





## Predicting queues under uncertainty

50% Average percentage of a visitor's day spent in waiting lines

Proportion of French travellers reporting waiting time as a systemic friction in amusement parks

30' Average time spent in queues for each headliner attraction at Euro Park

- Revenue leakage from non-monetized queue time
- Capacity misallocation
- Decreased visitor satisfaction
- Incomplete guest experience

#### **CONTEXT & OBJECTIVES**

#### Success KPIs:

**Model**: RMSE between predicted waiting time and real time.

#### **Business:**

- Minutes saved per guest
- Extra rides per guest
- € spend per hour uplift
- NPS & complaints
- Downtime minutes.

# Turning raw data into model ready features

FEATURE ENGINEERING

### Creating new pertinent features from raw metrics

#### FEATURE ENGINEERING

Business driver	Observable signal	Engineered features	Expected outcome on waiting time +2h
Guest demand cycles	Hour, day-of- week, month	sin/cos of hour, day, month weekend, opening peak, lunch, dinner, closing peak	Peaks in affluence at opening, lunch and dinner. Higher number of visitors on the weekends
System pressure	All rides current waits	park-wide capacity, mean, median, std of waiting time, ride shares of capacity	High mean / std : congestion persists High rank per ride : risk of spillover or future congestion
Operational constraints	Capacity, downtime	Capacity, downtime flag	Low capacity, recent downtime : forecasts longer future waits
Exogenous shocks	Weather, events	Rain, snow, time to parade 1, time to night show. Temp < 10°C, wind > 8mph	Rain, wind and snow can suppress outdoor rides Pre-parade surges







- Predictions are made in 5-minute intervals, with few observations between 85 and 155 minutes.
- The variable is discrete but ordered and nearly continuous,
   making it naturally well-suited for regression.
- XGBoost provides greater flexibility than a strict classification into fixed categories.
- The model remains robust despite the limited data for longer durations and reduces the risk of overfitting.
- It combines accuracy and stability, ensuring reliable predictions even for rare values.

## 8.81 mins

Average precision on the model's waiting time 2h predictions



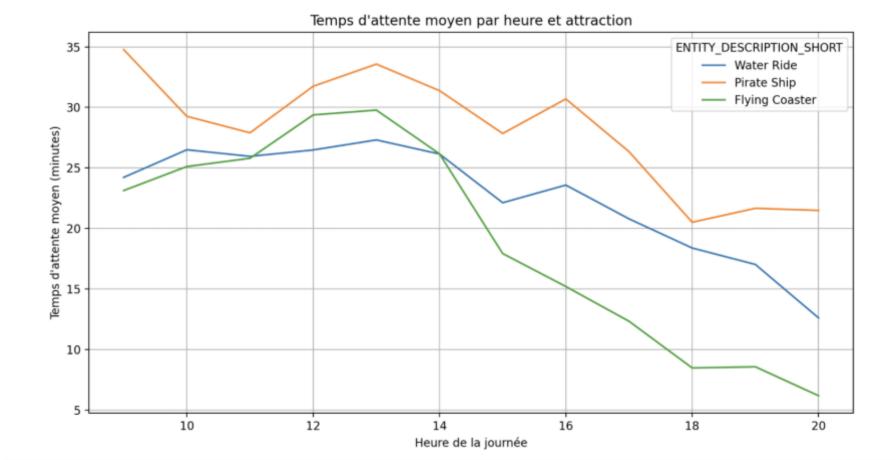
## Optimizing visitor flow – the next steps

OUR SOLUTION TO CONGESTION ENHANCED BY MACHINE LEARNING: FLOW INDICATION PANELS

Enhancing customer experience and focus the park teams on the crowd



Select the attractions you want to ride within the day > receive an all-day guidance to enhance your journey through the park and reduce your waiting time



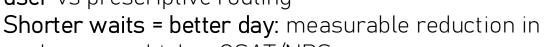
## Prospected impact and business perspectives

#### Prospected impact :

- 12 M guests per year
- Average wait per guest of 200 mins
- 10‰ reduction in waiting time (-20mins / guest)
- 4 M waiting hours saved
- Average 12 mins per ride







peak queues, higher CSAT/NPS.

Personal: recommendations by ride, time, weather

Personal: recommendations by ride, time, weather Fairness & flow: balance loads without penalizing any group

Seamless by design (existing app, signage, and ops dashboards)

Low incremental cost: reuses current data and app



- Time  $\rightarrow$  + spend: less queuing translates to more F&B/retail and extra experiences.

**Trust through accuracy:** posted vs. actual waits within a ±30% band.



## From endless lines to seamless journeys

DEPLOYMENT ROADMAP



Pilot test: deploy queue prediction in 1–2 highdemand attractions

m + 0 m + 1



**Measure KPIs:** minutes saved, rides per guest

m + 4



Integrate within app: push notifications + flow guidance



Scale park-wide if results confirm