



# Taming Time Series!

Data Science Day 2019 @ THU

A very short tutorial on time series analysis and forecasting in the context of business analytics!

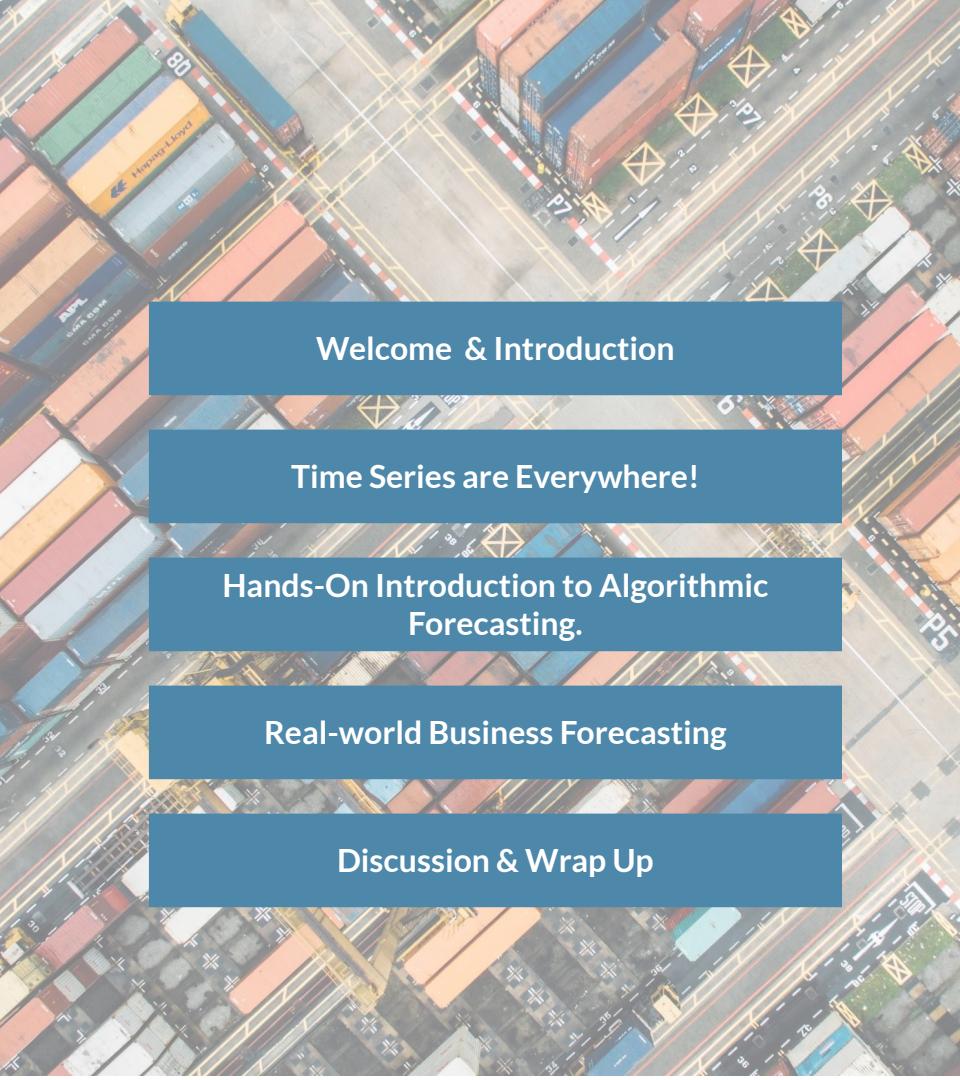
Dr. Simon Müller, Joachim Rosskopf  
Ulm, 22.11.2019.

---

# Agenda for Today.

Time series are everywhere and especially relevant for data science in the enterprise context.

Today we give a very short hands on intro into algorithmical forecasting with R. Further we provide an outlook what is necessary to do real world business forecasting.



Welcome & Introduction

Time Series are Everywhere!

Hands-On Introduction to Algorithmic Forecasting.

Real-world Business Forecasting

Discussion & Wrap Up

**Dr. Simon Müller** has a PhD in mathematics and has worked as a postdoc in the field of biostatistics and is since six years a data science freelancer.

**Joachim Rosskopf** is lead of the DataTeam at Kärcher, where he tries to combine experience from software architecture and technology with business analytics and data science to build interesting, valuable data solutions.



---

# Who is in the audience? Why are you here?



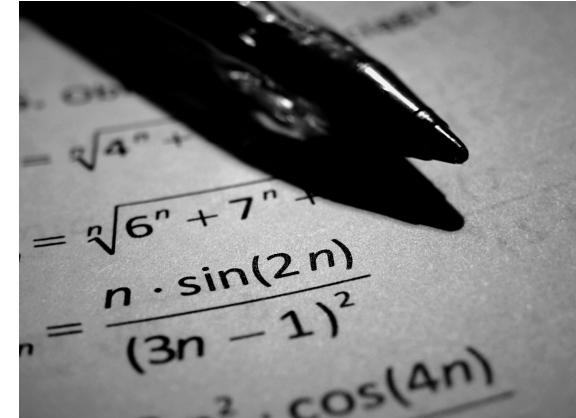
Data Analyst

Analyze business, discover data opportunities, drive projects and produce anchorage.



Data Engineer

Mainly concerned with technology and systems design and operations.

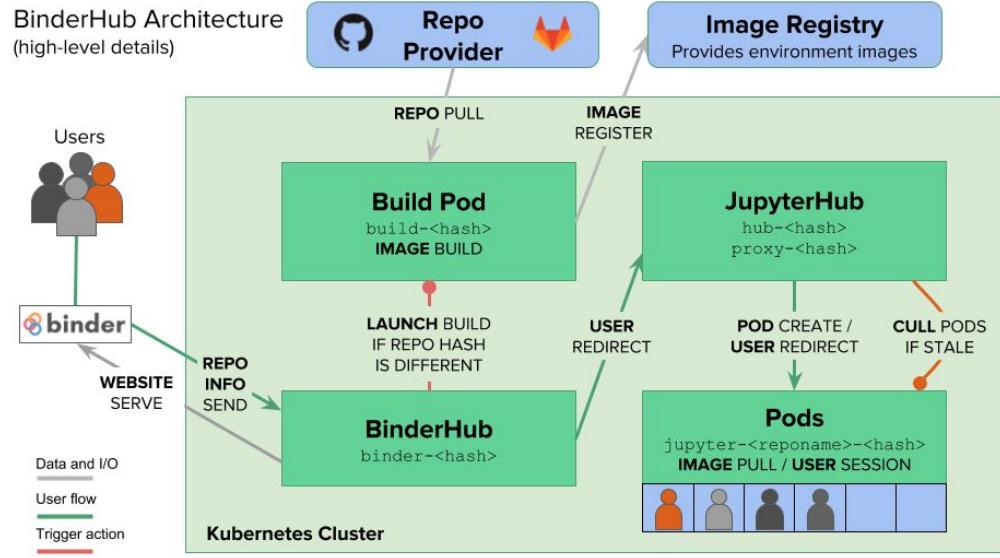


Data Scientist

Have deep method understanding, like statistics or machine learning.

# Interactive Part:

## Start your session on Binderhub



Go To : [https://github.com/anofox/data science tag 2019](https://github.com/anofox/data-science-tag-2019)

# Real-world Business Forecasting.

By observing and **forecasting** key business processes one can optimize to gain efficiency and enable new business models.

The challenge is to provide this at a **scale, automation and quality** which is relevant to enterprises.

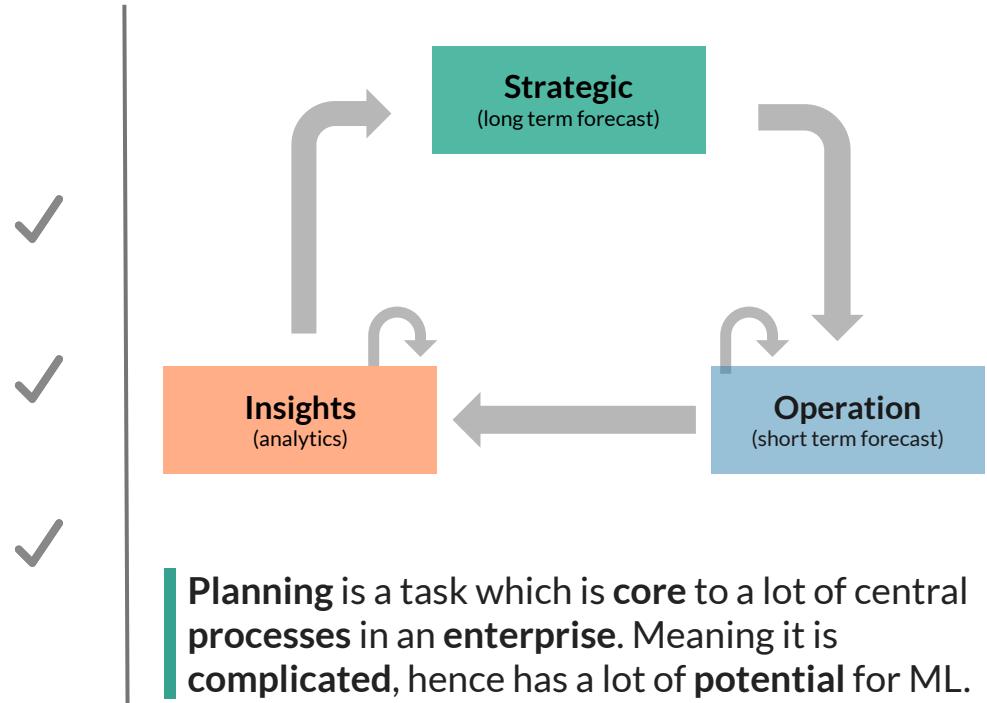
## Where does this matter.



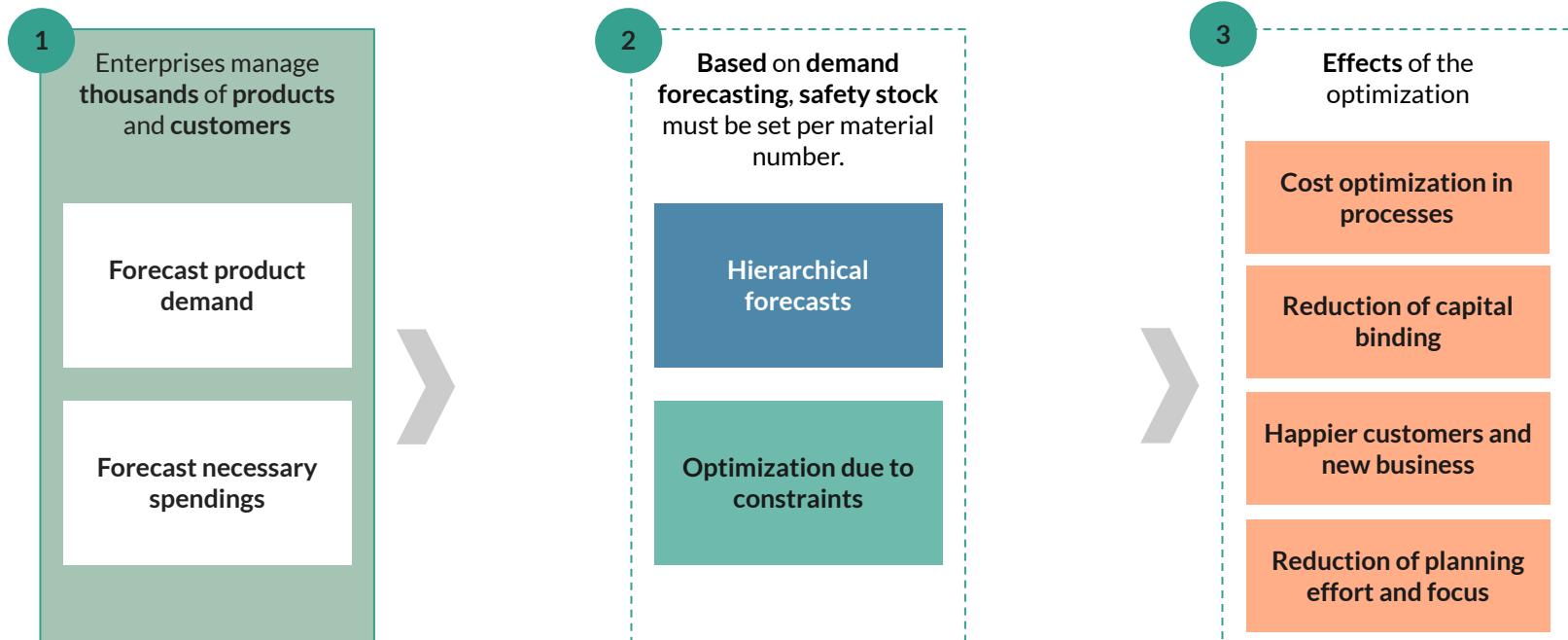
# Predictive analytics on enterprise processes is a great data opportunity.

## Key questions:

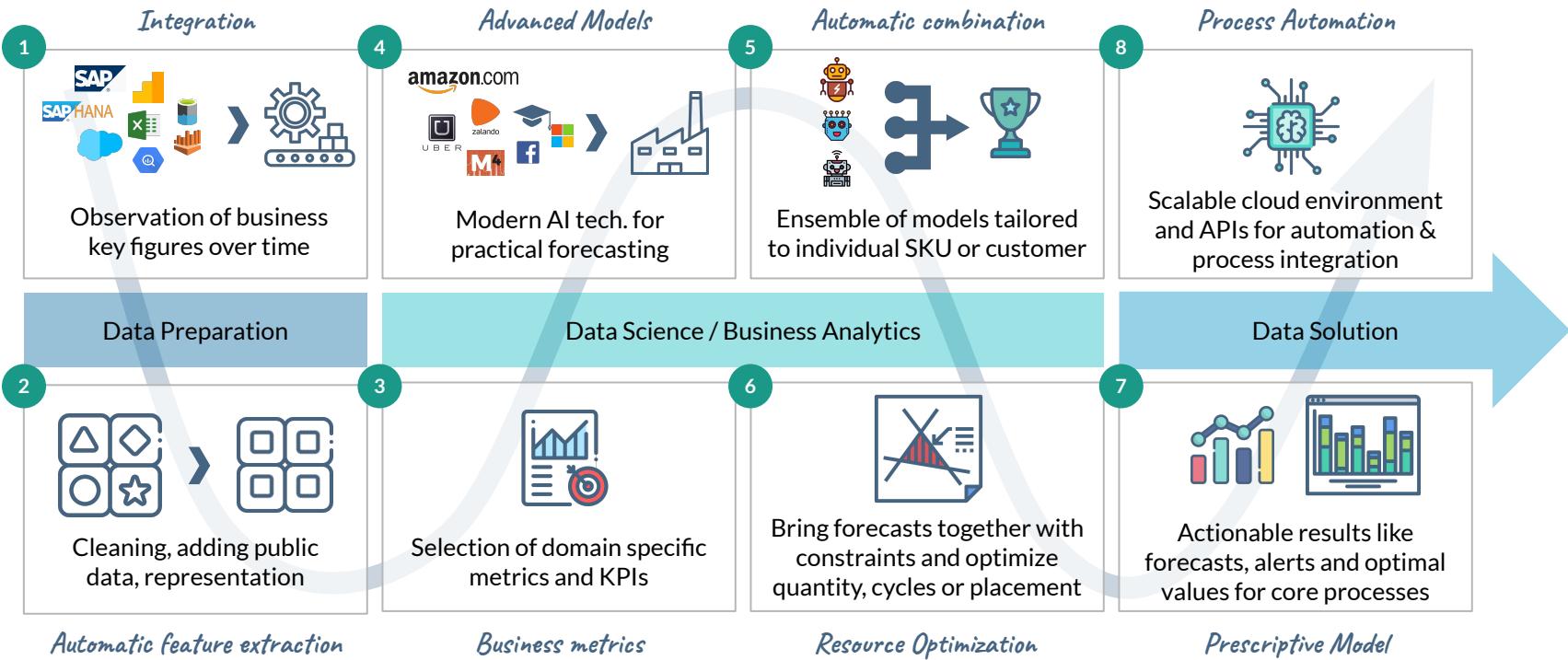
- 1 Planning and demand forecasting in industry is mainly a data-driven task!
- 2 Since almost **15 years** data on processes is captured core processes!
- 3 On a **tactical level** enterprises have thousands of products and **tens- to hundred-thousand customers**!



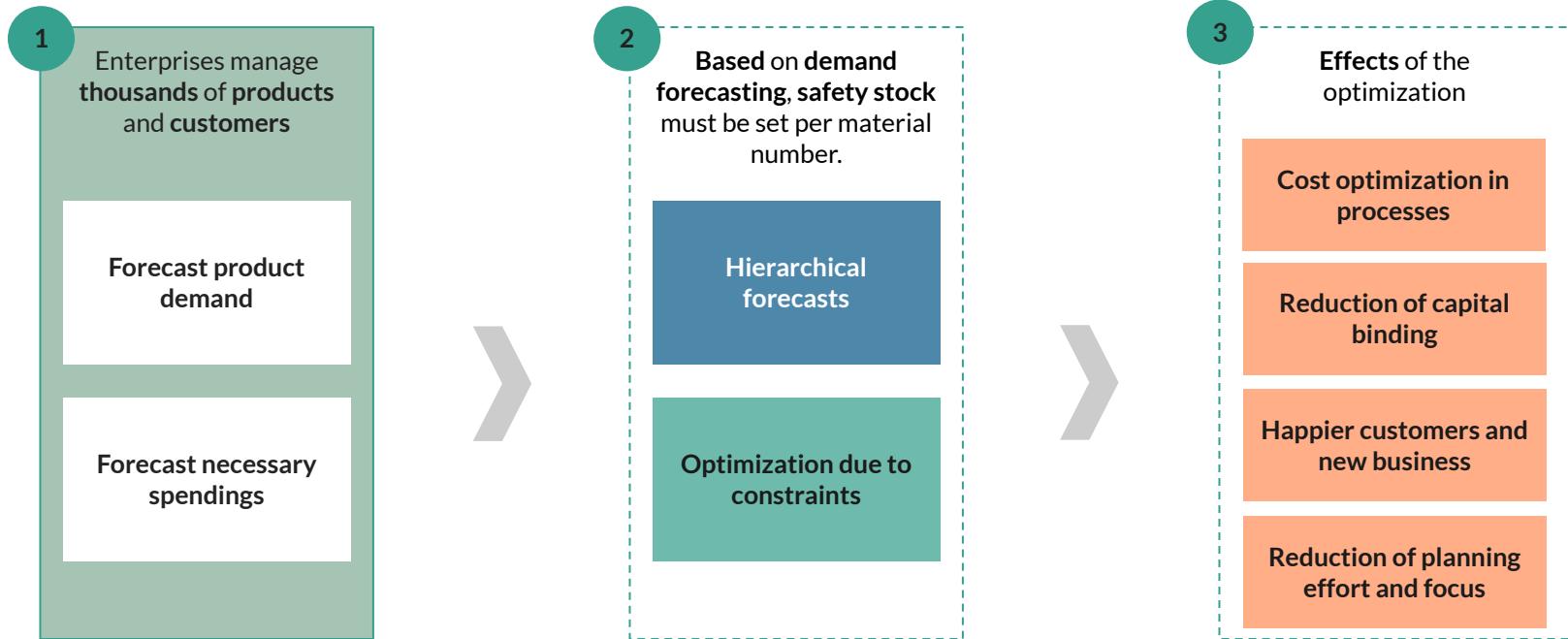
# Planning is a optimization problem. Forecasting is the beginning of the scenarios.



# For a real world solution several challenges have to be solved.



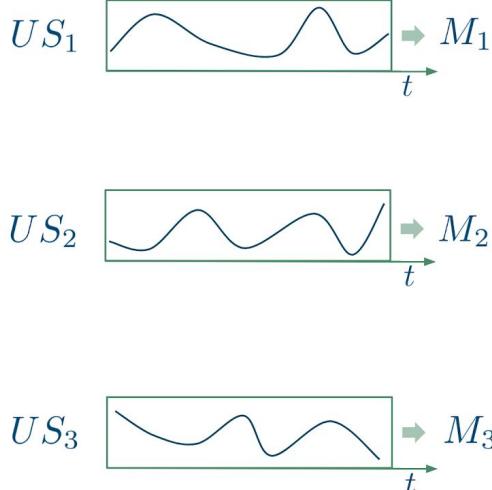
# Planning is a optimization problem. Forecasting is the beginning of the scenarios.



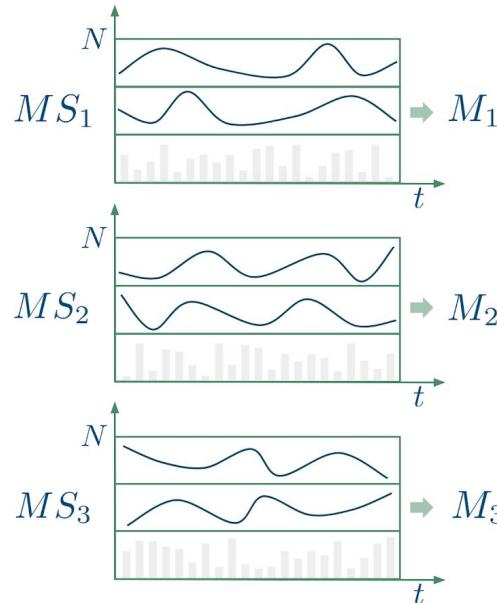
Forecasting is the starting point for a lot of complex planning problems. The better its results are, the easier is good downstream planning quality. Especially for stochastic planning predictions are key.

# Advanced models improve quality for intermittent series with additional features.

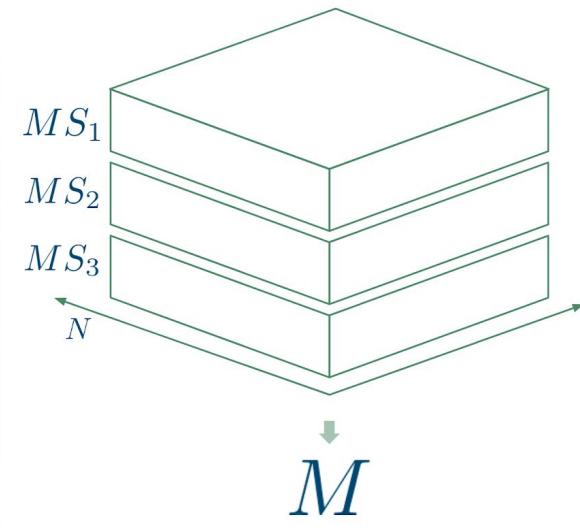
Univariate Modelle



Multivariate Modelle



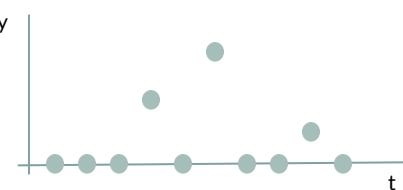
"One-fits-all" Modelle



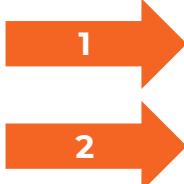
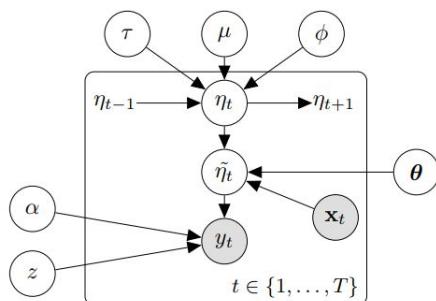
Academia and the research institutions of digital giants like Amazon, Uber or SAP publish parts of their research results. Based on these results, one direction is to **build one model**, that fits all data **concurrently**, instead of one model per time series.

# Example Algorithm: Hierarchical Bayesian Methods (HBM)

Intermittent demands



Single spare part



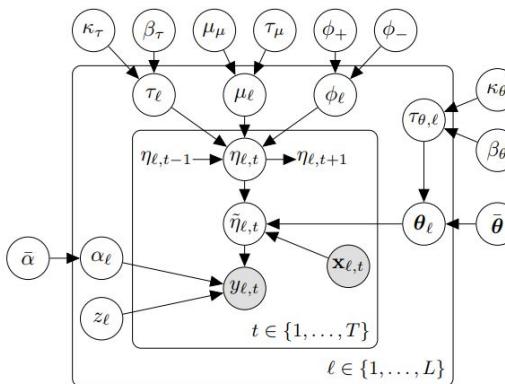
Mathematical model

$$y_t \sim \text{NB}(\exp \eta_t, \alpha).$$

$$\begin{aligned}\eta_1 &= \mu + \epsilon_1, \\ \eta_t &= \mu + \phi(\eta_{t-1} - \mu) + \epsilon_t, \quad t > 1, \\ \epsilon_1 &\sim \mathcal{N}(0, 1/\tau_0 + 1/\tau), \\ \epsilon_t &\sim \mathcal{N}(0, 1/\tau), \quad t > 1,\end{aligned}$$

Discrete distribution to model "0"

Multi spare part (one fits all)



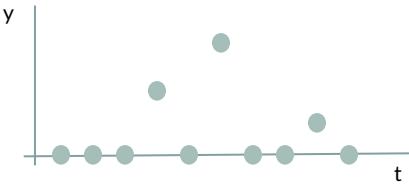
Autoregressive model for demands ">0"

"One fits all" approach done via sharing latent variables between part time series.

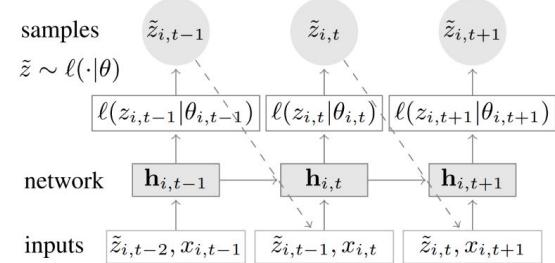
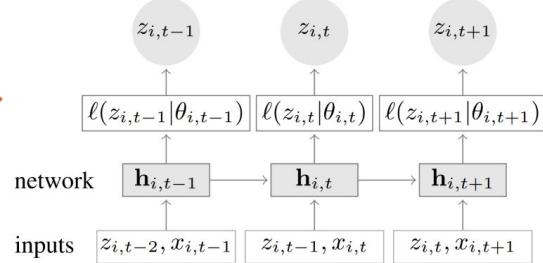
The algorithm is a mixture of Bayes nets and autoregressive models and shows great promise, and practical use in retail- & warehouse forecasting.

# Example Algorithm: Autoregressive Recurrent Networks

Intermittent demands



Recurrent Neural Network



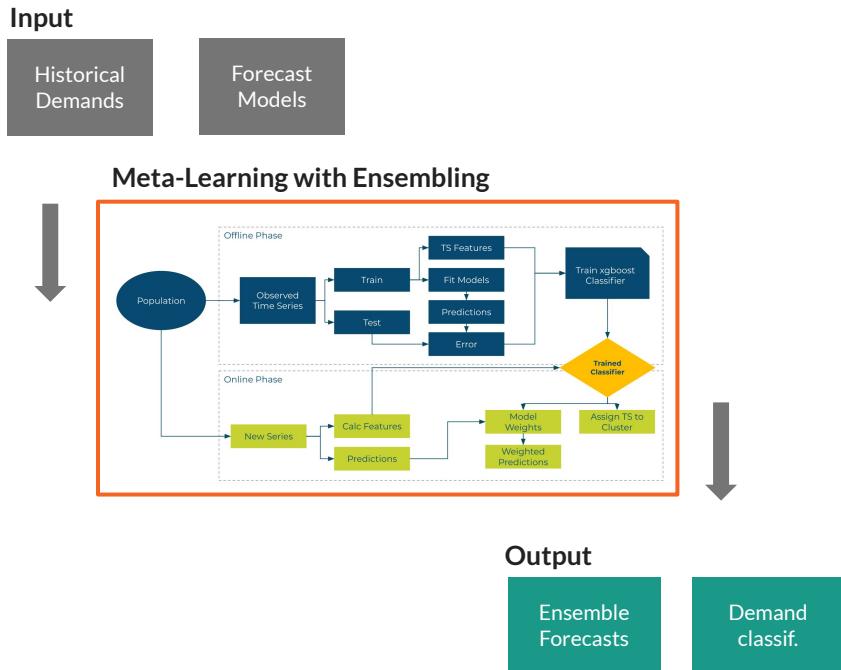
"One fits all" approach optimizes the loss function that depends on all N series and is considering the intermittent data structure

$$\mathcal{L} = \sum_{i=1}^N \sum_{t=t_0}^T \log \ell(z_{i,t} | \theta(\mathbf{h}_{i,t}))$$

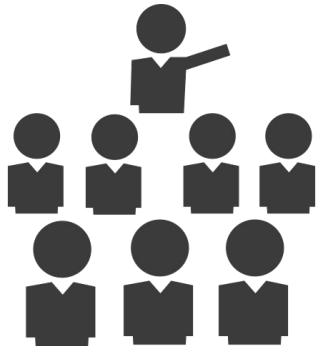
The algorithm uses **recurrent neural networks** with a special **quantile loss** function to predict future demands. It is developed by Amazon Labs in Berlin.

# Automatic combination reduces effort while improving robustness of forecasts.

Learns to build an ensemble of algorithms automatically:

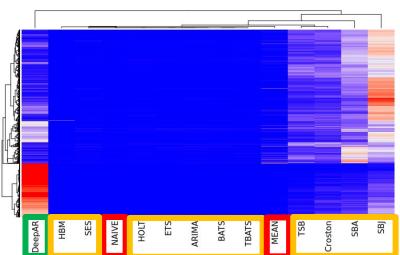
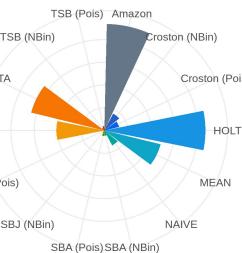


An ensemble is the optimal combo of individual models:

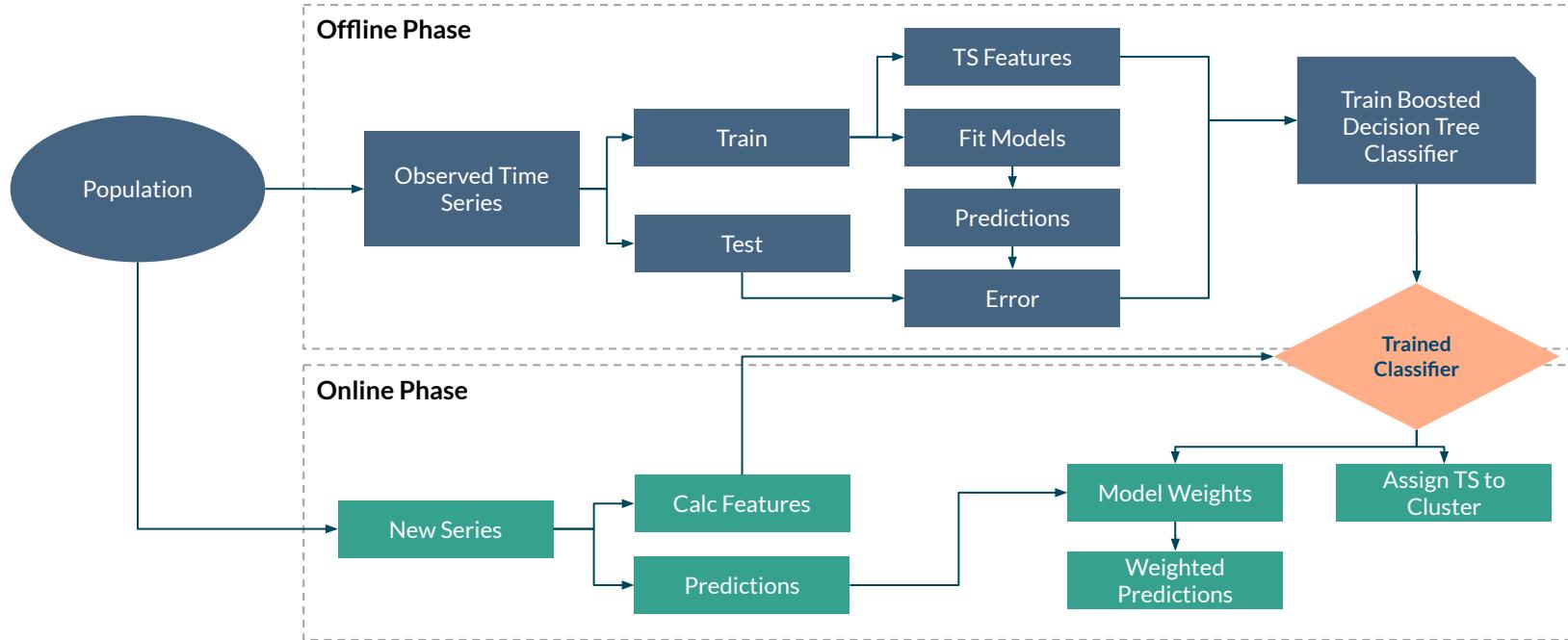


- Each algorithm has strength
  - Dependant on situation
  - No free lunch
- Combination of learners is beneficial
  - Better precision
  - More robust
  - Automatic training
- Can be used to classify / group series

$$g_{ens}(\cdot) = \sum_{k=1}^N c_k g_k(\cdot)$$



# Automatic combination reduces effort while improving robustness of forecasts.



Again machine learning is used to learn in which situation which combination of models should be used. This can also be used to classify customers or parts.

# A core challenge to successfully solve the business problem is to choose the right error metric.

1

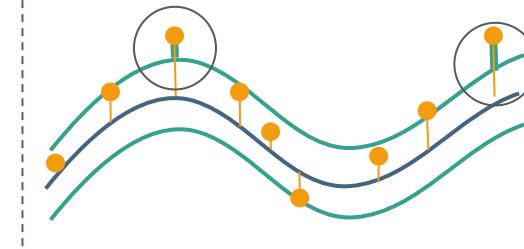
Try to predict the expected value of the time series as good as possible.



Suitable for high-freq. IoT predictions.  
Limited value for logistics

2

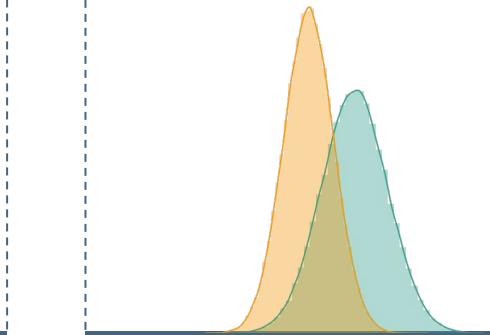
On top of expected value  
Penalize predictions not fitting inside the the error bounds.



Already contains the central idea, that logistics is more concerned on variability and intervals.

3

Optimize to make the ML algorithm predict the right distribution of demands.



For a low amount of data, this measure really captures the key questions: What are the demands to be prepared for?

Traditional objective function for time series like MAPE or MASE don't fully capture the problem of demand forecasting. Alternative measures concentrate on optimizing the distribution of demands. This is especially useful for stochastic demand planning.



# Meet the AnoFox!

## Key features:

1

Scalable, unsupervised **time series forecasting** and **anomaly prediction** on business and IoT data (machine learning and statistical methods).

2

**Quickly deployable** as building block into the **virtual private clouds** of customers. We come, where the data already resides!

3

We rely on **cloud services**, **open source** software and **modern data science** methods. At its core we rely on **battle tested data analysis**. For higher level intelligence we utilize **state of the art machine learning** research.

## Use cases in the wild:



**Optimize inventory** and **forecast part or service demands**. Focus on tricky intermittent demands (e.g. spare parts, customer purchases)

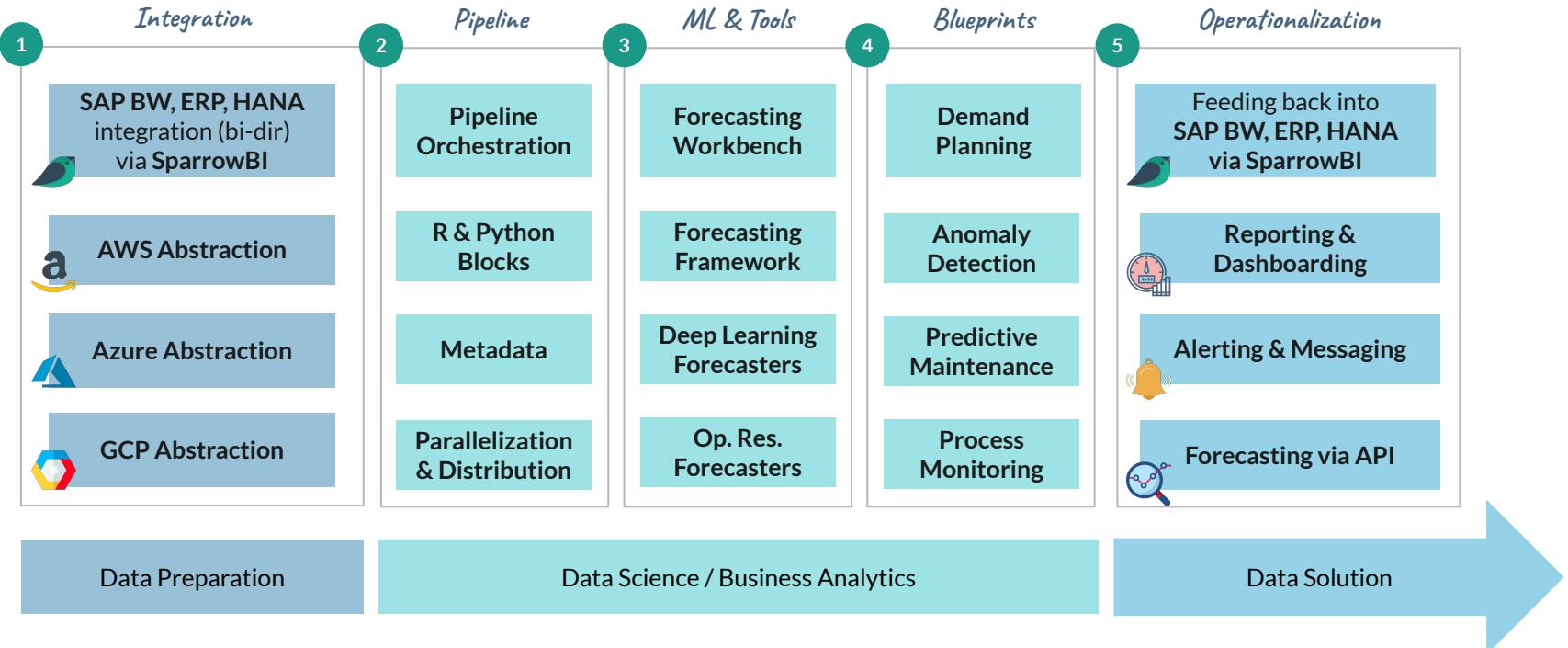
**Predict customer demand** and **steer sales and marketing**. Focus on recurrent buying behavior for consumables and spares.

**Do condition monitoring** and **anomaly detection** on **internet of things (IoT)** devices or **group customers** by device utilization.

Focus of **AnoFox** are **data driven core processes** of **manufacturing companies** with **high business value** and a **clear return on investment**.



# AnoFox: enterprise grade forecasting out of the box





**Thank you for the opportunity  
to present our ideas!**

Contact us:

Telephone: +49 177 30 73 73 7

Email: [contact@data-zoo.de](mailto:contact@data-zoo.de)