AI for railway passenger forecasting – a UK case study

ARIC Brownbag / HH / 20 May 2025

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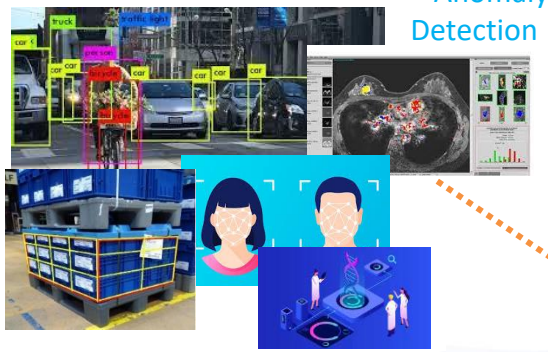
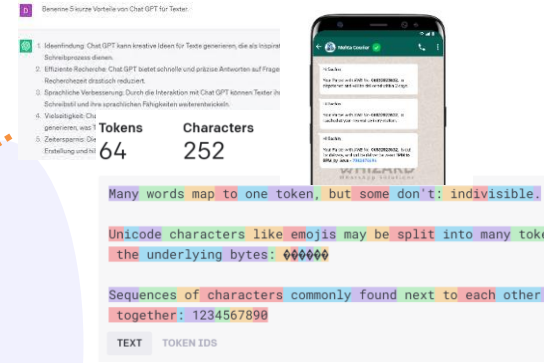
CEO & Founder of iqast

AI in Forecasting

Pattern Recognition in Pictures + Anomaly Detection

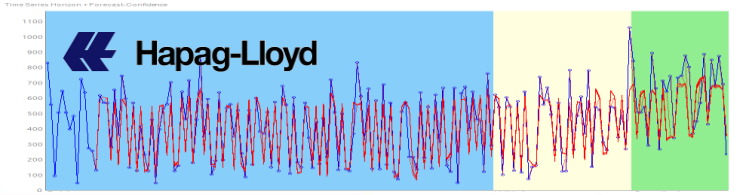


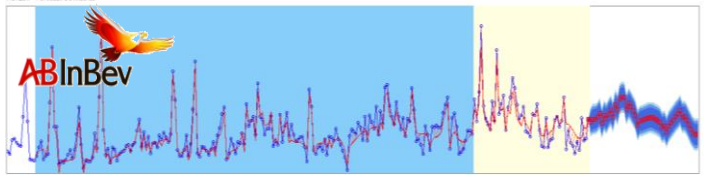
Pattern Recognition in Text

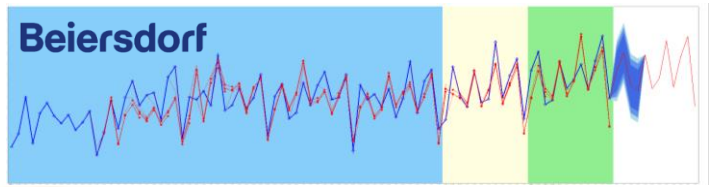


Pattern Recognition in Speech

Pattern Recognition in Time Series Data (aka structured data)

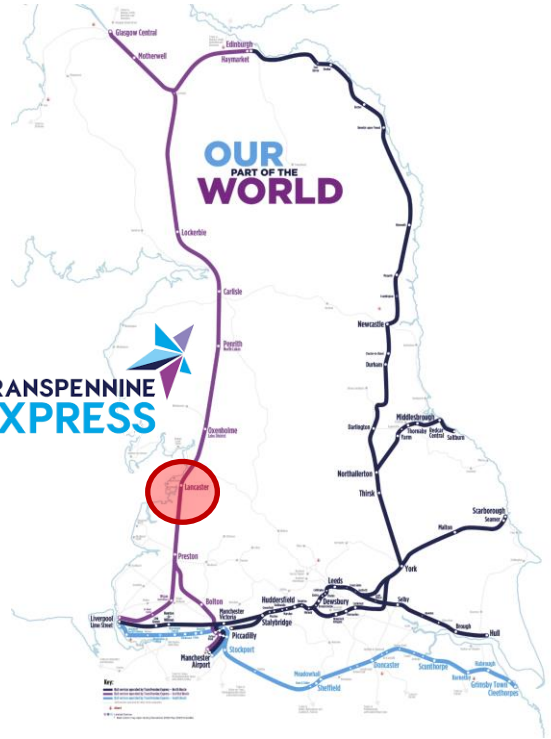




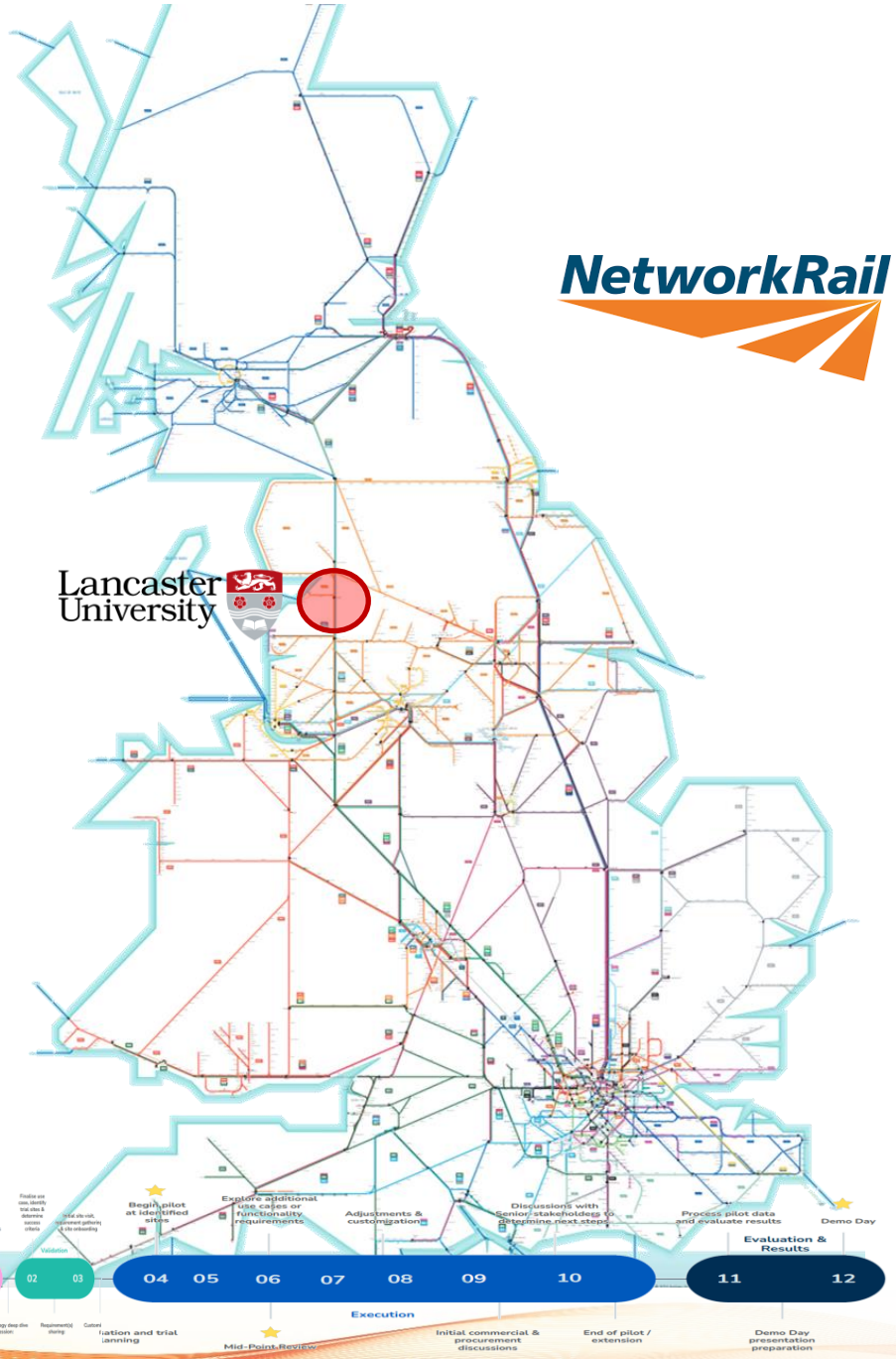


AI forecasting software
code-free AutoAI
10x faster ½x resources

Our Study

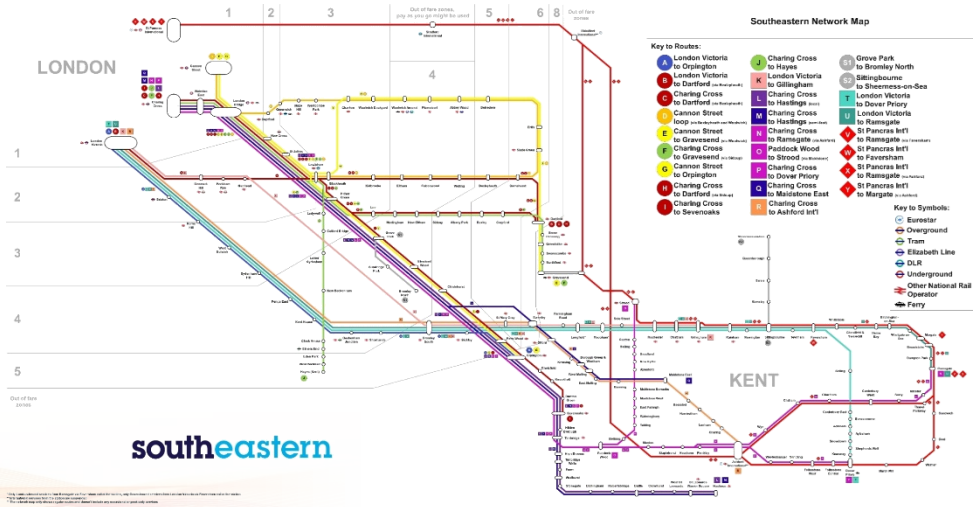


78 stations
3 Routes / 2 directions
2500 employees
160 trains



24 Train Operator Companies

176 stations
18 Routes / 2 directions
4500 employees
400 trains (1700 per day)



Future Labs

❶ revenue forecasting
Stratford International

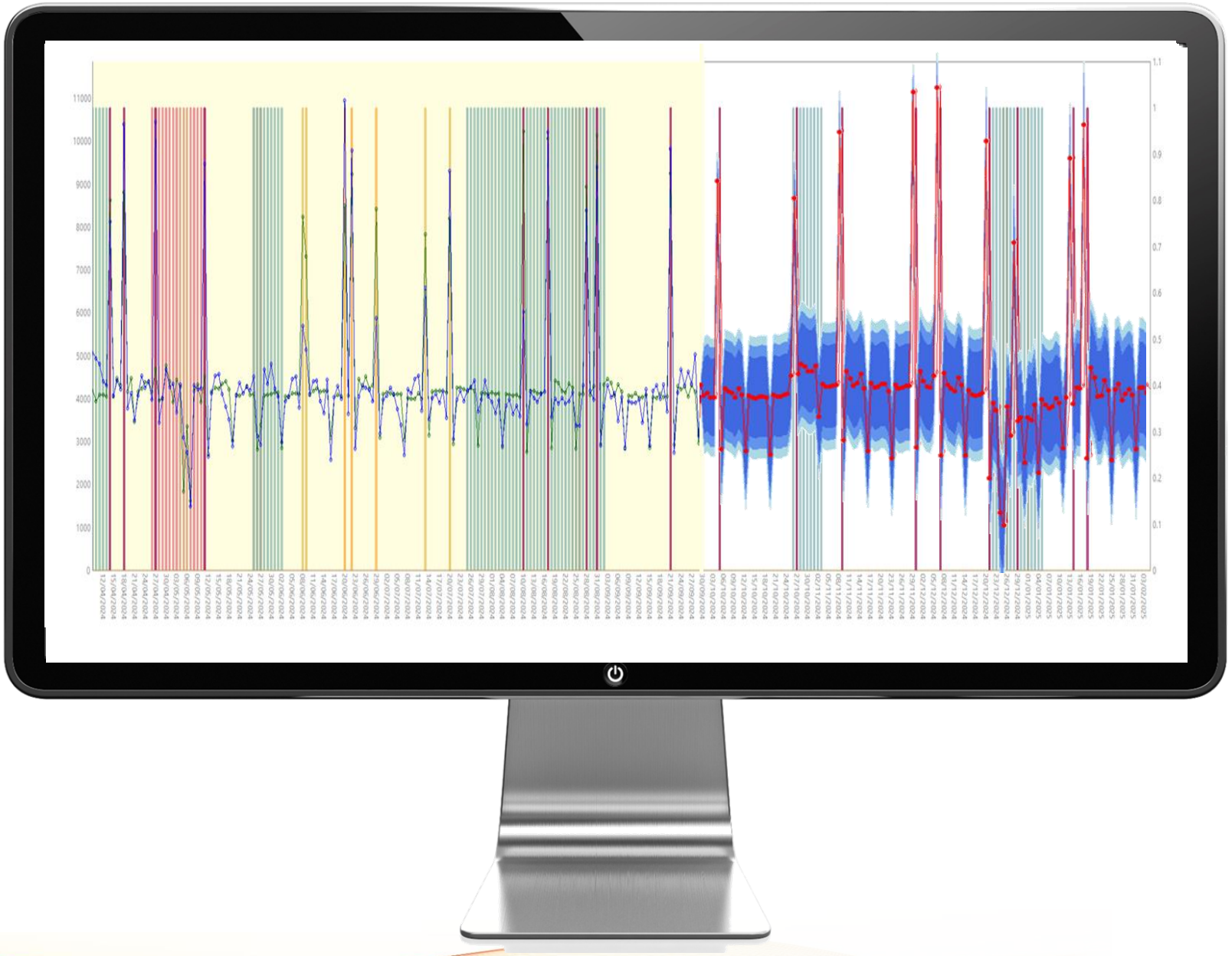
Revenue Manager

Increase revenue in events
set effective prices for Stratford International (SFA) @ West Ham United

Limited Visibility in Tools
Expects uplift in journeys on Saturday home games, but lacks visibility

Measure revenue Impact
align prices 2 weeks out & estimate revenue uplift £230k+ pa (one-way!)

[end of week 1]



Forecast Analyst

Extract Data & Events
loads data & combines with events in iqast

Provide Event Insight
visualise local events & quantifies their uplifts

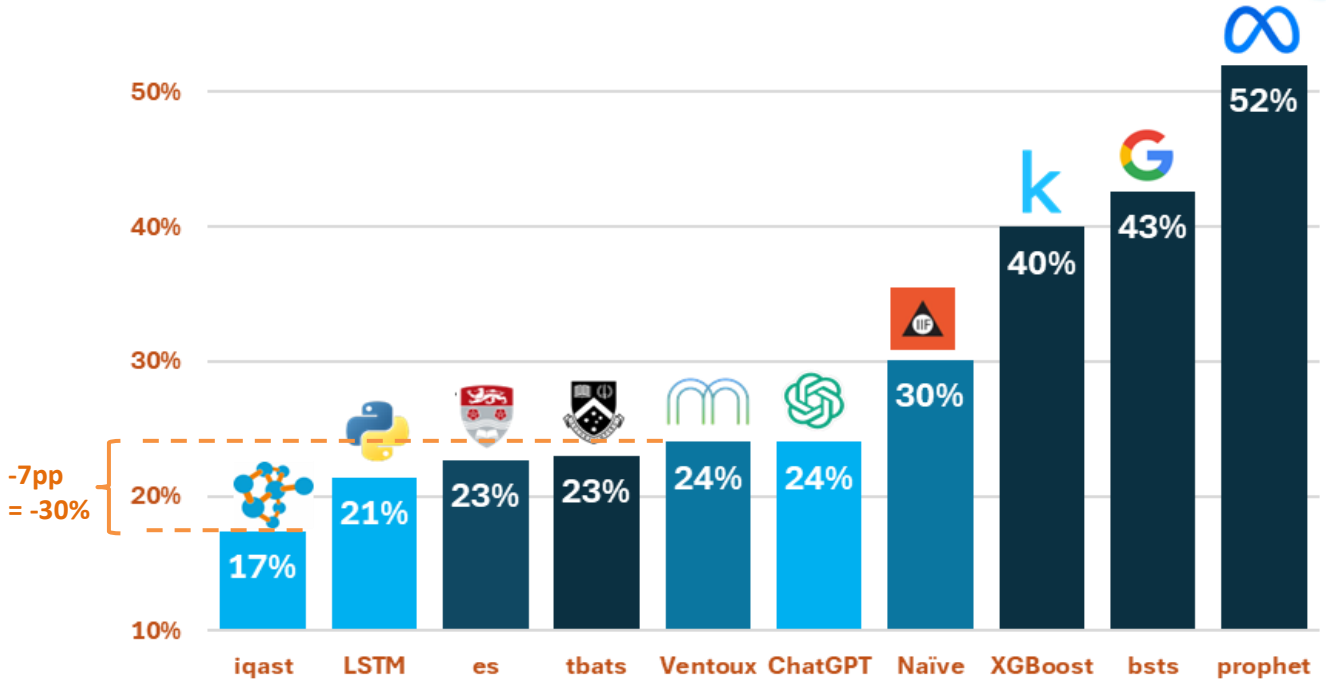
Predict next 84 days
train AutoAI on journey data & extract forecasts to MS Excel (weekly pilot)

Benchmark AI errors
iqast reduces -30% on industry standard

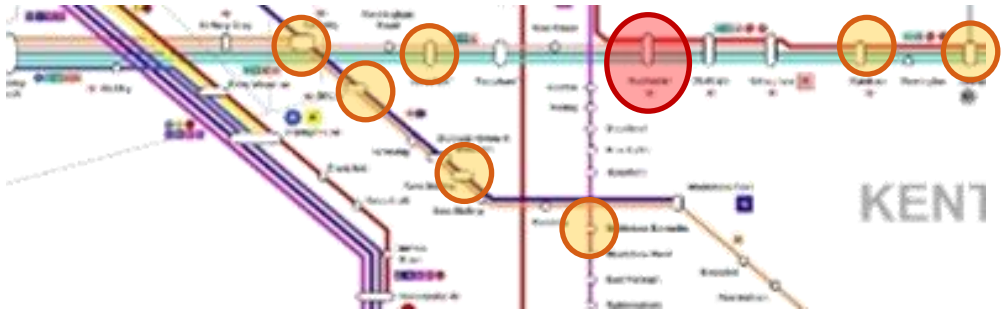
1. Measure Forecast Errors

*Univariate modelling

Model Name	Origin	Mean-H(15-28) sMAPE%	Error diff	Error diff in %	Runtime
iqast_AI	iqast	17.4	-12.6	-42%	0:03:04
LSTM*		21.4	-8.6	-29%	1:41:13
es	Lancaster University	22.7	-7.3	-24%	0:00:38
tbats	Monash University	23.0	-7.0	-23%	0:01:12
ets		24.0	-6.1	-20%	0:00:31
Naïve7	Benchmark	30.1	0.0	0%	0:00:01
Naïve364	Benchmark	31.8	1.7	6%	0:00:01
XGBoost*	kaggle	70.2	40.2	134%	1:17:42
bsts*		72.6	42.5	141%	0:12:10
prophet*	Meta	128.2	98.1	326%	5:05:05



2. Measure Revenue Changes



→ identify most important inbound stations (no outbound effect!)
- → extract # of journeys, revenue & yield per price point
- → Remove lowest 2 price points (i.e. increase by £1-£2 each)
- → 24% uplift / 10% journey loss / 19% net uplift = £225k in 24 games

Origin <-> Destination	Product Description
ASHFORD (KENT) <-> STRATFORD INTERNATIONAL	SE ADVANCE T01 2HUJ
ASHFORD (KENT) <-> STRATFORD INTERNATIONAL	SE ADVANCE T02 2HUI
ASHFORD (KENT) <-> STRATFORD INTERNATIONAL	SE ADVANCE T03 2HUH
ASHFORD (KENT) <-> STRATFORD INTERNATIONAL	SUPEROFFPEAK DAY RETURN 2SUB
ASHFORD (KENT) <-> STRATFORD INTERNATIONAL	SUPEROFFPEAK DAY SINGLE 2SUA

❶ revenue forecasting
extended to more stations

Revenue Manager

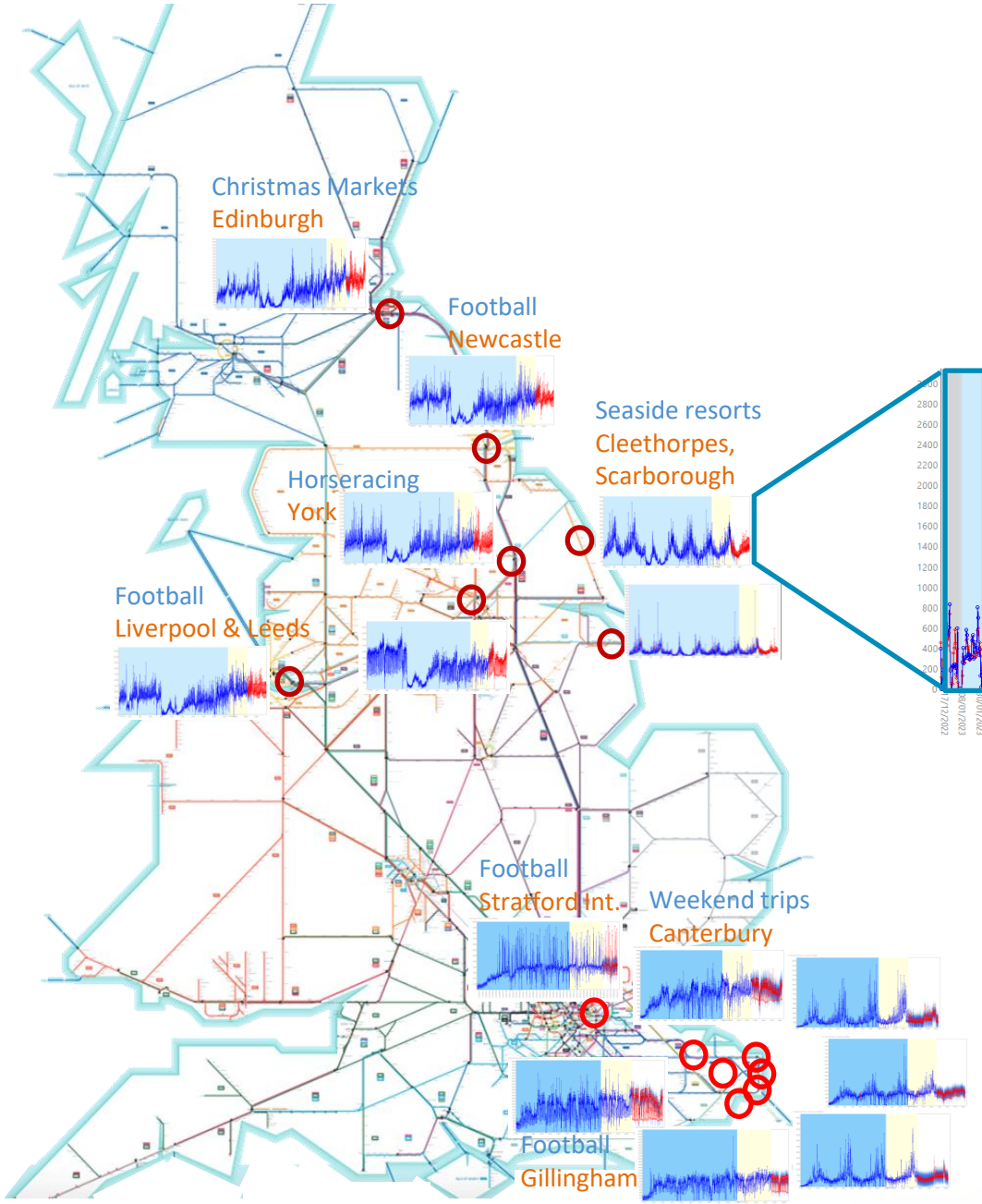
Forecast Analyst

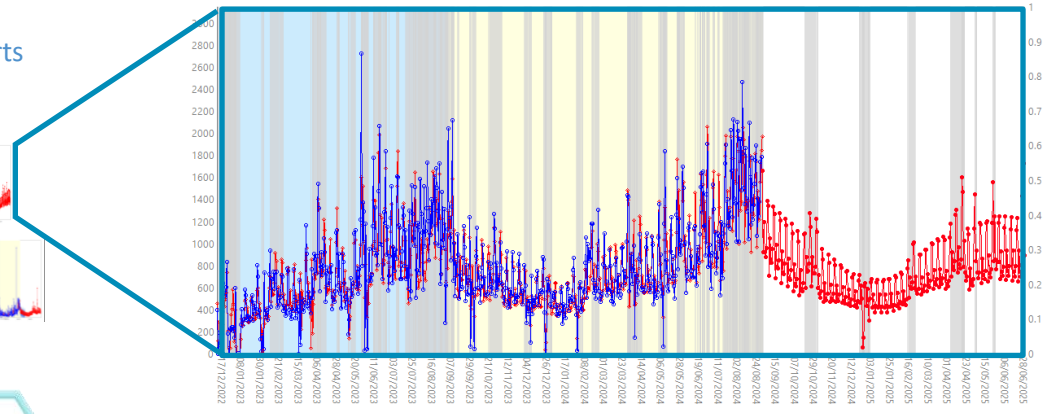
Extending SE analysis ⤢
5 more stations: smaller football
/ weekend trips / seaside weather effects
☑ confirmed across events in south-east

Revenue Manager

Forecast Analyst

Extending analysis to TPE ⤢
6 TPE stations with football /concerts
weekend trips / seaside weather effects
☑ confirmed across events in the north



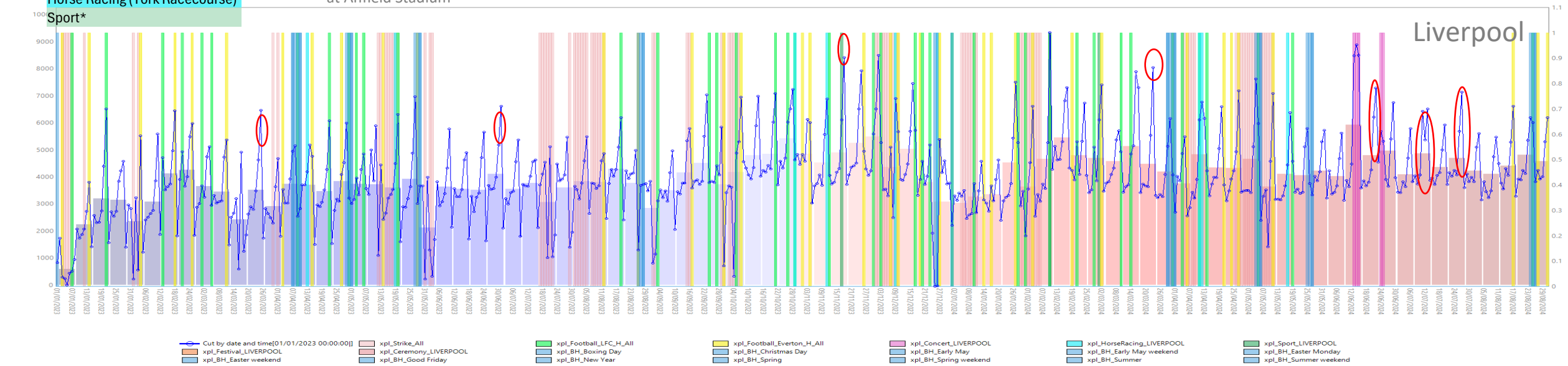


AI forecasts improve revenue for events!
- ☑ across event types
- ☑ across destinations types
- ☑ across TOCs
- ☒ not (yet) confirmed for weather uplifts

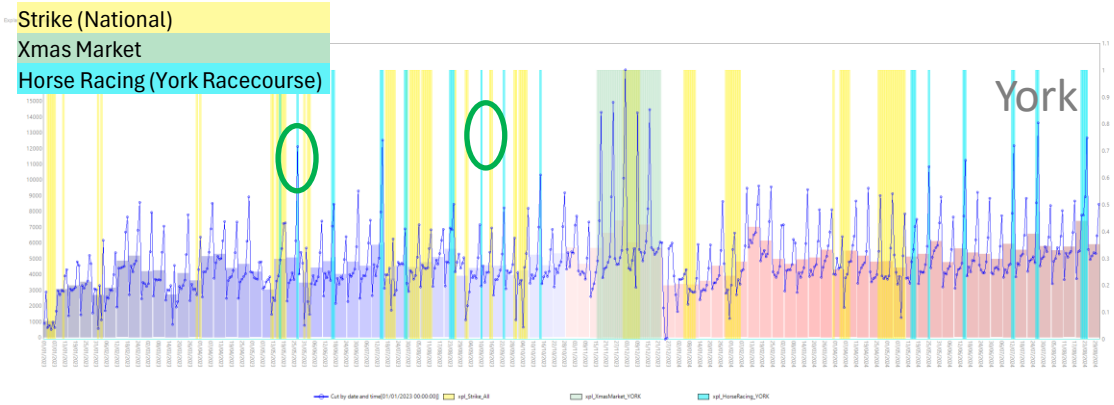
Special Events
large variation by station

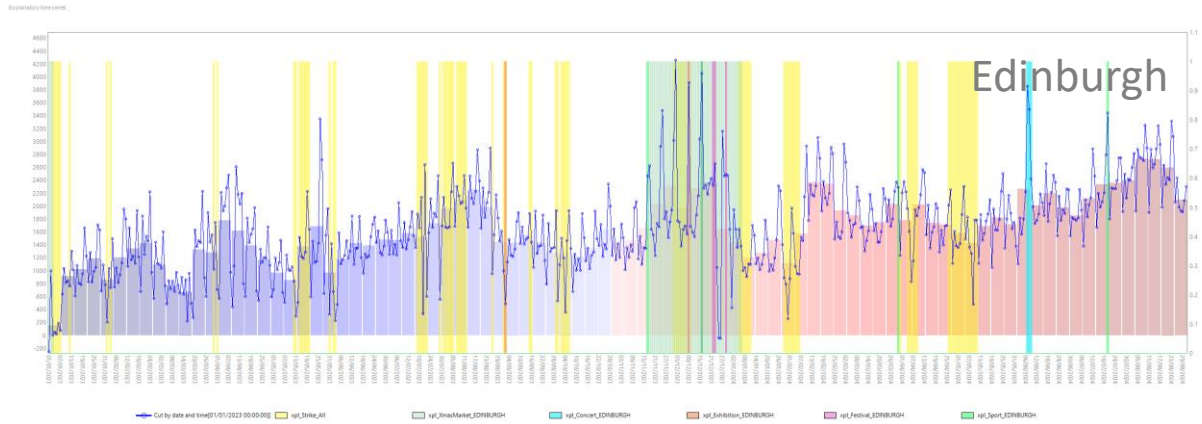
Strike (National)
Liverpool FC home game
Everton FC home game
Concert*
Horse Racing (York Racecourse)
Sport*

*at Anfield Stadium



Strike (National)
Xmas Market
Horse Racing (York Racecourse)





→ Various larger spikes are not explained by football or additional events
→ Developed automatic event / outlier identification in MLP residuals

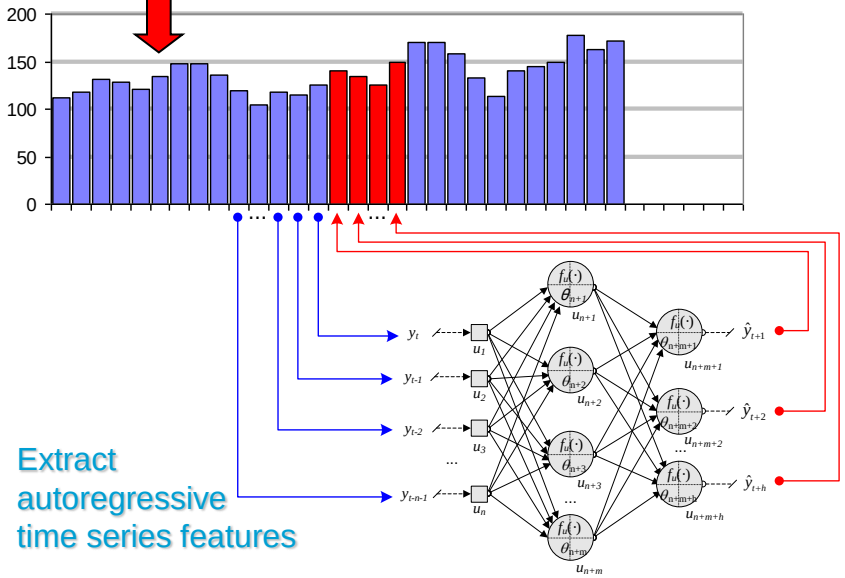
Only concerts festival and sport events at the biggest venue capture large spikes – but only few occurrences in last 2 yrs

Beiersdorf

1st to 2nd gen AI

1st Generation NeuralNet Models

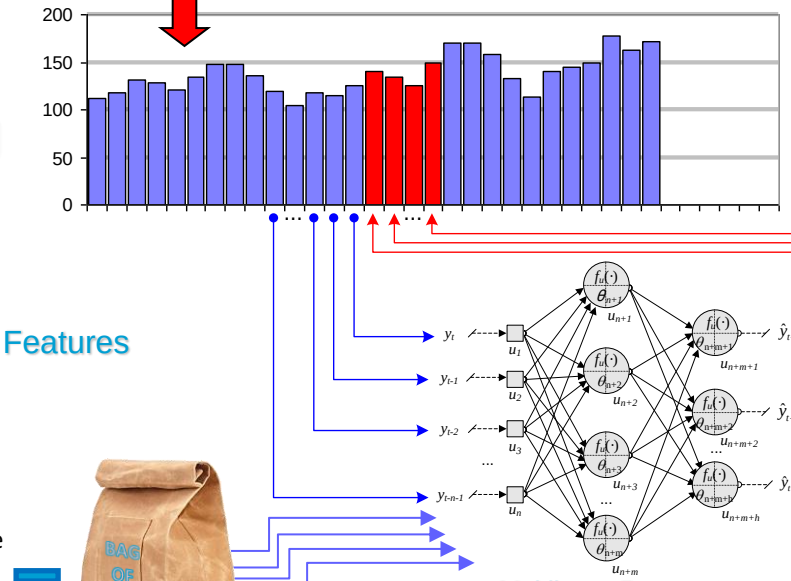
$$\hat{y}_{t+h} = f\left(x_t, x_{t-1}, \ldots, x_{t-n}\right) + \varepsilon_{t+h}$$



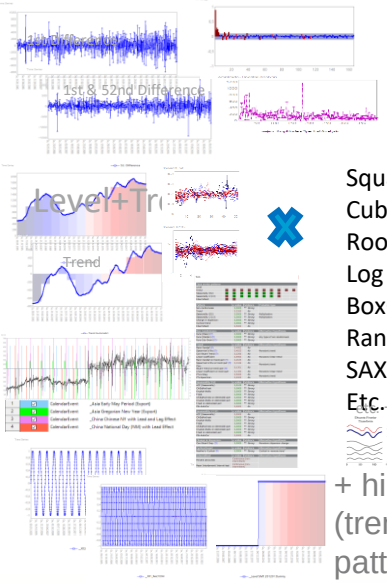
Extract autoregressive time series features

2nd Generation NeuralNet Models

$$\hat{y}_{t+h} = f\left(x_t, x_{t-1}, \ldots, x_{t-n}\right) + \varepsilon_{t+h}$$



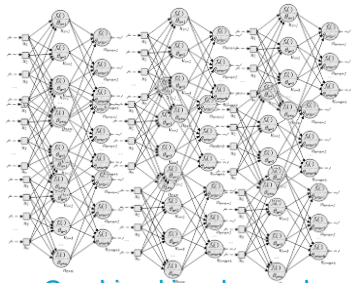
Extract multiple Time Series Features



Square
Cube
Root
Log
BoxCox
Rank
SAX
Etc.

+ permutate features
+ auto select features
+ auto select topology

Multilayer Percperton



Combined in a bagged ensemble of 10 MLP variants

+ hierarchical (trend/season) patterns of products, markets, channels

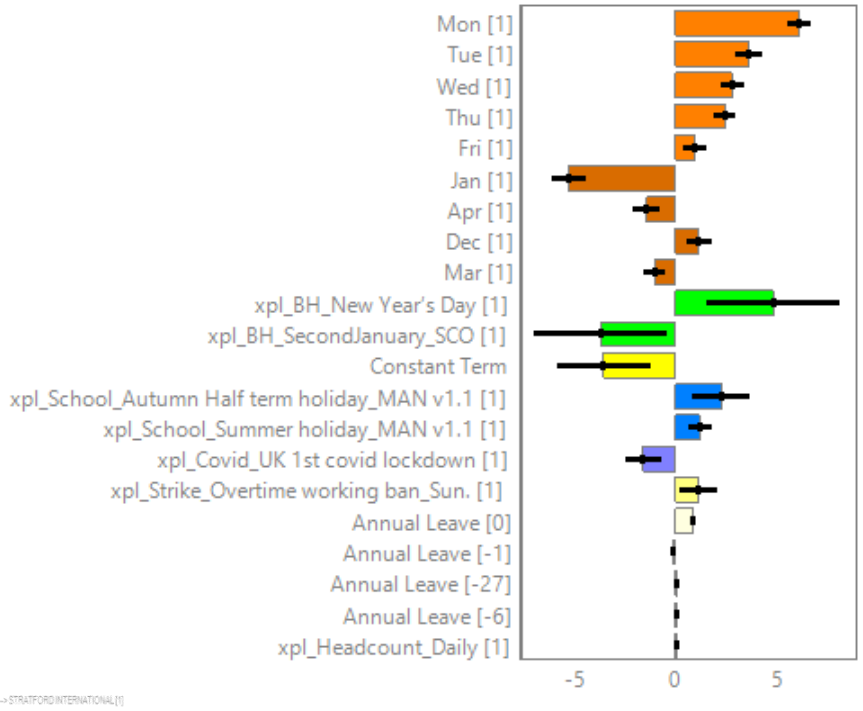
"Basic" Feature Engineering

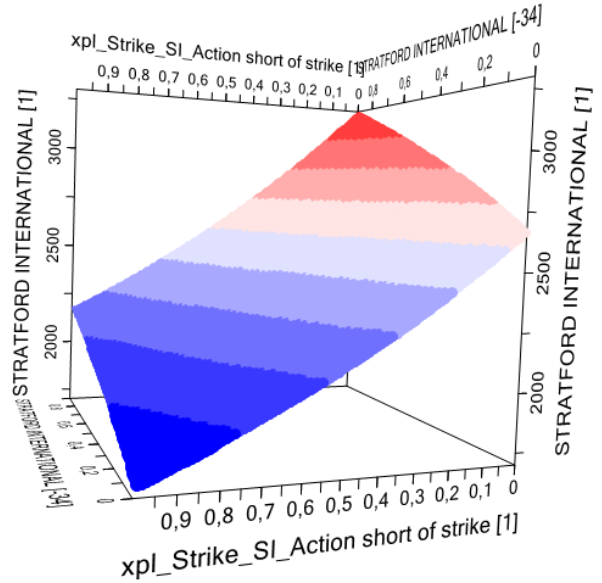
1. Create "Lag Features" y_{t-1}, y_{t-2}, …, y_{t-p}
2. Create Dummy features from time-stamps
   - Minutes elapsed for the day, Hour of day
   - Business hours or not, Weekend or not
   - Season of the year, Business quarter of the year.
   - Daylight savings or not, Leap year or not.
   - Public holiday or not, …

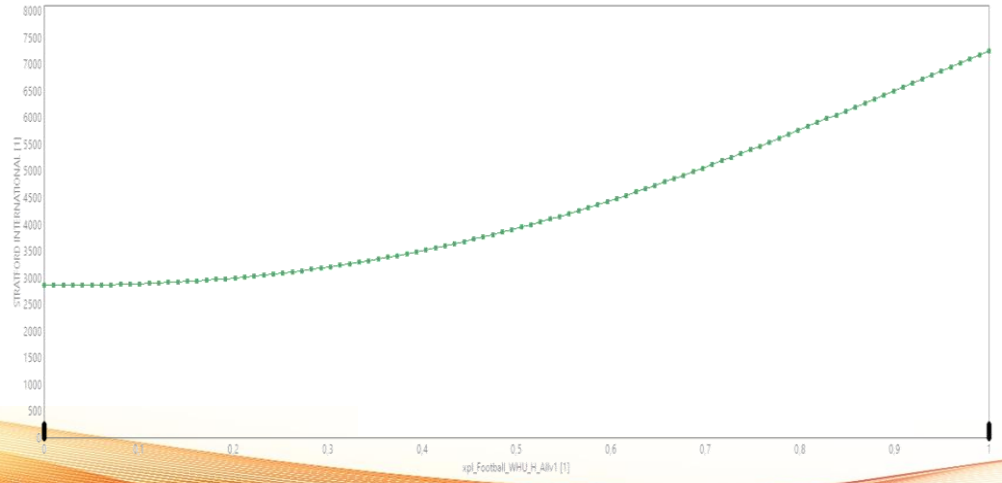
   (beware: data spillage for exogeneous vars!)

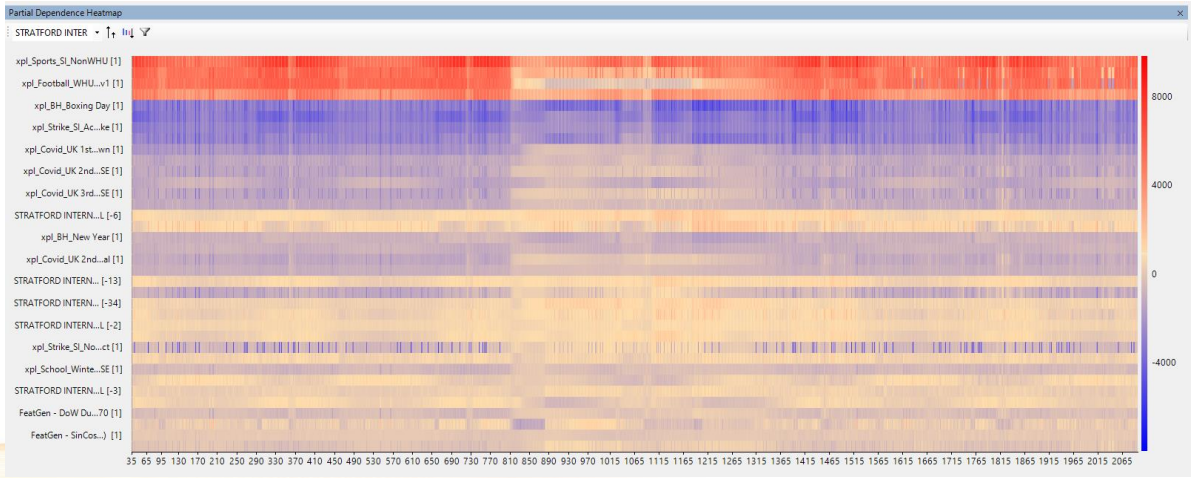
→ Enhance AUTO feature engineering of AI, not invent new AI!

Explainability Analysis









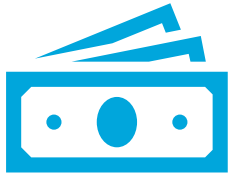
❶ revenue forecasting benefits

4 >> 2 days for go-live

all forecasts live in pilot

78% event accuracy

industry std: 62% +25%



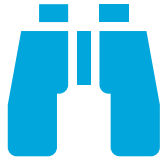
+ £1.6mio revenue pa

Σ at only 9 stations inbound journeys!

→ x75TPE/ 178 SE
x2500 total UK

new insights in daily data

armed forces↑ races ↑↑



Foresight 6-52 weeks

seasonality predictable

Free-up expert time

empower & automate

❶ revenue forecasting
extended to more stations