



## The Passenger Experience Gap

### **Punctuality**

### **Development in the year under review**

			× iii
PUNCTUALITY / %	2024	2023	2022
DB Group (rail) in Germany	89.4	90.1	90.9
DB rail passenger transport in Germany	89.5	90.3	91.0
DB Long-Distance	62.5	64.0	65.2
DB Regional <sup>1)</sup>	90.7	91.4	92.2
DB Cargo (Germany)	68.0	70.5	66.1
DB Regional (bus)	85.9	85.2	86.0
DB Cargo	68.2	69.7	66.3
Punctuality (whole journey) (DB Long-Distance)	67.4	68.9	69.3

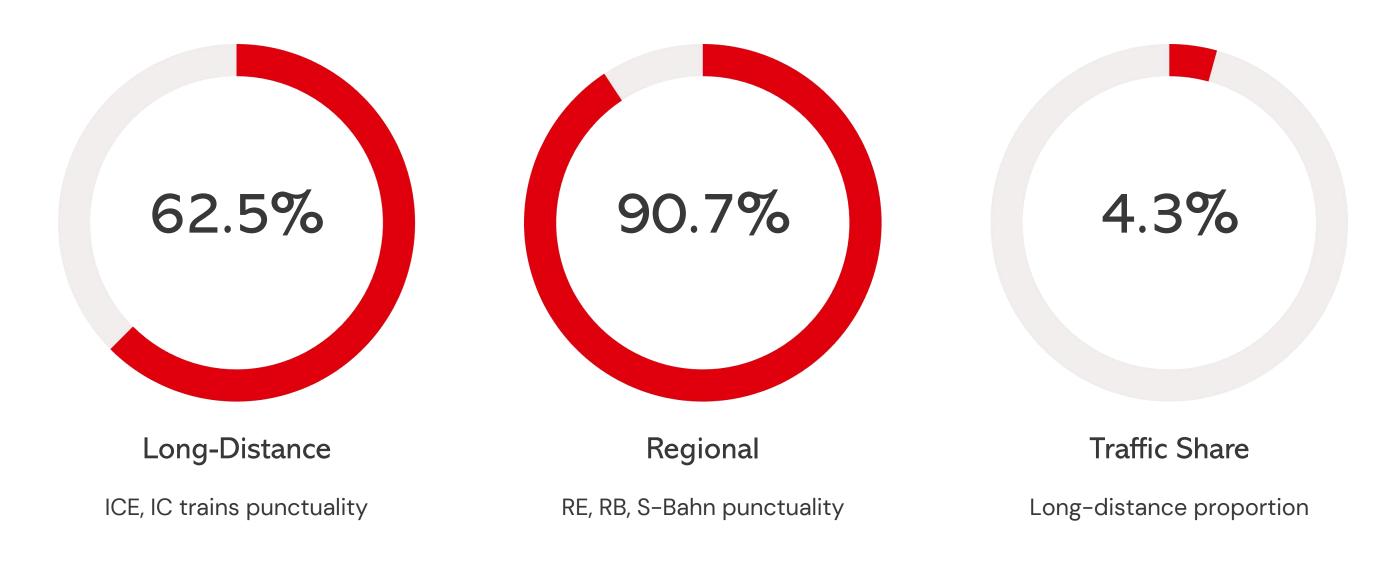
89.5%

Official Rate

DB's reported punctuality

Official statistics told a different story than passenger reality.

## The Statistical Illusion



Regional trains' high punctuality statistically "dilutes" poor long-distance performance, masking severity of delays.

## RESEARCH MISSION

Reassess DB's reporting methodology and build a realistic, data-driven delay prediction model that exposes structural biases in official statistics.



# Methodological Bias #1 Overly Lenient Definition

#### **Punctuality**

Share of on-time stops in relation to all stops along and at the end of lines in Germany. A stop is considered operationally punctual if the scheduled arrival time is exceeded by less than six minutes in passenger transport or by less than 16 minutes in freight transport. At DB Regional Rail, punctuality has been reported since 2024 on a third-weighted basis between S-Bahn (metro) alternating current, S-Bahn (metro) direct current and DB Regional Rail without S-Bahn (metro). At DB Regional Road, buses that leave more than one minute early have also been counted as unpunctual with retroactive effect since 2020. For the arrival time punctuality of passengers, see punctuality (whole journey).

"Züge gelten als pünktlich, wenn sie mit weniger als 6 Minuten Verspätung ankommen."

Trains arriving within 5 minutes 59 seconds classified as "on time"

France SNCF

5 minutes

Japan JR

1 minute

Deutsche Bahn

6 minutes

## The Passenger Perspective

1 2 3

1-2 Minute Delay Causes Anxiety Erodes Trust

Disrupts tight transfers Uncertainty compounds System reliability questioned

Six-minute tolerance fails to reflect actual traveler experience and obscures network inefficiencies.

## Our Stricter Standard

## 1min

### **Delay Threshold**

Trains delayed if ≥1 minute late

Enhance analysis sensitivity

## Purpose

- Capture micro-level deviations
- Reveal systemic inefficiencies
- Reflect passenger-centered reality

# Methodological Bias #2 Exclusion of Cancelled Services

### Ersatzverkehr

Substitute bus services excluded from statistics

### Ausfälle

Cancelled trains removed from dataset

### Our Approach

Cancellations = extreme delays, included in analysis

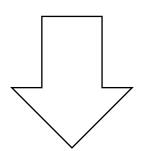
## Methodological Bias #3

Oversimplified Classification

DB's System

- Long-distance (ICE, IC)
- Regional (RE, RB, S-Bahn)

S-Bahn's high punctuality artificially inflates regional average



### Our Three-Tier System

Long-Distance	ICE, IC, EC, ECE, RJ, RJX, TGV, FLX, FEX, D, EN, NJ, UEX, ES, EST, WB					
Regional	RE, RB, IRE, ALX RE, BRB RE, WFB RE, NWB, NWB RS,					
	VIA, ME, MET, HLB RE, MEX, MEX a, MEX c, R, HBX, SVG					
Urban	S, S X, SE					



## Data Collection Challenge

### The Problem

DB doesn't publicly release detailed delay data. Real-time boards refresh every few seconds, showing only short-term records.

### The Solution

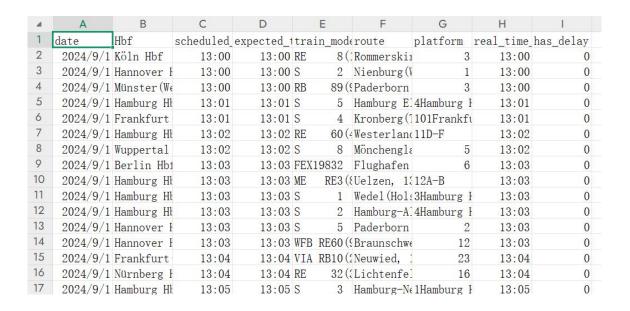
Third-party Kaggle dataset from independent developers' automated web scraping of DB's real-time boards.

### Coverage

July 20–25, 2024 and September 1–2, 2024 across 20 major German cities.



### **Trains and Delays Deutsche Bahn**



## Data Processing: remaining useful info

departure_city(H -	∢route_cleaned	train_model_cleaned	▼ scheduled_time ▼	arrival_hour_bucket	<b>▼</b> e	expected_time -	expected_delay •	re	eal_time -	has_delc -	real_delay_min	causes -
Berlin	Baruth (Mark)	RE	13:11		13	13:14		3	13:14	1		0
Duisburg	K?ln/Bonn Flughafen	RE	13:11		13	13:14		3	13:14	1		0
Hannover	Norddeich Mole	IC	13:13		13	13:14		1	13:14	1		0
Bonn	Walporzheim	RB	13:13		13	13:14		1	13:14	1		0
Hamburg	Stuttgart Hbf	ICE	13:14		13	13:14		0	13:31	1	1	7 Grund: V
Hannover	Koblenz Hbf	ICE	13:14		13	13:14		0	13:34	1	2	O Grund: T
Duisburg	Dresden Hbf	FLX	13:14		13	13:14		0	13:35	1		1 Grund: V
Düsseldorf	Kaarster See	S	13:14		13	13:14		0 F	ahrt f?ll	1		
Hannover	Koblenz Hbf	ICE	13:14		13	13:14		0 F	ahrt f?l	1		
Köln	Berlin Ostbahnhof	ICE	13:11		13	13:15		4	13:15	1		0
Münich	Herrsching	S	13:13		13	13:15		2	13:15	1		0
Leipzig	Hannover Hbf	IC	13:14		13	13:15		1	13:15	1		O Grund: V
Nürnberg	Regensburg Hbf	RE	13:15		13	13:15		0	13:24	1		9 Grund: W
Duisburg	Arnhem Centraal	VIA RE	13:15		13	13:15		0	13:23	1		8

- Removing Numbers/Words
- Splitting Complex Phrases
- Create hour buckets with scheduled\_time
- Calculating "real\_delay\_minutes" = "real\_time\_due\_to\_delay" "expected\_time"

## Data Processing for modelling

### Raw Dataset

30+ train categories including bus services

### Reclassification

Three operational categories by service characteristics

### Cleaning

Removed all Ersatzverkehr bus records

### **Final Attributes**

Date, stations, category, time, punctuality status

## Delay Definition

Train classified as **delayed** if arrival delay exceeded **one minute** 

Cancelled trains for any reason assigned delay status

Binary variable: has\_delay

- 0 = on-time
- 1 = delayed

0/1

**Binary Classification** 

## Final Data for Modeling

1	date Hbf	▼ arrive_station	▼ train_category	▼ depart_hour_bucket ▼ has_delay	•
2	2024/7/20 Hannover Hbf	Wien Hbf	long-distance	20	1
3	2024/7/25 Nürnberg Hbf	München Hbf	long-distance	8	1
4	2024/7/23 Hamburg Hbf	Karlsruhe Hbf	long-distance	11	1
5	2024/7/22 Berlin Hbf	München Hbf	long-distance	12	0
6	2024/9/2 Berlin Hbf	Wünsdorf-Waldstadt	long-distance	8	1
7	2024/7/20 Hamburg Hbf	Leipzig Hbf	long-distance	9	0
8	2024/9/1 Berlin Hbf	München Hbf	long-distance	17	0
9	2024/7/23 Hannover Hbf	München Hbf	long-distance	15	1
10	2024/7/21 Nürnberg Hbf	Karlsruhe Hbf	long-distance	20	0
11	2024/7/20 Bremen Hbf	Norddeich	long-distance	8	0
12	2024/7/21 Hannover Hbf	Hamburg Hbf	long-distance	11	1
13	2024/9/2 Dortmund Hbf	Hamburg-Altona	long-distance	8	1
14	2024/7/25 Stuttgart Hbf	Karlsruhe Hbf	long-distance	12	0
15	2024/7/24 Dortmund Hbf	Münster (Westf) Hbf	long-distance	7	1
16	2024/9/2 Leipzig Hbf	Berlin Hbf	long-distance	8	0
17	2024/9/2 Stuttgart Hbf	Nürnberg Hbf	long-distance	7	0
18	2024/7/24 Berlin Hbf	Aachen Hbf	long-distance	14	1
19	2024/7/20 Hannover Hbf	Berlin Ostbahnhof	long-distance	17	0
20	2024/7/21 Köln Hbf	Berlin Ostbahnhof	long-distance	1	1
21	2024/7/25 Bielefeld Hbf	Berlin Ostbahnhof	long-distance	9	1
22	2024/7/20 Nürnberg Hbf	München Hbf	long-distance	7	0
23	2024/9/1 Duisburg Hbf	Frankfurt (Main) Hbf	long-distance	22	1
24	2024/7/20 Hamburg Hbf	Lübeck Hbf	long-distance	8	1
25	2024/7/23 Hannover Hbf	Wien Hbf	long-distance	20	1
26	2024/7/24 Leipzig Hbf	Hannover Hbf	long-distance	8	1
27	2024/7/21 Köln Hbf	Amsterdam Centraal	long-distance	19	1
28	2024/7/20 Dresden Hbf	Praha hl.n.	long-distance	22	1
29	2024/7/20 Leipzig Hbf	Norddeich Mole	long-distance	22	1
30	2024/7/23 Hannover Hbf	Hamburg Hbf	long-distance	15	1



### **Preliminary Observation**

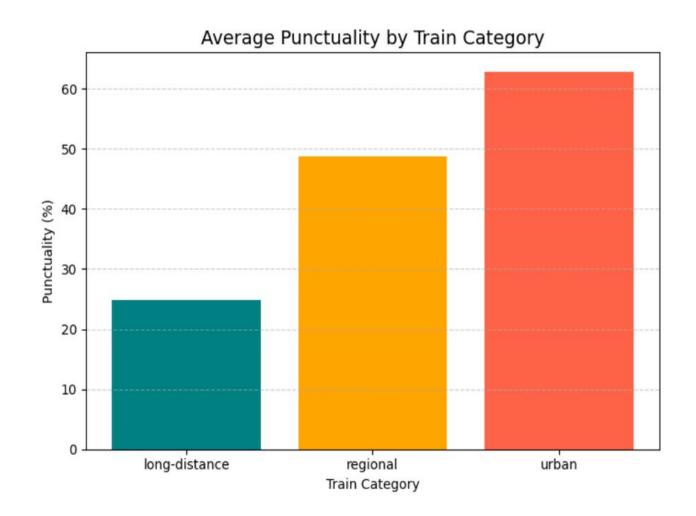
- The total average value of actual delay time was 4.6 minutes. Among the trains that experienced delays, the average delay duration increased to 8.84 minutes, with the maximum delay reaching over 400 minutes.
- Regarding the causes of delays, track changes (Gleisweckseln) accounted for 3.8%, delays caused by preceding trains represented 13.3%, construction work (Bauarbeiten) contributed 1.6%, and technical issues such as maintenance depot problems made up 7.31%. Among all delayed services, 1.3% were recorded as "Verkehrt" (wrong routing), and 5.9% were marked as "Fällt aus" (cancelled).

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2024/7/23 Berlin	Budapest-Nyugati		EC		18:43	18	18:43	0	1:35	1	412
2024/7/24 Berlin	Budapest-Nyugati		EC		18:43	18	18:43	0	1:37	1	414
2024/7/24 Berlin	Budapest-Nyugati		EC		18:43	18	18:43	0	1:40	1	417
2024/7/23 Dresden	Budapest-Nyugati		EC		16:50	16	16:50	0	23:48	1	418
50, 06											

## Punctuality by Common Train Model

Train Type	Delay Rate (%)	Average Delay (min)
S-Bahn	36.9	1.95
ICE	77.3	16.91
RE	57.1	6.69
IC	65.3	13.60
RB	45.4	3.74
EC	78.1	41.57

### Punctuality by Train Category

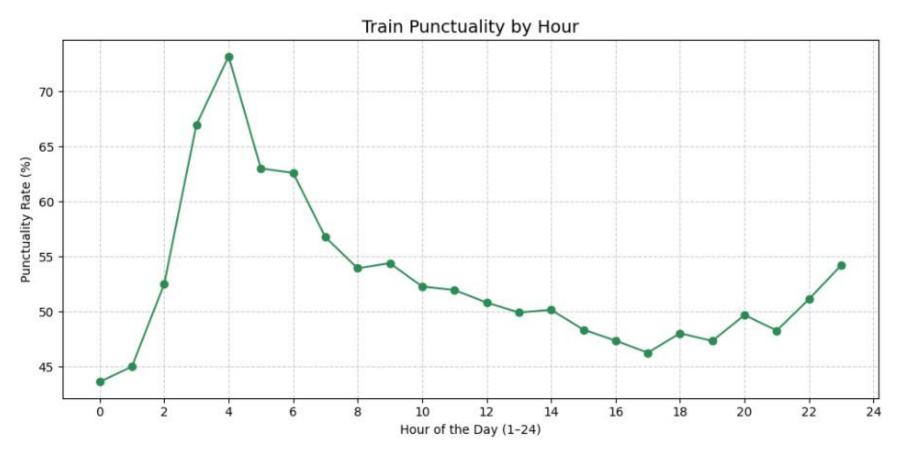


Long-distance trains achieved an on-time rate of only 24.84%, meaning roughly one in four arrived as scheduled. Regional trains reached 48.74%, showing moderate stability. Urban trains (S-Bahn) performed best at **62.90%,** reflecting the resilience of short-distance commuter operations.



## Temporal Patterns

## Inverted-U Throughout the Day



highest between 03:00-04:00 (67-74%),

relatively low between 15:00–21:00 (46–50%),

slightly recover in the late evening,

sink to the bottom at mid-night.

Traffic density and infrastructure load strongly affect on-time performance.

## Overall: Below 50%

Under stricter one-minute threshold, DB's actual punctuality substantially lower than official 89.5%



## Machine Learning Approach

### Data Split

Merged July and September samples

- 80% training
- 20% testing

Balanced distributions for robust generalization

### Four Models

- Logistic Regression
- Random Forest
- LightGBM
- XGBoost

## Model 1: Logistic Regression

### **Baseline Model**

$$logit(p) = ln \frac{p}{1-p} = \beta_0 + \beta_1(departure station) + \beta_2(arrival station) + \beta_3(train category) + \beta_4(departure hour)$$

$$p=rac{1}{1+e^{-(eta_0+\sum_ieta_ix_i)}}.$$

### Characteristics

- Linear model with interpretability
- OneHotEncoder for categorical variables
- Recall: 0.80 on-time, 0.75 delayed
- Stable, transparent baseline

77.4% 0.77

Accuracy

F1-Score

## Model 2: Random Forest

## Advantage

Captures nonlinear relationships

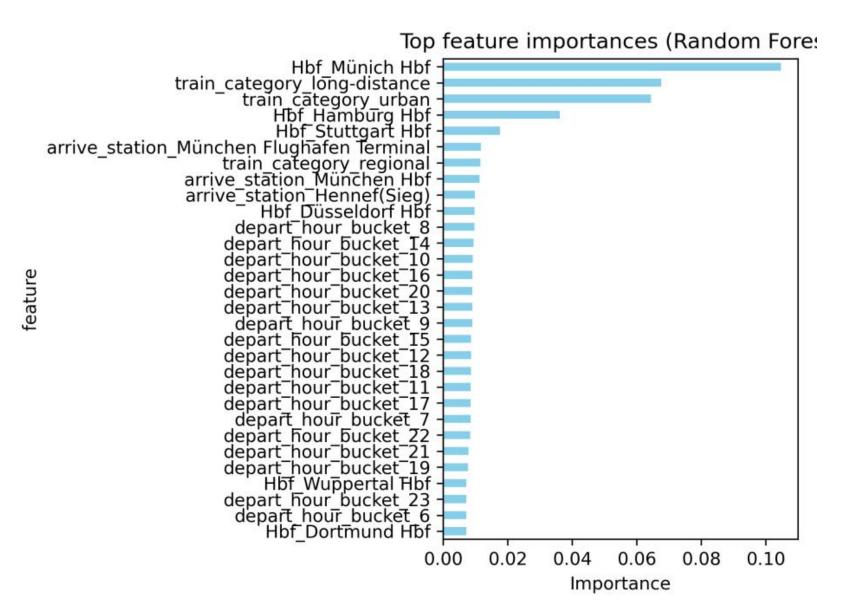
Better on borderline cases

78.2% 0.78

Accuracy

F1-Score

### Feature Importance Revealed



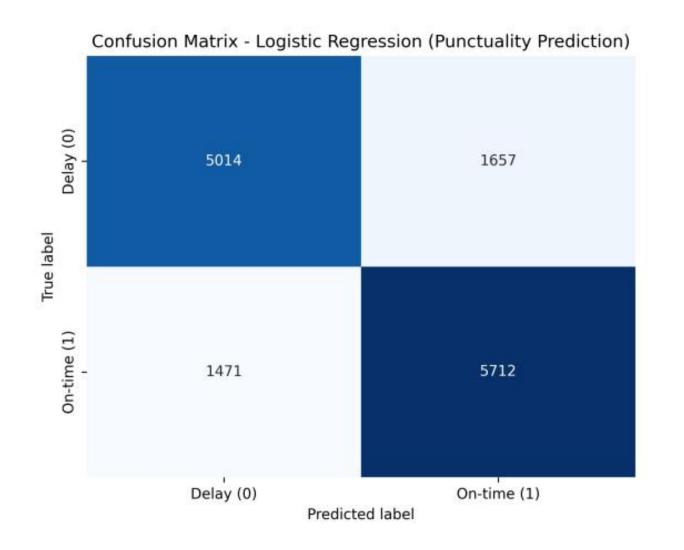
Departure and arrival stations

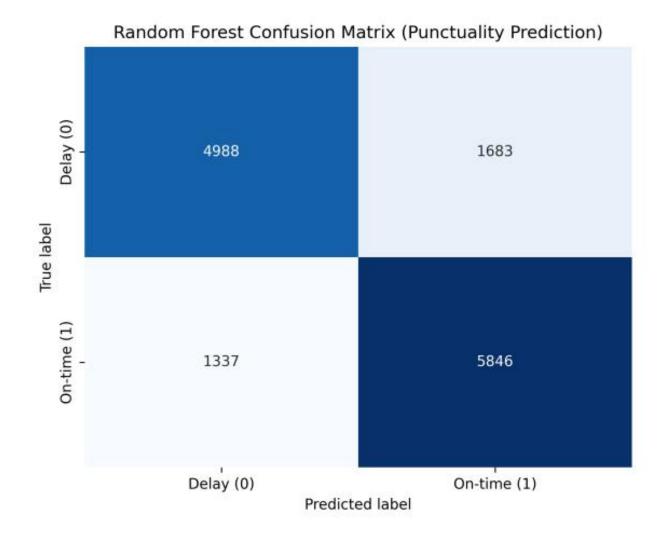
most influential.

Major hubs

-Munich, Hamburg, Stuttgart-

dominate rankings.





### Improvement

More on-time trains identified (5846 vs 5712)

Reduced false negatives (1337 vs 1471)

# Model 3 & 4: Gradient Boosting LightGBM and XGBoost

### LightGBM

Accuracy: 0.7925

F1: 0.8019

AUC: 0.8727

Best performance

### **XGBoost**

Accuracy: 0.7864

F1: 0.7969

AUC: 0.8689

Slightly lower but more stable

## Model Comparison: ROC Curves

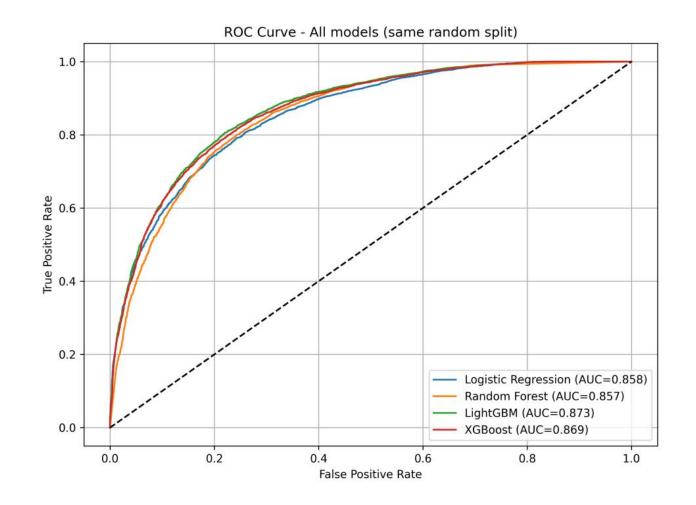
77-79%

**Accuracy Range** 

All four models

Similar overall performance indicates available features nearly exhaust dataset's explanatory power

Nonlinear models offer stronger flexibility but limited improvement without dynamic features



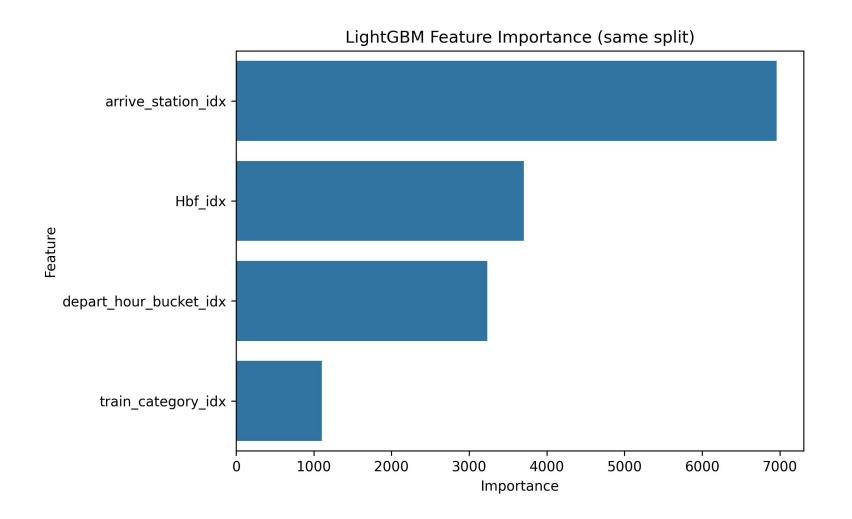
## Why LightGBM Wins

Histogram-Based Splits
Leaf-Wise Growth

Efficient handling of sparse data
Enhanced efficiency in high-dimensional spaces

Enhanced efficiency in high-dimensional relationships

## Key Finding: Nonlinear Interactions



### Key points:

- Punctuality is strongly influenced by nonlinear interactions
- •Departure—arrival station combinations contribute over 60% of total feature importance
- •Strong interactions among train type, departure time, and departure station

## Practical Implications

### For Travelers

### High-Risk Corridors

Journeys between Frankfurt
(Main), Munich(München),
Cologne(Köln) carry significantly
higher delay risk

### **Buffer Time**

Allow extra time for transfers on major hub routes

### **Timing Strategy**

Avoid peak hours (15:00–21:00) and holidays when possible

# Practical Implications For Deutsche Bahn



### **Critical Areas**

High-risk routes need capacity management priority



### **Scheduling Optimization**

Focus on densest traffic corridors



### **Operational Discipline**

Enhance reliability through systemic improvements



## Limitations

Feature Ceiling

Categorical variables (stations, types, time) mostly linear relationships. Limited room for improvement.

Missing Dynamics

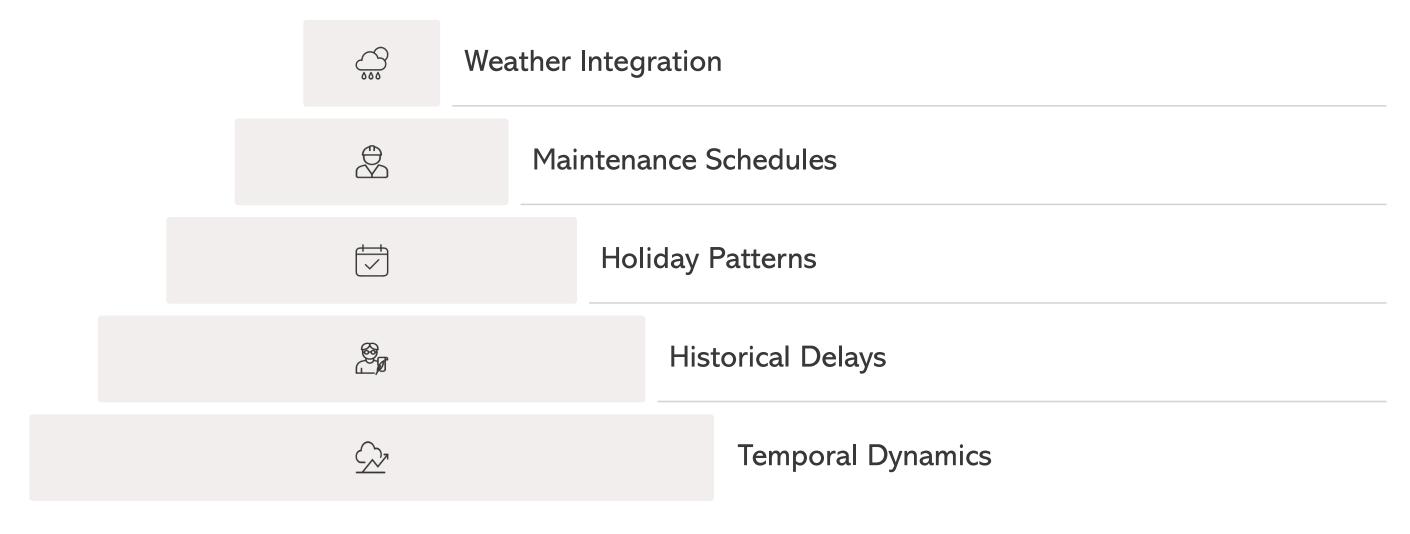
No weather, congestion, maintenance, or construction data etc in current dataset.

Time Scope

3

Only two time windows (July, September 2024). Seasonal patterns not captured.

## Future Research Directions



Expanding data scope will enable models to capture broader dynamics and achieve higher predictive precision.



### References

- 1. <a href="https://www.kaggle.com/datasets/santiagoravotti/trains-and-delays-deutsche-bahn?resource=download">https://www.kaggle.com/datasets/santiagoravotti/trains-and-delays-deutsche-bahn?resource=download</a>
- 2. <a href="https://ibir.deutschebahn.com/2024/en/combined-management-report/product-quality-and-digitalization/the-customer-is-at-the-center-of-our-actions/punctuality/?utm\_source=chatgpt.com">https://ibir.deutschebahn.com/2024/en/combined-management-report/product-quality-and-digitalization/the-customer-is-at-the-center-of-our-actions/punctuality/?utm\_source=chatgpt.com</a>
- 3.https://ibir.deutschebahn.com/2024/en/glossary/
- 4.https://github.com/FabreXUYY/Deutsche-Bahn-Delay