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Dresden Database Systems Group

Beyond the Crystal Ball – Time Series Analysis and Forecasting

Claudio Hartmann – Lehrstuhl Datenbanken

System Architecture

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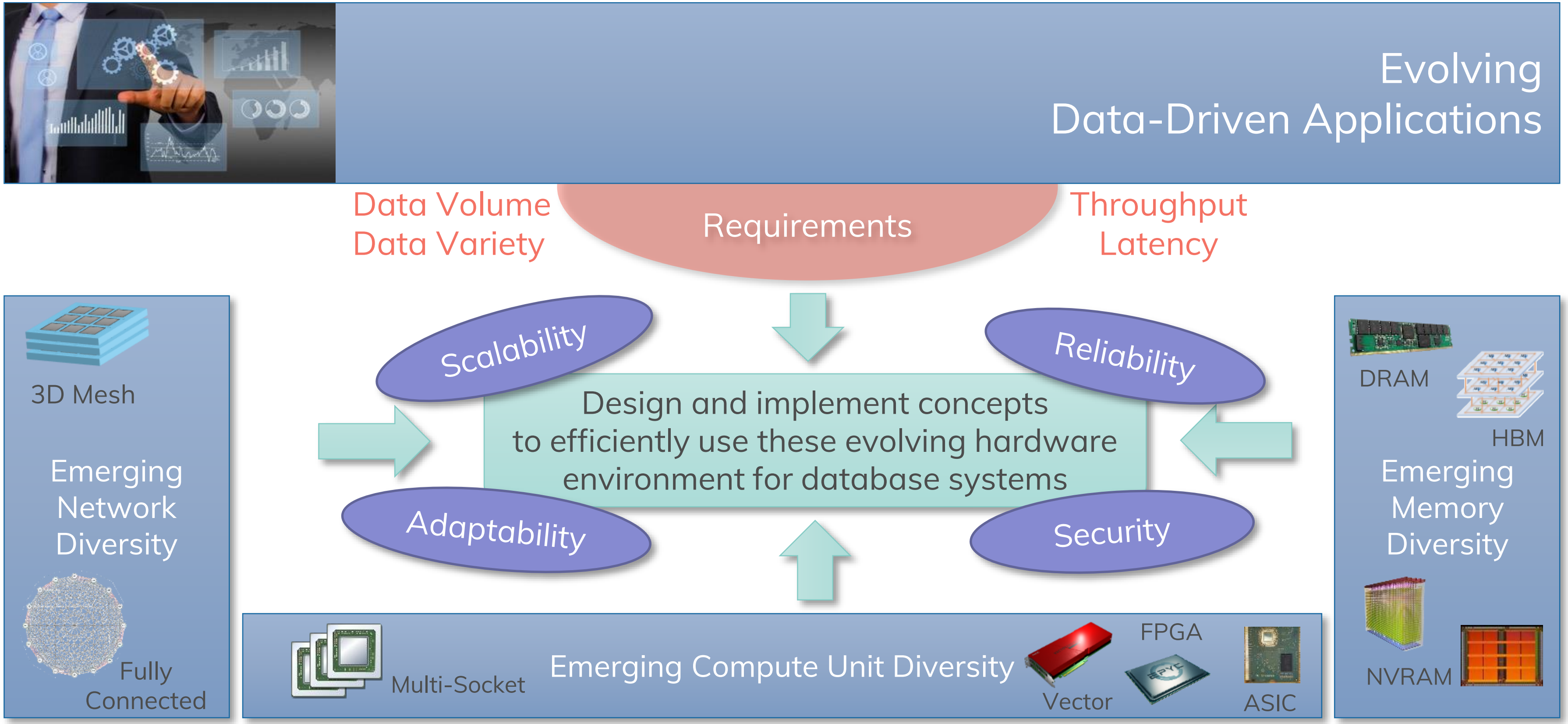
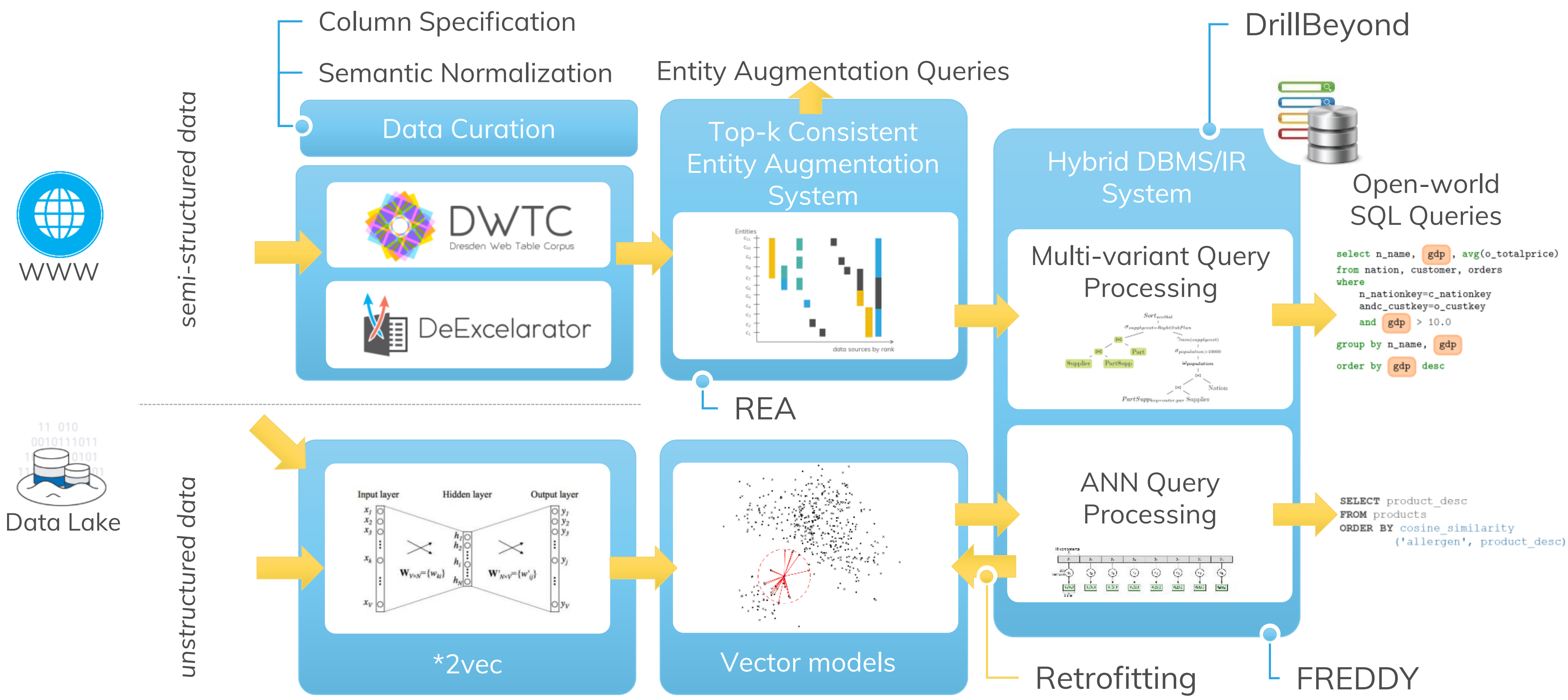


Documents and Information Retrieval



Data Analytics

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Support/Extend Database Technology

- Sampling Techniques
- Integration of Machine Learning into RDBMS
- Cardinality estimation using Artificial Neural Networks
- Monitoring database health status

Working with Data

- Time series Forecasting
- Time series properties and generation
- Clustering with human feedback

Flash Forward Query

ReEF
Renewable Energy Forecasting

GOFLEX

Agenda

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What is a time series?

Health of a Database System

- Monitoring and Target
- Techniques

Feature-based Time Series Engineering

- Time Series Features
- What-if analysis

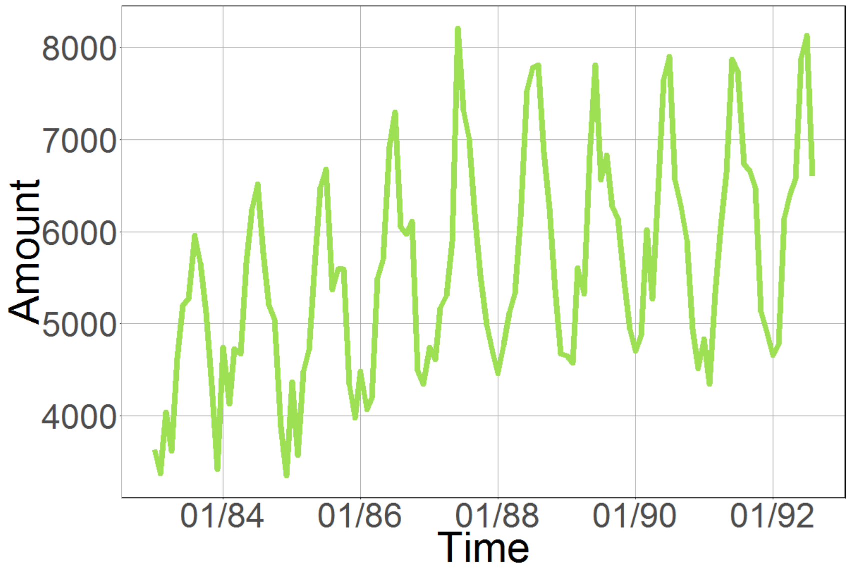
Forecasting Large-scale Time Series Data

- Forecasting Process
- Big Data Implications
- CSAR

Terminology

Time Series

- Sequence of measure values
- Ordered by time
- Equidistant
  - Constant time distance between measure values
- Complete
  - No missing values



Health of a Database System

Health of a Database System

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Monitoring

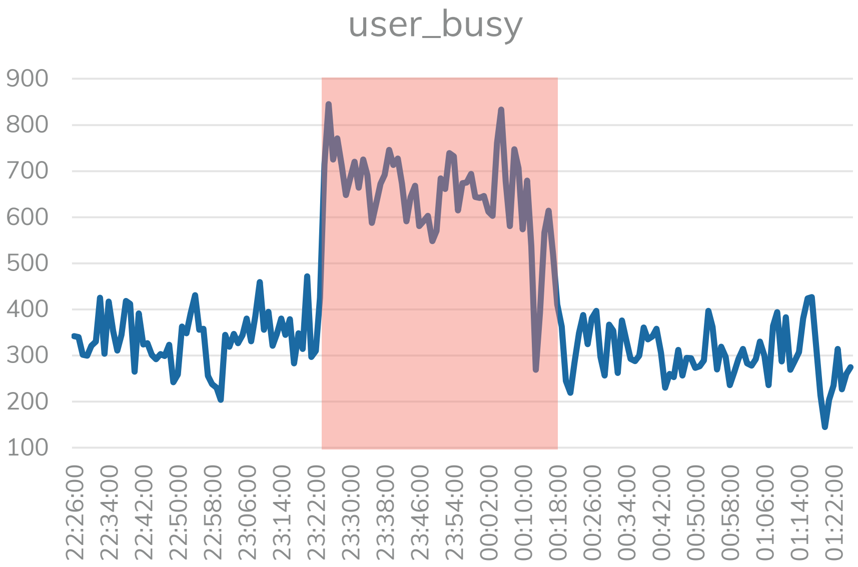
- Several measurements that serve as indicator for the health status of the database

Target

- Issue automatic warning for situations that would lead to customer complaints

Possible Health indicators

- CPU (user_busy, io_busy, system_busy, idle)
- user connections
- physical reads/writes, …



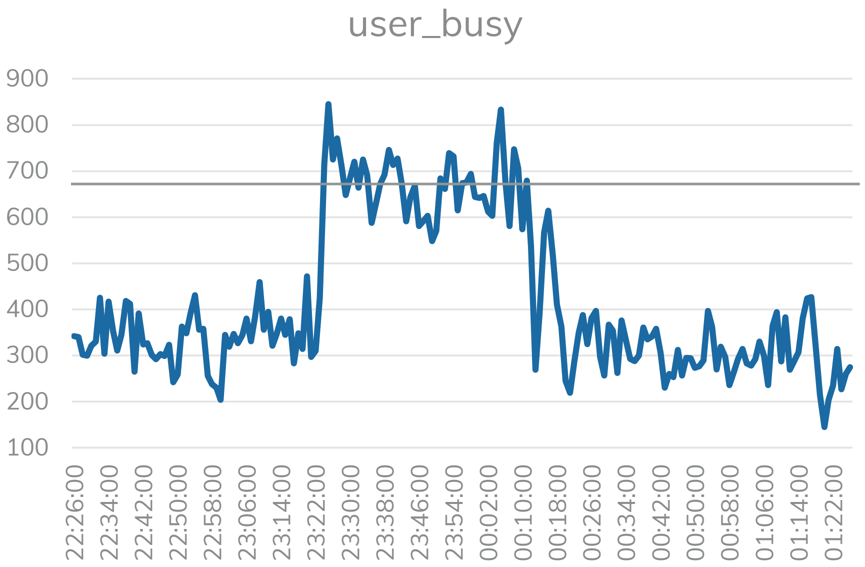
Health of a Database System

Threshold/Limits

- Define upper threshold
- Issue warning when threshold is exceeded

Problem

- Manual work
- Proper definition of threshold
  - Too high → Warning too late
  - Too low → Waring when there is no issue



Health of a Database System

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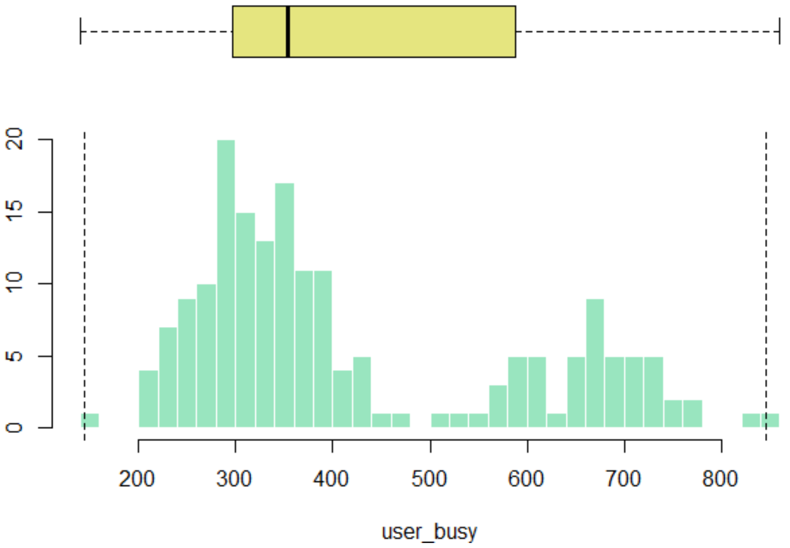
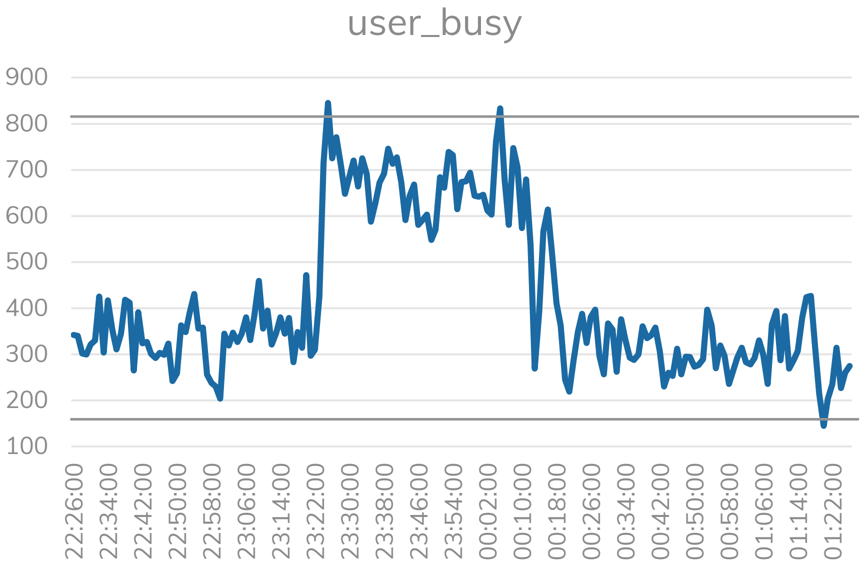
Automatic threshold using IQR

- Define threshold based on box plot statistics
- Issue warning when threshold is exceeded



Problem

- May detect normal states as outliers



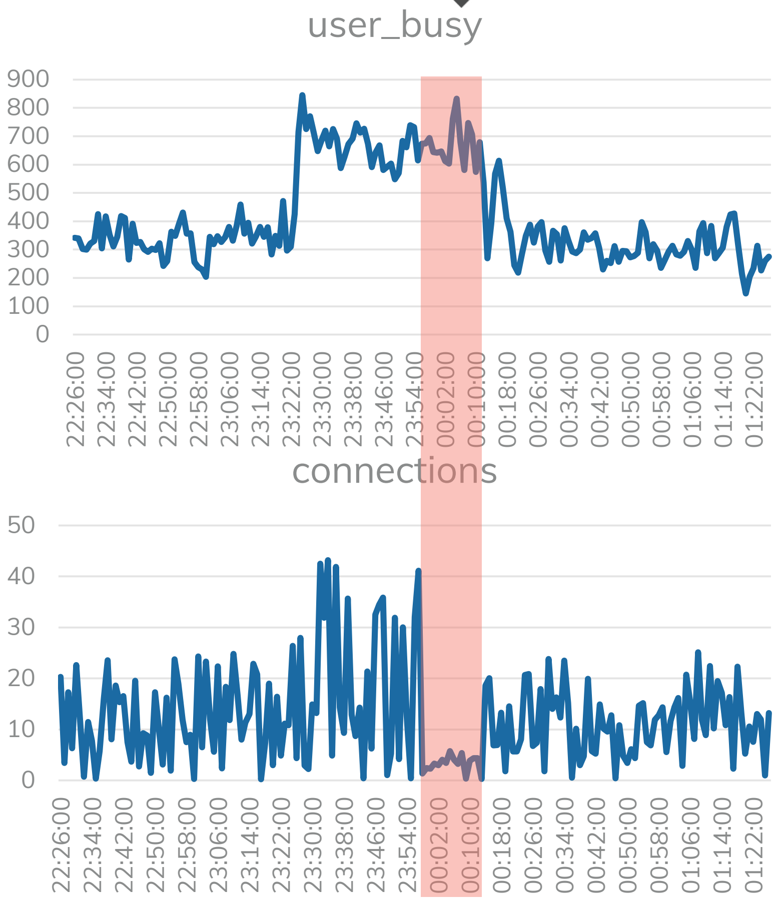
Health of a Database System

Co-development of measurements

- Examine proportions of several measurements
- Issue warnings for abnormal proportions

Problem

- Know all effects in advance
- Lots of manual work



Health of a Database System

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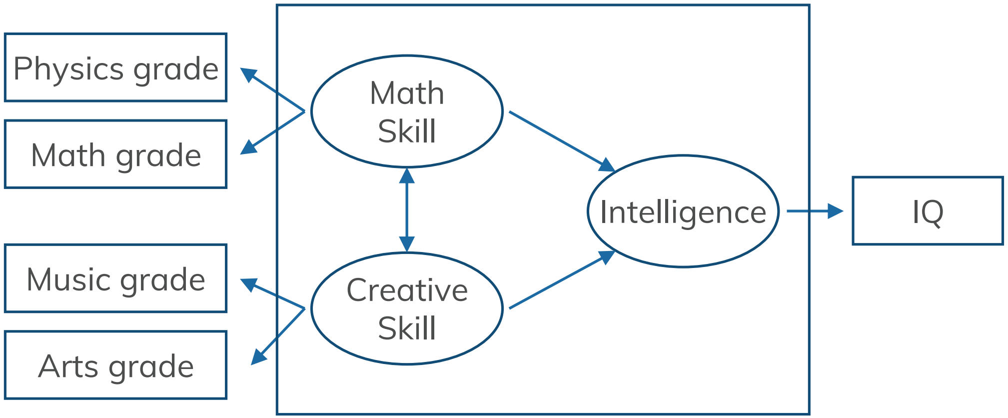
Structural Equation Modeling

- Model influences between system components
- Analysis of Latent Factors

Model Properties

- Item
  - Measurable variables
- Latent Factor
  - Not measurable variables
- Measurement model
  - Model connections between items and factors using covariance



Health of a Database System

Structural Equation Modeling

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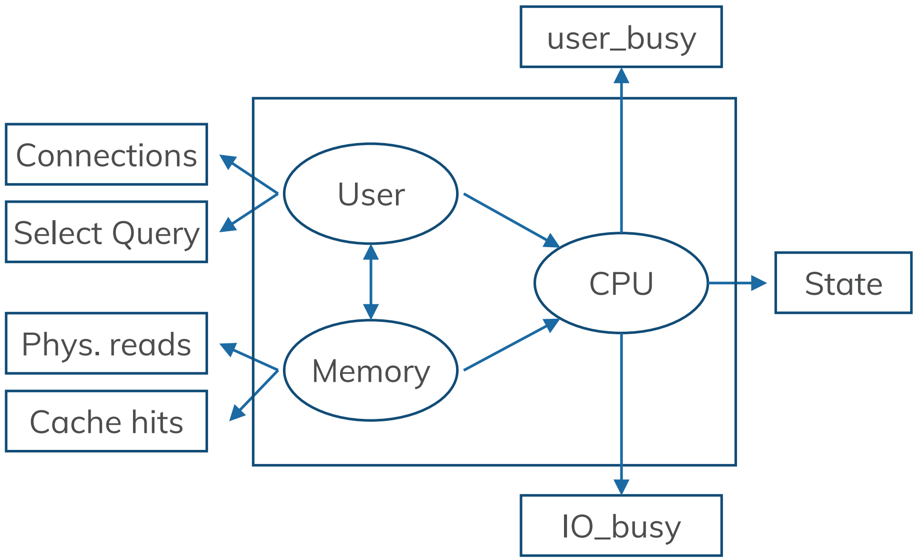

Feature-based Time Series Engineering

Process of Time Series Engineering

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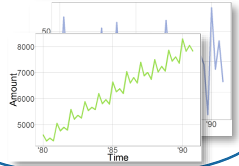
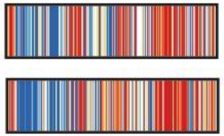
Time Series Dataset



Representation Engineering

Represent

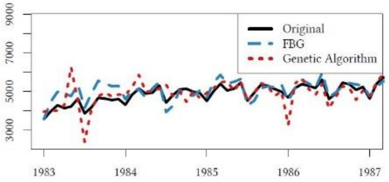
Representation Dataset



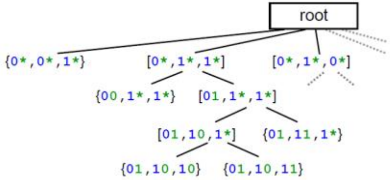
Distance

Data-mining Tasks

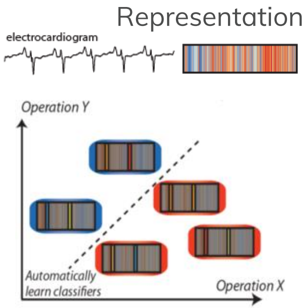
Generation



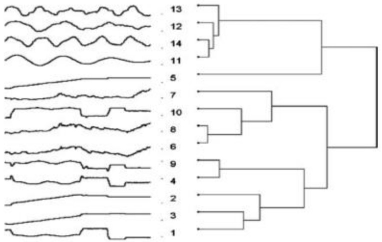
Indexing



Classification



Clustering



Figures: Kegel et al., 2018; Shieh and Keogh, 2013; Fulcher et al., 2013; Wang et al., 2006

Example Time Series Features

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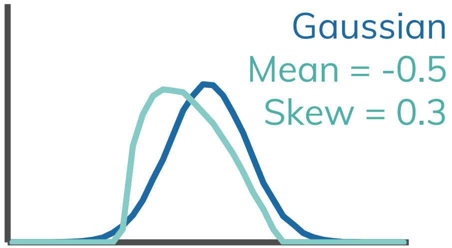
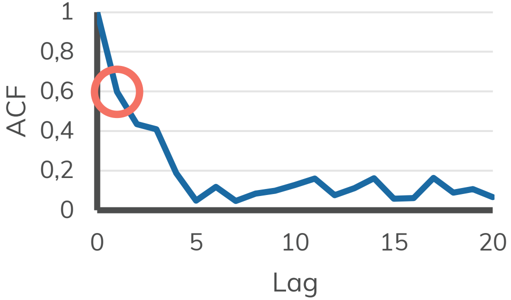
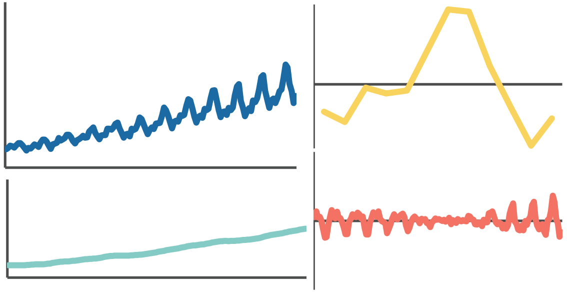
Distribution



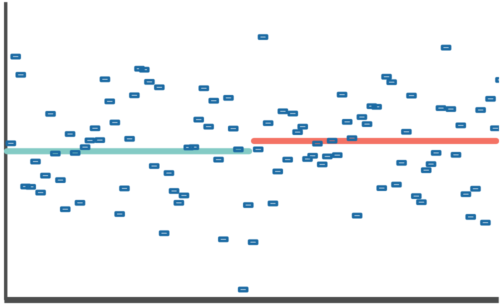
Correlation



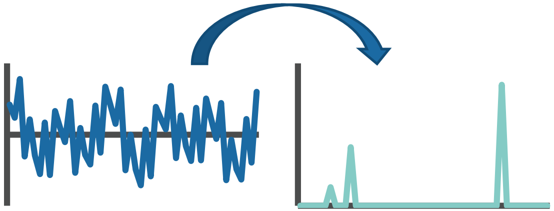
Components



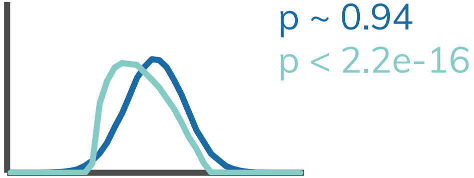
Stationarity



Frequency Domain



Tests



p-value of Normality test

Time Series Components

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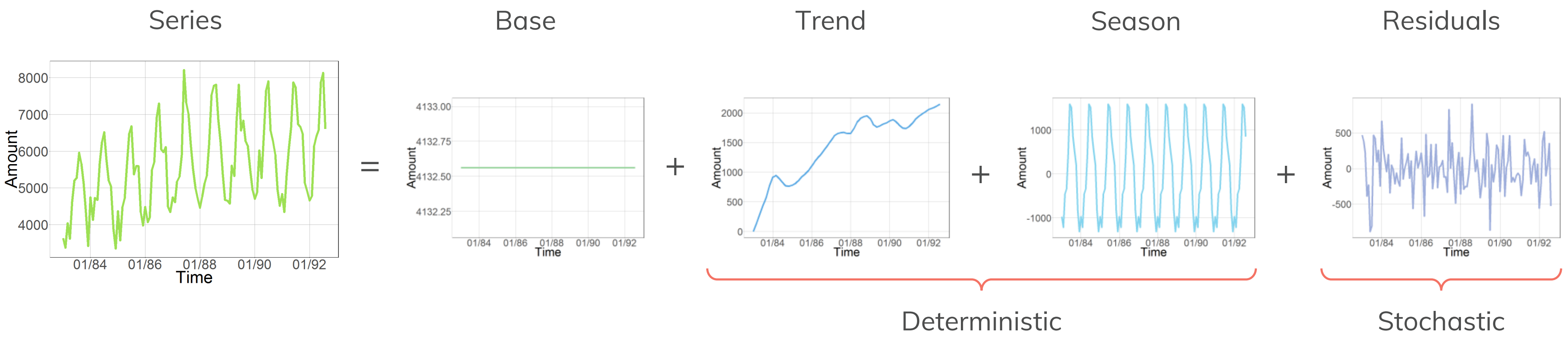
Decomposition

- Base: stationary part of the time series
- Trend: long-term change in the mean level
- Season: cyclical repeated behavior
- Residuals: unstructured information assumed to be random

Often, base is part of the trend component!

Additive Composition $x_t = base_t + \ trend_t + season_t + res_t$



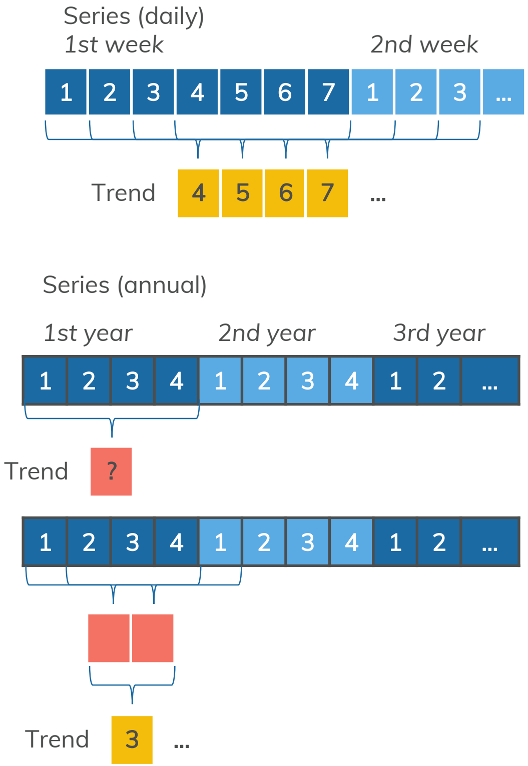
Time Series Decomposition

Basic Idea

- Moving-average filter of continuous windows
- $tr_t = \frac{x_t + x_{t-1} + x_{t-2} + \dots + x_{t-N+1}}{N}$
- Extraction of trend by windows that take into account the season length
- Extraction of season by averaging each time instance of the same seasonal position (all Mondays, all Tuesdays,…)
- Disadvantage: does not decompose the endpoints

Average Centering

- A technique needed if season length is even
- Take two moving averages and average their result

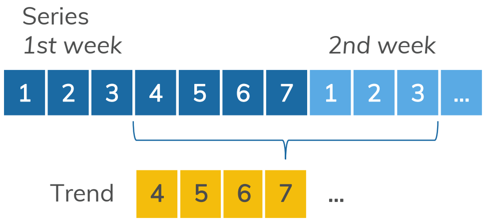


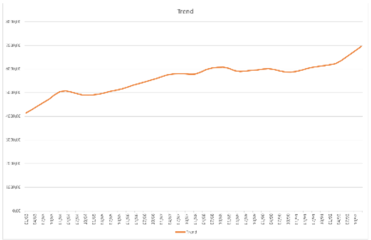
A season of length 7 such as
- Monday (1)
- Tuesday (2)
- …

Time Series Decomposition

Retrieval of Trend

- Moving-average filtering
- In case of even season length, centralize first



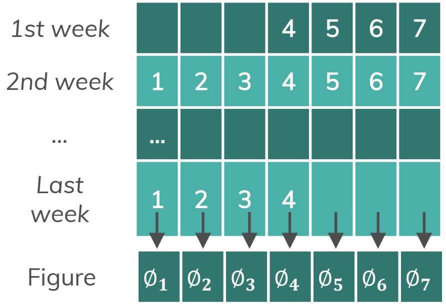


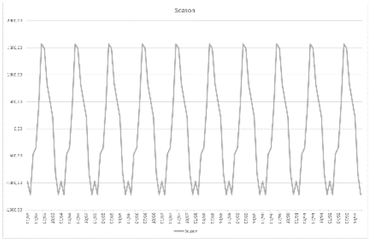

```
trend <- filter(series, rep_len(1,7)/7)
```

Season Retrieval

- Detrend series
- Figure represents the average of each time instance of a season
- De-mean figure

```
detrend <- series - trend
```



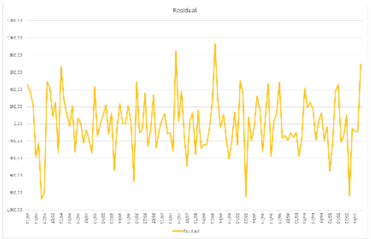



```
season <- figure - mean(figure)
```

Residuals

- Subtract components

```
residuals <- series - season - trend
```



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Feature-based Generation Method (FBG)

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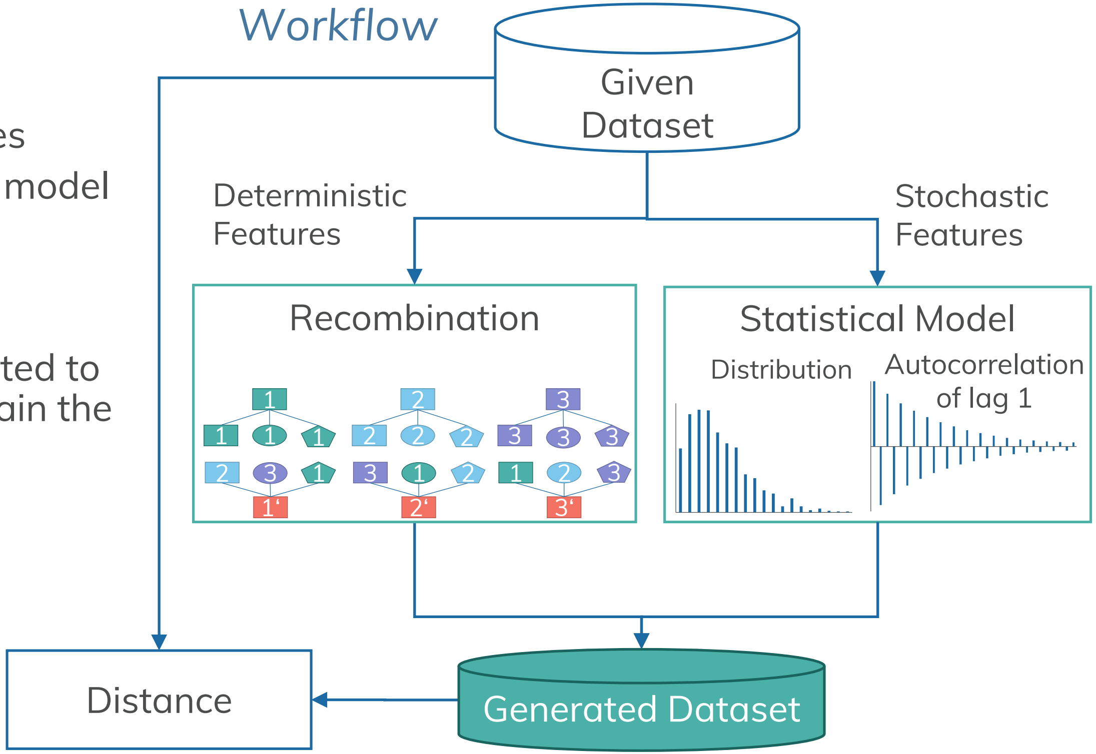
Idea

- Feature-based representation
- Recombination of deterministic features
- Simulation of residuals with statistical model

Use cases

- Anonymization of data sets
- Generate a data set that is closely related to the original data set but does not contain the actual data

Workflow

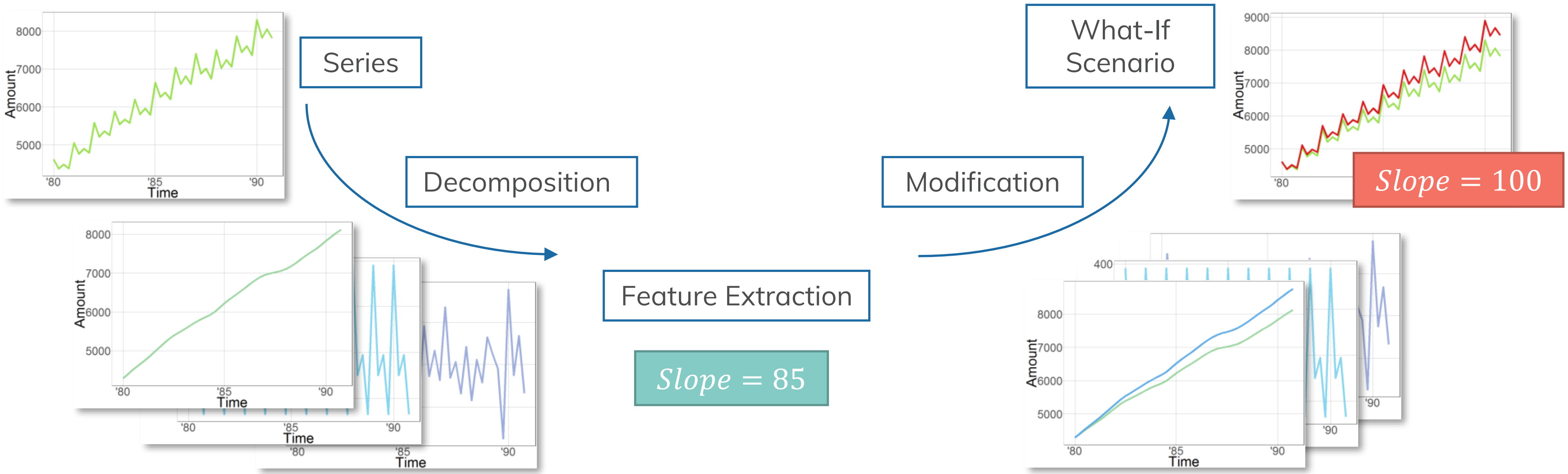


Kegel et al., 2018

What-if Analysis

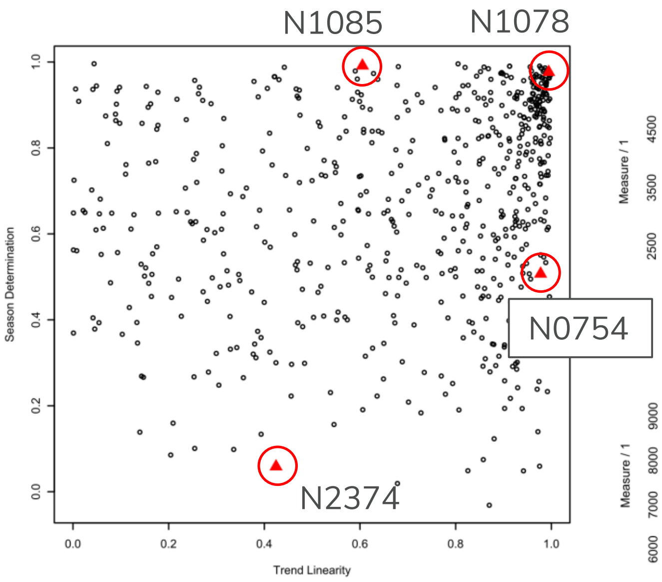
General Idea

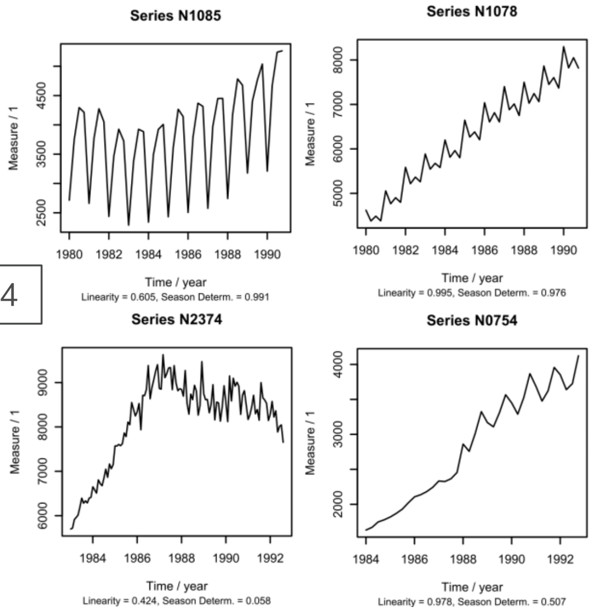
- Represent time series by their features
- Generate a what-if scenario by setting factors that modify features



Feature Extraction

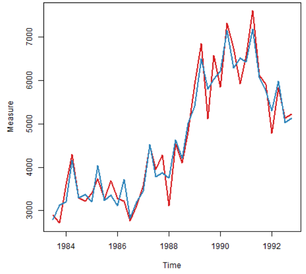
Feature Space and Selected Time Series



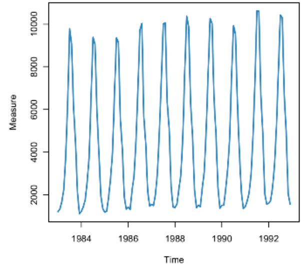


Season Determination R^2_{seas}

- $R^2_{seas} = 1 - \frac{var(res_t)}{var(res_t + seas_t)}$



Weak Season

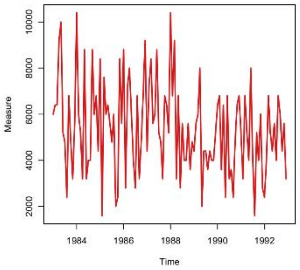


Strong Season

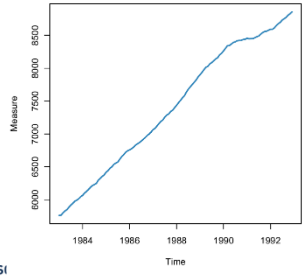
Feature Extraction

Trend Determination R^2_{tr}

- $R^2_{tr} = 1 - \frac{var(res_t)}{var(res_t + tr_t)}$



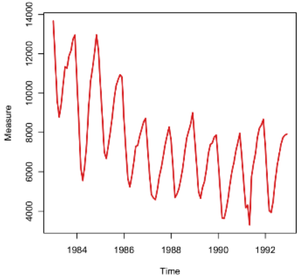
Weak Trend



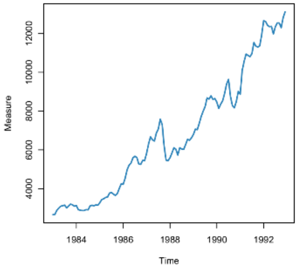
Strong Trend

Trend Slope θ_2

- Suppose a linear trend within STL trend: $tr_t = \theta_1 + \theta_2 \cdot l_t + \delta_t$



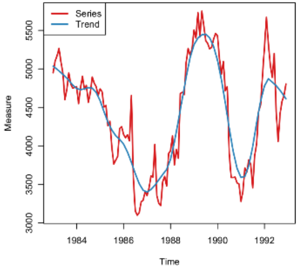
Negative Trend



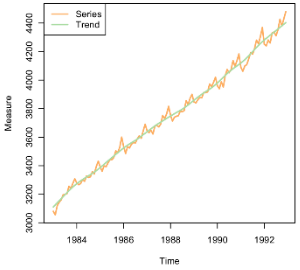
Positive Trend

Trend Linearity R^2_{lin}

- $R^2_{lin} = 1 - \frac{var(\delta_t)}{var(tr_t)}$



Non-linear Trend



Linear Trend

Component Modification

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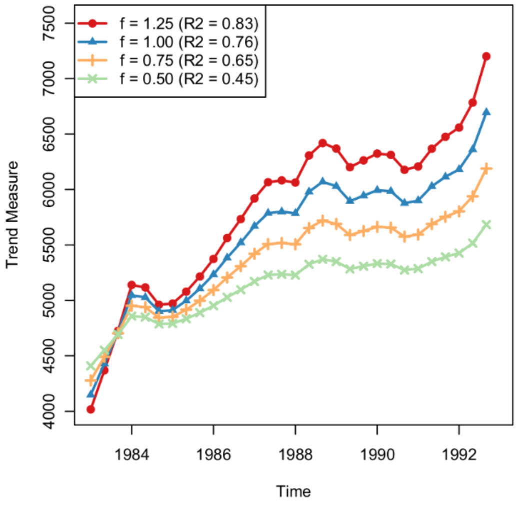
Trend Determination Factor

- Strengthen/weaken trend

$$tr_{t,f} = \theta_1 + f \cdot (\theta_2 \cdot l_t + \delta_t)$$

$$R^2_{tr} = 1 - \frac{var(res_t)}{var(res_t + tr_{t,f})}$$

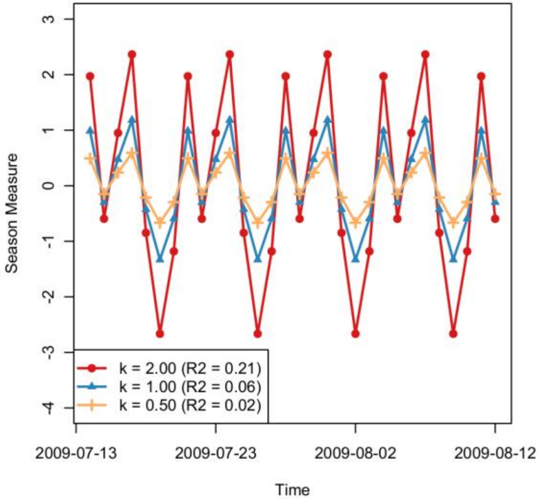


Season Determination Factor

- Strengthen/weaken season

$$seas_{t,k} = k \cdot seas_t$$

$$R^2_{seas} = 1 - \frac{var(res_t)}{var(res_t + seas_{t,k})}$$



Forecasting Large-scale Time Series Data

Forecasting Process

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1. Model Identification

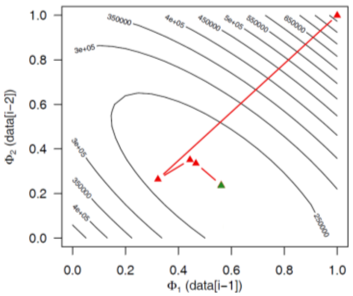
Method	Error	AIC
ARIMA	23.47	25.72
HoltWinters	18.38	20.43
VAR		
MARS		

Optimize

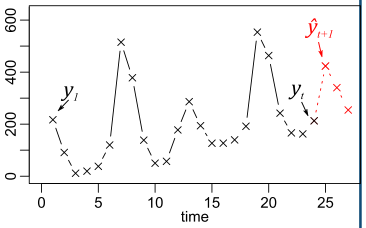
Predict

Evaluate

2. Model Estimation



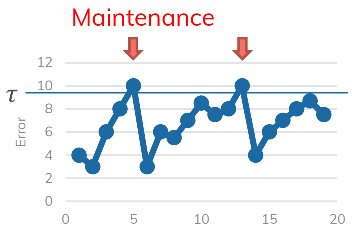
3. Forecast Calculation



4. Model Evaluation

$$SMAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|x_t - \hat{x}_t|}{(x_t + \hat{x}_t)/2}$$

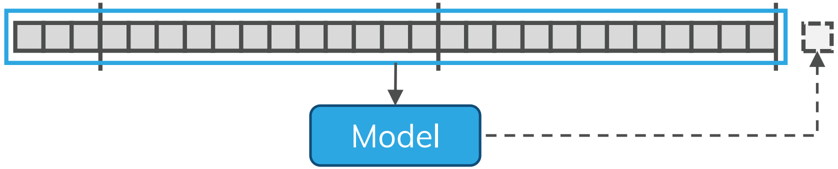
5. Model Adaptation



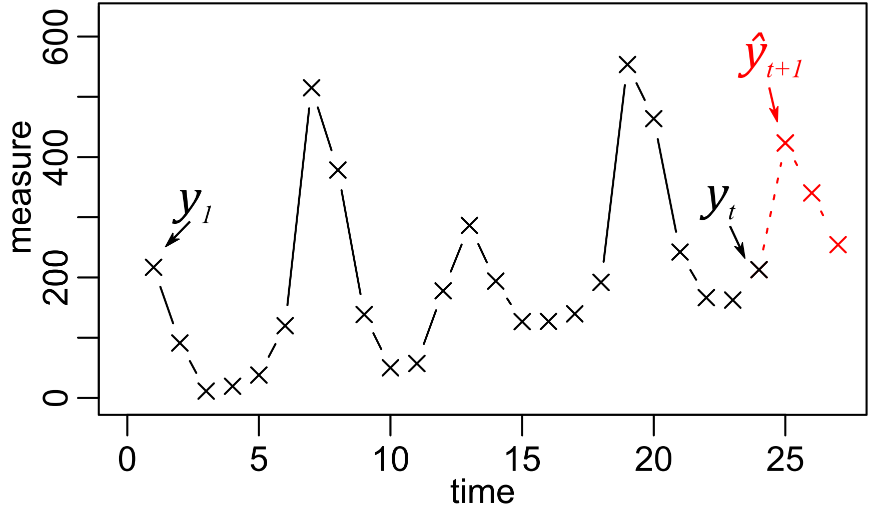
Traditional Time Series Forecasting

Univariate Forecast Models

- ARIMA/Exponential Smoothing
- Focus on only one time series at a time
- Widely applied in many domains
- auto.ARIMA/ETS to properly configure the model for a given time series



$$\hat{y}_{t+1} = c + \epsilon_t + \sum_{i=1}^{p} \phi_i y_{t-i+1} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j+1}$$



Large-scale Time Series Data

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Many and Long Series

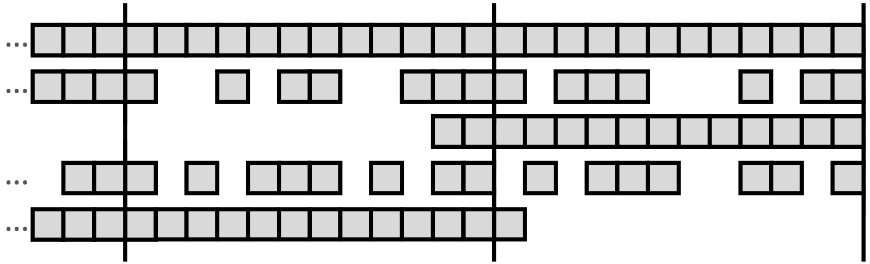
- High number of monitored objects (Smart Meter in every household, sales of individual products)
- Fine monitoring granularity leads to very long time series histories

High Levels of Noise

- Time series on fine granularity tend to be very noisy

Missing values

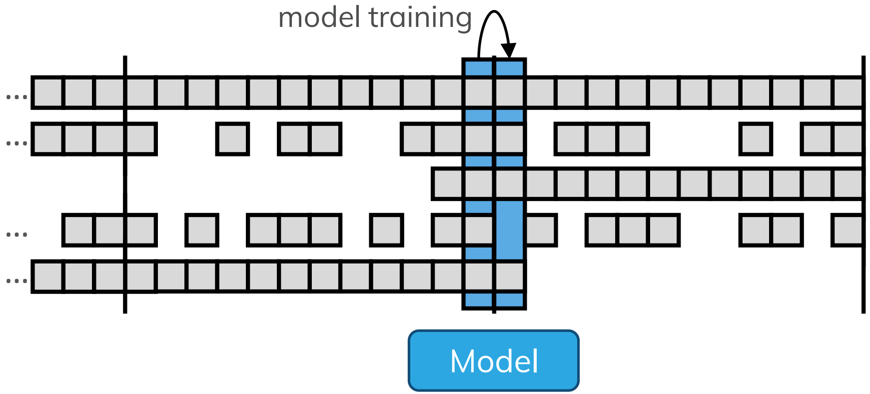
- Missing values lead to inapplicability of all most conventional models



Cross-sectional Forecasting

Core Approach

- Represent a whole data set with one model
- Focus on cross-sections instead of the entire time series
- Model transition from one cross-section to the next one
- All time series with values in the blue cross-sections contribute to the model training
- The model represents the average transition of the entire data set



$$\hat{\vec{y}}_{t+1} = c + \phi_1 \cdot \vec{y}_t$$

Cross-sectional Forecasting

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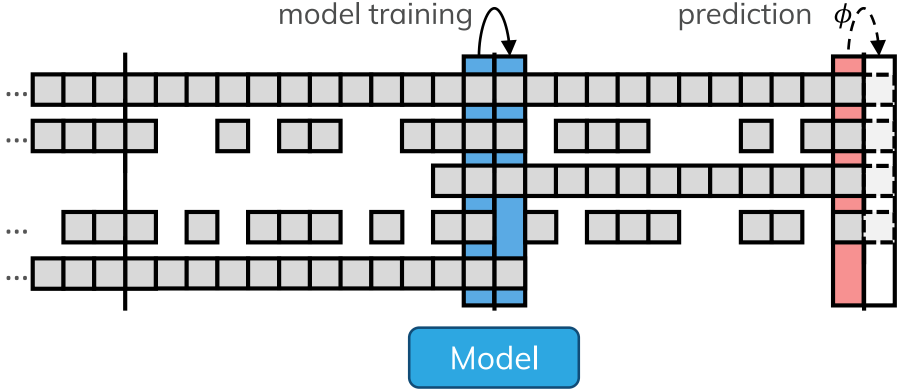
Model Application

- Assume the transition remains constant over seasons
- Apply model on the most current data
- Train a specific model for every transition in a season



$$\vec{\hat{y}}_{t+1} = c + \phi_1 \cdot \vec{y}_t$$

Still misses adaptability!

CSAR – Autoregression

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Non-seasonal Autoregression

- Model the dependency of future values of their direct predecessors

$$\hat{\vec{y}}_{t+1} = c + \phi_1 \cdot \vec{y}_t + \cdots + \phi_p \cdot \vec{y}_{t-p+1}$$

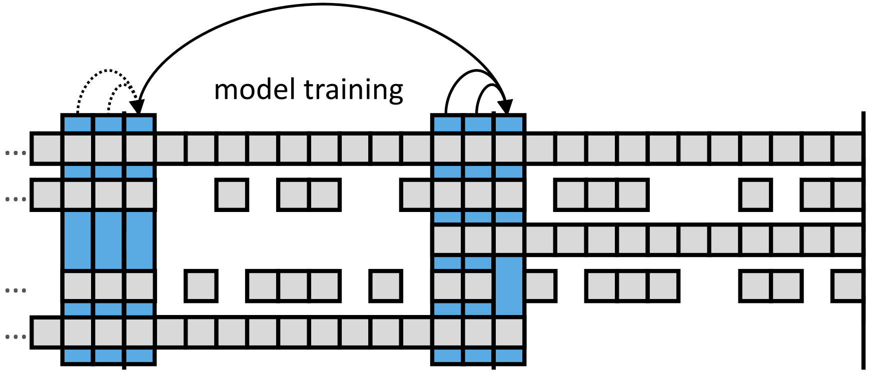
Seasonal Autoregression

- Model the dependency of future values of their seasonal predecessors

$$\hat{\vec{y}}_{t+1} = c + \Phi_1 \cdot \vec{y}_{t-s+1} + \cdots + \Phi_P \cdot \vec{y}_{t-P \cdot s+1}$$

Correction Terms

- Necessary if non-seasonal and seasonal components are combined



$$\hat{\vec{y}}_{t+1} = c + \phi_1 \cdot \vec{y}_t$$

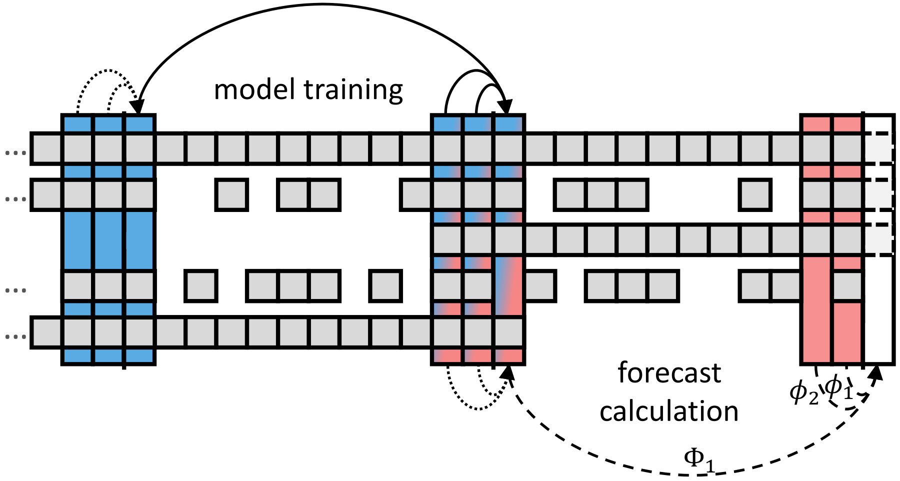
CSAR – Autoregression

Model Application

- On most recent data
- On all time series which have all necessary values

Behavioral Deviation

- Some time series do not follow the common behavior of the majority



$$\hat{\vec{y}}_{t+1} = c + \phi_1 \cdot \vec{y}_t + \phi_2 \cdot \vec{y}_{t-1} + \Phi_1 \cdot \vec{y}_{t-s+1} \\ +(-\Phi_1\phi_1) \cdot \vec{y}_{t-s} +(-\Phi_1\phi_2) \cdot \vec{y}_{t-s-1}$$

CSAR – Error Terms

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Non-seasonal Error Terms

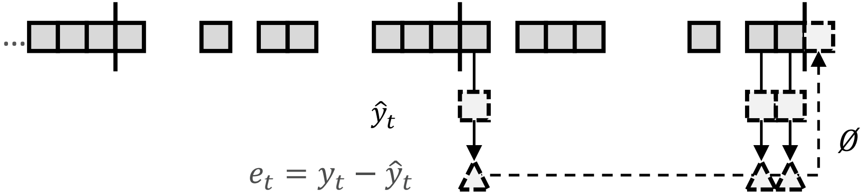
- Adjust forecasts according to systematic non-seasonal misprediction
- Deviation of individual time series from the general model for the data set

Seasonal Error Terms

- Adjust forecasts according to systematic seasonal misprediction
- Systematic deviation in the seasonal pattern

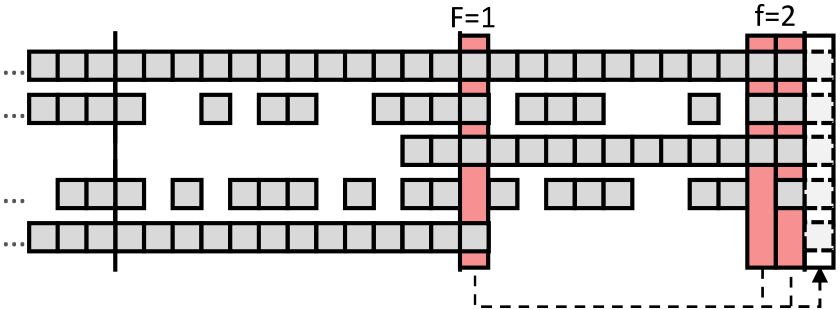
Missing Data

- If real value or forecast is missing, the value is ignored



$$\overline{e^n_{t+1}} = \frac{1}{f+F}\left(\sum_{i=0}^{f-1} e^n_{t-i} + \sum_{j=1}^{F} e^n_{t+1-j\cdot s}\right)$$

$$\hat{y}^n_{t+1} = c + \overline{e^n_{t+1}}$$



CSAR – Model Components

Autoregression

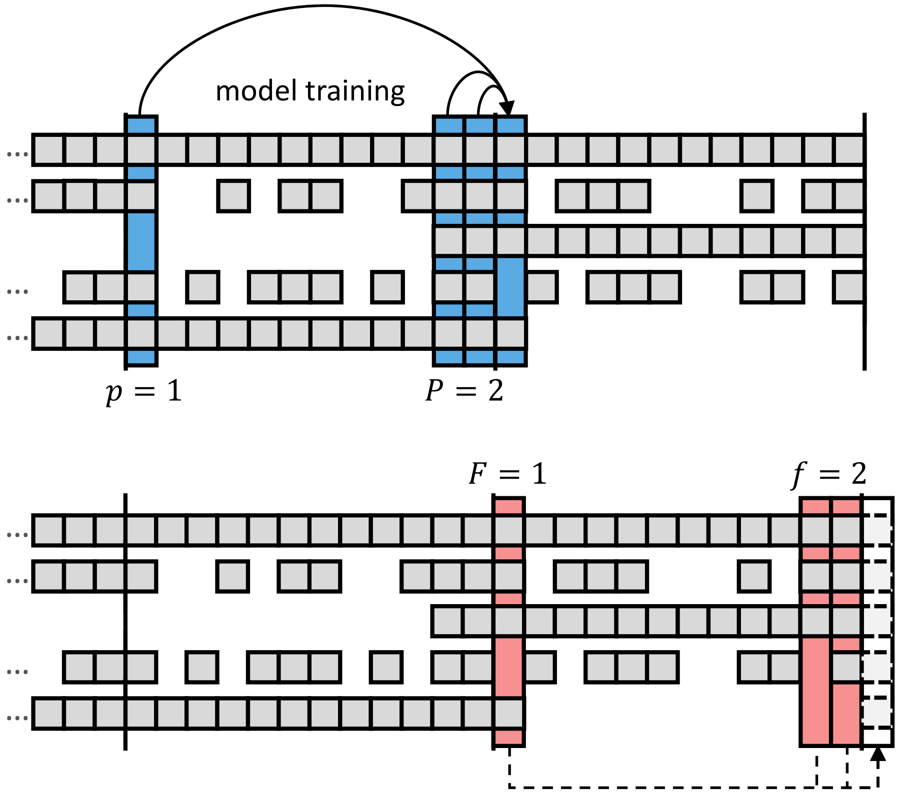
- p specifies number of non-seasonal AR terms
- P specifies number of seasonal AR terms

Error Terms

- f specifies number of non-seasonal error terms
- F specifies number of seasonal error terms

Model Configuration

- Adaptation to data set specific characteristics
- Influence on forecast accuracy
- Influence on execution time



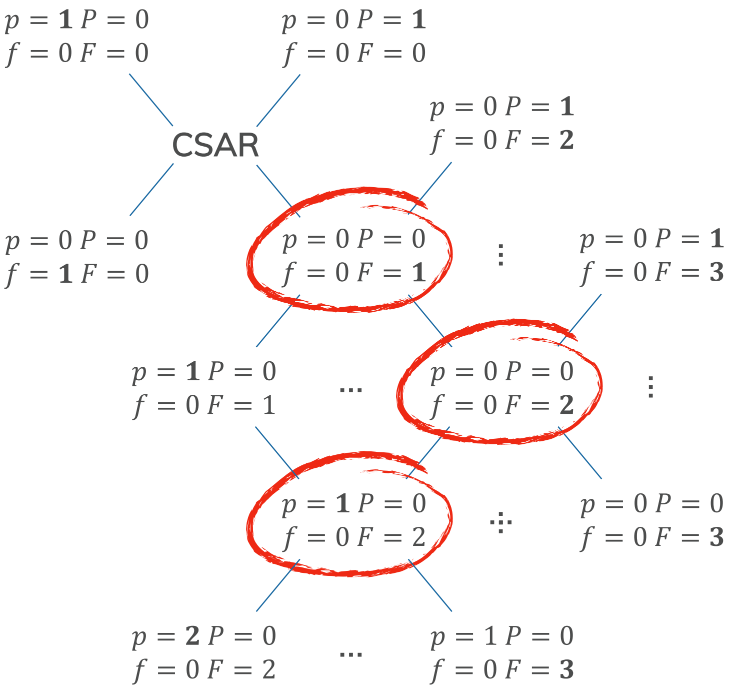
auto.CSAR – Structured Greedy Search

Step 1 – Base Models

- Compare basic model components
- Choose model with lowest error to identify most important model component

Step 2 – Search Around the best Model

- Based on result from Step 1
- Vary optimal model components by +/- 1
- Vary seasonal and non-seasonal components by +/- 1
- Invert the constant
- Repeat until an iteration returns no new best model

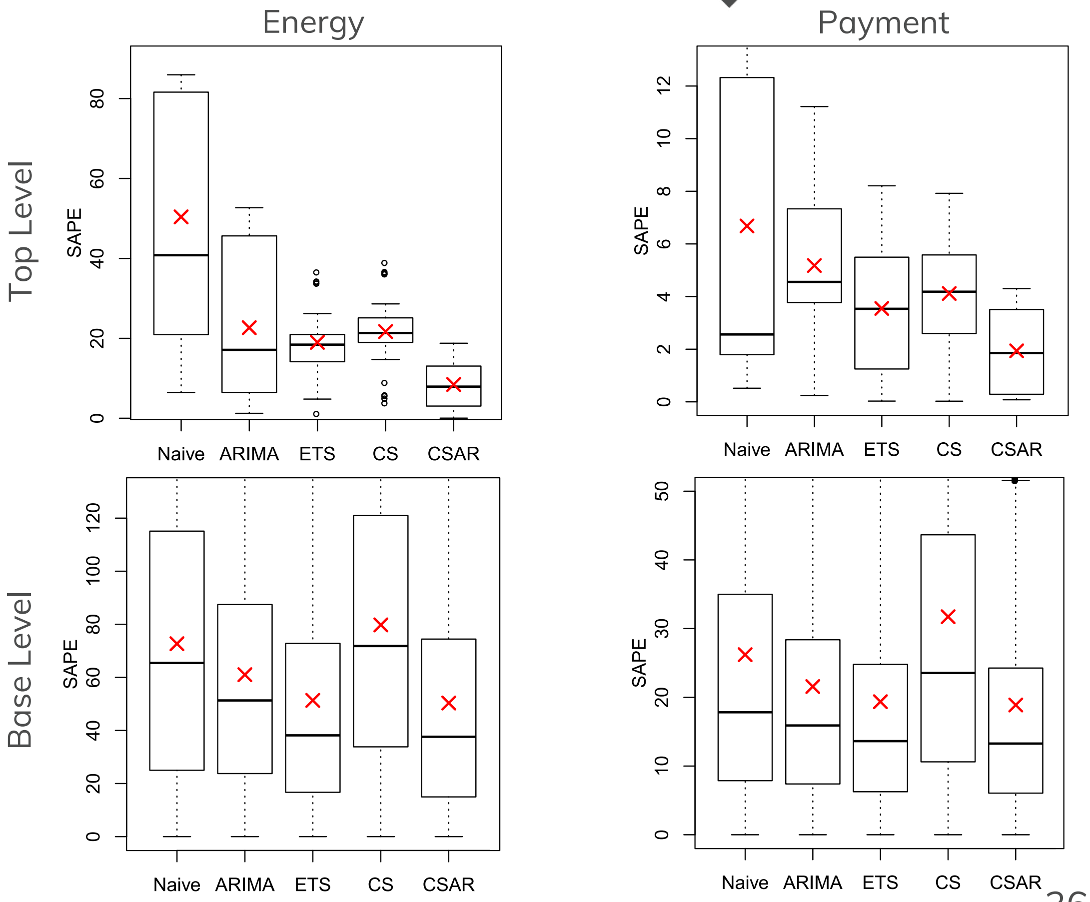


Forecast Accuracy

Experimental Set-Up

- Calculate long-range forecasts
  - Energy – 1 week (h=28)
  - Payment – 2 weeks (h=14)
- Calculate SAPE error between forecast and real time series values (Symmetric Absolute Percentage Error)

$$SAPE = \frac{|y - \hat{y}|}{(|y| + |\hat{y}|)/2} \cdot 100$$



Data Set Partitioning

Univariate vs. CSAR

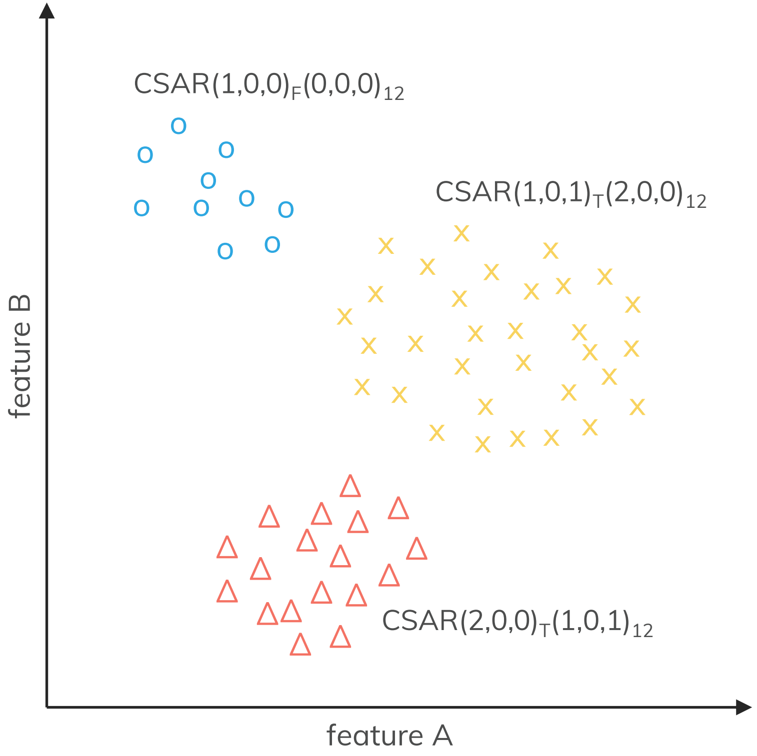
- Opposite extremes
- Univariate one model per time series
- CSAR one model for all time series

Partitioning

- Split data set into several Partitions
- Create one CSAR model for each partition

Expectation

- Better representation of time series
- Higher forecast accuracy



Model Adviser

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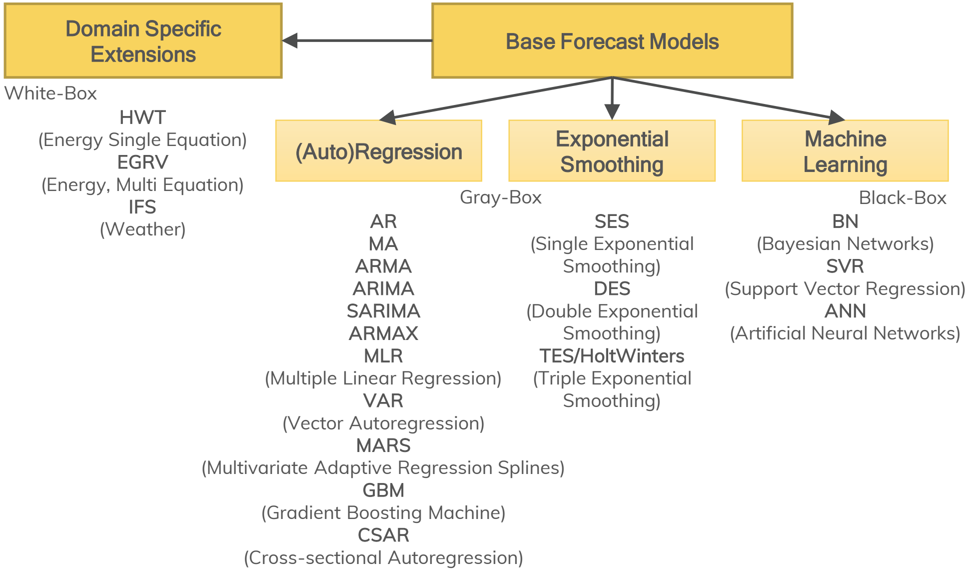
Model Suitability

- Different models work well with different time
- Some are designed for very specific use cases

Which one to use?

- Not an easy decision for non-experts



Student Thesis Topics

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Topics for Student Theses

https://wwwdb.inf.tu-dresden.de/study/theses/themen-fuer-arbeiten/

Student Theses at the Chair of Databases

Themenschwerpunkte

Aktuell werden studentische Arbeiten in folgenden Themenschwerpunkten vergeben:

Bereiche und aktuelle Angebote	Ansprechpartner
DB-Systemarchitektur, skalierbare und sichere Datenverarbeitung, DB-Systeme auf moderner Hardware Eine Auswahl aktueller Themen. ▪ Benchmark Design für adaptive Datenbanksysteme ▪ Integration des ERIS Storage Systems in Apache Spark ▪ Implementierung und Optimierung eines Codesgenerators für Kompressionsalgorithmen ▪ Evaluierung der Intel SGX Erweiterung für eine sichere Datenverarbeitung ▪ Implementierung und Evalution eines Storage Moduls für Graphdaten in ERIS	Dirk Habich
Informationsextraktion, Information Retrieval, Machine Learning Eine Auswahl aktueller Themen. ▪ Word2Vec-Modell über Webtabellen ▪ Column-specification mit System T ▪ Zeitreihenanalyse und -prognose	Maik Thiele
Für weitere individuelle Angebote kontaktieren Sie bitte den zuständigen Ansprechpartner.	