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Using Data to Improve MLB Attendace

	month	day	attend	day_of_week	opponent	temp	skies	day_night	сар	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

Coverting column values into numbers

```
# Convert columns, values to numbers
In [3]:
            # Define the mappings for the specified columns
            mappings = {
                'NO': 0,
                'YES': 1,
                'Day': 0,
                'Night': 1,
                'Clear ': 0,
                'Cloudy': 1,
                'Monday': 1,
                'Tuesday': 2,
                'Wednesday': 3,
                'Thursday': 4,
                'Friday': 5,
                'Saturday': 6,
                'Sunday': 7
            # Apply the mappings to the specified columns
            columns_to_map = ['bobblehead', 'cap', 'shirt', 'fireworks', 'day_night', 'skies', 'day_of_week']
            mlb df = mlb attendance.copy() # Create a copy of the original DataFrame
            for column in columns_to_map:
                mlb_df[column] = mlb_df[column].replace(mappings)
            mlb_df.head(20)
```

Out[3]:

	month	day	attend	day_of_week	opponent	temp	skies	day_night	сар	shirt	fireworks	bobblehead
0	APR	10	56000	2	Pirates	67	0	0	0	0	0	0
1	APR	11	29729	3	Pirates	58	1	1	0	0	0	0
2	APR	12	28328	4	Pirates	57	1	1	0	0	0	0
3	APR	13	31601	5	Padres	54	1	1	0	0	1	0
4	APR	14	46549	6	Padres	57	1	1	0	0	0	0
5	APR	15	38359	7	Padres	65	0	0	0	0	0	0
6	APR	23	26376	1	Braves	60	1	1	0	0	0	0
7	APR	24	44014	2	Braves	63	1	1	0	0	0	0
8	APR	25	26345	3	Braves	64	1	1	0	0	0	0
9	APR	27	44807	5	Nationals	66	0	1	0	0	1	0
10	APR	28	54242	6	Nationals	71	0	1	0	0	0	1
11	APR	29	48753	7	Nationals	74	0	0	0	1	0	0
12	MAY	7	43713	1	Giants	67	0	1	0	0	0	0
13	MAY	8	32799	2	Giants	75	0	1	0	0	0	0
14	MAY	9	33993	3	Giants	71	0	1	0	0	0	0
15	MAY	11	35591	5	Rockies	65	0	1	0	0	1	0
16	MAY	12	33735	6	Rockies	65	0	1	0	0	0	0
17	MAY	13	49124	7	Rockies	70	0	0	0	0	0	0
18	MAY	14	24312	1	Snakes	67	0	1	0	0	0	0
19	MAY	15	47077	2	Snakes	70	0	1	0	0	0	1

Finding the mean of attendance

The mean attendance is: 41040.07407407407

Finding unique values in the columns

```
In [5]: 

# List of columns to find unique values
            columns_of_interest = ["day_of_week", "opponent", "skies", "day_night", "cap", "shirt", "fireworks", "bot
            # Finds unique values in each specified column
            unique_values = {col: mlb_df[col].unique() for col in columns_of_interest}
            # Prints the unique values for each column
            for col, values in unique values.items():
                print(f"Unique values in column '{col}': {values}")
            Unique values in column 'day_of_week': [2 3 4 5 6 7 1]
            Unique values in column 'opponent': ['Pirates' 'Padres' 'Braves' 'Nationals' 'Giants' 'Rockies' 'Snake
            s'
             'Cardinals' 'Astros' 'Brewers' 'Angels' 'White Sox' 'Mets' 'Reds'
             'Phillies' 'Cubs' 'Marlins']
            Unique values in column 'skies': [0 1]
            Unique values in column 'day_night': [0 1]
            Unique values in column 'cap': [0 1]
            Unique values in column 'shirt': [0 1]
            Unique values in column 'fireworks': [0 1]
            Unique values in column 'bobblehead': [0 1]
```

In [6]: print(mlb_df.dtypes)

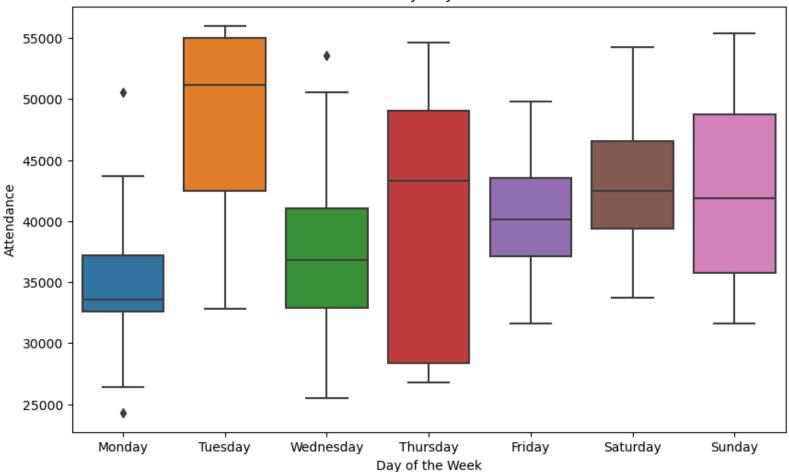
month object day int64 attend int64 day_of_week int64 opponent object temp int64 skies int64 day_night int64 int64 сар shirt int64 fireworks int64 bobblehead int64 dtype: object

Analyzing attendance by day of the week

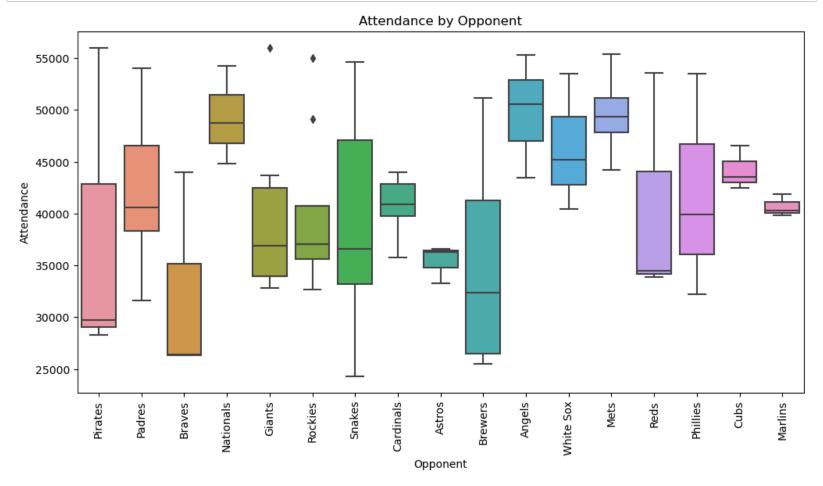
```
In [7]: # Maps day_of_week to actual days for better readability
    day_map = {1: 'Monday', 2: 'Tuesday', 3: 'Wednesday', 4: 'Thursday', 5: 'Friday', 6: 'Saturday', 7: 'Sunce
    mlb_df['day_name'] = mlb_df['day_of_week'].map(day_map)

# Plots attendance by day of the week
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='day_name', y='attend', data=mlb_df, order=['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'plt.title('Attendance by Day of the Week')
    plt.xlabel('Day of the Week')
    plt.ylabel('Attendance')
    plt.show()
```

Attendance by Day of the Week

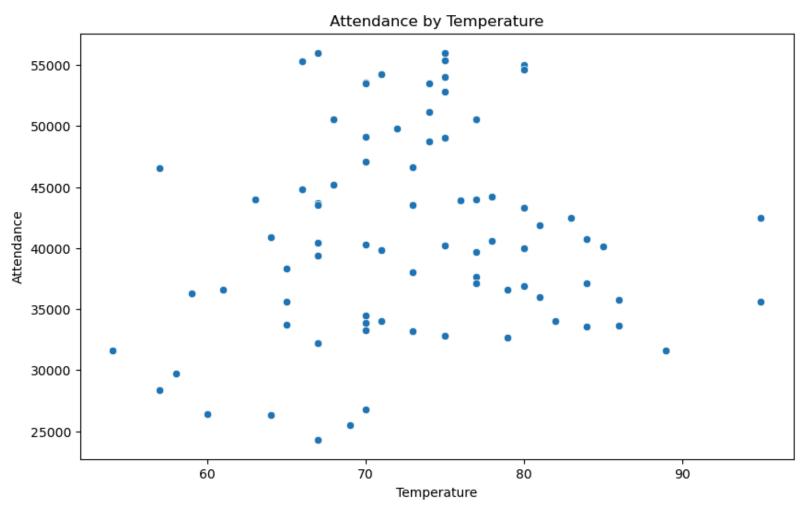


Analyzing attendance by Opponent



Analyzing Attendance by Temperature

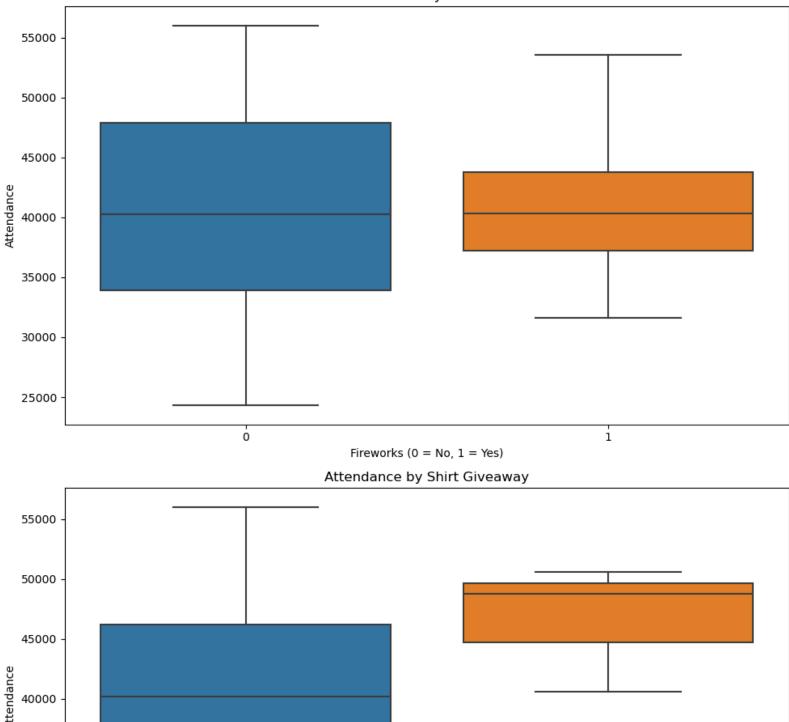
```
In [9]:  # Plots attendance by temperature
  plt.figure(figsize=(10, 6))
    sns.scatterplot(x='temp', y='attend', data=mlb_df)
    plt.title('Attendance by Temperature')
    plt.xlabel('Temperature')
    plt.ylabel('Attendance')
    plt.show()
```

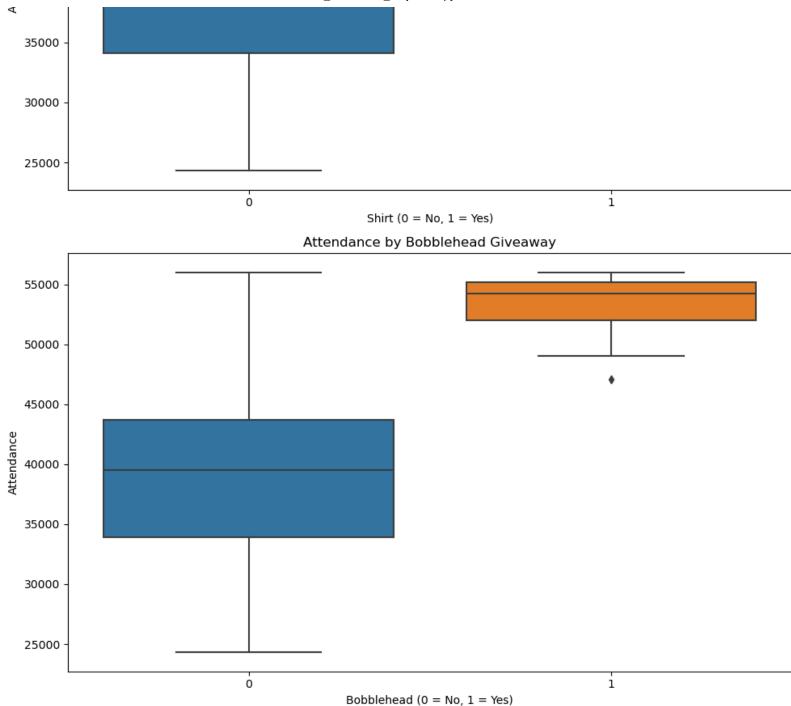


Analyzing Attendance by Promotional Events

```
# Plots attendance by promotional events
In [10]:
             fig, axes = plt.subplots(3, 1, figsize=(10, 18))
             # Fireworks
             sns.boxplot(x='fireworks', y='attend', data=mlb_df, ax=axes[0])
             axes[0].set title('Attendance by Fireworks')
             axes[0].set xlabel('Fireworks (0 = No, 1 = Yes)')
             axes[0].set ylabel('Attendance')
             # Shirt
             sns.boxplot(x='shirt', y='attend', data=mlb df, ax=axes[1])
             axes[1].set title('Attendance by Shirt Giveaway')
             axes[1].set xlabel('Shirt (0 = No, 1 = Yes)')
             axes[1].set ylabel('Attendance')
             # Bobblehead
             sns.boxplot(x='bobblehead', y='attend', data=mlb_df, ax=axes[2])
             axes[2].set title('Attendance by Bobblehead Giveaway')
             axes[2].set xlabel('Bobblehead (0 = No, 1 = Yes)')
             axes[2].set ylabel('Attendance')
             plt.tight layout()
             plt.show()
```

Attendance by Fireworks





OLS Regression Model

OLS Regression Results

Dep. Variable:	attend	R-squared:	0.435					
Model:	0LS	Adj. R-squared:	0.372					
Method:	Least Squares	F-statistic:	6.925					
Date:	Wed, 31 Jul 2024	<pre>Prob (F-statistic):</pre>	1.00e-06					
Time:	17:01:57	Log-Likelihood:	-822.24					
No. Observations:	81	AIC:	1662.					
Df Residuals:	72	BIC:	1684.					
Df Model:	8							

Covariance Type: nonrobust

coef	std err	t	P> t	[0.025	0.975]
3.594e+04	8181.420	4.393	0.000	1.96e+04	5.22e+04
437.3228	418.539	1.045	0.300	-397.019	1271.665
35.3887	97.514	0.363	0.718	-159.002	229.780
-903.6655	1877.887	-0.481	0.632	-4647.165	2839.834
-2482.4928	2407.584	-1.031	0.306	-7281.924	2316.938
-732.5436	4807.409	-0.152	0.879	-1.03e+04	8850.850
8305.8134	3954.428	2.100	0.039	422.805	1.62e+04
3222.8209	2191.802	1.470	0.146	-1146.456	7592.098
1.568e+04	2264.179	6.923	0.000	1.12e+04	2.02e+04
=======	:=========	======== 11	 		2.015
٠١.		3.773			
,,,					
		•	•	0.152	
	3.2	40 Cond. N	10.		837.
	3.594e+04 437.3228 35.3887 -903.6655 -2482.4928 -732.5436 8305.8134 3222.8209	3.594e+04 8181.420 437.3228 418.539 35.3887 97.514 -903.6655 1877.887 -2482.4928 2407.584 -732.5436 4807.409 8305.8134 3954.428 3222.8209 2191.802 1.568e+04 2264.179 	3.594e+04 8181.420 4.393 437.3228 418.539 1.045 35.3887 97.514 0.363 -903.6655 1877.887 -0.481 -2482.4928 2407.584 -1.031 -732.5436 4807.409 -0.152 8305.8134 3954.428 2.100 3222.8209 2191.802 1.470 1.568e+04 2264.179 6.923	3.594e+04 8181.420 4.393 0.000 437.3228 418.539 1.045 0.300 35.3887 97.514 0.363 0.718 -903.6655 1877.887 -0.481 0.632 -2482.4928 2407.584 -1.031 0.306 -732.5436 4807.409 -0.152 0.879 8305.8134 3954.428 2.100 0.039 3222.8209 2191.802 1.470 0.146 1.568e+04 2264.179 6.923 0.000 4.411 Durbin-Watson: 0.110 Jarque-Bera (JB): 0.515 Prob(JB):	3.594e+04 8181.420 4.393 0.000 1.96e+04 437.3228 418.539 1.045 0.300 -397.019 35.3887 97.514 0.363 0.718 -159.002 -903.6655 1877.887 -0.481 0.632 -4647.165 -2482.4928 2407.584 -1.031 0.306 -7281.924 -732.5436 4807.409 -0.152 0.879 -1.03e+04 8305.8134 3954.428 2.100 0.039 422.805 3222.8209 2191.802 1.470 0.146 -1146.456 1.568e+04 2264.179 6.923 0.000 1.12e+04

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Final insights and recomendations

Based on the OLS regression results, several key insights can be derived to recommend strategies for improving crowd attendance. Promotional events, particularly shirt and bobblehead giveaways, have a significant positive impact on attendance. The regression model shows that shirt giveaways can boost attendance by approximately 8,305 people, and bobblehead giveaways have an even more substantial effect, increasing attendance by around 15,680 people. Although fireworks nights show a positive trend in increasing attendance, this effect is not statistically significant.

The analysis suggests less significant effects from the day of the week, temperature, and sky conditions on attendance. The coefficients for these variables are not statistically significant, indicating that they have a weaker or negligible influence on the number of attendees. Similarly, the preference for day versus night games is not clear, as the regression results do not show a significant impact. Interestingly, cap giveaways appear to have a negative coefficient, suggesting they may not be effective in drawing larger crowds.

To enhance attendance, increasing the frequency of highly effective promotional events like bobblehead and shirt giveaways is recommended. These events should be heavily marketed to attract more fans and create a vibrant game-day atmosphere. While the day of the week and game timing do not show significant effects in this model, further experiments or surveys could reveal preferences among different fan segments. Weather factors, such as temperature and sky conditions, seem less critical and thus should not be a primary concern in scheduling games.

