OPTIMISING CAR SHARING PROFITABILITY WITH A REGIONAL PRICING STRATEGY

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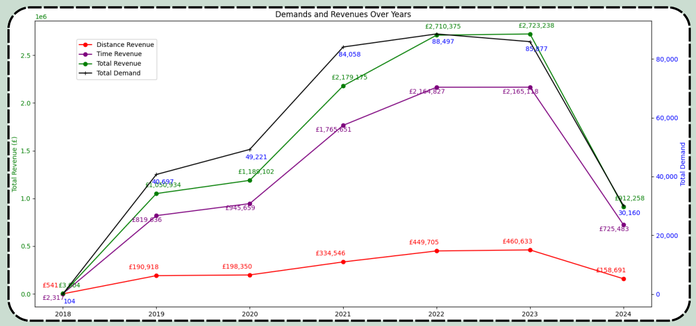
Github

INTRODUCTION

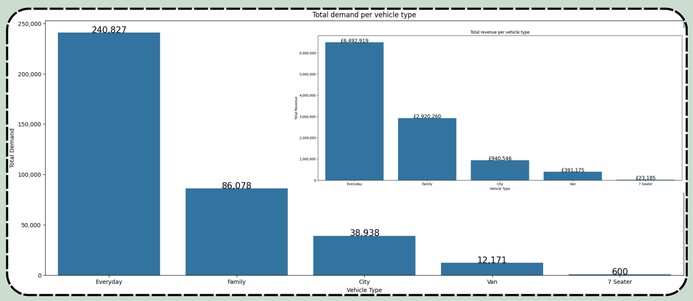
1. This project aims to optimise regional car sharing profitability for Co-Wheels Car Club using Dynamic Pricing [1] and machine learning [2]. The fleet includes five vehicle types (City, Everyday, Family, Van, and 7 Seater) with hourly and daily rates data.
2. Various machine learning models [3] are employed for various vehicle types.
3. Historical booking data from Co-Wheels, collected via the TripIQ System [4], supports this analysis and pricing strategy.

DEMAND AND REVENUE

1. **Distance Revenue:** Revenue from distance traveled by the car.
2. **Time Revenue:** Revenue from the time car used.
3. **Total Revenue:** Distance + Time Revenues.



1. The **highest demand (240,827)** and **revenue (£6,492,919)** are generated by the Everyday vehicle type.



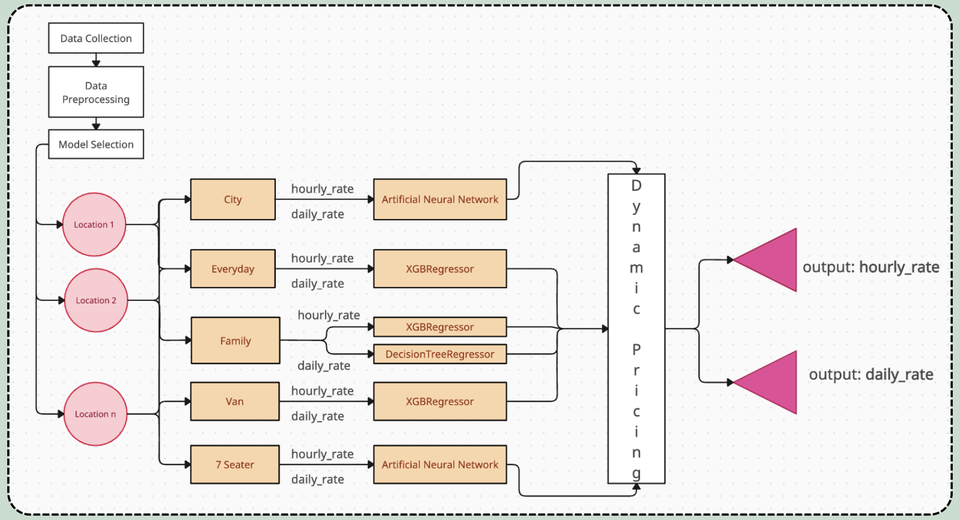
RELATED WORKS

This project extends the application of machine learning models as demonstrated by M. Ahmad et al. [5] in their work, "Car Price Prediction using Machine Learning."

METHODOLOGY

The entire methodology is outlined in the diagram below.
It includes:

- **Data Collection and Preprocessing.**
- **Model Selection for each location and vehicle type.**
- **Implement Dynamic Pricing.**



TECHNOLOGIES USED

Language:

Data Collection: co wheels, TRIP iQ, CSV

Analysis: pandas

Visualisation: matplotlib, plotly, seaborn

Machine Learning: learn, K

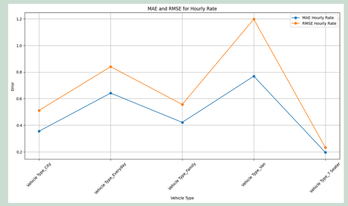
Other Technologies: SQL

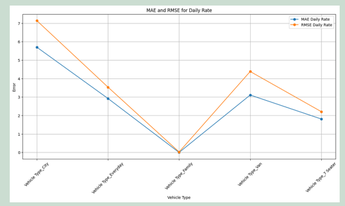
DYNAMIC PRICING

MACHINE LEARNING

TensorFlow

RESULTS





Vehicle Type	Time Period	Model	Mean Absolute Error	Root Mean Squared Error
City	Hourly	Artificial Neural Networks	0.35853	0.51447
	Daily		6.22280	7.56040
Everyday	Hourly	XGBRegressor	0.64146	0.83981
	Daily		2.92157	3.53526
Family	Hourly	XGBRegressor	0.42164	0.55623
	Daily	DecisionTreeRegressor	0.00046	0.02727
Van	Hourly	XGBRegressor	0.76837	1.19642
	Daily		3.10934	4.3839
7-Seater	Hourly	Artificial Neural Networks	0.69682	0.71469
	Daily		2.75597	3.07452

FUTURE WORKS

1. **Real-Time Data Integration:** Implement real-time data collection and analysis for more responsive dynamic pricing adjustments.
2. **User Feedback Mechanisms:** Implement feedback systems to continuously refine and optimise the pricing model based on user satisfaction and user behaviour.
3. **Dynamic Fleet Allocation:** Use algorithms to allocate vehicles based on real-time demand, ensuring availability and improving efficiency and satisfaction.

REFERENCES

[1] Bertsimas, Dimitris & Perakis, Georgia. (2006). Dynamic Pricing: A Learning Approach. 101. 10.1007/0-387-29645-X_3.
[2] Balcioglu, Yavuz & Sezen, Bulent. (2024). CAR PRICE PREDICTION USING MACHINE LEARNING TECHNIQUES. 10.5281/zenODO.10893330.
[3] Kenny, J. et al. (2021) 'Price Prediction using Machine Learning Methods', International Journal for Research in Applied Science & Engineering Technology (IJRASET), 9(5), pp. 661–668.
[4] Limited, T.S. Modern management for car-sharing operators, TripIQ. Available at: https://www.tripiq.eu/ (Accessed: 31 July 2024).
[5] M. Ahmad et al., "Car Price Prediction using Machine Learning," 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), Pune, India, 2024, pp. 1-5, doi: 10.1109/I2CT61223.2024.10544124