# COMPSCI762: Foundations of Machine Learning

## Data Preprocessing

Katerina Taskova and Jörg Simon Wicker

The University of Auckland

THE UNIVERSITY OF AUCKLAND
Te Whare Wānanga o Tāmaki Makaurau
NEW ZEALAND

SCIENCE
SCHOOL OF COMPUTER SCIENCE

# Data Preprocessing

# This lecture will cover

## Data Preprocessing

- Noisy Data
- Data Transformation and Data Discretization
- Imbalanced Data

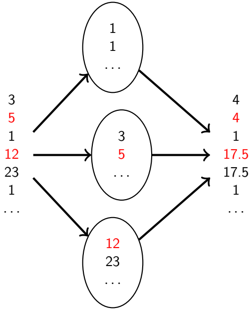
# Noisy Data

# Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may be due to
  - Faulty data collection instruments
  - Data entry problems
  - Data transmission problems
  - Technology limitation
  - Inconsistency in naming convention
- Other data problems which require data cleaning
  - Duplicate records
  - Incomplete data
  - Inconsistent data

# Handling Noisy Data

- So how could we handle noisy data?
- Binning



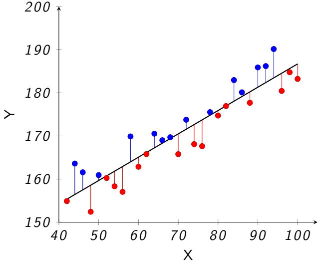

- First sort data and partition into (equal-frequency) bins
- Then one can smooth by different methods (bin means, bin medians, bin boundaries).

# Handling Noisy Data

- So how could we handle noisy data?
- Binning
  - Sorted data: 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34
  - Partition into equal-frequency (equi-depth) bins:
    - Bin 1: 4, 8, 9, 15
    - Bin 2: 21, 21, 24, 25
    - Bin 3: 26, 28, 29, 34
  - Smoothing by bin means:
    - Bin 1: 9, 9, 9, 9
    - Bin 2: 23, 23, 23, 23
    - Bin 3: 29, 29, 29, 29
  - Smoothing by bin boundaries:
    - Bin 1: 4, 4, 4, 15
    - Bin 2: 21, 21, 25, 25
    - Bin 3: 26, 26, 26, 34

# Handling Noisy Data

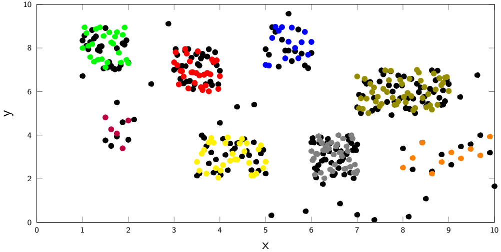
- So how could we handle noisy data?
- Regression




- Smooth by fitting the data into regression functions

# Handling Noisy Data

- So how could we handle noisy data?
- Clustering




- Detect and remove outliers

# Data Transformation and Data Discretization

# Data Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values (each old value can be identified with one of the new values).
- Methods
  - Smoothing: Remove noise from data
  - Attribute/feature construction
    - New attributes constructed from the given ones
  - Normalization: Scaled to fall within a smaller, specified range
    - Min-max normalization
    - Z-score normalization
    - Normalization by decimal scaling
  - Discretization: Concept hierarchy climbing

# Normalization

- Min-max normalization to $new\_min_A, new\_max_A$

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

e.g. $v = 20$ from the range [0,40] maps to $v' = 0$ in the range [-1,1]

- Z-score normalization – mean $\mu$, standard deviation $\sigma$

$$v' = \frac{v - \mu_A}{\sigma_A}$$

- Normalization by decimal scaling

$$v' = \frac{v}{10^j}$$

Where $j$ is the smallest integer such that $Max(|v'|) < 1$

e.g. Let 200 be the largest value of attribute A, then $j = 3$.

# Discretization

- There are three type of attributes
  - Nominal – values from an unordered set, e.g. color
  - Ordinal – values from an ordered set, e.g. rank
  - Numeric – real numbers, e.g. integers or reals
- Discretization divides a range of continuous attributes into intervals
  - Interval labels can then be used to replace actual data values
  - Discretization can be performed recursively on an attribute
  - Reduce data size by discretization
  - Prepare for further analysis, e.g. classification
  - The resulting mined patterns are typically easier to understand
  - Mining on different level of data abstraction (concept hierarchies)

# Discretization Methods

- Top-down vs bottom-up (w.r.t which direction it proceeds)
- Supervised vs unsupervised (w.r.t class information usage)
- Example methods
  - Binning (top-down split, unsupervised)
  - Histogram analysis (top-down split, unsupervised)
  - Clustering analysis (unsupervised, top-down split or bottom-up merge)
  - Decision-tree analysis (supervised, top-down split)
  - Correlation analysis (supervised, bottom-up merge)

# Binnning

- How could you discretize the data into bins?
- Equal-width (distance) partitioning
  - Divides the range into N intervals of equal size: uniform grid
  - If A and B are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$
  - The most straightforward, but?
    - Outliers may dominate presentation
    - Skewed data is not handled well
- Equal-depth (frequency) partitioning
  - Divides the range into $N$ intervals, each containing approximately same number of samples
  - Good data scaling
  - Managing categorical attributes can be tricky

# Discretization by Correlation Analysis

- Chi-merge: $\chi^2$-based discretization
  - Supervised: use class information
  - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e. low $\chi^2$ values) to merge
  - Merge performed recursively, until a predefined stopping condition

# Correlation Analysis

- Given two nominal variables $C$ and $B$ with values $c_1, \ldots, c_k$ and $b_1, \ldots, b_r$ the correlation can be calculated using the $\chi^2$ test:

$$\chi^2 = \sum_{i=1}^{k} \sum_{j=1}^{r} \frac{(o_{ij} - e_{ij})^2}{e_{ij}}$$

  - With $o_{ij}$ being the actual frequency of the event $(c_i, b_j)$
  - And $e_{ij}$ the expected frequency ($n$ is the number of instances)

$$e_{ij} = \frac{count(C = c_i) \times count(B = b_j)}{n}$$

- The larger $\chi^2$, the less likely the two variables are independent

# Discretization by Correlation Analysis

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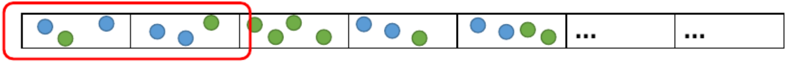


Contingency table A:

| | Class 1 | Class 2 | Sum |
|---|---|---|---|
| Interval 1 | 1 | 2 | 3 |
| Interval 2 | 1 | 2 | 3 |
| Sum | 2 | 4 | 6 |

$$\chi^2 = \sum_{i=1}^{2}\sum_{j=1}^{2}\frac{(A_{ij} - e_{ij})^2}{e_{ij}} = 0$$

The class variable is independent to the two intervals

→ the class distribution is similar in the two intervals

# Discretization by Correlation Analysis

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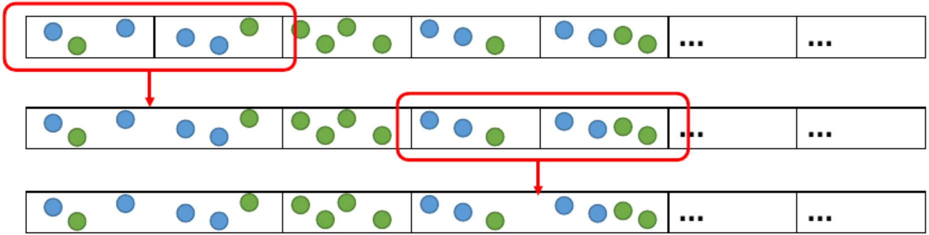


# Imbalanced Data

# Imbalanced Data

- In this context, imbalanced data refers to an imbalanced class distribution
- For example if there are far more 1s than 0s in the class
- What are problems arising from this?
  - Problems with evaluation
    - $Accuracy = \frac{TP+TN}{P+N}$
    - What is a good accuracy?
    - Alternatively, use Precision-Recall, ROC curves
  - Classifiers try to reduce the overall error so they could over-predict the majority class.
    - How do we address this?

# Sampling the data

- Under- and oversampling with replacement can significantly improve the prediction of the minority class
- Randomly undersampling the majority class
  - Randomly remove instances from the majority class
  - Balances the data set
  - Discarded observations could have important information
  - Can introduce bias
- Randomly oversampling the minority class
  - Randomly add more instances from minority class
  - No information loss
  - Risk of overfitting
- Alternatives to random sampling?

# Cluster-Based Oversampling

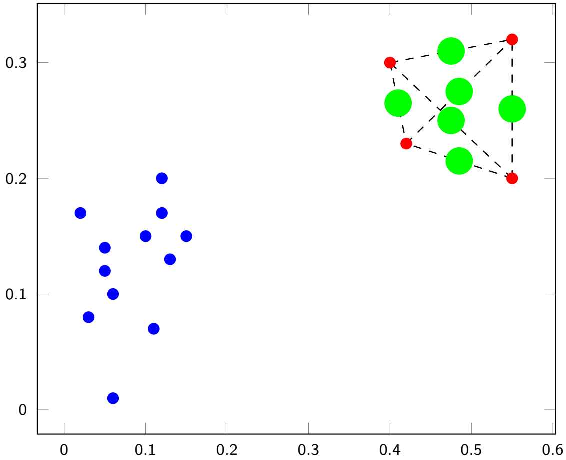


- Cluster positive and negative instances independently
- Then apply over- or undersampling techniques to each single cluster
- What's the advantage?
- Does that solve overfitting?

# SMOTE - Synthetic Minority Oversampling Technique (Chawla et al. 2002)

- Generally, create new artificial instances
- Process
  - Find pairs of instances in the minority class that are closest to each other
    - Nearest neighbours within the class
  - Create a new instance between these instances, assign it to the minority class

# SMOTE



# Conclusion

- Preprocessing is an important part in machine learning and data analysis
- Missing values can be caused by various reasons depending on what the reasons are, they must be addressed differently
- Various imputation approaches exist, they use the information of other instances and values to impute the missing values
- Noisy data can be addressed for example by binning, clustering, or regression
- Sampling can be used to overcome class imbalance problems

# Literature

- Material in Chapter 3 in Han's *Data Mining*

Thank you for your attention!

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