CS 418: Final Project - Regression

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Description: In this code, we will be utilizing regression to determine the poverty and child poverty of a specified county

In [1]:
```
# Load libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import linear_model
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn import metrics
from scipy.cluster.hierarchy import linkage, fcluster
from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import mean_squared_error
import math
```

In [2]:
```
# Load Election dataset
data_census = pd.read_csv('train_dp_output.csv')
data_census.head()
```

Out[2]:

	Unnamed: 0	CountyId	State	County	TotalPop	Percent_Women	Hispanic	White	Black	Income	...	WorkAtHome	MeanCommute	PrivateWork	PublicWor
0	0	1001	Alabama	Autauga County	55036.0	51.124718	2.7	75.4	18.9	55317	...	2.5	25.8	74.1	20.
1	1	1003	Alabama	Baldwin County	203360.0	51.058714	4.4	83.1	9.5	52562	...	5.6	27.0	80.7	12.
2	2	1007	Alabama	Bibb County	22580.0	45.744021	2.4	74.6	22.0	43404	...	1.5	30.0	76.0	17.
3	3	1009	Alabama	Blount County	57667.0	50.595661	9.0	87.4	1.5	47412	...	2.1	35.0	83.9	11.
4	4	1011	Alabama	Bullock County	10478.0	46.401985	0.3	21.6	75.6	29655	...	3.0	29.8	81.4	13.

5 rows × 25 columns

In [3]:
```
#Remove unnamed first column
data_census = data_census.loc[:, ~data_census.columns.str.contains('^Unnamed')]
data_census.head()
```

Out[3]:

	CountyId	State	County	TotalPop	Percent_Women	Hispanic	White	Black	Income	IncomePerCap	...	WorkAtHome	MeanCommute	PrivateWork	Public
0	1001	Alabama	Autauga County	55036.0	51.124718	2.7	75.4	18.9	55317	27824	...	2.5	25.8	74.1	
1	1003	Alabama	Baldwin County	203360.0	51.058714	4.4	83.1	9.5	52562	29364	...	5.6	27.0	80.7	
2	1007	Alabama	Bibb County	22580.0	45.744021	2.4	74.6	22.0	43404	20911	...	1.5	30.0	76.0	
3	1009	Alabama	Blount County	57667.0	50.595661	9.0	87.4	1.5	47412	22021	...	2.1	35.0	83.9	
4	1011	Alabama	Bullock County	10478.0	46.401985	0.3	21.6	75.6	29655	20856	...	3.0	29.8	81.4	

5 rows × 24 columns

In [4]:
```
x_train_full, x_validation_full, y_train, y_validation = train_test_split(data_census[['CountyId', 'State', 'County', 'T
otalPop', 'Percent_Women', 'Hispanic', 'White', 'Black', 'Income', 'IncomePerCap', 'Professional', 'Service', 'Productio
n', 'Carpool', 'WorkAtHome', 'PrivateWork', 'PublicWork', 'SelfEmployed', 'Unemployment','Poverty','ChildPoverty']], dat
a_census['Poverty Category'], test_size = 0.25, random_state = 0)
```

In [5]:
```
# Selecting required variables for x_train
x_train = x_train_full.select_dtypes(include=[np.int64,np.float64])
x_train = x_train.iloc[:,1:17]

# Selecting required variables for x_validation
x_validation = x_validation_full.select_dtypes(include=[np.int64,np.float64])
x_validation = x_validation.iloc[:,1:17]

# Standardizing the data
scaler = StandardScaler()
scaler.fit(x_train)
x_train_scaled = scaler.transform(x_train)
x_validation_scaled = scaler.transform(x_validation)
x_train_scaled_df = pd.DataFrame(x_train_scaled,index = x_train.index,columns=x_train.columns)
x_validation_scaled_df = pd.DataFrame(x_validation_scaled,index = x_validation.index,columns=x_validation.columns)
```

In [6]:
```
x_train_scaled_df.head()
```

Out[6]:

	TotalPop	Percent_Women	Hispanic	White	Black	Income	IncomePerCap	Professional	Service	Production	Carpool	WorkAtHome	Private
1380	-0.118525	0.045865	-0.424669	0.689223	-0.436854	0.351729	0.262281	-0.089405	0.020679	0.311605	-0.525450	-0.722745	0.27
712	-0.204940	0.230015	-0.377088	0.737585	-0.534862	0.566678	0.567576	0.684500	-0.272313	0.465626	-0.828094	-0.486424	0.43
31	0.737568	0.484634	-0.340081	-0.436288	1.075267	0.889286	1.285452	2.232309	-0.778390	-0.903448	-1.197992	-0.452664	0.19
1969	-0.095083	0.500355	0.082856	-0.493443	0.886252	-0.045923	-0.098784	0.123039	-0.591940	0.380059	-1.164364	-0.317624	0.79
655	-0.010013	-0.916455	-0.414095	0.416639	-0.471857	0.251228	0.246021	2.293007	-0.219042	-1.091695	-1.231619	0.087498	-1.14

In [7]:
```
x_validation_scaled_df.head()
```

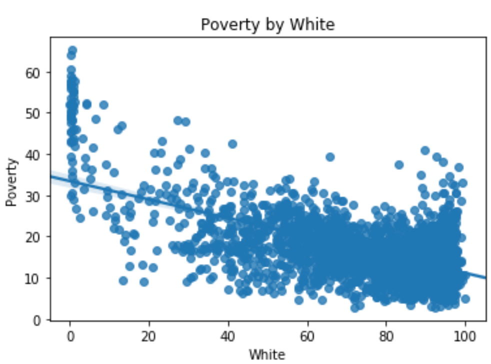
Out[7]:

	TotalPop	Percent_Women	Hispanic	White	Black	Income	IncomePerCap	Professional	Service	Production	Carpool	WorkAtHome	Private
2054	-0.266679	-1.052672	1.690019	-1.210077	-0.205836	-0.839971	-1.047797	-0.195627	0.287036	-0.184684	-0.794467	-0.081303	-0.35
743	-0.271908	-0.538295	1.272368	-0.572580	-0.597867	0.607557	-0.164433	0.214087	-1.843815	0.499853	0.819632	-0.283863	-0.40
2298	-0.104267	-0.877347	-0.498683	0.829912	-0.513861	0.440793	0.189490	-0.241151	-0.378855	1.030369	-0.491823	0.425100	0.91
1534	0.802903	0.416973	-0.350655	0.315519	-0.058824	0.953482	0.603591	1.048690	-0.432127	-0.338705	-0.760840	-0.182583	1.34
1841	-0.213595	0.389020	-0.466963	0.746378	-0.345847	-0.750760	-0.371559	-1.121278	0.260400	1.150163	-1.298873	1.235343	-0.39

REGRESSION - PREDICTING POVERTY

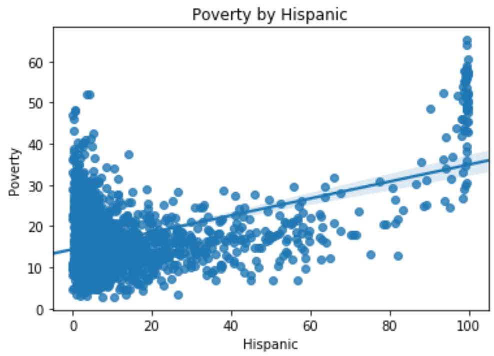
In [8]:
```
# Plot scatter plot
ax = sns.regplot(data_census['White'], data_census['Poverty'])
ax.set(title = 'Poverty by White', xlabel = 'White', ylabel = 'Poverty')
```

Out[8]:
```
[Text(0, 0.5, 'Poverty'),
 Text(0.5, 0, 'White'),
 Text(0.5, 1.0, 'Poverty by White')]
```



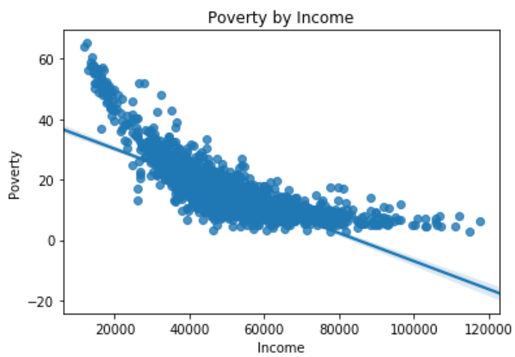
In [9]:
```
# Plot scatter plot
ax = sns.regplot(data_census['Hispanic'], data_census['Poverty'])
ax.set(title = 'Poverty by Hispanic', xlabel = 'Hispanic', ylabel = 'Poverty')
```

Out[9]:
```
[Text(0, 0.5, 'Poverty'),
 Text(0.5, 0, 'Hispanic'),
 Text(0.5, 1.0, 'Poverty by Hispanic')]
```



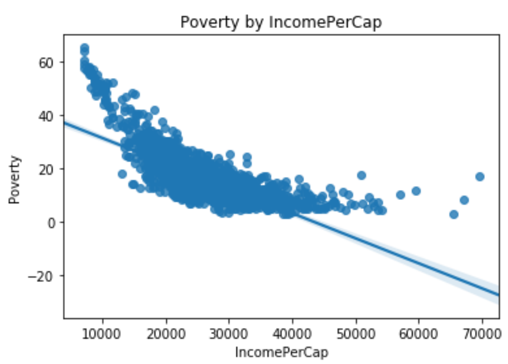
In [10]:
```
# Plot scatter plot
ax = sns.regplot(data_census['Income'], data_census['Poverty'])
ax.set(title = 'Poverty by Income', xlabel = 'Income', ylabel = 'Poverty')
```

Out[10]:
```
[Text(0, 0.5, 'Poverty'),
 Text(0.5, 0, 'Income'),
 Text(0.5, 1.0, 'Poverty by Income')]
```



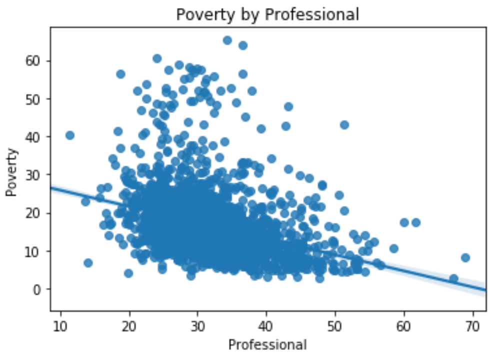
In [11]:
```
# Plot scatter plot
ax = sns.regplot(data_census['IncomePerCap'], data_census['Poverty'])
ax.set(title = 'Poverty by IncomePerCap', xlabel = 'IncomePerCap', ylabel = 'Poverty')
```

Out[11]:
```
[Text(0, 0.5, 'Poverty'),
 Text(0.5, 0, 'IncomePerCap'),
 Text(0.5, 1.0, 'Poverty by IncomePerCap')]
```



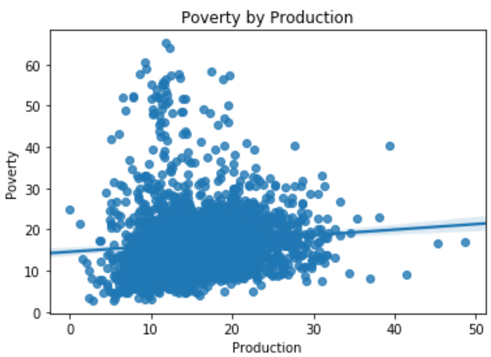
In [12]:
```python
# Plot scatter plot
ax = sns.regplot(data_census['Professional'], data_census['Poverty'])
ax.set(title = 'Poverty by Professional', xlabel = 'Professional', ylabel = 'Poverty')
```

Out[12]:
```
[Text(0, 0.5, 'Poverty'),
 Text(0.5, 0, 'Professional'),
 Text(0.5, 1.0, 'Poverty by Professional')]
```



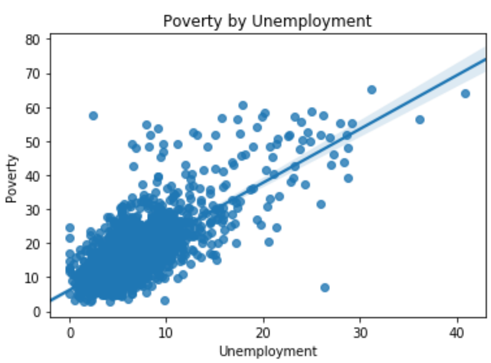
In [13]:
```python
# Plot scatter plot
ax = sns.regplot(data_census['Production'], data_census['Poverty'])
ax.set(title = 'Poverty by Production', xlabel = 'Production', ylabel = 'Poverty')
```

Out[13]:
```
[Text(0, 0.5, 'Poverty'),
 Text(0.5, 0, 'Production'),
 Text(0.5, 1.0, 'Poverty by Production')]
```



In [14]:
```python
# Plot scatter plot
ax = sns.regplot(data_census['Unemployment'], data_census['Poverty'])
ax.set(title = 'Poverty by Unemployment', xlabel = 'Unemployment', ylabel = 'Poverty')
```

Out[14]:
```
[Text(0, 0.5, 'Poverty'),
 Text(0.5, 0, 'Unemployment'),
 Text(0.5, 1.0, 'Poverty by Unemployment')]
```



Model 1 - Poverty - Including all variables

In [15]:
```python
# Create the linear regression model
model = linear_model.LinearRegression()
fitted_model = model.fit(X = x_train_scaled_df, y = x_train_full['Poverty'])
print(fitted_model.coef_)
```

```
[-0.05521991  0.5248399   0.21762343 -2.37039385 -0.62024317 -4.22871821
 -1.19391616  1.75855918  0.37486429  0.65621463 -0.11628558 -0.06142195
  0.32942775  0.52436081 -0.43542048  1.84329435]
```

In [16]:
```
# Predict the values
y_predicted = fitted_model.predict(x_validation_scaled_df)
```

In [17]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_train_scaled_df.columns)
print(n)
print(p)
print(n-p-1)
```

```
607
16
590
```

In [18]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['Poverty'])[1, 0]

R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['Poverty']))
print('RMSE -',rmse)
```

```
R squared: 0.8513298077255884
Adjusted R squared: 0.8472980736978077
RMSE - 3.4209848294802594
```

In [19]:
```
#Evaluate model with all predictors
score_train = model.score(X = x_train_scaled_df, y = x_train_full['Poverty']) # R squared (training)
score_val = model.score(X = x_validation_scaled_df, y = x_validation_full['Poverty']) # R squared (validation)
print([score_train, score_val])
```

```
[0.8272983071536646, 0.8504796157247451]
```

Model 2 - Poverty - LASSO Regression

In [20]:
```
# Generating model
model = linear_model.Lasso(alpha = 1)
fitted_model = model.fit(X = x_train_scaled_df, y = x_train_full['Poverty'])
print(fitted_model.coef_)
```

```
[ 0.          0.          0.         -1.82929859  0.         -3.41317623
 -0.34644058  0.          0.         -0.         -0.         -0.
 -0.          0.         -0.          1.86348561]
```

In [21]:
```
# Predict the values
y_predicted = fitted_model.predict(x_validation_scaled_df)
```

In [22]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_validation_scaled_df.columns)
n-p-1
print(n)
print(p)
print(n-p-1)
```

```
607
16
590
```

In [23]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['Poverty'])[1, 0]

R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['Poverty']))
print('RMSE: ',rmse)
```

```
R squared: 0.8336599709647284
Adjusted R squared: 0.829149054923094
RMSE:  3.9933497011553434
```

Model 3 - Poverty - Includes: 'Percent_Women', 'White', 'Income', 'IncomePerCap', 'Professional', 'Unemployment'

In [24]:
```
# Generating model
model = linear_model.LinearRegression()
fitted_model = model.fit(X = x_train_scaled_df[['Percent_Women', 'White', 'Income', 'IncomePerCap', 'Professional', 'Une
mployment']], y = x_train_full['Poverty'])
print(fitted_model.coef_)
```

```
[ 0.54355202 -2.28065951 -3.71926111 -1.64630369  1.21432919  2.05606681]
```

In [25]:
```
# Predict the values
y_predicted = fitted_model.predict(x_validation_scaled_df[['Percent_Women', 'White', 'Income', 'IncomePerCap', 'Professi
onal', 'Unemployment']])
```

In [26]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_train_scaled_df[['Percent_Women', 'White', 'Income', 'IncomePerCap', 'Professional', 'Unemployment']].columns)
n-p-1
print(n)
print(p)
print(n-p-1)
```

```
607
6
600
```

In [27]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['Poverty'])[1, 0]
R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['Poverty']))
print('RMSE: ',rmse)
```

```
R squared: 0.8471259545707236
Adjusted R squared: 0.8455972141164309
RMSE:  3.473878047933116
```

Model 4. Linear Regression - (BEST MODEL) Includes: 'Hispanic', 'White', 'Income', 'IncomePerCap', 'Professional', 'Production', 'Unemployment'

In [28]:
```
# Generating model
model = linear_model.LinearRegression()
fitted_model_poverty = model.fit(X = x_train_scaled_df[['Hispanic', 'White', 'Income', 'IncomePerCap', 'Professional',
'Production', 'Unemployment']], y = x_train_full['Poverty'])
print(fitted_model.coef_)
```

```
[ 0.54355202 -2.28065951 -3.71926111 -1.64630369  1.21432919  2.05606681]
```

In [29]:
```
# Predict the values
y_predicted = fitted_model_poverty.predict(x_validation_scaled_df[['Hispanic', 'White', 'Income', 'IncomePerCap', 'Profe
ssional', 'Production', 'Unemployment']])
```

In [30]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_train_scaled_df[['Hispanic', 'White', 'Income', 'IncomePerCap', 'Professional', 'Production', 'Unemployment']]
.columns)
n-p-1
print(n)
print(p)
print(n-p-1)
```

```
607
7
599
```

In [31]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['Poverty'])[1, 0]
R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['Poverty']))
print('RMSE: ',rmse)
```

```
R squared: 0.851443310856924
Adjusted R squared: 0.8497072560589248
RMSE:  3.422593507053814
```

In [32]:
```
#Evaluate model with above predictors
score_train = model.score(X = x_train_scaled_df[['Hispanic', 'White', 'Income', 'IncomePerCap', 'Professional', 'Product
ion', 'Unemployment']], y = x_train_full['Poverty']) # R squared (training)
score_val = model.score(X = x_validation_scaled_df[['Hispanic', 'White', 'Income', 'IncomePerCap', 'Professional', 'Prod
uction', 'Unemployment']], y = x_validation_full['Poverty']) # R squared (validation)
print([score_train, score_val])
```

```
[0.8142781696578959, 0.8503389622847699]
```

Model 5 - Poverty - Includes: 'Percent_Women', 'Hispanic', 'White', 'Black', 'Income', 'IncomePerCap', 'Unemployment'

In [33]:
```
# Generating model
model = linear_model.LinearRegression()
fitted_model = model.fit(X = x_train_scaled_df[['Percent_Women', 'Hispanic', 'White', 'Black', 'Income', 'IncomePerCap',
'Unemployment'
]], y = x_train_full['Poverty'])
print(fitted_model.coef_)
```

```
[ 0.64364625 -0.30240318 -2.99304925 -0.7419177  -3.8865889  -0.69936745
  2.06843827]
```

In [34]:
```
# Predict the values
y_predicted = fitted_model.predict(x_validation_scaled_df[['Percent_Women', 'Hispanic', 'White', 'Black', 'Income', 'Inc
omePerCap', 'Unemployment']])
```

In [35]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_train_scaled_df[['Percent_Women', 'Hispanic', 'White', 'Black', 'Income', 'IncomePerCap', 'Unemployment']].col
umns)
n-p-1
print(n)
print(p)
print(n-p-1)
```

```
607
7
599
```

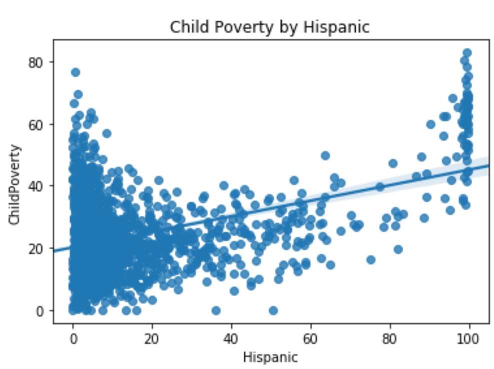
In [36]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['Poverty'])[1, 0]
R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['Poverty']))
print('RMSE: ',rmse)
```

```
R squared: 0.833280730505654
Adjusted R squared: 0.8313324251860206
RMSE:  3.626887234067272
```

REGRESSION - PREDICTING CHILD POVERTY

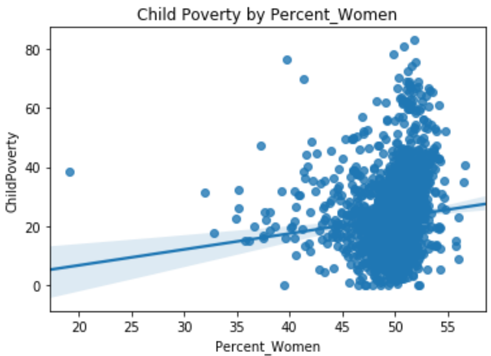
In [37]:
```
# Plot scatter plot
ax = sns.regplot(data_census['Hispanic'], data_census['ChildPoverty'])
ax.set(title = 'Child Poverty by Hispanic', xlabel = 'Hispanic', ylabel = 'ChildPoverty')
```

Out[37]:
```
[Text(0, 0.5, 'ChildPoverty'),
 Text(0.5, 0, 'Hispanic'),
 Text(0.5, 1.0, 'Child Poverty by Hispanic')]
```



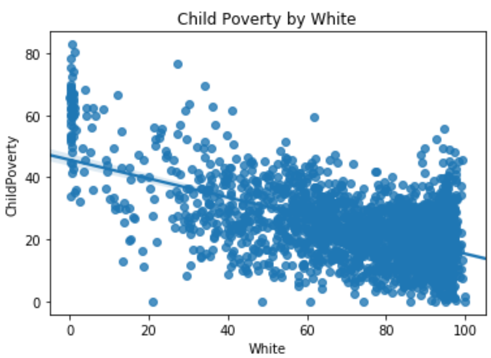
In [38]:
```
# Plot scatter plot
ax = sns.regplot(data_census['Percent_Women'], data_census['ChildPoverty'])
ax.set(title = 'Child Poverty by Percent_Women', xlabel = 'Percent_Women', ylabel = 'ChildPoverty')
```

Out[38]:
```
[Text(0, 0.5, 'ChildPoverty'),
 Text(0.5, 0, 'Percent_Women'),
 Text(0.5, 1.0, 'Child Poverty by Percent_Women')]
```



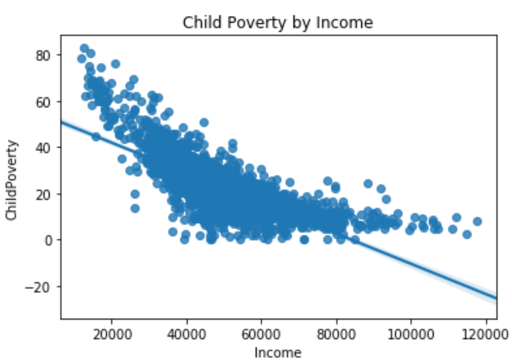
In [39]:
```
# Plot scatter plot
ax = sns.regplot(data_census['White'], data_census['ChildPoverty'])
ax.set(title = 'Child Poverty by White', xlabel = 'White', ylabel = 'ChildPoverty')
```

Out[39]:
```
[Text(0, 0.5, 'ChildPoverty'),
 Text(0.5, 0, 'White'),
 Text(0.5, 1.0, 'Child Poverty by White')]
```



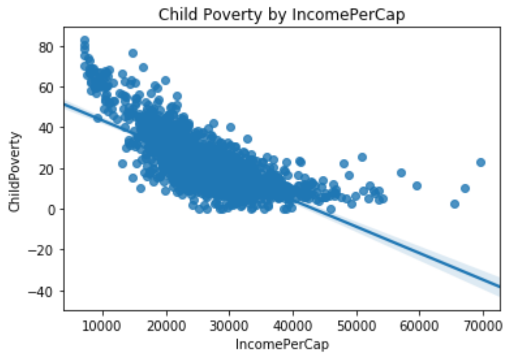
In [40]:
```
# Plot scatter plot
ax = sns.regplot(data_census['Income'], data_census['ChildPoverty'])
ax.set(title = 'Child Poverty by Income', xlabel = 'Income', ylabel = 'ChildPoverty')
```

Out[40]:
```
[Text(0, 0.5, 'ChildPoverty'),
 Text(0.5, 0, 'Income'),
 Text(0.5, 1.0, 'Child Poverty by Income')]
```



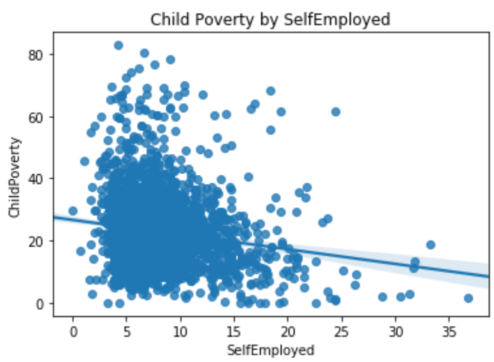
In [41]:
```
# Plot scatter plot
ax = sns.regplot(data_census['IncomePerCap'], data_census['ChildPoverty'])
ax.set(title = 'Child Poverty by IncomePerCap', xlabel = 'IncomePerCap', ylabel = 'ChildPoverty')
```

Out[41]:
```
[Text(0, 0.5, 'ChildPoverty'),
 Text(0.5, 0, 'IncomePerCap'),
 Text(0.5, 1.0, 'Child Poverty by IncomePerCap')]
```



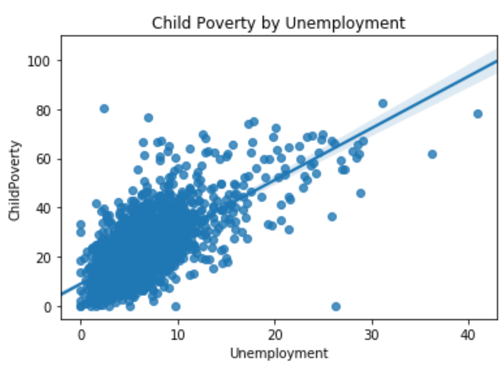
In [42]:
```
# Plot scatter plot
ax = sns.regplot(data_census['SelfEmployed'], data_census['ChildPoverty'])
ax.set(title = 'Child Poverty by SelfEmployed', xlabel = 'SelfEmployed', ylabel = 'ChildPoverty')
```

Out[42]:
```
[Text(0, 0.5, 'ChildPoverty'),
 Text(0.5, 0, 'SelfEmployed'),
 Text(0.5, 1.0, 'Child Poverty by SelfEmployed')]
```



In [44]:
```
# Plot scatter plot
ax = sns.regplot(data_census['Unemployment'], data_census['ChildPoverty'])
ax.set(title = 'Child Poverty by Unemployment', xlabel = 'Unemployment', ylabel = 'ChildPoverty')
```

Out[44]:
```
[Text(0, 0.5, 'ChildPoverty'),
 Text(0.5, 0, 'Unemployment'),
 Text(0.5, 1.0, 'Child Poverty by Unemployment')]
```



Model 1 - Child poverty - All variables

In [45]:
```
# Generating model
model = linear_model.LinearRegression()
fitted_model = model.fit(X = x_train_scaled_df, y = x_train_full['ChildPoverty'])
print(fitted_model.coef_)
```

```
[ 0.06877829  0.53344814 -0.28921513 -3.69419934 -0.04516057 -6.57441374
 -0.23857924  0.22545993 -0.04384931  0.23054347  0.00771652  0.12998892
  5.07497383  3.95159524  1.77511433  2.36696767]
```

In [46]:
```
# Predict the values
y_predicted = fitted_model.predict(x_validation_scaled_df)
```

In [47]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_train_scaled_df.columns)
n-p-1
print(n)
print(p)
print(n-p-1)
```

```
607
16
590
```

In [48]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['ChildPoverty'])[1, 0]
R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['ChildPoverty']))
print('RMSE: ',rmse)
```

```
R squared: 0.7725131347267584
Adjusted R squared: 0.7663439993973146
RMSE:  5.989999440186332
```

Model 2 - Child Poverty - LASSO Regression

In [49]:
```
# Generating model
model = linear_model.Lasso(alpha = 1)
fitted_model = model.fit(X = x_train_scaled_df, y = x_train_full['ChildPoverty'])
print(fitted_model.coef_)
```

```
[ 0.          0.          0.         -2.81472074  0.         -5.66498538
 -0.1058546  -0.          0.          0.          0.         -0.
  0.          0.         -0.05624678  2.32627694]
```

In [50]:
```
# Predict the values
y_predicted = fitted_model.predict(x_validation_scaled_df)
```

In [51]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_validation_scaled_df.columns)
n-p-1
print(n)
print(p)
print(n-p-1)
```

```
607
16
590
```

In [52]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['ChildPoverty'])[1, 0]

R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['ChildPoverty']))
print('RMSE: ',rmse)
```

```
R squared: 0.7680747760798697
Adjusted R squared: 0.7617852784820357
RMSE:  6.264814834157485
```

Model 3 - Child Poverty - (BEST MODEL) Includes: 'Percent_Women', 'Hispanic', 'White', 'Income', 'IncomePerCap', 'SelfEmployed', 'Unemployment'

In [53]:
```
# Generating model
model = linear_model.LinearRegression()
fitted_model_childPoverty = model.fit(X = x_train_scaled_df[['Percent_Women', 'Hispanic', 'White', 'Income', 'IncomePerCap', 'SelfEmployed', 'Unemployment']], y = x_train_full['ChildPoverty'])
print(fitted_model.coef_)
```

```
[ 0.          0.          0.         -2.81472074  0.         -5.66498538
 -0.1058546  -0.          0.          0.          0.         -0.
  0.          0.         -0.05624678  2.32627694]
```

In [54]:
```
# Predict the values
y_predicted = fitted_model_childPoverty.predict(x_validation_scaled_df[['Percent_Women', 'Hispanic', 'White', 'Income', 'IncomePerCap', 'SelfEmployed', 'Unemployment']])
```

In [55]:
```
# Determining values to calculate evaluation metrics
n = len(x_validation_scaled_df.index)
p = len(x_train_scaled_df[['Percent_Women', 'Hispanic', 'White', 'Income', 'IncomePerCap', 'SelfEmployed', 'Unemployment']].columns)
n-p-1
print(n)
print(p)
print(n-p-1)
```

```
607
7
599
```

In [56]:
```
# Generating Evaluation metrics
corr_coef = np.corrcoef(y_predicted,x_validation_full['ChildPoverty'])[1, 0]
R_squared = corr_coef ** 2
print("R squared:",R_squared)

adjusted_r = 1 - (((1-R_squared)*(n-1))/(n-p-1))
print("Adjusted R squared:",adjusted_r)

rmse = math.sqrt(mean_squared_error(y_predicted, x_validation_full['ChildPoverty']))
print('RMSE: ',rmse)
```

```
R squared: 0.7724443465917777
Adjusted R squared: 0.7697850985552877
RMSE:  5.992641178686747
```

PREDICT VALUES FOR TEST - LINEAR REGRESSION

In [57]:
```
# Load Census test dataset
test_census = pd.read_csv('test_dp_output.csv')
test_census.head()
```

Out[57]:

	Unnamed: 0	CountyId	State	County	TotalPop	Percent_Women	Hispanic	White	Black	Income	...	Professional	Service	Production	Carpool	WorkAtH
0	0	1005	Alabama	Barbour County	26201.0	46.658524	4.2	45.7	47.8	33368	...	25.0	16.8	24.1	11.1	
1	1	1025	Alabama	Clarke County	24625.0	52.694416	0.2	53.0	45.7	33827	...	21.6	14.3	25.6	11.9	
2	2	1037	Alabama	Coosa County	10955.0	50.031949	0.1	65.3	33.2	34792	...	17.6	23.2	20.9	9.7	
3	3	1047	Alabama	Dallas County	40755.0	53.848608	1.0	27.7	70.2	30065	...	26.7	18.2	25.3	8.9	
4	4	1053	Alabama	Escambia County	37621.0	48.629755	2.2	60.2	32.2	35026	...	24.6	21.2	18.3	7.0	

5 rows × 21 columns

In [58]:
```
#Remove unnamed first column
test_census = test_census.loc[:, ~test_census.columns.str.contains('^Unnamed')]
test_census.head()
```

Out[58]:

	CountyId	State	County	TotalPop	Percent_Women	Hispanic	White	Black	Income	IncomePerCap	Professional	Service	Production	Carpool	WorkAtH
0	1005	Alabama	Barbour County	26201.0	46.658524	4.2	45.7	47.8	33368	17561	25.0	16.8	24.1	11.1	
1	1025	Alabama	Clarke County	24625.0	52.694416	0.2	53.0	45.7	33827	20765	21.6	14.3	25.6	11.9	
2	1037	Alabama	Coosa County	10955.0	50.031949	0.1	65.3	33.2	34792	20342	17.6	23.2	20.9	9.7	
3	1047	Alabama	Dallas County	40755.0	53.848608	1.0	27.7	70.2	30065	18248	26.7	18.2	25.3	8.9	
4	1053	Alabama	Escambia County	37621.0	48.629755	2.2	60.2	32.2	35026	18164	24.6	21.2	18.3	7.0	

In [59]:
```
test_census = test_census[['CountyId', 'State', 'County', 'TotalPop', 'Percent_Women', 'Hispanic', 'White', 'Black', 'In
come', 'IncomePerCap', 'Professional', 'Service', 'Production', 'Carpool', 'WorkAtHome', 'PrivateWork', 'PublicWork', 'S
elfEmployed', 'Unemployment']]
test_census.head()
```

Out[59]:

	CountyId	State	County	TotalPop	Percent_Women	Hispanic	White	Black	Income	IncomePerCap	Professional	Service	Production	Carpool	WorkAtH
0	1005	Alabama	Barbour County	26201.0	46.658524	4.2	45.7	47.8	33368	17561	25.0	16.8	24.1	11.1	
1	1025	Alabama	Clarke County	24625.0	52.694416	0.2	53.0	45.7	33827	20765	21.6	14.3	25.6	11.9	
2	1037	Alabama	Coosa County	10955.0	50.031949	0.1	65.3	33.2	34792	20342	17.6	23.2	20.9	9.7	
3	1047	Alabama	Dallas County	40755.0	53.848608	1.0	27.7	70.2	30065	18248	26.7	18.2	25.3	8.9	
4	1053	Alabama	Escambia County	37621.0	48.629755	2.2	60.2	32.2	35026	18164	24.6	21.2	18.3	7.0	

In [60]:
```
x_test = test_census.select_dtypes(include=[np.int64,np.float64])
x_test = x_test.iloc[:,1:17]
x_test_scaled = scaler.transform(x_test)
x_test_scaled_df = pd.DataFrame(x_test_scaled,index = x_test.index,columns=x_test.columns)
```

In [61]:
```
x_test_scaled_df.head()
```

Out[61]:

	TotalPop	Percent_Women	Hispanic	White	Black	Income	IncomePerCap	Professional	Service	Production	Carpool	WorkAtHome	PrivateWorl
0	-0.212468	-1.435866	-0.366515	-1.289214	2.741401	-1.173131	-1.247933	-0.999881	-0.352220	1.423978	0.416107	-1.161627	-0.09120!
1	-0.217046	1.148828	-0.577984	-0.968268	2.594390	-1.139262	-0.761042	-1.515817	-1.018111	1.680679	0.685124	-1.296668	1.08188(
2	-0.256761	0.008704	-0.583271	-0.427495	1.719319	-1.068055	-0.825322	-2.122801	1.352461	0.876348	-0.054672	-0.182583	0.52140!
3	-0.170186	1.643077	-0.535690	-2.080589	4.309528	-1.416858	-1.143534	-0.741913	0.020679	1.629339	-0.323688	-1.195387	0.52140!
4	-0.179290	-0.591744	-0.472249	-0.651718	1.649314	-1.050788	-1.156299	-1.060579	0.819748	0.431399	-0.962602	-1.330428	0.10431'

In [62]:
```
y_predicted_poverty = fitted_model_poverty.predict(x_test_scaled_df[['Hispanic', 'White', 'Income', 'IncomePerCap', 'Pro
fessional', 'Production', 'Unemployment']])
test_census['Poverty'] = y_predicted_poverty
```

In [63]:
```
y_predicted_childPoverty = fitted_model_childPoverty.predict(x_test_scaled_df[['Percent_Women', 'Hispanic', 'White', 'In
come', 'IncomePerCap', 'SelfEmployed', 'Unemployment']])
test_census['ChildPoverty'] = y_predicted_childPoverty
```

In [64]:
```
sample_output = test_census[['CountyId', 'State', 'County', 'Poverty', 'ChildPoverty']]
sample_output.head()
```

Out[64]:

	CountyId	State	County	Poverty	ChildPoverty
0	1005	Alabama	Barbour County	27.773252	38.212651
1	1025	Alabama	Clarke County	27.235754	40.508661
2	1037	Alabama	Coosa County	22.358539	34.926116
3	1047	Alabama	Dallas County	31.408525	45.562577
4	1053	Alabama	Escambia County	26.052590	36.944246

In [65]:
```
num_data = sample_output._get_numeric_data()
num_data[num_data < 0] = 0
sample_output.head()
```

Out[65]:

	CountyId	State	County	Poverty	ChildPoverty
0	1005	Alabama	Barbour County	27.773252	38.212651
1	1025	Alabama	Clarke County	27.235754	40.508661
2	1037	Alabama	Coosa County	22.358539	34.926116
3	1047	Alabama	Dallas County	31.408525	45.562577
4	1053	Alabama	Escambia County	26.052590	36.944246

In [66]:
```
sample_output.to_excel("sample_output.xlsx")
```

In [ ]: