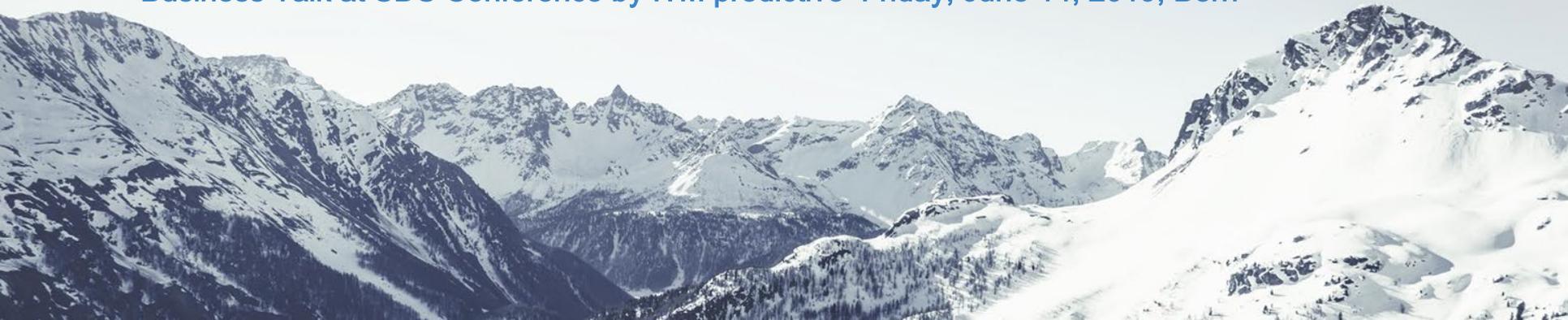




Dynamic pricing in shared mobility

Revenue and availability optimization approaches for shared mobility providers
Business Talk at SDS Conference by ITM predictive- Friday, June 14, 2019, Bern





**Services
pricing**

**Future of
on demand rental cars**

**Properties of
algorithm**

**Data
sources**



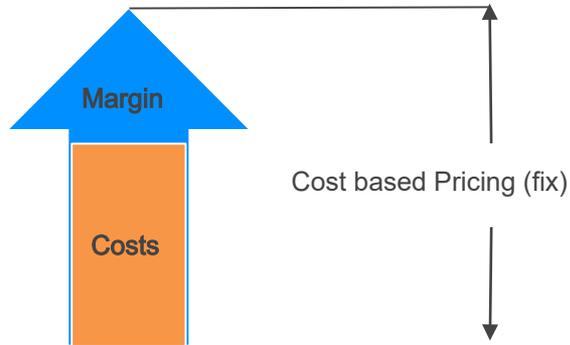
ITM Predictive - who we are

- Focus on
 - (1) **Organizational transition to the ML age** (lighthouse projects, explorative workshops)
 - (2) **Software implementation and maintenance** (open, no lock-in)
 - (3) **Algorithmic pricing** (Services, products with high fix-costs, etc.)
- Offices in Pfäffikon SZ (Switzerland) and Karlsruhe (Germany)
- Team started in 2002 with machine learning. ITM founded in 2013
- 13 Employees - most common academic background: PhD in Physics
- 5 SMI/ DAX/ MDAX/ SDAX, as well as 3 government institutions among clients

We like soccer: More at the end of our presentation.



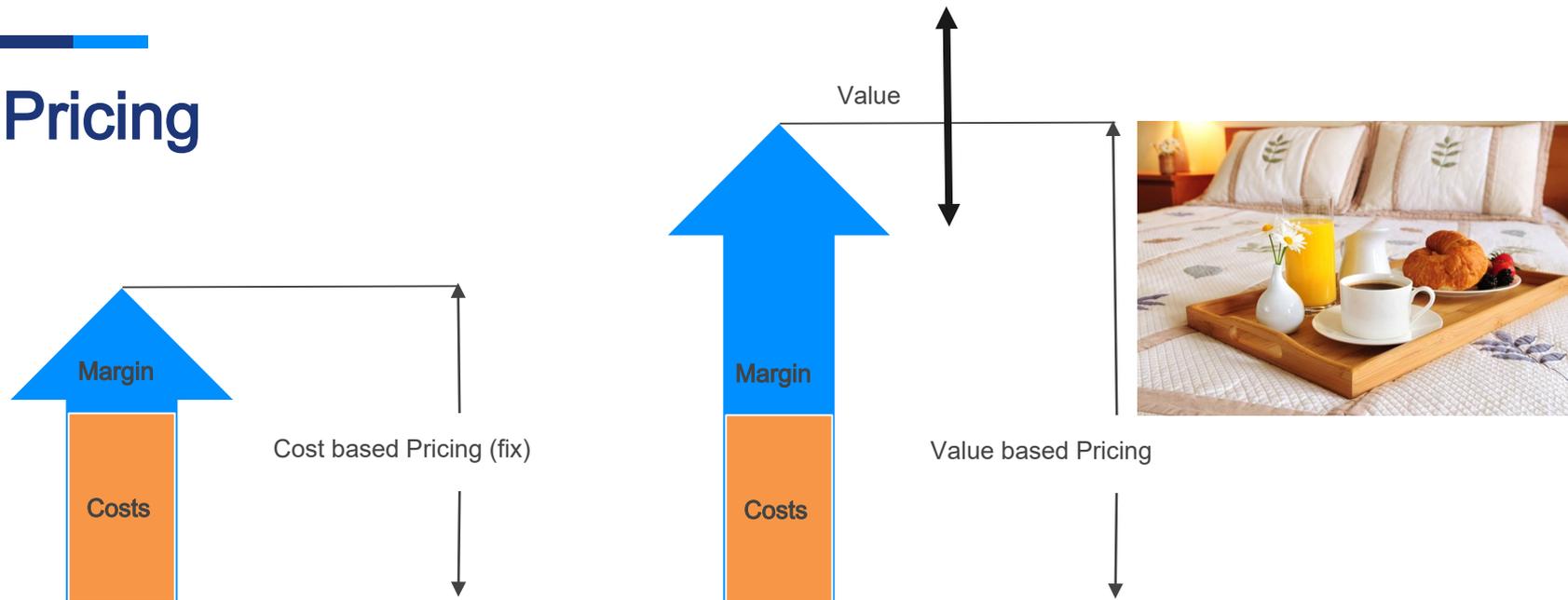
Pricing



Example 1: Cost based pricing: Craftsmans' service offerings for households with minimal differentiation and lots of competition. Price is similar for each customer and stable over the year.



Pricing



The value of service varies over time, location, weather, competitors ...
“Hotel room in Mallorca has more value in summer than in winter”

Cinema Example - Fixed Price

Cinema Example :

Customers leave the Cinema and have the choice to take car 1 within 150 meters or car 2 within 550 meters.

Customer choice :

In case both of the cars costs the same, most customers would take car 1 as long as it is available.



Cinema Example - Dynamic Price

Cinema Example :

Customers leave the Cinema and have the choice to take car 1 within 150 meters or car 2 within 550 meters.

Customer choice :

In case of different prices some cinema visitors would be willing to take the 550 m walk to get a cheaper car ride while others are willing to pay the higher price in order to get away faster.

Operator advantages :

Car 1 is placed well to match the demand
-> increase profitability.

Car 2 with attractive price to fight off
competition/ substitution.

-> discount leads to more revenue at a profitable level.





Demand, Availability and Elasticity Determines Prices

Prices depend on

- Demand per area and time interval
- Availability per area and time interval
- Price Elasticity

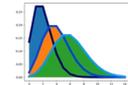
Assumptions

1. Two cars of the same type parked in the same area have the same minute rental price.
 2. No price discrimination based on individual user characteristics (phone, ISP, age, sex, ..).
 3. Prices are to pay per minute in the time the car is rented.
 4. Prices can be varied within a range of 0.5x - 3x the reference price, which itself is a cost based price.
 5. The reference price has to be specified for each type of car, located near the competitor's price.
-



Demand Forecasting

Layers	Data	Geospatial information, number of users that have App open, historic ride information, competitor offers, and other undisclosed data sources 😊
	Data Aggregation	Join data sources and aggregate transaction based data to current status including short-term history.
	Feature Engineering	Weekday (1-7), Hour (0-23), School Holiday (yes/ no), #users have the app open, #users zoomed to given area, time series #rides, #rides last hour per AA, #rides hour before last hour per area, moving average, #rides
	Machine Learning	ITM supervised ML-algos deliver fast and reliable results (no manual fine-tuning required), dealing with hundreds of input-features, <u>predictions as densities</u>
	Target / Prediction	prediction horizon: 1h up to 24h into the future, prediction = density distribution, mean and uncertainty





Price Elasticity is actually measurable

What: Price elasticity is the change in demand caused by a change in price.

But changes in demand can in general be caused by many other reasons.

How: Is there a chance to observe changes in demand which are systematically caused by price changes and for sure not by other systematic effects?

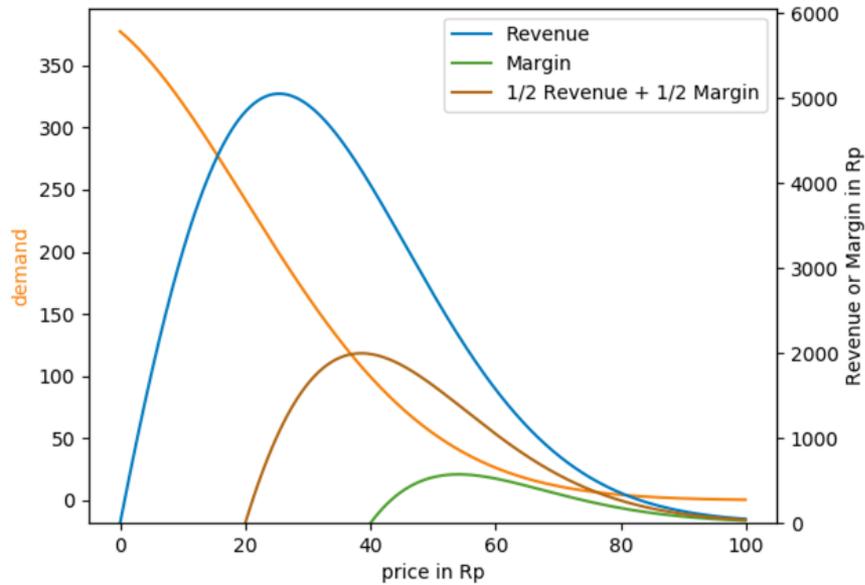


Yes, by adding random components on prices!

Measuring the effect on demand change caused by the random component on the price is what we can call Price Elasticity .

Solving the Car Sharing Optimisation using reinforcement + simulation

Goals	short-term	<ul style="list-style-type: none"> • Satisfy customers by offering high availabilities of cars • Maximise revenue to grow quickly
	long-term	<ul style="list-style-type: none"> • Satisfy customers by offering high availabilities of cars • Maximise profit



→ Finding the best price in car sharing is an **optimisation problem** .

The best pricing strategy maximises an optimisation function, such as **revenue, availability or a mix of both at the same time** . The optimisation problem is solved for every price decision that has to be made.

*The exact shape depends on the exact definition of availability and on the situation at other atomic areas, $rP = Rappen = 0.01 \text{ CHF}$



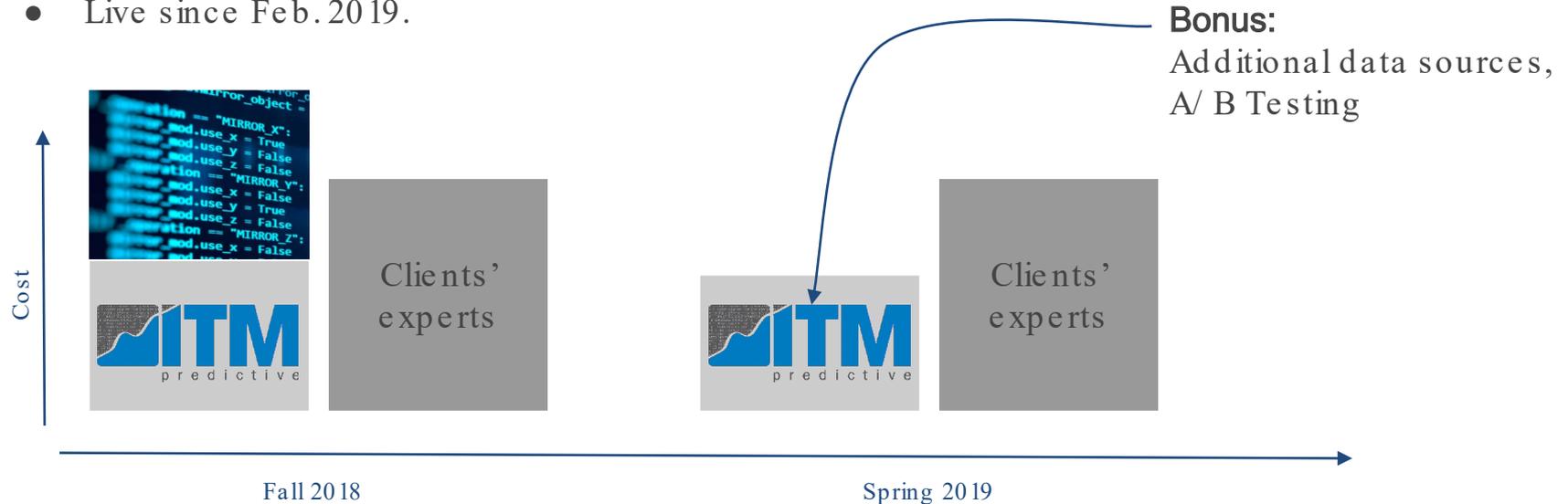
Benchmarking: ITM vs. Experts (1/2) - What is the right metric?

- We benchmarked our dynamic pricing approach against the expert pricing group.
- Within 8 month, our scalable solution's performance*was better/ equally good than the expert pricing team.
- Project went live ahead of schedule (from test to operation, 9 month after initiation).



Benchmarking: ITM vs. Experts (2/2)

- More importantly, we can run the pricing at **minimal effort**.
- The manual pricing task was not very popular among client's employees.
- Live since Feb. 2019.





Other Use Cases for ITM's Dynamic Pricing

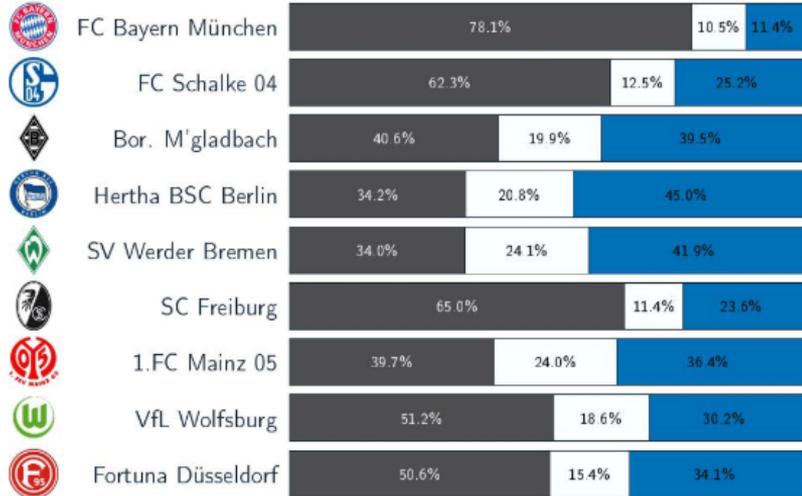
- e-Scooters and Bikes
- Hospitality (Hotels, apartment rental, AirBnB)
- Recreational vehicles, mobile homes, personal car sharing
- Ski passes
- Guided tours
- Concerts and Museums
- Theme- and waters parks
- Online shops





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Call us...

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Backup Slides





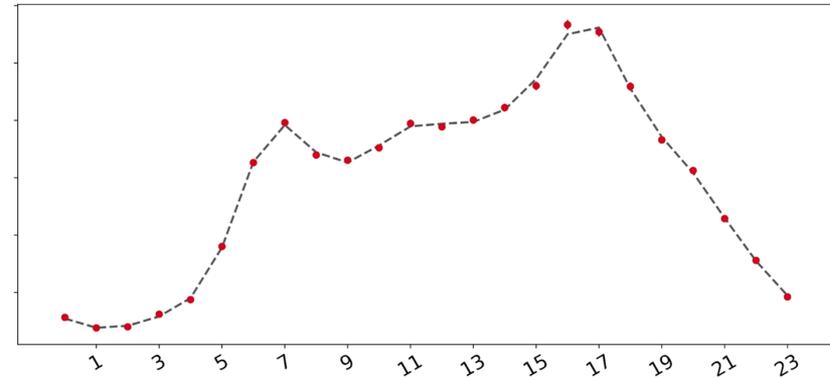
Demand Forecasting - Quality and Features

MAD: ~0.2

Intraday profile of number of rides

Importance of Feature Groups:

1. Time series features, derived from the own history
2. Area-ID itself
3. Geo-location features, e.g. # Restaurant, # Cinemas, # Trainstations
4. Weekday and Hour of the day





Availability Forecasting

- There are 2 approaches for availability forecasts:
 - similar to demand forecast: # cars available per area and time interval
 - forecast in which area the car will be dropped during a ride



Cities will crack down on random scooter placements



Solving the Car Sharing Optimisation using reinforcement + simulation

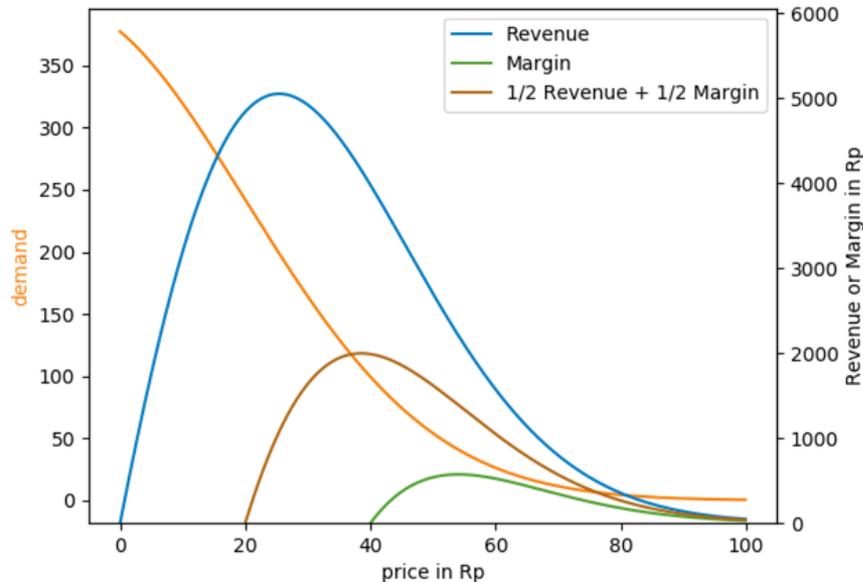
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short-term

- Satisfy customers by offering high availabilities of cars
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long-term

- Satisfy customers by offering high availabilities of cars
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