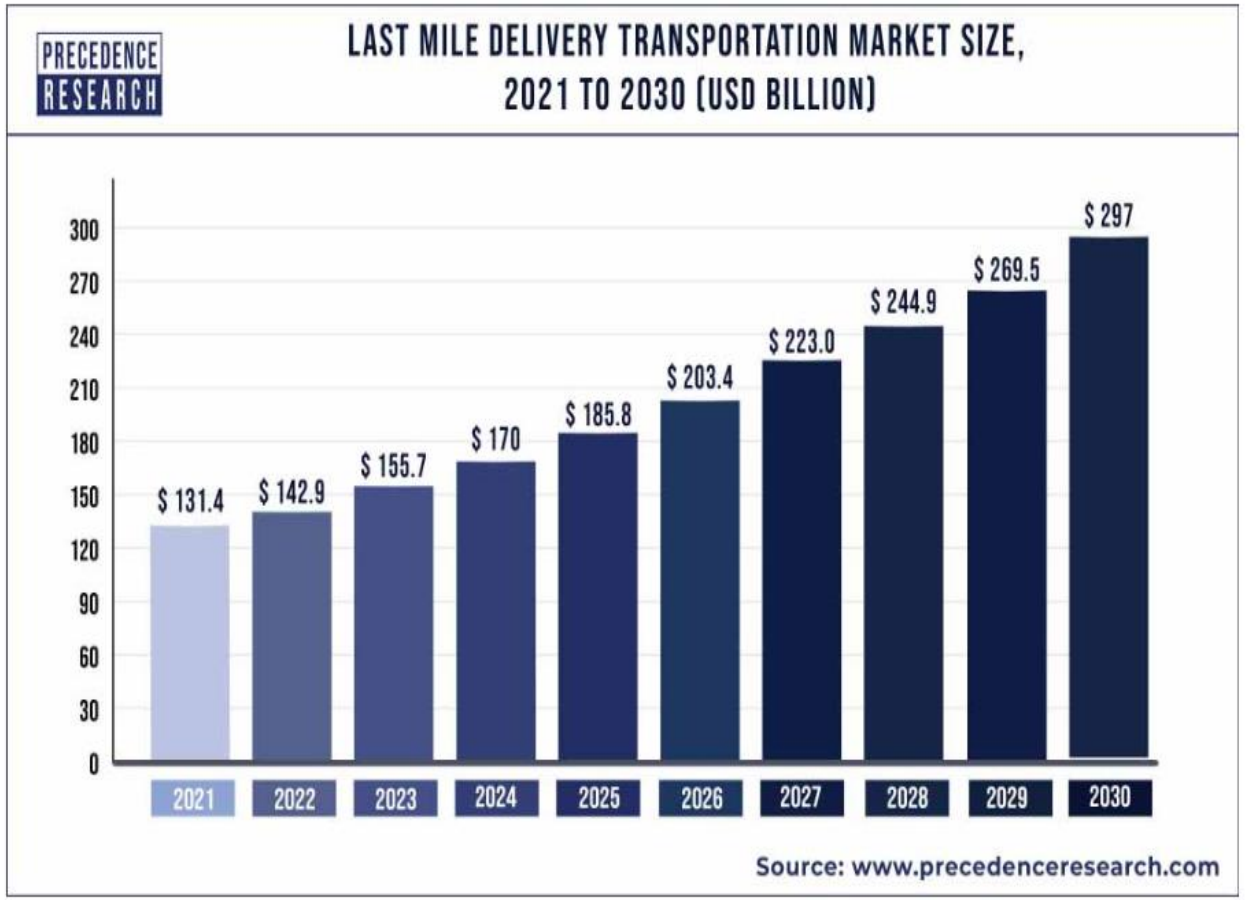
Rise in Last-Mile Delivery

Revolutionary era of rapid delivery to **our doorstep**

Online sales surged due to the COVID-19 pandemic, leading to a significant rise in e-commerce companies

E-commerce and retail delivery services heavily rely on the **Last-Mile delivery system**

The last-mile delivery industry is projected to grow at a **9.6% CAGR** (Compound Annual Growth Rate) from 2022 to 2030



Last-mile Delivery Driver

- **Frontline workers** in last-mile logistics
- Logistics companies provide their drivers with recommended optimized routes to complete their deliveries
- Frequently **deviations** from these suggested routes are observed **in actual delivery cases**
- Despite numerous research and improvements in last-mile delivery solutions employing various route optimization algo rithms,the practical application of these models is still **challengin g due to the influence of many real-world factors on the ground**

https://reliantcouriers.co.uk/large-items/

Delivery Driver Behaviour

- Dang Bao Le (2022) stated that experienced drivers have **implicit knowledge of local conditions** that is hard to quantify in optimization models, and **these factors all influence** how well a planned optimized route will be **executed on the real ground** [1].
- According to the study of Dai et al. (2016), drivers choose alternative routes for a particular route based on the variables such as **traffic conditions, weather, road maintenance, or even their own mood** [2].
- Srivatsa and Gajanand (2017) did empirical studies and found that **in non-congested settings**, drivers typically adhere to the planned route,while **in congested settings**, route-choice behaviour is more affected by factors such **as recurrent congestion (traffic flow)** and **non- recurrent congestion(sudden incidents)** [4] **.**

Research Objective

Analyse and predict the **driver's behaviour** in case of compliance or deviation with
the suggested optimized routes **in the last-mile delivery**

Identify patterns and trends in driver behaviour through **data visualization**

Develop **quantitative metric** to measure on compliance

Employ and formulate **modelling approaches** to predict binary decision on compliance

Quantify and compare the **effects of the relevant factors** that influence drivers' decisions regarding compliance

Actual Last-mile Delivery Dataset

- We used **historical data** from actual driving routes within the last-mile delivery plans of **a large e-commerce parcel delivery company.**
- The company offers effective **last-mile delivery solutions** to its retailer clients, enabling them to provide delivery services to their customers.
- The dataset consists of **daily last-mile delivery records** of this company **for the year 2022.**
- These records pertain to the delivery activities **of their professional drivers** operating from two of their **major warehouses located in Lisbon and Barcelona**.

Raw Dataset

Shipments	DataType	Data Description
shipment_id	Integer	unique shipment identifier
order_id	Integer	unique retailer order id (there can be multiple shipments for the same order_id)
route_id	Integer	Unique id of route where the shipment was planned to be performed
latitude_delivery	Float	latitude of delivery location
longitude_delivery	Float	longitude of delivery location
timewindow_start	Datetime	start of time slot for delivery in format DD/MM/YYYY HH:MM:SS
timewindow_end	Datetime	end of time slot for delivery in format DD/MM/YYYY HH:MM:SS
latitude_attempted_time	Float	estimated driver's latitude at the time of the attempt, if any
longitude_attempted_time	Float	estimated driver longitude at the time of the attempt, if any
company_id	Integer	unique identifier of the retailer who placed the order
Attempted	Bool	1 if attempted, 0 otherwise
Delivered	Bool	1 if successfully delivered, 0 otherwise
Country	String	country name
City	String	city name
driver_id	Integer	unique driver identifier
scheduled_sort_order	Integer	planned route position within the sequence of deliveries represented by ordered numbers(1,2,3,...)
attempted_time	Datetime	time at which delivery was attempted if attempted in format DD/MM/YYYY HH:MM:

Data Cleaning,Filtering and Imputation

- Dropped the rows corresponding to **the missing values** in 'route_id' , 'scheduled_sort_order', or 'attempted_time'
- Box plots to **identify and remove outliers** in latitude and longitude values
- Used KNN(K-Nearest Neighbour) technique **to impute the missing data** for ‘latitude_attempted_time’ and ‘longitude_attempted_time’
- **Removed duplicates** with identical delivery locations and attempted times
- Refined the raw data into a precise format for in-depth analysis resulting in approximately **600,000 delivery orders from around 10,000 distinct routes** for each warehouse

Feature Engineering

- 'tw_month' and 'tw_duration‘ were generated from the 'timewindow_start' and 'timewindow_end' columns
- **Haversine formula (1)** to calculate the distance between the **consecutive stops in the routes**,

$$a = sin^2\left(\frac{\Delta lat}{2}\right) + cos\, lat1 \cdot cos\, lat2 \cdot sin^2\left(\frac{\Delta lon}{2}\right)$$

$$c = 2 \cdot tan^{-1}\left(\frac{\sqrt{(a)}}{\sqrt{1-a}}\right)$$

$$distance = R\,.c \qquad (1)$$

- The **total planned distance** for each route_id was then **determined by adding these consecutive distances**

Defining Compliance Metric

- Defined **a new metric called 'stop_compliance'** which takes binary values (0 and 1) to indicate whether a driver visits **a specific delivery stop in the suggested sequence order in a route or not**
- Created **a new column named 'actual_order'** assigning chronological numbers(1,2,3,…) **to represent the actual delivery sequence** by sorting the 'attempted_time' column in ascending time within each route
- Compared the driver's actual delivery sequence i.e. ‘actual_order’ with the suggested delivery sequence i.e ‘scheduled_sort_order’ **to determine the compliance for each delivery stop in the routes**

Defining Compliance Metric

The stop_compliance variable denoted by C_{ri} **evaluates pairwise stop compliances** in route subsequence using the following formula,

$$C_{ri} = 1 \quad when \{ \left|(i-1)_{r(i-1)} - (i)_{ri}\right| - \left|(j-1)_{r(i-1)} - (j)_{ri}\right| = 0$$

$$or,$$

$$\left|(i-1)_{r(i-1)} - (i)_{ri}\right| - \left|(j+1)_{r(i-1)} - (j)_{ri}\right| = 0$$

$$or,$$

$$\left|(i+1)_{r(i+1)} - (i)_{ri}\right| - \left|(j+1)_{r(i+1)} - (j)_{ri}\right| = 0$$

$$or,$$

$$\left|(i+1)_{r(i+1)} - (i)_{ri}\right| - \left|(j-1)_{r(i+1)} - (j)_{ri}\right| = 0 \}$$

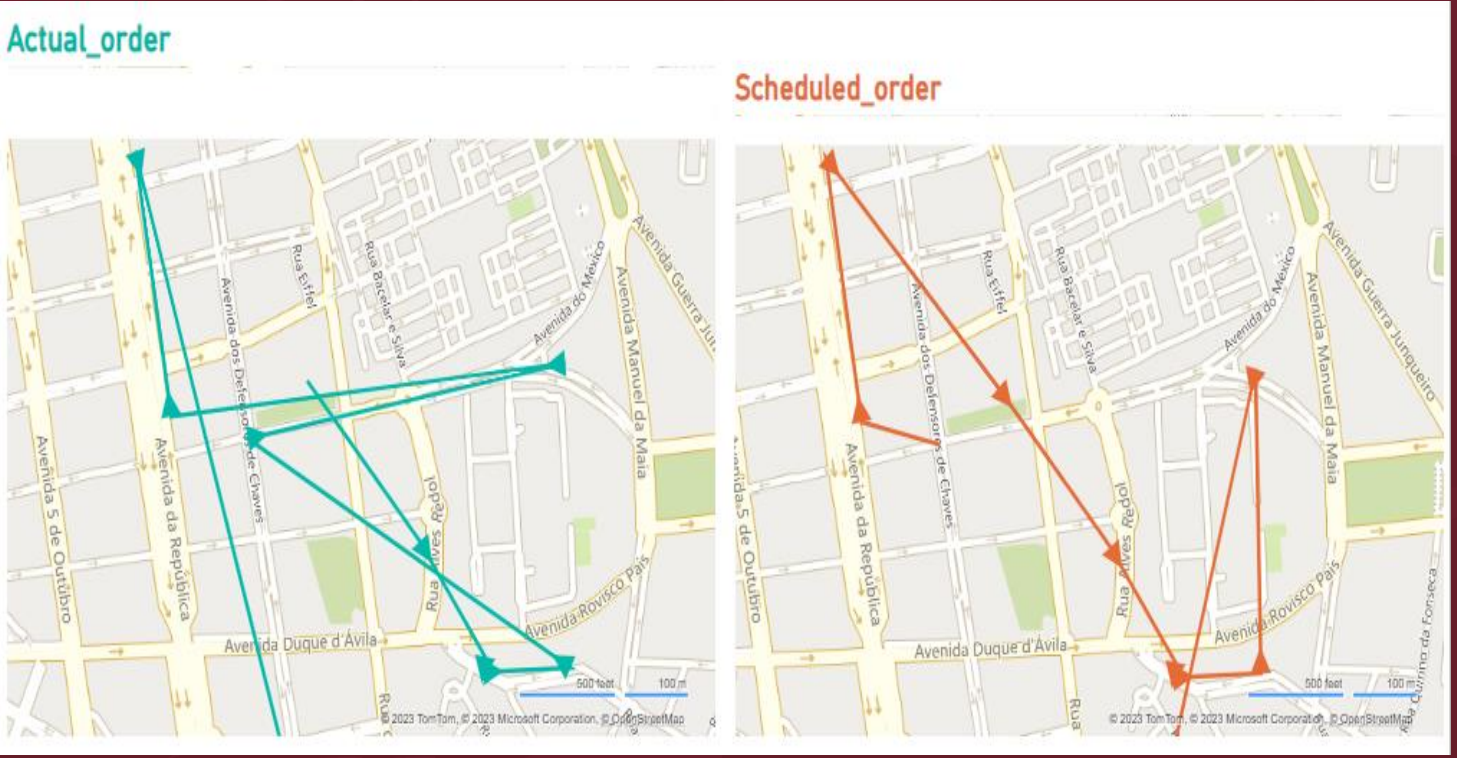
$$C_{ri} = 0, \; Otherwise \qquad (2)$$

The formula (2) assigned a **value of 1** to the corresponding 'stop_compliance' column for **two consecutive pair of stops** if for any route instance r, there are two adjacent suggested stops denoted as j_r and $(j+1)_r$ or $(j-1)_r$ and j_r, such that the driver **follows these adjacent stops** regardless of the direction to deliver products,by comparing with actual order index denoted as i_r and $(i+1)_r$ or i_r and $(i-1)_r$. If not, a **value of 0** is assigned.

Compliance from Forward Direction

The compliance metric evaluates whether a driver adheres to two adjacent scheduled orders, **irrespective of the direction** they are following—be it from **the front or the back**.

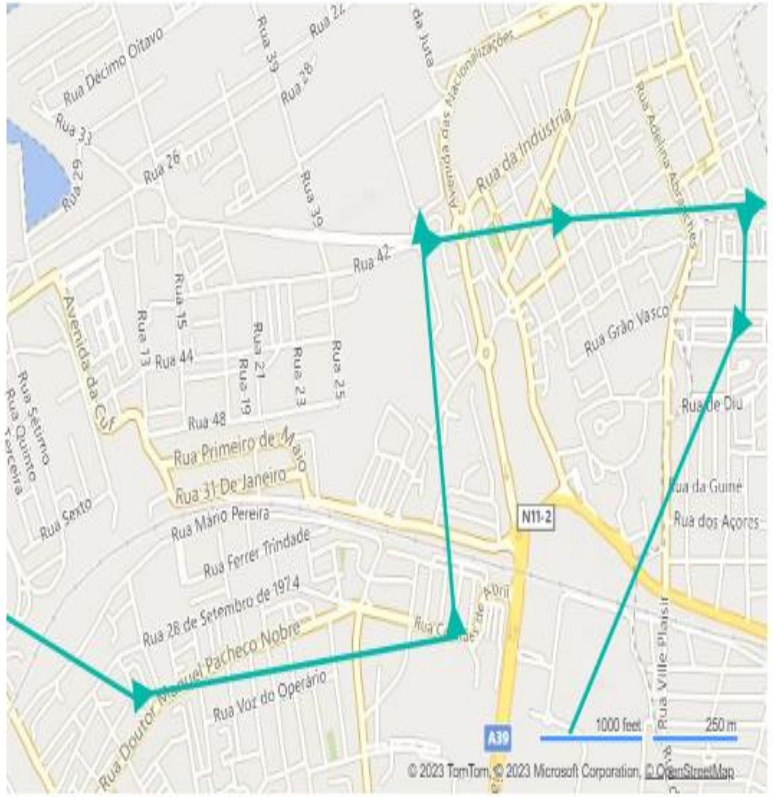
	route_id	order_id	scheduled_sort_order	actual_order	stop_compliance
58827	996545.0	448819	69.0	47	1
58828	996545.0	294344	70.0	48	1
58829	996545.0	477874	71.0	49	1
58830	996545.0	400604	72.0	50	1
58831	996545.0	65009	73.0	51	1
58832	996545.0	595385	48.0	52	0
58833	996545.0	560149	74.0	53	0
58834	996545.0	341143	49.0	54	1
58835	996545.0	583352	50.0	55	1



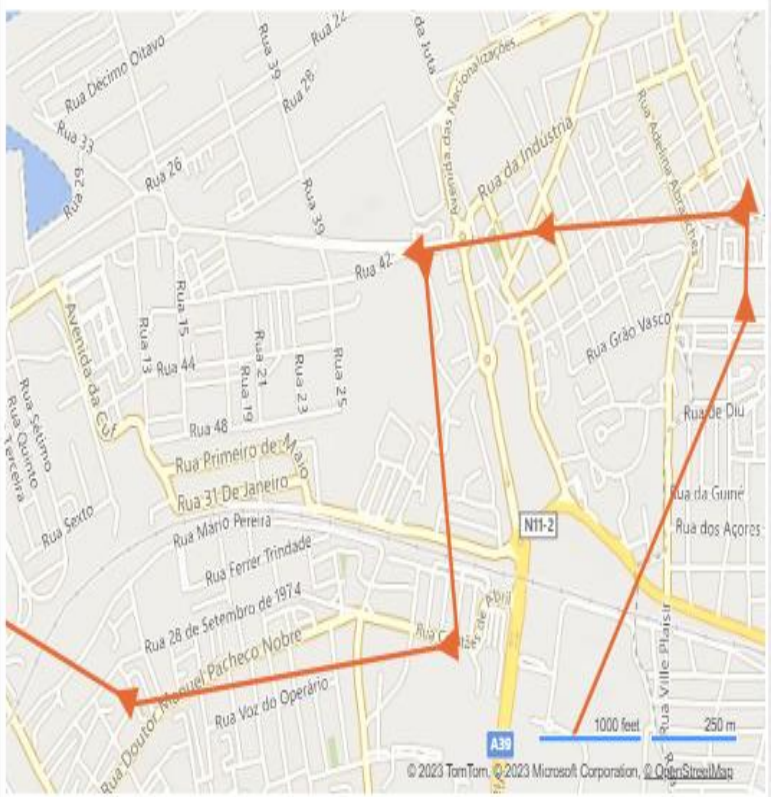
Compliance from Backward Direction

	route_id	order_id	scheduled_sort_order	actual_order	stop_compliance
58877	997607.0	428330	47.0	38	1
58878	997607.0	279218	46.0	39	1
58879	997607.0	611269	45.0	40	1
58880	997607.0	352493	44.0	41	1
58881	997607.0	589681	43.0	42	1
58882	997607.0	503289	42.0	43	1
58883	997607.0	309688	41.0	44	1
58884	997607.0	338438	40.0	45	1
58885	997607.0	612300	39.0	46	1
58886	997607.0	334266	38.0	47	1

Actual_order



Scheduled_order



Additional Features on Demographic, Weather and Urban Morphology

Explanatory Features

Route Level Features

- Time-window duration
- Stop count
- Company count
- Municipality count
- Total planned distance

Municipality Level Features

- Population Density (km^2)
- Number of trunk roads
- Intersection_count
- Average speed limit
- Street length average
- Average daily temperature
- Average daily precipitation

Route Category

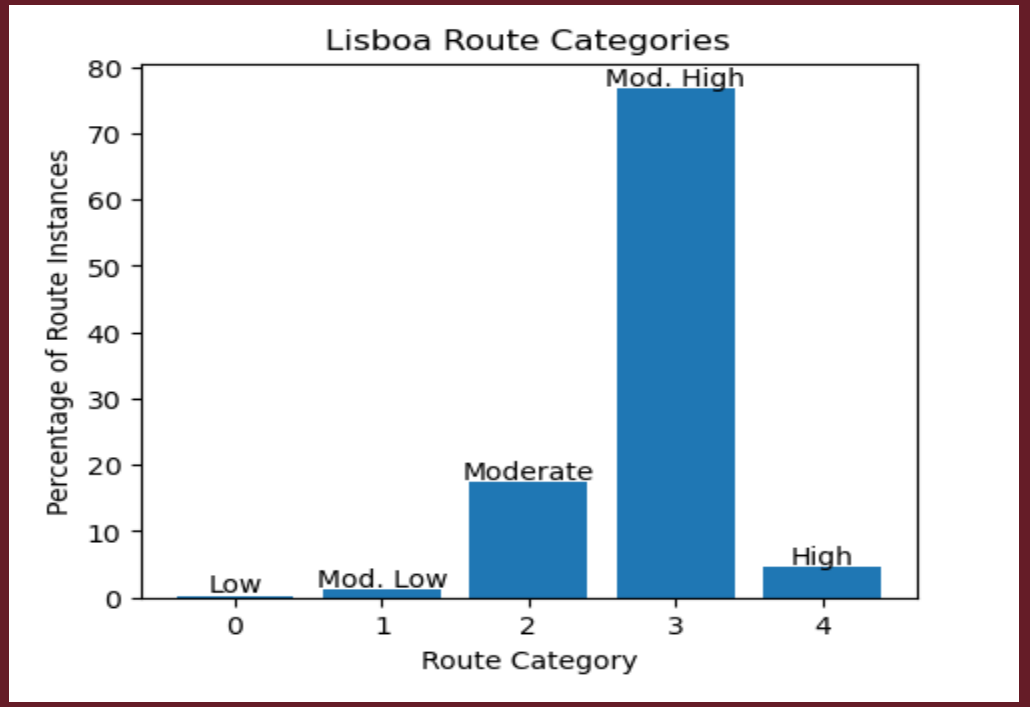
- 'compliance_ratio' represents **the proportion of stops followed by a driver** in a route is given by,

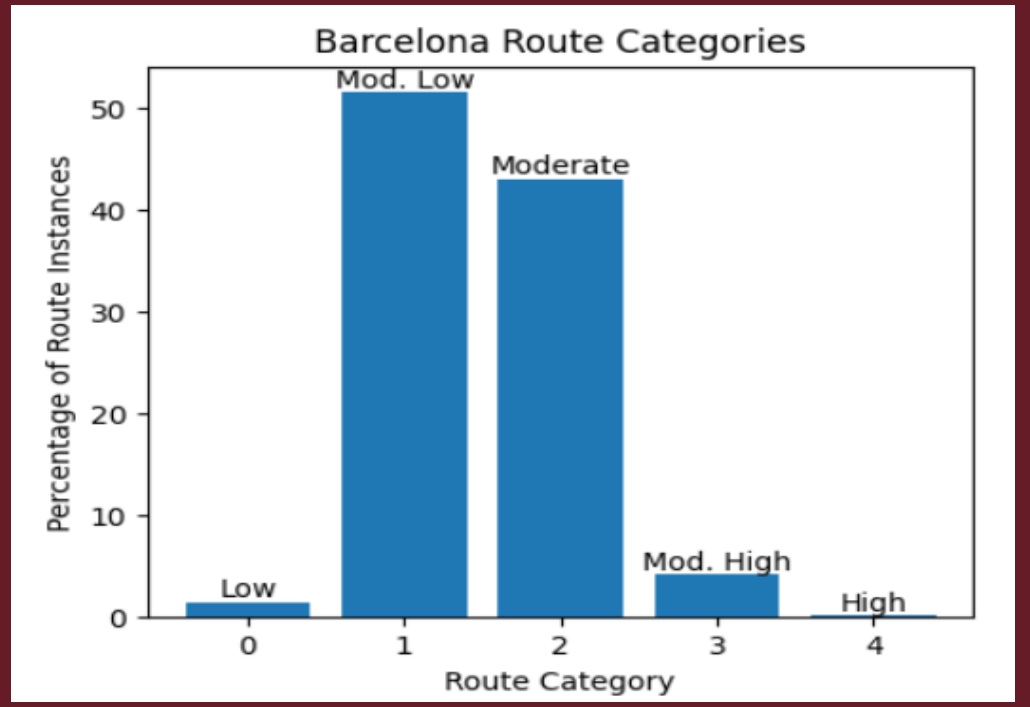
$$compliance_{ratio} = \frac{total\ followed\ delivery\ stops\ in\ a\ route}{total\ delivery\ stops\ in\ a\ route} = \frac{\sum_{i=1}^{N_r} C_{ri}}{N_r}$$

$$compliance_{rate} = compliance_{ratio} * 100$$

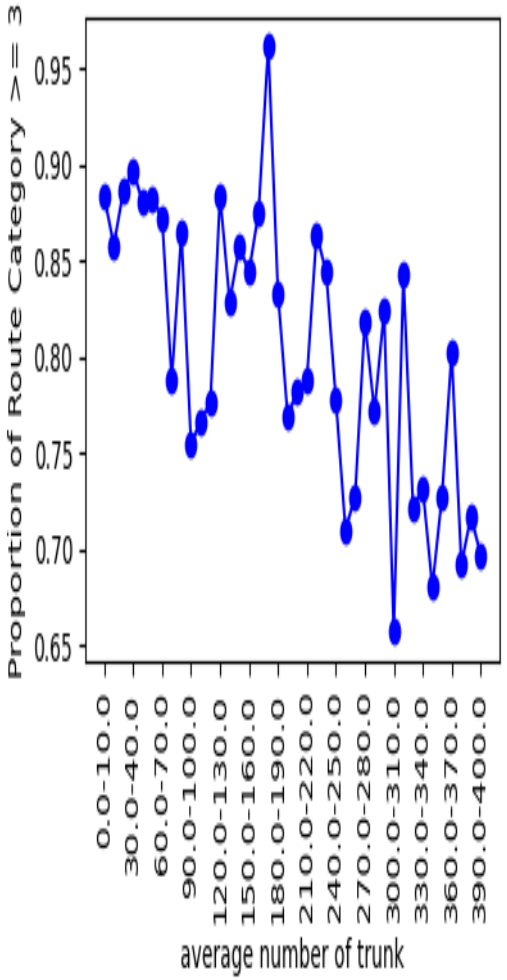
- **Category 4** =$compliance_{rate}$=100% = **High Category Route**
- **Category 3** =$70\% \leq compliance_{rate} < 100\%$ = **Moderately High Category Route**
- **Category 2** =$40\% \leq compliance_{rate} < 70\%$ = **Moderate Category Route**
- **Category 1** = $0\% < compliance_{rate} < 40\%$ = **Moderately Low Category Route**
- **Category 0** = $compliance_{rate}$= 0% = **Low Category Route**

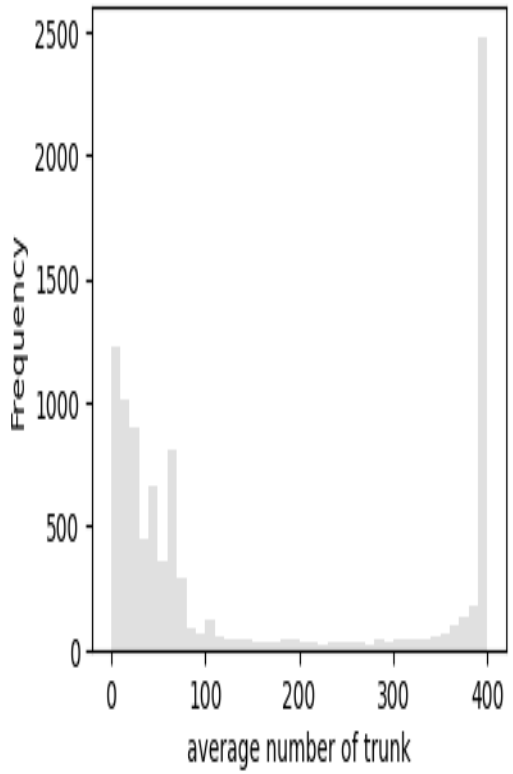
Route Category

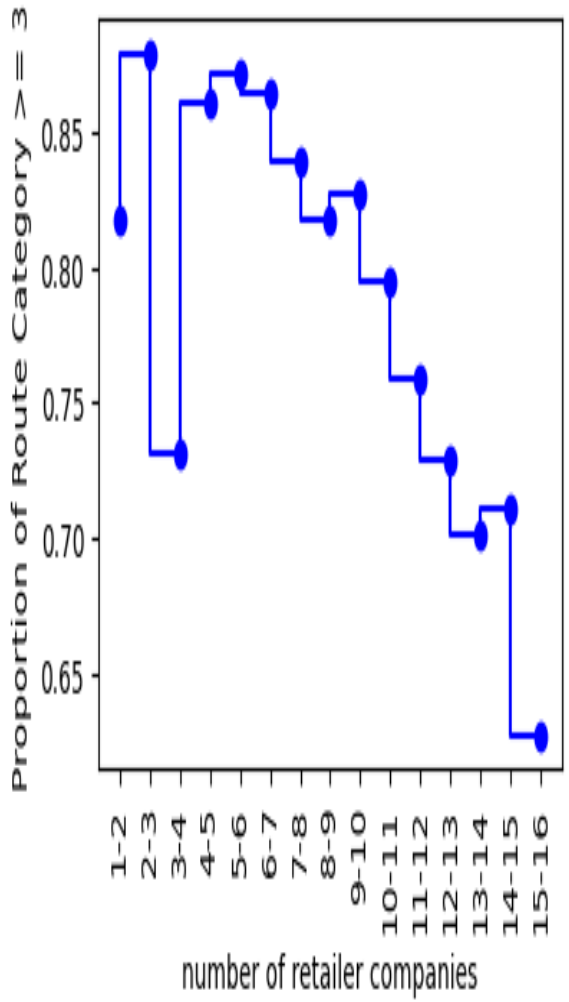


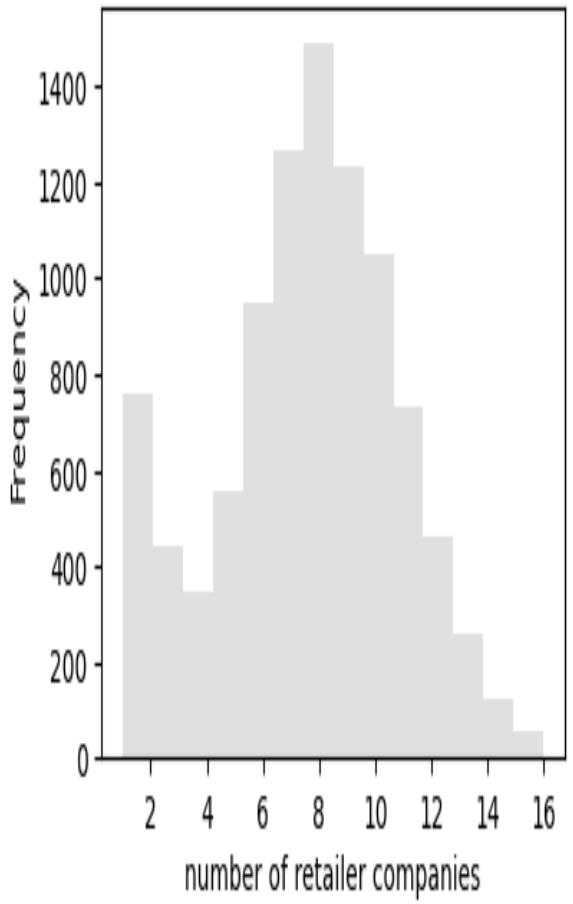


EDA on Lisboa Dataset

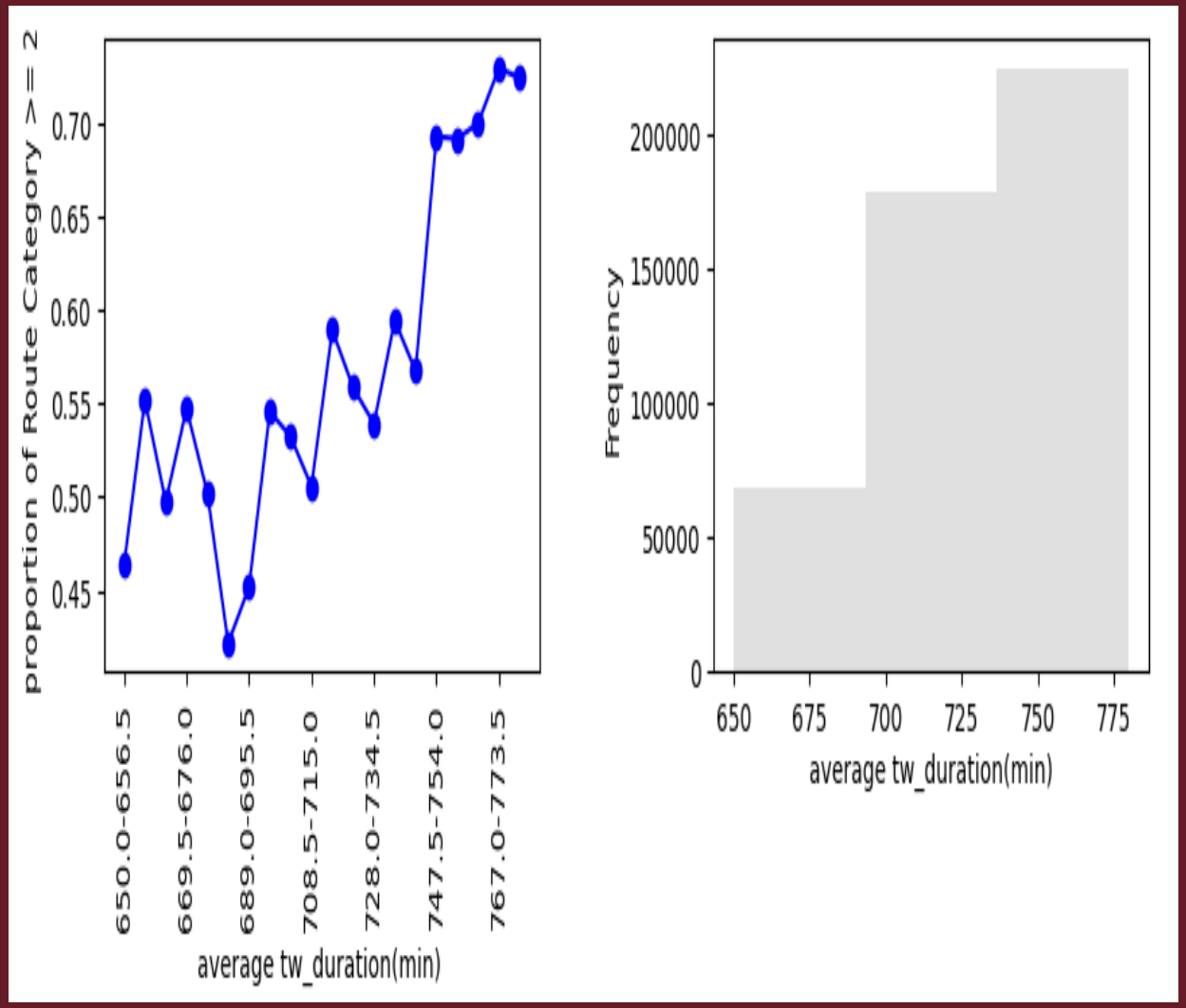


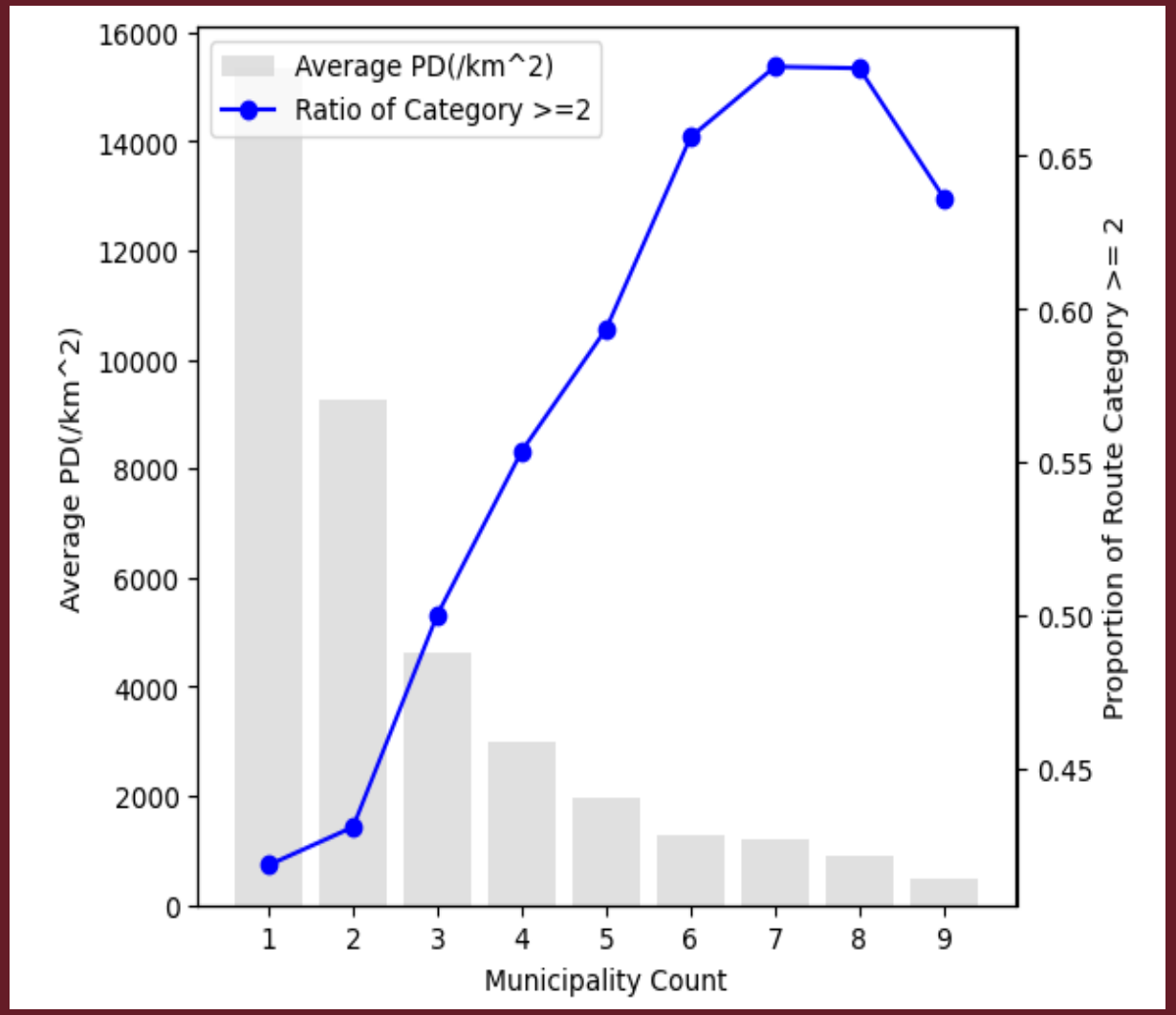




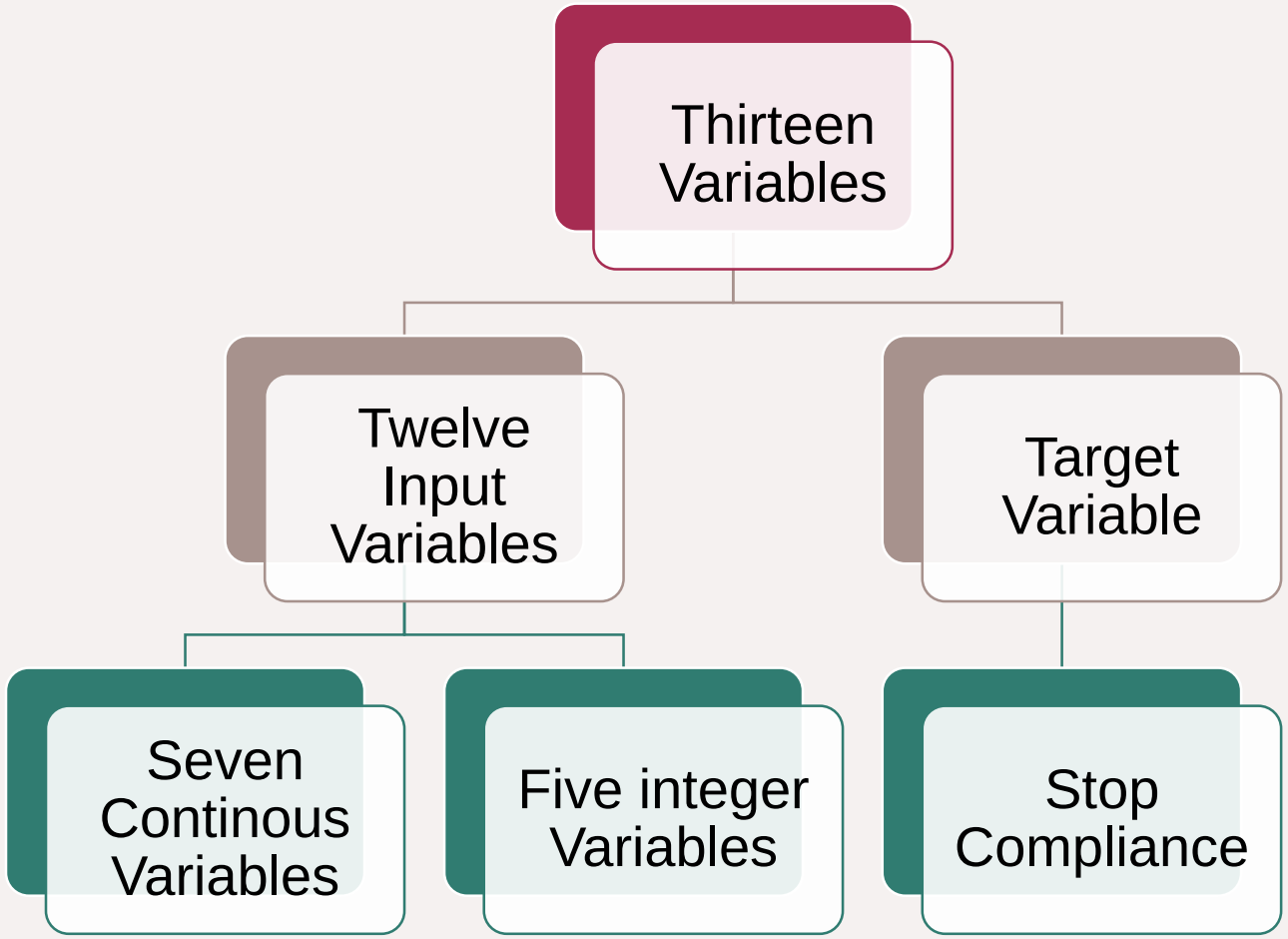


EDA on Barcelona Dataset





Input Variables and Target Variable for Quantitative Modelling



Binomial Logistic Regression Model

- Fits the **logistic function** $\boldsymbol{\sigma(z)}$ to model the relationship between input features and the predicted probability of the binary target being 1

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

where, $z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n$

- If we consider, σ(z) = p i.e. the probability of stop_compliance being 1

  then, (1 - σ(z)) = (1-p) i.e the probability of stop_compliance being 0

- $\boldsymbol{log(odd\ ratio)} = ln\left(\frac{\sigma(z)}{1-\sigma(z)}\right)$

$$= ln\left(\frac{\frac{e^z}{e^z+1}}{1-\frac{e^z}{e^z+1}}\right) = ln(e^z) = \boldsymbol{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n} \qquad (3)$$

- **MLE** is used to learn **the optimal values of the coefficients** $\beta_0, \beta_1, .. \beta_n$ of the input features such that the model achieves **the best possible fit** to the observed dataset

Hypotheses on Expected Behaviours

H1: Stop compliance behaviour is **hindered by increased** population density and more trunk roads in the routes

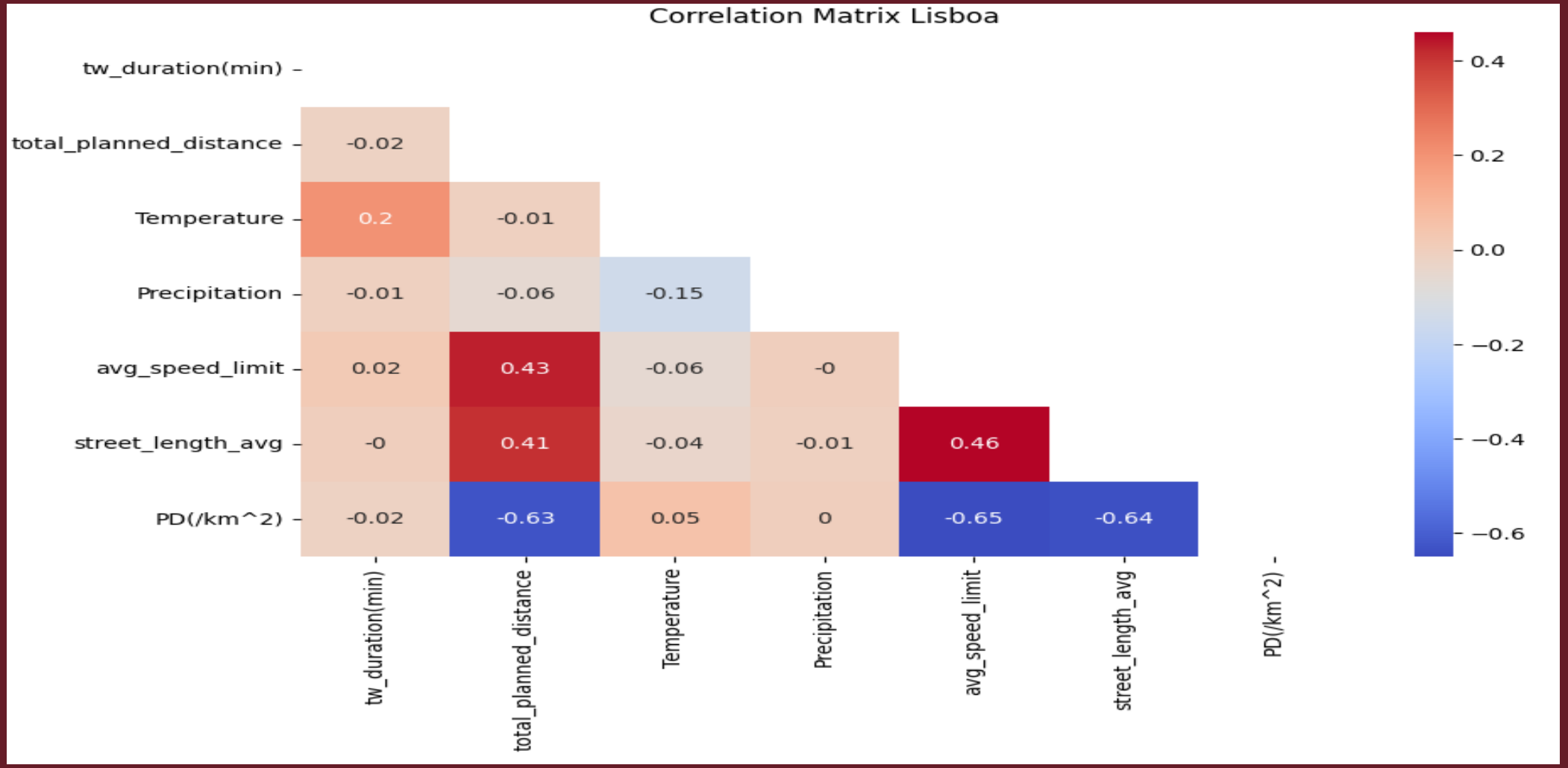
H2: The **shorter** the time window durations, the **lower** the odds of following the suggested stop orders

H3: As number of retailer company **grows** in the routes, driver stop compliance probability **drops**

H4: An **increase** in the number of delivery stops **reduces** the likelihood of compliance

H5: Offering deliveries in a **higher** number of different municipalities in a route **increases** the probability of compliance with suggested stop orders

Multicollinearity Check on Lisboa Dataset



Dummy Encoding of the Integer Variables

Categorical Variables	Intervals	Dummy Encoding			
trunk_category_low	[0,134]			1	0
trunk_category_high	[278,399]			0	1
municipality_category_low	[1,3]			1	0
municipality_category_high	[4,7]			0	1
stop_category_low	[10,34]	1	0	0	0
stop_category_medium	[35,59]	0	1	0	0
stop_category_med-high	[60,84]	0	0	1	0
stop_category_high	[85,100]	0	0	0	1
company_category_low	[1,5]		1	0	0
company_category_medium	[6,10]		0	1	0
company_category_high	[11,16]		0	0	1
intersection_category_low	[829,4238]		1	0	0
intersection_category_medium	[4239,7648]		0	1	0
intersection_category_high	[7649,11058]		0	0	1

Logistic Regression on Lisboa Dataset

	y1 (1)	y2 (2)
V1		
tw_duration.min.	0.270*** (0.003)	0.272*** (0.003)
PD..km.2.	-0.201*** (0.009)	-0.063*** (0.011)
avg_speed_limit	0.144*** (0.005)	0.030*** (0.009)
street_length_avg	-0.240*** (0.006)	-0.113*** (0.010)
Temperature	-0.061*** (0.004)	-0.048*** (0.004)
Precipitation	-0.097*** (0.004)	-0.074*** (0.004)
total_planned_distance	0.036*** (0.005)	0.027*** (0.005)
trunk_category_high		-0.187*** (0.011)
municipality_category_high		0.022*** (0.004)
stop_category_medium		-0.013 (0.017)
stop_category_med.high		-0.105*** (0.017)
stop_category_high		-0.032*** (0.005)
company_category_medium		-0.053*** (0.004)
company_category_high		-0.103*** (0.004)
intersection_category_medium		-0.014*** (0.004)
Constant	1.590*** (0.004)	1.597*** (0.004)

- Time-window duration is the **most important factor**.
- The **second strongest factor** is the dummy variable trunk_category_high.
- The intersection count category turns out to be **the least important factor** in predicting compliance .

Factor Interpretation

	y1 (1)	y2 (2)
V1		
tw_duration.min.	0.270*** (0.003)	0.272*** (0.003)
PD..km.2.	-0.201*** (0.009)	-0.063*** (0.011)
avg_speed_limit	0.144*** (0.005)	0.030*** (0.009)
street_length_avg	-0.240*** (0.006)	-0.113*** (0.010)
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total_planned_distance	0.036*** (0.005)	0.027*** (0.005)
trunk_category_high		-0.187*** (0.011)
municipality_category_high		0.022*** (0.004)
stop_category_medium		-0.013 (0.017)
stop_category_med.high		-0.105*** (0.017)
stop_category_high		-0.032*** (0.005)
company_category_medium		-0.053*** (0.004)
company_category_high		-0.103*** (0.004)
intersection_category_medium		-0.014*** (0.004)
Constant	1.590*** (0.004)	1.597*** (0.004)

The **negative coefficients** for the variables **PD(/km2) and trunk_category_high** reveal that stop compliance behaviour is **hindered** by increased population density and more trunk roads in the routes might be **due to higher traffic volumes and busy areas** . **Therefore, hypothesis-1 cannot be rejected.**

Factor Interpretation

	y1 (1)	y2 (2)
V1		
tw_duration.min.	0.270*** (0.003)	0.272*** (0.003)
PD..km.2.	-0.201*** (0.009)	-0.063*** (0.011)
avg_speed_limit	0.144*** (0.005)	0.030*** (0.009)
street_length_avg	-0.240*** (0.006)	-0.113*** (0.010)
Temperature	-0.061*** (0.004)	-0.048*** (0.004)
Precipitation	-0.097*** (0.004)	-0.074*** (0.004)
total_planned_distance	0.036*** (0.005)	0.027*** (0.005)
trunk_category_high		-0.187*** (0.011)
municipality_category_high		0.022*** (0.004)
stop_category_medium		-0.013 (0.017)
stop_category_med.high		-0.105*** (0.017)
stop_category_high		-0.032*** (0.005)
company_category_medium		-0.053*** (0.004)
company_category_high		-0.103*** (0.004)
intersection_category_medium		-0.014*** (0.004)
Constant	1.590*** (0.004)	1.597*** (0.004)

One standard deviation **increase in time window duration** leads to a $(e^{0.272} - 1) * 100 \approx 31.3$ % **increase in the odds of stop compliance**. Therefore, as **the time window duration increases**, the probability of following the stops with suggested order also **increases. Thus , hypothesis-2 cannot be rejected**.

Factor Interpretation

	y1 (1)	y2 (2)
v1		
tw_duration.min.	0.270*** (0.003)	0.272*** (0.003)
PD..km.2.	-0.201*** (0.009)	-0.063*** (0.011)
avg_speed_limit	0.144*** (0.005)	0.030*** (0.009)
street_length_avg	-0.240*** (0.006)	-0.113*** (0.010)
Temperature	-0.061*** (0.004)	-0.048*** (0.004)
Precipitation	-0.097*** (0.004)	-0.074*** (0.004)
total_planned_distance	0.036*** (0.005)	0.027*** (0.005)
trunk_category_high		-0.187*** (0.011)
municipality_category_high		0.022*** (0.004)
stop_category_medium		-0.013 (0.017)
stop_category_med.high		-0.105*** (0.017)
stop_category_high		-0.032*** (0.005)
company_category_medium		-0.053*** (0.004)
company_category_high		-0.103*** (0.004)
intersection_category_medium		-0.014*** (0.004)
Constant	1.590*** (0.004)	1.597*** (0.004)

Both medium and high category company counts reveal **a consistent linear decreasing effect** for compliance. Therefore, as the number of retailer companies **increases**, the probability of driver compliance **decreases**, **as supported by hypothesis-3.**

Factor Interpretation

	y1 (1)	y2 (2)
v1		
tw_duration.min.	0.270*** (0.003)	0.272*** (0.003)
PD..km.2.	-0.201*** (0.009)	-0.063*** (0.011)
avg_speed_limit	0.144*** (0.005)	0.030*** (0.009)
street_length_avg	-0.240*** (0.006)	-0.113*** (0.010)
Temperature	-0.061*** (0.004)	-0.048*** (0.004)
Precipitation	-0.097*** (0.004)	-0.074*** (0.004)
total_planned_distance	0.036*** (0.005)	0.027*** (0.005)
trunk_category_high		-0.187*** (0.011)
municipality_category_high		0.022*** (0.004)
stop_category_medium		-0.013 (0.017)
stop_category_med.high		-0.105*** (0.017)
stop_category_high		-0.032*** (0.005)
company_category_medium		-0.053*** (0.004)
company_category_high		-0.103*** (0.004)
intersection_category_medium		-0.014*** (0.004)
Constant	1.590*** (0.004)	1.597*** (0.004)

- The stop_category_medium shows **no significant change** on compliance.
- Routes with moderately high number of stops displays **a relatively stronger negative** impact on compliance.
- But stop_category_high group shows **a smaller magnitude effect** than the stop_category_med.high group. Therefore, a **non-linear trend** is observed for stop count categories. **Thus, Hypothesis-4 would be rejected for stop count categories.**

Factor Interpretation

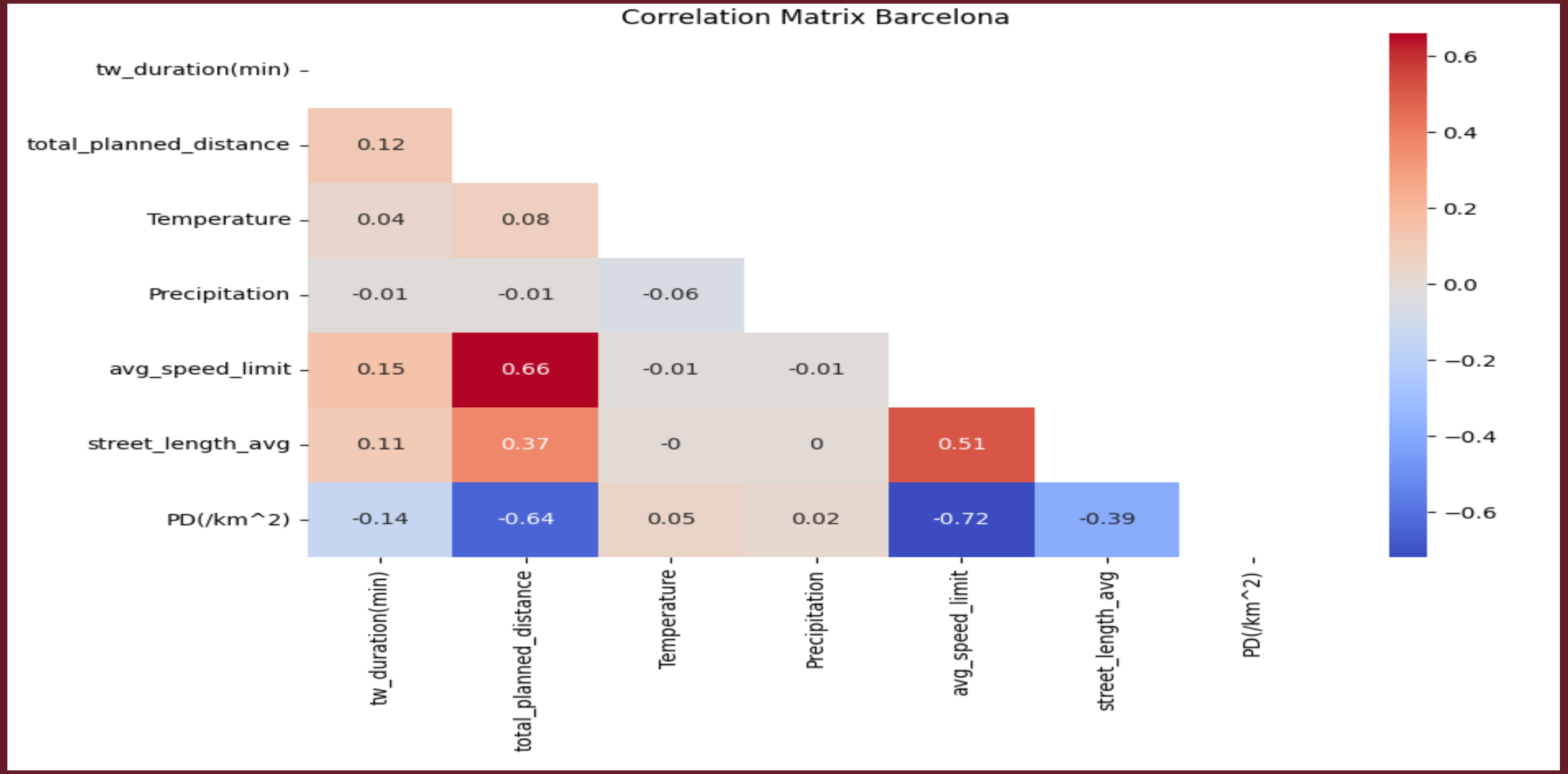
	y1 (1)	y2 (2)
v1		
tw_duration.min.	0.270*** (0.003)	0.272*** (0.003)
PD..km.2.	-0.201*** (0.009)	-0.063*** (0.011)
avg_speed_limit	0.144*** (0.005)	0.030*** (0.009)
street_length_avg	-0.240*** (0.006)	-0.113*** (0.010)
Temperature	-0.061*** (0.004)	-0.048*** (0.004)
Precipitation	-0.097*** (0.004)	-0.074*** (0.004)
total_planned_distance	0.036*** (0.005)	0.027*** (0.005)
trunk_category_high		-0.187*** (0.011)
municipality_category_high		0.022*** (0.004)
stop_category_medium		-0.013 (0.017)
stop_category_med.high		-0.105*** (0.017)
stop_category_high		-0.032*** (0.005)
company_category_medium		-0.053*** (0.004)
company_category_high		-0.103*** (0.004)
intersection_category_medium		-0.014*** (0.004)
Constant	1.590*** (0.004)	1.597*** (0.004)

The ‘municipality_category_high’ variable reveals that the stops of the routes offering deliveries in 4 to 7 different municipalities **are 2.3% more likely to be followed** than the stops of the routes offering deliveries in 1 to 3 different municipalities. **Therefore, drivers tend to follow the suggestion in the routes incorporating more unfamiliar places as expected from hypothesis-5.**

Factor Interpretation

	y1 (1)	y2 (2)
V1		
tw_duration.min.	0.270*** (0.003)	0.272*** (0.003)
PD..km.2.	−0.201*** (0.009)	−0.063*** (0.011)
avg_speed_limit	0.144*** (0.005)	0.030*** (0.009)
street_length_avg	−0.240*** (0.006)	−0.113*** (0.010)
Temperature	−0.061*** (0.004)	−0.048*** (0.004)
Precipitation	−0.097*** (0.004)	−0.074*** (0.004)
total_planned_distance	0.036*** (0.005)	0.027*** (0.005)
trunk_category_high		−0.187*** (0.011)
municipality_category_high		0.022*** (0.004)
stop_category_medium		−0.013 (0.017)
stop_category_med.high		−0.105*** (0.017)
stop_category_high		−0.032*** (0.005)
company_category_medium		−0.053*** (0.004)
company_category_high		−0.103*** (0.004)
intersection_category_medium		−0.014*** (0.004)
Constant	1.590*** (0.004)	1.597*** (0.004)

Multicollinearity Check on Barcelona Dataset



Dummy Encoding of the Integer Variables

Categorical Variables	Intervals	Dummy Encoding			
trunk_category_low	[0,42]			1	0
trunk_category_high	[95,123]			0	1
municipality_category_low	[1,4]			1	0
municipality_category_high	[5,9]			0	1
stop_category_low	[11,41]	1	0	0	0
stop_category_medium	[42,72]	0	1	0	0
stop_category_med-high	[73,103]	0	0	1	0
stop_category_high	[104,132]	0	0	0	1
company_category_low	[1,11]		1	0	0
company_category_medium	[12,22]		0	1	0
company_category_high	[23,34]		0	0	1
intersection_category_low	[9,3419]		1	0	0
intersection_category_medium	[3420,6830]		0	1	0
intersection_category_high	[6831,10240]		0	0	1

Logistic Regression on Barcelona Dataset

	y1 (1)	y2 (2)
v1		
tw_duration.min.	0.013*** (0.003)	0.009*** (0.003)
total_planned_distance	-0.065*** (0.004)	-0.055*** (0.004)
Temperature	-0.042*** (0.003)	-0.030*** (0.003)
Precipitation	-0.005* (0.003)	0.001 (0.003)
avg_speed_limit	0.058*** (0.005)	0.032*** (0.005)
street_length_avg	-0.003 (0.003)	0.013*** (0.004)
PD..km.2.	-0.123*** (0.005)	-0.070*** (0.006)
trunk_category_high		-0.048*** (0.005)
municipality_category_high		0.034*** (0.003)
stop_category_medium		-0.022*** (0.005)
stop_category_med.high		-0.031*** (0.005)
stop_category_high		-0.014*** (0.003)
company_category_medium		-0.062*** (0.003)
company_category_high		-0.078*** (0.004)
intersection_category_medium		0.001 (0.003)
Constant	-0.387*** (0.003)	-0.388*** (0.003)

- Time window duration has **the least effect size** on compliance
- Precipitation **don't show any statistically significant effect** on changing compliance
- Population density has become **the second strongest factor**
- The **most significant factor** is the dummy variable company_category_high
- Intersection count category also **shows no statistically significant effect** on compliance

Logistic Regression on Barcelona Dataset

	y1 (1)	y2 (2)
V1		
tw_duration.min.	0.013*** (0.003)	0.009*** (0.003)
total_planned_distance	-0.065*** (0.004)	-0.055*** (0.004)
Temperature	-0.042*** (0.003)	-0.030*** (0.003)
Precipitation	-0.005* (0.003)	0.001 (0.003)
avg_speed_limit	0.058*** (0.005)	0.032*** (0.005)
street_length_avg	-0.003 (0.003)	0.013*** (0.004)
PD..km.2.	-0.123*** (0.005)	-0.070*** (0.006)
trunk_category_high		-0.048*** (0.005)
municipality_category_high		0.034*** (0.003)
stop_category_medium		-0.022*** (0.005)
stop_category_med.high		-0.031*** (0.005)
stop_category_high		-0.014*** (0.003)
company_category_medium		-0.062*** (0.003)
company_category_high		-0.078*** (0.004)
intersection_category_medium		0.001 (0.003)
Constant	-0.387*** (0.003)	-0.388*** (0.003)

One standard deviation **increase in population density** leads to a $(e^{-0.070}-1) * 100 \approx 7\%$ **decrease in the odds of stop compliance**. The **negative coefficient** of **high trunk road category** variable also supports a **decreasing** effect in compliance. **Thus,hypothesis -1 can not be rejected**.

Logistic Regression on Barcelona Dataset

	y1 (1)	y2 (2)
V1		
tw_duration.min.	0.013*** (0.003)	0.009*** (0.003)
total_planned_distance	-0.065*** (0.004)	-0.055*** (0.004)
Temperature	-0.042*** (0.003)	-0.030*** (0.003)
Precipitation	-0.005* (0.003)	0.001 (0.003)
avg_speed_limit	0.058*** (0.005)	0.032*** (0.005)
street_length_avg	-0.003 (0.003)	0.013*** (0.004)
PD..km.2.	-0.123*** (0.005)	-0.070*** (0.006)
trunk_category_high		-0.048*** (0.005)
municipality_category_high		0.034*** (0.003)
stop_category_medium		-0.022*** (0.005)
stop_category_med.high		-0.031*** (0.005)
stop_category_high		-0.014*** (0.003)
company_category_medium		-0.062*** (0.003)
company_category_high		-0.078*** (0.004)
intersection_category_medium		0.001 (0.003)
Constant	-0.387*** (0.003)	-0.388*** (0.003)

Though time window duration turns out to be the **least important factor** for Barcelona dataset, longer time window duration still **positively effects compliance, as expected from hypothesis-2.**

Logistic Regression on Barcelona Dataset

	y1 (1)	y2 (2)
v1		
tw_duration.min.	0.013*** (0.003)	0.009*** (0.003)
total_planned_distance	-0.065*** (0.004)	-0.055*** (0.004)
Temperature	-0.042*** (0.003)	-0.030*** (0.003)
Precipitation	-0.005* (0.003)	0.001 (0.003)
avg_speed_limit	0.058*** (0.005)	0.032*** (0.005)
street_length_avg	-0.003 (0.003)	0.013*** (0.004)
PD..km.2.	-0.123*** (0.005)	-0.070*** (0.006)
trunk_category_high		-0.048*** (0.005)
municipality_category_high		0.034*** (0.003)
stop_category_medium		-0.022*** (0.005)
stop_category_med.high		-0.031*** (0.005)
stop_category_high		-0.014*** (0.003)
company_category_medium		-0.062*** (0.003)
company_category_high		-0.078*** (0.004)
intersection_category_medium		0.001 (0.003)
Constant	-0.387*** (0.003)	-0.388*** (0.003)

Drivers are about **6% less likely** to follow the suggestion when dealing with **medium numbers of company products** and nearly **8% less likely** to follow the suggestion when dealing with **high numbers of company products**. **Therefore, hypothesis-3 cannot be rejected**

Logistic Regression on Barcelona Dataset

	y1 (1)	y2 (2)
v1		
tw_duration.min.	0.013*** (0.003)	0.009*** (0.003)
total_planned_distance	-0.065*** (0.004)	-0.055*** (0.004)
Temperature	-0.042*** (0.003)	-0.030*** (0.003)
Precipitation	-0.005* (0.003)	0.001 (0.003)
avg_speed_limit	0.058*** (0.005)	0.032*** (0.005)
street_length_avg	-0.003 (0.003)	0.013*** (0.004)
PD..km.2.	-0.123*** (0.005)	-0.070*** (0.006)
trunk_category_high		-0.048*** (0.005)
municipality_category_high		0.034*** (0.003)
stop_category_medium		-0.022*** (0.005)
stop_category_med.high		-0.031*** (0.005)
stop_category_high		-0.014*** (0.003)
company_category_medium		-0.062*** (0.003)
company_category_high		-0.078*** (0.004)
intersection_category_medium		0.001 (0.003)
Constant	-0.387*** (0.003)	-0.388*** (0.003)

Hypothesis-4 would be rejected for stop count categories due to non-linearity , as the **'stop_category_high'** shows **a lesser impact size** than other categories which leads to a non-linear trend

Logistic Regression on Barcelona Dataset

	y1 (1)	y2 (2)
v1		
tw_duration.min.	0.013*** (0.003)	0.009*** (0.003)
total_planned_distance	-0.065*** (0.004)	-0.055*** (0.004)
Temperature	-0.042*** (0.003)	-0.030*** (0.003)
Precipitation	-0.005* (0.003)	0.001 (0.003)
avg_speed_limit	0.058*** (0.005)	0.032*** (0.005)
street_length_avg	-0.003 (0.003)	0.013*** (0.004)
PD..km.2.	-0.123*** (0.005)	-0.070*** (0.006)
trunk_category_high		-0.048*** (0.005)
municipality_category_high		0.034*** (0.003)
stop_category_medium		-0.022*** (0.005)
stop_category_med.high		-0.031*** (0.005)
stop_category_high		-0.014*** (0.003)
company_category_medium		-0.062*** (0.003)
company_category_high		-0.078*** (0.004)
intersection_category_medium		0.001 (0.003)
Constant	-0.387*** (0.003)	-0.388*** (0.003)

Routes offering deliveries in **a high number of municipalities** have **a higher likelihood of compliance** compared to the routes with a **low number of municipalities**. **Therefore, hypothesis 5 cannot be rejected.**

Predictive Modelling

- The **classification problem** involves **predicting the likelihood** of a stop along a route being compliant
- The target variable, **"stop compliance"** is classified as **level 1** when a driver visits a stop in the suggested sequence order in undirected case and as **level 0** otherwise.
- Three commonly used algorithms are used for predicting classification: **logistic regression, random forest classifier, and gradient boosting classifier**
- Logistic regression is **a linear classifier** that assumes a **linear relationship** between the independent variables and the binary dependent variable. On the contrary, random forest and gradient boosting are **tree-based ensemble methods** that excel in capturing **non-linear relationships** between the dependent and independent variables

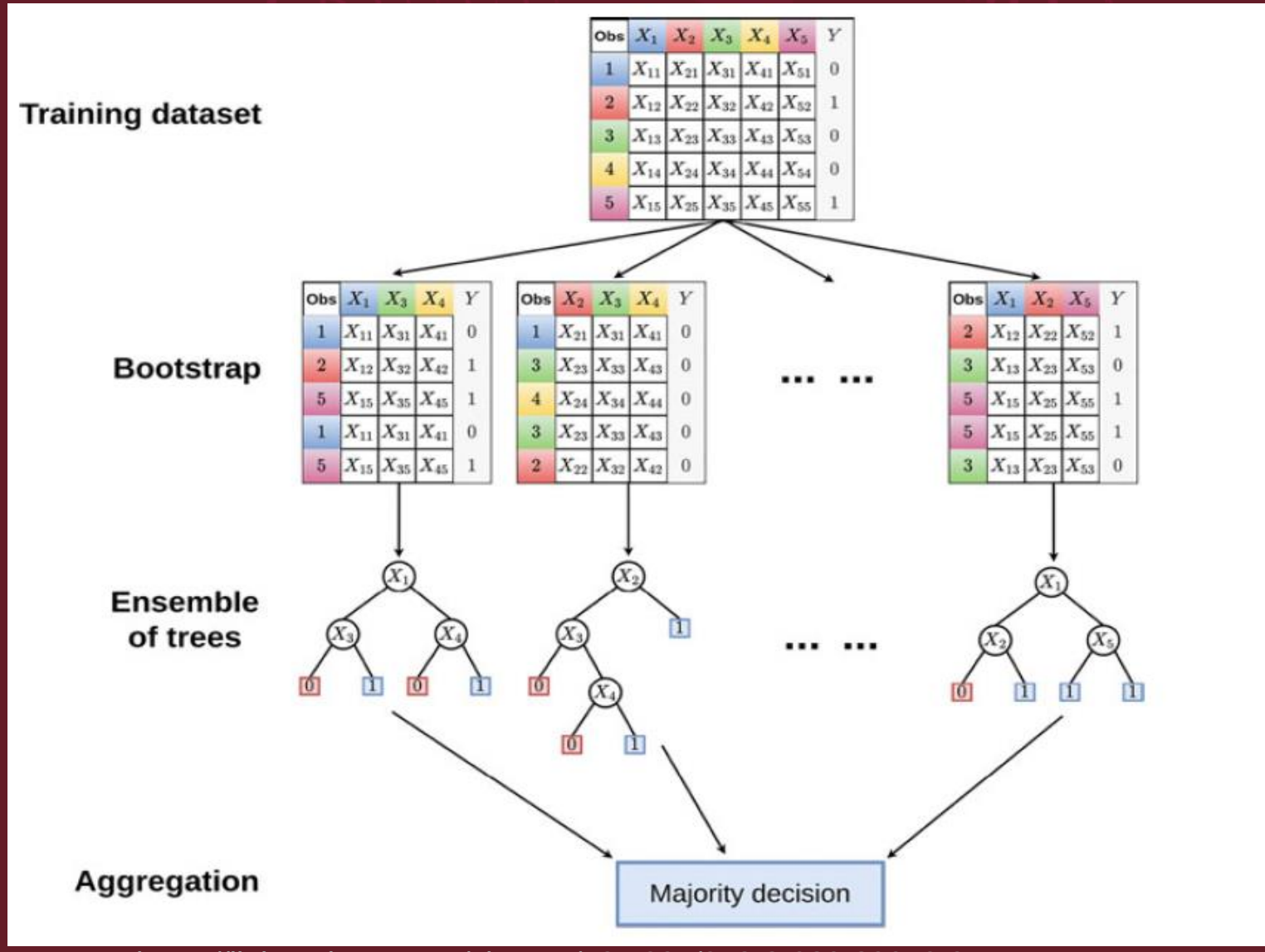
Random Forest Classifier

- Builds **an ensemble of decision trees simultaneously** using **bootstrapped** samples from the training data
- Each tree grows by **splitting nodes to minimize Gini impurity** calculated by

$$Gini(t) = 1 - \sum_{i=1}^{k} P_{i,t}^2$$

$$Gini(t_s) = \frac{|t_{right}|}{|t|} Gini(t_{right}) + \frac{|t_{left}|}{|t|} Gini(t_{left})$$

- **Final Prediction** is done by **Majority Voting** for decisions from all individual trees



https://link.springer.com/chapter/10.1007/978-3-030-89010-0_15

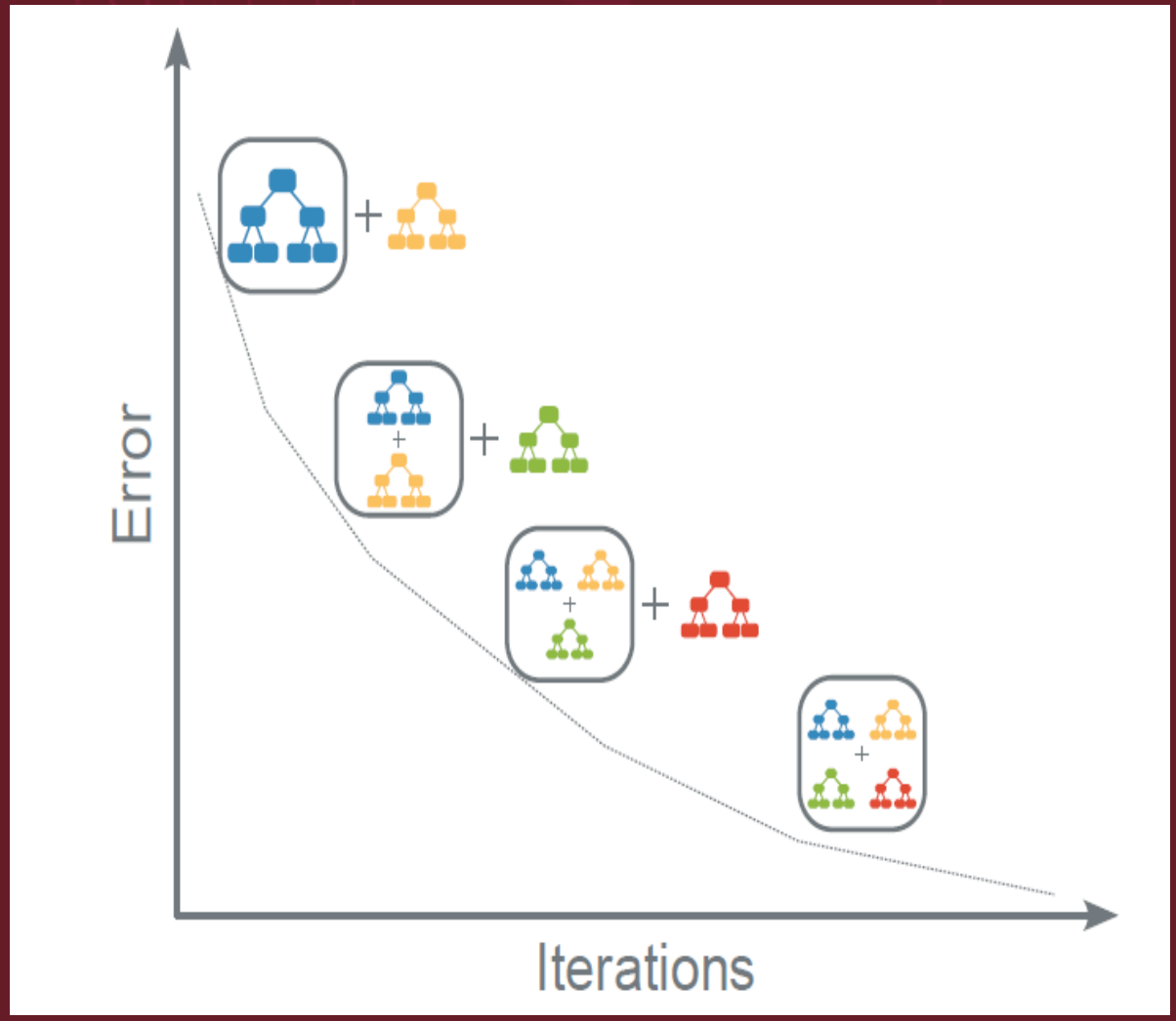
Gradient Boosting Classifier

- Constructs **an ensemble of decision trees sequentially**
- Starts with an **initial prediction** function F_o and **iteratively builds regression trees** h_m to correct the **errors of the preceding model's** predictions as

$$F_o(X_i) = log(\frac{P(Y=1)}{P(Y=0)})$$

$$F_m(X_i) = F_{m-1}(X_i) + \gamma_m * h_m(X_i)$$

- The **final prediction** is obtained by **summing the predictions of all decision trees** in the ensemble



https://www.researchgate.net/publication/368507910_Multi-teacher_knowledge_distillation_as_an_effective_method_for_compressing_ensembles_of_neural_networks

Performance Matrics

- **Specificity (true negative rate):** It measures the proportion of noncompliant stops correctly identified by a classifier.

$$Specificity = \frac{TN}{TN + FP}$$

- **Sensitivity (true positive rate):** It measures the proportion of compliant stops correctly identified by a classifier.

$$Sensitivity = \frac{TP}{TP + FN}$$

- **Accuracy:** It measures the **overall correctness** of a classifier by calculating the proportion of correct predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Model Evaluation

To ensure a fair evaluation, we split each dataset into two parts: **80% for training and 20% for testing performance.**

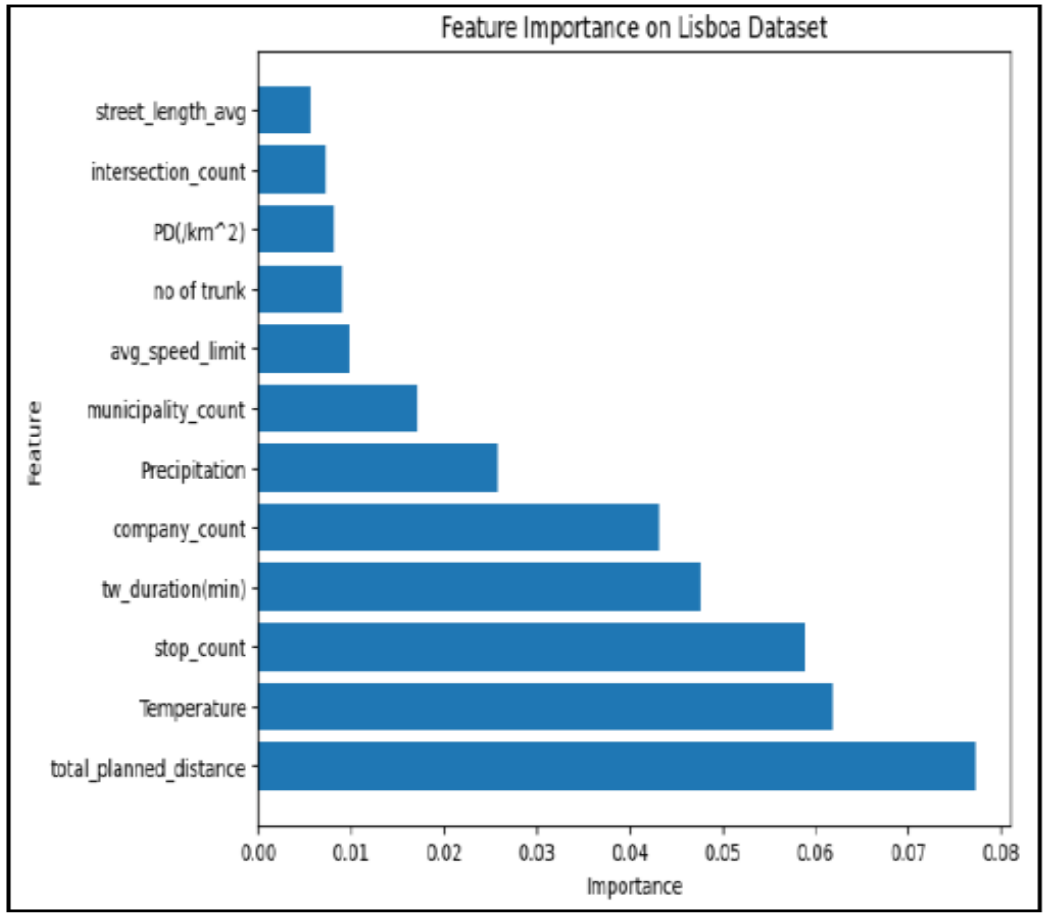
Model	Accuracy	Specificity	Sensitivity
Logistics Regression	0.59	0.56	0.60
Random Forest Classification	0.75	0.68	0.77
Gradient Boosting Classification	0.62	0.59	0.63

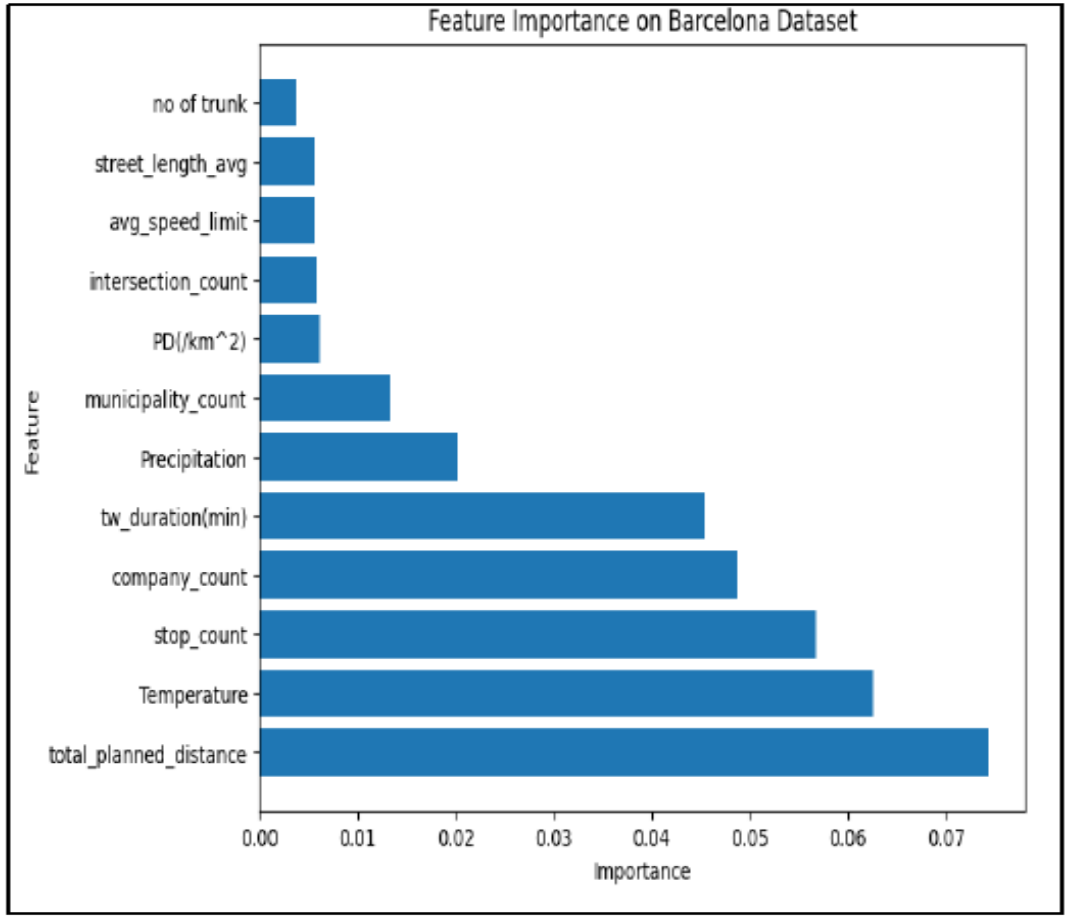
Table 5: Model Performance for Lisboa Dataset

Model	Accuracy	Specificity	Sensitivity
Logistics Regression	0.57	0.60	0.52
Random Forest Classification	0.73	0.79	0.64
Gradient Boosting Classification	0.64	0.70	0.56

Table-6: Model Performance for Barcelona Dataset

Feature Importance from Random Forest Classifier





Partial Dependence Plots

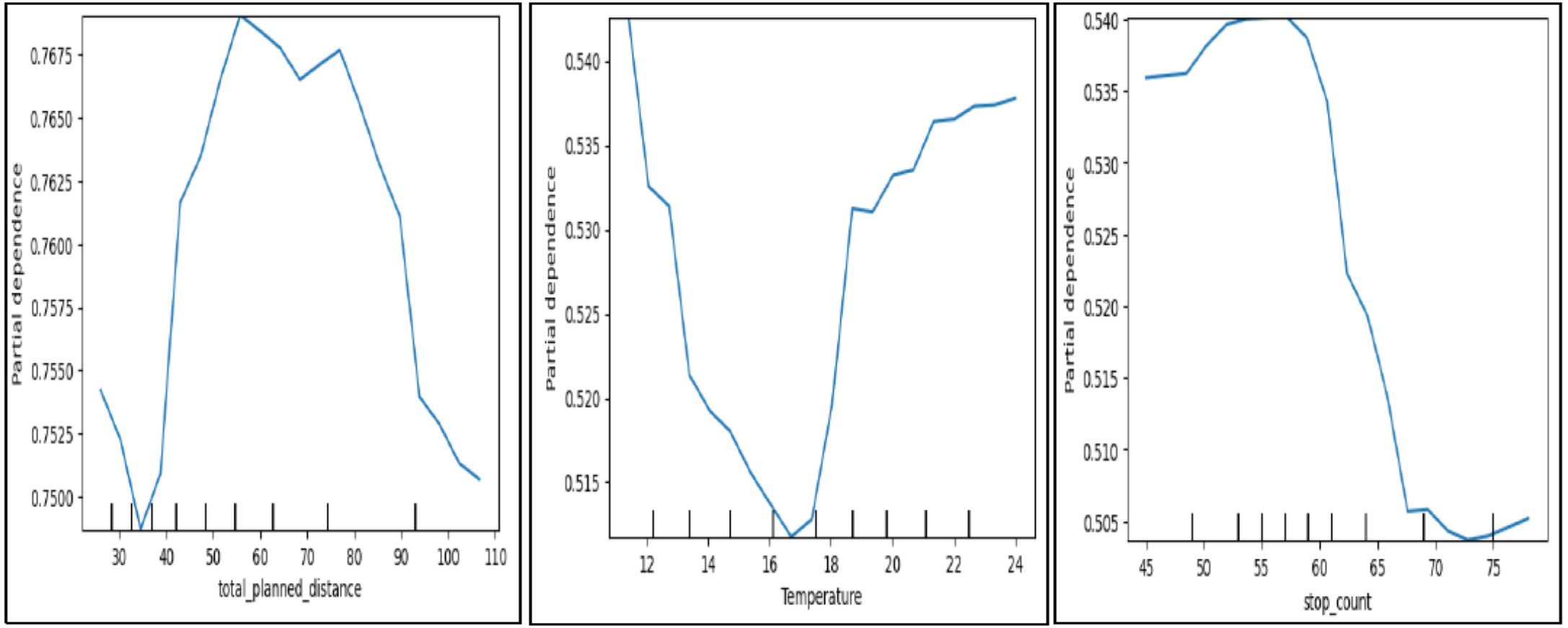


Figure-36: PDP for Random Forest Model (RF) from Lisboa Dataset

Partial Dependence Plots

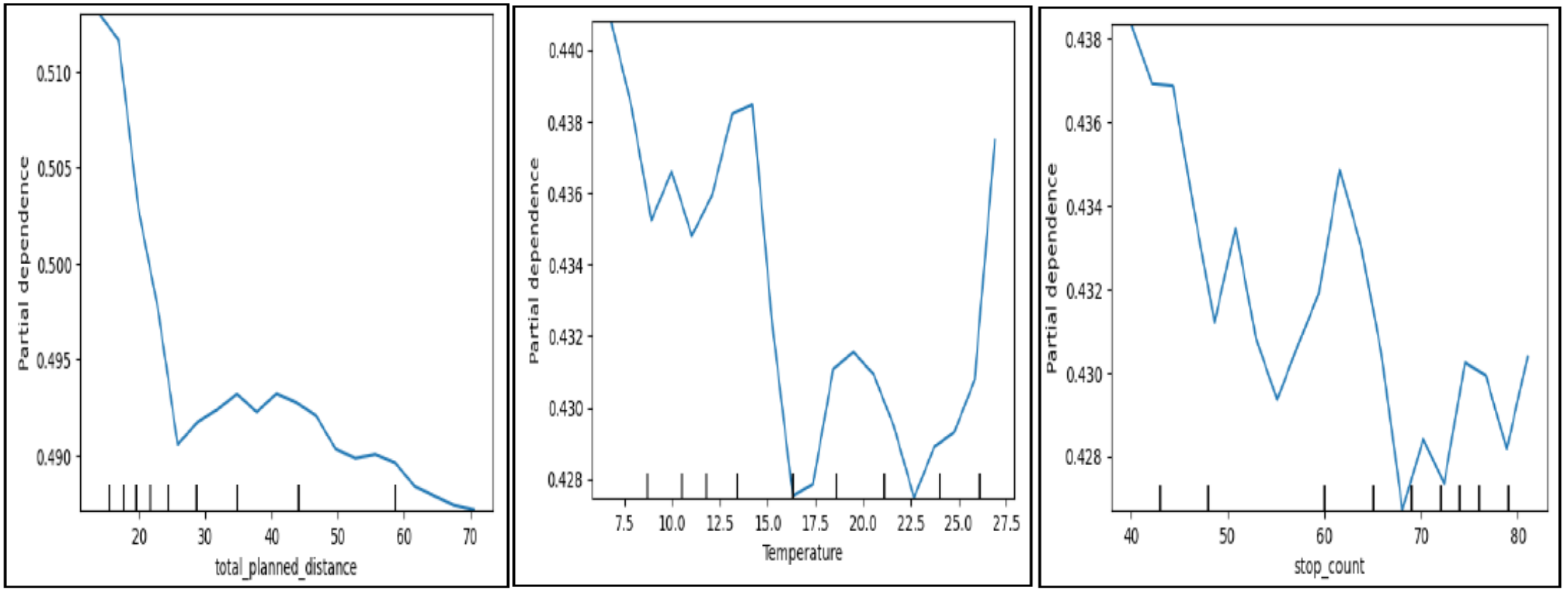


Figure-37: PDP for Random Forest Model (RF) from Barcelona Dataset

Conclusion and Future Work

- Real-life situations are **complex**, which makes it **challenging for drivers** to always follow **the fastest or shortest suggested routes** from conventional optimization tools.
- This study uncovered some valuable insights **into driver behaviour patterns** which will help for more **realistic route planning**.
- **Predicting driver's compliance behaviour** can be useful for companies to identify orders that might not be delivered as planned and **notify the customers accordingly**.
- We examined compliance for **single-stop observation** with certain assumptions where studying compliance **over longer stop sequences** will allow academics to expand on this analysis in the future.
- A more intuitive prediction can be made by adding **more relevant variables**, such as **drivers' personal characteristics and real-time information** on traffic, weather conditions, etc. However, it is difficult to **properly understand drivers' compliance patterns** due to subtle factors like **habits or personal concerns** that may affect their actions.

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