For this week's assignment we're going to use Dodgers Major League Baseball data from 2012. The data file you will be using is contained in the dodgers.csv file. I would like you to determine what night would be the best to run a marketing promotion to increase attendance. It is up to you if you decide to recommend a specific date or if you recommend a day of the week (e.g., Tuesdays) or month and day of the week (e.g., July Tuesdays). Use R and/or Python to accomplish this assignment. It is important to remember, there will be lots of ways to solve this problem. Explain your thought process and how you used various techniques to come up with your recommendation.

Reading in data

In [138…

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
```

In [138…

```
#dodgers.csv file
dodgers_pd = pd.read_csv("C:/Users/phill/OneDrive/Desktop/Predictive-630/data/dodgers.csv")
dodgers_pd.head()
```

Out[138…

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

Identifying Missing Data

In [138…

```
#looking at the data when reviews.val.title is NULL --> empty review
dodgers_pd.isnull().sum()
```

Out[138…

```
month          0
day            0
attend         0
day_of_week    0
opponent       0
temp           0
skies          0
day_night      0
cap            0
shirt          0
fireworks      0
bobblehead     0
dtype: int64
```

There is no missing data in the DataFrame!!

Building Promo Variable

In looking over the data and thinking about our problem statement, I wanted to build a derivative variable that denoted if any promotion was offered at a given Dodgers game. Our original dataset had a 'YES' or 'NO' marker for the various promotion items such as shirt, cap, etc. However, for the problem, I want to know plainly whether a promotion should be offered on a given day. Therefore, I just want a variable that marks the records with games that offered promotions or did not offer promotions.

In [139…

```
#function to determine if a promotion was overall offered at a Dodgers game
def mark_promo(df):
    #if any 'YES' values among the promotions, assign a 'YES' for the new column
    if df['cap'] == 'YES' or df['shirt'] == 'YES' or df['fireworks'] == 'YES' or df['bobblehead'] == 'YES':
        df['promo'] = 'YES'
    #no 'YES' assign 'NO'
    else:
        df['promo'] = 'NO'
    return df
```

In [139…

```
#apply the mark_promo function to the dataframe to create the new 'promo column'
dodgers_pd = dodgers_pd.apply(mark_promo,axis=1)
```

Creating Promo & Day of Week Interaction Term

Similar to above, as related to the problem statement, now that we have a marker for games with and without promotions. I also want to explore the interaction between day of the week and offering a promotion. Therefore, I want to create a new column with those possibilities of day of the week and promotion offering to explore in the regression modeling.

In [139…

```
#creating a new column 'day_promo'
#created out of the current 'day_of_week' and 'promo' variables
dodgers_pd['day_promo'] = dodgers_pd['day_of_week'] + dodgers_pd['promo']
```

In [139…

```
dodgers_pd['day_promo'].head()
```

Out[139…

```
0      TuesdayNO
1    WednesdayNO
2     ThursdayNO
3      FridayYES
4     SaturdayNO
Name: day_promo, dtype: object
```

In [139…

```
dodgers_pd['day_promo'].value_counts()
```

Out[139…

```
FridayYES       13
MondayNO        11
SaturdayNO      11
WednesdayNO     11
SundayNO        10
TuesdayYES       8
TuesdayNO        5
SundayYES        3
ThursdayNO       3
ThursdayYES      2
SaturdayYES      2
WednesdayYES     1
MondayYES        1
Name: day_promo, dtype: int64
```

Friday games with promotions hold the maximum number of data values, with 13 out of 81 games. The other leading values are days where promotions weren't offered. Therefore, we will have to do some digging to see which days will bring the highest increase in attendance when promotions are given.

From looking initially at these value counts, one would think that promotions should be offered on Fridays as they have the highest representation in the dataset. However, what is the change in attendance that they bring?

Descriptive Statistics

In [139…

```
#describing the overall dataframe

#retrieving rows and columns
print("The dimension of the table is: ",dodgers_pd.shape)
print("81 rows and 14 columns")
```

```
The dimension of the table is:  (81, 14)
81 rows and 14 columns
```

In [139…

```
dodgers_pd.dtypes
```

Out[139…

```
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
promo          object
day_promo      object
dtype: object
```

Numerical variables --> day, attend, temp

Categorical variables --> month, day_of_week, opponent, skies, day_night, cap, shirt, fireworks, bobblehead,day_promo, promo

Describing the Date/Time Variables

In [139…

```
#looking at date features for prediction
dates_targets = dodgers_pd[['month','day','day_of_week','day_night']]
dates_targets
```

Out[139…

	month	day	day_of_week	day_night
0	APR	10	Tuesday	Day
1	APR	11	Wednesday	Night
2	APR	12	Thursday	Night
3	APR	13	Friday	Night
4	APR	14	Saturday	Night
...	...	...	...	...
76	SEP	29	Saturday	Night
77	SEP	30	Sunday	Day
78	OCT	1	Monday	Night
79	OCT	2	Tuesday	Night
80	OCT	3	Wednesday	Night

81 rows × 4 columns

In [139…

```
#describe the data
desc = dates_targets.describe()
desc
```

Out[139…

	day
count	81.000000
mean	16.135802
std	9.605666
min	1.000000
25%	8.000000
50%	15.000000
75%	25.000000
max	31.000000

This result shows the summary statistics for the 'day' variable in the dataset, which just marks the day of the month for the corresponding Dodgers MLB game. Given that there are usually around 30-31 days in a month, these statistics don't give us very much information around the target variable. This variable will be more useful when combined with the other date/time variables!

In [139…

```
dates_targets['day_night'].value_counts()
```

Out[139…

```
Night    66
Day      15
Name: day_night, dtype: int64
```

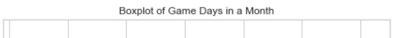
In [140…

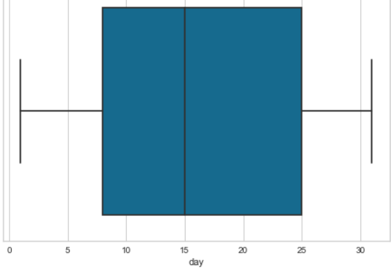
```
#boxplot of 'day'
sns.boxplot(dates_targets['day'])
plt.title("Boxplot of Game Days in a Month")
```

```
C:\Users\phill\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[140…

```
Text(0.5, 1.0, 'Boxplot of Game Days in a Month')
```



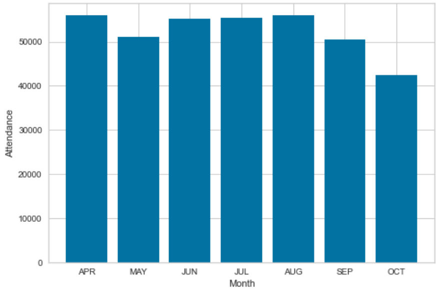


In [140…

```
#bar graph visualization for attendance counts per month
plt.bar(dodgers_pd['month'],dodgers_pd['attend'])
plt.xlabel('Month')
plt.ylabel('Attendance')
```

Out[140…

```
Text(0, 0.5, 'Attendance')
```

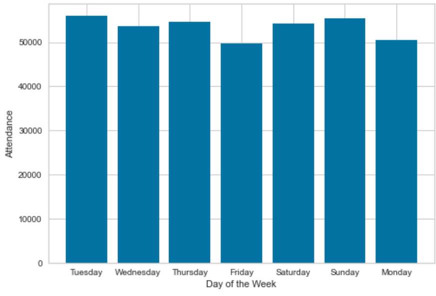


In [140…

```
#bar graph visualization for attendance counts for day of the week
plt.bar(dodgers_pd['day_of_week'],dodgers_pd['attend'])
plt.xlabel('Day of the Week')
plt.ylabel('Attendance')
```

Out[140…

```
Text(0, 0.5, 'Attendance')
```



Just from visualizing the other potential target variables of 'month', 'day_of_week' and 'day_night', it can be seen where most of the values in the dataset lie. The months as per the baseball season fall during summer and fall with the majority of games being in May and August. Also, with the days of the week, most of the games are held during the weekend from Friday to Sunday, with Tuesday being a weekday that holds majority popularity. Also, night games are much more popular than day games ... these classes are imbalanced.

The boxplot of 'day' is not uniform or normal; it has three peaks at the beginning of the months (~1-3), middle of the months (~day 15), and the end of the months (~29-31). It could be that each baseball season has a different schedule, so I'm not sure there is much significance to the frequency of the days during a month that are played and attended, since it depends on other teams and availability of sporting venues.

As we are trying to gather results in relation to running a marketing promotion on a certain night in order to increase attendance, I am going to use 'month' and 'day_of_week' variables as the target variables for my regression since I think they will be the most influential in being able to provide valuable information around targeted marketing. Also, with marketing promotions especially in social media, it is more applicable to know a month and day of the week rather than just a day which can vary month to month.

Describing the Other Features

In [140…

```
features = dodgers_pd[['attend','opponent','temp','skies','cap','shirt','fireworks','bobblehead','promo']]
features
```

Out[140…

	attend	opponent	temp	skies	cap	shirt	fireworks	bobblehead	promo
0	56000	Pirates	67	Clear	NO	NO	NO	NO	NO
1	29729	Pirates	58	Cloudy	NO	NO	NO	NO	NO
2	28328	Pirates	57	Cloudy	NO	NO	NO	NO	NO
3	31601	Padres	54	Cloudy	NO	NO	YES	NO	YES
4	46549	Padres	57	Cloudy	NO	NO	NO	NO	NO
...	...	...	...	...	...	...	...	...	...
76	40724	Rockies	84	Cloudy	NO	NO	NO	NO	NO
77	35607	Rockies	95	Clear	NO	NO	NO	NO	NO
78	33624	Giants	86	Clear	NO	NO	NO	NO	NO
79	42473	Giants	83	Clear	NO	NO	NO	NO	NO
80	34014	Giants	82	Cloudy	NO	NO	NO	NO	NO

81 rows × 9 columns

In [140…

```
desc_features = features.describe()
desc_features
```

Out[140…

	attend	temp
count	81.000000	81.000000
mean	41040.074074	73.148148
std	8297.539460	8.317318
min	24312.000000	54.000000
25%	34493.000000	67.000000
50%	40284.000000	73.000000
75%	46588.000000	79.000000
max	56000.000000	95.000000

In [140…

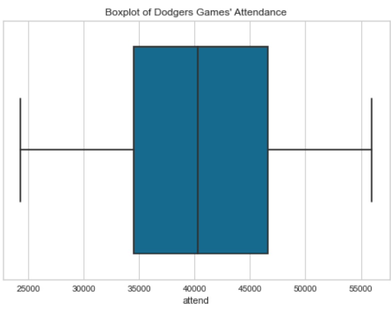
```
#boxplot of 'attend'
sns.boxplot(features['attend'])

plt.title("Boxplot of Dodgers Games' Attendance")
```

```
C:\Users\phill\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[140…

```
Text(0.5, 1.0, "Boxplot of Dodgers Games' Attendance")
```



In [140…

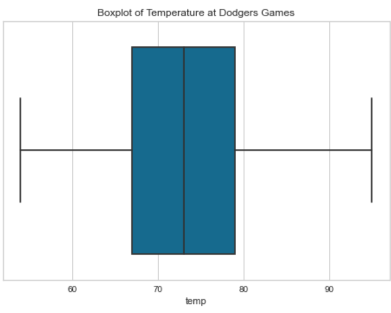
```
#boxplot of 'temp'
sns.boxplot(features['temp'])

plt.title("Boxplot of Temperature at Dodgers Games")
```

```
C:\Users\phill\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variabl
e as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[140…

```
Text(0.5, 1.0, 'Boxplot of Temperature at Dodgers Games')
```



The distribution for 'attend' is neither normal nor uniform. It is more right-skewed, but there is lower frequency at the higher-end of the attendance counts after the peak around ~45,000 people. It is more rare for there to be more than 45,000 people in attendance at the games, and those higher counts could be due to special events or holidays such as the 4th of July.

The distribution of game temperatures is relatively normal! The concentration of temperatures are around 70-75 degrees Fahrenheit, which makes sense given the months that the games are held during. Summer to fall seasons range around mildly warm and hot temperatures, so this distribution makes sense with that weather.

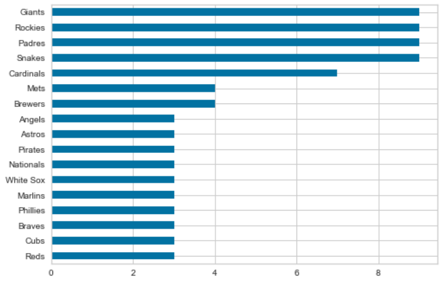
In [140…

```
#value counts for categorical variables
print(features['opponent'].value_counts())
features['opponent'].value_counts().sort_values().plot(kind = 'barh')
```

```
Giants       9
Rockies      9
Padres       9
Snakes       9
Cardinals    7
Mets         4
Brewers      4
Angels       3
```

```
Reds           3
Nationals      3
White Sox      3
Marlins        3
Phillies       3
Braves         3
Cubs           3
Pirates        3
Astros         3
Name: opponent, dtype: int64
<AxesSubplot:>
```

Out[140…



In [140…

```
print(features['skies'].value_counts())
```

```
Clear     62
Cloudy    19
Name: skies, dtype: int64
```

In [140…

```
print(features['cap'].value_counts())
```

```
NO     79
YES     2
Name: cap, dtype: int64
```

In [141…

```
print(features['shirt'].value_counts())
```

```
NO     78
YES     3
Name: shirt, dtype: int64
```

In [141…

```
print(features['fireworks'].value_counts())
```

```
NO     67
YES    14
Name: fireworks, dtype: int64
```

In [141…

```
print(features['bobblehead'].value_counts())
```

```
NO     70
YES    11
Name: bobblehead, dtype: int64
```

In [141…

```
print(features['promo'].value_counts())
```

```
NO     51
YES    30
Name: promo, dtype: int64
```

The balance for the categorical variables with 'skies', 'cap', 'shirt', 'fireworks' and 'bobblehead' is quite imbalanced. There is a value that holds the majority, which would need to be handled when going into regression modeling. Most of these are in correspondence to promotional objects, and it seems that 'NO' is the majority value which shows that the past promotion items were not so popularly taken at the baseball games.

Out of the 81 Dodgers games in the dataset, some sort of promotion was offered at 30 of them ... a little less than half. There is a higher amount where no promotions were offered, but it allow us to compare the days where promotions were and weren't offered and anaylze the change on attendance in comparison.

Creating Label Encoders for Categorical Variables

In order to utilize categorical variables in our models, we need to encode them as numbers. The pieces of code below do exactly this!

In [141…

```
#month, day_of_week, opponent, skies, day_night, cap, shirt, fireworks, bobblehead
cat_cols = ['month','day_of_week','opponent','skies','day_night','cap','shirt','fireworks','bobblehead','promo'

#turning categories into their numerical counterparts using LabelEncoder
for var in cat_cols:
    number = LabelEncoder()
    dodgers_pd[var+"cat"] = number.fit_transform(dodgers_pd[var].astype('str'))
```

In [141…

```
dodgers_pd.head()
```

Out[141…

	month	day	attend	day_of_week	opponent	temp	skies	day_night	cap	shirt	...	day_of_weekcat	opponentcat	skiescat	day_nightcat
0	APR	10	56000	Tuesday	Pirates	67	Clear	Day	NO	NO	...	5	12	0	0
1	APR	11	29729	Wednesday	Pirates	58	Cloudy	Night	NO	NO	...	6	12	1	1
2	APR	12	28328	Thursday	Pirates	57	Cloudy	Night	NO	NO	...	4	12	1	1
3	APR	13	31601	Friday	Padres	54	Cloudy	Night	NO	NO	...	0	10	1	1
4	APR	14	46549	Saturday	Padres	57	Cloudy	Night	NO	NO	...	2	10	1	1

5 rows × 25 columns

In [141…

```
print(dodgers_pd['month'].value_counts())
print(dodgers_pd['monthcat'].value_counts())
```

```
MAY    18
AUG    15
APR    12
JUL    12
SEP    12
JUN     9
OCT     3
Name: month, dtype: int64
4    18
1    15
0    12
2    12
6    12
3     9
5     3
Name: monthcat, dtype: int64
```

----------------MONTH CATEGORIES----------------

4: MAY

1: AUG

0: APR

2: JUL

6: SEP

3: JUN

5: OCT

In [141…

```
print(dodgers_pd['day_of_week'].value_counts())
print(dodgers_pd['day_of_weekcat'].value_counts())
```

```
Saturday     13
Tuesday      13
Sunday       13
Friday       13
Monday       12
Wednesday    12
Thursday      5
Name: day_of_week, dtype: int64
0    13
2    13
3    13
5    13
1    12
6    12
4     5
Name: day_of_weekcat, dtype: int64
```

----------------DAY OF WEEK CATEGORIES----------------

0: Saturday

2: Tuesday

3: Sunday

5: Friday

1: Monday

6: Wednesday

4: Thursday

---------PROMOTION CATEGORIES-----------------

0: NO

1: YES

In [141…

```
print(dodgers_pd['day_promo'].value_counts())
print(dodgers_pd['day_promocat'].value_counts())
```

```
FridayYES       13
MondayNO        11
SaturdayNO      11
WednesdayNO     11
SundayNO        10
TuesdayYES       8
TuesdayNO        5
SundayYES        3
ThursdayNO       3
ThursdayYES      2
SaturdayYES      2
WednesdayYES     1
MondayYES        1
Name: day_promo, dtype: int64
0     13
1     11
3     11
11    11
5     10
10     8
9      5
6      3
7      3
4      2
8      2
2      1
12     1
Name: day_promocat, dtype: int64
```

Investigating Relationships between Variables

We want to explore the correlation between our features to ensure that we are not performing modeling on features which have a relationship and therefore an effect on each other. In regression, we purely want to see which features have an effect on our predictor variable, and by removing highly-correlated features or ones with multicollinearity, we can ensure that our features will represent the effect on the dependent variable and not on eachother.

In [141…

```
#correlation plot
dodgers_pd_regress = dodgers_pd.copy()

print(dodgers_pd_regress.columns)
```

```
Index(['month', 'day', 'attend', 'day_of_week', 'opponent', 'temp', 'skies',
       'day_night', 'cap', 'shirt', 'fireworks', 'bobblehead', 'promo',
       'day_promo', 'monthcat', 'day_of_weekcat', 'opponentcat', 'skiescat',
       'day_nightcat', 'capcat', 'shirtcat', 'fireworkscat', 'bobbleheadcat',
       'promocat', 'day_promocat'],
      dtype='object')
```

In [142…

```
#creating new dataframe with only needed columns for regression
dodgers_pd_regress = dodgers_pd_regress[['day','monthcat','day_of_weekcat','opponentcat','skiescat','day_nightc
```

In [142…

```
#subset dataframe to only have night games --> where day_nightcat = 1
dodgers_pd_regress = dodgers_pd_regress[dodgers_pd_regress['day_nightcat']==1]
```

In [142…

```
#drop day_nightcat column after only using 'Night'
dodgers_pd_regress = dodgers_pd_regress.drop(['day_nightcat'],axis=1)
```

In [142…

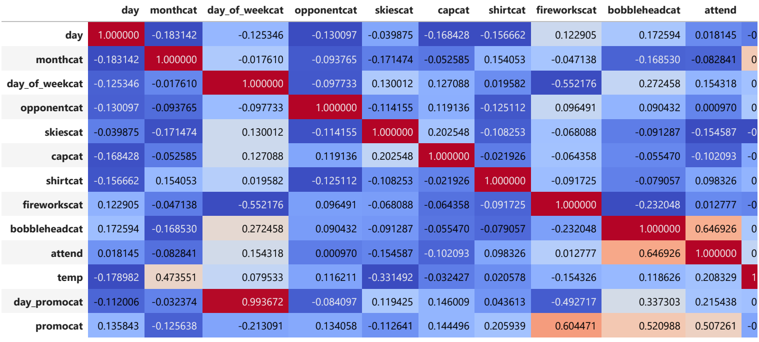
```
print(dodgers_pd_regress.shape)
print("66 rows and 13 columns for Dodgers Night Games")
```

```
(66, 13)
66 rows and 13 columns for Dodgers Night Games
```

In [142…

```
corr = dodgers_pd_regress.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[142…



	day	monthcat	day_of_weekcat	opponentcat	skiescat	capcat	shirtcat	fireworkscat	bobbleheadcat	attend	
day	1.000000	-0.183142	-0.125346	-0.130097	-0.039875	-0.168428	-0.156662	0.122905	0.172594	0.018145	-0
monthcat	-0.183142	1.000000	-0.017610	-0.093765	-0.171474	-0.052585	0.154053	-0.047138	-0.168530	-0.082841	0
day_of_weekcat	-0.125346	-0.017610	1.000000	-0.097733	0.130012	0.127088	0.019582	-0.552176	0.272458	0.154318	0
opponentcat	-0.130097	-0.093765	-0.097733	1.000000	-0.114155	0.119136	-0.125112	0.096491	0.090432	0.000970	0
skiescat	-0.039875	-0.171474	0.130012	-0.114155	1.000000	0.202548	-0.108253	-0.068088	-0.091287	-0.154587	-0
capcat	-0.168428	-0.052585	0.127088	0.119136	0.202548	1.000000	-0.021926	-0.064358	-0.055470	-0.102093	-0
shirtcat	-0.156662	0.154053	0.019582	-0.125112	-0.108253	-0.021926	1.000000	-0.091725	-0.079057	0.098326	0
fireworkscat	0.122905	-0.047138	-0.552176	0.096491	-0.068088	-0.064358	-0.091725	1.000000	-0.232048	0.012777	-0
bobbleheadcat	0.172594	-0.168530	0.272458	0.090432	-0.091287	-0.055470	-0.079057	-0.232048	1.000000	0.646926	0
attend	0.018145	-0.082841	0.154318	0.000970	-0.154587	-0.102093	0.098326	0.012777	0.646926	1.000000	0
temp	-0.178982	0.473551	0.079533	0.116211	-0.331492	-0.032427	0.020578	-0.154326	0.118626	0.208329	1
day_promocat	-0.112006	-0.032374	0.993672	-0.084097	0.119425	0.146009	0.043613	-0.492717	0.337303	0.215438	0
promocat	0.135843	-0.125638	-0.213091	0.134058	-0.112641	0.144496	0.205939	0.604471	0.520988	0.507261	-0

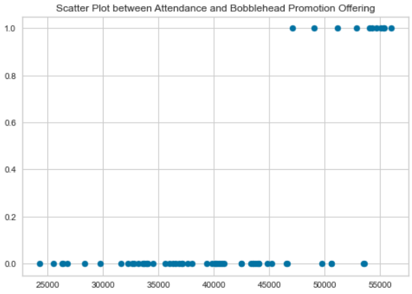
High correlations:

1. attend & bobbleheadcat are relatively highly correlated with one another as features: 0.646926
2. temp is also highly correlated with our target values of monthcat & month_day_weekcat: 0.473551 and 0.458327 respectively
3. fireworkscat and promocat are correlated at 0.604471 --> relatively positive relationship
4. bobbleheadcat and promocat have a correlation of 0.520988
5. promocat & attend also have a higher positive correlation of 0.507261

Scatterplots for Correlation Analysis

In [142…

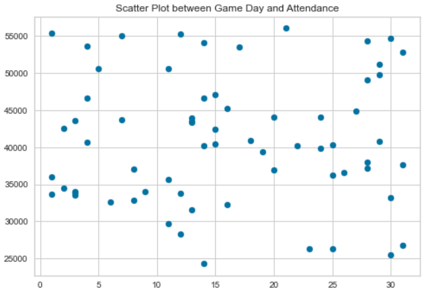
```
#scatterplot between attend and bobbleheadcat
plt.scatter(dodgers_pd_regress['attend'], dodgers_pd_regress['bobbleheadcat'])
plt.title('Scatter Plot between Attendance and Bobblehead Promotion Offering')
plt.show()
```



As the game attendance increases, it seems that the probability for a bobblehead to be offered increases as well. Bobbleheads seem to be given out more when game attendance is higher. This goes along with the 0.646926 positive correlation from the correlation heat map.

In [142…

```
#scatter plot between day and attend
plt.scatter(dodgers_pd_regress['day'], dodgers_pd_regress['attend'])
plt.title('Scatter Plot between Game Day and Attendance')
plt.show()
```



I wanted to visualize a scatter plot between two of the continuous variables in our dataset: day and attend. Day provides information around what day on a given month a Dodgers game is played.

It seems there is little to no relationship between these two variables, as also shown by their 0.0181 correlation value. This value is extremely close to zero, which signifies a neutral relationship where the variables do not have an effect on eachother. Given that a part of our problem is in relation to which day should be recommended in order to increase attendance, it looks like 'day' by itself may not have a significant impact on change in attendance at Dodgers games.

Using VIF for feature reduction

VIF or Variance-Inflation Factor will determine if collinearity exists among variables. In the below function, our bounday for feature removal based on VIF is set to 5.0, which would define whether any features are correlated with each other.

In [142…

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
#features --> all variables except for day_promocat
x=dodgers_pd_regress.drop(['day_promocat'],axis=1)
#target variable --> day_promocat
y= dodgers_pd_regress['day_promocat']
```

```python
#function for calculating the VIF score for each feature to determine if collinearity exists among variable
#finding values with large absolute values greater than 5
#function from https://medium.com/analytics-vidhya/feature-selection-techniques-2614b3b7efcd
def cal_vif(x):
    #threshold for VIF score
    #a VIF above 5 usually corresponds with high correlation
    thresh = 5
    output = pd.DataFrame()
    #number of columns
    k = x.shape[1]
    #calculate the VIF for the values in each column in the features
    vif = [variance_inflation_factor(x.values,i) for i in range(x.shape[1])]
    for i in range(1,k):
        print('Iteration no ',i)
        print(vif)
        #determine the feature with max VIF
        a = np.argmax(vif)
        print('Max vif is for variable no : ',a)
        #if max is not less than the threshold of 5.0, break and keep looking
        if(vif[a]<=thresh):
            break
        #else drop features and keep searching ... recursive
        if(i==1):
            output=x.drop(x.columns[a],axis=1)
            vif = [variance_inflation_factor(output.values,j)for j in range(output.shape[1])]
        elif(i>1):
            output = output.drop(output.columns[a],axis=1)
            vif = [variance_inflation_factor(output.values,j) for j in range(output.shape[1])]
    return(output)
```

```python
selected_features = cal_vif(x)
selected_features.head()
```

```
Iteration no  1
[4.061312572851412, 4.440967980742168, 4.020726635483109, 4.6543308944975195, 1.5021032201139872, inf, inf, inf, inf, 44.87762739550238, 56.39769369240696, inf]
Max vif is for variable no :  5
Iteration no  2
[4.061312572851412, 4.440967980742171, 4.020726635483109, 4.6543308944975195, 1.5021032201139872, 3.471238666243197, 18.174001632740552, 14.755203310198624, 44.87762739550238, 56.39769369240696, 31.61817261330915]
Max vif is for variable no :  9
Iteration no  3
[3.6792483491802526, 3.208545439449354, 3.9473741062305168, 3.87554666175938, 1.5020772040947643, 3.4203576096258073, 17.96551450431619, 13.895680620270461, 14.787379179442071, 31.526122266182337]
Max vif is for variable no :  9
Iteration no  4
[3.6255014792201257, 3.206155530071861, 3.8940574456582526, 3.77463521062613, 1.4481700097883912, 1.1554482029507003, 2.048617746464274, 1.8419859675485437, 14.743780421072724]
Max vif is for variable no :  8
Iteration no  5
[2.9003642182051856, 2.559158968170141, 3.044966485586377, 2.969045098019715, 1.4024888615453448, 1.0834836816892965, 1.711830683753264, 1.4757427069009128]
Max vif is for variable no :  2
C:\Users\phill\Anaconda3\lib\site-packages\statsmodels\stats\outliers_influence.py:193: RuntimeWarning: divide by zero encountered in double_scalars
  vif = 1. / (1. - r_squared_i)
```

	day	monthcat	day_of_weekcat	opponentcat	skiescat	shirtcat	fireworkscat	bobbleheadcat
1	11	0	6	12	1	0	0	0
2	12	0	4	12	1	0	0	0
3	13	0	0	10	1	0	1	0
4	14	0	2	10	1	0	0	0
6	23	0	1	2	1	0	0	0

By utilizing the VIF of the variables, we were able to remove/drop variables which had collinearity with each other. The importance of dropping these allows for us to have features which provide unique and indepentent information about the variance within the given dataset.

Through these iterations, the following features were dropped: attend, capcat, promocat, temp.

Multinomial Logistic Regression

Now that our features have been selected by looking into correlation and VIF, we are ready to apply a regression model to predict our target variable 'day_promocat'. This is a categorical variable which represents the days of the week as numbers; therfore, our options for a model are a multinomial logistic regression model as we have a multinomial categorical dependent variable.

In choosing a Multinomial Logistic Regression model, I envisioned the business users plugging in values for the features and being able to receive an output which lets them know the day of the week and whether a promotion should be offered that day. It is more brute-force though, and not as predictive as the linear regression model later in this report.

```python
from sklearn.linear_model import Lasso, LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,roc_curve, roc_auc_score, precision_score, recall_
# split X and y into training and testing sets
from sklearn.model_selection import train_test_split
```

```python
#split the dataset into training and test sets --> 75:25
#25% for testing
X_train,X_test,y_train,y_test=train_test_split(selected_features,y,test_size=0.25,random_state=0)
```

[illegible]

```
91, inf, inf, inf, inf, inf, inf, inf, 2.5919457313108176, 5.403337057771748, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf]
Max vif is for variable no :  2
Iteration no  2
[6.5751352674266395, 12.971195573863799, inf, inf, inf, inf, 26.944617278797217, 18.71197390440583, inf, 18.635311301176806, 10.239888948839722, 22.1364400090354, inf, inf, inf, inf, inf, inf, inf, 5.092696939168188, inf, inf, inf, inf, inf, inf, 2.5919457313108194, 5.403337057771748, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf]
Max vif is for variable no :  2
Iteration no  3
[6.5751352674266644, 12.971195573863378, inf, inf, inf, inf, 26.944617278797217, 18.71197390440583, inf, 18.635311301176845, 10.239888948839722, 22.1364400090354, inf, inf, inf, inf, inf, inf, 5.092696939168188, inf, inf, inf, inf, inf, 2.5919457313108185, 5.403337057771748, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf]
Max vif is for variable no :  2
Iteration no  4
[6.5751352674266395, 12.971195573863799, inf, inf, inf, 26.944617278797217, 18.71197390440583, inf, 18.635311301176845, 10.239888948839722, 22.1364400090354, inf, inf, inf, inf, inf, inf, 5.092696939168188, inf, inf, inf, inf, inf, 2.5919457313108194, 5.403337057771748, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf]
Max vif is for variable no :  2
Iteration no  5
[6.5751352674266644, 12.971195573863799, inf, inf, 26.944617278797217, 18.71197390440583, inf, 18.635311301176845, 10.239888948839722, 22.1364400090354, inf, inf, inf, inf, inf, 5.092696939168191, inf, inf, inf, inf, inf, 2.5919457313108176, 5.403337057771751, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf]
Max vif is for variable no :  2
Iteration no  6
[6.5751352674266395, 12.971195573863799, inf, 26.944617278797136, 18.71197390440583, inf, 18.635311301176845, 10.239888948839722, 22.1364400090354, inf, inf, inf, inf, inf, 5.092696939168188, inf, inf, inf, inf, inf, 2.5919457313108194, 5.403337057771748, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf]
Max vif is for variable no :  2
Iteration no  7
[6.5751352674266644, 12.971195573863799, 26.944617278797217, 18.71197390440583, inf, 18.635311301176845, 10.239888948839722, 22.1364400090354, inf, inf, inf, inf, inf, 5.092696939168191, inf, inf, inf, inf, inf, 2.5919457313108194, 5.403337057771751, inf, inf, inf, inf, inf, inf, inf, inf, inf, inf, 2.3309867204252477]
Max vif is for variable no :  4
Iteration no  8
[6.5751352674266395, 12.971195573863378, 26.944617278797217, 18.71197390440583, 18.635311301176806, 10.239888948839722, 22.1364400090354, 7.317255467727752, 3.5769229582714024, 10.950456636179133, 12.741411383939504, 7.908055637151569, 17.1047079794888, 7.398370951147953, 5.092696939168185, 3.0634498739421177, 11.742924360150086, 6.409402058267507, 2.978091550798693, 10.972349570173302, 14.201424012424186, 13.598688131609036, 2.5919457313108194, 5.403337057771748, inf, inf, inf, inf, 170.0057722753569, inf, 159.06271091020201, inf, 20.806761901045075, inf, 42.89114113820642, inf, 67.8154543026361, inf, 136.34360833076883, 2.330986720425248]
Max vif is for variable no :  24
Iteration no  9
[6.5751352674266395, 12.971195573863799, 26.944617278797217, 18.71197390440583, 18.635311301176845, 10.239888948839722, 22.1364400090354, 7.317255467727752, 3.5769229582714024, 10.950456636179133, 12.741411383939504, 7.908055637151569, 17.1047079794888, 7.398370951147953, 5.092696939168185, 3.0634498739421177, 11.742924360150086, 6.409402058267512, 2.9780915507986947, 10.972349570173302, 14.201424012424186, 13.598688131609036, 2.5919457313108194, 5.403337057771748, 9.659415003799262, inf, 23.11304061414605, inf, 170.0057722753569, inf, 159.06271091020201, inf, 20.806761901045075, inf, 42.89114113820663, inf, 67.8154543026361, inf, 136.34360833076883, 2.3309867204252477]
Max vif is for variable no :  25
Iteration no  10
[6.5751352674266395, 12.971195573863378, 26.944617278797136, 18.71197390440583, 18.635311301176845, 10.239888948839722, 22.1364400090354, 7.317255467727746, 3.5769229582714024, 10.950456636179133, 12.741411383939504, 7.908055637151569, 17.1047079794888, 7.398370951147953, 5.092696939168185, 3.0634498739421177, 11.742924360150086, 6.409402058267507, 2.9780915507986947, 10.972349570173302, 14.201424012424186, 13.598688131609057, 2.5919457313108185, 5.403337057771748, 9.659415003799262, 23.11304061414605, 423.7116575478275, 170.0057722753569, 6.72909256509132, 159.06271091020201, 6.424061591874251, 20.806761901045125, 7.767447747947191, 42.89114113820642, 6.709279105380703, 67.8154543026361, 20.27875211562753, 136.34360833076883, 2.330986720425248]
Max vif is for variable no :  26
Iteration no  11
[20.98021738168207, 79.31604634272672, 18.087616649558754, 11.239562151655045, 21.977088945174653, 7.238058911359995, 10.48348005951284, 6.227196959384772, 3.492249208091021, 11.656419679386247, 13.021705067191885, 5.782132172238672, 17.692498116047226, 5.922522778365233, 4.996527452692075, 3.147341758206516, 8.569307706477325, 4.219132321138154, 2.4264087839459894, 7.648763249848056, 13.57725059541717, 13.204482720318378, 2.6560751553465765, 7.394033545459964, 9.943468459261707, 27.735453065676204, 4.2966374813742565, 6.832595223787802, 2.278769060819775, 6.57831942897491, 1.4000675321786338, 6.384584089781157, 1.945243881180243, 6.840296924181476, 3.000059982198436, 23.063028697316593, 3.805628868140229, 2.3665357216595202]
Max vif is for variable no :  1
Iteration no  12
[17.028608387719252, 17.424487911192976, 11.106736783704601, 21.46328538181802, 6.434563124252048, 9.296300716371668, 6.00307868237647, 3.2985632728729852, 11.520305840573014, 10.892492383670815, 4.6112835627301685, 16.59724071893467, 5.515638931640375, 3.6677936519086054, 2.4596307560853843, 6.016644459563402, 3.9973348756009095, 2.0707864191308865, 6.624992561692604, 11.700491024978879, 12.100297405580749, 1.503204972504499, 7.3940322840999135, 9.892524626200592, 27.677924705811368, 3.0803255657194173, 5.745070276371375, 2.147804621557128, 6.557458185789346, 1.3842081860364914, 6.3129642500565435, 1.8053482731029447, 6.830846866555572, 2.3349828963916077, 22.248436610202738, 2.53311769901922, 2.2727769596835294]
Max vif is for variable no :  24
Iteration no  13
[16.68086654586736, 17.35952304385483, 11.098543480074483, 21.413800893681437, 6.432300596341862, 9.2872167235505, 5.976559696400939, 3.298555742607756, 11.470921533825667, 10.879672486161963, 4.578212081146072, 16.56070626936201, 5.511795536810056, 3.6303804056851887, 2.4517971224329345, 5.937406343054836, 3.9612123366978427, 2.057871922759222, 5.02056162876391, 11.699811375238122, 12.087488124671767, 1.4896674637273983, 6.805264770977775, 4.44926195148181, 2.917399726935214, 3.163314225186616, 2.12888446466155, 2.0775196352686605, 1.383644528575301, 3.345480004365521, 1.8000097082466782, 1.7935678602640714, 2.312198209806021, 2.7922774106395556, 2.4902607361298523, 1.7187763755859529]
Max vif is for variable no :  3
Iteration no  14
[15.54736647737555, 3.7033715824115876, 5.61703532091556, 2.1906085420286057, 2.3615706045437124, 2.003734955365583, 3.2527575253125405, 4.633024710752925, 3.241948940137971, 1.963430587038051, 5.072500428024219, 2.2826258813607296, 3.5743482177044568, 2.4262379937890195, 3.4163478512327443, 2.750216755137295, 2.0458593685695443, 3.5116705525059646, 2.7772053431807464, 3.8926648114341753, 1.4502216788683093, 6.774131135823908, 4.332435779434836, 2.8545681205937985, 3.1363722142629276, 2.0900308310863873, 2.0252611397640963, 1.3548737283667889, 2.9724563703644677, 1.7994006141642749, 1.7605392658509489, 2.2856062576535363, 2.7599116841296887, 2.3918430921055296, 1.7152513497115098]
Max vif is for variable no :  0
Iteration no  15
[3.492360980969639, 5.013767202887805, 1.847504762579911, 2.3608935039690047, 1.6043166023465132, 2.5593647334664356, 1.7397393515354824, 2.08738860379342, 1.9213454426103367, 3.647194117079607, 1.7453693726315727, 2.1510226074831604, 1.5033204164840526, 3.4143535901062014, 2.592593548697303, 2.011606064437333, 3.39687592147369, 1.9999201661995802, 2.3353637211544367, 1.1042496500636698, 5.820937182310944, 4.255948127653264, 2.744022911763135, 3.1279740638266316, 2.0849930012733986, 2.013281665936212, 1.3478981006322366, 2.1474414268264614, 1.7886790665650298, 1.7360602866217623, 2.252594434091885, 2.6809826368717564, 2.3575995742921383, 1.7122880805773657]
Max vif is for variable no :  20
Iteration no  16
[3.4211152352138847, 4.8691192186212096, 1.7284223725586076, 2.2945531459743242, 1.0959306217371967, 1.688107287586561, 1.6871875792432631, 2.0022763767054697, 1.7450539368193705, 3.633193371980791, 1.7450539368193705, 2.145423947803769, 1.437166234024457, 2.1479335705958604, 2.5671174009652393, 1.55724891446541, 3.3947114112293164, 1.9999101470391747, 2.316035832021084, 1.0959306217371967, 3.0518357615130025, 2.742991117544201, 2.525917880756501, 1.9186124347439344, 1.7486649360978281, 1.3337127294509117, 2.1415016537783336, 1.7694942428160476, 1.7211305274767168, 2.250193778613309, 2.1203530054348887, 2.260056570032327, 1.6906406947837929]
Max vif is for variable no :  1
```

	month_AUG	month_JUL	month_OCT	month_SEP	opponent_Astros	opponent_Braves	opponent_Brewers	opponent_Cardinals	opponent_Cub
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	
6	0	0	0	0	0	1	0	0	

5 rows × 33 columns

```python
#splitting data into training and test sets
#60/40 proportion
X_train2, X_test2, y_train2, y_test2 = train_test_split(selected_features2, Y, test_size=0.4, random_state=101)
print(X_train2.shape)
print(X_test2.shape)
print(y_train2.shape)
print(y_test2.shape)
```

```
(39, 33)
(27, 33)
(39, 1)
(27, 1)
```

```python
#fitting a Linear Regression model to our training set
model2 = LinearRegression()
model2.fit(X_train2,y_train2)
```

```
LinearRegression()
```

```python
# print the intercept
print(model2.intercept_)
```

```
[35755.30204866]
```

```python
#print the regression coefficients for our equation
model2.coef_
```

```
array([[ 3.60971004e+03,  3.45306208e+03,  5.21650420e+01,
         2.12307164e+03,  1.87883624e+02, -2.42515069e+02,
        -1.00993651e+04,  2.95081198e+03,  4.17198791e+03,
         1.15703654e+03, -3.86407461e+01,  1.40076980e+04,
         9.05169795e+03,  6.21227690e+03, -3.03599991e+03,
        -5.87936510e+03, -2.14410145e+04, -1.29586881e+03,
        -2.29350722e+03,  6.58688362e+03,  1.13686838e-12,
        -3.93436422e+03, -1.81898940e-12,  9.57628655e+02,
         9.43500000e+03, -1.81898940e-12, -4.54747351e-13,
         1.11706306e+03,  1.75494951e+04,  3.29879026e+03,
         1.61166504e+04, -1.46936945e+02,  0.00000000e+00]])
```

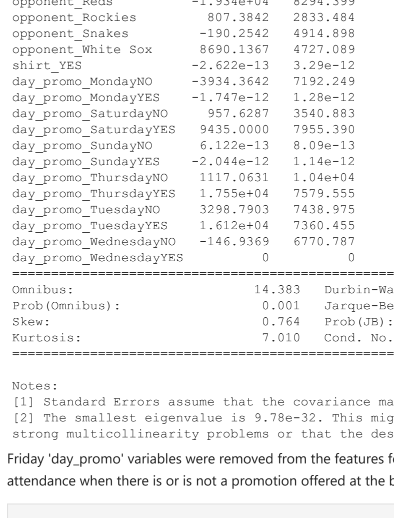
```python
#column names to show the features that were kept for the linear regression model
selected_features2.columns
```

```
Index(['month_AUG', 'month_JUL', 'month_OCT', 'month_SEP', 'opponent_Astros',
       'opponent_Braves', 'opponent_Brewers', 'opponent_Cardinals',
       'opponent_Cubs', 'opponent_Giants', 'opponent_Marlins', 'opponent_Mets',
       'opponent_Nationals', 'opponent_Padres', 'opponent_Phillies',
       'opponent_Pirates', 'opponent_Reds', 'opponent_Rockies',
       'opponent_Snakes', 'opponent_White Sox', 'shirt_YES',
       'day_promo_MondayNO', 'day_promo_MondayYES', 'day_promo_SaturdayNO',
       'day_promo_SaturdayYES', 'day_promo_SundayNO', 'day_promo_SundayYES',
       'day_promo_ThursdayNO', 'day_promo_ThursdayYES', 'day_promo_TuesdayNO',
       'day_promo_TuesdayYES', 'day_promo_WednesdayNO',
       'day_promo_WednesdayYES'],
      dtype='object')
```

```python
#make predictions from the test set and our model
predictions = model2.predict(X_test2)
```

```python
#visualize the plot of actual vs. predicted
sns.regplot(y_test2,predictions)
```

```
C:\Users\phill\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
<AxesSubplot:xlabel='attend'>
```



This plot visualizes the fit of our linear regression model, also with a 95% confidence interval band. There are many data points which do not fall along the regression model, which could show that there is another model which would better fit our data. However, it does look like there is a general linear trend.

```python
import statsmodels.api as sm

#getting summary statistics for our linear regression model
X_train_Sm= sm.add_constant(X_train2)
X_train_Sm= sm.add_constant(X_train2)
ls=sm.OLS(y_train2,X_train_Sm).fit()
print(ls.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 attend   R-squared:                       0.862
Model:                            OLS   Adj. R-squared:                  0.524
Method:                 Least Squares   F-statistic:                     2.549
Date:                Sat, 18 Dec 2021   Prob (F-statistic):             0.0526
Time:                        19:23:01   Log-Likelihood:                -367.42
No. Observations:                  39   AIC:                             790.8
Df Residuals:                      11   BIC:                             837.4
Df Model:                          27
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                   3.365e+04   3086.770     10.902      0.000    2.69e+04    4.04e+04
month_AUG               3609.7100   4632.813      0.779      0.452   -6587.043    1.38e+04
month_JUL               3453.0621   1.08e+04      0.320      0.755   -2.03e+04    2.72e+04
month_OCT                 52.1650   4521.874      0.012      0.991   -9900.413       1e+04
month_SEP               2123.0716   5558.363      0.382      0.710   -1.01e+04    1.44e+04
opponent_Astros         2291.1367   4727.089      0.485      0.637   -8113.117    1.27e+04
opponent_Braves         1860.7380   6964.911      0.267      0.794   -1.35e+04    1.72e+04
opponent_Brewers       -7996.1120   7851.580     -1.018      0.330   -2.53e+04    9285.099
opponent_Cardinals      5054.0650   5780.424      0.874      0.401   -7668.562    1.78e+04
opponent_Cubs           6275.2410   7172.613      0.875      0.400   -9511.574    2.21e+04
opponent_Giants         3260.2896   4812.422      0.677      0.512   -7331.780    1.39e+04
opponent_Marlins        2064.6123   7898.698      0.261      0.799   -1.53e+04    1.94e+04
opponent_Mets           1.611e+04   6119.594      2.633      0.023    2641.815    2.96e+04
opponent_Nationals      1.115e+04   6119.594      1.823      0.096   -2314.185    2.46e+04
opponent_Padres         8315.5300   7960.805      1.045      0.319   -9206.084    2.58e+04
opponent_Phillies       -932.7468   8403.034     -0.111      0.914   -1.94e+04    1.76e+04
opponent_Pirates       -3776.1120   7851.580     -0.481      0.640   -2.11e+04    1.35e+04
opponent_Reds          -1.934e+04   8294.399     -2.331      0.040   -3.76e+04   -1081.913
opponent_Rockies        807.3842    2833.484      0.285      0.781   -5429.071    7043.840
opponent_Snakes         -190.2542   4914.898     -0.039      0.970    -1.1e+04    1.06e+04
opponent_White Sox      8690.1367   4727.089      1.838      0.093   -1714.117    1.91e+04
shirt_YES              -2.622e-13    3.29e-12    -0.080      0.938   -7.51e-12    6.99e-12
day_promo_MondayNO     -3934.3642   7192.249     -0.547      0.595   -1.98e+04    1.19e+04
day_promo_MondayYES    -1.747e-12    1.28e-12    -1.362      0.201   -4.57e-12    1.08e-12
day_promo_SaturdayNO     957.6287   3540.883      0.270      0.792   -6835.802    8751.060
day_promo_SaturdayYES   9435.0000   7955.390      1.186      0.261   -8074.696    2.69e+04
day_promo_SundayNO      6.122e-13   8.09e-13      0.757      0.465   -1.17e-12    2.39e-12
day_promo_SundayYES    -2.044e-12   1.14e-12     -1.790      0.101   -4.56e-12    4.69e-13
day_promo_ThursdayNO    1117.0631   1.04e+04      0.107      0.917   -2.19e+04    2.41e+04
day_promo_ThursdayYES   1.755e+04   7579.555      2.315      0.041     867.008    3.42e+04
day_promo_TuesdayNO     3298.7903   7438.975      0.443      0.666   -1.31e+04    1.97e+04
day_promo_TuesdayYES    1.612e+04   7360.455      2.190      0.051     -83.603    3.23e+04
day_promo_WednesdayNO   -146.9369   6770.787     -0.022      0.983    -1.5e+04    1.48e+04
day_promo_WednesdayYES          0          0        nan        nan           0           0
==============================================================================
Omnibus:                       14.383   Durbin-Watson:                   2.334
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               29.925
Skew:                           0.764   Prob(JB):                     3.18e-07
Kurtosis:                       7.010   Cond. No.                     2.30e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 9.78e-32. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Friday 'day_promo' variables were removed from the features for the model. Therefore, how can we account for this day's effect on the attendance when there is or is not a promotion offered at the baseball game?

```python
#reading OLS summary from HTML to a DataFrame
summ_df = pd.read_html(ls.summary().tables[1].as_html(),header=0,index_col=0)[0]
```

```python
summ_df
```

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.365000e+04	3.086770e+03	10.902	0.000	2.690000e+04	4.040000e+04
month_AUG	3.609710e+03	4.632813e+03	0.779	0.452	-6.587043e+03	1.380000e+04
month_JUL	3.453062e+03	1.080000e+04	0.320	0.755	-2.030000e+04	2.720000e+04
month_OCT	5.216500e+01	4.521874e+03	0.012	0.991	-9.900413e+03	1.000000e+04
month_SEP	2.123072e+03	5.558363e+03	0.382	0.710	-1.010000e+04	1.440000e+04
opponent_Astros	2.291137e+03	4.727089e+03	0.485	0.637	-8.113117e+03	1.270000e+04
opponent_Braves	1.860738e+03	6.964911e+03	0.267	0.794	-1.350000e+04	1.720000e+04
opponent_Brewers	-7.996112e+03	7.851580e+03	-1.018	0.330	-2.530000e+04	9.285099e+03
opponent_Cardinals	5.054065e+03	5.780424e+03	0.874	0.401	-7.668562e+03	1.780000e+04
opponent_Cubs	6.275241e+03	7.172613e+03	0.875	0.400	-9.511574e+03	2.210000e+04
opponent_Giants	3.260290e+03	4.812422e+03	0.677	0.512	-7.331780e+03	1.390000e+04
opponent_Marlins	2.064612e+03	7.898698e+03	0.261	0.799	-1.530000e+04	1.940000e+04
opponent_Mets	1.611000e+04	6.119594e+03	2.633	0.023	2.641815e+03	2.960000e+04
opponent_Nationals	1.115000e+04	6.119594e+03	1.823	0.096	-2.314185e+03	2.460000e+04
opponent_Padres	8.315530e+03	7.960805e+03	1.045	0.319	-9.206084e+03	2.580000e+04
opponent_Phillies	-9.327468e+02	8.403034e+03	-0.111	0.914	-1.940000e+04	1.760000e+04
opponent_Pirates	-3.776112e+03	7.851580e+03	-0.481	0.640	-2.110000e+04	1.350000e+04
opponent_Reds	-1.934000e+04	8.294399e+03	-2.331	0.040	-3.760000e+04	-1.081913e+03
opponent_Rockies	8.073842e+02	2.833484e+03	0.285	0.781	-5.429071e+03	7.043840e+03
opponent_Snakes	-1.902542e+02	4.914898e+03	-0.039	0.970	-1.100000e+04	1.060000e+04
opponent_White Sox	8.690137e+03	4.727089e+03	1.838	0.093	-1.714117e+03	1.910000e+04
shirt_YES	-2.622000e-13	3.290000e-12	-0.080	0.938	-7.510000e-12	6.990000e-12
day_promo_MondayNO	-3.934364e+03	7.192249e+03	-0.547	0.595	-1.980000e+04	1.190000e+04
day_promo_MondayYES	-1.747000e-12	1.280000e-12	-1.362	0.201	-4.570000e-12	1.080000e-12
day_promo_SaturdayNO	9.576287e+02	3.540883e+03	0.270	0.792	-6.835802e+03	8.751060e+03
day_promo_SaturdayYES	9.435000e+03	7.955390e+03	1.186	0.261	-8.074696e+03	2.690000e+04
day_promo_SundayNO	6.122000e-13	8.090000e-13	0.757	0.465	-1.170000e-12	2.390000e-12
day_promo_SundayYES	-2.044000e-12	1.140000e-12	-1.790	0.101	-4.560000e-12	4.690000e-13
day_promo_ThursdayNO	1.117063e+03	1.040000e+04	0.107	0.917	-2.190000e+04	2.410000e+04
day_promo_ThursdayYES	1.755000e+04	7.579555e+03	2.315	0.041	8.670080e+02	3.420000e+04
day_promo_TuesdayNO	3.298790e+03	7.438975e+03	0.443	0.666	-1.310000e+04	1.970000e+04
day_promo_TuesdayYES	1.612000e+04	7.360455e+03	2.190	0.051	-8.360300e+01	3.230000e+04
day_promo_WednesdayNO	-1.469369e+02	6.770787e+03	-0.022	0.983	-1.500000e+04	1.480000e+04
day_promo_WednesdayYES	0.000000e+00	0.000000e+00	NaN	NaN	0.000000e+00	0.000000e+00

```python
#finding difference between coefficients for each day of the week, isolating promotion effect'

#MONDAY
mon_no = summ_df['coef'].values[22] #MondayNO
mon_yes = summ_df['coef'].values[23]
print("Monday: " + str(mon_yes-mon_no))
```

```
Monday: 3934.364199999998
```

```python
#SATURDAY
sat_no = summ_df['coef'].values[24] #SaturdayNO
sat_yes = summ_df['coef'].values[25]
print("Saturday: " + str(sat_yes-sat_no))
```

```
Saturday: 8477.3713
```

```python
#SUNDAY
sun_no = summ_df['coef'].values[26] #SundayNO
sun_yes = summ_df['coef'].values[27]
print("Sunday: " + str(sun_yes-sun_no))
```

```
Sunday: -2.6562e-12
```

```python
#THURSDAY
thurs_no = summ_df['coef'].values[28] #ThursdayNO
thurs_yes = summ_df['coef'].values[29]
print("Thursday: " + str(thurs_yes-thurs_no))
```

```
Thursday: 16432.9369
```

```python
#TUESDAY
tues_no = summ_df['coef'].values[30] #TuesdayNO
tues_yes = summ_df['coef'].values[31]
print("Tuesday: " + str(tues_yes-tues_no))
```

```
Tuesday: 12821.2097
```

```python
#WEDNESDAY
wed_no = summ_df['coef'].values[32] #WednesdayNO
wed_yes = summ_df['coef'].values[33]
print("Wednesday: " + str(wed_yes-wed_no))
```

```
Wednesday: 146.9369
```

Although there are other features in the linear regression model, my focus is on the interaction parameters between day of the week and promotion offering (YES or NO). As the target variable is 'attend' or attendance, the parameter coefficients will allow us to determine the relationship between independent and dependent variables when holding the other parameters constant.

In terms of statistical significance at 0.1 (90%), the following two interaction parameters are significant: ThursdayYES & TuesdayYES at 0.041 and 0.051 respectively. If we are looking with a significance level of 95% or 0.05, the parameter that is statistically significant is ThursdayYES. With these significances, it indicates strong evidence against the null hypothesis. Therefore, we can reject the null hypothesis, and accept the alternative hypothesis that the parameters have a signifant relationship with our attendance target variable.

Therefore, with TuesdayYES & ThursdayYES, if promotions are given on these days, the changes in attendance are both positive at 16,120 people & 17,550 people respectively. Both are relatively good increases in attendance, and would bring in a good population of people for the Dodgers!

However, in order to recommend one specific day to offer promotions at Dodgers games, I wanted to isolate the change that the promotion has on the attendance counts, given the day of the week. Therefore, I found the difference between each pair of interaction terms' coefficients such as ... MondayYES & MondayNO.

*One note to account for is that I am not sure how to account for Fridays. In our dataset, for any Friday games, at least one promotion was offered at them. Therefore, when creating the dummy variables for the linear regression model, it removed the FridayYES variable since it did not have a counterpart. I was going to evaluate Friday as being the change in attendance when all other variables are set to zero, which would be equal to the y-intercept of 33,650. However, given the other features in the model, I am not sure if that is accurate to say.

The day of the week which gave the greatest coefficient difference was Thursdays with a difference of 16,432.94 people. Therefore, I would recommend Thursdays as the best days to offer promotions at Dodgers games in order to increase attendance!