# **Catching Signals in RM**

Augment predictive Revenue Management models with contextual data

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Internal







Peaks & Trends







Peaks & Trends







Peaks & Trends





Peaks & Trends

Today

Human expert

(Sales/RM)



Historical bookings

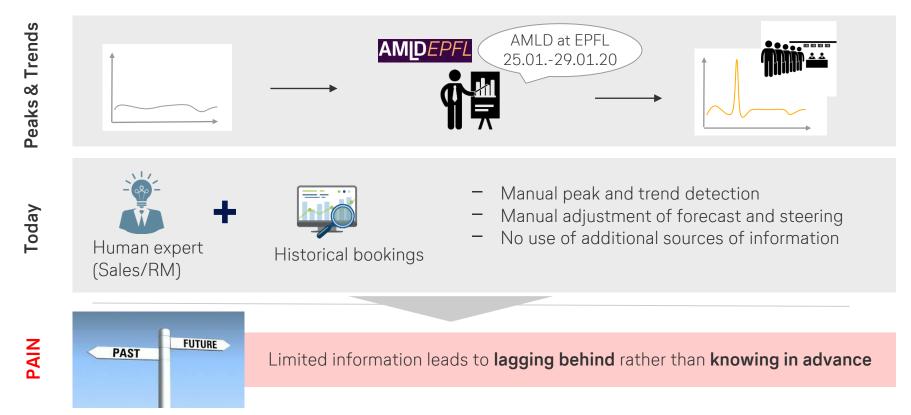
Manual peak and trend detection

AMLD at EPFL 25.01.-29.01.20

- Manual adjustment of forecast and steering
- No use of additional sources of information







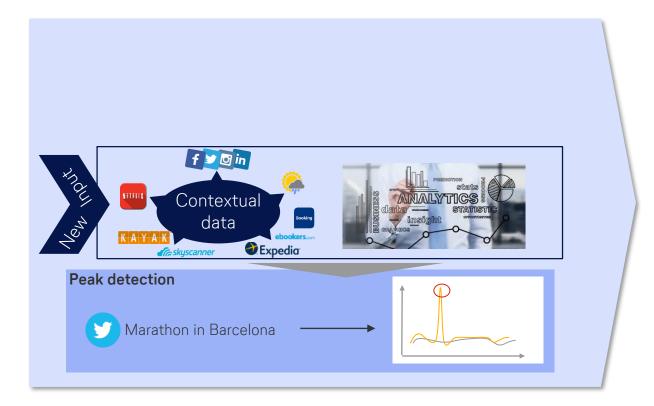






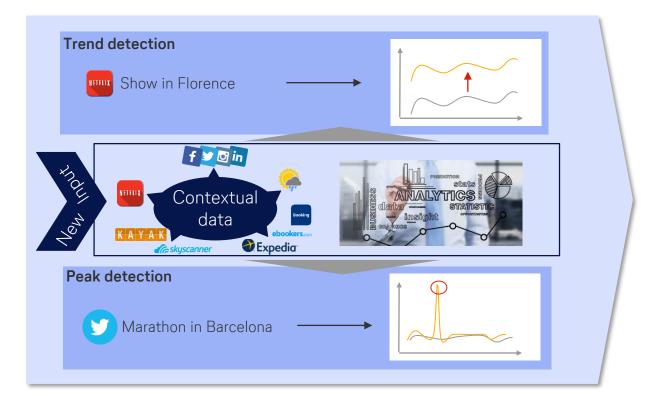






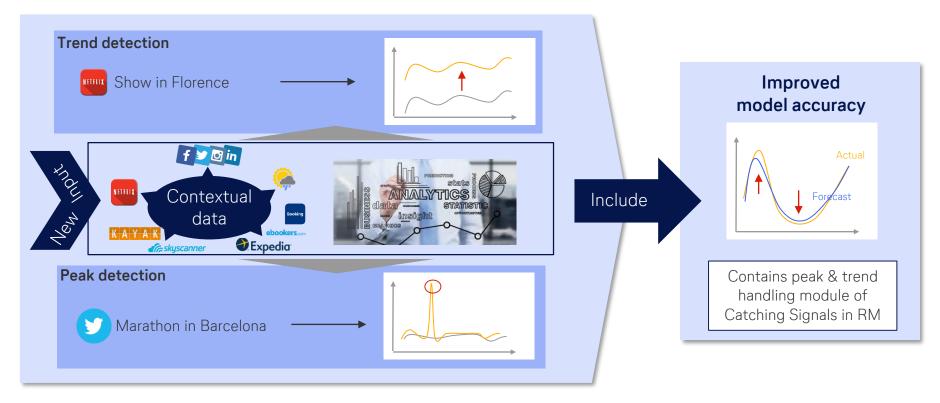








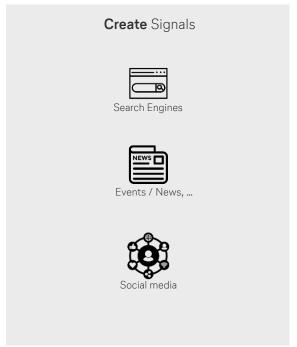


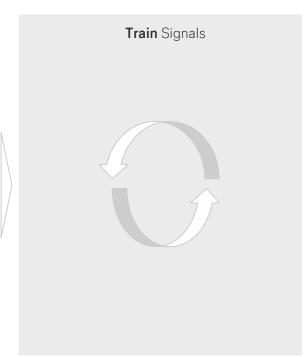






## Application: Create Data Signals for direct incorporation in Models





# Add signals to model

$$\begin{split} \log \left( \lambda(\mathbf{x}_{i,t},t) \right) &= \beta_0 + \beta_{\xi} \hat{\xi}_{i,t} + \sum_{j=1}^o \mathbf{1}_{\text{BDAY}_{i,t} = j} \beta_{1,j} + f_p \left( p_{i,t} \right) \\ &+ f_{p,t} \left( p_{i,t}, t \right) + f_{p,1} \left( p_{i,t}, \text{DTIME}_{i,t} \right) + f_{p,2} \left( p_{i,t}, \text{YDAY}_{i,t} \right) \\ &+ f_t \left( t \right) + f_1 \left( \text{DTIME}_{i,t} \right) + f_2 \left( \text{YDAY}_{i,t} \right) \\ &+ f_{t,1} \left( t, \text{DTIME}_{i,t} \right) + f_{t,2} \left( t, \text{YDAY}_{i,t} \right) + f_{1,2} \left( \text{DTIME}_{i,t}, \text{YDAY}_{i,t} \right) \\ &+ f_{p,a} \left( p_{i,t}, \text{INDEX}_{1,i,t} \right) + f_{p,b} \left( p_{i,t}, \text{INDEX}_{2,i,t} \right) + \dots \\ &+ f_{p,I} \left( p_{i,t}, \text{SIGNAL}_{1,i,t} \right) + f_{p,II} \left( p_{i,t}, \text{SIGNAL}_{2,i,t} \right) + \dots \\ &+ \dots \end{split}$$

+ additional Indexes/Signals

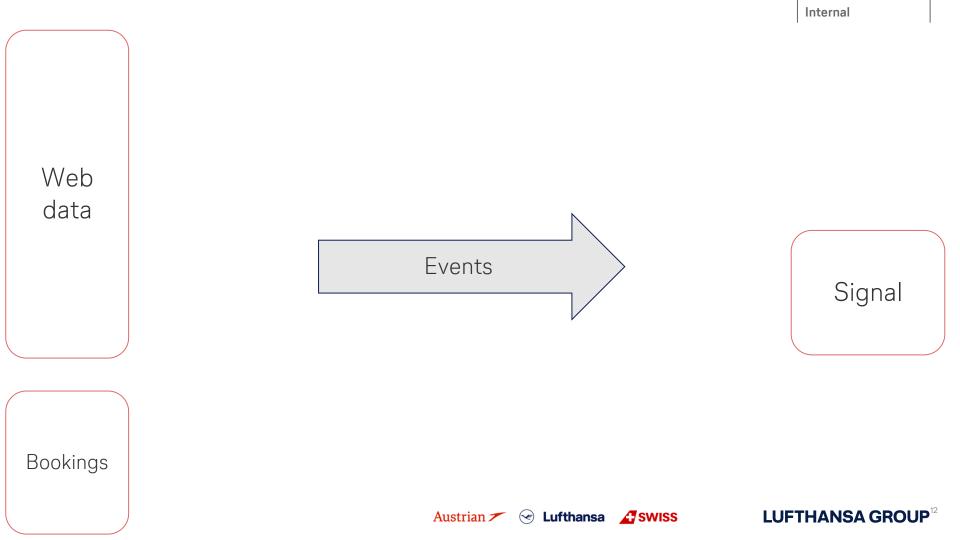
Regression Model

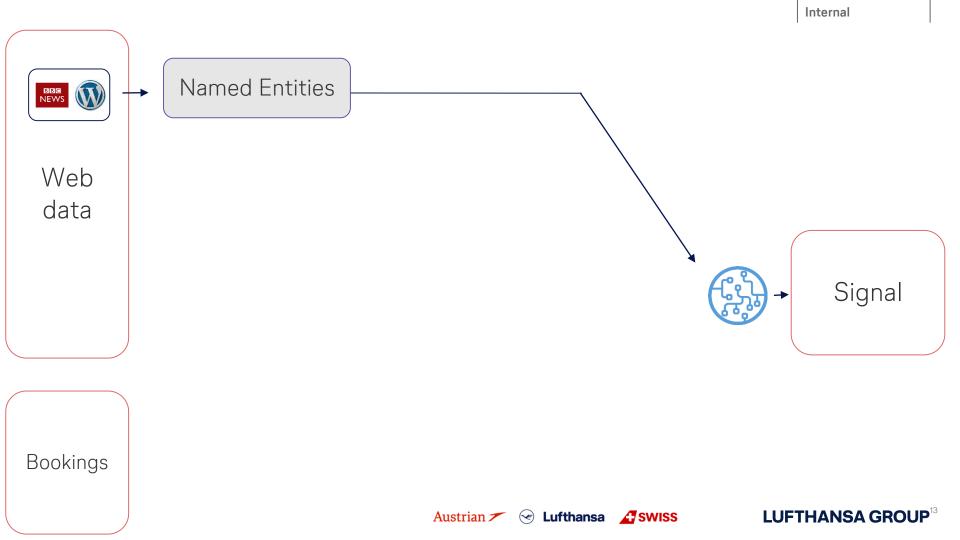
GLM/GAM

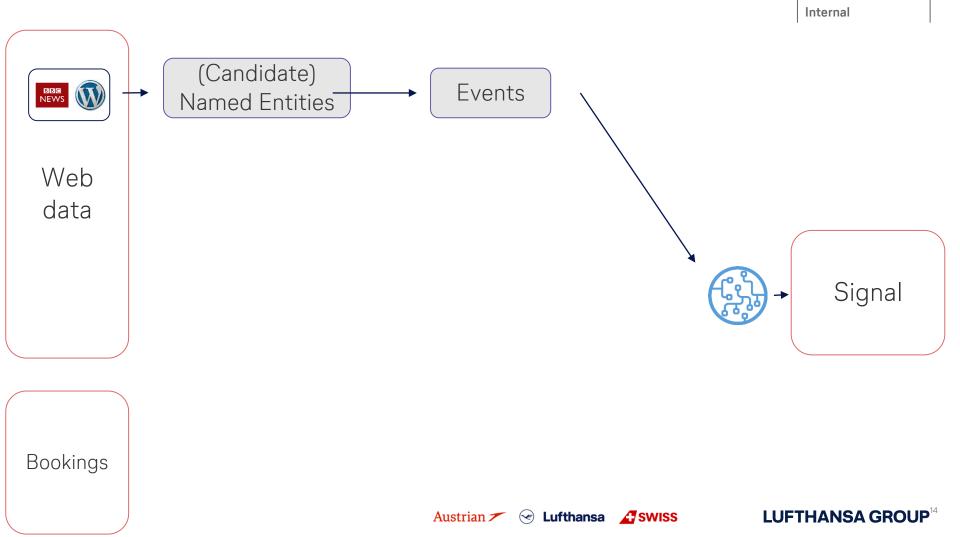
Count Data, Bookings

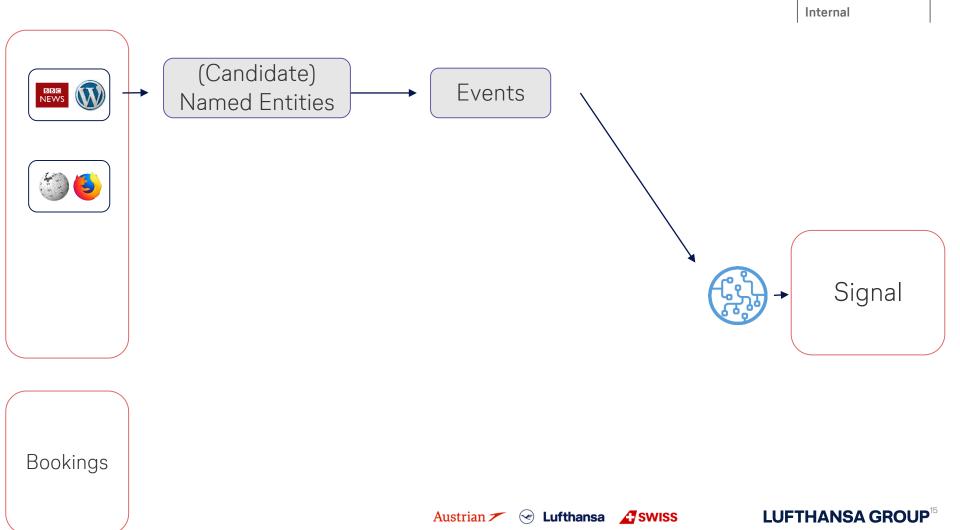






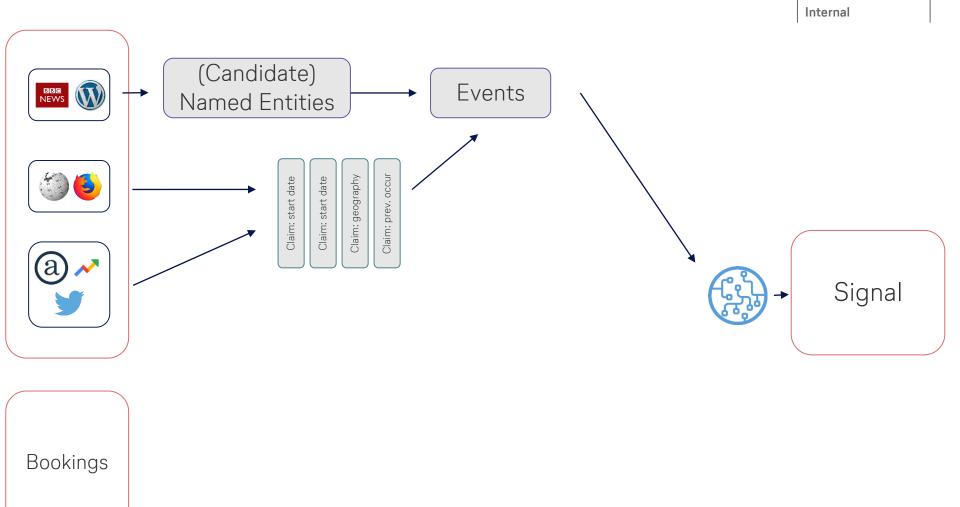








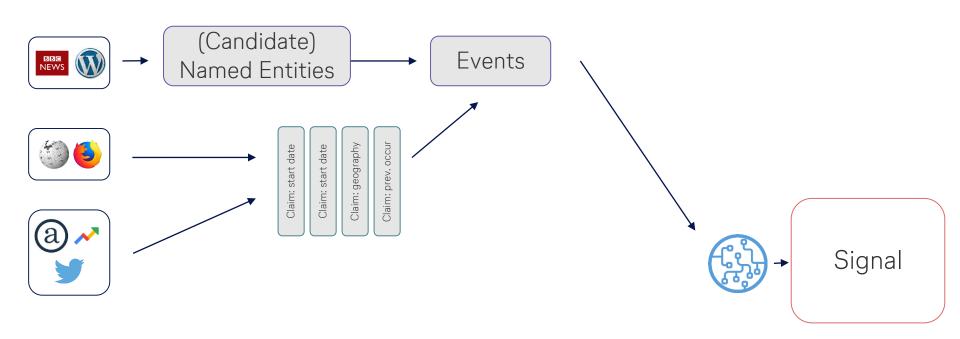


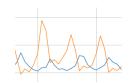


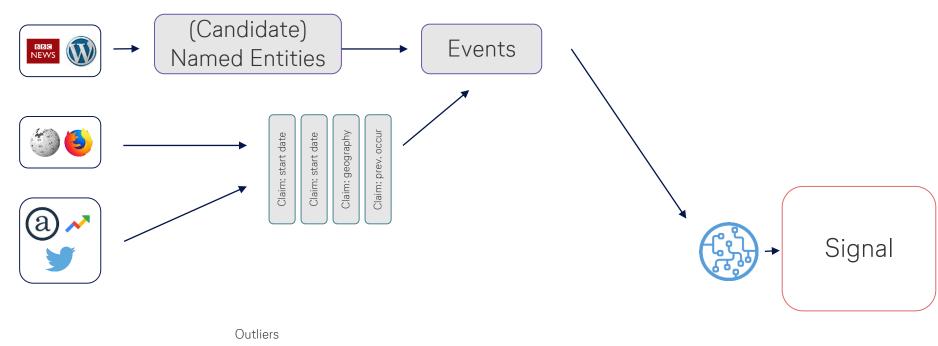
Austrian 🖊

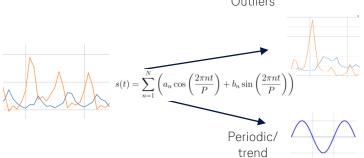
**SWISS** 

Lufthansa





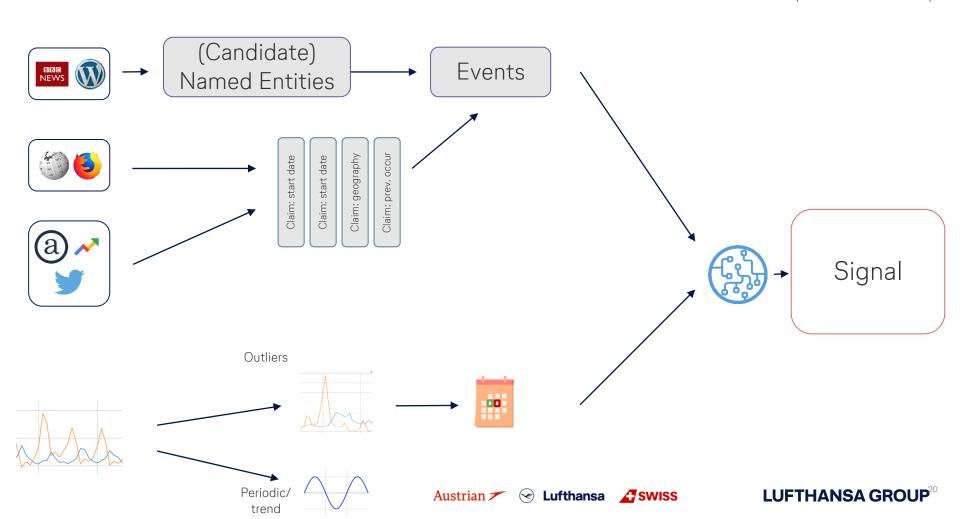


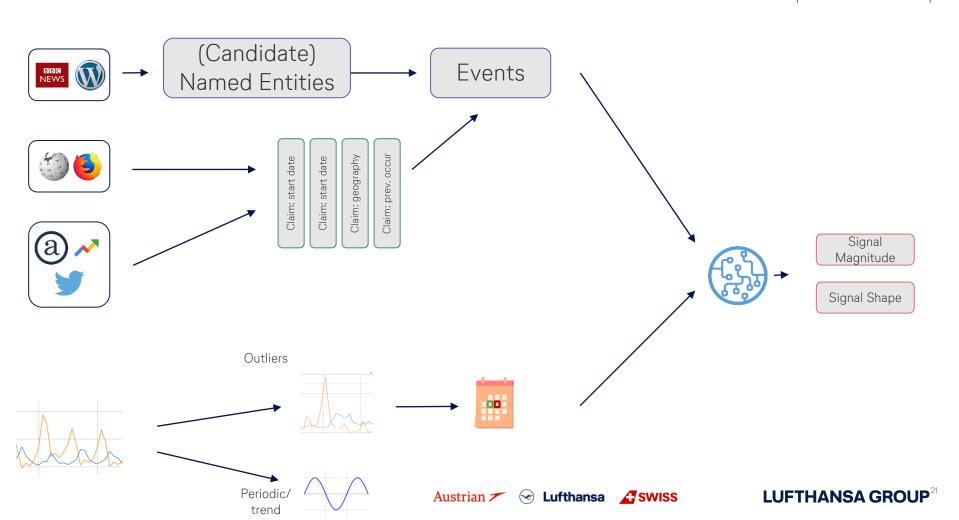


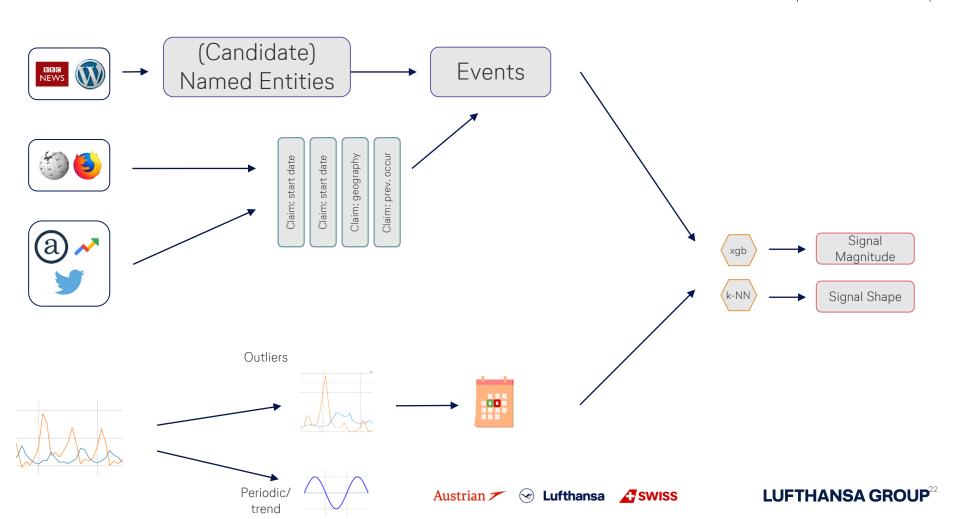


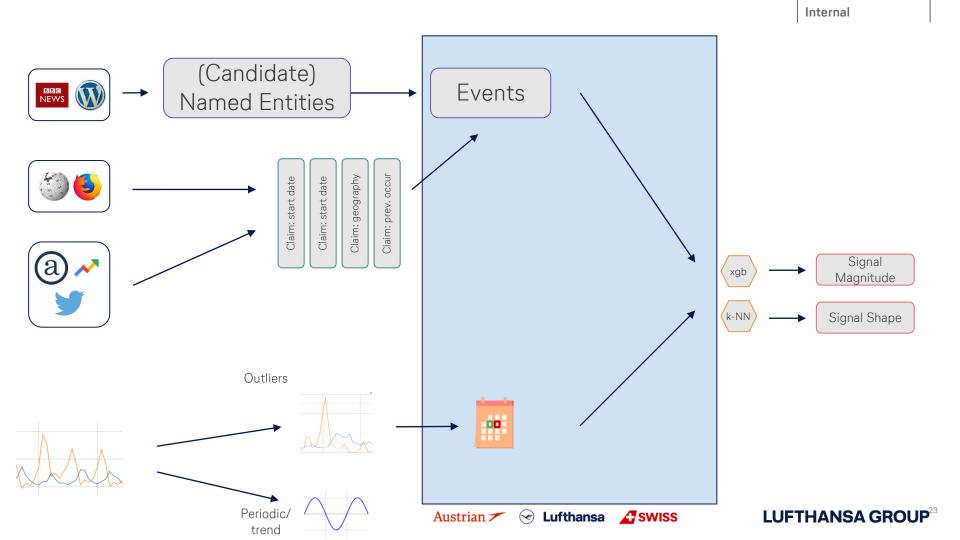












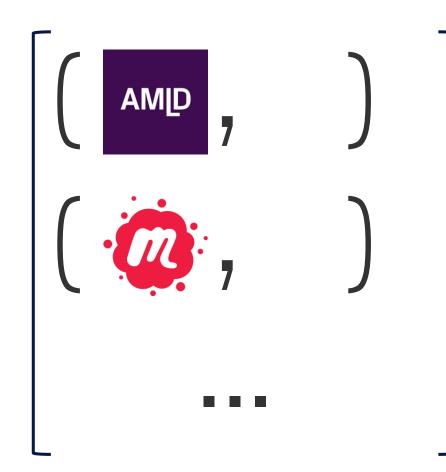
#### Deep dive: how do same-day events interact?



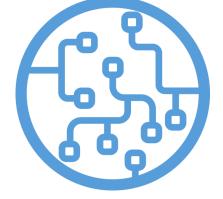


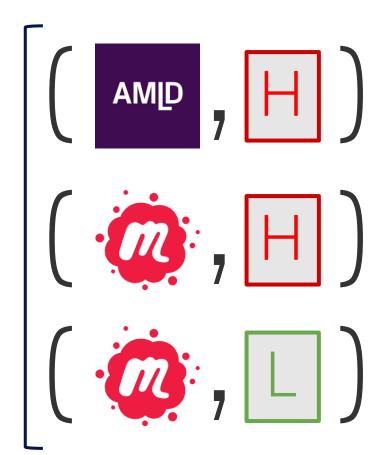




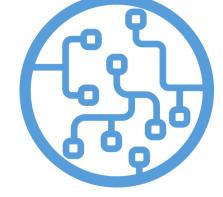




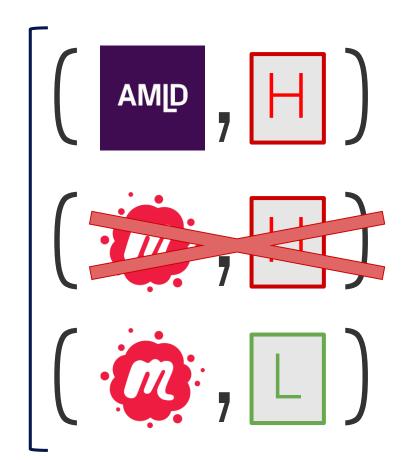


















## Alternative approach





### Events have (independent) probability to cause impact







#### Set up as maximum likelihood







### Set up as maximum likelihood

$$P(\mathbf{H}) = P(\mathbf{H}) \cdot \mathbf{H}$$

$$P(\text{data}) = \prod_{D \in \mathcal{D}} P(D) \prod_{\overline{D} \in \overline{\mathcal{D}}} P(\overline{D}) \quad \text{where } P(\overline{D}) = \prod_{e_i \in \overline{D}} (1 - p_{e_i})$$
$$P(D) = 1 - \prod_{e_i \in \overline{D}} (1 - p_{e_i})$$



 $e_i \in D$ 

If two events are similar, their impact probabilities should be similar







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subject to 
$$\sum_{i,j} (p_i - p_j) \cdot \text{sim}(e_i, e_j) < C$$





## Putting it all together

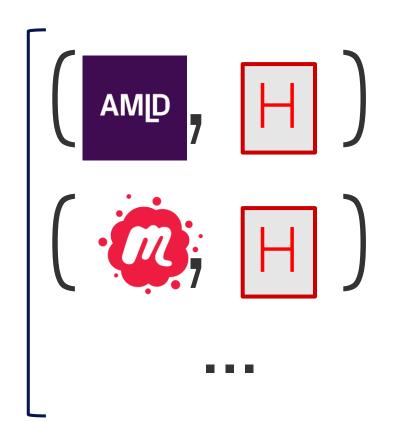
Maximize

$$P(\text{data}) = \prod_{D \in \mathcal{D}} P(D) \prod_{\overline{D} \in \overline{\mathcal{D}}} P(\overline{D}) \quad \text{where } P(\overline{D}) = \prod_{e_i \in \overline{D}} (1 - p_{e_i})$$

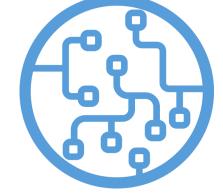
$$P(D) = 1 - \prod_{e_i \in D} (1 - p_{e_i})$$

subject to 
$$\sum_{i,j} (p_i - p_j) \cdot \text{sim}(e_i, e_j) < C$$

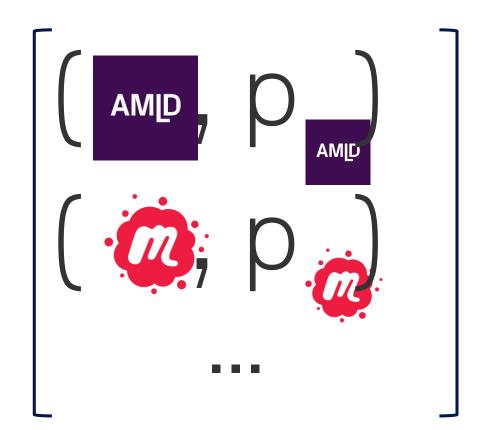
#### So instead of this...



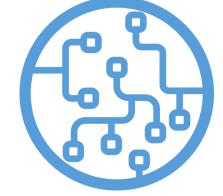




#### ... we can have this!

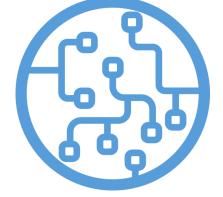


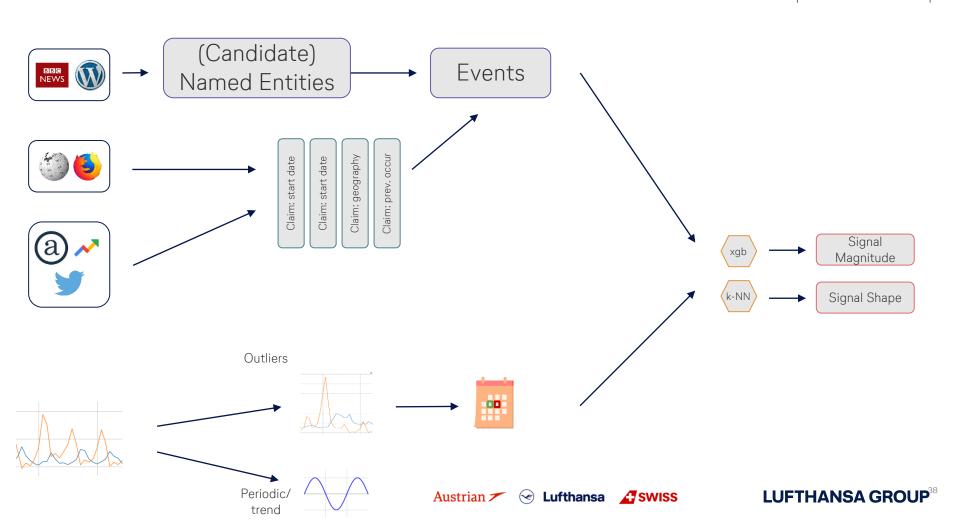




#### ... we can have this!

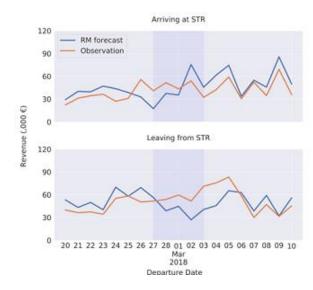






#### Results: Event Information reveals significant Forecasting Improvement

#### **Current Forecast**







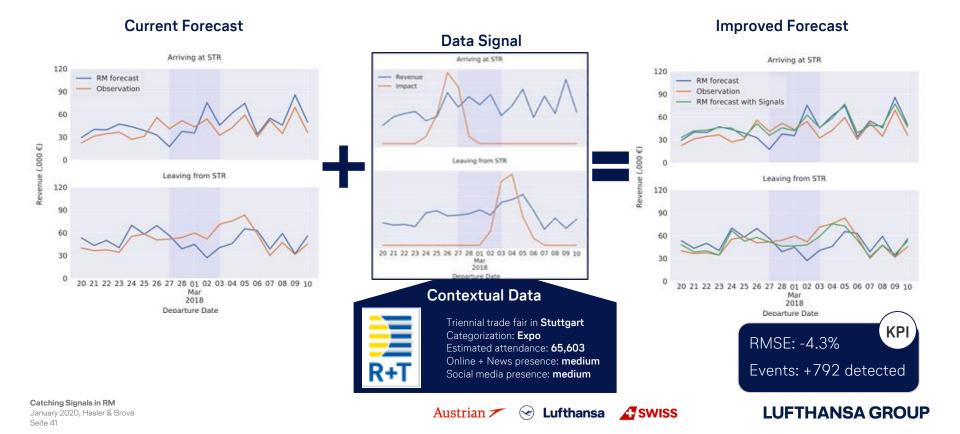
#### Results: Event Information reveals significant Forecasting Improvement

#### **Current Forecast Data Signal** Arriving at STR Arriving at STR 120 Revenue RM forecast - Impact 60 Revenue (,000 €) Leaving from STR Leaving from STR 120 90 60 20 21 22 23 24 25 26 27 28 01 02 03 04 05 06 07 08 09 10 Mar 2018 21 22 23 24 25 26 27 28 01 02 03 04 05 06 07 08 09 10 **Contextual Data** 2018 Departure Date Triennial trade fair in Stuttgart Categorization: Expo Estimated attendance: 65,603 Online + News presence: medium Social media presence: medium





### Results: Event Information reveals significant Forecasting Improvement



## Outlook: Prove potential for Catching Signals in price elasticity estimation, vision to use additional data sources in all models and further departments

#### **Done: Demand**

**Model:** Demand Volume Forecast

**Timeline**: 3-month test case up to

MAR 2019

**Scope**: 14 routes, 1.5 years training

and 3 months validation data

**Evaluation**: Forecast vs. observed

demand (RMSE)

**Result**: Significantly lower forecasting error of 4.3%

**Limitation**: No technical implementation so far

#### **Ongoing: Price Elasticity**

**Model:** Demand Volume Forecast

**Timeline**: 3-month test case up to APR 2020 incl. 6+ weeks of testing

**Scope**: 6+ ODs, 2 years training and

6+ weeks of validation data

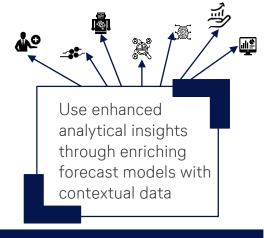
**Evaluation**: Observed revenue

during live test

**Result**: Clear potential detected in simulation, test evaluation awaited

**Limitation**: No proven revenue

increase so far



#### Vision: All Models

- Revenue Management
- Sales
- Marketing







