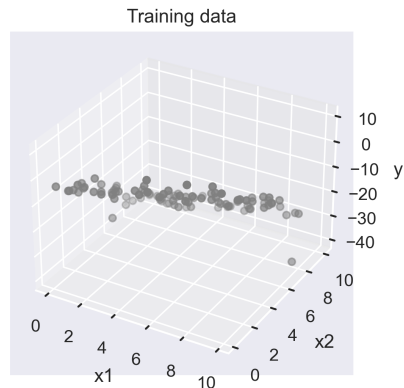
- It compares the fit of the chosen model with that of a horizontal straight line
- With perfect fitting the numerator of the second term is zero and  $R^2 = 1$
- If the model does not follow the trend of the data the numerator of the second term can reach or exceed the denominator, and  $R^2$  can also be negative
- Despite the name,  $R^2$  isn't the square of anything

# $R^2$ and Mean Squared Error

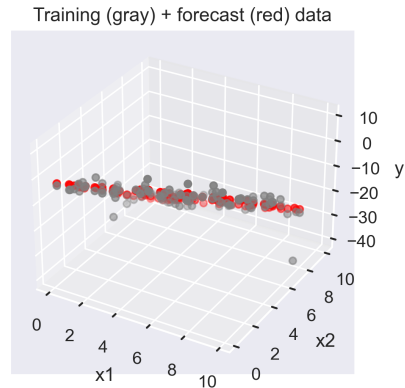
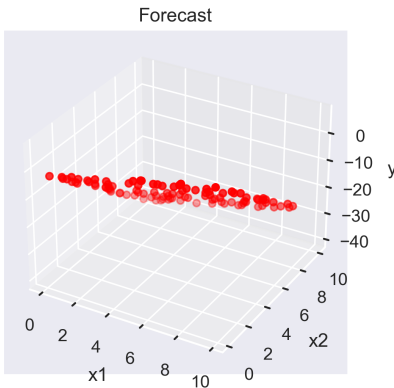
- Both refer to the error of the predictions
- $R^2$  is a standardised index,
- $RMSE$  measures the mean error, this it is influenced by the order of magnitude of the data,
- Both  $RMSE$  and  $R^2$  quantifies how well a linear regression model fits a dataset
- The  $RMSE$  tells how well a regression model can predict the value of a response variable in absolute terms
- $R^2$  tells how well the predictor variables can *explain the variation in the response variable*
- For comparing the accuracy among different linear regression models,  $RMSE$  is a better choice than  $R$  Squared
- $R^2$  is not meaningful for non-linear or non-algebraic regression models

# Multiple regression

- The response variable depends by more than one features
- The regression technique is quite similar to that of simple regression
- In `scikit-learn` the estimator is the same



# Multiple regression - forecast

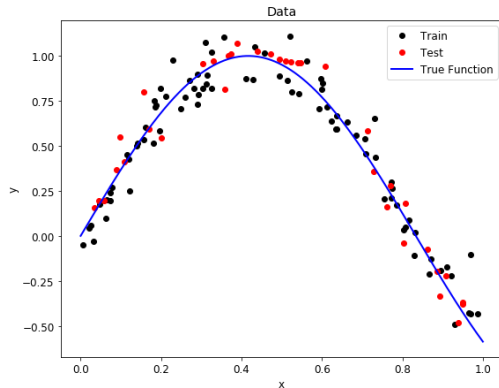


# Overfitting and Regularisation

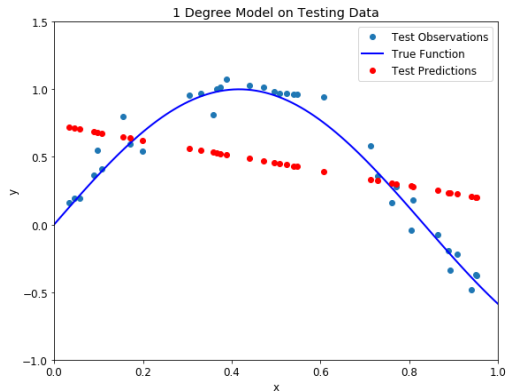
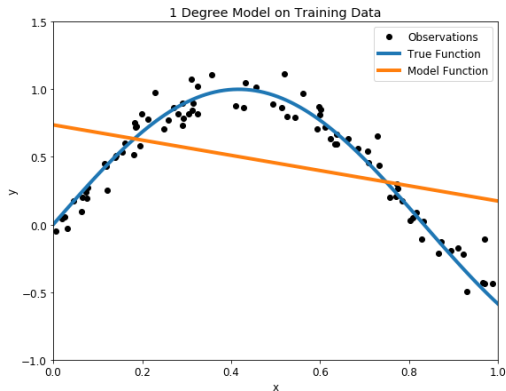
- In presence of high number of features **overfitting** is possible
  - performance on test data becomes much worse
- Regularisation reduces the influence of less interesting attributes and therefore reduces overfitting

# Polynomial regression

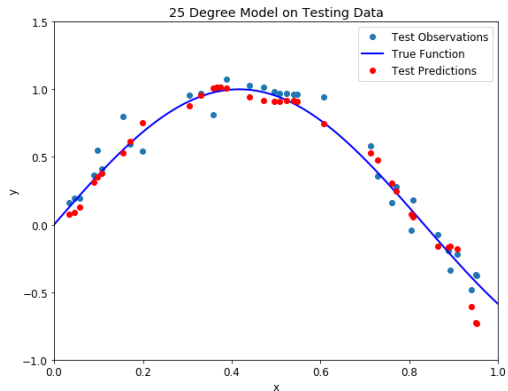
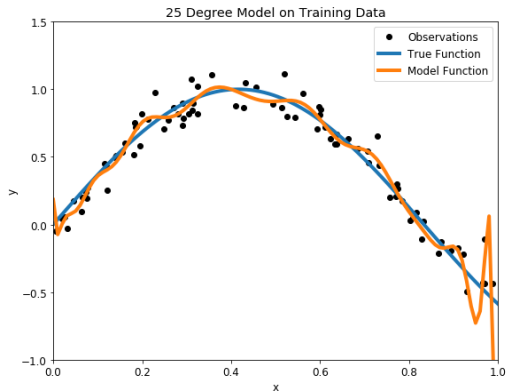
- Target is influenced by a single feature
- The relationship cannot be described by a straight line



# Underfitting

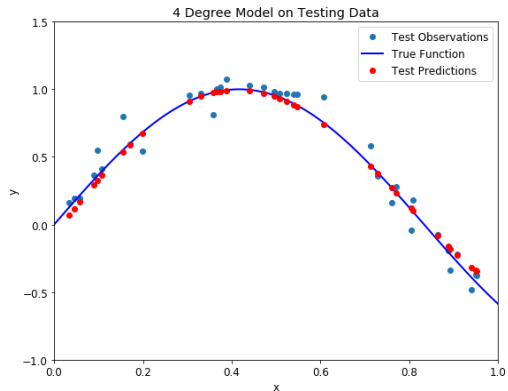
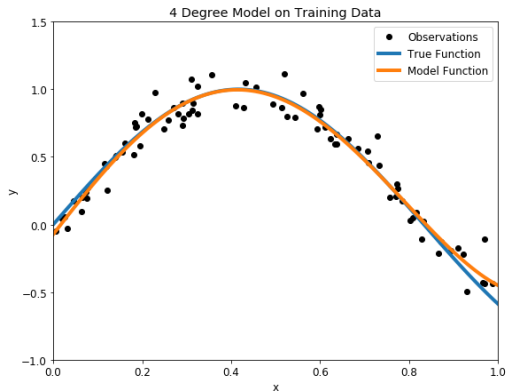


# Overfitting

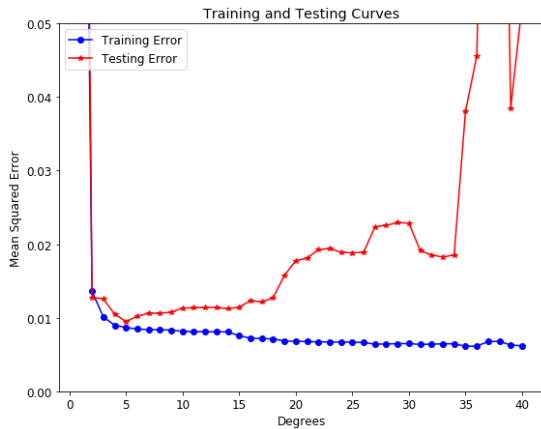




# Good fitting



# Model complexity vs fitting



# Selection of Regression Models

<i>Method</i>	<i>Library</i>	<i>Model Name</i>
Linear Regression	sklearn.linear_model	LinearRegression
Elastic Net Regression	sklearn.linear_model	ElasticNet
Stochastic Gradient Descent Regression	sklearn.linear_model	SGDRegressor
Bayesian Ridge Regression	sklearn.linear_model	BayesianRidge
Lasso Regression	sklearn.linear_model	Lasso
Support Vector Machine	sklearn.svm	SVR
Kernel Ridge Regression	sklearn.kernel_ridge	KernelRidge
Gradient Boosting Regression	sklearn.ensemble	GradientBoostingRegressor
XGBoost Regressor	xgboost	XGBRegressor
CatBoost Regressor	catboost	CatBoostRegressor
LGBM Regressor	lightgbm	LGBMRegressor