Data Preprocessing

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Content

- Data Cleaning
- Missing Data
  - Imputation
- Data Reduction
  - Dimensionality Reduction
  - PCA
  - Feature Selection
- Noisy Data
- Data Transformation and Data Discretization
  - Normalization
  - Discretization
- Imbalanced Data
  - Sampling
  - SMOTE

Why preprocess?

- Preprocessing means to transform the data before we feed it to a learning algorithm
- Why would we do that?
- What would we for example do?

```
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```

In this topic we will...

- Talk about problems that can appear in data
- Introduce strategies to solve these problems
- Talk about feature selection, a very important technique in machine learning

Major Tasks in Data Preprocessing

- Data cleaning
  - Missing values
  - Noisy data
  - Outliers
- Data reduction
  - Dimensionality reduction
  - Data compression
- Transformation and discretization
  - Normalization
  - Hierarchy generation

Data Cleaning

Data Cleaning

- Basic assumption in machine learning?
  - The distributions of the training and test data are the same
- But, real-world data are, in most cases, dirty
- This can lead to problems, if data are
  - Incomplete lacking attribute values, certain attributes, or containing only aggregate data
  - Noisy containing noise, errors, or outliers
  - Inconsistent containing discrepancies in codes or names
  - Intentially wrong for example, there are a lot of pictures with a GPS location just a bit west of Africa

Missing Data

Incomplete (Missing) Data

- Data are not always available
  - Many tuples have no recorded value for several attributes
  - E.g. customer income in sales data
- Missing data may be due to
  - Equipment malfunction
  - Inconsistent with other recorded data and thus deleted
  - Data not entered due to misunderstanding
  - Certain data may not be considered important at the time of entry
  - Not register history or changes of the data
- Missing data may need to be inferred
  - When, for example?

What to Consider When Handling Missing Data?

- Why are data missing?
- Three types of missing data (Rubin, D. B., 1974)
  - **Missing completely at random (MCAR)**
    - Completely unrelated to the data
    - Potential problem?

Name	Country	Income
Jane	NZ	$50k
Kate	NZ	$75k
Tom	US	$53k
George	UK	$64k
Mark	UK	$77k
Philippe	US	$80k

MCAR →

Name	Country	Income
Jane	NZ	
	NZ	$75k
Tom	US	
George		$64k
	UK	$77k
Philippe	US	$80k

Missing data not related to the data

What to Consider When Handling Missing Data?

- Why are data missing?
- Three types of missing data (Rubin, D. B., 1974)
  - Missing at random (MAR)
    - The fact the data are missing is not related to the missing attribute itself, but to some other attributes in the data set
    - Potential problem?

Name	Country	Income
Jane	NZ	$50k
Kate	NZ	$75k
Tom	US	$53k
George	UK	$64k
Mark	UK	$77k
Philippe	US	$80k

MAR

Name	Country	Income
Jane	NZ	$50k
Kate	NZ	$75k
Tom	US	$53k
George	UK	
Mark	UK	
Philippe	US	$80k

Missing income report from UK

What to Consider When Handling Missing Data?

- Why are data missing?
- Three types of missing data (Rubin, D. B., 1974)
  - Missing not at random (MNAR)
    - The fact the data are missing is related to the missing attribute itself
    - Potential problem?

Name	Country	Income
Jane	NZ	$50k
Kate	NZ	$75k
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MNAR →

Name	Country	Income
Jane	NZ	
Kate	NZ	$75k
Tom	US	
George	UK	
Mark	UK	$77k
Philippe	US	$80k

People with income less than $70k might refuse to provide their income details

How to Handle Missing Data – Imputation

- Ignore the tuple

$$X = \begin{bmatrix} 0 & 1 & 1 & 1 & \cdots \\ {\color{red}?} & {\color{red}?} & {\color{red}?} & {\color{red}1} & {\color{red}\cdots} \\ {\color{red}1} & {\color{red}0} & {\color{red}?} & {\color{red}?} & {\color{red}\cdots} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & 0 & 1 & 0 & \cdots \end{bmatrix} \longrightarrow X' = \begin{bmatrix} 0 & 1 & 1 & 1 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & 0 & 1 & 0 & \cdots \end{bmatrix}$$

  - Usually done when the class label is missing (classification)
  - Not effective when the fraction of missing values varies considerably

How to Handle Missing Data – Imputation

- Fill in the missing data manually

$$X = \begin{bmatrix} 0 & 1 & 1 & 1 & \dots \\ ? & ? & ? & 1 & \dots \\ 1 & 0 & ? & ? & \dots \\ \dots & \dots & \dots & \dots & \dots \\ 1 & 0 & 1 & 0 & \dots \end{bmatrix} \longrightarrow X' = \begin{bmatrix} 0 & 1 & 1 & 1 & \dots \\ 1 & 0 & 0 & 1 & \dots \\ 1 & 0 & 1 & 1 & \dots \\ \dots & \dots & \dots & \dots & \dots \\ 1 & 0 & 1 & 0 & \dots \end{bmatrix}$$

  - Tedious and sometimes infeasible

How to Handle Missing Data – Imputation

- Fill in automatically
  - A global constant

X

sunny	warm	Mon	May	…
cloudy	?	?	July	…
sunny	cold	?	?	…
…	…	…	…	…
overcast	cold	Sat	June	…

→

X'

sunny	warm	Mon	May	…
cloudy	missing	missing	July	…
sunny	cold	missing	missing	…
…	…	…	…	…
overcast	cold	Sat	June	…

  - E.g. " missing"
  - A new class

How to Handle Missing Data – Imputation

- Fill in automatically
  - The attribute mean

$$X = \begin{bmatrix} 12 & 2 & 22 & 38 & \dots \\ 11 & ? & ? & 90 & \dots \\ 2 & 23 & ? & ? & \dots \\ \dots & \dots & \dots & \dots & \dots \\ 9 & 11 & 54 & 23 & \dots \end{bmatrix} \rightarrow X' = \begin{bmatrix} 12 & 2 & 22 & 38 & \dots \\ 11 & 12 & 38 & 90 & \dots \\ 2 & 23 & 38 & 30 & \dots \\ \dots & \dots & \dots & \dots & \dots \\ 9 & 11 & 54 & 23 & \dots \end{bmatrix}$$

  - A very commonly used method
  - Changes relationship with other variables ⇒ bias in data

How to Handle Missing Data – Imputation

- Fill in automatically
  - The attribute mean of the samples belonging to the same class

$X|Y$

12	2	22	38	…	1
11	?	?	90	…	0
2	23	?	?	…	1
…	…	…	…	…	…
9	11	54	23	…	0

→

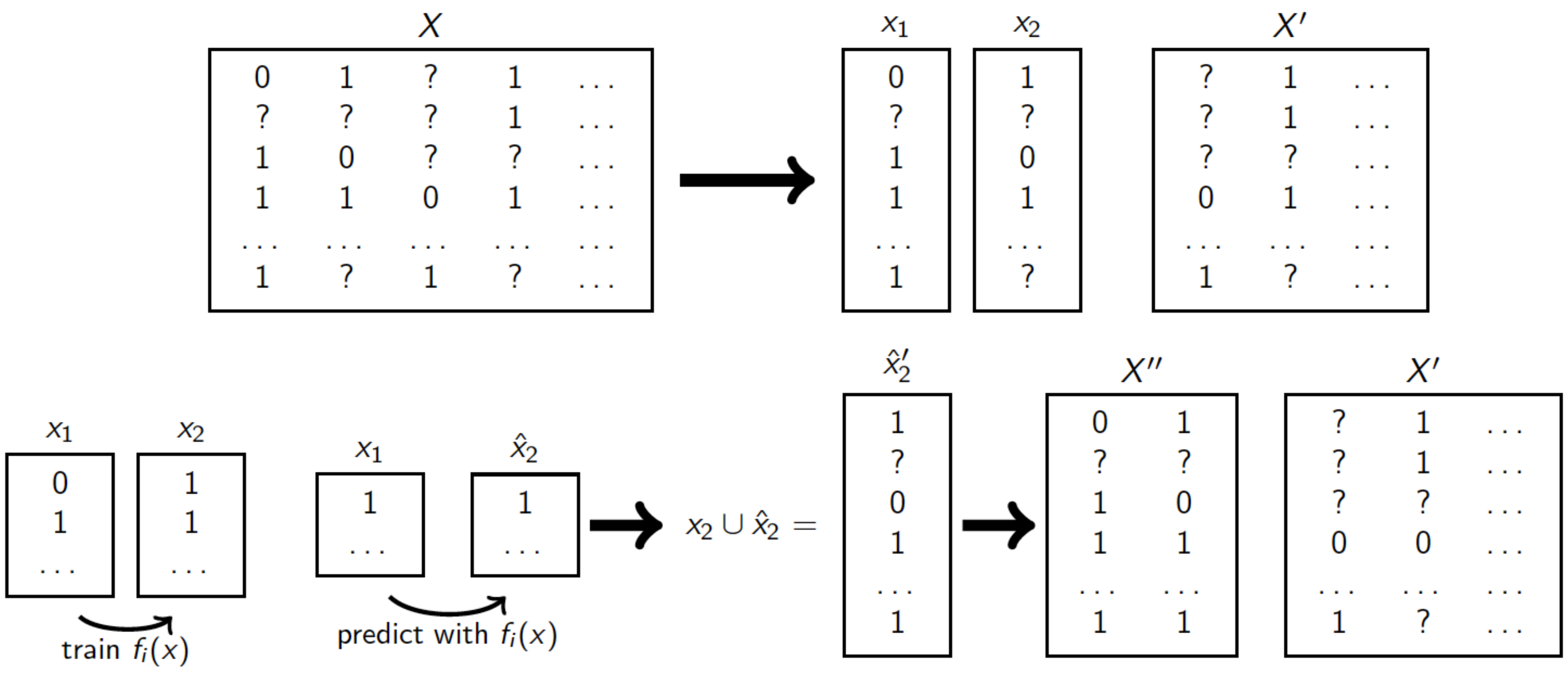
$X'|Y$

12	2	22	38	…	1
11	12	38	90	…	0
2	23	38	30	…	1
…	…	…	…	…	…
9	11	54	23	…	0

  - Might change relationship with other variables other than class ⇒ bias in data

How to Handle Missing Data – Imputation

- Fill in automatically
  - The most probable value



  - Inference-based such as decision tree, linear regression, Bayesian formula, nearest neighbour,...

More on Imputation

- Matrix decomposition approaches
  - Decompose matrix using, for example, Singular Value Decomposition (SVD)
    - Decompose the data matrix X such that $X = U\Lambda V$
    - Create imputed matrix X' by multiplying $U \times \Lambda \times V$

$$\underset{n \times d}{\overset{M}{\begin{bmatrix} x_{11} & \cdots & x_{1d} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nd} \end{bmatrix}}} \approx \underset{n \times k}{\overset{U}{\begin{bmatrix} u_{11} & \cdots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{n1} & \cdots & u_{nk} \end{bmatrix}}} \underset{k \times k}{\overset{\Lambda}{\begin{bmatrix} \lambda_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_{kk} \end{bmatrix}}} \underset{k \times d}{\overset{V}{\begin{bmatrix} v_{11} & \cdots & v_{1d} \\ \vdots & \ddots & \vdots \\ v_{k1} & \cdots & v_{kd} \end{bmatrix}}}$$

Minimize the Sum of Squared Errors

$$\min_{U,\Lambda,\Sigma} \sum_{x_{ij} \in X} \left(x_{ij} - [U\Lambda V]_{ij}\right)^2$$

Even More on Imputation

- EM imputation
  - Expectation Maximization
  - Use other variables to impute the values (Expectation)
  - Check if value is most probable (Maximization)
- Multiple imputation (e.g., MICE)
  - 1. Impute missing values using appropriate model (for example using classifier / regression model to predict the missing value)
  - 2. Repeat the step multiple times (3-5)
  - 3. Carry out required full analysis of data (e.g. build classifier and evaluate)
  - 4. Average the results (predictions or evaluation)
- So what is the best approach?

Preprocessing and Evaluation

- So now we know a preprocessing example
- Where would you put the preprocessing step in the evaluation?
- For example, for imputation:
  - Impute the values before splitting in train and test?
  - Impute the values in the training set – then how about the test set?