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Fundamentals of Machine Learning

Data Transformation

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Data Transformation

Data Transformation

- Data transformation techniques include methods, that may help to transform data before any machine learning algorithm is applied.
- The goal is to remove the unnecessary data and highlight the most important aspects of the data to process.
- The techniques includes:
  - Attribute selection
  - Attribute discretization
  - Data projections
  - Sampling
  - Data cleansing
  - Converting multi-class problems to two-class ones.

Data Transformation- Attribute selection

- Most machine learning algorithms are designed to learn which are the most appropriate attributes to use for making their decisions.
- In practice, even a random variable may decrease the performance of the classifier (chaotic behavior in deeper levels).
- Moreover, even a relevant attribute may decrease the performance (fragmentation due to splitting near the root).

Data Transformation- Attribute selection- Scheme-independent

- Scheme-independent selection, also called a filter method prepares the dataset before a machine learning algorithm is applied.
- Selection of the *Relevance* measure universally is impossible.
- The first possibility is to select just enough attribute to optimally cover the required classes.
- Another possibility is to use model that select the useful attributes, e.g. Decision Tree, before a target algorithm is used.

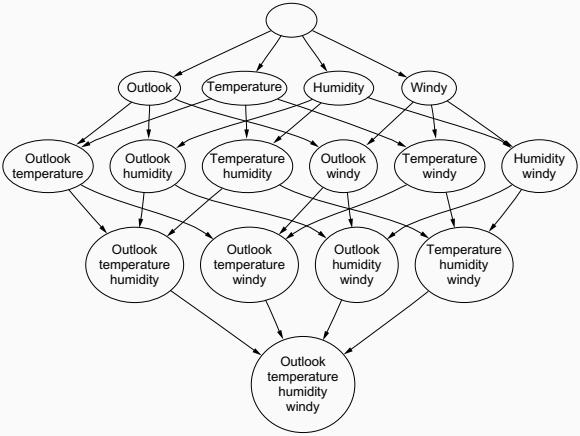
Data Transformation- Attribute selection- Scheme-independent

- Described algorithm may fail when two almost identical attributes exists - both are rejected or accepted.
- Another way of eliminating redundant attributes as well as irrelevant ones is to select a subset of attributes that individually correlate well with the class but have little inter-correlation
- One possibility is *symmetric uncertainty*.
- Subset may be generated using exhaustive search.

Data Transformation- Attribute selection- Scheme-independent

- Greedy search for optimal subset of features may be used with evaluation using the mentioned metric.
- There are two possible direction of the greedy algorithm:
  - Forward selection
  - Backward elimination
- Each approach have its start and stopping criterion.

Data Transformation - Attribute selection- Scheme-independent



Data Transformation- Attribute selection- Scheme-Specific

- The selected set of attributes is evaluated using the concrete Machine Learning model.
- The cross-validation, holdout or bootstrap estimation may be used to precisely predict the efficiency.
- Greedy algorithm is again used.
- Backward elimination produces larger set of attributes.

Data Transformation- Discretizing of Numeric Attributes

- Numeric attributes are problematic for many algorithms.
- Even the algorithms that accept numeric attributes works faster and/or more effective.
- Main reason is the assumption of the probability distribution about the numeric attribute.
- Discretization may be unsupervised or supervised (with respect to the classes).

Data Transformation- Discretizing of Numeric Attributes

- Unsupervised discretization distribute instances according the valud into predefined bins.
- Equal-interval binning simply divide the full range into equal sized bins.
- Equal-frequency binning distribute instances to the bins with equal frequency based on the histogram.

Data Transformation- Discretizing of Numeric Attributes

- Supervised discretization distribute instances according the value and classes.
- Entropy-based discretization follow the approach used in Decision Tree.
- The bins are generated dynamically based on the split criterion until intervals with the same class remains.
- The split point is always between different class labels not the same, which may be used in optimization.
- The stopping criterion may be confused by multiple class values.

Data Transformation- Projection

- Projection is a mapping that transform data in a some way.
- Data often need application of some mathematical algorithms, e.g. difference between two dates (age), ...
- Other transformation may involve general knowledge, e.g. holidays, day in a week, chemical atomic numbers, ...
- Clustering may be another type of transformation that produces a new attribute.
- Special kind of transformation is able to map data into lover dimension.

Data Transformation- Projection- Principal Component Analysis

- Principal Component Analysis (PCA) is a linear algebra transformation that is able to map data into a space with lower dimension.
- Data with k numeric attributes may be visualized as a points i k-dimension space.
- The axis used in visualization are based on the used projection.
- The axis may be computed in completely different way, but we prefer orthogonal axis (i.e., each axis is at right angles to the others).
- The variance (distribution of points) along the axis may be easily computed.

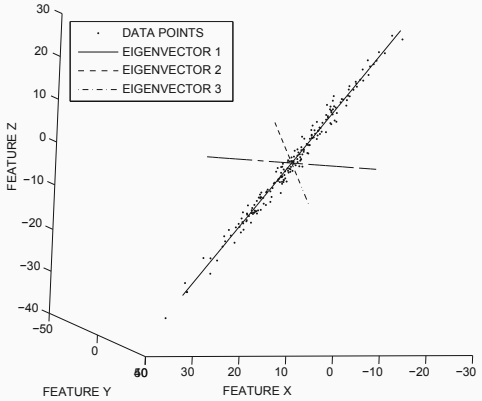
Data Transformation- Projection- Principal Component Analysis

- Principal Component Analysis places the first axis in the direction of the largest variance.
- The second axis is perpendicular to the first and maximized the remaining variance.
- The computation procedure requires a covariance matrix and decomposition into so called *eigen-vectors* and *eigen-values*.
- This process is called eigen-decomposition and it is possible in general for any square matrix.

$$A = P\lambda P^{-1}$$

Data Transformation - Projection- Principal Component Analysis

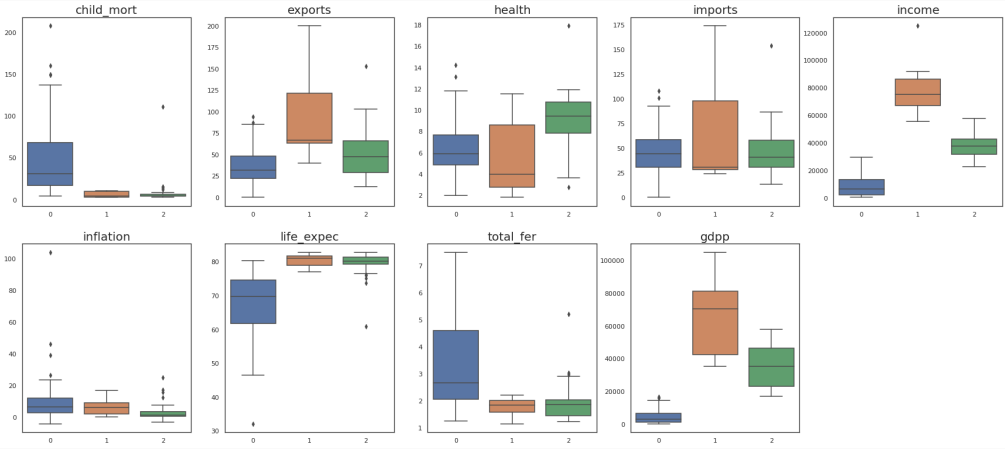
- The goal of PCA is to rotate the data into an axis-system where the greatest amount of variance is captured in a small number of dimensions.



Data Transformation - Projection - Principal Component Analysis

- Other approaches includes:
  - Random Projection - generate a random mapping into lower dimension.
  - Singular Value Decomposition - More general version of PCA.
  - Independent Component Analysis - decomposed data into a statistically independent parts.
  - Fisher's Linear Discriminant analysis - includes a class labes into decomposition.

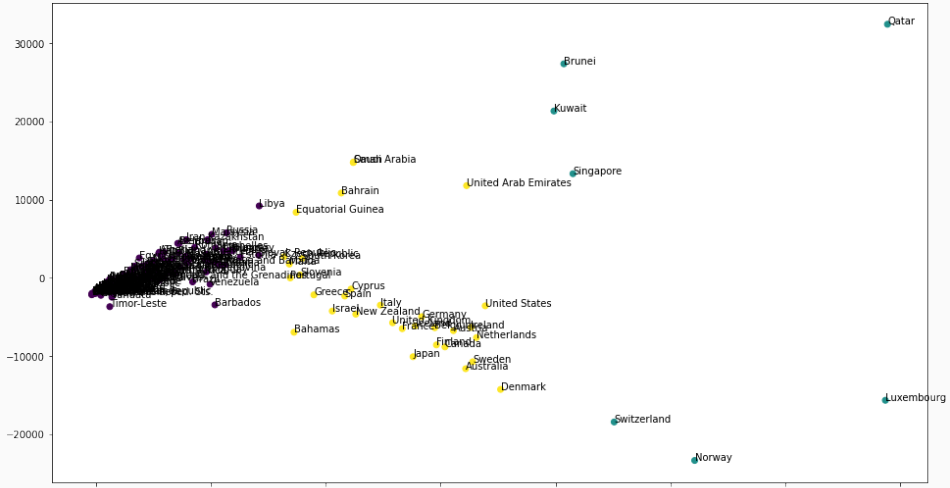
Data Transformation - Projection - Example



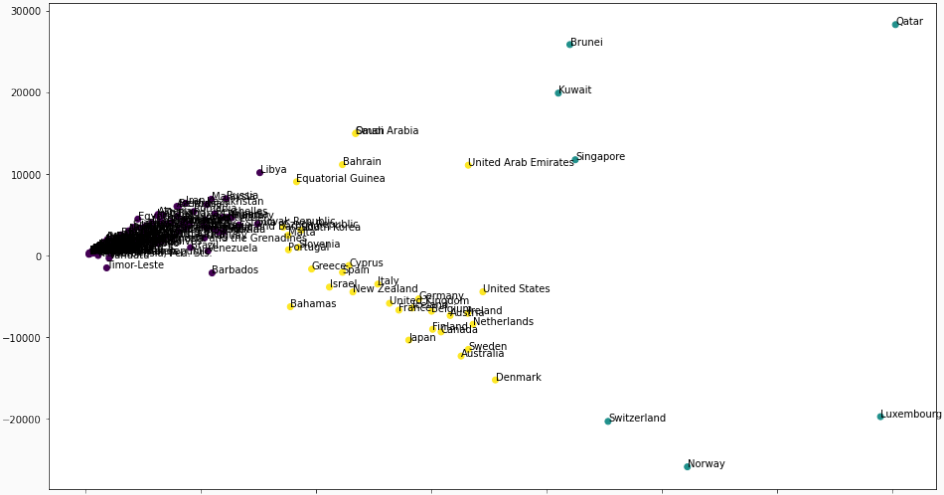
Data Transformation - Projection - Example

Cluster 0	Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, Bangladesh, Barbados, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo, Dem. Rep., Congo, Rep., ...
Cluster 1	Brunei, Kuwait, Luxembourg, Norway, Qatar, Singapore, Switzerland
Cluster 2	Australia, Austria, Bahamas, Bahrain, Belgium, Canada, Cyprus, Czech Republic, Denmark, Equatorial Guinea, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Malta, Netherlands, New Zealand, Oman, Portugal,

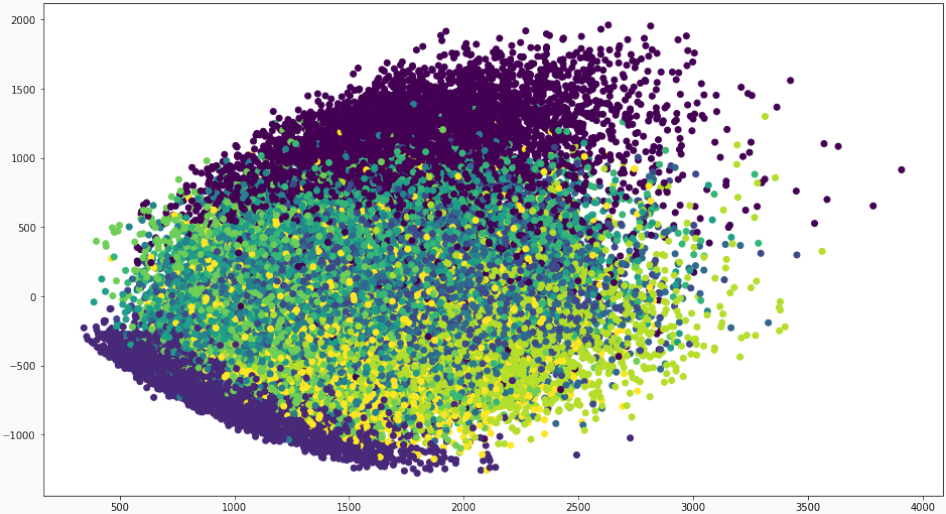
Data Transformation - Projection - PCA



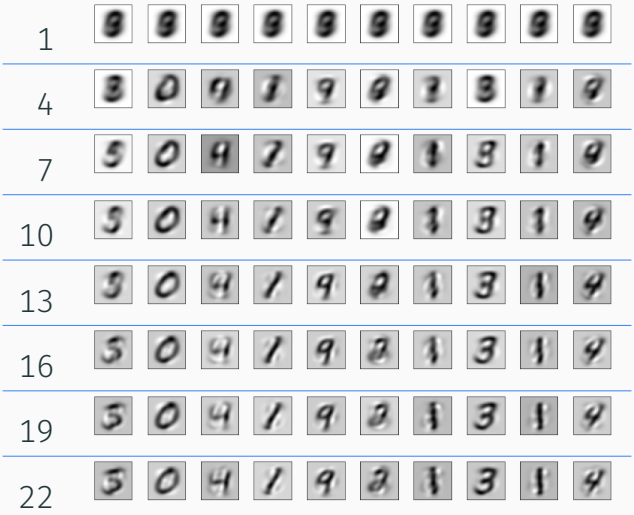
Data Transformation - Projection - SVD



Data Transformation - Projection - SVD - Mnist



Data Transformation - Projection - SVD - Mnist



Data Transformation- Sampling

- Sampling enables processing of large amount of data by a standard algorithms.
- Sampling may choose the same instance several times (with replacement) or only once (without replacement).
- Reservoir sampling the sampling solution for data stream where data are not stored locally.
- The reservoir of size r is used as a cache for sampled instances.
- The i-th instance has the chance r/i to be placed into a reservoir.

Data Transformation- Cleansing

- Data are in general noise and corrupted.
- The manual check of the data is hard and expensive, sometimes even impossible.
- Removing misclassified instances from the dataset may improve the precision and reduces the size of the decision tree model. (these instances are probably corrupted or a noise)
- Moreover, training model on clean data leads to worse performance on noisy test data.

Data Transformation- Cleansing - Anomaly detection

- Anomalies are not exactly the same as noise data, it represents an error or incorrect data.
- Extreme data may be identified using exploratory analysis.
- Some methods combines several classifiers to decide about anomaly of the data.
- Erroneous data are usually misclassified by some of the classifier.

Data Transformation- Multiple Classes into Binary Classification

- Some algorithm does not support multiple class classification, neural networks, logistic regression, etc.
- Multi-class variants may be developed but complicate the procedure.
- Clever selected strategies may be used instead.
- Decomposition of class into binary problems simplifies the solution.
- Basic variants are *one-vs-rest* and *one-vs-one*.

Data Transformation- Multiple Classes into Binary Classification

- *one-vs-rest*
  - A new dataset is generated for each class with two classes only.
  - On each dataset a classifier is built.
  - Final decision is made based on the partial results and/or confidence of models.
- *one-vs-one*
  - Each pair of classes create a new dataset.
  - On each dataset a classifier is built.
  - Majority voting is used for final decision.
  - $k(k-1)/2$ classifiers is constructed.

Questions