

Machine Learning

Supervised learning 1

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Supervised learning

Is a task of inferring function (training a model) on the basis of labeled training data. The goal is to construct a function (train a model) which would mimic (in a certain sense) behaviour of the underlying process.

- Regression: Dependent variable (continuous) plays a role of labels.
 - ▶ Linear
 - ▶ Nonlinear
 - ▶ Application of trees and SVM for regression.
 - ▶ Advanced methods like Neural Networks, etc.
- Classification labels are discrete (categorical values).
 - ▶ k -nearest neighbours.
 - ▶ Decision trees.
 - ▶ Support Vector Machines.
 - ▶ Neural networks.
 - ▶ Ensemble (committee).
 - ▶ Boosted techniques.
- Markov models.

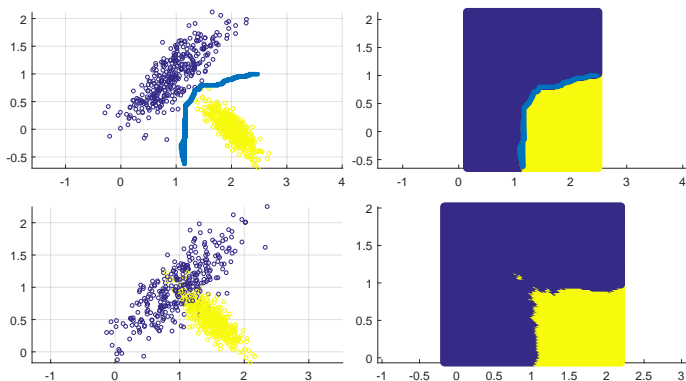
Classification

- Learning existing grouping on the basis of the labeled (training) set.
- The goal is to generate (choose the structure and train) a model which would mimic existing grouping.
- Based on the features of the element model should estimate which class element belong to or estimate value of dependent variable.
- Unlike the case of unsupervised learning miss classification may be precisely measured.
- What is the cost of miss classification or error in the case of regression?

k - nearest neighbours (k -NN)

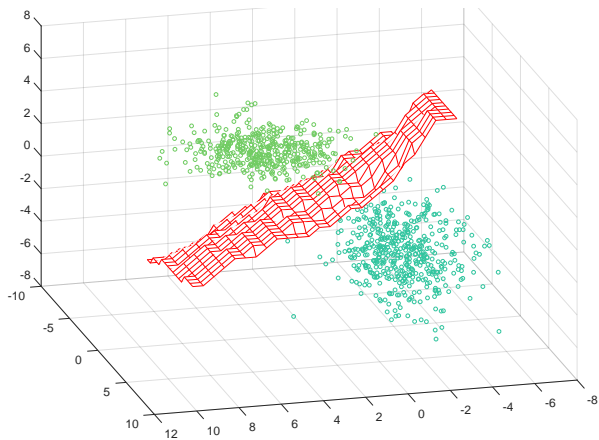
- Let D denote training (labeled) data set.
- For each unlabeled point (point to be classified)
 - ▶ Find k - nearest neighbours.
 - ▶ Assign mode (majority) label of k - nearest neighbours.

k - nearest neighbors, geometric interpretation, 2D



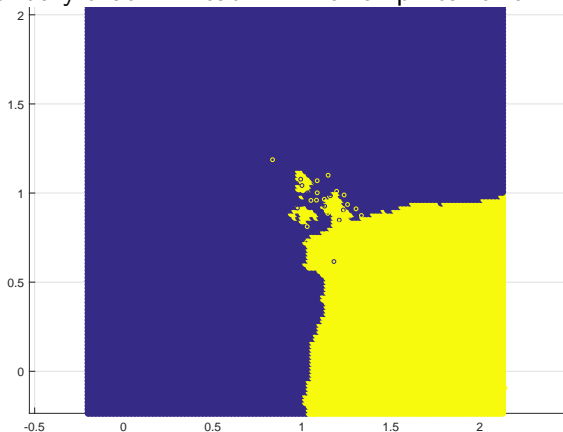
- Decision boundary (decision surface) (statistical classification with two classes) is a hypersurface that partitions the data set into two subsets, one for each class.
- Classifier tries to learn (construct) decision boundary that will lead minimal empirical error.

k - nearest neighbors, 3D



Accuracy

During the training (learning) process classifier tries to learn (construct) decision boundary that will lead minimal empirical error.



How good is trained classifier?

Validation

- Overall accuracy and Confusion matrix (table), computed for the validation subset, are the goodness parameters of trained classifier.

	Predicted Class 1	Predicted class 2
Actual class 1	58	2
Actual class 2	6	134

- How reliable these parameters are ?

Cross validation

- Non-exhaustive do not use all possible ways of splitting into training and validation sets
 - ▶ k - fold.
 - ▶ Holdout.
 - ▶ Repeated random sub-sampling.
- Exhaustive: use all possible ways to divide the data set into training and validation sets
 - ▶ Leave p -out cross validation.
 - ▶ Leave one out cross validation.

Cross validation: k - fold validation

- Divide the training data (after removing test data) randomly into k - folds.
- Perform following k experiments:
 - ▶ Compose the training data by concatenating $k-1$ folds leaving one fold out.
 - ▶ Train the model on those $k-1$ folds
 - ▶ Test it on the left-out fold
 - ▶ Record the result
- Report the average of the k experiments.

Learning: Underfitting and overfitting

- *Underfitting* the learned function is too simple In the context of human learning: underfitting similar to the case when one learns too little.
- *Overfitting* the learned function is too complex In the context of human learning: overfitting is more similar to memorizing than learning.

Feature selection for classification

- Case of categorical data: Gini Index or Entropy

$$G(v_i) = 1 - \sum_{j=1}^k p_j^2; \quad E(v_i) = -\sum_{j=1}^k p_j \log_2(p_j)$$

where p_j is the fraction of data points containing attribute value v_i . Lower values of Gini index or Entropy imply greater discriminative power.

- Case of numeric data: Fisher score

$$F = \frac{\sum_{j=1}^k p_j (\mu_j - \mu)^2}{\sum_{j=1}^k p_j \sigma_j^2}$$

Greater values imply greater discriminative power of the variable.

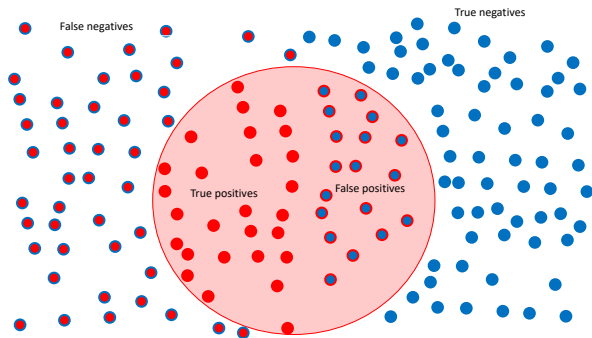
- Wrapper methods.

Classification model goodness!

- How good is the model?
- What is the goal of modeling?

Classification outcome

- Consider binary classifier.
- In the data set there are two classes: Positive (P) and negative (N)
- Outcomes of the classification: True positive, true negative, false positive (type I error), false negative (type II error).



Context of information retrieval

NB! Observe notions!

- Relevant elements of the data set. One is interested to find (retrieve elements of the certain class).
- Precision is defined as:

$$\text{precision} = \frac{|\text{relevant} \cap \text{retrieved}|}{|\text{retrieved}|}$$

- Recall is defined as:

$$\text{recall} = \frac{|\text{relevant} \cap \text{retrieved}|}{|\text{relevant}|}$$

Context of classification I

Denote: tp - true positive, tn - true negative, fp - false positive and fn - false negative.

- Precision:

$$\text{Precision} = \frac{tp}{tp + fp}$$

- Recall:

$$\text{Recall} = \frac{tp}{tp + fn}$$

- True negative rate (Specificity):

$$\text{TNR} = \frac{tn}{tn + fp}$$

- Accuracy:

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

- Predicted positive condition rate

$$\text{Predicted positive condition rate} = \frac{tp + fp}{tp + tn + fp + fn}$$

F-measure *not to be confused with similarly named values!!!*

Frequently referred as F_1 -score ... is harmonic average of precision and recall.



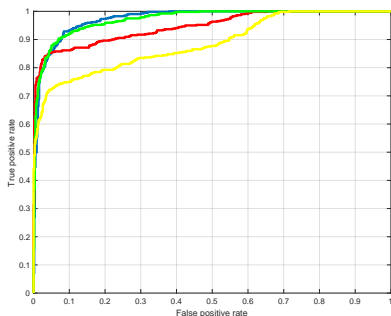
$$F = 2 * \frac{\text{precisionrecall}}{\text{precision} + \text{recall}}$$

- More general definition:

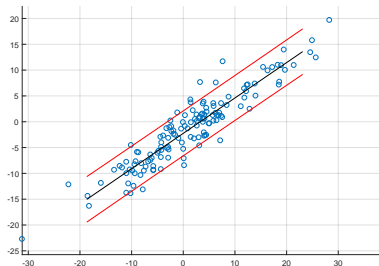
$$F_{\beta} = (1 + \beta^2) \frac{\text{precisionrecall}}{\beta^2 \text{precision} + \text{recall}}$$

Receiver Operating Characteristic or ROC curve

- Let $\mathcal{D} = \{x_i, y_i\}$ is the labeled data set.
- Assume also that $\delta(x) = \mathbb{I}(f(x) > \tau)$ - decision rule. $f(x)$ is the confidence function and τ threshold parameter
- Each particular value of τ corresponds to a certain decision rule.
- For each decision rule one may compute recall and false positive rate.
- Associate recall values with the axis Y and false positive rate values with axis X.



Linear regression: probably the oldest machine learning technique



- Find learner correlation coefficient.
- Compute coefficients of the linear equation

$$\hat{y} = ax + b$$

- Evaluate the model

- In multivariate case it is required to identify coefficients of the model

$$\hat{y} = a_1x_1 + a_2x_2 + \dots + a_nx_n + b.$$

This leads the necessity to choose variables (perform model building).

Linear regression

- Correlation coefficient.

$$\rho = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

where, n - is the sample size, x and y are the variable of interest.

- $-1 \leq \rho \leq 1$
- Assumption there are exist α and β such that for any $i = 1, \dots, n$ $y_i = \alpha x_i + \beta + \varepsilon_i$ holds. Assumption: ε is sufficiently small normally distributed.
- The goal of regression is to find estimates of the coefficients α and β , such that for a and b

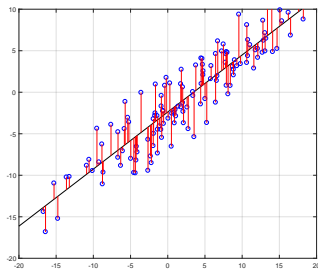
$$y_i = ax_i + b + \hat{\varepsilon}_i$$

sum of squares of $\hat{\varepsilon}_i$ would be minimal. NB! notation $\hat{\alpha}$ and $\hat{\beta}$ is also widely use.

Least squares method

Least squares method:

$$a = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}; \quad b = \bar{y} - a\bar{x}$$



For an arbitrary number of variables:

$$y = b_1 x_1 + \dots + b_n x_n + b_0$$

then

$$\hat{b} = (X^T X)^{-1} X^T y.$$

where each row of matrix X is input vector with 1 in the first position.

Model validation

- Coefficient of determination R^2 and adjusted R^2 .
- Significance of the model and model coefficients.
- Verify assumption that residuals are normally distributed.
- Residual sum squares. $RSS = \sum_{i=1}^N (y_i - x_i^T x_i \beta)^2$.
- Sum squares of the regression $SSR = \sum_{i=1}^N (\hat{y}_i - \bar{y}\beta)^2$.
- Total sum squares or sum of squares about the mean $SSR = \sum_{i=1}^N (y_i - \bar{y}\beta)^2$.
- R^2 computed as the ratio of Sum squares of the regression to total sum squares or one minus ratio of Residual sum squares to total sum squares whereas adjusted R^2 is one minus ratio of residual sum squares computed for $n - 1$ to Total sum squares for $n - p$ observation points.

Statistical hypothesis testing (brief reminder I)

- Assumption about a parameter of population is a statistical hypothesis.
- Usually a pair of hypothesis is stated (H_0, H_1) , notation (H_0, H_a) .
 - ▶ H_0 the null hypothesis usually states that there is no statistically significant relationship between two phenomena.
 - ▶ H_1 the alternative hypothesis usually states the opposite to the H_0 .
- Choose and compute test statistic and rejection rule.
- Interpret the results.
- What can possibly go wrong?

Statistical hypothesis testing (brief reminder II)

	Accept H_0	Reject H_0
H_0 is true	Correct	Type 1 Error
H_0 is false	Type II Error	Correct

Model building (feature selection)

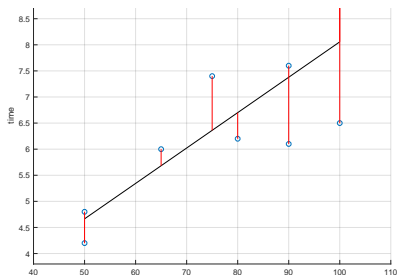
Let us suppose that observed process has p independent variables x_1, \dots, x_p and one dependent variable y . Should one build the regression equation using all p variables or not?

- Are all the variables x_1, \dots, x_p uncorrelated?
- Which subset of variables result in a "better" model?
- How to prove that as a result of adding or deleting a variable model quality has improved?

"Butler tracking company" example

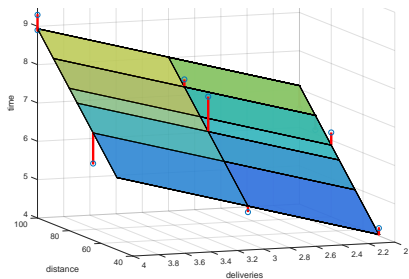
- Independent variables: Distance to drive and number of parcels to deliver. Dependent variable: time.
- Distances to drive for each assignment: 100, 50, 100, 100, 50, 80, 75, 65, 90, 90.
- Number of parcels to deliver: 4, 3, 4, 2, 2, 2, 3, 4, 3, 2
- Time in hours: 9.3, 4.8, 8.9, 6.5, 4.2, 6.2, 7.4, 6, 7.6, 6.1.
- Pearson correlation coefficient between distance and time is 0.81.

"Butler tracking company" example continued



Model 1

Is significant $p = 0.004$,
 $F = 15.1846$ whereas
 $R^2 = 0.6641$.



Model 2

Is significant $p = 0.000276$,
 $F = 32.9$ whereas adjusted
 $R^2 = 0.87$.

Is it enough to say that model 2 is more precise?

Quality comparison

- To compare different models *residual sum of squares* (RSS) is used.
- Hypothesis statements: $H_0 : \text{RSS}_s \leq \text{RSS}_c$ $H_1 : \text{RSS}_s > \text{RSS}_c$.
- Test statistic (empirical parameter) for ANOVA:

$$F_{stat} = \left(\frac{\text{RSS}_s - \text{RSS}_c}{m} \right) \left(\frac{\text{RSS}_c}{n - p - 1} \right)^{-1}$$

where RSS_c is the residuals sum squares of model with more variables, RSS_s - is the residuals sum squares of model with less variables, m number of variables added or removed, n is the number of observation points, p - is the number of variables in more complicated model.

- Rejection rule for α (significance level), degrees of freedom: first is the number of variables added or removed, second is $n - p - 1$.
- Decision:
 - ▶ (if adding variables) rejected null hypothesis proves that adding variables caused model quality to increase significantly.
 - ▶ (if deleting variables) rejected alternative hypothesis proves that deleting variables did not cause model quality to significant decrease.

"Butler tracking company" example continued

- $RSS_1 = 15.8713$, $RSS_2 = 2.2994$ NB! Observe that corresponding MATLAB notation is SSE!!!
- choose $\alpha = 0.05$ degrees of freedom: first will be 1 (one variable (number of parcels)) were added, second 7 ($n = 10, p = 2$).
- Rejection rule: reject H_0 if $F_{stat} > 5.5914$
- Compute $F_{stat} = 17.4411$. (use table, or MATLAB or EXCEL)
- Reject H_0 . Adding the variable has increased the model quality.

MLE for regression least squares

- Linear regression is the model of the form $p(y|x, \theta) = \mathcal{N}(y|\beta^T x, \sigma^2)$.
- Parameter estimation of a statistical model is usually performed by computing MLE $\hat{\theta} = \arg \max_{\theta} \log p(\mathcal{D}|\theta)$.
- Assumption: elements of the training set are independent and identically distributed.
- Then log likelihood is given by
 $\ell(\theta) = \log p(\mathcal{D}|\theta) = \sum_{i=1}^N \log p(y_i|x_i, \theta)$.
- Ass usually instead of maximizing the log-likelihood one may minimize negative log likelihood.
-

$$\begin{aligned}\ell(\theta) &= \sum_{i=1}^N \log \left[\left(\frac{1}{2\pi\sigma^2} \right) \exp \left(-\frac{1}{2\sigma^2} (y_i - \beta^T x_i)^2 \right) \right] \\ &= \frac{-1}{2\sigma^2} \text{RSS}(\beta) - \frac{N}{2} \log(2\pi\sigma^2).\end{aligned}$$

MLE for regression least squares

- In order to minimize RSS differentiate its equation which lead

$$\nabla\theta = X^T X\beta - X^T y.$$

- Equate it to zero and solve for β

$$\beta = (X^T X)^{-1} X^T Y$$

last equation is referred as *normal equation*.

Questions for self practice

- Program your own k-nearest neighbours algorithm.