A Road Trip Through Data: Predicting Used Car Prices

We're going to travel through our data, stopping at interesting landmarks along the way

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Why are we here?

Unpredictable used car prices

2021 Mercedes CLA Coupe

€34,000

2021 Mercedes CLA Coupe

€70,000

Many buyers don’t know **what truly affects a car’s price**

Our goal: Find **key patterns that influence pricing** and make **better buying decisions**

Let us take you on a journey

- A road trip through rows of data and columns of possibilities

The Map: Understanding Our Dataset

Numerical

- Price
- Km
- Year
- kW
- Horse
- Order

Categorical

- Country
- Manufacturer
- Model
- Automatic_Manual
- Fuel

Total Number of records: 100,000

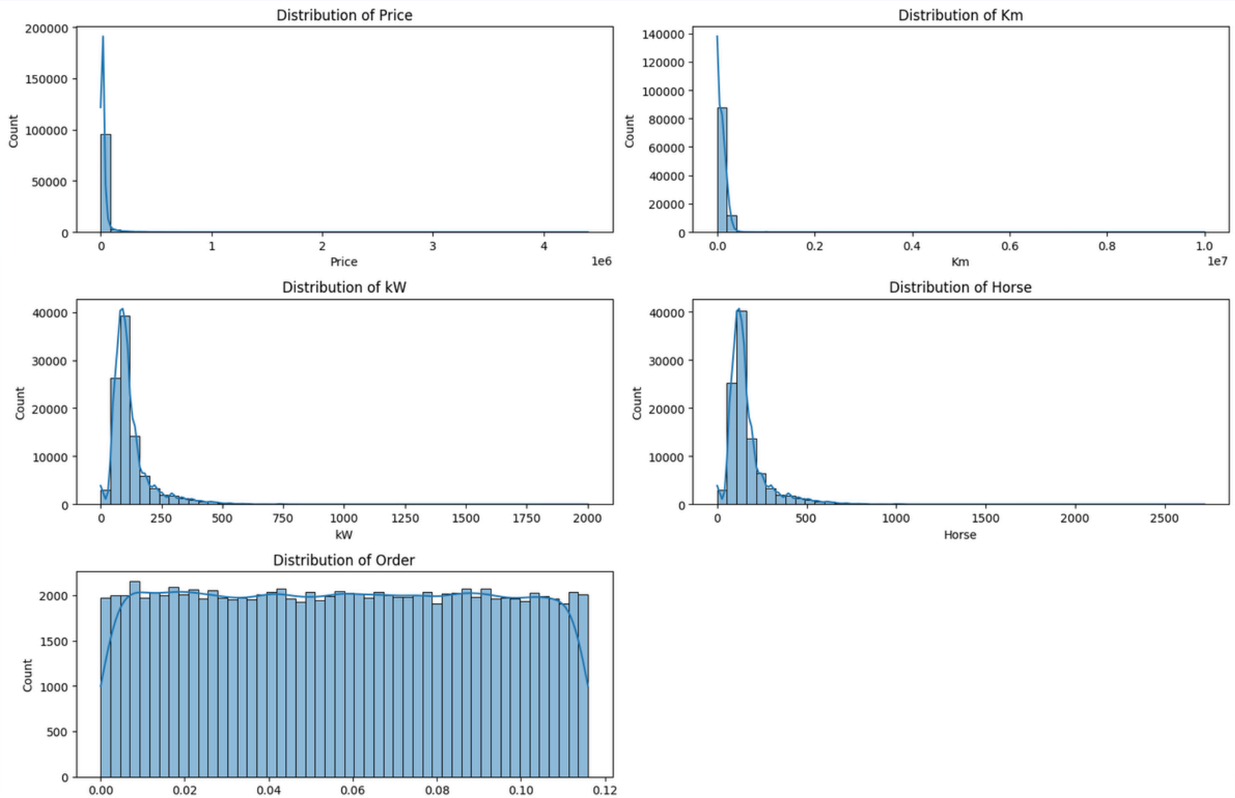
Total Number of variables: 11

Number of missing values: 0

Number of duplicates: 0

Data Types: object; int64; float64

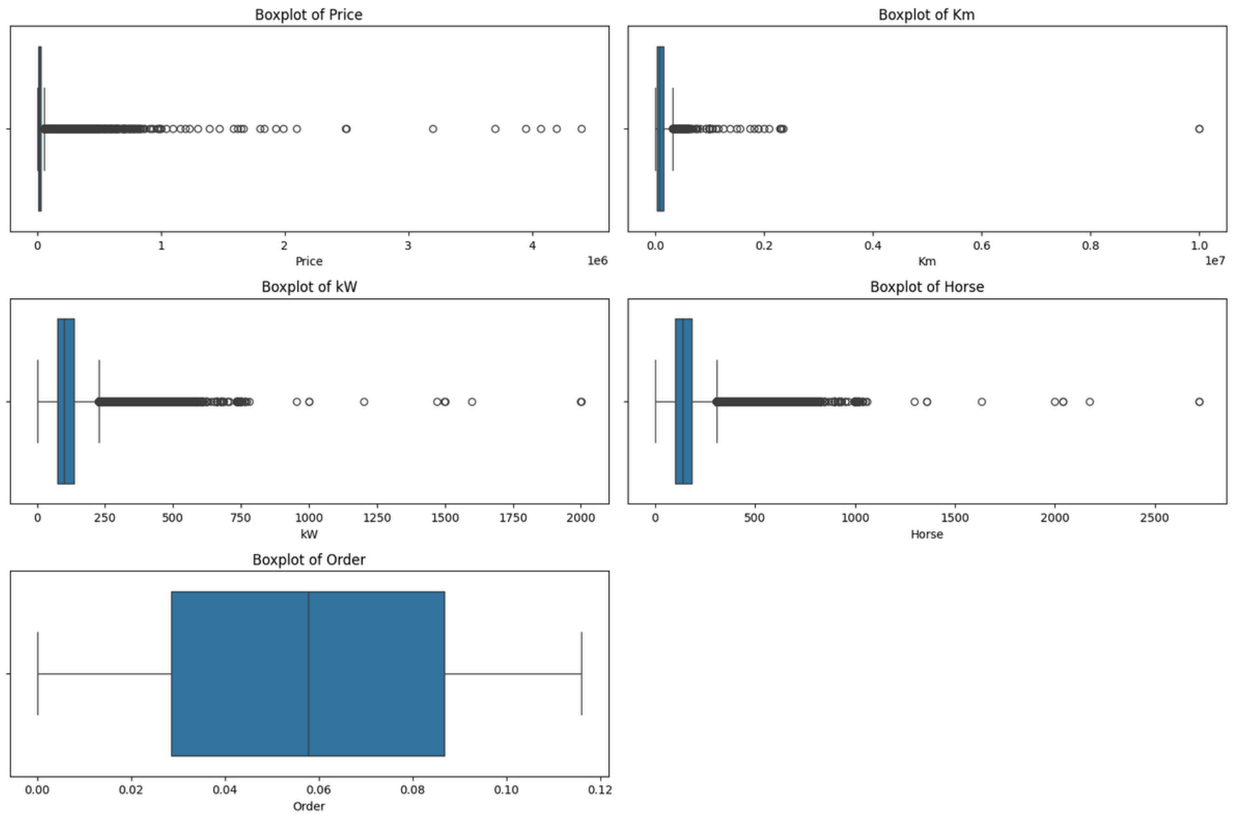
Investigating Our Clues: Preliminary Descriptive Statistics



Insights:

- **Price**: skewed to the right with high-priced outliers.
- **Km**: wide range; some vehicles extremely high mileage.
- **Kw & Horsepower**: Most cars have moderate power, but high-performance models exist.
- **Order**:Seems to be a ranking column rather than a meaningful variable.

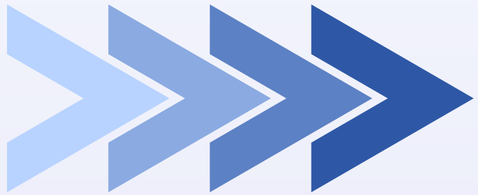
Investigating Our Clues: Preliminary Descriptive Statistics



Insights:

- Price, Km, kW, and Horsepower all contain outliers.
- These **extreme values** will need further investigation, as they could be errors or rare high-value vehicles.

Paving the Road: Data Cleaning



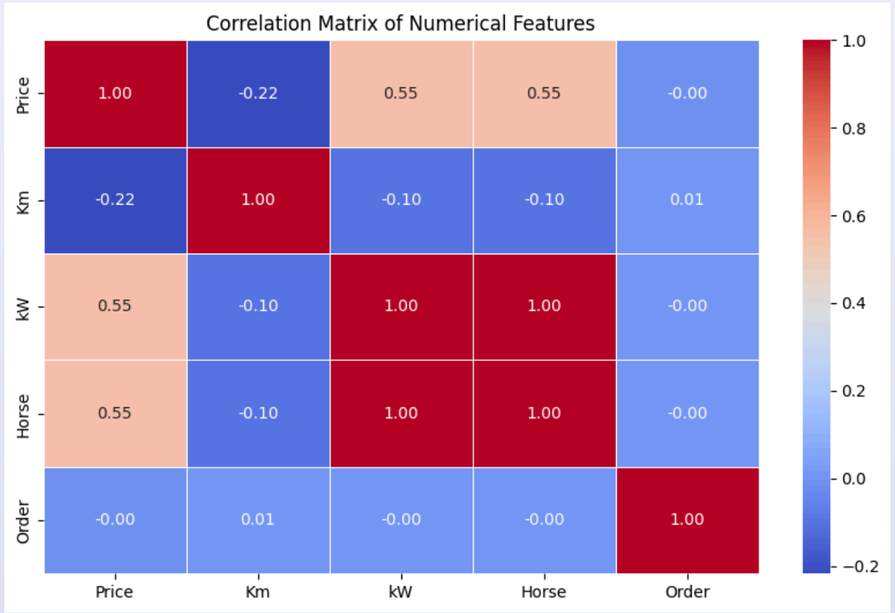
Horse

Order

Outliers

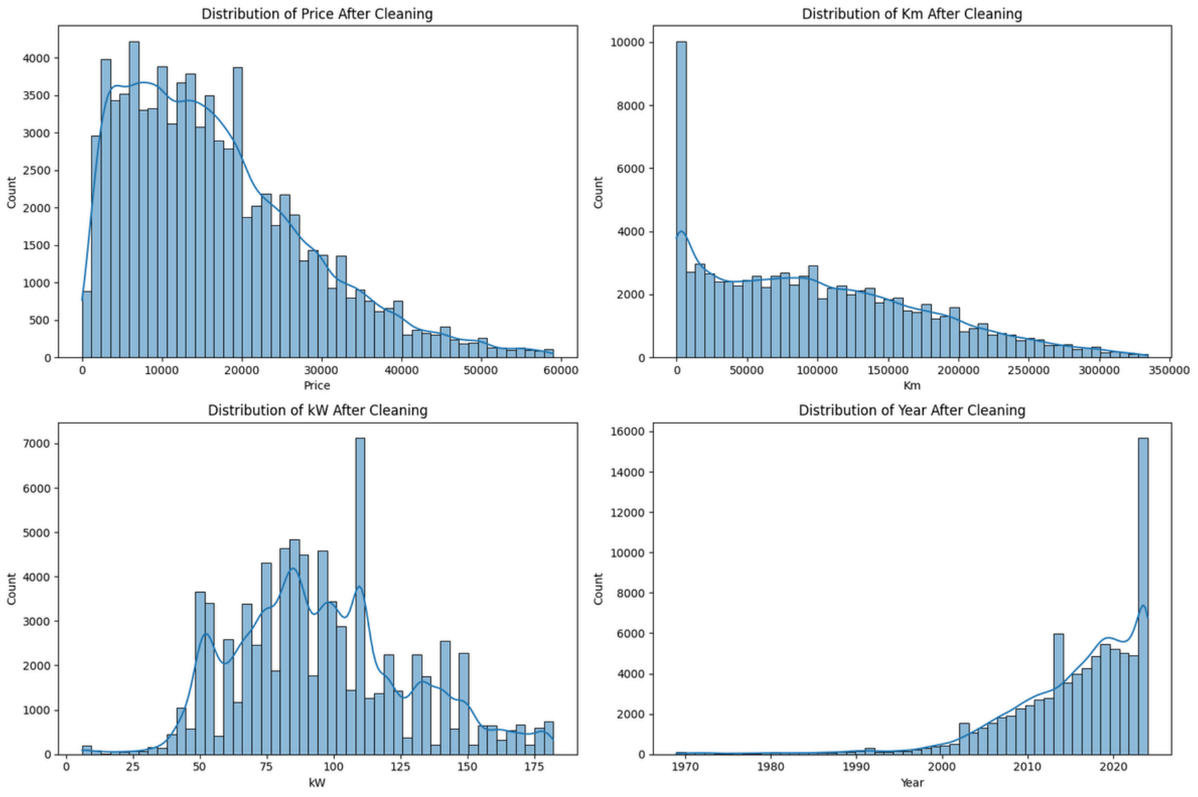
Year

Standardize text data



"Quality data for accurate predictions"

Investigating Our Clues: Outlier Detection & Removal



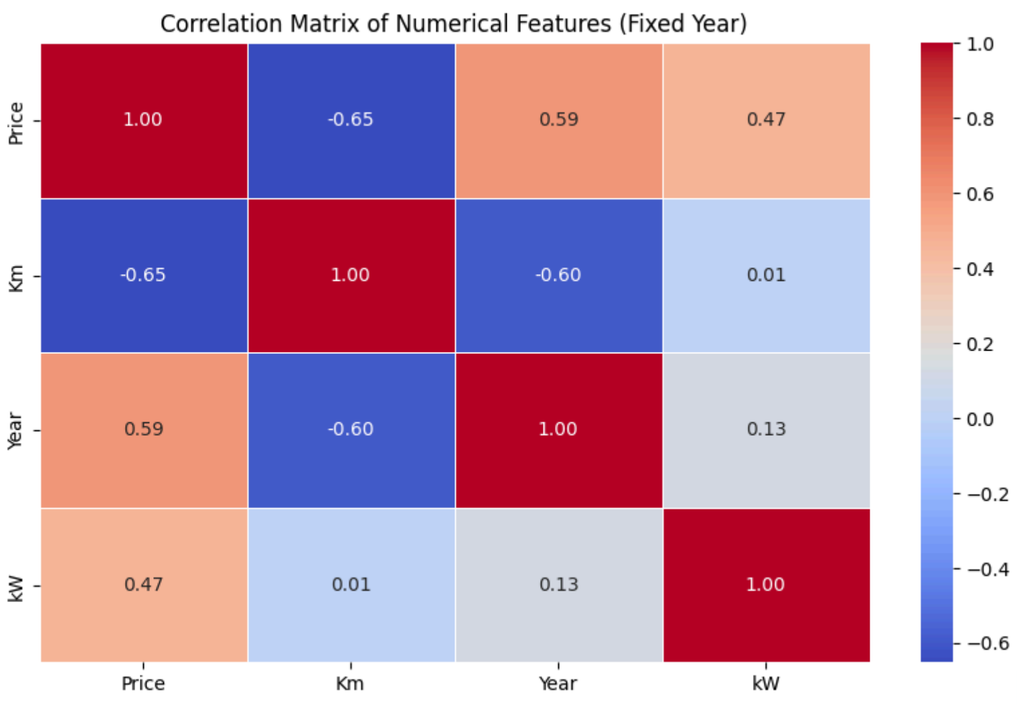
Methods:

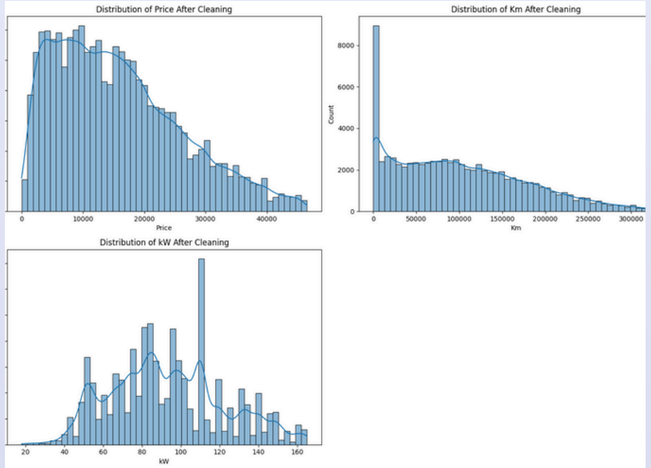
- Used **IQR (Interquartile Range)** to detect outliers in Price, Km, kW.
- Removed **extreme values** to reduce skew.
- **IsolationForest** also demonstrated for anomaly detection (though not the final approach).

Outcome:

- Significantly **improved** data distributions
- Final record count dropped from **100k** to **~82k** after outlier removal.

Exploratory Data Analysis (Post-Cleaning)





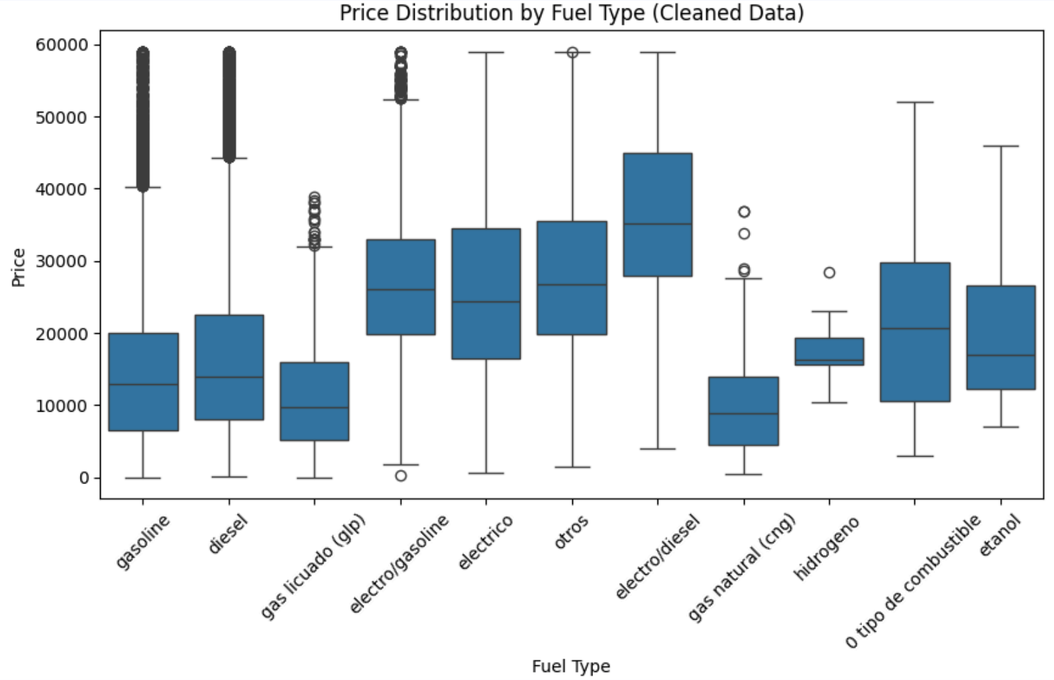
Key Plots:

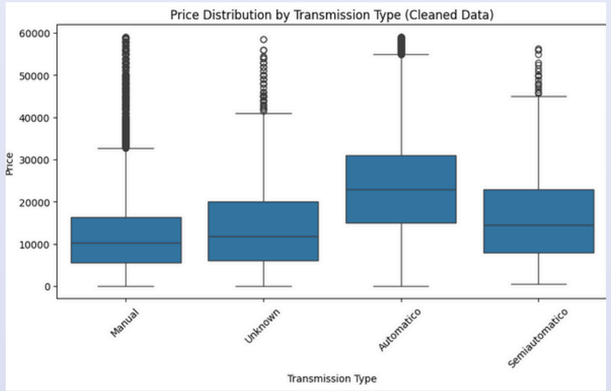
- Updated **Histograms & Boxplots** (Price, Km, kW).
- **Correlation Heatmap** (including encoded categorical features).

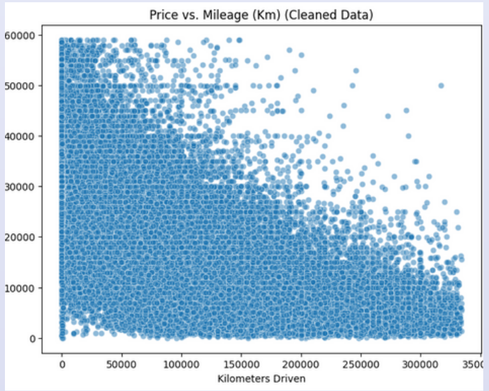
Findings:

- **Negative correlation** between Price & Km (*older, higher-mileage cars cost less*)
- **Positive correlation** between Price & kW (*more powerful cars command higher prices*)

Pit Stops: Hypothesis Testing







Understand which features drive used car prices

Hypotheses

Price vs Transmission Type: T-test results showed a statistically significant difference ($p \approx 0.0$).

Price vs Fuel Type: Gasoline vs. Diesel also significant difference in mean price ($p \approx 2.19e\text{-}141$).

Price vs Mileage (Km): Pearson correlation indicated an inverse relationship.

Conclusions

- **Transmission** (manual vs. automatic) and **Fuel Type** are associated with price variations.
- **Mileage** strongly impacts depreciation.

Refining the Clues: Feature Engineering

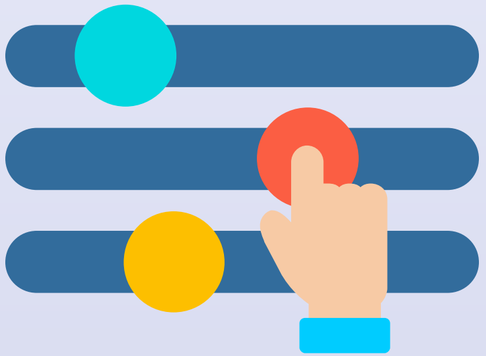
Raw Data	Label Encoding	Model Input
Manufacturer	182 Unique Values	Mercedes-benz -> 109
Automatic_Manual	4 Unique Values	Automatic -> 0; Manual -> 1
Fuel	11 Unique Values	Diesel -> 1; Electrico -> 2

Why not one-hot encoding?

High-dimensional data: feature has many unique categories

Tree-based model: Random Forest

These transformations help the model "read the map" more effectively



Finding the Right Vehicle: Model Selection

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Convert "Year" column to Car Age
df["Car_Age"] = 2025 - df["Year"]


# Select Features (Keep kW, Remove Horsepower)
features = ["Km", "Car_Age", "kW", "Fuel", "Automatic_Manual", "Manufacturer"]
target = "Price"

X = df[features]
y = df[target]


X = df[features]
y = df[target]

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train Random Forest Regressor
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predictions
y_pred = rf_model.predict(X_test)

# Evaluate Model Performance
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
```

Random Forest (Baseline):

- R^2 ~ 0.86
- MAE ~ 2724.32
- RMSE ~ 4210.97

Split data into **training** (80%) and **testing** (20%)

Takeaways:

- Model explains ~86% of price variability.
- Car_Age, kW (power), Km, and Manufacturer rank as the most important features

We needed a model that handles both **numerical** and **categorical** data effectively.

Hitting the Road: Model Development

Hyperparameter Tuning (Gradient Boosting: GridSearchCV)

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV, train_test_split

# Define parameter grid
param_grid = {
    "n_estimators": [100, 200, 300],  # Number of trees in the forest
    "max_depth": [10, 20, None],  # Maximum depth of trees
    "min_samples_split": [2, 5, 10],  # Minimum samples to split a node
    "min_samples_leaf": [1, 2, 4]  # Minimum samples per leaf node
}

# Perform Grid Search
grid_search = GridSearchCV(RandomForestRegressor(random_state=42), param_grid, cv=3, scoring="r2", n_jobs=-1)
grid_search.fit(X_train, y_train)
```

Model Improvement

Random Forest (Optimized):

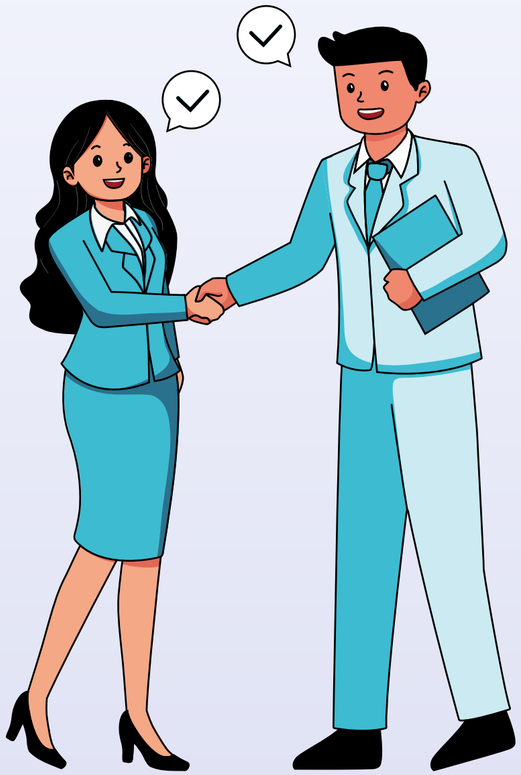
- R^2 ~ 0.8670
- MAE ~ 2660.12

Iterated to find the **best model** and how well it **fits** your data

Hitting the Road: Model Development

Determining whether it's a good deal

	Actual Price	Predicted Price	Price Difference	Percentage Difference	Deal Label
75721	5199	5053.88	-145.12	-2.791306	Fair Price
80184	67900	69942.41	2042.41	3.007968	Fair Price
19864	15395	15957.35	562.35	3.652809	Fair Price
76699	17001	25303.59	8302.59	48.835892	Good Deal
92991	18495	14555.25	-3939.75	-21.301703	Overpriced
...	...	...	...	...	...
32595	6200	6863.27	663.27	10.697903	Good Deal
29313	68900	67337.58	-1562.42	-2.267663	Fair Price
37862	6900	5280.06	-1619.94	-23.477391	Overpriced
53421	1490	3873.82	2383.82	159.987919	Good Deal
42410	34000	25303.10	-8696.90	-25.579118	Overpriced



Predict Price Specifications:

- Km, kW, Transmission, Fuel, Car_Age

Percentage Differences

Good Deal: >=10%

Fair Price: <= -10%

What We Learned from the Drive

Insights:

Feature Importance

which strongly influence a car's resale price

- **Depreciation**: Price drops as Km and Car_Age increase.
- **Performance**: Higher kW = higher price.
- **Fuel & Transmission**: Both matter; automatics & certain fuels often priced higher.

Recommendations:

- **Sellers** can highlight low-mileage or high-power aspects to maximize **price**.
- **Dealers** can use model predictions to set fair market prices.
- **Additional data** (maintenance history, accidents) could further refine the model.

Next Steps:

- Include **external market data** or brand reputation scores.
- **Resale Value Forecasting:** predict future resale price (need historical data)

Crossing the Finish Line: The Joy of Data Discovery

The Best Part?

This journey shows how numbers can tell stories, **helping dealers set fair prices**, **helping buyers find good deals**, and, ultimately, helping us **understand the hidden forces shaping the market**.