In [809]: #load relevant packages

import pandas as pd

from scipy.stats import uniform

import statsmodels.api as sm

import statsmodels.formula.api as smf

import seaborn as sns

from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_squared_error

from sklearn.metrics import r2_score

In [810]: #load baseline coaches file

coaches = pd.read_csv('https://raw.githubusercontent.com/barrettfranks/ist718/master/coaches_baseline.csv') coaches.head(10)

Out[810]:

	School	Conference	Coach	SchoolPay	TotalPay	Bonus	BonusPaid	AssistantPay	Buyout
0	Air Force	Mt. West	Troy Calhoun	885000	885000	247000		\$0	
1	Akron	MAC	Terry Bowden	\$411,000	\$412,500	\$225,000	\$50,000	\$0	\$688,500
2	Alabama	SEC	Nick Saban	\$8,307,000	\$8,307,000	\$1,100,000	\$500,000	\$0	\$33,600,000
3	Alabama at Birmingham	C-USA	Bill Clark	\$900,000	\$900,000	\$950,000	\$165,471	\$0	\$3,847,500
4	Appalachian State	Sun Belt	Scott Satterfield	\$712,500	\$712,500	\$295,000	\$145,000	\$0	\$2,160,417
5	Arizona	Pac-12	Kevin Sumlin	\$1,600,000	\$2,000,000	\$2,025,000		\$0	\$10,000,000
6	Arizona State	Pac-12	Herm Edwards	\$2,000,000	\$2,000,000	\$3,010,000		\$0	\$8,166,667
7	Arkansas	SEC	Chad Morris	\$3,500,000	\$3,500,000	\$1,000,000		\$0	\$12,500,000
8	Arkansas State	Sun Belt	Blake Anderson	\$825,000	\$825,000	\$185,000	\$25,000	\$0	\$300,000
9	Army	Ind.	Jeff Monken	932521	932521			\$0	

In [811]: #load ancilary revenue data

revenue = pd.read_csv('https://raw.githubusercontent.com/barrettfranks/ist718/master/revenue.csv') revenue.head(10)

Out[811]:

	RK	School	Conference	Revenue	Expenses
0	1	Texas	Big 12	\$223,879,781	\$204,234,897
1	2	Texas A&M	SEC	\$212,748,002	\$169,012,456
2	3	Ohio State	Big Ten	\$210,548,239	\$220,572,956
3	4	Michigan	Big Ten	\$197,820,410	\$190,952,175
4	5	Georgia	SEC	\$174,042,482	\$143,299,554
5	6	Penn State	Big Ten	\$164,529,326	\$160,369,805
6	7	Alabama	SEC	\$164,090,889	\$185,317,681
7	8	Oklahoma	Big 12	\$163,126,695	\$157,958,270
8	9	Florida	SEC	\$159,706,937	\$141,829,002
9	10	LSU	SEC	\$157,787,782	\$148,977,880

In [812]: #load ancilary stadium size data
 size = pd.read_csv('https://raw.githubusercontent.com/barrettfranks/ist718/master/Stadium_Size.csv')
 size.head(10)

Out[812]:

	Stadium	College	Conference	Capacity	Opened
0	Michigan Stadium	Michigan	Big Ten	107,601	1927
1	Beaver Stadium	Penn State	Big Ten	106,572	1960
2	Ohio Stadium	Ohio State	Big Ten	104,944	1922
3	Kyle Field	Texas A&M	SEC	102,733	1904
4	Neyland Stadium	Tennessee	SEC	102,521	1921
5	Bryant Denny Stadium	Alabama	SEC	101,821	1929
6	Tiger Stadium	LSU	SEC	100,500	1924
7	Royal Memorial Stadium	Texas	Big 12	100,119	1924
8	Los Angeles Coliseum	USC	Pac 12	93,607	1923
9	Sanford Stadium	Georgia	SEC	92,746	1929

In [813]: #load ancilary coach win data

coach = pd.read_csv('https://raw.githubusercontent.com/barrettfranks/ist718/master/coach_win.csv')
coach.head(10)

Out[813]:

	team	conf	coach	firstyear	currwin	currloss	currwin%	win	loss	win_percent	ос	dc	stc
0	Cincinnati Bearcats	The American	Luke Fickell	2017	35.0	14.0	0.714	41	21	0.661	Mike Denbrock	Mike Tressel	Brian Mason
1	East Carolina Pirates	The American	Mike Houston	2019	7.0	14.0	0.333	7	14	0.333	Donnie Kirkpatrick	Blake Harrell	Tim Daoust
2	Houston Cougars	The American	Dana Holgorsen	2019	7.0	13.0	0.35	68	54	0.557	Shannon Dawson	Doug Belk	Mark Scott
3	Memphis Tigers	The American	Ryan Silverfield	2020	8.0	4.0	0.667	8	4	0.667	Kevin Johns	Mike MacIntyre	Charles Bankins
4	Navy Midshipmen	The American	Ken Niumatalolo	2007	101.0	67.0	0.601	101	67	0.601	Ivin Jasper	Brian Newberry	Danny O'Rourke
5	SMU Mustangs	The American	Sonny Dykes	2018	22.0	14.0	0.611	63	59	0.516	Garrett Riley	Jim Leavitt	Kenny Perry
6	South Florida Bulls	The American	Jeff Scott	2020	1.0	8.0	0.111	1	8	0.111	Charlie Weis Jr.	Glenn Spencer	Daniel Da Prato
7	Temple Owls	The American	Rod Carey	2019	9.0	11.0	0.45	61	41	0.598	Mike Uremovich	Jeff Knowles	Brett Diersen
8	Tulane Green Wave	The American	Willie Fritz	2016	29.0	33.0	0.468	46	40	0.535	Chip Long	Chris Hampton	Willie Fritz
9	Tulsa Golden Hurricane	The American	Philip Montgomery	2015	31.0	40.0	0.437	31	40	0.437	Philip Montgomery	Joseph Gillespie	Calvin Lowry

In [814]: #load ancilary grad rate win data
 grad = pd.read_csv('https://raw.githubusercontent.com/barrettfranks/ist718/master/grad_rates.csv')
 grad.head(10)

Out[814]:

	x	school	conf	sport	state	gsr	fgr	Unnamed: 7
0	2012	Abilene Christian	Southland Conference	Football	TX	70	47.0	NaN
1	2012	Akron	Mid-American Conference	Football	ОН	75	61.0	NaN
2	2012	Alabama A&M	Southwestern Athletic Conf.	Football	AL	59	49.0	NaN
3	2012	Alabama State	Southwestern Athletic Conf.	Football	AL	58	39.0	NaN
4	2012	Alabama	Southeastern Conference	Football	AL	85	65.0	NaN
5	2012	Alabama at Birmingham	Conference USA	Football	AL	71	51.0	NaN
6	2012	University at Albany	Colonial Athletic Association	Football	NY	88	63.0	NaN
7	2012	Alcorn State	Southwestern Athletic Conf.	Football	MS	58	40.0	NaN
8	2012	Appalachian State	Sun Belt Conference	Football	NC	75	67.0	NaN
9	2012	Arizona State	Pac-12 Conference	Football	AZ	75	60.0	NaN

In [815]: #join data sets temp = pd.merge(coaches,revenue,how='outer',left_on=['School'],right_on=['School']) temp1 = pd.merge(temp,size,how='outer',left_on=['School'],right_on=['Coalege']) temp2 = pd.merge(temp1,coach,how='outer',left_on=['Coach'],right_on=['coach']) temp2 = pd.merge(temp1,coach,how='outer',left_on=['Coach'],right_on=['school']) temp2 = pd.merge(temp2,grad,how='outer',left_on=['School'],right_on=['school']) temp1 = pd.merge(temp1,grad,how='outer',left_on=['School'],right_on=['school']) temp1.head(10) #len(df2)

Out[815]:

	School	Conference_x	Coach	SchoolPay	TotalPay	Bonus	BonusPaid	AssistantPay	Buyout	RK	 Capacity	Opened	x
0	Air Force	Mt. West	Troy Calhoun	885000	885000	247000		\$0		57.0	 52,237	1962.0	2012.0
1	Akron	MAC	Terry Bowden	\$411,000	\$412,500	\$225,000	\$50,000	\$0	\$688,500	84.0	 30,000	2009.0	2012.0
2	Alabama	SEC	Nick Saban	\$8,307,000	\$8,307,000	\$1,100,000	\$500,000	\$0	\$33,600,000	7.0	 101,821	1929.0	2012.0
3	Alabama at Birmingham	C-USA	Bill Clark	\$900,000	\$900,000	\$950,000	\$165,471	\$0	\$3,847,500	86.0	 NaN	NaN	2012.0
4	Appalachian State	Sun Belt	Scott Satterfield	\$712,500	\$712,500	\$295,000	\$145,000	\$0	\$2,160,417	81.0	 24,150	1962.0	2012.0
5	Arizona	Pac-12	Kevin Sumlin	\$1,600,000	\$2,000,000	\$2,025,000		\$0	\$10,000,000	38.0	 56,037	1928.0	2012.0
6	Arizona State	Pac-12	Herm Edwards	\$2,000,000	\$2,000,000	\$3,010,000		\$0	\$8,166,667	27.0	 56,232	1958.0	2012.0
7	Arizona State	Pac-12	Herm Edwards	\$2,000,000	\$2,000,000	\$3,010,000		\$0	\$8,166,667	27.0	 56,232	1958.0	2012.0
8	Arkansas	SEC	Chad Morris	\$3,500,000	\$3,500,000	\$1,000,000		\$0	\$12,500,000	20.0	 72,000	1938.0	2012.0
9	Arkansas State	Sun Belt	Blake Anderson	\$825,000	\$825,000	\$185,000	\$25,000	\$0	\$300,000	92.0	 30,964	2002.0	NaN

10 rows × 26 columns

```
In [816]: for col in temp1.columns:
              print(col)
          School
          Conference_x
          Coach
          SchoolPay
          TotalPay
          Bonus
          BonusPaid
          AssistantPay
          Buyout
          RK
          Conference_y
          Revenue
          Expenses
          Stadium
          College
          Conference
          Capacity
          Opened
          х
          school
          conf
          sport
          state
          gsr
          fgr
```

Unnamed: 7

```
#drop meaningless columns
In [817]:
          temp2 = temp2.drop(['Conference y', 'AssistantPay', 'SchoolPay', 'Bonus', 'BonusPaid',
                               'Stadium', 'Buyout', 'RK', 'College', 'Conference', 'Opened', 'team',
                               'coach', 'firstyear', 'currwin', 'currloss', 'win', 'loss', 'school', 'x',
                               'sport', 'state', 'Unnamed: 7'], axis=1)
          temp1 = temp1.drop(['Conference y', 'AssistantPay', 'SchoolPay', 'Bonus', 'BonusPaid',
                               'Stadium', 'Buyout', 'RK', 'College', 'Conference', 'Opened', 'school', 'x',
                               'sport', 'state', 'Unnamed: 7'], axis=1)
          0.000
          Want to keep two data frames. temp2 has the coaches win%
          which could be a helpful variable but the coaches name
          is more difficult to join on and limits the dataset to
          about 60 rows. I want to be able to test the more limited
          dataset; however, it may not be as useful as temp1
          for column in list(temp2):
            temp2[column].replace('--', np.nan, inplace=True)
          temp2.dropna(inplace=True)
          for column in list(temp1):
            temp1[column].replace('--', np.nan, inplace=True)
          temp1.dropna(inplace=True)
          #convert columns that should be numbers to float
          temp2['TotalPay'] = temp2['TotalPay'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).ast
          temp1['TotalPay'] = temp1['TotalPay'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).asty
          temp2['Revenue'] = temp2['Revenue'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).astype
          temp1['Revenue'] = temp1['Revenue'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).astype
          temp2['Expenses'] = temp2['Expenses'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).asty
          temp1['Expenses'] = temp1['Expenses'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).asty
          temp1['Capacity'] = temp1['Capacity'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).asty
          temp2['Capacity'] = temp2['Capacity'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',','')).asty
          temp2['win percent'] = temp2['win percent'].apply(lambda x: x.replace('$', '')).apply(lambda x: x.replace(',',''
```

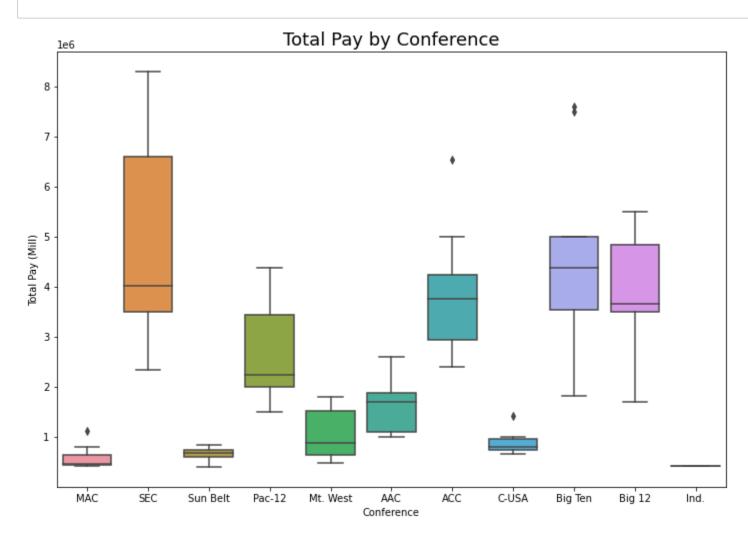
School
Conference_x
Coach
TotalPay
Revenue
Expenses
Capacity
conf
gsr
fgr

Out[818]: 97

In [781]: temp1.head(10)
#len(temp2)

Out[781]:

	School	Conference_x	Coach	TotalPay	Revenue	Expenses	Capacity	conf	gsr	fgr
1	Akron	MAC	Terry Bowden	412500.0	37194485.0	37275978.0	30000.0	Mid-American Conference	75.0	61.0
2	Alabama	SEC	Nick Saban	8307000.0	164090889.0	185317681.0	101821.0	Southeastern Conference	85.0	65.0
4	Appalachian State	Sun Belt	Scott Satterfield	712500.0	37996512.0	37773447.0	24150.0	Sun Belt Conference	75.0	67.0
5	Arizona	Pac-12	Kevin Sumlin	2000000.0	105091389.0	100565835.0	56037.0	Pac-12 Conference	76.0	58.0
6	Arizona State	Pac-12	Herm Edwards	2000000.0	121698840.0	118404377.0	56232.0	Pac-12 Conference	75.0	60.0
7	Arizona State	Pac-12	Herm Edwards	2000000.0	121698840.0	118404377.0	56232.0	Sun Belt Conference	80.0	62.0
8	Arkansas	SEC	Chad Morris	3500000.0	137497788.0	129620361.0	72000.0	Southeastern Conference	67.0	47.0
11	Auburn	SEC	Gus Malzahn	6705656.0	152455416.0	139260711.0	87451.0	Southeastern Conference	76.0	67.0
12	Ball State	MAC	Mike Neu	435689.0	27678480.0	27911602.0	22500.0	Mid-American Conference	73.0	63.0
14	Boise State	Mt. West	Bryan Harsin	1650010.0	50599483.0	49758472.0	37000.0	Mountain West Conference	87.0	63.0



```
In [783]:
    based on review of the box plot there are conference that will be
    meaningless in this analysis. I will be removing the MAC, Conf USA,
    Sun Belt and independent schools
    """
    cf_data = temp1[temp1.Conference_x != "MAC"]
    cf_data = cf_data[cf_data.Conference_x != "C-USA"]
    cf_data = cf_data[cf_data.Conference_x != "Sun Belt"]
    cf_data = cf_data[cf_data.Conference_x != "Ind."]
    cf_data.head(10)
```

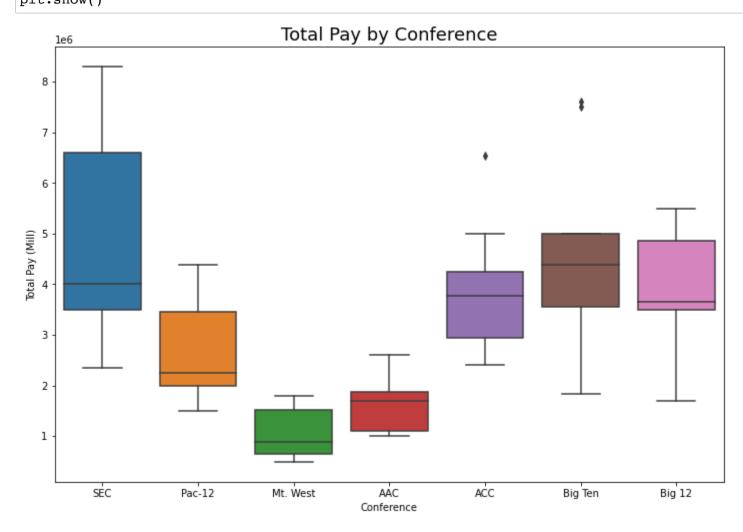
Out[783]:

	School	Conference_x	Coach	TotalPay	Revenue	Expenses	Capacity	conf	gsr	fgr
2	Alabama	SEC	Nick Saban	8307000.0	164090889.0	185317681.0	101821.0	Southeastern Conference	85.0	65.0
5	Arizona	Pac-12	Kevin Sumlin	2000000.0	105091389.0	100565835.0	56037.0	Pac-12 Conference	76.0	58.0
6	Arizona State	Pac-12	Herm Edwards	2000000.0	121698840.0	118404377.0	56232.0	Pac-12 Conference	75.0	60.0
7	Arizona State	Pac-12	Herm Edwards	2000000.0	121698840.0	118404377.0	56232.0	Sun Belt Conference	80.0	62.0
8	Arkansas	SEC	Chad Morris	3500000.0	137497788.0	129620361.0	72000.0	Southeastern Conference	67.0	47.0
11	Auburn	SEC	Gus Malzahn	6705656.0	152455416.0	139260711.0	87451.0	Southeastern Conference	76.0	67.0
14	Boise State	Mt. West	Bryan Harsin	1650010.0	50599483.0	49758472.0	37000.0	Mountain West Conference	87.0	63.0
19	California	Pac-12	Justin Wilcox	1500000.0	87500758.0	106676734.0	62717.0	Pac-12 Conference	75.0	62.0
20	Central Florida	AAC	Josh Heupel	1700000.0	69121887.0	67916343.0	45323.0	American Athletic Conference	84.0	64.0
23	Cincinnati	AAC	Luke Fickell	2000000.0	68845672.0	66832326.0	40000.0	American Athletic Conference	85.0	65.0

In [784]: #view descriptive stats of the cleaned data
print(cf_data.describe())

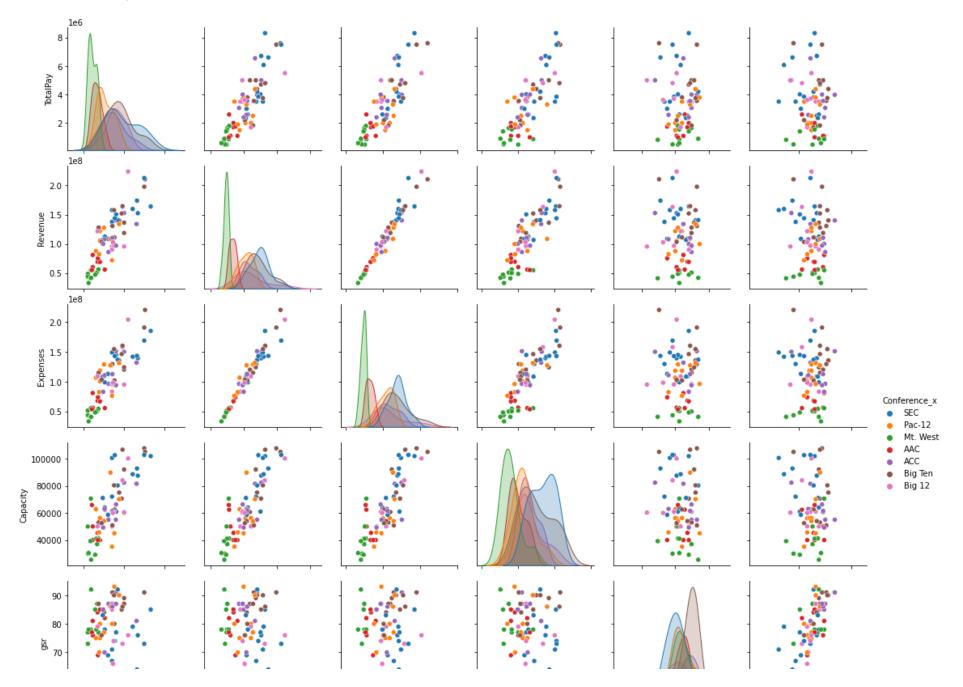
TotalPay	Revenue	Expenses	Capacity	gsr	\
6.900000e+01	6.900000e+01	6.900000e+01	69.000000	69.000000	
3.332885e+06	1.113592e+08	1.085395e+08	63800.376812	79.289855	
1.892218e+06	4.465077e+07	4.194030e+07	21303.282126	8.583674	
4.865040e+05	3.278738e+07	3.318407e+07	25513.000000	54.000000	
1.830000e+06	8.090040e+07	8.081417e+07	50000.000000	75.000000	
3.500000e+06	1.084424e+08	1.087859e+08	60862.000000	79.000000	
4.377500e+06	1.400109e+08	1.368797e+08	80250.000000	86.000000	
8.307000e+06	2.238798e+08	2.205730e+08	107601.000000	93.000000	
	6.900000e+01 3.332885e+06 1.892218e+06 4.865040e+05 1.830000e+06 3.500000e+06 4.377500e+06	6.900000e+01 6.900000e+01 3.332885e+06 1.113592e+08 1.892218e+06 4.465077e+07 4.865040e+05 3.278738e+07 1.830000e+06 8.090040e+07 3.500000e+06 1.084424e+08 4.377500e+06 1.400109e+08	6.900000e+01 6.900000e+01 6.900000e+01 3.332885e+06 1.113592e+08 1.085395e+08 1.892218e+06 4.465077e+07 4.194030e+07 4.865040e+05 3.278738e+07 3.318407e+07 1.830000e+06 8.090040e+07 8.081417e+07 3.500000e+06 1.084424e+08 1.087859e+08 4.377500e+06 1.400109e+08 1.368797e+08	6.900000e+016.900000e+016.900000e+0169.0000003.332885e+061.113592e+081.085395e+0863800.3768121.892218e+064.465077e+074.194030e+0721303.2821264.865040e+053.278738e+073.318407e+0725513.0000001.830000e+068.090040e+078.081417e+0750000.0000003.500000e+061.084424e+081.087859e+0860862.0000004.377500e+061.400109e+081.368797e+0880250.000000	6.900000e+01 6.900000e+01 6.900000e+01 69.000000 69.000000 3.332885e+06 1.113592e+08 1.085395e+08 63800.376812 79.289855 1.892218e+06 4.465077e+07 4.194030e+07 21303.282126 8.583674 4.865040e+05 3.278738e+07 3.318407e+07 25513.000000 54.00000 1.830000e+06 8.090040e+07 8.081417e+07 50000.00000 75.000000 3.500000e+06 1.084424e+08 1.087859e+08 60862.000000 79.000000 4.377500e+06 1.400109e+08 1.368797e+08 80250.00000 86.000000

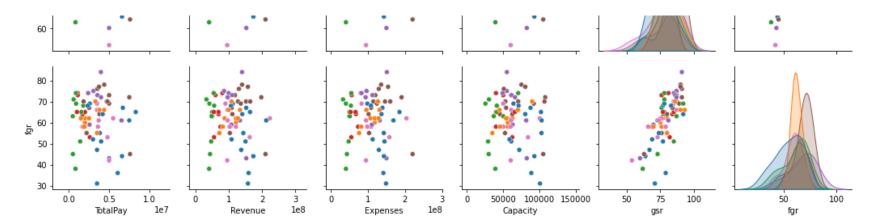
fgr count 69.000000 62.086957 mean std 10.795886 min 31.000000 25% 58.000000 50% 64.000000 75% 70.000000 max 84.000000



In [786]: #visualize all numeric relationships to understand by conference
 #how inputs are related (this seemed easier than doing it 1 by 1)
 sns.pairplot(cf_data, hue="Conference_x")

Out[786]: <seaborn.axisgrid.PairGrid at 0x1309e5b80>





School
Conference_x
Coach
TotalPay
Revenue
Expenses
Capacity
conf
gsr
fgr

Out[787]: 69

#understand the structure of the dataframes In [788]: cf data.info() temp2.info()

<class 'pandas.core.frame.DataFrame'> Int64Index: 69 entries, 2 to 129 Data columns (total 10 columns): # Column Non-Null Count Dtype ----_____ ____ 0 School 69 non-null object Conference_x 69 non-null object 1 2 69 non-null Coach object 3 69 non-null TotalPay float64 69 non-null 4 Revenue float64 5 Expenses 69 non-null float64 69 non-null 6 Capacity float64 7 69 non-null conf object 69 non-null 8 gsr float64 69 non-null float64 fgr dtypes: float64(6), object(4) memory usage: 8.0+ KB <class 'pandas.core.frame.DataFrame'> Int64Index: 60 entries, 1 to 129 Data columns (total 16 columns): # Column Non-Null Count Dtype ____ ----_____ 0 School 60 non-null object 60 non-null 1 Conference x object 2 60 non-null Coach object 3 TotalPay 60 non-null float64 60 non-null 4 Revenue float64 5 60 non-null Expenses float64 60 non-null 6 Capacity float64 7 60 non-null conf x object 8 currwin% 60 non-null object 60 non-null 9 win percent float64 60 non-null object 10 oc 60 non-null 11 dc object 12 stc 60 non-null object 13 conf y 60 non-null object 60 non-null 14 gsr float64 15 fgr 60 non-null float64 dtypes: float64(7), object(9)

memory usage: 8.0+ KB

```
In [789]: #total pay run against revenue and capacity. note, expenses added no additional value to the model
    #model_str = ('TotalPay ~ Revenue + Capacity + gsr + fgr')
    #^this added no value to the model
    model_str = ('TotalPay ~ Revenue + Capacity')
    model = smf.ols(model_str, data=cf_data).fit()
    model.summary()
```

Out[789]:

OLS Regression Results

TotalPay 0.722 Dep. Variable: R-squared: OLS 0.713 Model: Adj. R-squared: Method: Least Squares F-statistic: 85.57 **Date:** Sun, 25 Jul 2021 **Prob (F-statistic):** 4.68e-19 21:29:29 Log-Likelihood: -1050.6 Time: 2107. No. Observations: 69 AIC: 66 2114. **Df Residuals:** BIC: Df Model: 2 **Covariance Type:** nonrobust t P>|t| [0.025 0.975]coef std err Intercept -1.122e+06 3.88e+05 -2.895 0.005 -1.9e+06 -3.48e+05 Revenue 0.0244 0.005 4.857 0.000 0.014 0.034 27.1635 10.549 2.575 0.012 6.103 48.224 Capacity 1.953 **Omnibus:** 1.635 **Durbin-Watson:**

Prob(Omnibus): 0.442 Jarque-Bera (JB): 1.529

Skew: 0.354 **Prob(JB):** 0.466

Kurtosis: 2.826 **Cond. No.** 3.81e+08

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 3.81e+08. This might indicate that there are strong multicollinearity or other numerical problems.

```
#looping in win percentage
In [790]:
           #limitation is a reduced data set
           #this is being looked at by all conferences
           #model str = ('TotalPay ~ Revenue + Capacity + win percent + qsr + fqr')
           #^this added no value to the model
           model str = ('TotalPay ~ Revenue + Capacity + win percent')
           model = smf.ols(model str, data=temp2).fit()
           model.summary()
Out[790]:
           OLS Regression Results
               Dep. Variable:
                                  TotalPay
                                               R-squared:
                                                           0.853
                                     OLS
                                                           0.845
                     Model:
                                           Adj. R-squared:
                              Least Squares
                                                            108.3
                    Method:
                                               F-statistic:
                      Date: Sun, 25 Jul 2021 Prob (F-statistic):
                                                         2.69e-23
                                  21:29:29
                                                          -902.59
                      Time:
                                           Log-Likelihood:
```

Df Residuals: 56

No. Observations:

Df Model:

Covariance Type: nonrobust

t P>|t| [0.025 0.975] coef std err Intercept -2.494e+06 5.38e+05 -4.638 0.000 -3.57e+06 -1.42e+06 0.008 0.0190 0.006 3.311 0.002 0.031 Revenue 31.5103 11.948 2.637 0.011 7.575 55.445 Capacity 3.128e+06 1.02e+06 3.054 0.003 1.08e+06 5.18e+06 win percent

60

3

AIC:

BIC:

1813.

1822.

Omnibus: 0.301 Durbin-Watson: 2.015

Prob(Omnibus): 0.860 Jarque-Bera (JB): 0.079

Skew: -0.087 **Prob(JB):** 0.961

Kurtosis: 3.037 **Cond. No.** 1.05e+09

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.05e+09. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [791]:
```

Given a coach could be hired from outside power 5 minor conferences, from the NFL, etc. I am going to use all conferences but leverage the win percentage field as it seems to have added more to the model than isolating major conferences

Out[791]: '\nGiven a coach could be hired from outside power 5\nminor conferences, from the NFL, etc. \nI am going to us e all conferences but leverage\nthe win percentage field as it seems to have added \nmore to the model than is olating major conferences\n'

In [792]: temp2.info()

Int64Index: 60 entries, 1 to 129 Data columns (total 16 columns): # Column Non-Null Count Dtype ----_____ ____ School 60 non-null object 0 60 non-null object 1 Conference x 2 Coach 60 non-null object 3 TotalPay 60 non-null float64 60 non-null 4 Revenue float64 5 60 non-null Expenses float64 60 non-null float64 Capacity conf x 60 non-null object currwin% 60 non-null object 60 non-null float64 9 win_percent 60 non-null object 10 oc 60 non-null 11 dc object 12 stc 60 non-null object 60 non-null 13 conf y object 14 gsr 60 non-null float64 60 non-null float64 15 fgr dtypes: float64(7), object(9)

<class 'pandas.core.frame.DataFrame'>

memory usage: 8.0+ KB

```
In [793]: #syr projected salary
          syr = temp2.loc[temp2['School'] == 'Syracuse']
          model.predict(syr)
Out[793]: 103
                  2.468638e+06
          dtype: float64
In [794]: #view of the big 10
          syr = temp2.loc[temp2['Conference_x'] == 'Big Ten']
          model.predict(syr)
Out[794]: 44
                  3.241235e+06
                  4.540959e+06
                  6.680307e+06
           63
           71
                  4.668913e+06
           89
                  6.064071e+06
           91
                  3.393591e+06
           128
                  5.115489e+06
          dtype: float64
In [802]: temp2.loc[temp2['School'] == 'Syracuse', 'Conference x'] = "Big Ten"
In [803]: temp2[temp2['School'] == 'Syracuse']
Out[803]:
               School Conference_x Coach
                                        TotalPay
                                                          Expenses Capacity conf_x currwin% win_percent
```

49250.0

ACC

0.4

ОС

0.483

Sterlin Tony

Gilbert White

dc

stc

Vacant

conf_y Atlantic

Conference

Coast {

Revenue

2401206.0 99800000.0 82900000.0

Dino Babers

103 Syracuse

```
In [804]: # run regression model with dummy big ten input
syr = temp2.loc[temp2['School'] == 'Syracuse']
model.predict(syr)
"""

I realized after running this model I needed to have created
several new columns and mark conference with a 1 or 0
depending on the membership then run that as a variable in a
logit regression. I have run out of time to pull that off, however...
So I decided to proxy syracuse against Indiana University as they
were very similar in terms of stadium size, revenue, win% and
graduation rates.
"""
```

Out[804]: '\nI realized after running this model I needed to have created \nseveral new columns and mark conference with a 1 or 0 \ndepending on the membership then run that as a variable in a \nlogit regression. I have run out of time to pull that off, however...\nSo I decided to proxy syracuse against Indiana University as they \nwere ve ry similar in terms of stadium size, revenue, win% and\ngraduation rates.\n'

```
In [805]: # run regression model with dummy big ten input
    syr_proxy = temp2.loc[temp2['School'] == 'Indiana']
    model.predict(syr_proxy)
```

Out[805]: 44 3.241235e+06 dtype: float64

```
In [806]: #What is the recommended salary for the Syracuse football coach?
              #The recommended salary for the Syracuse football coach is:
                  #$2.46 Million
                  #$2.25 Million looks to be actual salary...
          #What would his salary be if we were still in the Big East? What if we went to the Big Ten?
              #Using Indiana University as a proxy recommended salary for the Syracuse football coach is:
                  #$3.24 Million
          #What schools did we drop from our data and why?
              #I didn't just drop schools I dropped entire conferences to try interpret the data...
              #after viewing some of the visuals some of the conferences looked to be meaningless
              #in comparison to Syracuse's conference (ACC). To be specific Baylor, BYU and SMU
              #were always dropped across all models as total pay was missing
          #What effect does graduation rate have on the projected salary?
              #Based on the mix of inclusion and exclusion of graduation rates it proved to be a
              #largely insignificant variable and did not add much to any model judging by its
              #impact on the R^2 and adj. R^2
          #How good is our model?
              #Reasonable - the R^2 says that ~85% of the variance is explained in my better model
          #What is the single biggest impact on salary size?
              #Stadium size and athletic budget seemed to be the two largest impacts on salary size
              #I mention two because in isolation they were virtually equal in impact. Intuitively,
              #these make sense as bigger budget schools with big fan bases may have a larger
              #propensity to spend money on a coach's salary
  In [ ]:
```

In []: