

Predict The Fare Amount Of Future Rides Using Regression Analysis

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Problem

The fare amount of a ride is influenced by various factors such as distance, duration, traffic conditions, time of day, and demand.

Goal

In this project I am going to develop a regression model that can predict the fare amount based on most important features.

Why this is a Regression problem

- ▶ First of all our Target variable is a continuous variable.
- ▶ Second there is a Linear Correlation between Independent and Dependent variable.
- ▶ The distribution of Target variable is Normally distribution.
- ▶ In Regression model we create a straight best fit line to predict the Target variable .

STEPS OF PROJECT

- 1 Data reading
- 2 Exploratory Data Analysis and Data Cleaning
- 3 Data Visualization
- 4 Feature Engineering
- 5 Splitting the Data in to Train and Test set
- 6 Standardization
- 7 Building Linear Regression Model
- 8 Checking VIF
- 9 Residual Analysis
- 10 Model Evaluation

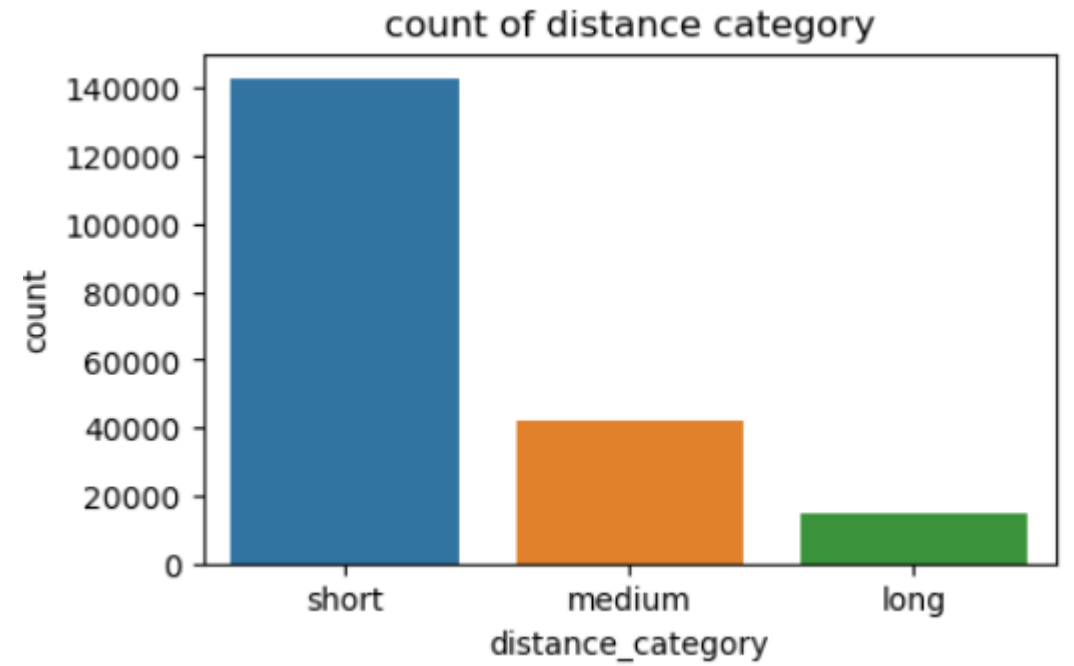
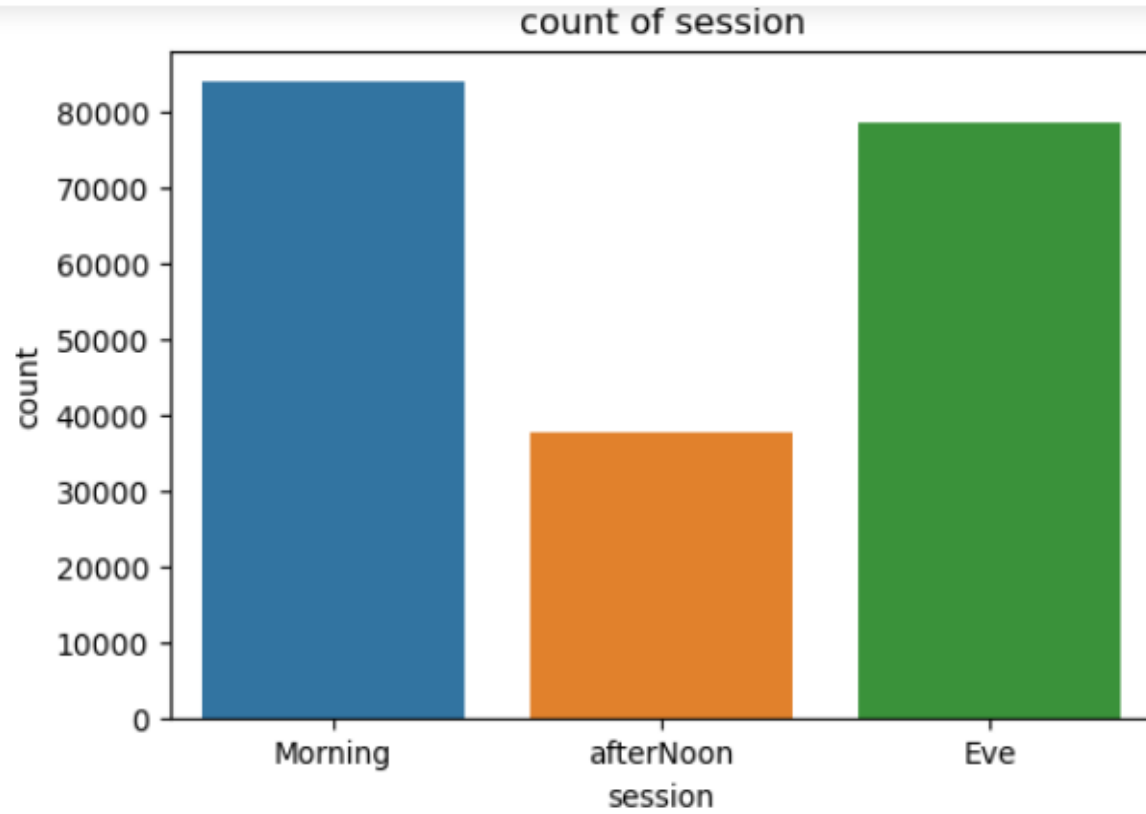
Data Reading

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 9 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Unnamed: 0            200000 non-null  int64
1   key                   200000 non-null  object
2   fare_amount          200000 non-null  float64
3   pickup_datetime      200000 non-null  object
4   pickup_longitude     200000 non-null  float64
5   pickup_latitude      200000 non-null  float64
6   dropoff_longitude    199999 non-null  float64
7   dropoff_latitude     199999 non-null  float64
8   passenger_count      200000 non-null  int64
dtypes: float64(5), int64(2), object(2)
memory usage: 13.7+ MB
```

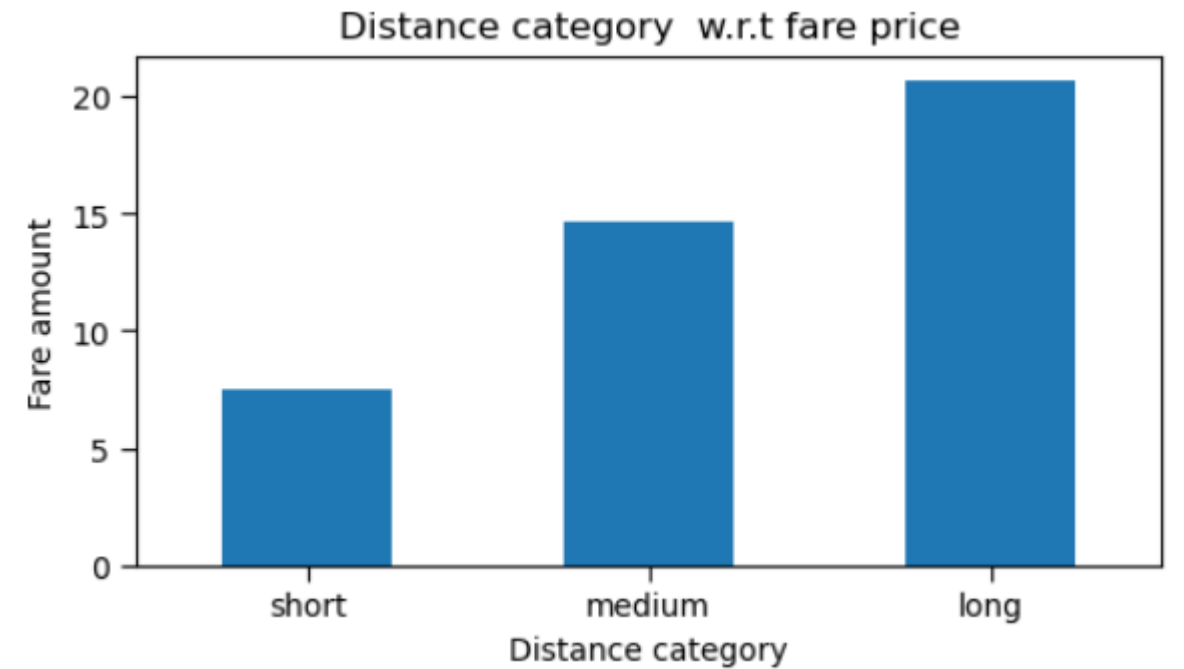
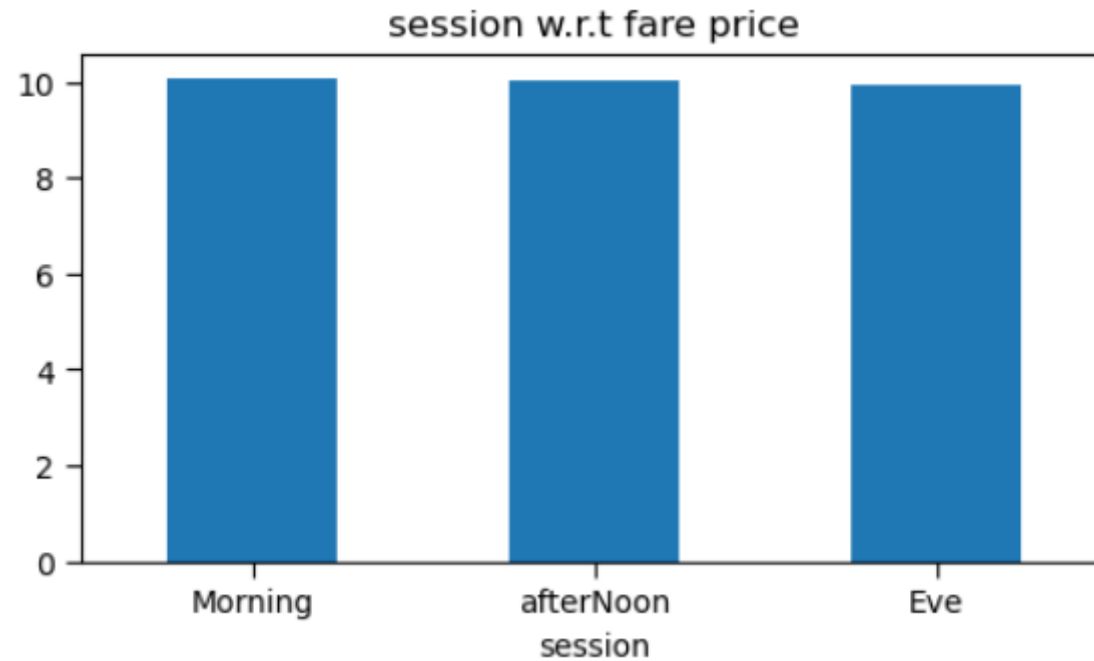
```
df.shape
```

```
(200000, 9)
```

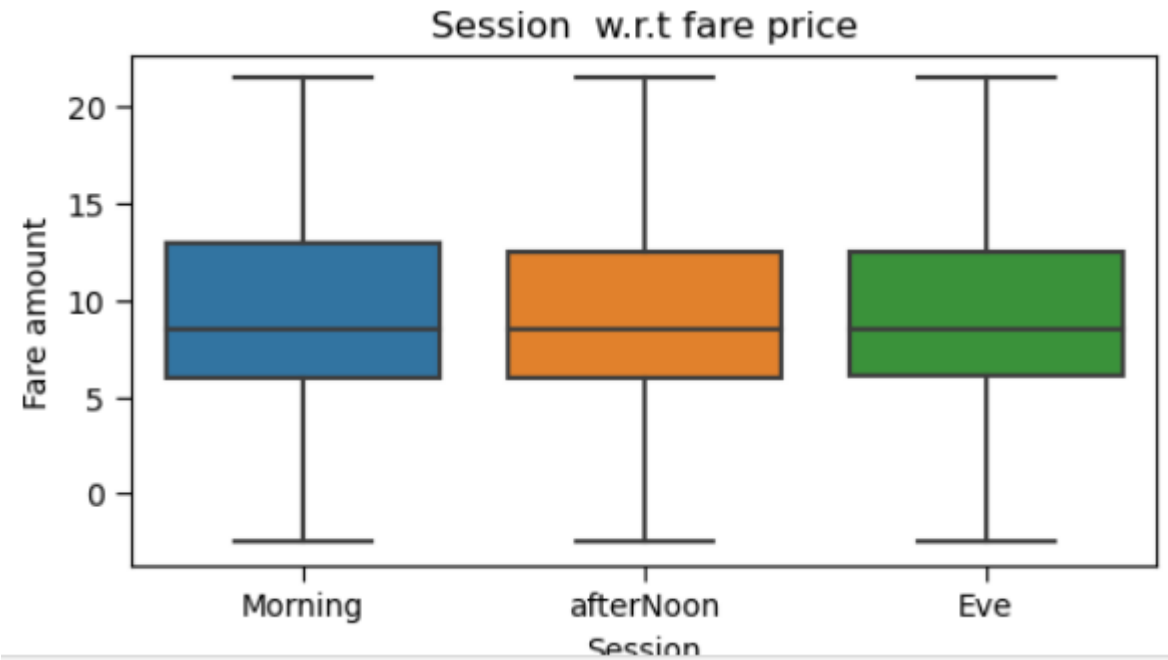
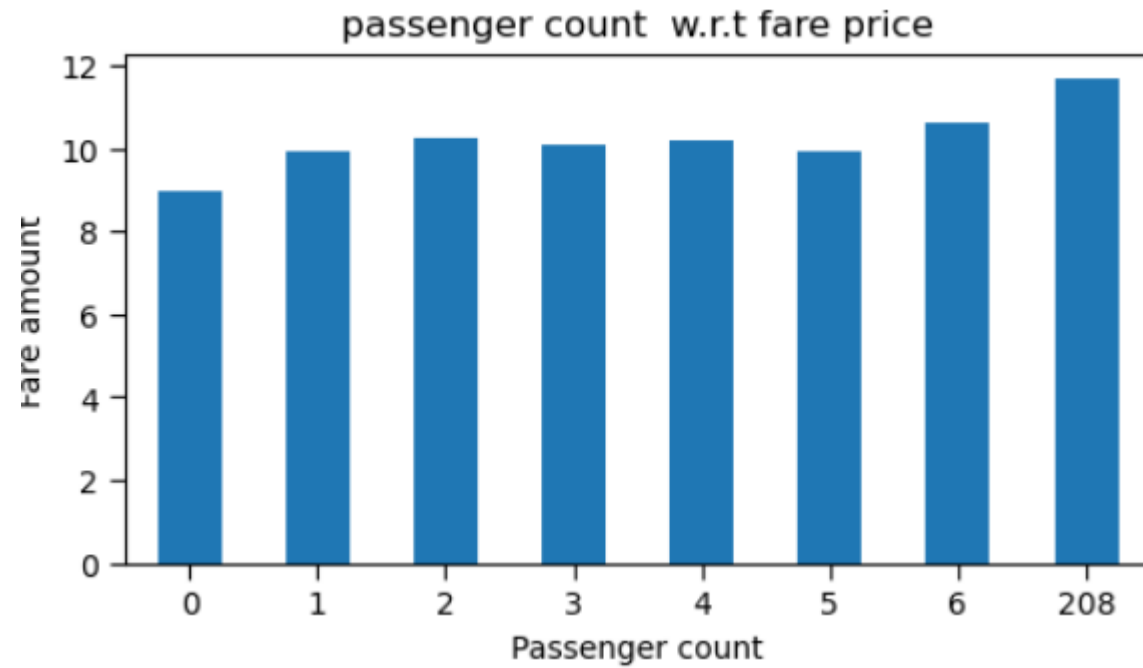
Visualization



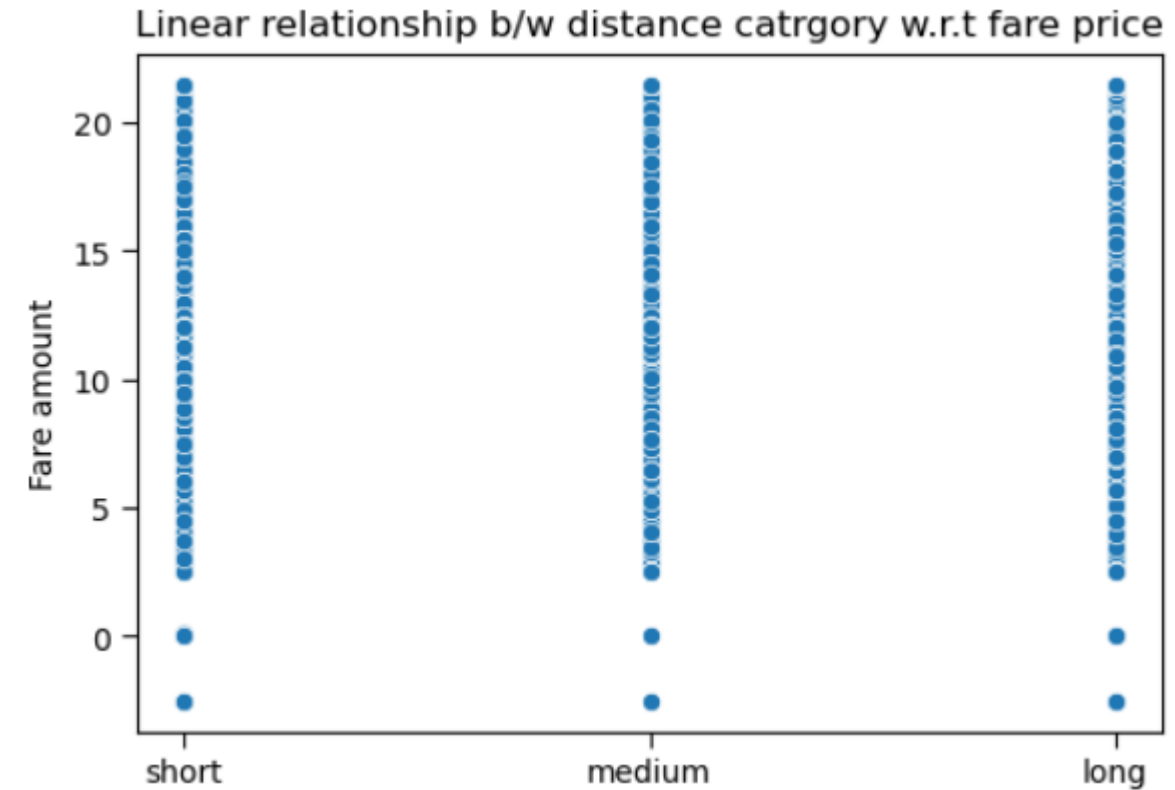
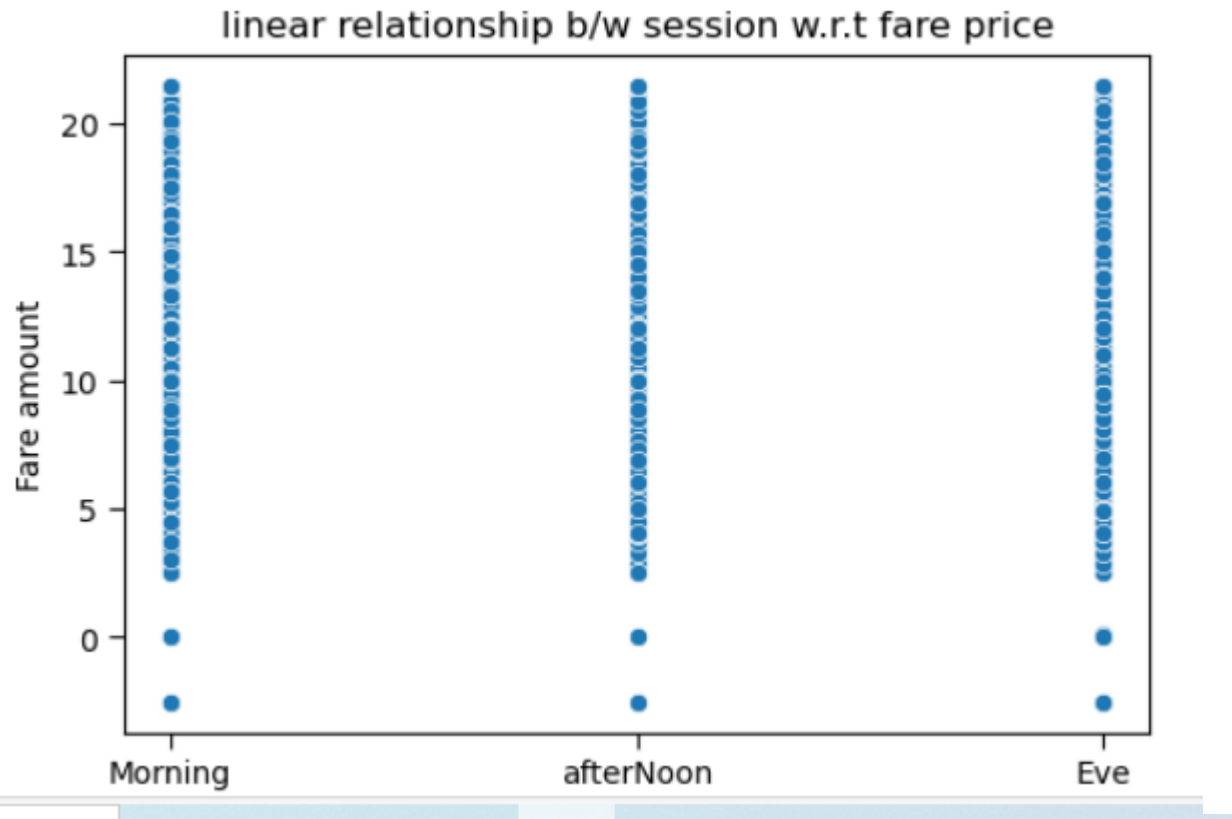
Bivariate Analysis



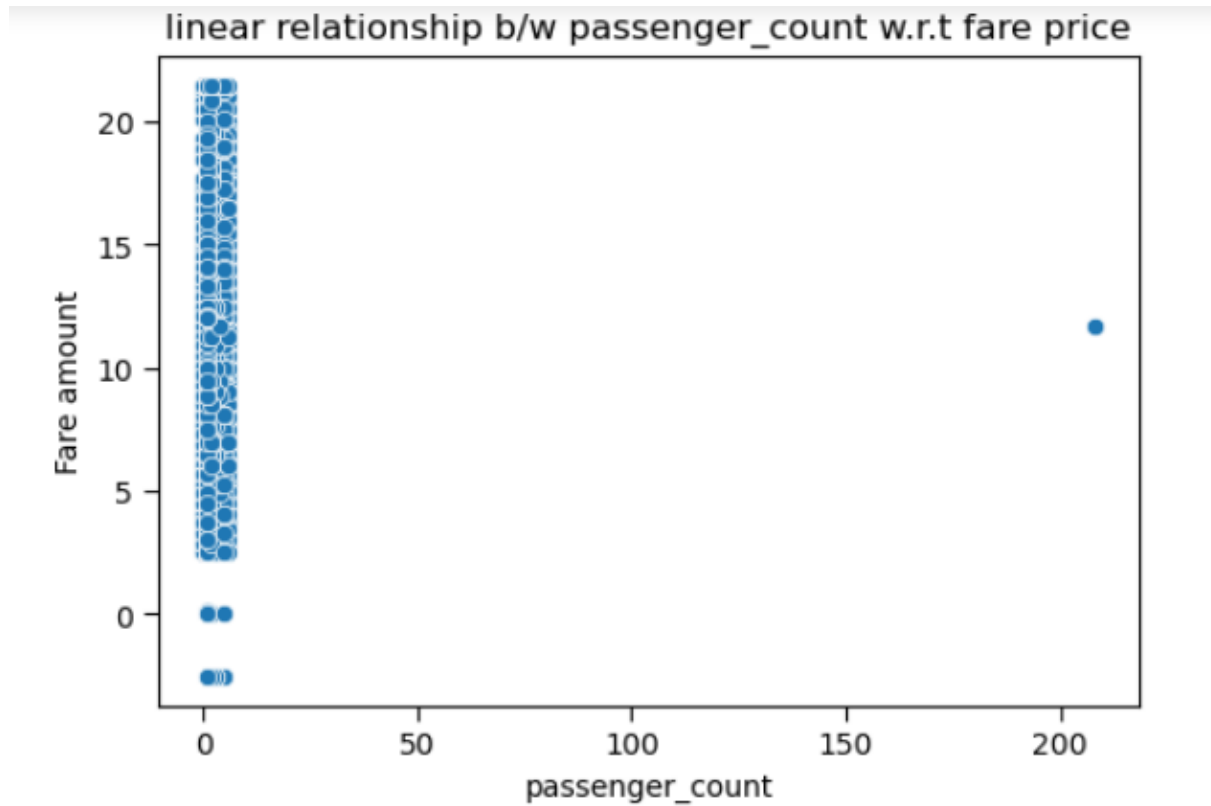
Bivariate Analysis



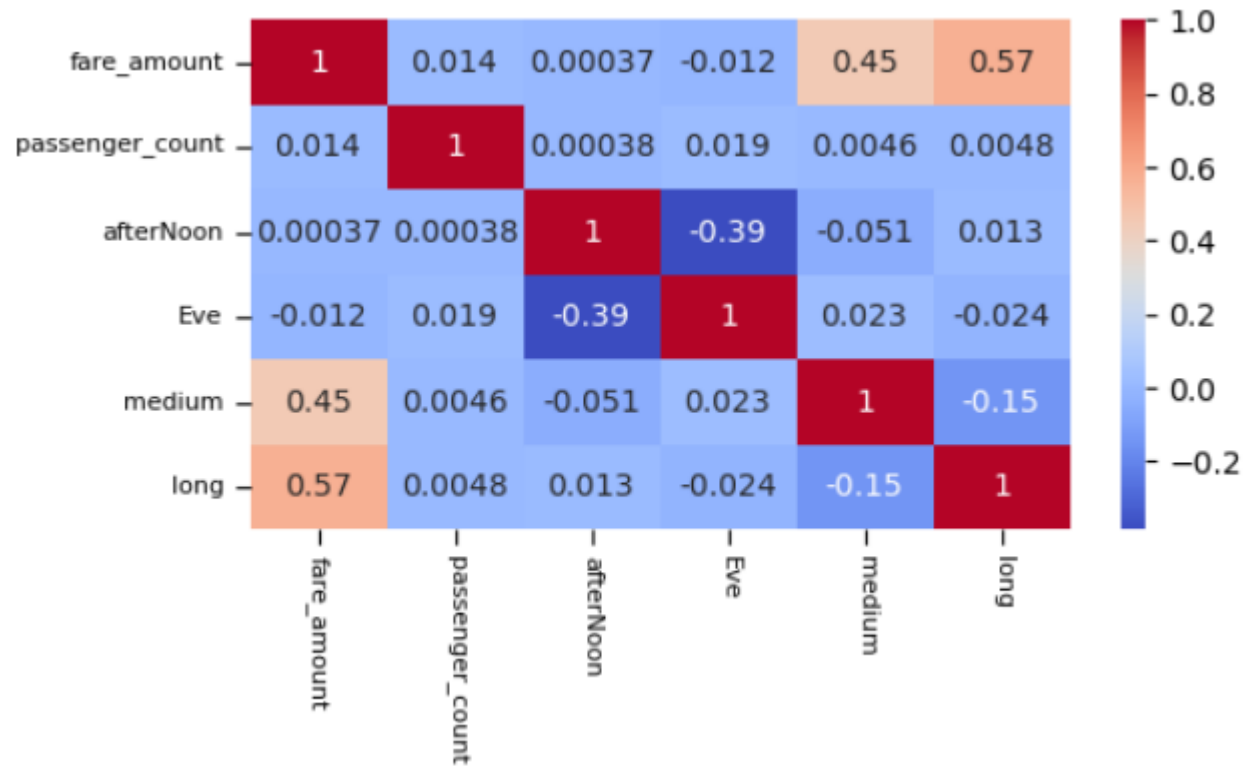
Linear relationship between Independent and Target Variable



Linear Relationship b/w Passenger Count w.r.t Target variable



Correlation matrix of all Independent feature and Target variable



Model accuracy by taking all Independent features

	coef	std err	t	P> t	[0.025	0.975]
const	-0.4745	0.003	-171.496	0.000	-0.480	-0.469
passenger_count	0.0090	0.002	5.462	0.000	0.006	0.012
afterNoon	0.0451	0.005	9.865	0.000	0.036	0.054
Eve	-0.0018	0.004	-0.483	0.629	-0.009	0.005
medium	1.3435	0.004	328.574	0.000	1.335	1.351
long	2.4915	0.006	391.516	0.000	2.479	2.504
Omnibus:	21689.605	Durbin-Watson:		1.994		
Prob(Omnibus):	0.000	Jarque-Bera (JB):		66964.924		
Skew:	0.809	Prob(JB):		0.00		
Kurtosis:	5.977	Cond. No.		4.44		

OLS Regression Results

Dep. Variable:	fare_amount	R-squared:	0.620
Model:	OLS	Adj. R-squared:	0.620
Method:	Least Squares	F-statistic:	4.576e+04
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	0.00
Time:	10:20:24	Log-Likelihood:	-1.3084e+05
No. Observations:	140000	AIC:	2.617e+05
Df Residuals:	139994	BIC:	2.618e+05
Df Model:	5		
Covariance Type:	nonrobust		

Model accuracy improve by Dropping “Eve” Independent Variable

OLS Regression Results

Dep. Variable:	fare_amount	R-squared:	0.620
Model:	OLS	Adj. R-squared:	0.620
Method:	Least Squares	F-statistic:	5.720e+04
Date:	Fri, 26 Apr 2024	Prob (F-statistic):	0.00
Time:	10:20:25	Log-Likelihood:	-1.3084e+05
No. Observations:	140000	AIC:	2.617e+05
Df Residuals:	139995	BIC:	2.617e+05
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	-0.4754	0.002	-224.505	0.000	-0.480	-0.471
passenger_count	0.0090	0.002	5.453	0.000	0.006	0.012
afterNoon	0.0459	0.004	10.905	0.000	0.038	0.054
medium	1.3435	0.004	328.575	0.000	1.335	1.351
long	2.4915	0.006	391.598	0.000	2.479	2.504
Omnibus:	21694.127	Durbin-Watson:	1.994			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	66984.822			
Skew:	0.809	Prob(JB):	0.00			
Kurtosis:	5.977	Cond. No.	4.10			

The background features abstract, overlapping green geometric shapes, primarily triangles and polygons, in various shades of green, creating a modern and dynamic design. The shapes are concentrated on the left and right sides of the frame, leaving a large white central area.

THANK YOU