

TEAM AQUILA

BUNDESLIGA HACKATHON - CHALLENGE 5
11. APRIL 2025



AGENDA

1

SIMPLE APPROACH

- Linear Regression Model
- Ticket prices based on the opponent

2

SOPHISTICATED APPROACH

- Limitations of the given data
- Forecasting ticket-shop traffic
- Calculating price adaptions

3

Q&A



BOY, FYNN-LUKA



LEICHT, ALEXANDRA LORENA



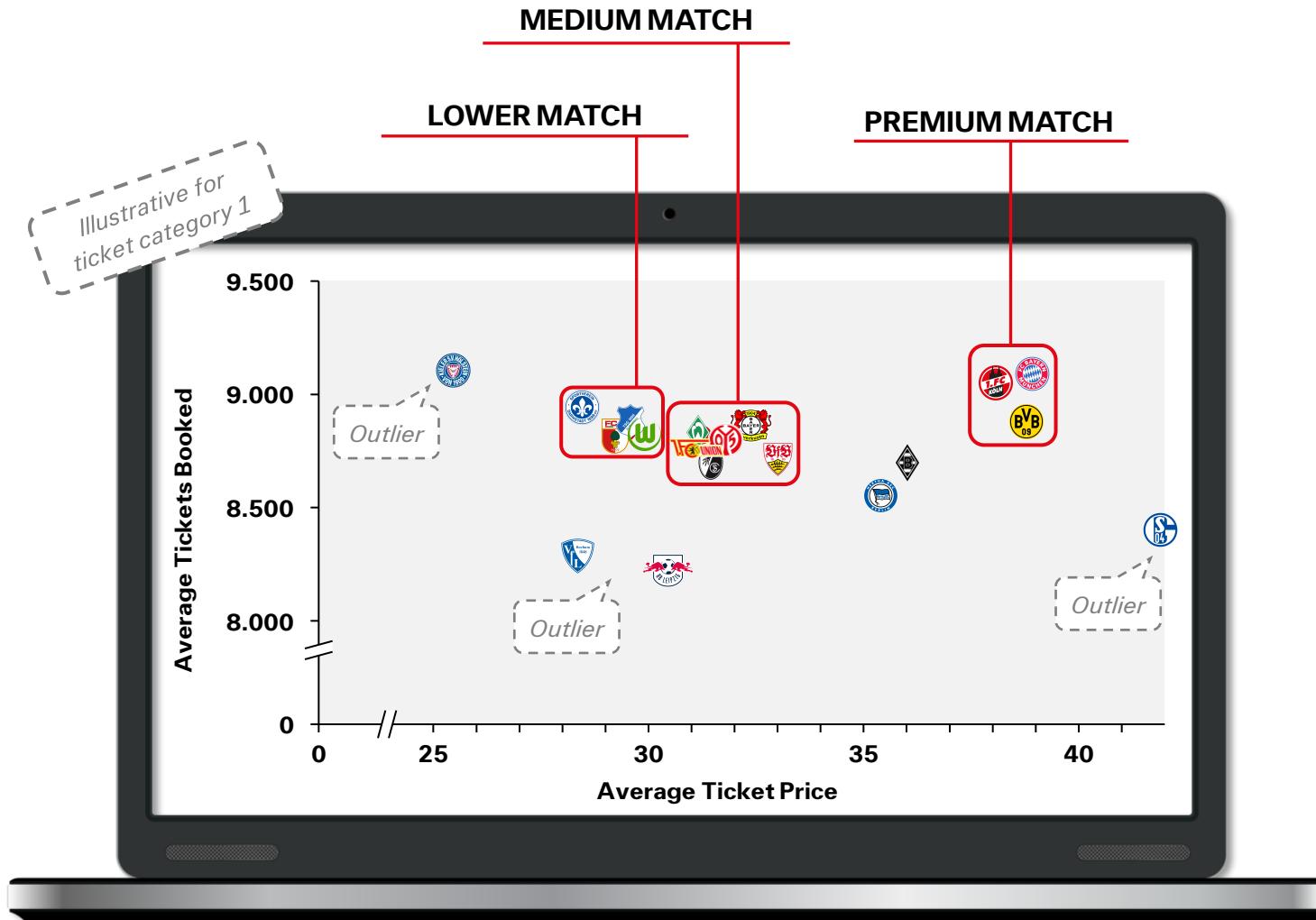
REICHARD, FIDELIO-LUC



SCHMIDT, LEON WERNER



A SIMPLE APPROACH CAN BE APPLIED TO FIND A QUICK FIX FOR NEXT SEASON HOWEVER, USING A LINEAR REGRESSION MODEL LEADS TO FLAWED PRICING AND OUTLINES LIMITATIONS



APPROACH

- Historical sales data **with factors** competition, opponent, date and time as input for prediction
- **Linear regression** approach applied to forecast future **revenue per opponent** as output
- Revenue as a **function of booked tickets and average price**



LIMITATIONS

- Certain opponents seem **misplaced** in the emerging categories (e.g., 1. FC Köln)
- Current **flaws** in pricing **transition**
- Unknown how to encode the Opponent and other features



AS A RESULT, WE PRICE TICKETS BASED ON THE OPPONENT THE FACTOR DEMAND – HOW MUCH COULD HAVE BEEN SOLD – IS NEGLECTED IN THIS APPROACH

Bundesliga Example

- Clubs like Borussia Mönchengladbach, VfL Wolfsburg, etc. **differentiate ticket prices depending on opponent**
- Prices for **premium matches** are up to double the prices compared to lower-ranked matches
- Tickets for standings** (active fan scene) are always significantly **lower than seated tickets**



Eintracht Frankfurt

STEHPLATZ
AB xx€
SITZPLATZ
AB xx€



STEHPLATZ
AB xx€
SITZPLATZ
AB xx€



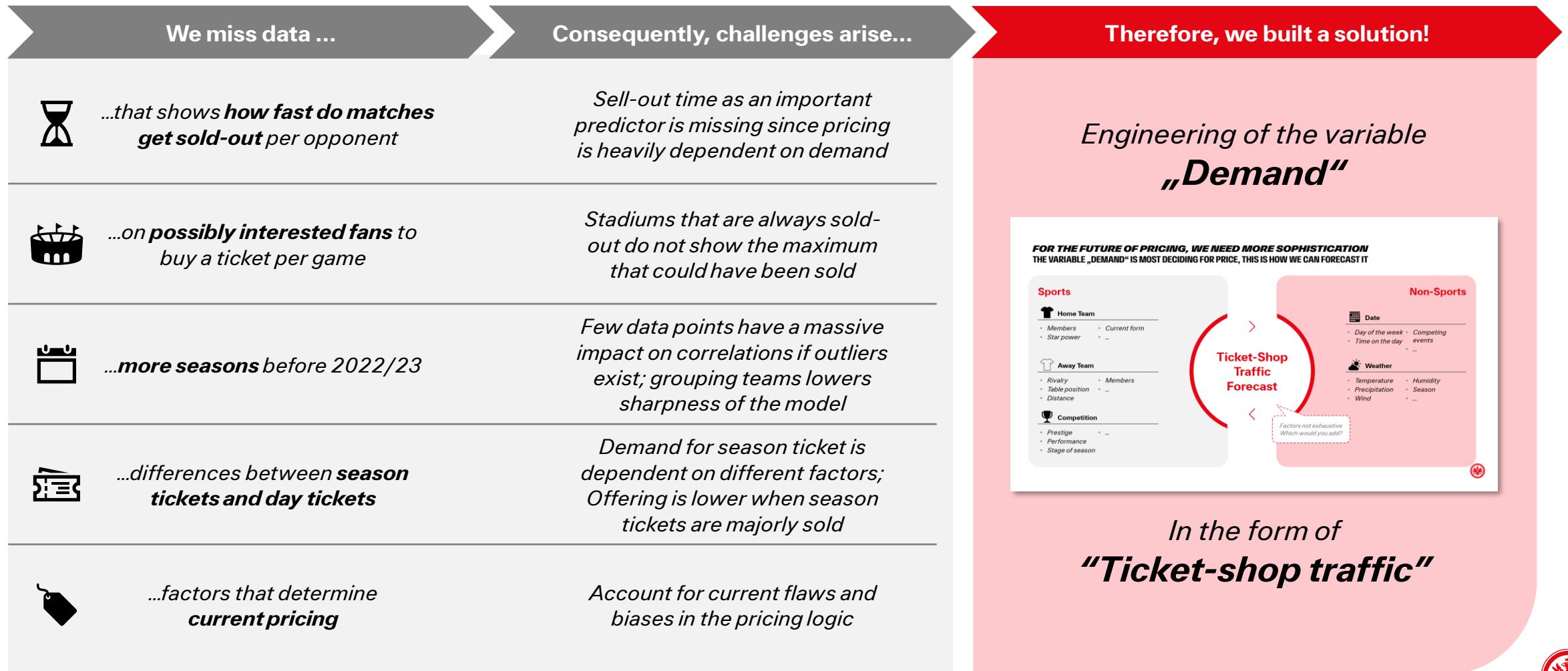
STEHPLATZ
AB xx€
SITZPLATZ
AB xx€



Pricing is only dependent historic data on opponent, competition and date – however, **demand is not a factor!**
Therefore, **current flaws transition to next season!**



THE GIVEN DATA LACKS DETAILS FOR DYNAMIC PRICING THEREFORE, WE APPLIED FEATURE ENGINEERING TO FIND AN APPROACH



FOR THE FUTURE OF PRICING, WE NEED MORE SOPHISTICATION

THE VARIABLE „DEMAND“ IS MOST DECIDING FOR PRICE, THIS IS HOW WE CAN FORECAST IT

Sports

Home Team

- Members
- Star power
- Current form
- ...

Away Team

- Rivalry
- Table position
- Distance
- Members
- ...

Competition

- Prestige
- Performance
- Stage of season
- ...

Non-Sports

Date

- Day of the week
- Time on the day
- Competing events
- ...

Weather

- Temperature
- Precipitation
- Wind
- Humidity
- Season
- ...

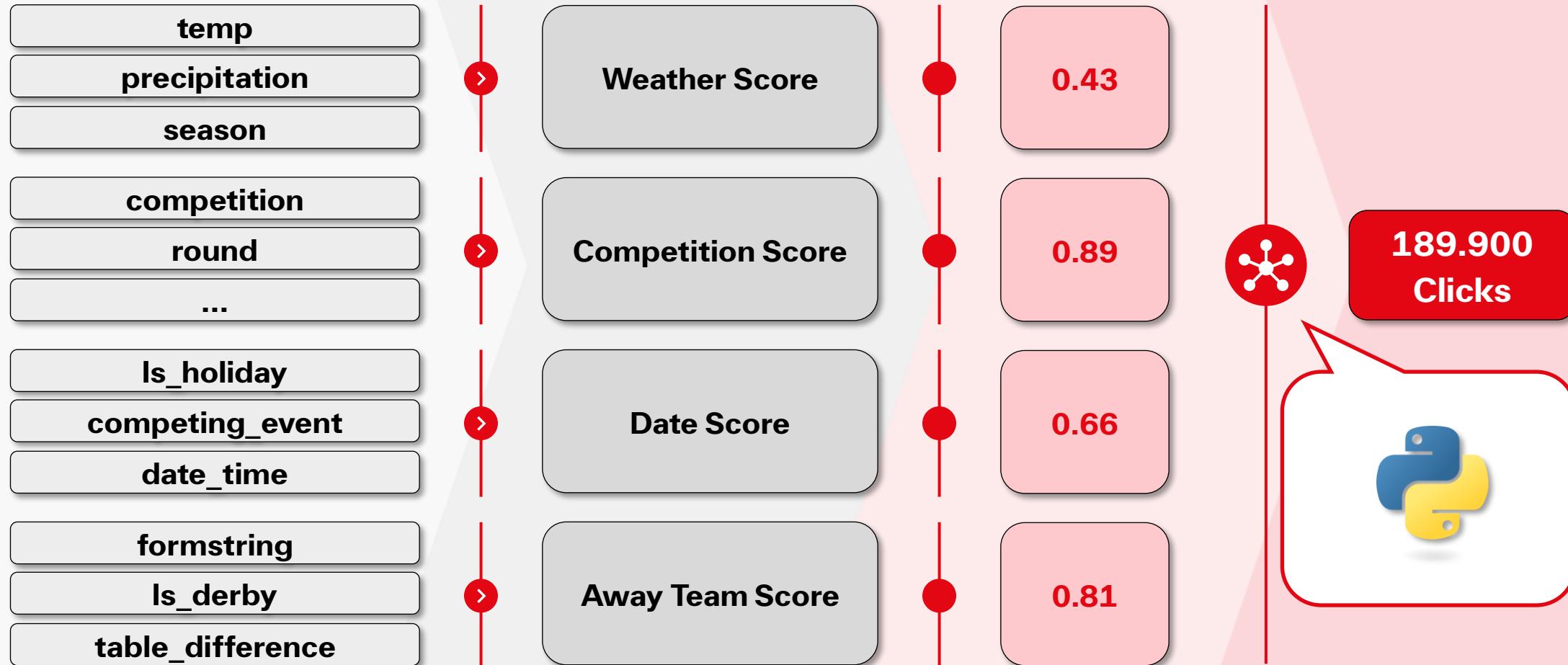
Ticket-Shop Traffic Forecast

*Factors not exhaustive
Which would you add?*



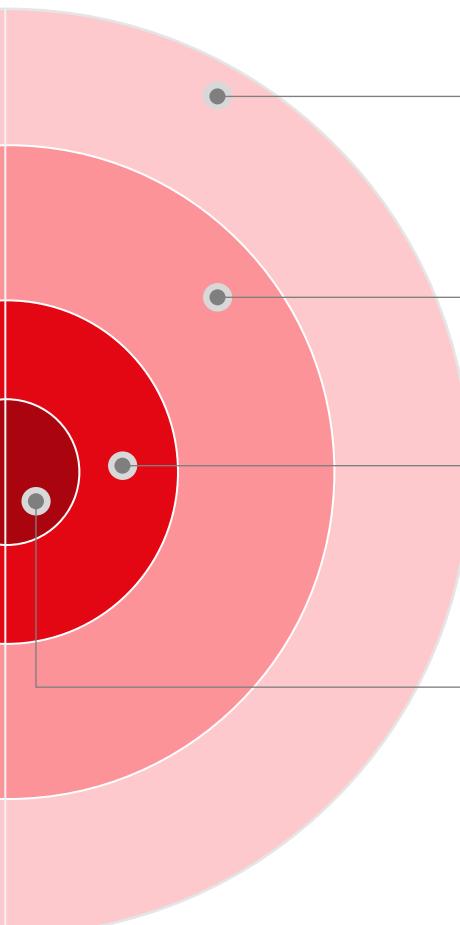
Highly illustrative

THE ADVANCED MODEL IS IMPLEMENTED BY USING FEATURE SCORES DIFFERENT DATA SOURCES FLOW THROUGH THE PIPELINE AND RESULT IN A SCORE



USING FORECASTED TICKET-SHOP TRAFFIC WE CAN PRICE DYNAMICALLY

4 STEPS TO PRICE SGE HOME MATCH TICKETS IN THE FUTURE



1 Forecast TICKET-SHOP TRAFFIC by using machine learning

Using the engineered variables Home- and Away Team, Competition, Weather, Date, etc. we can forecast traffic

Hypothesis: Sports tickets as an emotional product will show rather equal conversion rates independent of price

2 Use historic CONVERSION RATE to calculate TICKET DEMAND

Multiplying ticket-shop traffic with historic conversion rates from the shop (e.g., how many clicks lead to a sold ticket) gives the theoretical demand for a match: How many tickets could have been sold in total?

3 Take HISTORIC PRICING as a starting point to adapt pricing in upcoming seasons

Ticket prices from last season serve as the foundation to increase (or decrease) prices based on total demand; with each season with this system the prices become more accurate and optimized

4 Calculate PRICE ELASTICITIES to increase/decrease prices according to TICKET DEMAND

Ticket demand (Q) and historic prices (P) are the input to calculate price elasticities which ultimately tell how prices should be adapted based on demand



$$|E| = \frac{\frac{Q_2 - Q_1}{Q_1}}{\frac{P_2 - P_1}{P_1}}$$



LET'S TAKE A LOOK AT AN EXAMPLE

SGE VS. "CL TEAM"

Highly illustrative

PRE-REQUISITES

PL	TEAM	SP.	S	U	N	TORE	DIFF.	PUNKTE
1	Bayer 04 Leverkusen	34	28	6	0	89:24	65	90
2	VfB Stuttgart	34	23	4	7	78:39	39	73
3	Bayern München (M)	34	23	3	8	94:45	49	72
4	RB Leipzig (P)	34	19	8	7	77:39	38	65
5	Borussia Dortmund	34	18	9	7	68:43	25	63
6	Eintracht Frankfurt	34	11	14	9	51:50	1	47

- Find **2 similar matches**
- Ticket prices** per category
- Conversion rates** per category

Calculate per ticket category

TICKET-SHOP TRAFFIC



feature_scores.py



demand_prediction.py

TICKET DEMAND

Ticket-shop traffic
 $Q_1 = \times$
Conversion rate

$P_1 =$ *Last season's price to start*

! *Pricing accuracy increases once system is implemented*

PRICE ADAPTION

$$|E| = \frac{Q_2 - Q_1}{Q_1} \quad \frac{P_2 - P_1}{P_1}$$

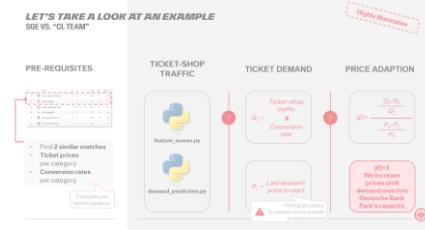
$|E| < 1$
We increase prices until demand matches Deutsche Bank Park's capacity



ULTIMATELY WHAT DO WE DO ABOUT THE SECONDARY MARKET?

THE SAME APPROACH WITH DIFFERENT MECHANISMS IS APPLIED

PRICING OF ORDINARY TICKETS



PRICING OF SECONDARY MARKET TICKETS

Hypothesis 1: As soon as tickets are “sold out”, secondary market “goes live”

Hypothesis 2: Stadium occupancy should be maximized (no free seats)

Hypothesis 3: No profit for active resellers

→ Current system: Fixed fee of 5 EUR per sale

↗ Envisioned system: Variable fee of xx% per sale



- Q and P are dependent
- Sellers get charged
- Additional revenue

1

Ticket is added to secondary market for ordinary Price P

2

Quantity Q gets forecasted for time between sold-out until begin of match

3

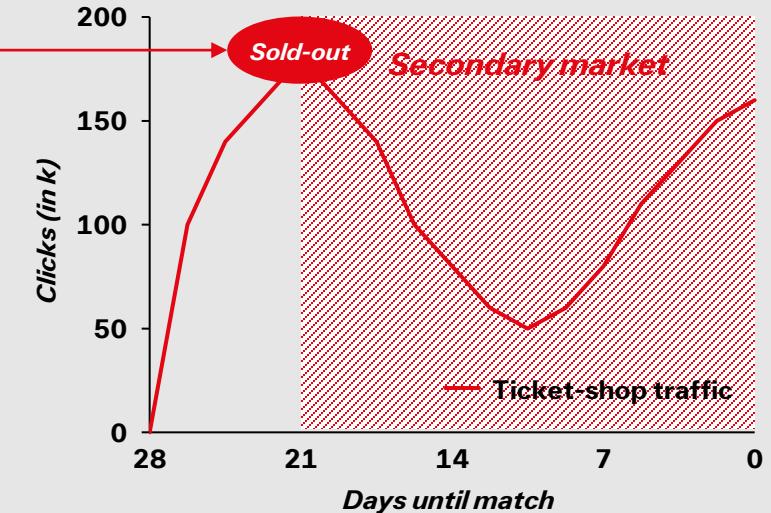
Elasticity E gets calculated to increase price via a % fee on ticket

4

% fee is equally split up between buyer and seller

KEY QUESTION TO CONSIDER

How does website shop traffic **distribute over time**, and what is the **optimal price/fee increase rate**?



Happy to exchange thoughts!



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LET'S TAKE A LOOK AT AN EXAMPLE

PRICING OF SECONDARY MARKET TICKETS

Highly illustrative

1

Fynn's ticket is **listed** on the secondary ticket market **for the original price of 50€**

2

From data EF knows **demand** on the secondary market just **2 days before the match is really high**

3

The formula suggests an increase of **30% on the original price**

4

Fynn pays 15% of the fee
Lorena pays 15% of the fee
Eintracht earns 30% more as the original ticket price



Fynn wants to **sell** his ticket he bought for 50€ because he won tickets for free



They meet on the SGE secondary ticket market



Lorena **really wants to visit** the SGE match against Heidenheim with her friends



Hypothesis 1: As soon as tickets are "sold out", secondary market "goes live"

→ Needed to **forecast demand Q** through ticket-shop traffic during the secondary market

Hypothesis 2: Stadium occupancy should be maximized (no free seats)

Hypothesis 3: No profit for active resellers

→ *This is why we sell the ticket for the original price AND charge the sellers a certain %*

→ *Additional profit due to higher demand can be achieved by the fee for the buyer (price increase)*