DA 420 - Project 2

Matt Graham

Imports

In [ ]:
```
# Traditional Conjoint Analysis (Python)

# prepare for Python version 3x features and functions
from __future__ import division, print_function

# import packages for analysis and modeling
import pandas as pd  # data frame operations
import numpy as np  # arrays and math functions
from numpy import unique
import statsmodels.api as sm  # statistical models (including regression)
import statsmodels.formula.api as smf  # R-like model specification
from patsy.contrasts import Sum
from scipy.stats import uniform  # for training-and-test split
import matplotlib.pyplot as plt  # 2D plotting
import seaborn as sns
```

Get an clean data

In [ ]:
```
# read in Dodgers bobbleheads data and create data frame
dodgers = pd.read_csv("dodgers.csv")

# examine the structure of the data frame
# print("\nContents of dodgers data frame ---------------")

# attendance in thousands for plotting
dodgers['attend_000'] = dodgers['attend']/1000

# print the first five rows of the data frame
# print(pd.DataFrame.head(dodgers))

mondays = dodgers[dodgers['day_of_week'] == 'Monday']
tuesdays = dodgers[dodgers['day_of_week'] == 'Tuesday']
wednesdays = dodgers[dodgers['day_of_week'] == 'Wednesday']
thursdays = dodgers[dodgers['day_of_week'] == 'Thursday']
fridays = dodgers[dodgers['day_of_week'] == 'Friday']
saturdays = dodgers[dodgers['day_of_week'] == 'Saturday']
sundays = dodgers[dodgers['day_of_week'] == 'Sunday']

# convert days' attendance into list of vectors for box plot
data = [mondays['attend_000'], tuesdays['attend_000'],
    wednesdays['attend_000'], thursdays['attend_000'],
    fridays['attend_000'], saturdays['attend_000'],
    sundays['attend_000']]
ordered_day_names = ['Mon', 'Tue', 'Wed', 'Thur', 'Fri', 'Sat', 'Sun']

april = dodgers[dodgers['month'] == 'APR']
may = dodgers[dodgers['month'] == 'MAY']
june = dodgers[dodgers['month'] == 'JUN']
july = dodgers[dodgers['month'] == 'JUL']
august = dodgers[dodgers['month'] == 'AUG']
september = dodgers[dodgers['month'] == 'SEP']
october = dodgers[dodgers['month'] == 'OCT']

data = [april['attend_000'], may['attend_000'],
    june['attend_000'], july['attend_000'],
    august['attend_000'], september['attend_000'],
    october['attend_000']]
ordered_month_names = ['April', 'May', 'June', 'July', 'Aug', 'Sept', 'Oct']

dodgers
```

Out[ ]:

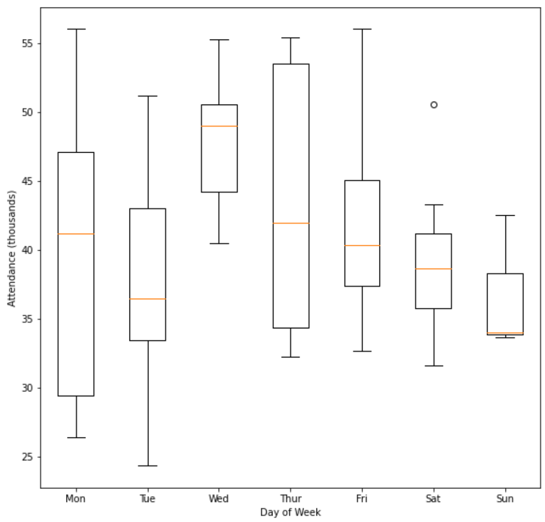
	month	day	attend	day_of_week	opponent	temp	skies	day_night	cap	shirt	fireworks
0	APR	10	56000	Tuesday	Pirates	67	Clear	Day	NO	NO	NO
1	APR	11	29729	Wednesday	Pirates	58	Cloudy	Night	NO	NO	NO
2	APR	12	28328	Thursday	Pirates	57	Cloudy	Night	NO	NO	NO
3	APR	13	31601	Friday	Padres	54	Cloudy	Night	NO	NO	YES
4	APR	14	46549	Saturday	Padres	57	Cloudy	Night	NO	NO	NO
...	...	...	...	...	...	...	...	...	...	...	...
76	SEP	29	40724	Saturday	Rockies	84	Cloudy	Night	NO	NO	NO
77	SEP	30	35607	Sunday	Rockies	95	Clear	Day	NO	NO	NO
78	OCT	1	33624	Monday	Gians	86	Clear	Night	NO	NO	NO
79	OCT	2	42473	Tuesday	Gians	83	Clear	Night	NO	NO	NO
80	OCT	3	34014	Wednesday	Gians	82	Cloudy	Night	NO	NO	NO

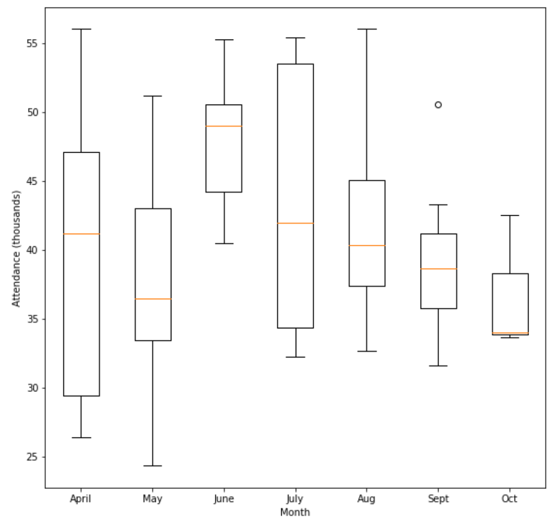
81 rows × 13 columns

Box plots and analysis

In [ ]:

```
fig = plt.figure(figsize=(20,20))

set_I = fig.add_subplot(2, 2, 1)
set_I.set_xlabel('Day of Week')
set_I.set_ylabel('Attendance (thousands)')
day_plot = plt.boxplot(data, sym='o', vert=1, whis=1.5)
plt.setp(day_plot['boxes'], color = 'black')
plt.setp(day_plot['whiskers'], color = 'black')
plt.setp(day_plot['fliers'], color = 'black', marker = 'o')
set_I.set_xticklabels(ordered_day_names)

set_II = fig.add_subplot(2, 2, 2)
set_II.set_xlabel('Month')
set_II.set_ylabel('Attendance (thousands)')
day_plot = plt.boxplot(data, sym='o', vert=1, whis=1.5)
plt.setp(day_plot['boxes'], color = 'black')
plt.setp(day_plot['whiskers'], color = 'black')
plt.setp(day_plot['fliers'], color = 'black', marker = 'o')
set_II.set_xticklabels(ordered_month_names)

plt.subplots_adjust(left=0.1, right=0.925, top=0.925, bottom=0.1,
    wspace = 0.3, hspace = 0.4)
```





Analysis

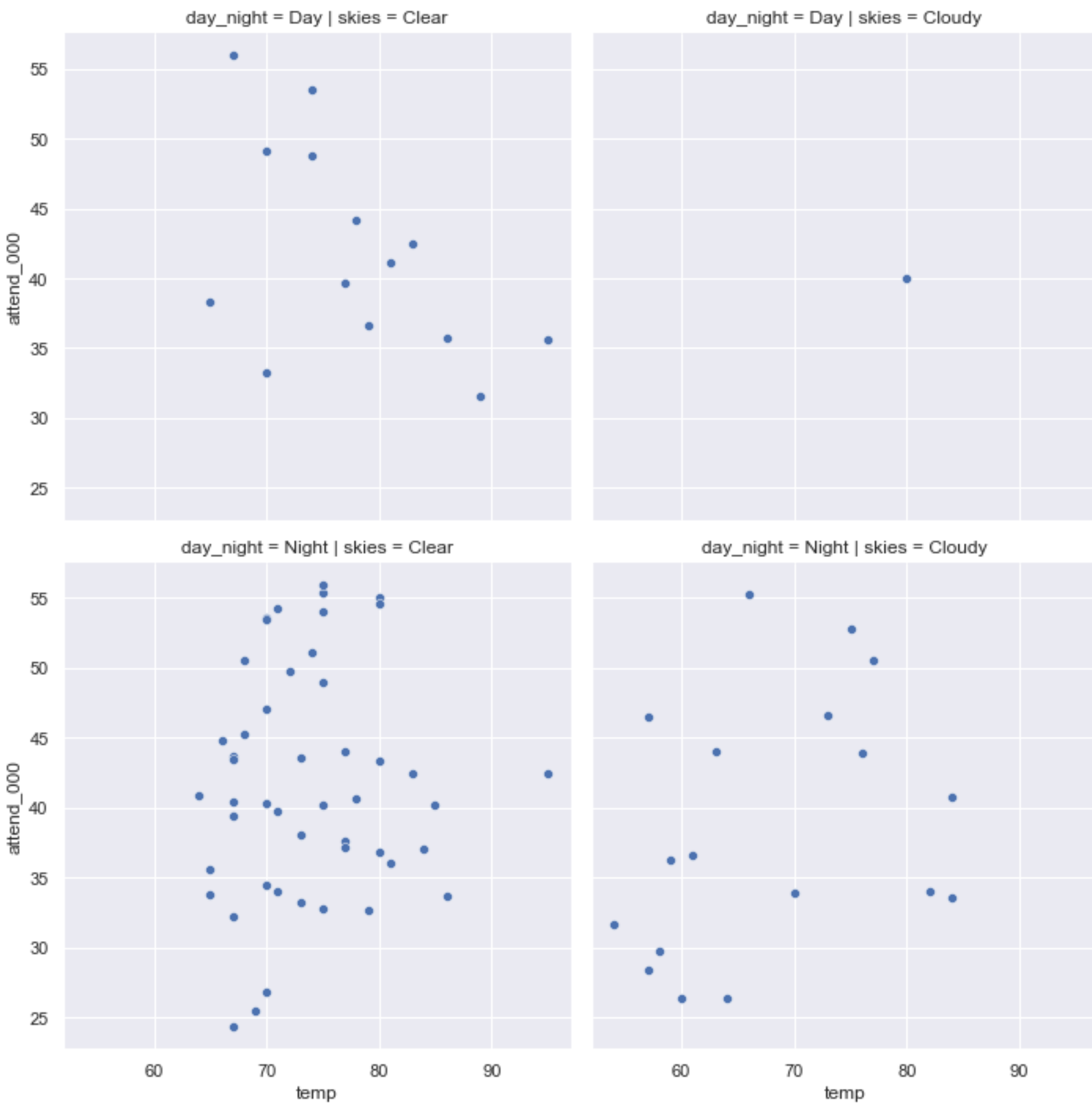
We an see that Saturday's are an outlier, and so is September. This appears to maybe be the same value as the attendance in thousands is equal on both occassions. Otherwise, spread across most months and days are consistent; some being wide, such as early in the week and year, respectively. This can be due to seasonality!

Scatter plots and analysis

Weather attedance analysis

In [ ]:
```
g = sns.FacetGrid(dodgers, row = 'day_night', col = 'skies', height=5, aspect=1)
g.map(sns.scatterplot, "temp", "attend_000")
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x1e62a801510>
```



We can see that a majority of attendance data lives within the clear night segment with a single datapoint existing on a cloudy day. There appears to be a coorelation between lower attendance and lower temperatures - especially on cloudy nights.

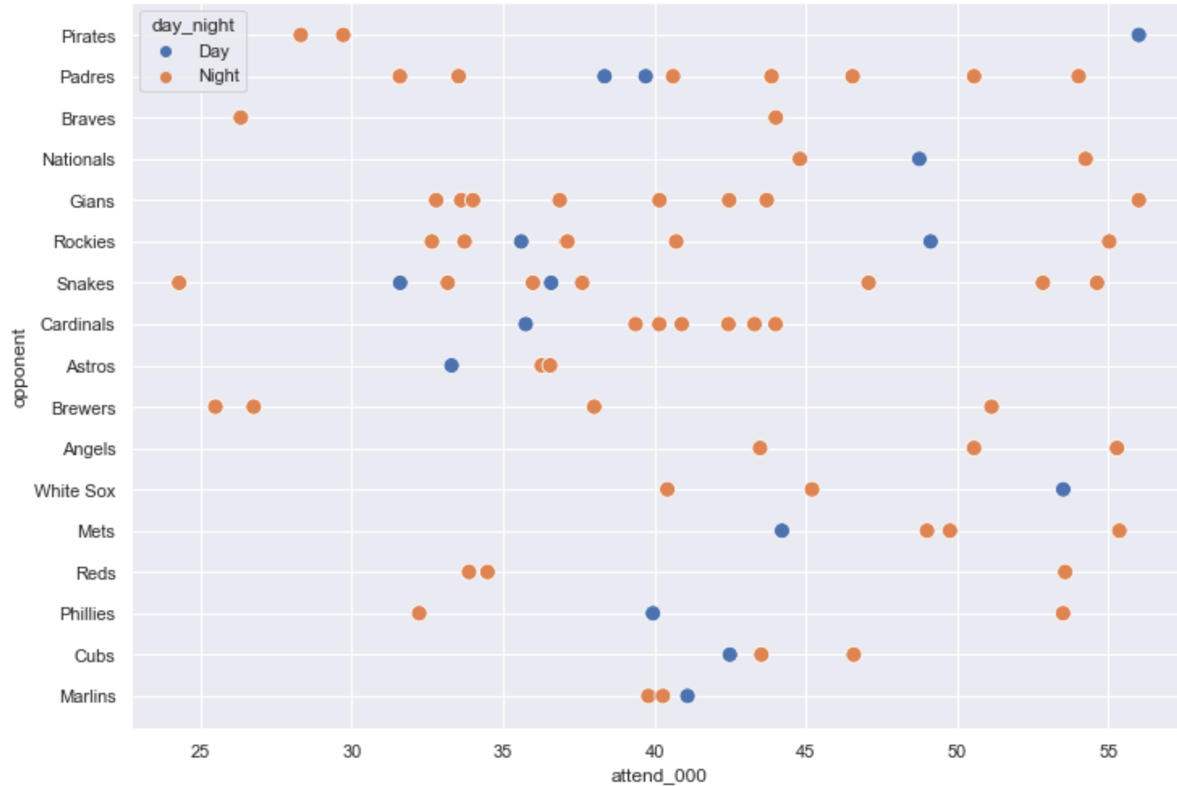
Opponent attendance analysis

In [ ]:

```
sns.set(rc={'figure.figsize':(11.7,8.27)})

sns.scatterplot(data=dodgers, x="attend_000", y="opponent", hue="day_night", s=100)
```

Out[ ]:

```
<AxesSubplot:xlabel='attend_000', ylabel='opponent'>
```



We can see the lowest attended games were against: Braves, Snakes, and Brewers. The Rockies, Pirates, Angels, and Mets all yielded great attendance!

Regression model performance

In [ ]:
```
# map day_of_week to ordered_day_of_week
day_to_ordered_day = {'Monday' : '1Monday',
     'Tuesday' : '2Tuesday',
     'Wednesday' : '3Wednesday',
     'Thursday' : '4Thursday',
     'Friday' : '5Friday',
     'Saturday' : '6Saturday',
     'Sunday' : '7Sunday'}
dodgers['ordered_day_of_week'] = dodgers['day_of_week'].map(day_to_ordered_day)

# map month to ordered_month
month_to_ordered_month = {'APR' : '1April',
     'MAY' : '2May',
     'JUN' : '3June',
     'JUL' : '4July',
     'AUG' : '5Aug',
     'SEP' : '6Sept',
     'OCT' : '7Oct'}
dodgers['ordered_month'] = dodgers['month'].map(month_to_ordered_month)

# employ training-and-test regimen for model validation
np.random.seed(1234)
dodgers['runiform'] = uniform.rvs(loc = 0, scale = 1, size = len(dodgers))
dodgers_train = dodgers[dodgers['runiform'] >= 0.33]
dodgers_test = dodgers[dodgers['runiform'] < 0.33]
# check training data frame
print('\ndodgers_train data frame (rows, columns): ',dodgers_train.shape)
print(dodgers_train.head())
# check test data frame
print('\ndodgers_test data frame (rows, columns): ',dodgers_test.shape)
print(dodgers_test.head())

# specify a simple model with bobblehead entered last
my_model = str('attend ~ ordered_month + ordered_day_of_week + bobblehead')

# fit the model to the training set
train_model_fit = smf.ols(my_model, data = dodgers_train).fit()
# summary of model fit to the training set
print(train_model_fit.summary())
# training set predictions from the model fit to the training set
dodgers_train['predict_attend'] = train_model_fit.fittedvalues

# test set predictions from the model fit to the training set
dodgers_test['predict_attend'] = train_model_fit.predict(dodgers_test)

# compute the proportion of response variance
# accounted for when predicting out-of-sample
print('\nProportion of Test Set Variance Accounted for: ',\
    round(np.power(dodgers_test['attend'].corr(dodgers_test['predict_attend']),2),3

# use the full data set to obtain an estimate of the increase in
# attendance due to bobbleheads, controlling for other factors
my_model_fit = smf.ols(my_model, data = dodgers).fit()
print(my_model_fit.summary())

print('\nEstimated Effect of Bobblehead Promotion on Attendance: ',\
    round(my_model_fit.params[13],0))
```

```
# Suggestions for the student: Reproduce the figures in this chapter
# using matplotlib, ggplot, and/or rpy2 calls to R graphics.
# Examine regression diagnostics for the fitted model.
# Examine other linear predictors and other explanatory variables.
# See if you can improve upon the model with variable transformations.
```

```
dodgers_train data frame (rows, columns):  (57, 16)
  month  day  attend day_of_week opponent  temp   skies day_night cap shirt  \
1   APR   11   29729   Wednesday  Pirates    58  Cloudy     Night  NO    NO
2   APR   12   28328    Thursday  Pirates    57  Cloudy     Night  NO    NO
3   APR   13   31601      Friday   Padres    54  Cloudy     Night  NO    NO
4   APR   14   46549    Saturday   Padres    57  Cloudy     Night  NO    NO
7   APR   24   44014     Tuesday   Braves    63  Cloudy     Night  NO    NO

  fireworks bobblehead  attend_000 ordered_day_of_week ordered_month  runiform
1        NO         NO      29.729          3Wednesday        1April  0.622109
2        NO         NO      28.328           4Thursday        1April  0.437728
3       YES         NO      31.601             5Friday        1April  0.785359
4        NO         NO      46.549           6Saturday        1April  0.779976
7        NO         NO      44.014            2Tuesday        1April  0.801872

dodgers_test data frame (rows, columns):  (24, 16)
   month  day  attend day_of_week   opponent  temp   skies day_night cap  \
0    APR   10   56000     Tuesday    Pirates    67   Clear       Day  NO
5    APR   15   38359      Sunday     Padres    65   Clear       Day  NO
6    APR   23   26376      Monday     Braves    60  Cloudy     Night  NO
17   MAY   13   49124      Sunday    Rockies    70   Clear       Day  NO
22   MAY   20   44005      Sunday  Cardinals    77   Clear     Night  NO

   shirt fireworks bobblehead  attend_000 ordered_day_of_week ordered_month  \
0     NO        NO         NO      56.000            2Tuesday        1April
5     NO        NO         NO      38.359             7Sunday        1April
6     NO        NO         NO      26.376             1Monday        1April
17    NO        NO         NO      49.124             7Sunday          2May
22    NO        NO         NO      44.005             7Sunday          2May

    runiform
0   0.191519
5   0.272593
6   0.276464
17  0.013768
22  0.075381
                            OLS Regression Results
==============================================================================
Dep. Variable:                 attend   R-squared:                       0.584
Model:                            OLS   Adj. R-squared:                  0.459
Method:                 Least Squares   F-statistic:                     4.649
Date:                Mon, 16 Jan 2023   Prob (F-statistic):           6.31e-05
Time:                        15:15:22   Log-Likelihood:                -570.92
No. Observations:                  57   AIC:                             1170.
Df Residuals:                      43   BIC:                             1198.
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
                                        coef    std err          t      P>|t|
------------------------------------------------------------------------------
Intercept                           3.54e+04   3357.834     10.543      0.000      2.
ordered_month[T.2May]             -2893.7482   2719.222     -1.064      0.293     -83
ordered_month[T.3June]             9143.5964   3197.080      2.860      0.007      26
ordered_month[T.4July]             4329.9891   3467.491      1.249      0.219     -26
```

```
ordered_month[T.5Aug]                3351.1314   2865.583      1.169      0.249   -24
ordered_month[T.6Sept]               1116.4035   3073.903      0.363      0.718   -50
ordered_month[T.7Oct]                -804.9265   6877.957     -0.117      0.907   -1.
ordered_day_of_week[T.2Tuesday]      5705.7798   3772.360      1.513      0.138   -19
ordered_day_of_week[T.3Wednesday]    -584.2730   3465.209     -0.169      0.867   -75
ordered_day_of_week[T.4Thursday]     2461.1039   4038.301      0.609      0.545   -56
ordered_day_of_week[T.5Friday]       3663.9450   3096.713      1.183      0.243   -25
ordered_day_of_week[T.6Saturday]     3651.9368   3178.006      1.149      0.257   -27
ordered_day_of_week[T.7Sunday]       3216.7909   3381.470      0.951      0.347   -36
bobblehead[T.YES]                    1.089e+04   3065.161      3.554      0.001    47
==============================================================================
Omnibus:                        3.790   Durbin-Watson:                   2.140
Prob(Omnibus):                  0.150   Jarque-Bera (JB):                3.112
Skew:                           0.567   Prob(JB):                        0.211
Kurtosis:                       3.153   Cond. No.                         10.6
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly sp

Proportion of Test Set Variance Accounted for:  0.176
                            OLS Regression Results
==============================================================================
Dep. Variable:                 attend   R-squared:                       0.481
Model:                            OLS   Adj. R-squared:                  0.380
Method:                 Least Squares   F-statistic:                     4.771
Date:                Mon, 16 Jan 2023   Prob (F-statistic):           8.77e-06
Time:                        15:15:22   Log-Likelihood:                -818.81
No. Observations:                  81   AIC:                             1666.
Df Residuals:                      67   BIC:                             1699.
Df Model:                          13
Covariance Type:            nonrobust
=====================================================================================
                                        coef    std err          t      P>|t|
-------------------------------------------------------------------------------------
Intercept                          3.362e+04   2690.485     12.496      0.000     2.
ordered_month[T.2May]             -2213.7290   2445.203     -0.905      0.369    -70
ordered_month[T.3June]             7627.9472   2915.679      2.616      0.011     18
ordered_month[T.4July]             3509.7591   2745.368      1.278      0.206    -19
ordered_month[T.5Aug]              2844.9804   2560.780      1.111      0.271    -22
ordered_month[T.6Sept]             -184.3500   2690.984     -0.069      0.946    -55
ordered_month[T.7Oct]              -889.0536   4319.843     -0.206      0.838    -95
ordered_day_of_week[T.2Tuesday]    9423.8885   2864.023      3.290      0.002     37
ordered_day_of_week[T.3Wednesday]  2490.4208   2683.748      0.928      0.357    -28
ordered_day_of_week[T.4Thursday]   3673.9410   3597.731      1.021      0.311    -35
ordered_day_of_week[T.5Friday]     4358.9674   2681.873      1.625      0.109     -9
ordered_day_of_week[T.6Saturday]   6972.1445   2720.147      2.563      0.013     15
ordered_day_of_week[T.7Sunday]     6998.3919   2674.559      2.617      0.011     16
bobblehead[T.YES]                  7486.0276   2477.928      3.021      0.004     25
==============================================================================
Omnibus:                        3.418   Durbin-Watson:                   2.214
Prob(Omnibus):                  0.181   Jarque-Bera (JB):                3.033
Skew:                           0.474   Prob(JB):                        0.219
Kurtosis:                       3.033   Cond. No.                         9.69
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly sp
```

```
Estimated Effect of Bobblehead Promotion on Attendance:  7486.0
C:\Users\graha\AppData\Local\Temp\ipykernel_18984\3406206324.py:41: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  dodgers_train['predict_attend'] = train_model_fit.fittedvalues
C:\Users\graha\AppData\Local\Temp\ipykernel_18984\3406206324.py:44: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  dodgers_test['predict_attend'] = train_model_fit.predict(dodgers_test)
```

In [ ]:

```
print('\nProportion of Test Set Variance Accounted for: ',\
    round(np.power(dodgers_test['attend'].corr(dodgers_test['predict_attend']),2),3
```

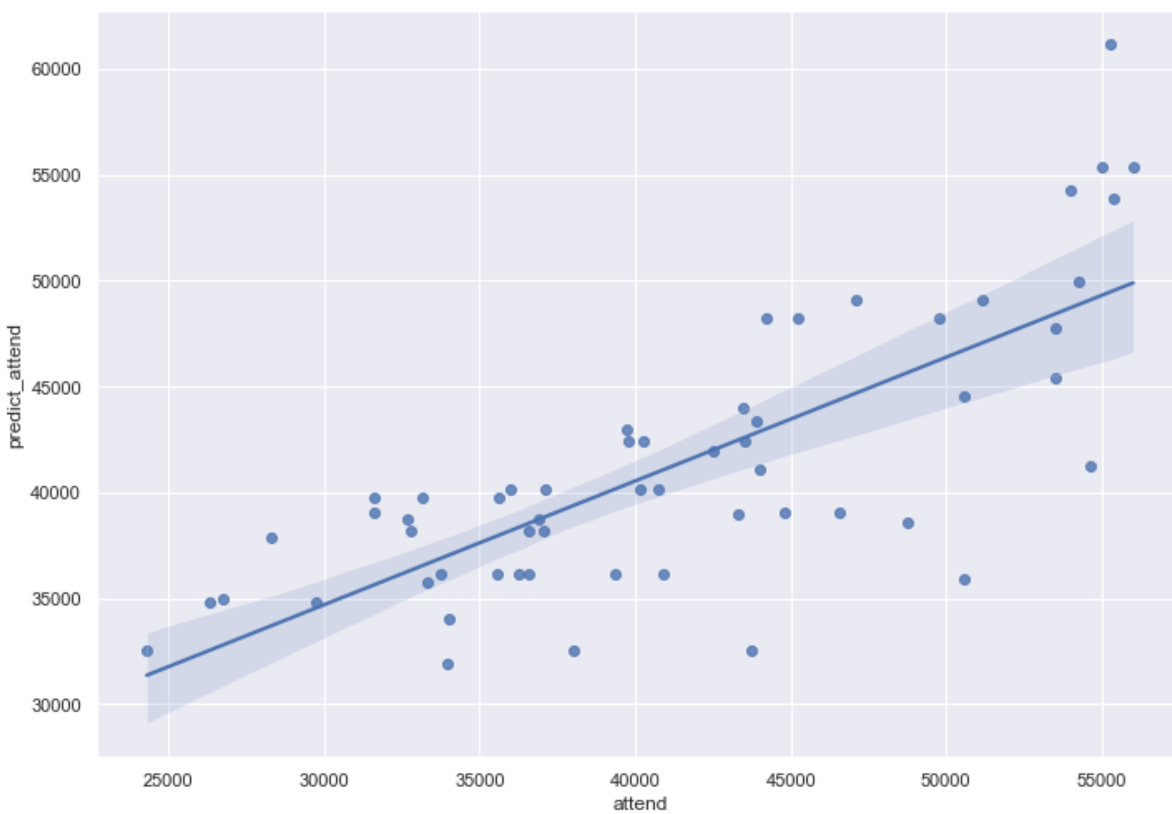
```
Proportion of Test Set Variance Accounted for:  0.176
```

In [ ]:

```
sns.regplot(data=dodgers_train, x="attend", y="predict_attend")
```

Out[ ]:

```
<AxesSubplot:xlabel='attend', ylabel='predict_attend'>
```

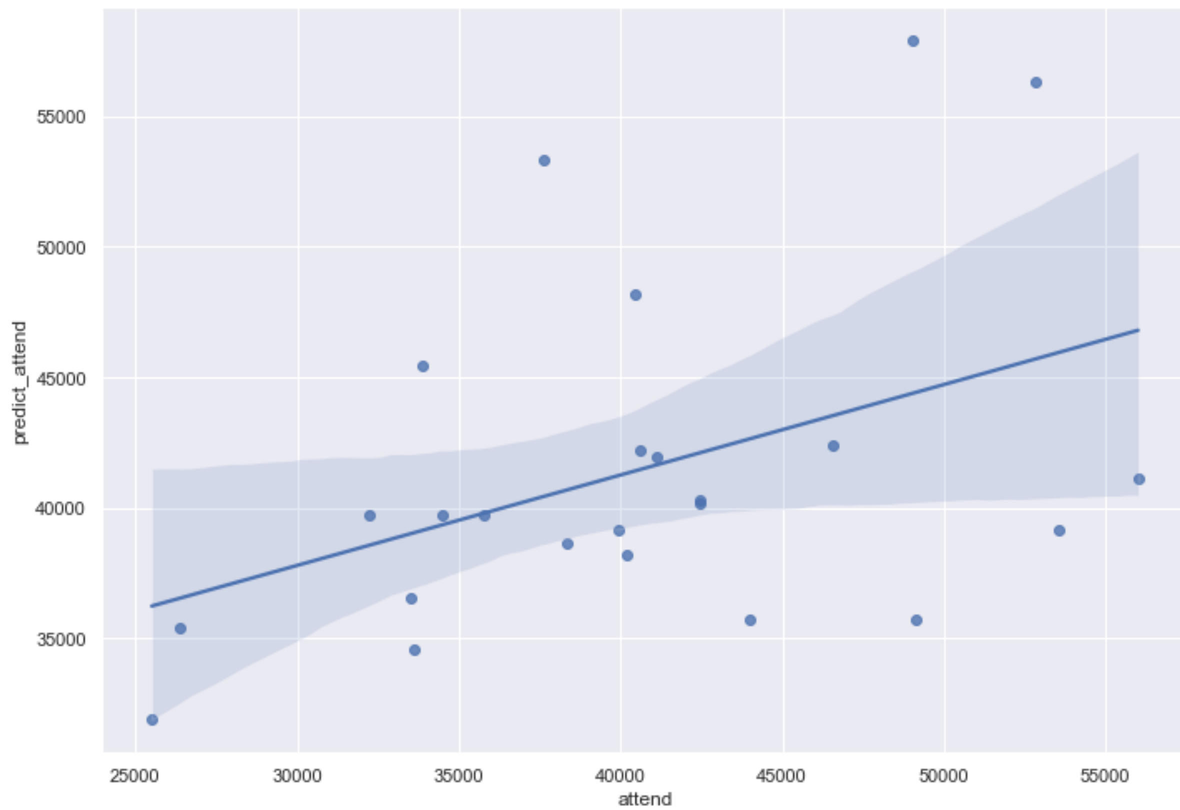


In [ ]:

```
sns.regplot(data=dodgers_test, x="attend", y="predict_attend")
```

Out[ ]:

```
<AxesSubplot:xlabel='attend', ylabel='predict_attend'>
```



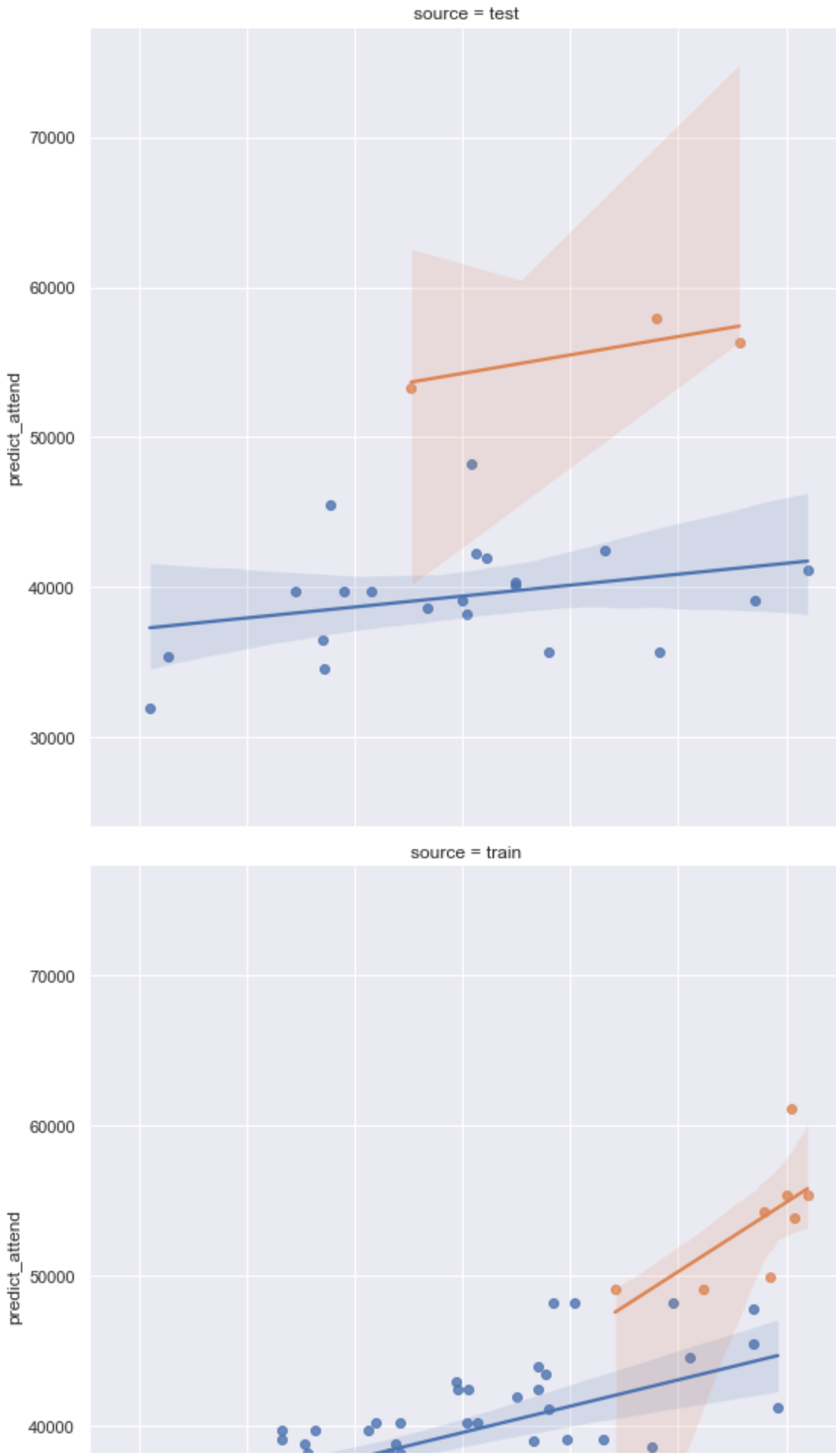
In [ ]:
```
dodgers_train['source'] = "train"
dodgers_test['source'] = "test"
joined_test = pd.concat([dodgers_test, dodgers_train])
# joined_test
```

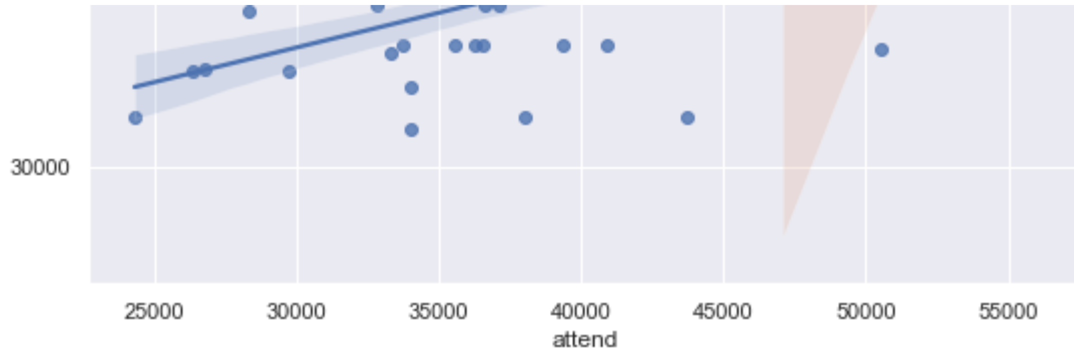
```
C:\Users\graha\AppData\Local\Temp\ipykernel_18984\1680184946.py:1: SettingWithCopyW
arning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  dodgers_train['source'] = "train"
C:\Users\graha\AppData\Local\Temp\ipykernel_18984\1680184946.py:2: SettingWithCopyW
arning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
user_guide/indexing.html#returning-a-view-versus-a-copy
  dodgers_test['source'] = "test"
```

Visualizing performance - segmenting bobbleheads

In [ ]:
```
g = sns.FacetGrid(joined_test, row = 'source', height=8, aspect=1, hue="bobblehead"
g.map_dataframe(sns.regplot, x="attend", y="predict_attend")
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x1e6337f38b0>
```

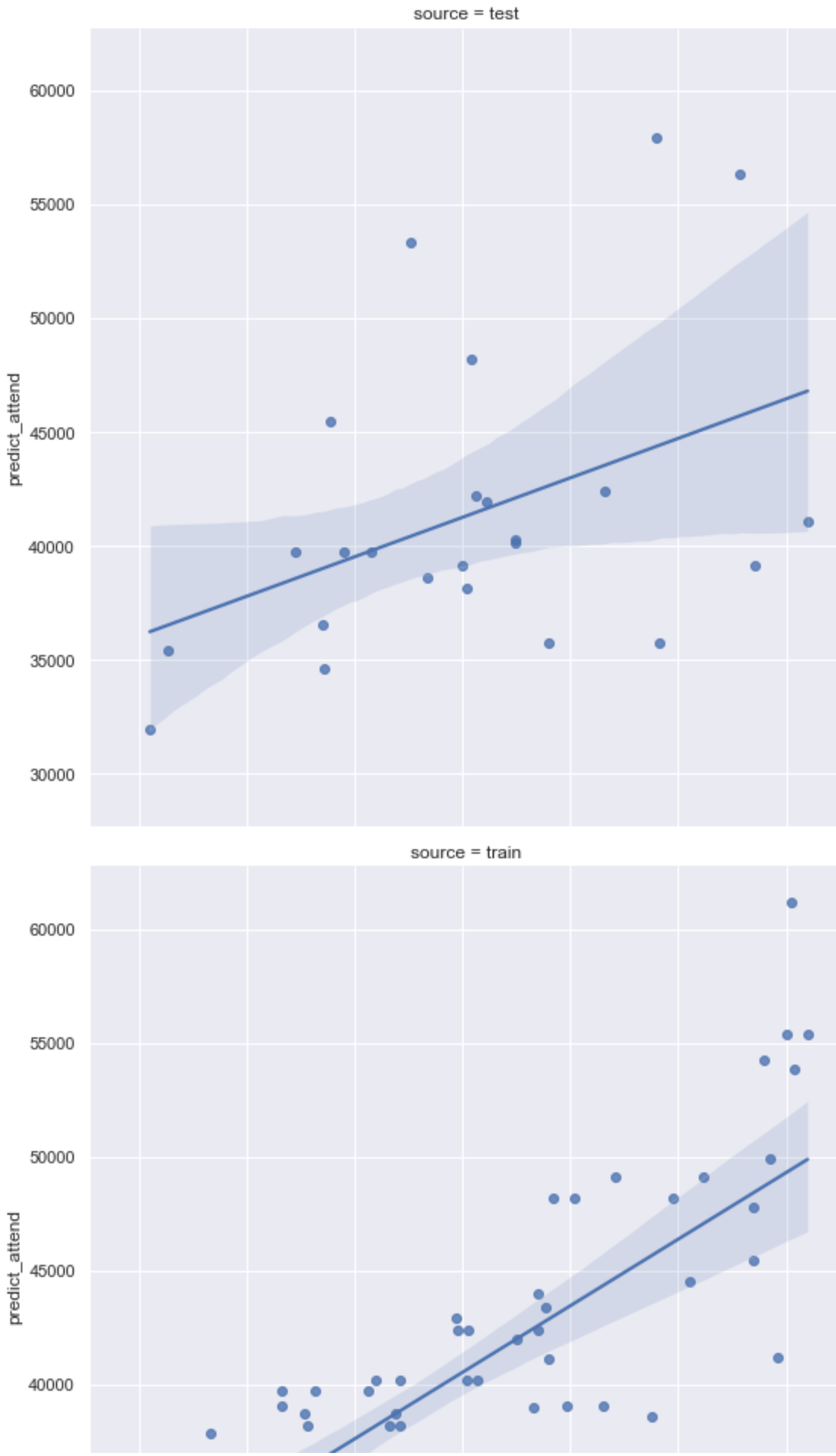

source = test
70000
60000
50000
40000
30000
predict_attend
source = train
70000
60000
50000
40000
predict_attend

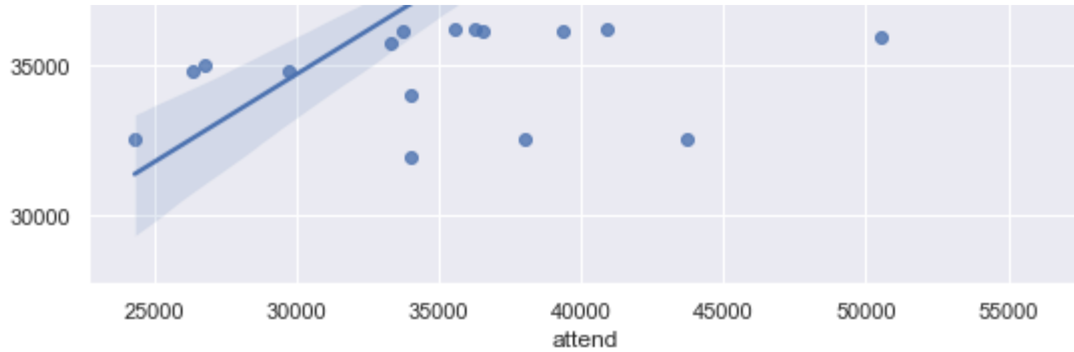


Visualizing performance - including bobbleheads

In [ ]:
```
g = sns.FacetGrid(joined_test, row = 'source', height=8, aspect=1)
g.map_dataframe(sns.regplot, x="attend", y="predict_attend")
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x1e6337a2ce0>
```


source = test
60000
55000
50000
45000
40000
35000
30000
predict_attend
source = train
60000
55000
50000
45000
40000
predict_attend



Given what our model produced and tested, then validated, we were only able to conclude a capture of ~18% total variability in the data. While that isn't bad, it can be improved upon. We can look into other factors, like time of year and which days may be more likely to sell. This can help us target our advertising and promote deals on slow sale days.