Week 3 Assignment

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Course: DSC630 - Predictive Analytics
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In this assignment, you will be using data on the Los Angeles Dodgers Major League Baseball (MLB) team located here: dodgers.csv. Use this data to make a recommendation to management on how to improve attendance. Tell a story with your analysis and clearly explain the steps you take to arrive at your conclusion. This is an open-ended question, and there is no one right answer. You are welcome to do additional research and/or use domain knowledge to assist your analysis, but clearly state any assumptions you make.

You can use R or Python to complete this assignment. Submit your code and output to the submission link. Make sure to add comments to all your code and to document your steps, process, and analysis.

1. Importing all the libraries required for this exercise

In [2]:

```
## Importing libraries required for this assignment
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import sklearn.metrics as metrics
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings("ignore")
```

2. Load the Dataset into dataframe

In [5]:

```
## Load the House data into a dataframe
bb_df = pd.read_csv('dodgers-2022.csv')
bb_df.head(5)
```

Out[5]:

	month	day	attend	day_of_week	opponent	temp	skies	day_night	cap	shirt	fireworks	bobb
0	APR	10	56000	Tuesday	Pirates	67	Clear	Day	NO	NO	NO	
1	APR	11	29729	Wednesday	Pirates	58	Cloudy	Night	NO	NO	NO	
2	APR	12	28328	Thursday	Pirates	57	Cloudy	Night	NO	NO	NO	
3	APR	13	31601	Friday	Padres	54	Cloudy	Night	NO	NO	YES	
4	APR	14	46549	Saturday	Padres	57	Cloudy	Night	NO	NO	NO	

In [6]:
```
## Printing number of rows and columns
bb_df.shape
```

Out[6]:
```
(81, 12)
```

In [7]:
```
## Printing the dtype for each of the column
bb_df.dtypes
```

Out[7]:
```
month          object
day             int64
attend          int64
day_of_week    object
opponent       object
temp            int64
skies          object
day_night      object
cap            object
shirt          object
fireworks      object
bobblehead     object
dtype: object
```

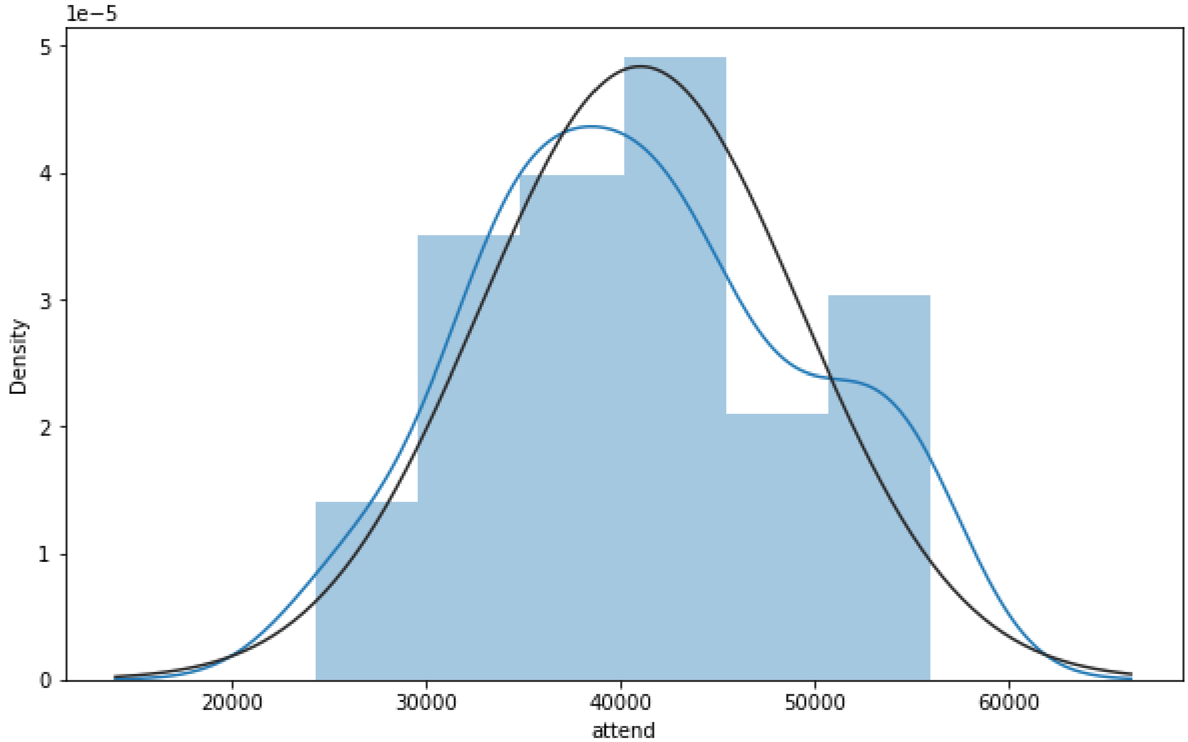
In [8]:
```
## Looking at summary information about your data (total, mean, min, max, freq, unique,
bb_df.describe()
```

Out[8]:

	day	attend	temp
count	81.000000	81.000000	81.000000
mean	16.135802	41040.074074	73.148148
std	9.605666	8297.539460	8.317318
min	1.000000	24312.000000	54.000000
25%	8.000000	34493.000000	67.000000
50%	15.000000	40284.000000	73.000000
75%	25.000000	46588.000000	79.000000
max	31.000000	56000.000000	95.000000

Visualizations

In [9]:
```
### Histogram and normal probability plot
plt.figure(figsize=(10,6))
sns.distplot(bb_df['attend'], fit=norm);
fig = plt.figure()
```




```
<Figure size 432x288 with 0 Axes>
```

In [10]:
```
## Printing skewness and kurtosis
print("Skewness: %f" % bb_df['attend'].skew())
print("Kurtosis: %f" % bb_df['attend'].kurt())
```

```
Skewness: 0.137615
Kurtosis: -0.753389
```

Observation

Skewness:

1. Skewness is a measure of the asymmetry of a distribution. A distribution is asymmetrical when its left and right side are not mirror images. A distribution can have right (or positive), left (or negative), or zero skewness.
2. The value of skewness is 0.13716 which lies between -0.5 and 0.5 for the above plot. So, the distribution is approximately symmetric.

Kurtosis

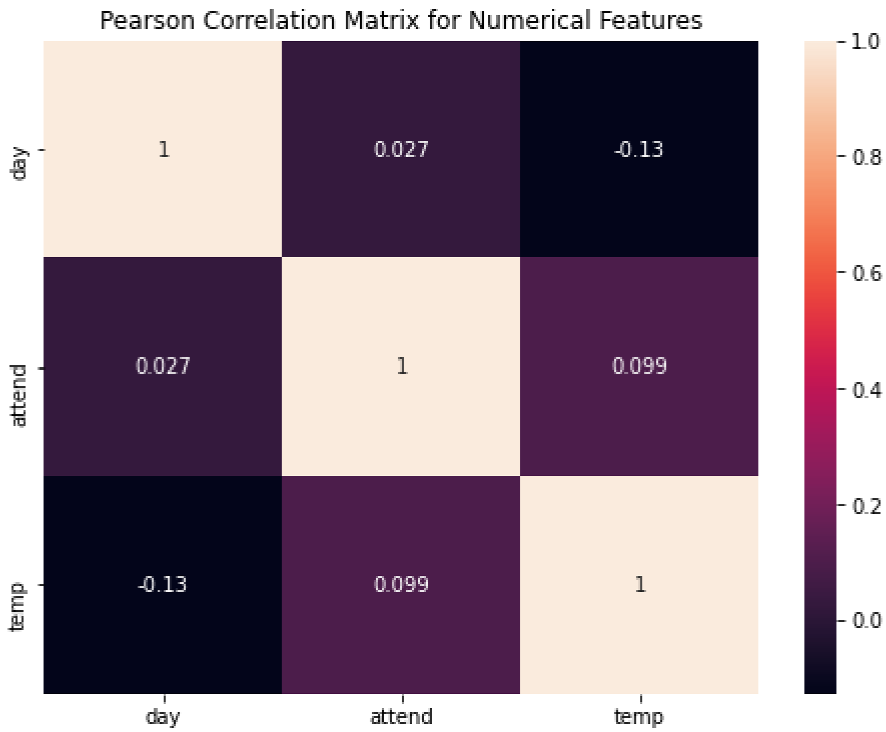
1. Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.
2. The value for Kurtosus is -0.753389 and is less than 3. So, the dataset has lighter tails than a normal distribution (less in the tails)

Correlation

Numerical Variables

In [11]:
```
# To find the correlations between the variables/features, a correlation matrix of the
# A correlation matrix is a tabular data representing the ‘correlations’ between pairs
correlation_mat = bb_df.corr()
```

```python
# Plotting heatmap using the correlation_mat created in the previous step
plt.figure(figsize=(8,6))
sns.heatmap(correlation_mat, annot = True)
plt.title('Pearson Correlation Matrix for Numerical Features', fontsize=12)
plt.show()
```



Observation

1. The above correlation matrix only shows the relationship between numerical or non-categorical variables present in the data set
2. Based on the above result, we see the attendance is postively correlated to the variable temperature. So, the increase in temperature results in increase in head count. This makes sense as people is interest to go out to see the match when temperature is good.
3. The day of the month is also positively correlated to the temperature. The people is somewhat less interested to go to the match during initial days of the month. However, they are interested to go during mid and end of the months.

Categorical Variables

In [12]:
```python
## Option to display all the columns present in the dataframe
pd.set_option('display.max_columns', None)
```

In [13]:
```python
# To support the Spearman Correlation Matrix, create dummy variables for the object typ
catCols = ['month', 'day_of_week', 'opponent','skies','day_night', 'cap', 'shirt', 'fir
bb_cat_df = pd.get_dummies(bb_df, columns=catCols)
bb_cat_df.head(5)
```

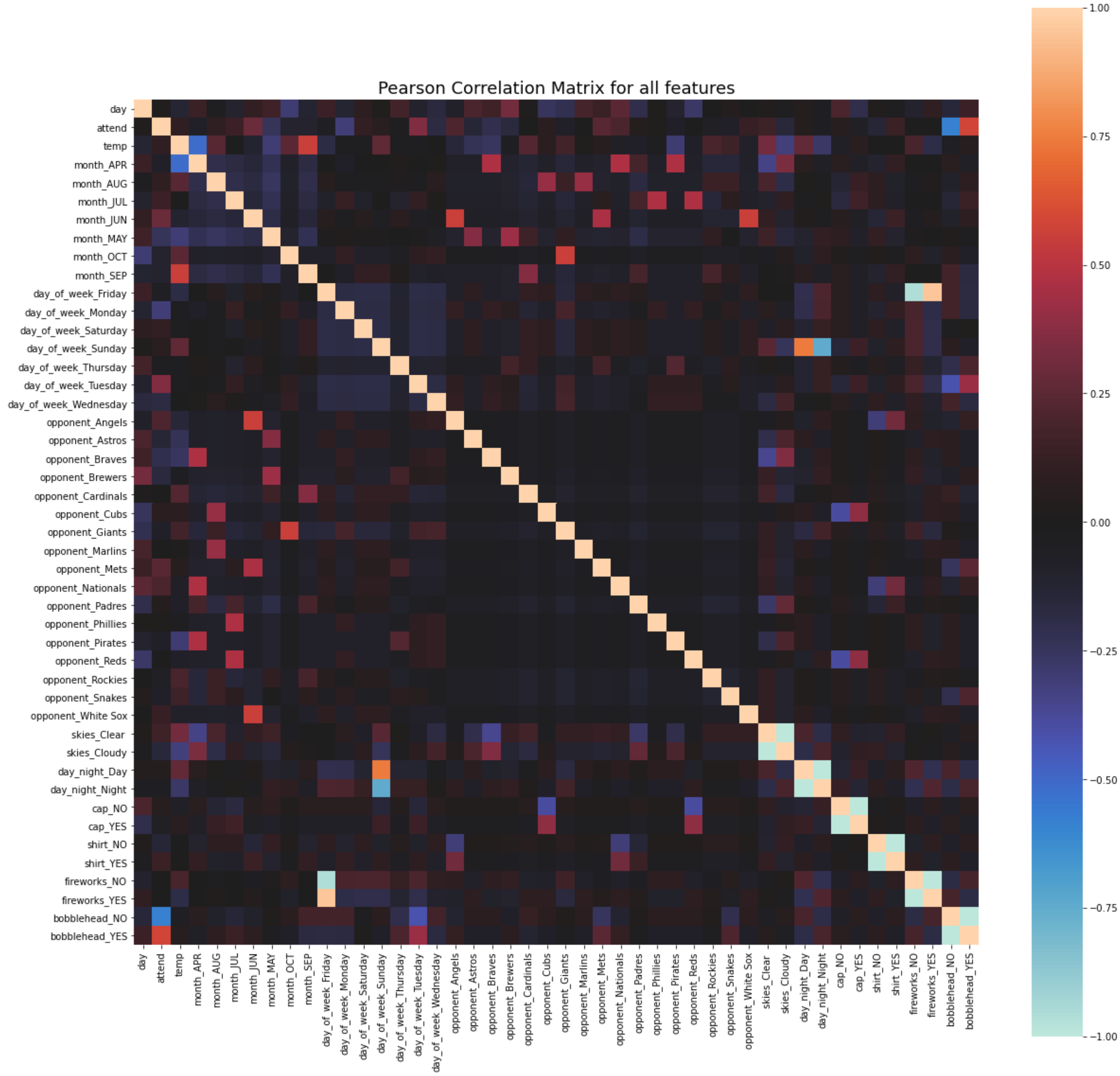
Out[13]:

	day	attend	temp	month_APR	month_AUG	month_JUL	month_JUN	month_MAY	month_OCT	mo

	day	attend	temp	month_APR	month_AUG	month_JUL	month_JUN	month_MAY	month_OCT	mo
0	10	56000	67	1	0	0	0	0	0	
1	11	29729	58	1	0	0	0	0	0	
2	12	28328	57	1	0	0	0	0	0	
3	13	31601	54	1	0	0	0	0	0	
4	14	46549	57	1	0	0	0	0	0	

In [14]:

```
## Plotting heat map matrix for the correlation
## look for multicollinearity of features
fig, ax = plt.subplots(figsize=(20, 20))
sns.heatmap(bb_cat_df.corr(), center=0,
           vmin=-1, vmax=1,  square=True)
# title
plt.title('Pearson Correlation Matrix for all features', fontsize=18)
plt.show()
```



In [15]:

```
# Create a Spearman Correlation Matrix: Relationship between the categorical and non-ca
bb_cat_df.corr('spearman').style.background_gradient(cmap="Blues")
```

Out[15]:

	day	attend	temp	month_APR	month_AUG	month_JUL	month_.
day	1.000000	0.063626	-0.123692	0.104875	-0.028569	-0.079586	0.108
attend	0.063626	1.000000	0.090628	-0.055739	0.101270	0.096614	0.314
temp	-0.123692	0.090628	1.000000	-0.495820	0.296848	0.012656	-0.132
month_APR	0.104875	-0.055739	-0.495820	1.000000	-0.198811	-0.173913	-0.147
month_AUG	-0.028569	0.101270	0.296848	-0.198811	1.000000	-0.198811	-0.168
month_JUL	-0.079586	0.096614	0.012656	-0.173913	-0.198811	1.000000	-0.147
month_JUN	0.108461	0.314192	-0.132964	-0.147442	-0.168550	-0.147442	1.000
month_MAY	0.153172	-0.223536	-0.337159	-0.222911	-0.254824	-0.222911	-0.188

	day	attend	temp	month_APR	month_AUG	month_JUL	month_J
month_OCT	-0.293820	-0.109043	0.268880	-0.081786	-0.093495	-0.081786	-0.069
month_SEP	-0.113057	-0.109991	0.527833	-0.173913	-0.198811	-0.173913	-0.147
day_of_week_Friday	0.134612	-0.030209	-0.167878	0.007013	0.051309	-0.087664	0.059
day_of_week_Monday	-0.119007	-0.325514	-0.024568	-0.076087	-0.019881	0.119565	-0.036
day_of_week_Saturday	0.083503	0.128028	-0.044672	0.007013	-0.035275	-0.087664	0.059
day_of_week_Sunday	0.035273	0.051787	0.237768	0.007013	-0.035275	0.007013	-0.047
day_of_week_Thursday	0.172376	-0.008776	0.014286	0.037438	0.009782	-0.106966	0.072
day_of_week_Tuesday	-0.090701	0.333736	-0.020895	0.007013	-0.035275	0.101690	-0.047
day_of_week_Wednesday	-0.165867	-0.167959	0.010423	0.021739	0.069584	0.021739	-0.036
opponent_Angels	-0.106335	0.204106	-0.184855	-0.081786	-0.093495	-0.081786	0.554
opponent_Astros	0.179090	-0.156575	-0.226868	-0.081786	-0.093495	-0.081786	-0.069
opponent_Braves	0.141313	-0.167758	-0.278683	0.470270	-0.093495	-0.081786	-0.069
opponent_Brewers	0.319518	-0.134038	-0.059812	-0.095050	-0.108657	-0.095050	-0.080
opponent_Cardinals	0.038556	0.015034	0.181659	-0.128262	-0.146625	-0.128262	-0.108
opponent_Cubs	-0.237854	0.109043	0.082625	-0.081786	0.411377	-0.081786	-0.069
opponent_Giants	-0.216080	-0.086529	0.196922	-0.147442	0.134840	-0.147442	-0.125
opponent_Marlins	0.159502	0.002796	0.032210	-0.081786	0.411377	-0.081786	-0.069
opponent_Mets	0.130490	0.248580	0.076901	-0.095050	-0.108657	0.065347	0.463
opponent_Nationals	0.225262	0.204106	-0.079824	0.470270	-0.093495	-0.081786	-0.069
opponent_Padres	-0.188335	0.038644	-0.010099	0.184302	-0.168550	0.184302	-0.125
opponent_Phillies	0.053167	-0.011184	-0.025208	-0.081786	-0.093495	0.470270	-0.069
opponent_Pirates	-0.131519	-0.082481	-0.273081	0.470270	-0.093495	-0.081786	-0.069
opponent_Reds	-0.264438	-0.030756	-0.092428	-0.081786	-0.093495	0.470270	-0.069
opponent_Rockies	-0.021860	-0.082328	0.161577	-0.147442	0.134840	-0.147442	-0.125
opponent_Snakes	0.052969	-0.089049	0.167468	-0.147442	0.134840	0.073721	-0.125
opponent_White Sox	0.029382	0.139799	-0.102230	-0.081786	-0.093495	-0.081786	0.554
skies_Clear	0.054252	0.144553	0.259024	-0.343251	0.188903	-0.097204	0.103
skies_Cloudy	-0.054252	-0.144553	-0.259024	0.343251	-0.188903	0.097204	-0.103
day_night_Day	0.052377	0.031944	0.249189	0.069584	0.018182	-0.019881	0.033
day_night_Night	-0.052377	-0.031944	-0.249189	-0.069584	-0.018182	0.019881	-0.033
cap_NO	0.194109	0.051039	-0.066466	0.066354	-0.128951	-0.157591	0.056
cap_YES	-0.194109	-0.051039	0.066466	-0.066354	0.128951	0.157591	-0.056
shirt_NO	0.037777	-0.139799	-0.011203	-0.102233	0.093495	0.081786	-0.138

	day	attend	temp	month_APR	month_AUG	month_JUL	month_J
shirt_YES	-0.037777	0.139799	0.011203	0.102233	-0.093495	-0.081786	0.138
fireworks_NO	-0.091546	-0.015361	0.178363	0.006808	-0.034245	0.006808	-0.046
fireworks_YES	0.091546	0.015361	-0.178363	-0.006808	0.034245	-0.006808	0.046
bobblehead_NO	-0.141919	-0.544860	-0.074884	0.063872	-0.089337	-0.139015	-0.089
bobblehead_YES	0.141919	0.544860	0.074884	-0.063872	0.089337	0.139015	0.089

In [16]:

```
## Check out all the variables correlationg with attend
## Pearson correlation is used
df_correlations = bb_cat_df.corr().stack().reset_index().sort_values(0, ascending=False
df_correlations.loc[df_correlations['level_0'] == 'attend'].sort_values(0, ascending=Fa
```

Out[16]:

	level_0	level_1	0
47	attend	attend	1.000000
91	attend	bobblehead_YES	0.581895
61	attend	day_of_week_Tuesday	0.355316
52	attend	month_JUN	0.295853
71	attend	opponent_Mets	0.236213
63	attend	opponent_Angels	0.207796
72	attend	opponent_Nationals	0.195667
80	attend	skies_Clear	0.150963
51	attend	month_JUL	0.143837
87	attend	shirt_YES	0.133269
79	attend	opponent_White Sox	0.127046
58	attend	day_of_week_Saturday	0.107788
48	attend	temp	0.098951
50	attend	month_AUG	0.098944
68	attend	opponent_Cubs	0.075310
59	attend	day_of_week_Sunday	0.065153
84	attend	cap_NO	0.055002
73	attend	opponent_Padres	0.045111
82	attend	day_night_Day	0.043544
46	attend	day	0.027093
74	attend	opponent_Phillies	0.020380
89	attend	fireworks_YES	0.002094

	level_0	level_1	0
88	attend	fireworks_NO	-0.002094
67	attend	opponent_Cardinals	-0.006967
70	attend	opponent_Marlins	-0.008912
76	attend	opponent_Reds	-0.009301
60	attend	day_of_week_Thursday	-0.019679
83	attend	day_night_Night	-0.043544
56	attend	day_of_week_Friday	-0.048948
85	attend	cap_YES	-0.055002
77	attend	opponent_Rockies	-0.060404
75	attend	opponent_Pirates	-0.071849
49	attend	month_APR	-0.073237
78	attend	opponent_Snakes	-0.073943
69	attend	opponent_Giants	-0.074763
54	attend	month_OCT	-0.103132
55	attend	month_SEP	-0.105443
86	attend	shirt_NO	-0.133269
64	attend	opponent_Astros	-0.134533
81	attend	skies_Cloudy	-0.150963
66	attend	opponent_Brewers	-0.157030
62	attend	day_of_week_Wednesday	-0.174723
65	attend	opponent_Braves	-0.209171
53	attend	month_MAY	-0.239471
57	attend	day_of_week_Monday	-0.307198
90	attend	bobblehead_NO	-0.581895

In [17]:

```
## Repeating the above step for spearman correlation
df_correlations = bb_cat_df.corr('spearman').stack().reset_index().sort_values(0, ascen
df_correlations.loc[df_correlations['level_0'] == 'attend'].sort_values(0, ascending=Fa
```

Out[17]:

	level_0	level_1	0
47	attend	attend	1.000000
91	attend	bobblehead_YES	0.544860
61	attend	day_of_week_Tuesday	0.333736
52	attend	month_JUN	0.314192
71	attend	opponent_Mets	0.248580

	level_0	level_1	0
72	attend	opponent_Nationals	0.204106
63	attend	opponent_Angels	0.204106
80	attend	skies_Clear	0.144553
79	attend	opponent_White Sox	0.139799
87	attend	shirt_YES	0.139799
58	attend	day_of_week_Saturday	0.128028
68	attend	opponent_Cubs	0.109043
50	attend	month_AUG	0.101270
51	attend	month_JUL	0.096614
48	attend	temp	0.090628
46	attend	day	0.063626
59	attend	day_of_week_Sunday	0.051787
84	attend	cap_NO	0.051039
73	attend	opponent_Padres	0.038644
82	attend	day_night_Day	0.031944
89	attend	fireworks_YES	0.015361
67	attend	opponent_Cardinals	0.015034
70	attend	opponent_Marlins	0.002796
60	attend	day_of_week_Thursday	-0.008776
74	attend	opponent_Phillies	-0.011184
88	attend	fireworks_NO	-0.015361
56	attend	day_of_week_Friday	-0.030209
76	attend	opponent_Reds	-0.030756
83	attend	day_night_Night	-0.031944
85	attend	cap_YES	-0.051039
49	attend	month_APR	-0.055739
77	attend	opponent_Rockies	-0.082328
75	attend	opponent_Pirates	-0.082481
69	attend	opponent_Giants	-0.086529
78	attend	opponent_Snakes	-0.089049
54	attend	month_OCT	-0.109043
55	attend	month_SEP	-0.109991
66	attend	opponent_Brewers	-0.134038

	level_0	level_1	0
86	attend	shirt_NO	-0.139799
81	attend	skies_Cloudy	-0.144553
64	attend	opponent_Astros	-0.156575
65	attend	opponent_Braves	-0.167758
62	attend	day_of_week_Wednesday	-0.167959
53	attend	month_MAY	-0.223536
57	attend	day_of_week_Monday	-0.325514
90	attend	bobblehead_NO	-0.544860

Difference between Pearson and Spearman Correlation

Pearson correlation evaluates the linear relationship between two continuous variables. Spearman correlation: Spearman correlation evaluates the monotonic relationship. The Spearman correlation coefficient is based on the ranked values for each variable rather than the raw data.

Observation

1. A positive correlation is a relationship between two variables that move in the same direction where as Negative correlation describes when two variables tend to move in opposite size and direction from one another
2. Based on Pearson and Spearman correlation results above, we see Attendance is highly postively correlated to: the months of June, July & August, Tuesday & Saturday games, games against the Angels, Cubs, Mets, Nationals & White Sox, games on clear sky days, and game days when free shirts and bobblehead are given out.
3. We also see Attedance is highly negatively correlated to: the months of April, May, September & October, Wednesday & Monday games, games against the Astros, Braves, Bruins, Pirates, Rockies & Snakes, games on cloudy days, and game days when no free shirts and no bobblehead are given out.

Linear Regression

In [43]:
```
#Setting the value for X and Y
df = bb_cat_df.copy()

y = df['attend']
x = df.drop('attend',1)
```

In [45]:
```
## Showing the values for x
x.head()
```

Out[45]:

	day	temp	month_APR	month_AUG	month_JUL	month_JUN	month_MAY	month_OCT	month_SEP
0	10	67	1	0	0	0	0	0	0

	day	temp	month_APR	month_AUG	month_JUL	month_JUN	month_MAY	month_OCT	month_SEP
1	11	58	1	0	0	0	0	0	0
2	12	57	1	0	0	0	0	0	0
3	13	54	1	0	0	0	0	0	0
4	14	57	1	0	0	0	0	0	0

In [46]:

```
## Showing the value for y
y.head()
```

Out[46]:

```
0    56000
1    29729
2    28328
3    31601
4    46549
Name: attend, dtype: int64
```

In [47]:

```
## Splitting the dataframe for  train and test
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_state
```

In [48]:

```
## Multiple Linear Regression
mlr = LinearRegression()
mlr.fit(x_train, y_train)
```

Out[48]:

```
LinearRegression()
```

In [49]:

```
#Intercept and Coefficient

print("Intercept: ", mlr.intercept_)
print("Coefficients:")
list(zip(x, mlr.coef_))
```

```
Intercept:  48020.11016548949
Coefficients:
```

Out[49]:

```
[('day', 434.35500034172725),
 ('temp', -53.28702163131573),
 ('month_APR', -5162.524705009923),
 ('month_AUG', 3252.9679797869258),
 ('month_JUL', -3729.480132314525),
 ('month_JUN', 1766.7257588288967),
 ('month_MAY', -3893.9432535064734),
 ('month_OCT', 8168.6910535974175),
 ('month_SEP', -402.4367013821127),
 ('day_of_week_Friday', -13352.694193805713),
 ('day_of_week_Monday', -3978.0441943458077),
 ('day_of_week_Saturday', 5313.480535971895),
 ('day_of_week_Sunday', -554.366898942626),
 ('day_of_week_Thursday', 2490.2665931914357),
 ('day_of_week_Tuesday', 10399.836747377092),
 ('day_of_week_Wednesday', -318.4785894464325),
 ('opponent_Angels', 4135.503696219863),
 ('opponent_Astros', -3366.40592605868),
```

```
 ('opponent_Braves', -2421.77296295778),
 ('opponent_Brewers', -6672.283749237914),
 ('opponent_Cardinals', -2123.060283675282),
 ('opponent_Cubs', 7205.26440922086),
 ('opponent_Giants', -4713.739008370042),
 ('opponent_Marlins', -10059.067173755366),
 ('opponent_Mets', -2415.750052827833),
 ('opponent_Nationals', 3409.813331805795),
 ('opponent_Padres', 7695.221367732398),
 ('opponent_Phillies', 4448.5225682102155),
 ('opponent_Pirates', 2382.7133774318963),
 ('opponent_Reds', 8256.53173182325),
 ('opponent_Rockies', -581.9926495306655),
 ('opponent_Snakes', -5226.47079146744),
 ('opponent_White Sox', 46.97211543675667),
 ('skies_Clear ', 3254.075366371817),
 ('skies_Cloudy', -3254.075366371842),
 ('day_night_Day', 3642.870280917164),
 ('day_night_Night', -3642.870280917142),
 ('cap_NO', 4624.466183277176),
 ('cap_YES', -4624.466183277177),
 ('shirt_NO', -5253.564759752592),
 ('shirt_YES', 5253.564759752595),
 ('fireworks_NO', -7190.400407900272),
 ('fireworks_YES', 7190.400407900244),
 ('bobblehead_NO', -2838.5185796062606),
 ('bobblehead_YES', 2838.5185796062624)]
```

In [50]:

```
#Prediction of test set
y_pred_mlr= mlr.predict(x_test)
#Predicted values
print("Prediction for test set: {}".format(y_pred_mlr))
```

```
Prediction for test set: [61112.14490535 50688.62495422 44441.81566532 49289.03661167
 42609.46252332 35508.12736722 36392.42139352 34985.92659206
 31947.84512894 45389.80584226 62754.08093432 50082.63692479
 37093.74548468 30701.01392035 32388.56614008 38632.25077381
 25695.74880189 45075.814302   57797.75681378 23857.82578383
 30606.84261022 34062.68411605 47054.54832527 35442.43761246
 37055.79617209]
```

In [52]:

```
#Actual value and the predicted value
mlr_diff = pd.DataFrame({'Actual value': y_test, 'Predicted value': y_pred_mlr})
mlr_diff.head()
```

Out[52]:

	Actual value	Predicted value
11	48753	61112.144905
77	35607	50688.624954
25	33306	44441.815665
5	38359	49289.036612
62	40284	42609.462523

In [53]:

```
## EValuating the model

meanAbErr = metrics.mean_absolute_error(y_test, y_pred_mlr)
meanSqErr = metrics.mean_squared_error(y_test, y_pred_mlr)
```

```
rootMeanSqErr = np.sqrt(metrics.mean_squared_error(y_test, y_pred_mlr))
print('R squared: {:.2f}'.format(mlr.score(x,y)*100))
print('Mean Absolute Error:', meanAbErr)
print('Mean Square Error:', meanSqErr)
print('Root Mean Square Error:', rootMeanSqErr)
```

```
R squared: 32.04
Mean Absolute Error: 9637.865409141375
Mean Square Error: 128425071.68335885
Root Mean Square Error: 11332.478620467758
```

Observation

1. R Square is the coefficient of determination. The value of R Square is 32.04, which indicates that 32.04% of the data fit the regression model.
2. Mean Absolute Error is the absolute difference between the actual or true values and the predicted values. The lower the value, the better is the model's performance. The mean Absolute Error is 9637.865 which is pretty bad as 0 indicates good value.
3. Mean Square Error is calculated by taking the average of the square of the difference between the original and predicted values of the data. The lower the value, the better is the model's performance. The mean square error obtained for this particular model is 128425071.636, which is pretty bad.
4. Root Mean Square Error is the standard deviation of the errors which occur when a prediction is made on a dataset. This is the same as Mean Squared Error, but the root of the value is considered while determining the accuracy of the model. The lower the value, the better is the model's performance. The root mean square error obtained for this particular model is 11332.47, which is pretty good.

Bascially, I ran the model on the raw data without removing outliers or performing any transformations. That may be the reason for the poor scores. Another reason for the poor score is due to volume of the data which is very less. I also noticed that coefficients are positive for the features those are positively correlated with Attendance and negative for negatively correlated with Attendance.

Recommendations

To increase attendance at LA Dodgers games, Dodgers management should specifically take the following recommendations into consideration:

1. Games played in the summer months and on clear sky days tend to be positively correlated with attendance, however management does not have control over these seasonality & weather factors. So the only recommendation is to schedule more games (if possible) in the summer months and on weeks with historically clear sky days in Los Angeles. And, schedule less games in the spring or fall seasons and historically cloudy weeks in Los Angeles.
2. Similarly, Games scheduled on Tuesday and Saturday tend to be positively correlated with attendance, while Wednesday & Monday games tend tend to be negatively correlated with attendance. Therefore, if the Dodgers management could schedule more games on Tuesdays & Saturdays, this could potentially increase attendance in the season.

3. Games played against the Angels, Cubs, Mets, Nationals & White Sox tend to be postively correlated with attendance. If it is possible to schedule more games against these teams (and less with Astros, Braves, Bruins, Pirates, Rockies & Snakes), that would have a greater chance of increasing Dodgers games attendance in the MLB season.
4. And finally, games where free t-shirts and bobbleheads are given out tend to be postively correlated with attendance, while games where no free t-shirts and bobbleheads are negatively correlated. Dodgers management should plan to give out more free t-shirts and Bobble heads if they want an increase the attendance for the season.

In [ ]:

```

```