

Prescriptive Analytics in Logistics & Supply Chain Management

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Most of you will have seen this...

The Gartner Analytic Continuum



› What does it imply for Logistics and SCM?

Every day, we take many routine decisions in logistics & supply chain management ...

Inventory

- Replenishment orders
- Stock allocation
- Safety buffer

Transportation

- Vehicle capacity
- Staffing
- Routing

Handling

- Inbound/outbound
- Capacity
- Staffing

Maintenance/Repair

- Capacity
- Spare parts inventory
- Contracts

... all of these decisions are taken under uncertainty

Uncertainty

- Demand
- Supply (labor, material)
- Shipping times
- Replenishment lead times
- Processing times
- Outages
- ...

Inventory

- Replenishment orders
- Stock allocation
- Safety buffer

Transportation

- Vehicle capacity
- Staffing
- Routing

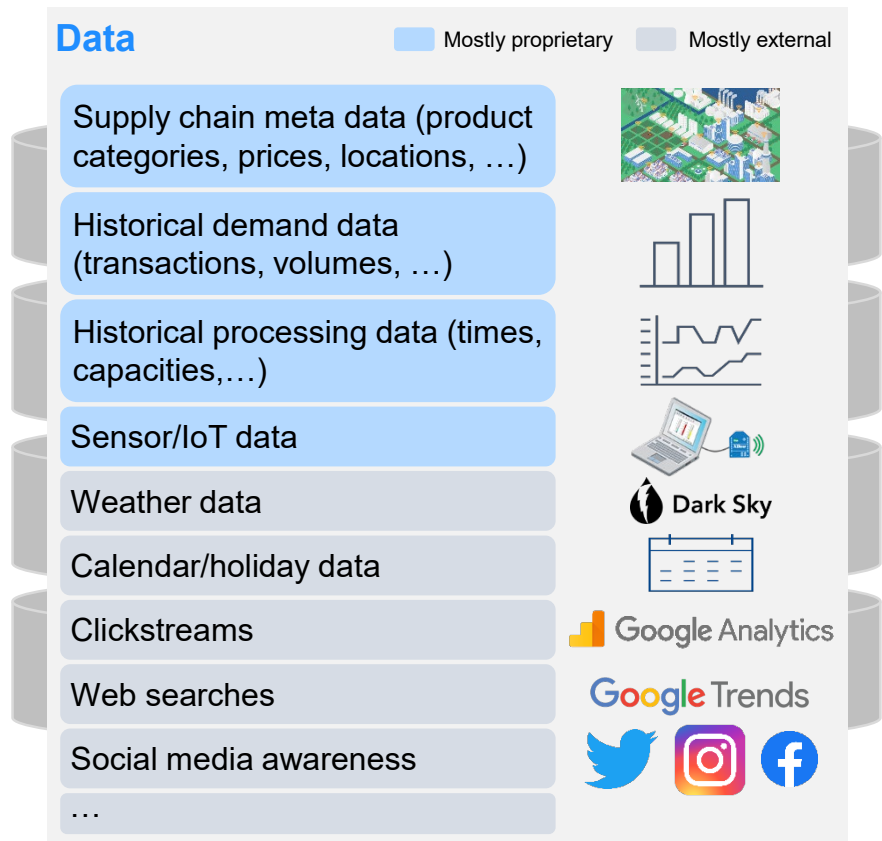
Handling

- Inbound/outbound
- Capacity
- Staffing

Maintenance/Repair

- Capacity
- Spare parts inventory
- Contracts

The good news: we have access to more and better data to predict the uncertain variables



Uncertainty

- Demand
- Supply (labor, material)
- Shipping times
- Replenishment lead times
- Processing times
- Outages
- ...

Inventory

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- Stock allocation
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Transportation

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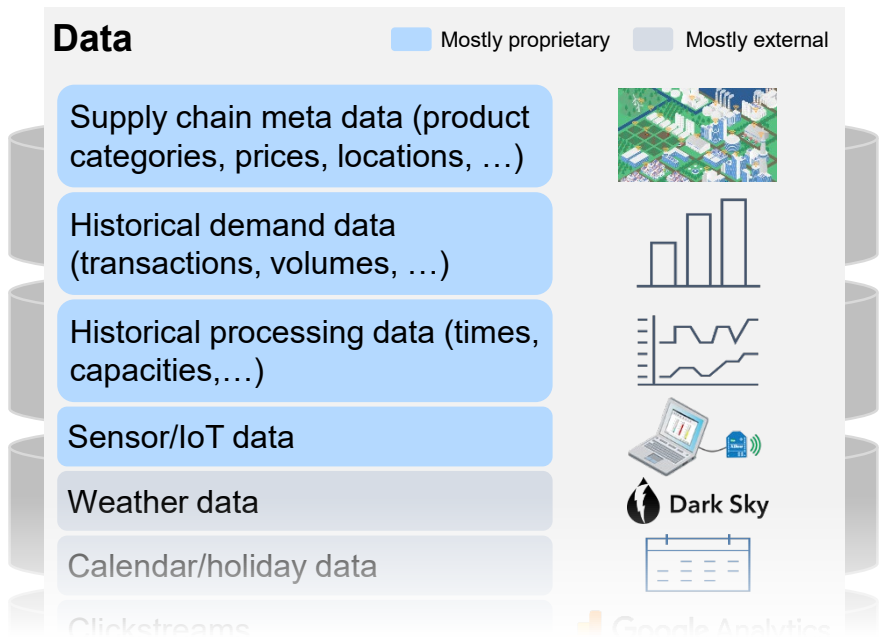
Handling

- Inbound/outbound
- Capacity
- Staffing

Maintenance/Repair

- Capacity
- Spare parts inventory
- Contracts

The bad news: current systems and people use simple decision logics that do not fully leverage available data



Uncertainty

- Demand
- Supply (labor, material)
- Shipping times
- Replenishment lead times
- Processing times
- Outages

Inventory

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- Stock allocation
- Safety buffer

Transportation

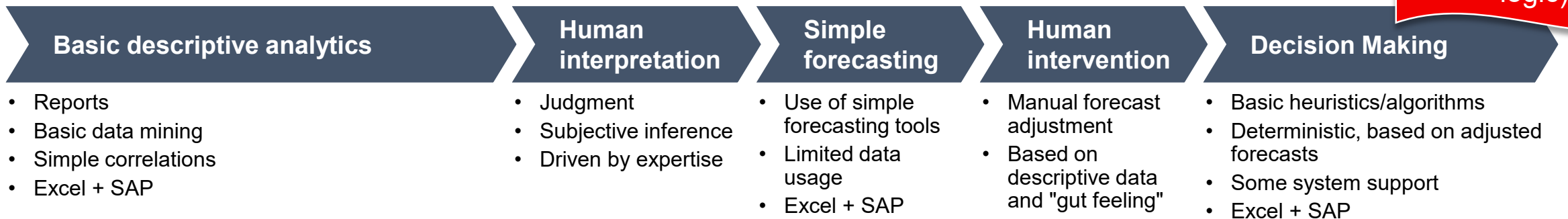
- Vehicle capacity
- Staffing
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Handling

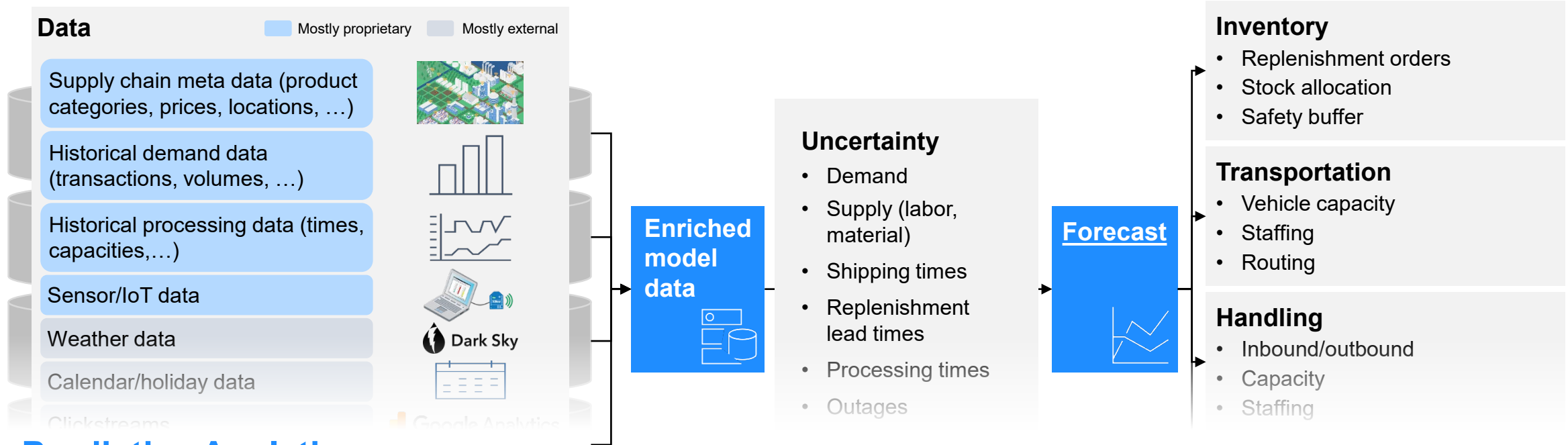
- Inbound/outbound
- Capacity
- Staffing

High effort but low decision quality (data not leveraged, simplistic decision logic)

What we see in many/most companies:



Predictive analytics: use machine learning to exploit rich data sources in order to derive better forecasts



Predictive Analytics

Data-driven forecasting

- Broad **extraction and engineering** of potentially predictive "input features" from enriched data
- Machine Learning models are **trained on broad data sets** using potentially predictive "input features" to **output point forecast** and error measures of uncertain variables
- **Examples:** (Deep) Neural Networks, Ensemble Methods (Extreme Gradient Boosting, Random Forests), Support Vector Machines, Generalized Linear Models

Human intervention

- Manual forecast adjustment
- Based on data-driven insights and "gut feeling"

Decision Making

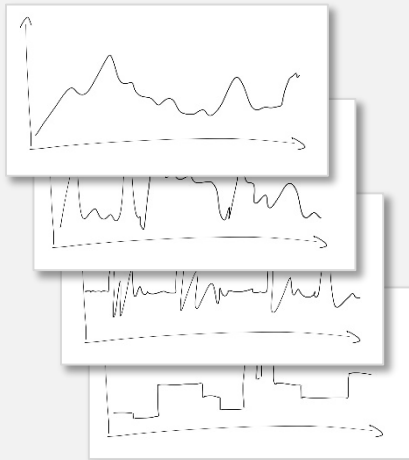
- Basic heuristics/algorithms
- Deterministic, based on adjusted forecasts
- Advanced system support

Deep-dive: ML models approximate an input-to-output relationship by learning a function that maps input features (x) to an output (y)

Enriched model data

INPUT

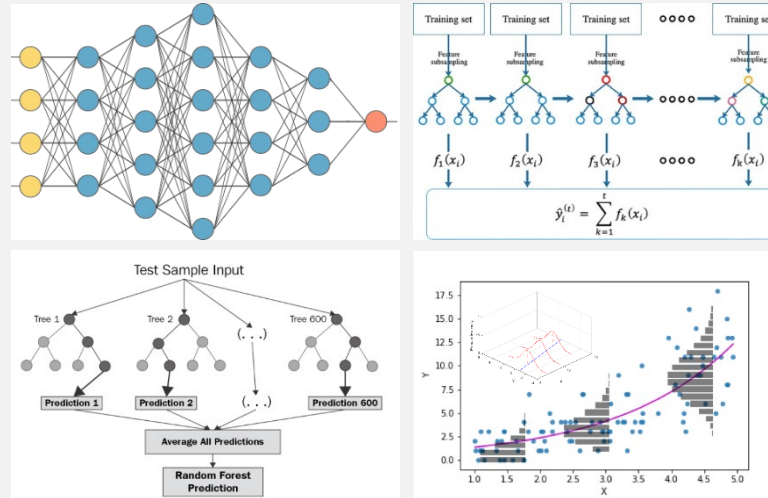
x



Usage of **hundreds of input features** possible
Typically **large "training sample sizes"** for the model to learn from

MACHINE LEARNING MODEL

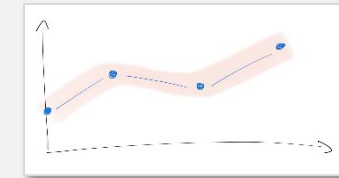
$$f_{\theta} : x \rightarrow y \quad \min_{f_{\theta} \in F} (y - f_{\theta}(x))^2$$



Which approximation f_{θ} can best predict the uncertain variable y (output) from known information x (input) such that the error is minimized?

OUTPUT

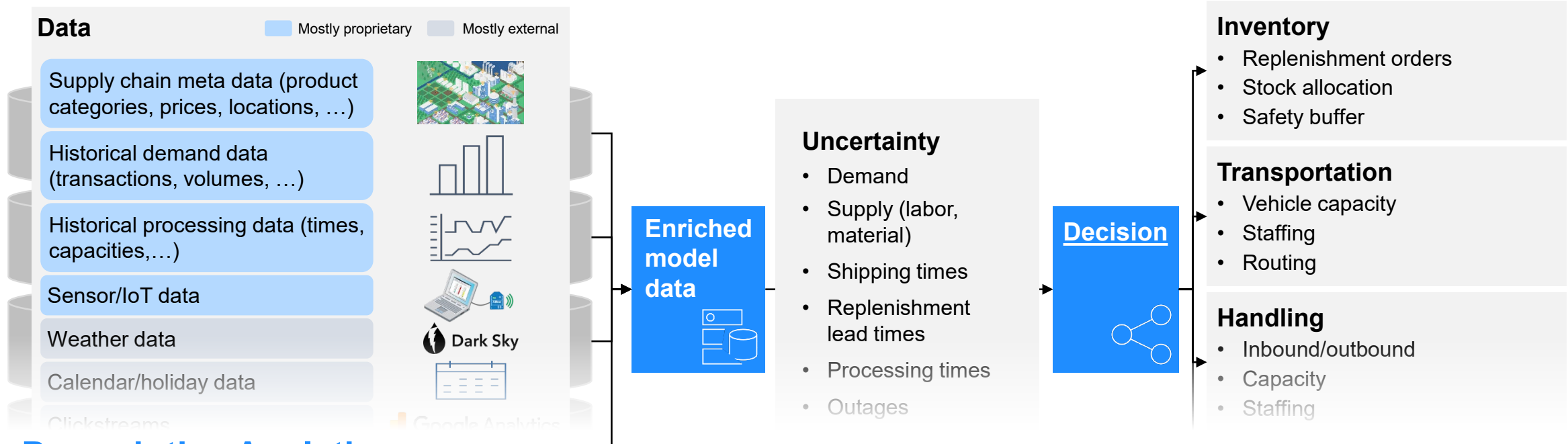
$$\hat{y} \approx f_{\theta}(x)$$



Point forecasts for single or multiple time instances
Classification predictions
Error estimates

Forecast

Prescriptive analytics: combine machine learning and optimization techniques to directly derive decisions (prescriptions) from data



Prescriptive Analytics

Data-driven decision making

- Broad **extraction and engineering** of potentially predictive "input features" from enriched data
- Machine Learning and Stochastic Optimization models are **integrated and trained on broad data sets** using potentially predictive "input features" to directly **output decisions** (prescriptions) for specified optimization problems/parametrizations under uncertainty
- **Examples:** (Deep) Reinforcement Learning, Stochastic Gradient Tree Boosting, Stochastic Optimization Forests, Weighted Sample Average Approximation, Kernelized Empirical Risk Minimization

Human intervention?

- Manual decision adjustment
- Based on data-driven insights and "gut feeling"

Deep-dive: ML optimization models directly learn to approximate optimal decisions (z) from observing input features (x)

Enriched model data

INPUT

x

Usage of **hundreds of input features** possible
Typically **large "training sample sizes"** for the model to learn from

ML OPTIMIZATION MODEL

$$h_{\theta} : x \rightarrow z \quad \min_{h_{\theta} \in H} C(h_{\theta}(x), y)$$

Algorithm 1. Approximate DP with rolling horizon weighted SAA

```

1: Get  $\mathcal{D}$ 
2: for  $t = 1, \dots, T$  do
3:    $r = T - \text{mod}(t, A, T)$ 
4:   while  $t \leq T$  do
5:     Get  $\{s^j\}_{j=1}^m$ 
6:     for  $j = 1, \dots, m$  do
7:       Get  $\{a^j\}_{a \in \mathcal{A}}$ 
8:       for  $a = 1, \dots, A$  do
9:          $R_{t+1}^j(a) = \max_{a' \in \mathcal{A}} \{ \sum_{s'} P(s'|s, a') R_{t+1}^j(s') + \gamma V_{t+1}^j(s) - V_t^j(s) \}$ 
10:         $R_{t+1}^j(a) = \max_{a' \in \mathcal{A}} \{ \sum_{s'} P(s'|s, a') R_{t+1}^j(s') + \gamma V_{t+1}^j(s) - V_t^j(s) \}$ 
11:      end for
12:    end for
13:  end while
14: end for
15: return  $\{R_{t+1}^j(a)\}_{t=1}^T$ 

```

Which approximation h_{θ} can best prescribe a decision z (output) from known information x (input) such that costs are minimized?

OUTPUT

$\hat{z} \approx h_{\theta}(x)$

Decisions (prescriptions) for single or multiple time instances

Decision

Case 1: Prescriptive Analytics for data-driven capacity planning without human interaction for logistics service providers

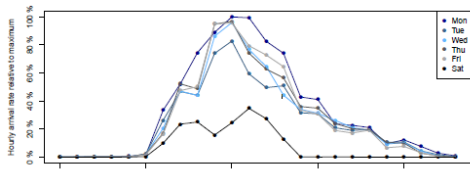


Gap to theoretical optimum

■ Prescriptive Analytics ■ Traditional best-in-class

Several data sources ...

Historical volumes/arrivals



Customer data

- Advanced order/shipping notifications
- Operational data (fleet size, usage, etc.)

Auxiliary data

- Public holidays
- Promotions
- Weather data

... are used by the Prescriptive Analytics Engine ...

New Machine Learning based optimization approaches

Random Forest-based weighted Sample Average Approximation



Kernelized Empirical Risk Minimization with Random Forest Kernel

$$\min_{\vec{y}} \lambda \|\vec{y}\|_2^2 + \frac{1}{N} \sum_{n=1}^N \left(\sum_j f_j y_j(\vec{x}^n) - \sum_{t=1}^T \left(\sum_{i,j} a_{ij} y_{ij}^n - \sum_i c_i d_i^n \right) \right)$$

$$\text{s.t. } \sum_j y_{ij}^n \leq d_i^n \quad \forall i, n, t$$

$$\sum_j y_{ij}^n \leq q_j(\vec{x}^n) \quad \forall j, n, t$$

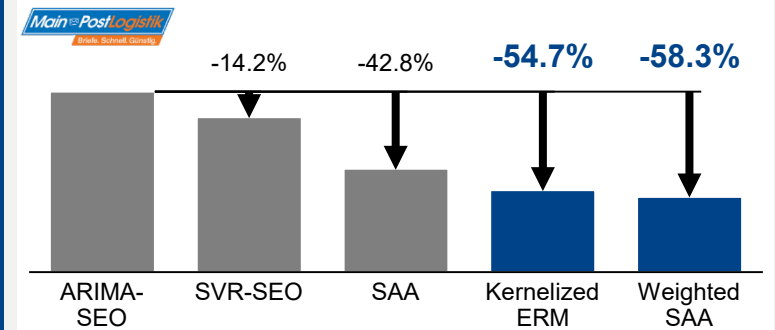
$$y_{ij}^n \geq 0 \quad \forall i, j, n, t$$

$$y_{ij}^n = 0 \quad \text{if } i < j \quad \forall n, t$$

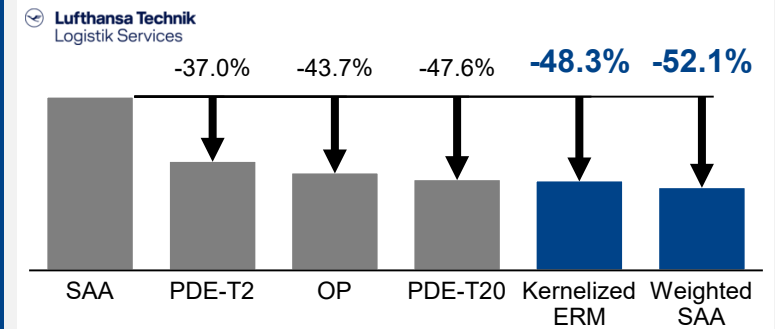
$$q_j(\vec{x}^n) \geq 0 \quad \forall j, n$$

... which outputs high quality prescriptions significantly outperforming traditional approaches

Capacities (staff, machines, vehicles)



Schedules





Case 2: Prescriptive Analytics for data-driven inventory control without human interaction for pharmacy networks



Gap to theoretical optimum

■ Prescriptive Analytics ■ Traditional best-in-class

Large data model across thousands of SKUs and hundreds of locations ...

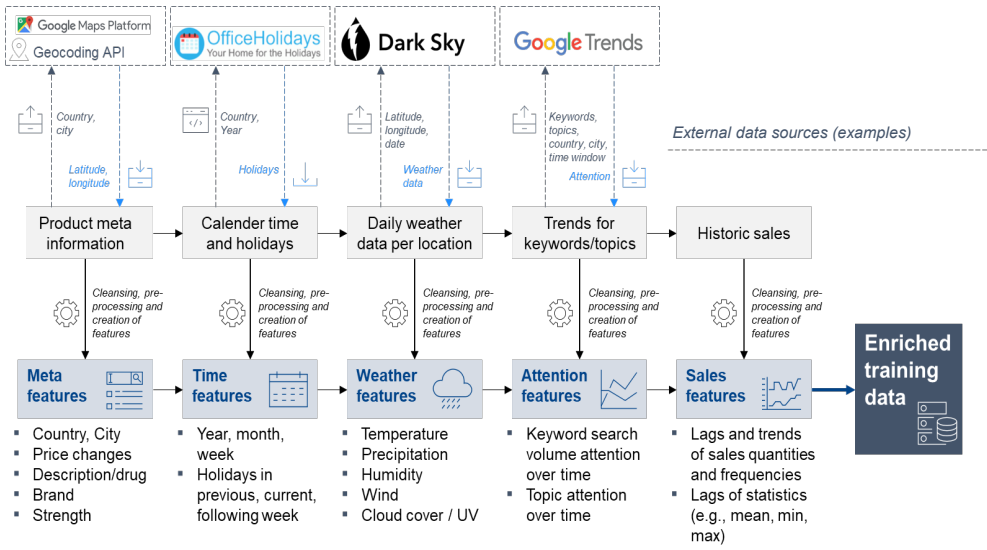


... is used by the Prescriptive Analytics Engine ...



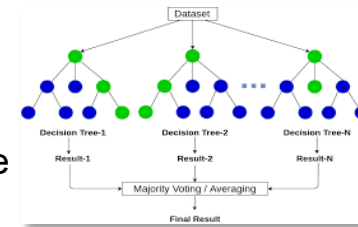
... which outputs high quality prescriptions significantly outperforming traditional approaches

Extensive feature extraction and engineering building on large data set combining internal historical transaction data and auxiliary information

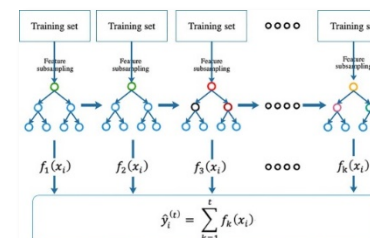


New Machine Learning based optimization approaches

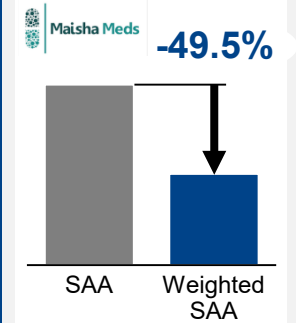
Random Forest-based weighted Sample Average Approximation



Hurdle-adjusted Extreme Gradient Boosting



Single- and multi-period inventory prescriptions (optimal inventory levels, ordering quantities)



mClinica pharmacy solutions
WIP – currently pure Predictive Analytics model achieving forecast error <15% for >25% of SKUs

Case 3: Predictive Analytics for data-driven Container demand flow prediction and subsequent network rebalancing optimization

Large set of network flow and container routing data ...

... is used by the Predictive Analytics Engine to forecast container demand as input to optimize network rebalancing ...

... which outputs high quality prescriptions

Container log data

- Customer demand flows
- Network balancing flows (manual repositioning flows)

Order data

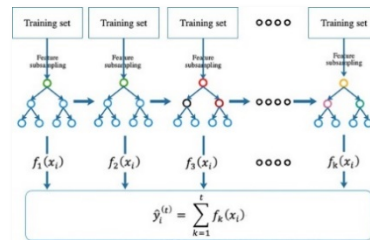
- Customer order specifications (type, size, lane information, order dates)

Freight cost data

- Freight rates for past balancing flows
- Freight rate index

New Machine Learning based forecasting approaches combined with subsequent network optimization model

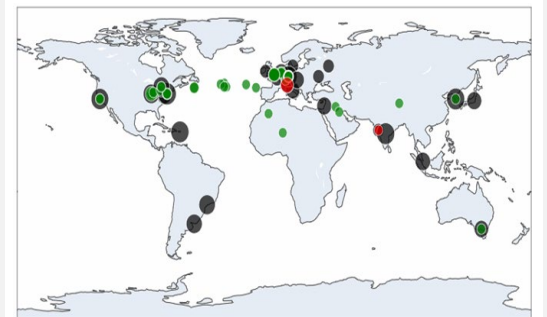
Forecasting:
Multi-step Extreme Gradient Boosting model for container demand



Optimization:
Stochastic multi-commodity network flow model

$$\min \sum_{t \in T} \sum_{s \in S} \sum_{c \in C} \tilde{z}_{s,c,t} \cdot c_c^{hold} + \sum_{t \in T} \sum_{c \in C} \sum_{(o,d) \in L} \sum_{m \in M} r_{o,d,c,t,m} \cdot c_{o,d,c,t,m}^{freight} \cdot b_{o,d,c,t,m}^{freight} + \sum_{t \in T} \sum_{c \in C} \sum_{(o,d) \in L} \left(\mu_{o,d,c,t} + \sum_{m \in M} r_{o,d,c,t,m} \cdot b_{o,d,c,t,m}^{freight} \right) \cdot (c_{o,c}^{out} + c_{d,c}^{in})$$

Container rebalancing flows for the entire network (multiple locations, multiple commodities)



Prescriptive analytics promises two obvious benefits ...

Better prescriptions and higher decision quality

- Better utilization of resources
- Lower costs
- Less fire fighting
- ...

Automation

- Substantially lower planning effort
- Quick re-planning
- ...

... but also raises a number of questions

- Human-Machine-Interaction (the future role of planners)?
- Required capabilities and skillsets (tooling, data, talent)?
- Organizational setup?
- Technology transformation?

The future will likely be...

“Hands off the Wheel!”



– not only for automated guided vehicles, but also for supply chain planning

How Amazon Automated Work and Put Its People to Better Use

by Alex Kantrowitz

September 16, 2020

<https://hbr.org/2020/09/how-amazon-automated-work-and-put-its-people-to-better-use>

Portfolio:

| | | |
|--|---|--|
| <p>Data-driven inventory management</p> <p>RIESE & MÜLLER</p> <p>Solution: AI predictions for optimized inventory management</p> | <p>Next-level sales planning</p> <p></p> <p>Solution: AI-based estimation of the value of a sales visit for optimized tour planning</p> | <p>Capacity management</p> <p> Lufthansa Technik Logistik Services</p> <p>Solution: AI predictions for optimized scheduling</p> |
|--|---|--|

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