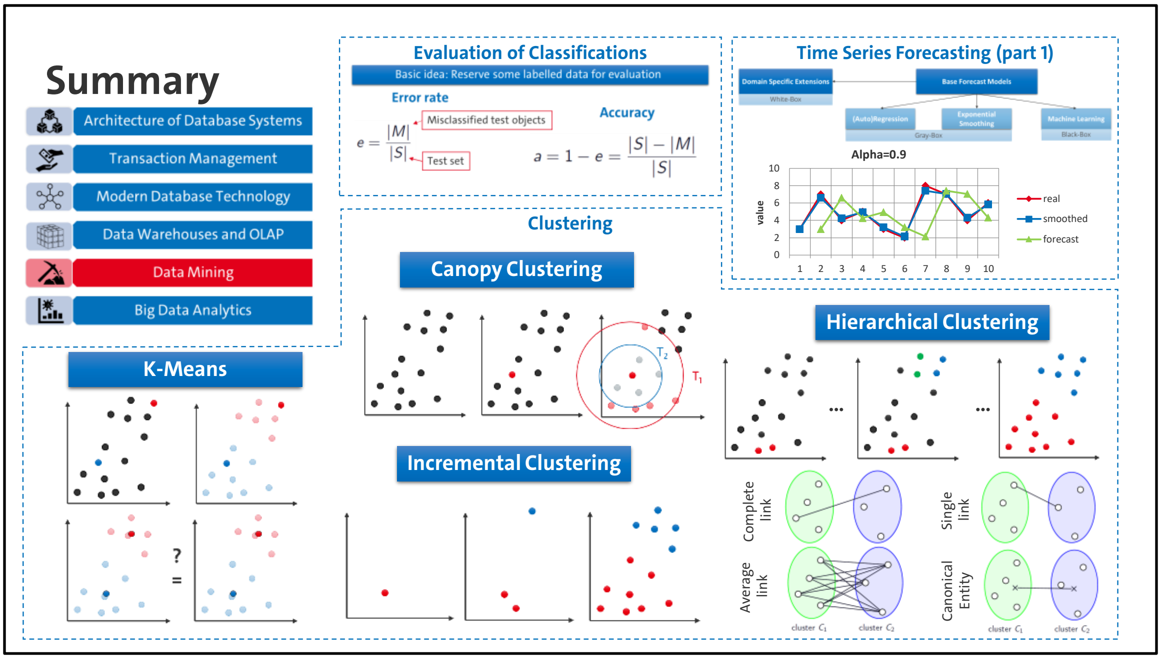

Summary
Architecture of Database Systems
Transaction Management
Modern Database Technology
Data Warehouses and OLAP
Data Mining
Big Data Analytics
Evaluation of Classifications
Basic idea: Reserve some labelled data for evaluation
Error rate
$e = \frac{|M|}{|S|}$
Misclassified test objects
Test set
Accuracy
$a = 1 - e = \frac{|S| - |M|}{|S|}$
Time Series Forecasting (part 1)
Domain Specific Extensions
Base Forecast Models
Alpha=0.9
value
real
smoothed
forecast
Clustering
Canopy Clustering
Incremental Clustering
K-Means
Hierarchical Clustering
Complete link
Single link
Average link
Canonical Entity

Model Types

Domain Specific Extensions ← **Base Forecast Models**

Base Forecast Models → **(Auto)Regression**, **Exponential Smoothing**, **Machine Learning**

Domain Specific Extensions
White-Box

HWT
(Energy Single Equation)
EGRV
(Energy, Multi Equation)
IFS
(Weather)

(Auto)Regression
Gray-Box

AR
MA
ARMA
ARIMA
SARIMA
ARMAX
MLR (Multiple Linear Regression)
VAR (Vector Autoregression)
MARS (Multivariate Adaptive Regression Splines)
GBM (Gradient Boosting Machine)

Exponential Smoothing
Gray-Box

SES
(Single Exponential Smoothing)
DES
(Double Exponential Smoothing)
TES/HoltWinters
(Triple Exponential Smoothing)

Machine Learning
Black-Box

BN
(Bayesian Networks)
SVR
(Support Vector Regression)
ANN
(Artificial Neural Networks)

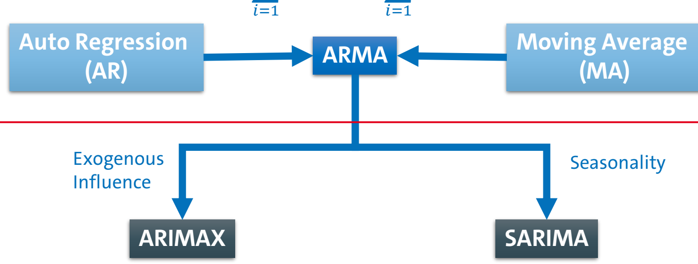
Data Mining

The ARMA Models

$$\hat{x}_t = c + \sum_{i=1}^{p} \phi_i \cdot x_{t-i}$$

$$\hat{x}_t = \sum_{i=1}^{p} \phi_i \cdot x_{t-i} + \sum_{i=1}^{q} \theta_i \cdot \varepsilon_{t-i} + c$$

$$\hat{x}_t = \sum_{i=1}^{q} \theta_i \cdot \varepsilon_{t-i}$$



$$\hat{x}_t = \sum_{i=1}^{p} \phi_i \cdot x_{t-i} + \sum_{i=1}^{q} \theta_i \cdot \varepsilon_{t-i} + c + \sum_{i=1}^{b} \gamma_i \cdot W_i$$

ARMA Models

t	1	2	3	4	5	6	7	8	9	10
x_t	3	7	4	5	3	2	8	7	4	6
AR	/	/	0.7*7+0.3*3 =**5.8**	0.7*4+0.3*7 =**4.9**	0.7*5+0.7*4 =**4.7**	3.6	2.3	6.2	7.3	4.9
MA	/	/	0.5*0+0.5*0 =**0**	0.5*0+0.5*4 =**2**	0.5*4+0.5*3 =**3.5**	1.25	0.125	4.3125	5.28125	0.703125
ε_i	0	0	4-0=**4**	5-2=**3**	3-3.5=**-0.5**	0.75	7.875	2.6875	-1.28125	5.296875

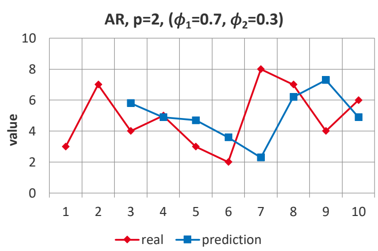
Box and Jenkins Methodology

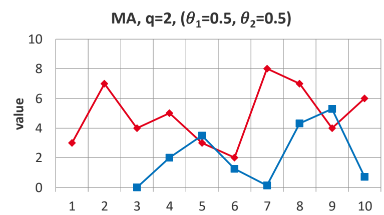
- Modeling time series with AutoRegression

Classification and Model Hierarchy

AR(p): $\hat{x}_t = c + \sum_{i=1}^{p} \phi_i \cdot x_{t-i}$
AutoRegression

MA(q): $\hat{x}_t = \sum_{i=1}^{q} \theta_i \cdot \varepsilon_{t-i}$
Moving Average
$\varepsilon_0, \cdots, \varepsilon_q = 0, \varepsilon_i = x_{t-i} - \hat{x}_{t-i}$

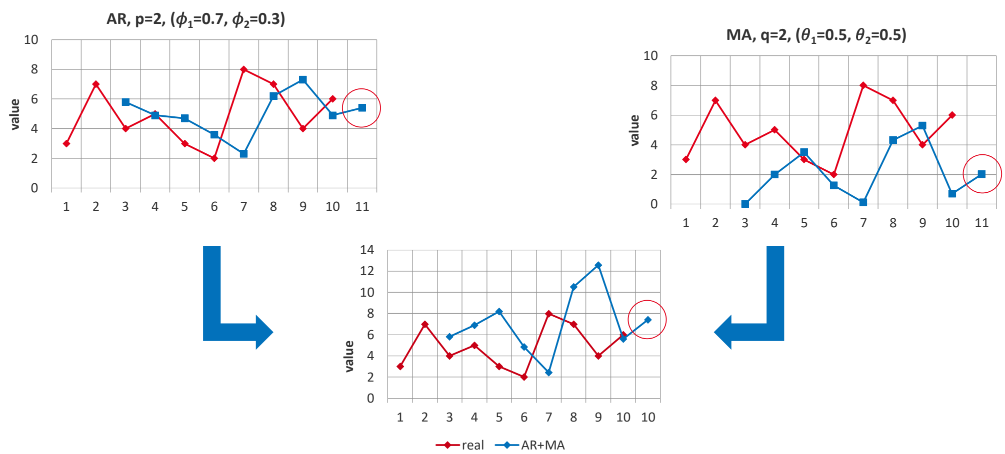




Data Mining

Here: c=0
Box and Jenkins do not assume trend and season components, but regard time series modelling as a stochastic process.

AR+MA



Exercise ARMA

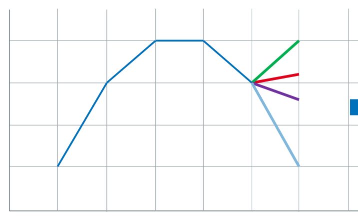
ϕ_1=0.7, ϕ_2=0.3
θ_1=0.5, θ_2=0.1

t	1	2	3	4	5	6
x_t	1	3	4	4	3	?
AR						
MA						
ε_i						

$$\hat{x}_t = \sum_{i=1}^{p} \phi_i \cdot x_{t-i}$$

$$\hat{x}_t = \sum_{i=1}^{q} \theta_i \cdot \varepsilon_{t-i}$$

$$\varepsilon_0, \cdots, \varepsilon_q = 0, \varepsilon_i = x_{t-i} - \hat{x}_{t-i}$$



Which one is the ARMA prediction?

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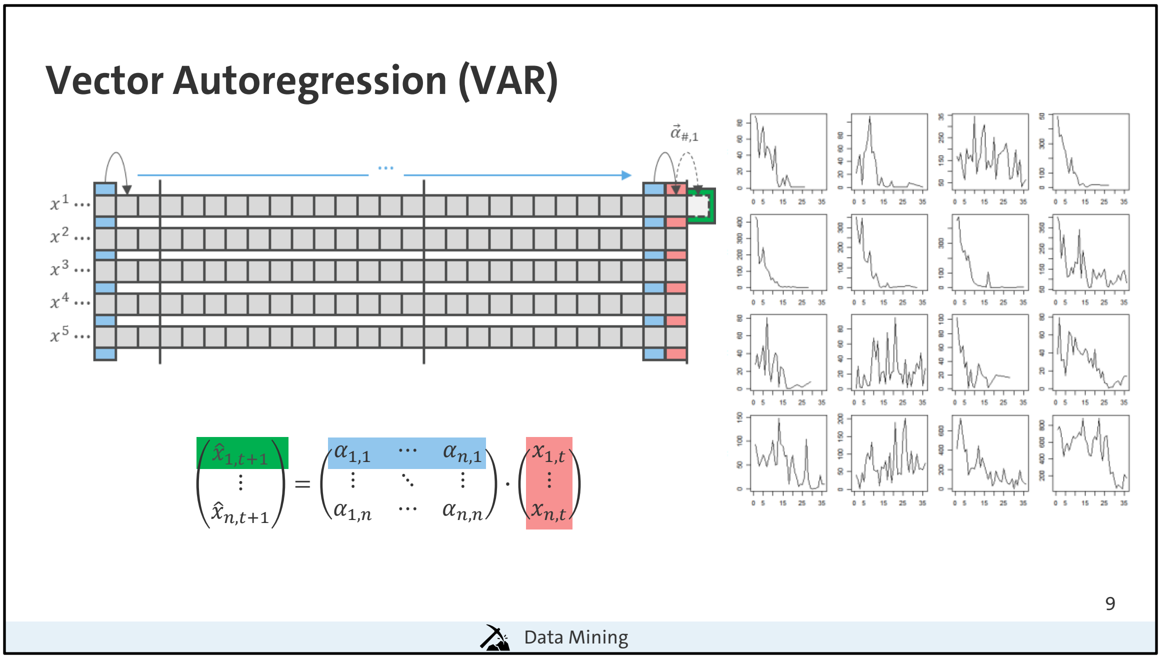

- Multivariate Modeling Technique
    - Based on the assumption, that time series from the same domain influence each other
    - Capable of compensating unexplainable behavior of individual time series
    - Can be extended by external influences
- Individual Model Optimization
    - In practice every line in the parameter matrix is implemented as an individual optimization process

Further Rreading

Riise, T., & Tjostheim, D. (1984). Theory and practice of multivariate arma forecasting. *Journal of Forecasting*, *3*(3).

Model Types

Domain Specific Extensions ← **Base Forecast Models**

White-Box

HWT
(Energy Single Equation)
EGRV
(Energy, Multi Equation)
IFS
(Weather)

Base Forecast Models → (Auto)Regression, Exponential Smoothing, Machine Learning

(Auto)Regression | **Exponential Smoothing** — Gray-Box

AR
MA
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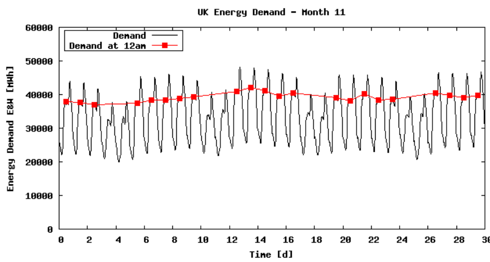
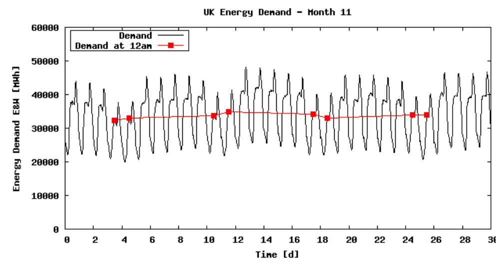
Machine Learning — Black-Box

BN
(Bayesian Networks)
SVR
(Support Vector Regression)
ANN
(Artificial Neural Networks)

EGRV Model (Engle, Granger, Ramanathan, and Vahid-Arraghi)



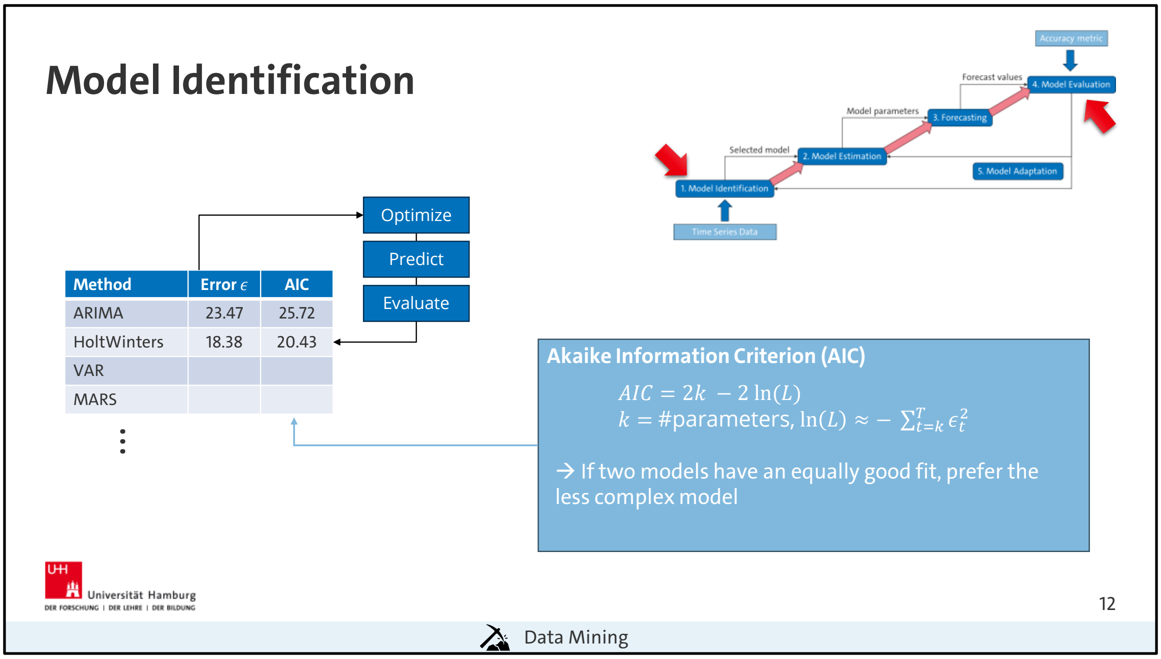


Ramanathan, R., Engle, R., Granger, C. W. J., Vahid-Araghi, F., & Brace, C. (1997). Short-run forecasts of electricity loads and peaks. *International Journal of Forecasting*, *13*(2).

Data Mining

Multi Equation Model

- One model for each hour (half hour, etc.) of a day (separation in weekdays/weekends)
- White-Box model tailor-made for energy demand
- Decomposition leads to almost constant time series that are easy to predict
- Basic idea works for all types of time series that follow certain pattern

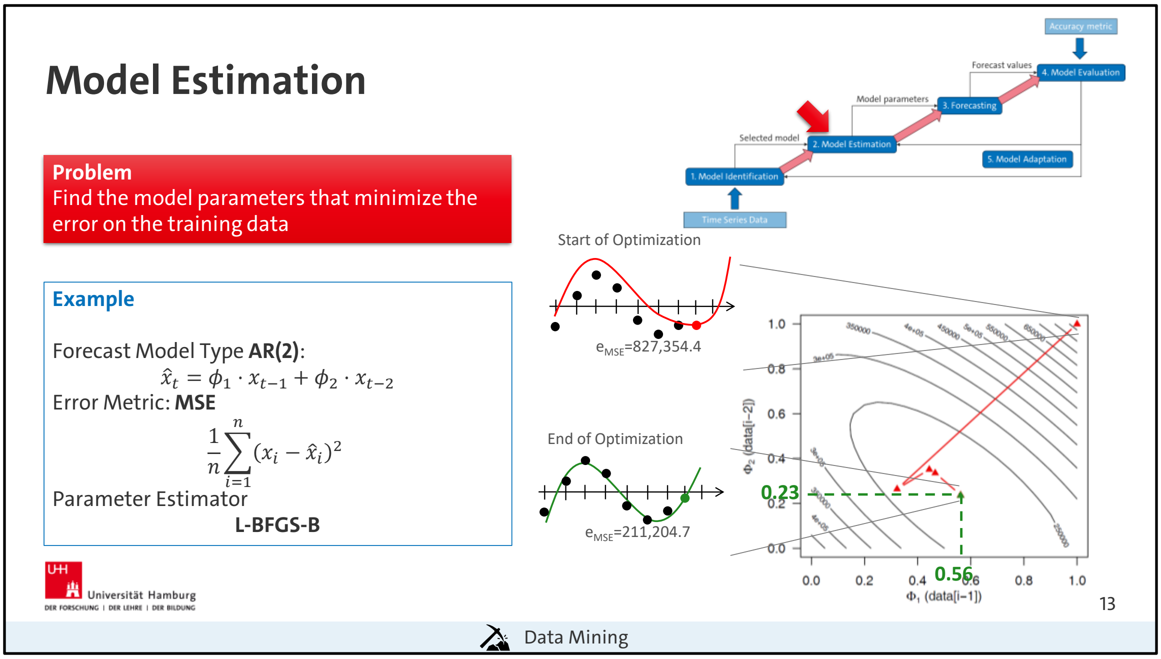


(Semi)Automatic Model Identification

- Test for every available model, how it performs on a test section of the current time series
- Use the error or more complex measures like AIC and BIC to find the optimal model

Akaike Information Criterion (AIC)

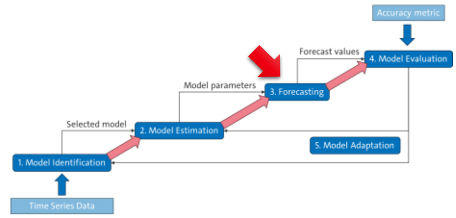
- A more sophisticated way to decide which is the optimal model
- Use the model with the lowest AIC
- Use the fit of the model to the training data and the model complexity
- L → Maximum likelihood



AR(2): Auto Regression with p=2
MSE: Mean Squared Error
L-BFGS-B: Limited memory Broyden–Fletcher–Goldfarb–Shanno with box constraints

Original BFGS was published independently by each of the 4 authors:
Broyden: https://doi.org/10.1093/imamat%2F6.1.76
Fletcher: https://doi.org/10.1093/comjnl%2F13.3.317
Goldfarb: https://doi.org/10.1090/S0025-5718-1970-0258249-6
Shanno: https://doi.org/10.1090/S0025-5718-1970-0274029-X

Model Usage



Model based Prediction
- Application of the identified and trained (optimized) model
- Typically very fast compared to the training process

Horizon
- Describes the number of forecasted values
- One step ahead (only one value), long range forecasting (many values, up to several seasons)

Example (Long Range)
- Single Exponential Smoothing, horizon 10 values
- Continue forecast calculation based on already calculated forecast values

Base:

$$x_1^* = x_1$$
$$x_t^* = \alpha \cdot x_t + (1-\alpha) \cdot x_{t-1}^*$$
$$\hat{x}_{t+1} = x_t^*$$

for(i in 1:10)

$$x_{t+i-1}^* = \alpha \cdot \hat{x}_{t+i-1} + (1-\alpha) \cdot x_{t-1}^*$$
$$\hat{x}_{t+i} = x_{t+i-1}^*$$

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Maintenance strategies

Error Threshold
- Define error threshold τ
- Update model parameter when $\text{Error} > \tau$
- May miss opportunities to improve the model performance or reestimate too often, based on whether τ is too high or too low

Time Threshold
- Reestimate the model parameter after a fixed number of update values
- May reestimate too often and without model improvement or tolerate too high errors within an interval

…as usual a combination works best

A somewhat higher error threshold
- And a somewhat longer time threshold

Time Series Storage

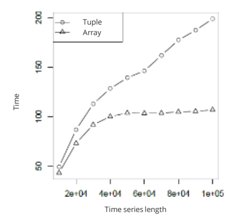
Relational Storage

ID	rec_date	sales
1	20.11.2021	3
1	21.11.2021	7
1	22.11.2021	4
1	23.11.2021	5
1	24.11.2021	3
1	25.11.2021	2
1	26.11.2021	8
1	27.11.2021	7
1	28.11.2021	4
1	29.11.2021	6
2	20.11.2021	7
2	21.11.2021	5
2	22.11.2021	8

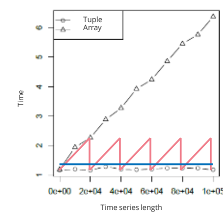
Array Storage

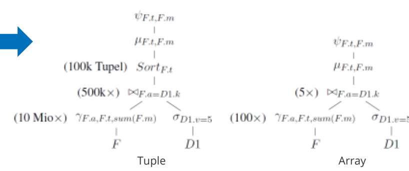
ID	start	interv	sales
1	20.11.2021	1 day	{3,7,4,5,3,2,8,7,4,6}
2	20.11.2021	1 day	{7,5,8,9,1,5,5,8,9,6}

Read performance
- Read entire data set into a forecast model
- Array storage outperforms tuple per value



Insert performance
- Append values to stored time series
- Tuple per value wins, less overhead
  - Counter steer by partitioning
- Ideal case, constant insert time





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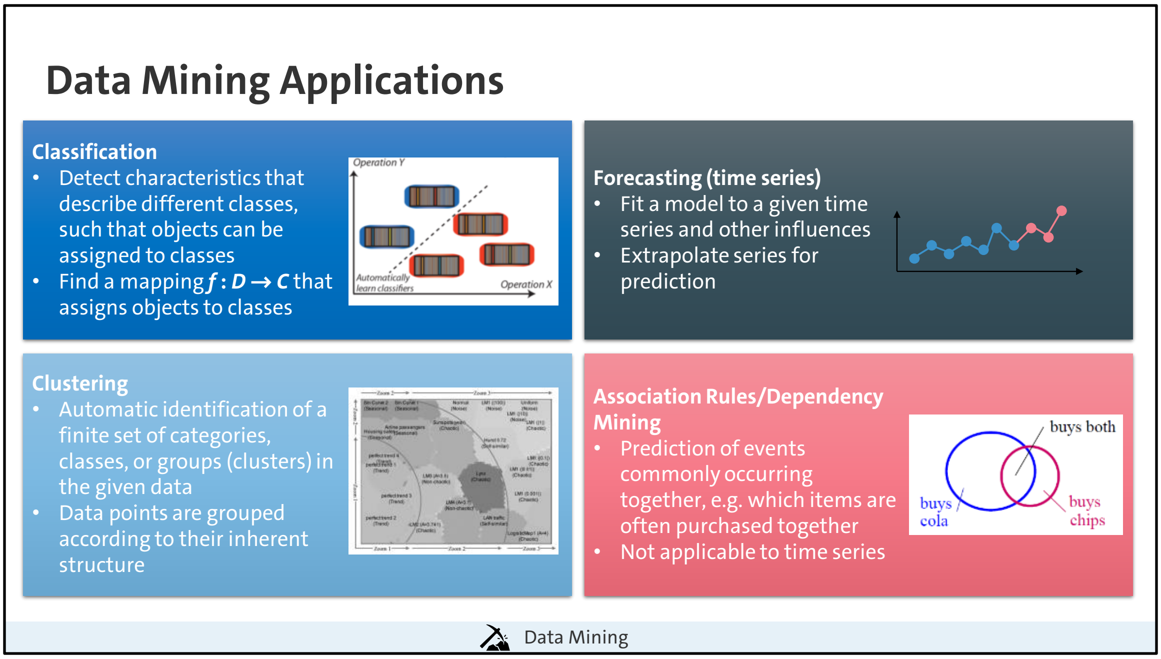
Relational Storage
- One tuple for each individual measure value
- Store alongside with
  - Time/date stamp
  - Time series identifier, e.g.
    - ID
    - Equipment
    - Sensor name

<u>Access</u>
- Usually no order guarantees
- Order by
  - Identifier first
  - Time last

Array Storage
- Store entire time series
  - Time series values are stored in an array
  - Alongside with
    - Time series identifier

        - Start
        - Time interval between values
- Constraints: Time series must be
    - Complete
    - Equidistant



Goal: Prediction of events commonly occurring together

Market basket analysis: Which items are often purchased together

- Placement of items in a store
- Layout of mail-order catalogues
- Targeted marketing campaigns

Association rules: Rules of the form a ∧ b ∧ . . . ∧ c → d ∧ e

Example: buys cola → buys chips

Challenge: Finding good combinations of premises and conclusions is a combinatorial problem

Association Rules

Example (transaction) database

trans-action	item
001	cola
001	chips
001	peanuts
002	beer
002	chips
002	cigarettes
...	...

I_k, i=2

trans-action	items
001	{chips, cola, peanuts}
002	{beer, chips, cigarettes}
003	{beer, chips, cigarettes, cola}
004	{beer, cigarettes}

T_k

D

I = SELECT DISTINCT item FROM example_table;

s({beer}) = 3/4

If (s_{cut} = ½) → s({beer}) is a frequent itemset

Definitions

Set of *n* different items *I* $\quad I = \{x_1, \ldots, x_n\}$

Itemset I_k $\quad I_k \subseteq I$

i-itemset $\quad I_k^i \subseteq I, \ |I_k^i| = i$

Transaction T_k $\quad T_k \subseteq I$

Database D $\quad D = \{(k, T_k) \mid k = 1, \ldots, m\}$

Support of an itemset = share of transactions which contain the itemset $\quad s(I_i) = \dfrac{|\{T_k \mid I_i \subseteq T_k\}|}{|D|}$

Frequent (strong, large) itemset $\quad s(I_i) \geq s_{cut}$

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Downward closure:

- Every subset of a frequent itemset is also a frequent itemset
- Every superset of a non-frequent itemset is also a non-frequent itemset

Association Rules

Association Rule
$X \rightarrow Y \; where \; X, Y \subseteq I, X \cap Y = \emptyset$

Support of a rule: Share of transactions which contain both, premise and conclusion of the rule

$$s(X \rightarrow Y) = s(X \cup Y) = \frac{|\{T_k | X \cup Y \subseteq T_k\}|}{|D|} = p(XY)$$

Confidence of a rule: Share of transactions supporting the rule from those supporting the premise

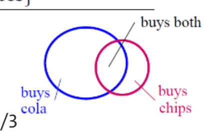
$$c(X \rightarrow Y) = \frac{s(X \cup Y)}{s(X)} = \frac{|\{T_k | X \cup Y \subseteq T_k\}|}{|\{T_k | X \subseteq T_k\}|} = p(Y|X)$$

Lift of a rule: Ratio of the observed support to that expected if *X* and *Y* were independent

$$lift(X \rightarrow Y) = \frac{s(X \cup Y)}{s(X) \times s(Y)} = \frac{p(Y|X)}{p(Y)}$$

trans-action	items
001	{chips, cola, peanuts}
002	{beer, chips, cigarettes}
003	{beer, chips, cigarettes, cola}
004	{beer, cigarettes}

Example:
[buys] chips → [buys] cola



s(chips→cola) = 2/4 = 0.5
c(chips→cola) = 0.5/(3/4) = 2/3
lift(chips→cola) = (2/3)/(0.75*0.5) = 1.78

Customers who buy chips are 1.78x as likely to also buy cola as compared to independent purchases.

Strong rule: High Support + High Confidence

Data Mining

- lift(X) > 1 → positive association
- lift(X) <1 → negative association
- lift(X) = 1 → items are independent

Detection of strong rules: Two pass algorithm

1. Find frequent (strong, large) itemsets (Apriori algorithm)
   - Necessary to generate rules with strong support
   - Uses the downward closure
   - Itemsets are ordered
2. Use the frequent itemsets to generate association rules
   - Find strong correlations in a frequent itemset

Apriori

I_k^1	#	$s(I_k^1)$
{chips}	3	0.75
{cola}	2	0.5
{peanuts}	1	0.25
{beer}	3	0.75
{cigarettes}	3	0.75

Step 1: Start with all itemsets of size one: I^1
Step 2: Select all items with sufficient support, e.g where $s(I_k)\geq 0.5$

I_k^2	#	$s(I_k^2)$
{chips, cola}	2	0.5
{beer, chips}	2	0.5
{chips, cigarettes}	2	0.5
{beer, cola}	1	0.25
{cigarettes, cola}	1	0.25
{beer, cigarettes}	3	0.75

Step 3: From the selected itemsets I^{n-1} generate larger itemsets I^n
→ *Already blocks some of the non-frequent itemsets, but not all of them*

I_k^2	#	$s(I_k^2)$
{chips, cola}	2	0.5
{beer, chips}	2	0.5
{chips, cigarettes}	2	0.5
{beer, cola}	1	0.25
{cigarettes, cola}	1	0.25
{beer, cigarettes}	3	0.75

Step 4: Remove itemsets which still contain a non-frequent subset
→ *Cannot have enough support because of downward closure*

I_k^3	#	$s(I_k^3)$
{beer, chips, cigar.}	2	0.5
{chips, cigar., cola}	1	0.25

Prune because of non-frequent subset

Step 5: *Repeat from step 2 until no further frequent itemsets can be generated*

D

trans-action	items
001	{chips, cola, peanuts}
002	{beer, chips, cigarettes}
003	{beer, chips, cigarettes, cola}
004	{beer, cigarettes}

Resulting frequent itemsets

i= 3: {beer, chips, cigarettes}
i=2: {chips, cola}, {beer, chips}, {chips, cigarettes}, {beer, cigarettes}
i=1: {beer}, {chips}, {cigarettes}, {cola}

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Apriori: Finding frequent itemsets of increasing size (itemsets are ordered!)

- Step 4 in the example: no items to prune
- Note: Itemset {*beer, chips, cola*} is not constructed because we only combine sets of I^2_k that have the first element in common
- However, this set cannot be frequent because otherwise the set {*beer, cola*} would be in I^2_k (and then we would have constructed {*beer, chips, cola*})

Exercise Apriori

k	T_k
1	{butter, bread}
2	{butter, bread, cheese, wine}
3	{bread, soda}
4	{cheese, pencils, pasta}
5	{cheese, pasta, wine}

$s_{cut} = 0.4$

Generation of Strong Association Rules

- For all frequent itemsets I_j with $|I_j| \geq 2$ determine all non-empty subsets I_k for which

$$c = \frac{s(I_j)}{s(I_k)} \geq c_{min}$$

- Add rule $I_k \rightarrow Y$ with $Y = I_j - I_k$ to the rule set

Example

$s(\{chips\}) = 0.75$, $s(\{cola\}) = 0.5$, $s(\{chips, cola\}) = 0.5$

rule	confidence
$\{\text{cola}\} \rightarrow \{\text{chips}\}$	1.00
$\{\text{chips}\} \rightarrow \{\text{cola}\}$	0.67

Confidence

$$c(X \rightarrow Y) = \frac{s(X \cup Y)}{s(X)} = \frac{|\{T_k | X \cup Y \subseteq T_k\}|}{|\{T_k | X \subseteq T_k\}|} = p(Y|X)$$

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Data Mining

Interesting association rules: Only those for which the confidence is greater than the support of the conclusion

$$c(X \rightarrow Y) > s(Y) \qquad (\equiv lift(X \rightarrow Y) > 1)$$

Rule modification: Confidence can be increased by shifting items from the conclusion to the premise

Negative border: Used to derive negative association rules (e.g. customers who buy cola and chips do not buy beer)

$$\{I_j \mid s(I_j) < s_{cut} \wedge \forall I_k \subset I_j \colon s(I_k) \geq s_{cut}\}$$

Apriori: Number of potential itemsets is exponential in the number of items

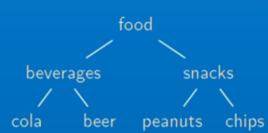
But:

- Data is sparse: $|T_i| << |I|$
- Itemsets are generated in separate scans of the database
- Size of generated itemsets grows monotonically
- Large itemsets are usually useless
- Only k scans required (k << |I|)

Modifications and Extensions of Apriori

Hierarchical Apriori

In addition to the base level of items, determine also frequent itemsets on a higher level in an is-a hierarchy
→ Sometimes regularities can only be found at higher levels of abstraction



Partitioned Apriori

1st step:
- Partition the database
- Compute locally frequent itemsets on each partition

2nd step:
- Determine the global support of all locally frequent itemsets
- Remove all itemsets which do not satisfy the minimal support

Heuristics:
- Idea: if an itemset is globally frequent it will be so locally in at least one partition

→ Second step deals with a superset of possible frequent itemsets

More

- Sampled transactions
- Incremental rule mining
- Non uniform support thresholds
- Class association rules
- Rule mining on relational data

Association Rules with Relational Data

- Relational data has to be transformed into transaction data
- Apriori requires categorical data → binning must be performed
- The same category can appear as value of different attributes
  - → Values must be combined with their attribute
  - → Attribute-value pairs are taken as items