JacobsonDSC640Milestone3

July 17, 2025

[2]:
```python
import pandas as pd
ndcp = pd.read_csv('NDCP2022.csv')
```

[3]:
```python
ndcp.head()
```

[3]:
```
  STATE_NAME STATE_ABBREVIATION     COUNTY_NAME  COUNTY_FIPS_CODE  STUDYYEAR  \
0    Alabama                 AL  Autauga County              1001       2008
1    Alabama                 AL  Autauga County              1001       2009
2    Alabama                 AL  Autauga County              1001       2010
3    Alabama                 AL  Autauga County              1001       2011
4    Alabama                 AL  Autauga County              1001       2012

   EMR_16  FEMR_16  MEMR_16  EMR_20to64  FEMR_20to64  …  \
0    61.5     56.1     67.3        71.4         66.3  …
1    60.6     54.8     67.0        72.5         66.9  …
2    60.4     54.9     66.4        72.3         67.4  …
3    58.7     52.4     65.6        71.0         64.9  …
4    57.7     52.2     63.8        70.7         65.1  …

   iFEMP_SERVICE_STATE  iEMP_SALES_STATE  iMEMP_SALES_STATE  \
0                    1                 1                  1
1                    1                 1                  1
2                    1                 1                  1
3                    1                 1                  1
4                    1                 1                  1

   iFEMP_SALES_STATE  iEMP_N_STATE  iMEMP_N_STATE  iFEMP_N_STATE  \
0                  1             1              1              1
1                  1             1              1              1
2                  1             1              1              1
3                  1             1              1              1
4                  1             1              1              1

   iEMP_P_STATE  iMEMP_P_STATE  iFEMP_P_STATE
0             1              1              1
1             1              1              1
2             1              1              1
3             1              1              1
```

```
4              1               1               1

[5 rows x 370 columns]
```

[4]:
```
ndcp.shape
```

[4]:
```
(48308, 370)
```

[5]:
```
import re
ndcp = ndcp.rename(columns=lambda x: x.strip().upper())

ndcp_key = pd.read_csv('technical-report-key.csv')
ndcp_key = ndcp_key.rename(columns=lambda x: x.strip())
for col in ndcp_key.columns:
    if ndcp_key[col].dtype == "object":
        ndcp_key[col] = ndcp_key[col].apply(lambda x: re.
↪sub('[\u2012\u2013\u2014]', '-',str(x)))
        ndcp_key[col] = ndcp_key[col].str.replace('-', ' - ')
        ndcp_key[col] = ndcp_key[col].str.replace('\xa0', ' ', regex=False) #␣
↪embedded new-lines
        ndcp_key[col] = ndcp_key[col].str.replace('  ', ' ', regex=False)
        ndcp_key[col] = ndcp_key[col].apply(lambda x: re.sub('(\d)\s*-\s*(\d)',␣
↪r'\1-\2',str(x)))
        ndcp_key[col] = ndcp_key[col].str.strip()
ndcp_key['Variable Name'] = ndcp_key['Variable Name'].str.upper()
ndcp_key['Variable Name'] = ndcp_key['Variable Name'].apply(lambda x: re.
↪sub('\s', '',str(x)))
ndcp_key['Variable Name'] = ndcp_key['Variable Name'].replace({'IURN_20T064':
↪'IUNR_20T064'})
ndcp_dict = dict(zip(ndcp_key['Variable Name'], ndcp_key['Variable Label']))
ndcp_key.head()
```

[5]:
```
  Variable Name                                   Variable Label  \
0    _75C12T017  75th Percentile Price of Center - Based Care -…
1    _75C18T023  75th Percentile Price of Center - Based Care -…
2    _75C24T029  75th Percentile Price of Center - Based Care -…
3    _75C30T035  75th Percentile Price of Center - Based Care -…
4    _75C36T041  75th Percentile Price of Center - Based Care -…

                              Variable Description Variable  Format  \
0  75th percentile price charged for Center - Bas…          Numeric
1  75th percentile price charged for Center - Bas…          Numeric
2  75th percentile price charged for Center - Bas…          Numeric
3  75th percentile price charged for Center - Bas…          Numeric
4  75th percentile price charged for Center - Bas…          Numeric

  Report  Table ID
```

```
0              nan
1              nan
2              nan
3              nan
4              nan
```

[6]:
```
file_columns = ndcp.columns.sort_values()
missing = []
for column in file_columns:
    if column in ndcp_dict:
        continue
    missing.append(column)
if len(missing):
    print("Missing from report: ",missing)
else:
    print("Every column in the file is also in the report.")
file_dict = dict(zip(file_columns,file_columns))
missing = []
for column in ndcp_dict.keys():
    if column in file_dict:
        continue
    missing.append(column)
if len(missing):
    print("Missing from file: ",missing)
else:
    print("Every column in the report is also in the file.")
print("The file has {} columns. The report has {} columns.".
 ↪format(len(file_columns),len(ndcp_dict.keys())))
```

```
Missing from report:  ['IEMP_M_STATE']
Every column in the report is also in the file.
The file has 370 columns. The report has 369 columns.
```

[7]:
```
def described_data (columns):
    upper_columns = [column.upper() for column in columns]
    data = ndcp[upper_columns]
    #for column in columns:
    #    print(column+": "+ndcp_dict[column.upper()])
    return data
```

[135]:
```
non_imputations = []
categories = ['STATE_ABBREVIATION','COUNTY_NAME','STUDYYEAR']
ignore = [
'STATE_NAME',
'COUNTY_FIPS_CODE',
'IEMP_M_STATE'
] + categories
for column in ndcp.columns:
```

```
    if column in ignore:
        continue
    if re.match('imput',ndcp_dict[column].lower()):
        continue
    non_imputations.append(column)
data = described_data(non_imputations)
matrix = data.corr()
data = described_data(non_imputations+categories)
```

[136]:
```
def search(search,exclude=False):
    for column in data.columns:
        full = ndcp_dict[column]
        if search.lower() in full.lower():
            print("{}|{}".format(column,full))
```

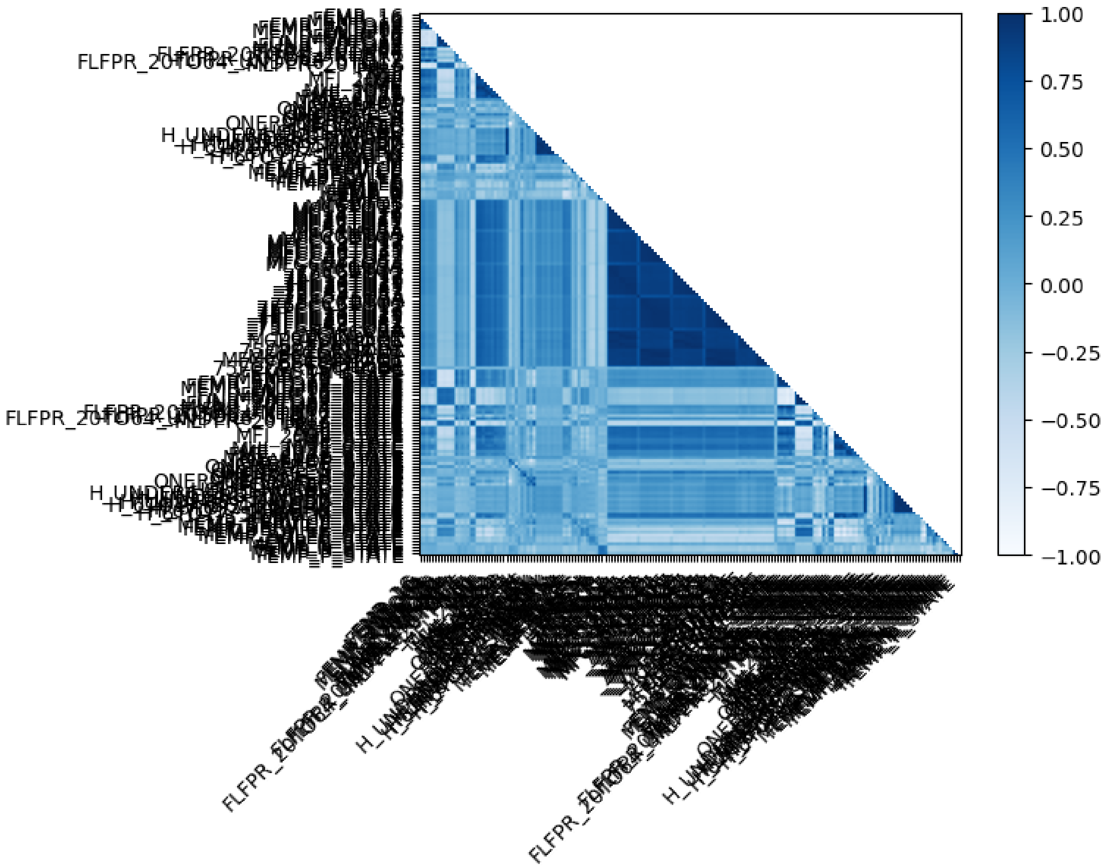
[147]:
```
#search('Civilian')
```

[148]:
```
cost_config = {
    'MCUNDER6': ['MC','Median Center Cost Under 6'],
    '_75CUNDER6':['_75C','75th Percentile Center Cost Under 6'],
    'MFCCUNDER6':['MFCC','Median Family Cost Under 6'],
    '_75FCCUNDER6':['_75FCC','75th Percentile Family Cost Under 6'],
}
temp = data.copy()
#temp = data[['STATE_ABBREVIATION','COUNTY_NAME','STUDYYEAR']].copy()
for key, value in cost_config.items():
    prefix = value[0]
    label = value[1]
    temp[key] =␣
 ↪(data[prefix+'INFANT']+data[prefix+'TODDLER']+data[prefix+'PRESCHOOL'])/3
    ndcp_dict[key] = label
for key, value in cost_config.items():
    temp[key+'PERC']=temp[key]*52/data['MFI_2022'] # 52 weeks full-time
    ndcp_dict[key+'PERC'] = label+' Percent'

age_config = {
    'H_UNDER6_': 'Households with Children Under 6',
    'H_6TO17_':'Households with Children 6-17',
    }
for age,label in age_config.items():
    temp[age+'PERC'] =␣
 ↪(data[age+'BOTHWORK']+data[age+'FWORK']+data[age+'MWORK']+data[age+'SINGLEM'])/
 ↪data['HOUSEHOLDS']
    ndcp_dict[age+'PERC'] = 'Percent '+label

temp['HOUSEHOLD_SIZE'] = data['TOTALPOP']/data['HOUSEHOLDS']
ndcp_dict['HOUSEHOLD_SIZE'] = 'Average people per household'
```

```
data = temp
```

[149]:

```
# Adapted from https://www.geeksforgeeks.org/
 ↪create-a-correlation-matrix-using-python/
import matplotlib.pyplot as plt
import matplotlib.colors as colors
import numpy as np
from sklearn import datasets
import pandas as pd

# Use green for > 0.5 correlation and red for < 0.5
colors_list = ['red','lightgray','lightgray','green']

# Create a colormap from the list of colors
cmap = colors.ListedColormap(colors_list)

# Mask the duplicated upper triangle and the diagonal
mask = np.triu(np.ones_like(matrix, dtype=bool))
masked_matrix = np.ma.masked_array(matrix, mask)

# plot the masked correlation matrix
plt.imshow(masked_matrix, vmin=-1, vmax=1, cmap="Blues")

# adding colorbar
plt.colorbar()

# extracting variable names
variables = []
for i in matrix.columns:
    variables.append(i)

# Adding labels to the matrix
plt.xticks(range(len(matrix)), variables, rotation=45, ha='right')
plt.yticks(range(len(matrix)), variables)

# Make the figure full screen
plt.rcParams['figure.figsize'] = [24, 24]

# Display the plot
plt.show()
```



[150]:
```python
# Set a threshold for strong correlations
threshold = 0.5
correlations = []
seen = {}
# Iterate through the correlation matrix and filter based on the threshold
for column in matrix.columns:
    for index in matrix.index:
        if index != column and abs(matrix.loc[index, column]) > threshold:
            seen_key = ''.join(sorted([index,column]))
            if seen_key in seen:
                continue
            seen[seen_key]=1
            correlation = matrix.loc[index, column]
            correlations.append({
                'correlation':correlation,
                'index':index,
                'column':column,
            })
```

```
cors = sorted(correlations, key=lambda d: d['correlation'])
print("There are {} correlations over {}. For example:".
 ↪format(len(cors),threshold))
for cor in cors[123:128]:
    print("{:.5f} {} -> {}".
 ↪format(cor['correlation'],ndcp_dict[cor['index']],ndcp_dict[cor['column']]))
```

```
There are 3459 correlations over 0.5. For example:
-0.63903 Male Median Earnings -> Poverty Rate (all people)
-0.63758 State Level Male Labor Force Participation Rate (20-64) -> Poverty Rate
(all people)
-0.63466 State Level Median Earnings -> State Level Unemployment Rate (16+)
-0.63407 State Level Median Earnings -> State Level Poverty Rate (all people)
-0.63379 State Level Female Employment Rate (20-64) -> Poverty Rate (all
families)
```

Some uninteresting correlations here are that childcare costs for the different brackets rise and fall together, that employment and unemployment rates rise and fall together, that wages and costs rise and fall together, and others.

But, from reviewing all these correlations, here are some I want to investigate further:

- -0.60497 State Level Female Labor Force Participation Rate (20-64) with Children 6-17 only -> State Level Female Unemployment Rate (16+)
- 0.50099 Median Price of Center - Based Care - Toddler -> Civilian Employed Pop. (16+) Management, business, science, and arts occupations
- 0.51337 Civilian Employed Pop. (16+) Management, business, science, and arts occupations -> Median Earnings - 2022 Adjusted

There seems to be a correlation between "Management, business, science, and arts occupations" and median income as well as one between employment in "Management, business, science, and arts occupations" and child care costs. I need to look at this closer to see if it is just the costs and wages correlation or if an argument can be made that reducing child care costs would increase "Management, business, science, and arts occupations" participation and therefore drive up median wages (and taxes).

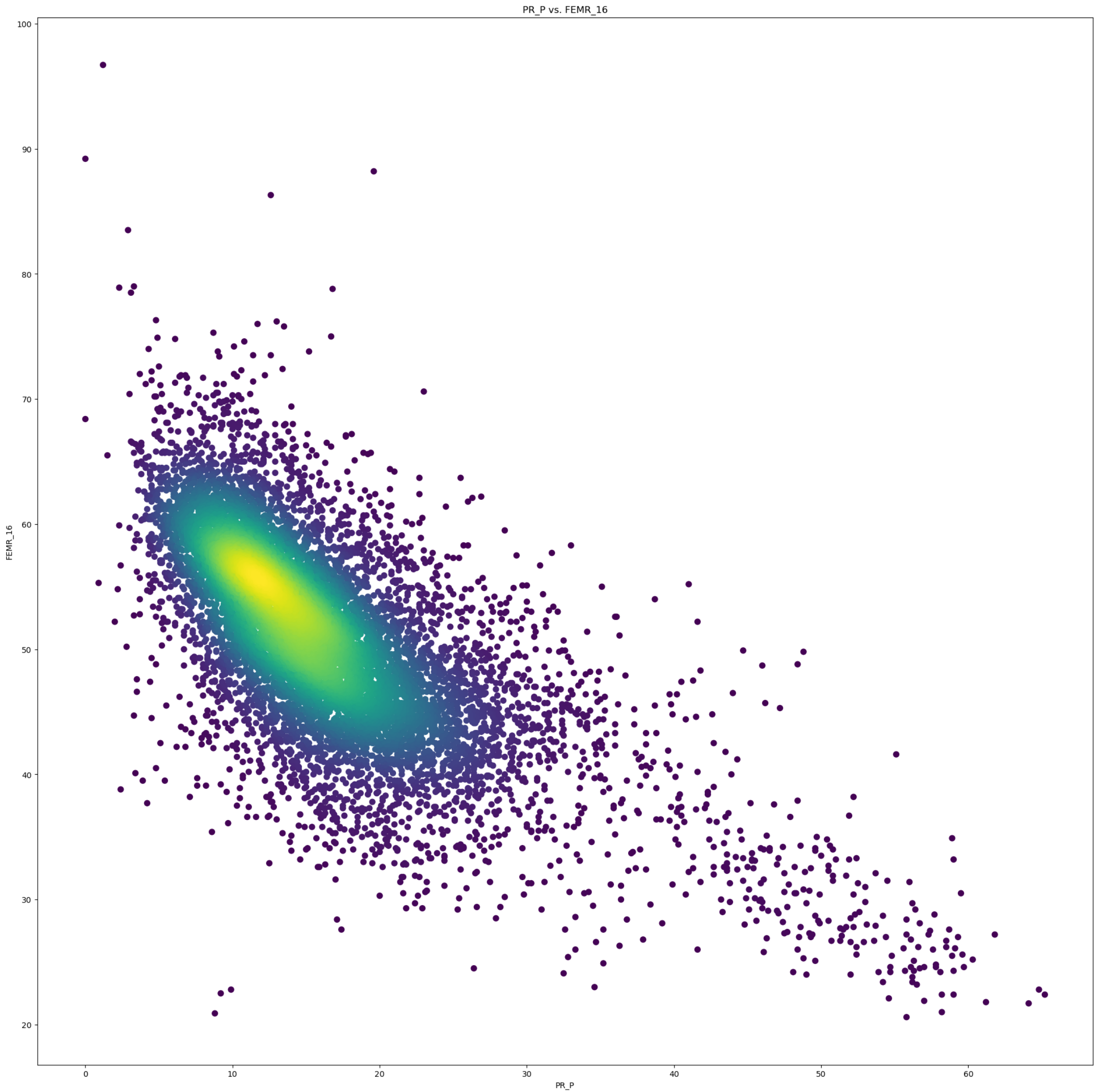
[151]:
```
def cor_search(search,exclude=False):
    print("Searching correlations for '{}'...:\n".format(search))
    for cor in cors:
        index = ndcp_dict[cor['index']]
        column = ndcp_dict[cor['column']]
        if search.lower() in index.lower():
            if exclude and exclude.lower() in column.lower():
                continue
            print("{:.5f} {} -> {}\n{}->{} ".
 ↪format(cor['correlation'],index,column,cor['index'],cor['column']))
```

[152]:
```
import matplotlib.pyplot as plt
from scipy.stats import gaussian_kde
```

```
# Here is a function to plot a scatter plot with density,
# adapted from https://stackoverflow.com/a/20107592.
def density_scatter(df,x_name,y_name):
    x,y = df[x_name].to_numpy(),df[y_name].to_numpy()

    # Calculate the point density
    xy = np.vstack([x,y])
    z = gaussian_kde(xy)(xy)

    # Sort the points by density, so that the densest points are plotted last
    idx = z.argsort()
    x, y, z = x[idx], y[idx], z[idx]

    fig, ax = plt.subplots()
    cax = ax.scatter(x, y, c=z, s=50, edgecolor=None)
    plt.title(x_name +" vs. "+y_name)
    plt.xlabel(x_name)
    plt.ylabel(y_name)
    plt.show()
```

[153]:
```
#cor_search('Management, business, science, and arts occupations','State')
```

[154]:
```
x = 'PR_P'
y = 'FEMR_16'
scatter = data[[x,y]]
scatter=scatter.dropna()
density_scatter(scatter.sample(n=10000),x,y)
```



[155]:
```
# cor_search('Poverty Rate (all people)','State')
# -0.72227 Poverty Rate (all people) -> Employment Rate (20-64)
# PR_P->EMR_20TO64
# -0.69734 Poverty Rate (all people) -> Female Employment Rate (16+)
# PR_P->FEMR_16
# -0.63074 Poverty Rate (all people) -> Male Employment Rate (16+)
# PR_P->MEMR_16

# cor_search('Participation Rate (20-64) with Children','State')
# 0.66990 Female Labor Force Participation Rate (20-64) with Children 6-17 only
 ↪-> Female Labor Force Participation Rate (20-64)
# FLFPR_20TO64_6TO17->FLFPR_20TO64
```

```
#cor_search('Median Price of Center','Price of ')
# 0.68750 Median Price of Center - Based Care - Preschool -> Median family␣
↪income
# MCPRESCHOOL->MFI
# 0.50618 Median Price of Center - Based Care - Preschool -> Civilian Employed␣
↪Pop. (16+) Management, business, science, and arts occupations
# MCPRESCHOOL->EMP_M
```

[213]:
```
def get_columns(search):
    return list(filter(lambda s: search.lower() in ndcp_dict[s].lower(),␣
↪list(data.columns)))

def reset_X_y(target):
    #columns = get_columns('Price of')
    columns = ['MCTODDLER']
    columns = columns + get_columns('Labor Force')
    columns = columns + get_columns('Households with Children')

    columns = columns + get_columns('Civilian Employed Pop.')
    columns = list(filter(lambda s: "male civilian employed" not in␣
↪ndcp_dict[s].lower(), columns))

    columns = columns + ['MFI','FME','MME','PR_P']

    #columns = columns + get_columns('Race')

    columns = list(filter(lambda s: "imputations" not in ndcp_dict[s].lower(),␣
↪columns))
    columns = list(filter(lambda s: "state level" not in ndcp_dict[s].lower(),␣
↪columns))
    independent = list(columns)
    #for item in independent:
    #    print(ndcp_dict[item]+"\n")
    independent.remove(target)
    df = data[data['STATE_ABBREVIATION']=='AL'].copy()
    df = df[independent+[target]]
    df = df.dropna()
    X = df[independent]
    y = df[target]
    return X,y

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics

def model_metrics(target,independent,sample=None):
    df = data[independent+[target]].copy()
```

```python
    df = df.dropna()
    X = df[independent]
    y = df[target]

    if sample:
        s=X.sample(n=1)
        print(s)

    # Split data into training and testing sets (optional but recommended)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

    # 3. Create and fit the linear regression model
    model = LinearRegression()
    model.fit(X_train, y_train)

    # Make predictions
    predictions = model.predict(X_test)
    if sample:
        print('orig',model.predict(s))
        s[sample]=70
        print(70,model.predict(s))
        s[sample]=90
        print(90,model.predict(s))
        s[sample]=95
        print(95,model.predict(s))

    def print_model_metrics(test,pred):
        mae = metrics.mean_absolute_error(test, pred)
        mse = metrics.mean_squared_error(test, pred)
        rmse = np.sqrt(mse) # or mse**(0.5)
        r2 = metrics.r2_score(test, pred)
        print("R-Squared:", r2)
        print("Root Mean Squared Error (RMSE):", rmse)
        print("Mean Absolue Error (MAE): ",mae)

    print_model_metrics(y_test,predictions)

    coefficients = model.coef_
    full_independent = [item+' '+ndcp_dict.get(item, item) for item in␣
↪independent]
    coef_df = pd.DataFrame({'Feature': full_independent, 'Coefficient':␣
↪coefficients})
    coef_df['Positive'] = coef_df['Coefficient'] > 0
    coef_df['Coefficient'] =coef_df['Coefficient'].abs()
    coef_df = coef_df.sort_values(by='Coefficient', ascending=False)
    print(coef_df)
```

[191]:
```
independent = ['H_6TO17_FWORK', 'MFI', 'H_6TO17_BOTHWORK', 'H_6TO17_MWORK',␣
↪'EMP_SERVICE', 'FME', 'H_6TO17_SINGLEM', 'FLFPR_20TO64', 'H_UNDER6_MWORK',␣
↪'MME']
model_metrics(target,independent)
```

```
34058    64.9
Name: FLFPR_20TO64, dtype: float64
       H_6TO17_FWORK    MFI  H_6TO17_BOTHWORK  H_6TO17_MWORK  EMP_SERVICE  \
34058             62  45907               161             17         28.6

         FME  H_6TO17_SINGLEM  FLFPR_20TO64  H_UNDER6_MWORK    MME
34058  20093            126.0          64.9               0  15253
orig [134.76415943]
70 [134.82711805]
90 [135.07401462]
95 [135.13573876]
R-Squared: 0.5470035254376662
Root Mean Squared Error (RMSE): 31.832794190688634
Mean Absolue Error (MAE):  23.366765202769564
                                            Feature  Coefficient  Positive
4  EMP_SERVICE Civilian Employed Pop. (16+) Servi…     2.038765      True
7  FLFPR_20TO64 Female Labor Force Participation …     0.012345      True
8  H_UNDER6_MWORK Households with Children Under …     0.008747      True
3  H_6TO17_MWORK Households with Children 6-17 wi…     0.007324      True
0  H_6TO17_FWORK Households with Children 6-17 wi…     0.002731     False
1                         MFI Median family income     0.001672      True
2  H_6TO17_BOTHWORK Households with Children 6-17…     0.001511      True
5                       FME Female Median Earnings     0.001059      True
9                         MME Male Median Earnings     0.000497     False
6  H_6TO17_SINGLEM Households with Children 6-17 …     0.000410     False
```

[108]:
```
from sklearn.feature_selection import RFE

X,y = reset_X_y()

from sklearn.preprocessing import StandardScaler
import pandas as pd
import numpy as np

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Convert back to DataFrame for easier processing
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

# Absolute correlation values
correlation_matrix = X_scaled_df.corr().abs()
```

```python
def drop_highly_correlated_features(corr_matrix, threshold=0.9):
    upper_triangle = corr_matrix.where(
        np.triu(np.ones(corr_matrix.shape), k=1).astype(bool)
    )

    to_drop = [column for column in upper_triangle.columns if any(upper_triangle[column] > threshold)]
    return to_drop

high_corr_features = drop_highly_correlated_features(correlation_matrix)

# Drop them from scaled data
X_reduced = X_scaled_df.drop(columns=high_corr_features)

top_10_variances = X_reduced.var().sort_values(ascending=False).head(10)
top_10_features = top_10_variances.index.tolist()

print("Top 10 selected features:", top_10_features)
model_metrics(top_10_features)
```

```
Top 10 selected features: ['ONERACE_H', 'ONERACE_I_STATE', 'ONERACE_H_STATE',
'MEMP_SALES_STATE', 'FME_STATE', 'ONERACE_A_STATE', 'EMP_SALES_STATE',
'FLFPR_20TO64_UNDER6_STATE', 'FEMP_SERVICE_STATE', 'ONERACE_I']
R-Squared: 0.2598331572290159
Root Mean Squared Error (RMSE): 7.061963408998715
Mean Absolue Error (MAE):  5.117362778570164
```

[214]:
```python
target='MCTODDLER'
X,y = reset_X_y(target)

from sklearn.linear_model import LassoCV
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import pandas as pd

# 1. Scale your features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 2. Fit Lasso with cross-validation
lasso = LassoCV(cv=5, max_iter=5000,random_state=42)
lasso.fit(X_scaled, y)

# 3. Extract selected features
selected_mask = lasso.coef_ != 0
selected_features = X.columns[selected_mask]
```

```
# 4. Sort by absolute coefficient value and pick top 10
top_10 = pd.Series(lasso.coef_, index=X.columns)[selected_mask].abs().
 ↪sort_values(ascending=False).head(10).index.tolist()

print("Top 10 features selected by Lasso:", top_10)
model_metrics(target,top_10)
```

```
Top 10 features selected by Lasso: ['MME', 'FME', 'MFI', 'PR_P',
'H_UNDER6_BOTHWORK', 'EMP_M', 'FLFPR_20T064_UNDER6_6T017', 'MLFPR_20T064',
'FLFPR_20T064_UNDER6', 'FLFPR_20T064_6T017']
R-Squared: 0.5036308930319395
Root Mean Squared Error (RMSE): 33.32189736364397
Mean Absolue Error (MAE):  24.57609389049964
                                                Feature  Coefficient  Positive
3                     PR_P Poverty Rate (all people)     0.401351      True
5  EMP_M Civilian Employed Pop. (16+) Management,…     0.139907      True
7  MLFPR_20T064 Male Labor Force Participation Ra…     0.109888     False
6  FLFPR_20T064_UNDER6_6T017 Female Labor Force P…     0.065931     False
8  FLFPR_20T064_UNDER6 Female Labor Force Partici…     0.019741     False
9  FLFPR_20T064_6T017 Female Labor Force Particip…     0.009542     False
2                           MFI Median family income     0.001913      True
1                        FME Female Median Earnings     0.001263      True
0                          MME Male Median Earnings     0.000948     False
4  H_UNDER6_BOTHWORK Households with Children Und…     0.000757      True
```

[127]:
```
X,y = reset_X_y('PR_P')

from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
import pandas as pd

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)

rf = RandomForestRegressor(n_jobs=-1,n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Rank features
importances = pd.Series(rf.feature_importances_, index=X.columns)
top_10_rf = importances.sort_values(ascending=False).head(10).index.tolist()

print("Top 10 features by Random Forest:", top_10_rf)
model_metrics(top_10_rf)
```

```
Top 10 features by Random Forest: ['MFI', 'MLFPR_20T064', 'MME',
'H_UNDER6_SINGLEM', 'FLFPR_20T064_UNDER6_6T017_STATE', 'FLFPR_20T064',
'H_6T017_SINGLEM', 'MEMP_N', 'EMP_N', 'FLFPR_20T064_6T017_STATE']
R-Squared: 0.6823475720190837
```

```
Root Mean Squared Error (RMSE): 4.623330743741631
Mean Absolue Error (MAE):  3.319848220768903
                                              Feature  Coefficient  Positive
5  FLFPR_20T064 Female Labor Force Participation …     0.343913     False
8  EMP_N Civilian Employed Pop. (16+) Natural res…     0.195438     False
4  FLFPR_20T064_UNDER6_6T017_STATE State Level Fe…     0.109195     False
7  MEMP_N Male Civilian Employed Pop. (16+) Natur…     0.079809     False
1  MLFPR_20T064 Male Labor Force Participation Ra…     0.067099     False
9  FLFPR_20T064_6T017_STATE State Level Female La…     0.040832      True
3  H_UNDER6_SINGLEM Households with Children Unde…     0.000284     False
2                         MME Male Median Earnings     0.000192     False
0                         MFI Median family income     0.000184     False
6  H_6T017_SINGLEM Households with Children 6-17 …     0.000169      True
```

[146]:
```python
def get_columns(search):
    return list(filter(lambda s: search.lower() in ndcp_dict[s].lower(),␣
 ↪list(data.columns)))

def reset_X_y(target):
    columns = []
    columns = columns + get_columns('Civilian Employed')
    columns = list(filter(lambda s: re.match('^e',s.lower()),columns))
    #columns = columns + list(data.columns)
    #print(columns)
    ignore = columns + ['MFI_2022','FME_2022',
        'UNR_20T064',
        'H_6T017_PERC',
        'H_UNDER6_PERC',
        'FLFPR_20T064_6T017',
        'FLFPR_20T064_UNDER6',
        'FLFPR_20T064',
                        'HOUSEHOLDS',
        'MFI_2022',
'FME_2022',
'EMP_SERVICE',
'HOUSEHOLDS',
'FEMP_N',
'FEMP_SALES',
'H_6T017_PERC',
'UNR_20T064',
'EMP_N',
'FLFPR_20T064_6T017',
    ]
    #print("Cost: ",columns)
    #columns = columns+get_columns('Under 6')

    #columns = columns + get_columns('Households with Children')
```

```python
    #columns = columns + get_columns('Employment Rate')

    columns = columns + get_columns('Civilian Employed Pop.')
    columns = list(filter(lambda s: "male civilian employed" not in␣
 ↪ndcp_dict[s].lower(), columns))

    columns = columns + ['MFI','HOUSEHOLDS','UNR_16','H_6TO17_PERC']

#    columns = columns + get_columns('Race')

    columns = list(filter(lambda s: s not in categories, columns))
    columns = list(filter(lambda s: "cost" not in ndcp_dict[s].lower(),␣
 ↪columns))
    columns = list(filter(lambda s: "price of" not in ndcp_dict[s].lower(),␣
 ↪columns))
    columns = list(filter(lambda s: "race" not in ndcp_dict[s].lower(),␣
 ↪columns))
    columns = list(filter(lambda s: "imputations" not in ndcp_dict[s].lower(),␣
 ↪columns))
    columns = list(filter(lambda s: "state level" not in ndcp_dict[s].lower(),␣
 ↪columns))


    #columns = list(filter(lambda s: "civilian employed" not in ndcp_dict[s].
 ↪lower(), columns))

    independent = list(columns)
    #for item in independent:
    #    print(ndcp_dict[item]+"\n")
    to_drop = [
        "FEMR_16",
        "MEMR_16",
        "FUNR_16",
        "MUNR_16",
        "PR_F",
        "MHI",
        "ME",
        "MHI_2022",
        "FME",
        "MME",
        "ME",
        "H_UNDER6_BOTHWORK",
        "H_UNDER6_FWORK",
        "H_UNDER6_MWORK",
        "H_UNDER6_SINGLEM",
        "H_6TO17_BOTHWORK",
```

```python
        "H_6TO17_FWORK",
        "H_6TO17_MWORK",
        "H_6TO17_SINGLEM",
        "FUNR_20TO64",
        "MUNR_20TO64",
        "MEMR_20TO64",
        "FLFPR_20TO64",
        "MLFPR_20TO64",
        #"MFI",
        "MME_2022",
        "MEMP_M",
        "MEMP_N",
        "MEMP_P",
        "MEMP_SERVICE",
        "MEMP_SALES",
        "TOTALPOP",
        "EMR_16",
        "UNR_16",
    ] + [target]
    for column in to_drop:
        independent = [ x for x in independent if x != column ]
    independent = list(dict.fromkeys(independent))  # removes duplicates,␣
↪preserves order
    df = data.copy()
    df = df[independent+[target]]
    df = df.dropna()
    X = df[independent]
    y = df[target]
    return independent,X,y

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics
import numpy as np

def model_metrics(target,independent,sample=None):
    df = data.copy()
    df = df[~df['STATE_ABBREVIATION'].isin(['AK', 'HI', 'PR'])]
    df = df[independent+[target]]
    df = df.dropna()

    X = df[independent]
    print(X.shape,len(independent))

    y = df[target]

    if sample:
```

```
        s=X.sample(n=1)
        print(s)

    # Split data into training and testing sets (optional but recommended)
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,␣
↪test_size=0.2, random_state=42)

    # 3. Create and fit the linear regression model
    model = LinearRegression()
    model.fit(X_train, y_train)

    # Make predictions
    predictions = model.predict(X_test)
    if sample:
        print('orig',model.predict(s))
        s[sample]=70
        print(70,model.predict(s))
        s[sample]=90
        print(90,model.predict(s))
        s[sample]=95
        print(95,model.predict(s))

    def print_model_metrics(test, pred, num_predictors):
        from sklearn import metrics
        import numpy as np

        mae = metrics.mean_absolute_error(test, pred)
        mse = metrics.mean_squared_error(test, pred)
        rmse = np.sqrt(mse)
        r2 = metrics.r2_score(test, pred)

        n = len(test)  # number of observations
        p = num_predictors  # number of predictors (features)
        adjusted_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)

        print("R-Squared:", r2)
        print("Adjusted R-Squared:", adjusted_r2)
        print("Root Mean Squared Error (RMSE):", rmse)
        print("Mean Absolute Error (MAE):", mae)


    print_model_metrics(y_test,predictions,len(independent))

    coefficients = model.coef_
```

```
    full_independent = [item+' '+ndcp_dict.get(item, item) for item in␣
↪independent]
    X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)  # Should match␣
↪df[independent].columns
    print(X_scaled_df.shape)  # Should clarify the mismatch
    coef_df = pd.DataFrame({'Feature': full_independent, 'Column':
↪independent,'Coefficient': coefficients})
    coef_df['Positive'] = coef_df['Coefficient'] > 0
    coef_df['Coefficient'] =coef_df['Coefficient'].abs()
    coef_df = coef_df.sort_values(by='Coefficient', ascending=False)
    print(coef_df[['Feature','Coefficient','Positive']].head(10))
    return list(coef_df['Column'].head(10))

target='MCUNDER6'.upper()
independent,X,y = reset_X_y(target)
print(ndcp_dict[target])
top_ten_simple = model_metrics(target,independent)
model_metrics(target,top_ten_simple)

from sklearn.linear_model import LassoCV
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import pandas as pd

# 1. Scale your features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 2. Fit Lasso with cross-validation
lasso = LassoCV(cv=5, max_iter=100000,random_state=42)
lasso.fit(X_scaled, y)

# 3. Extract selected features
selected_mask = lasso.coef_ != 0
selected_features = X.columns[selected_mask]

# 4. Sort by absolute coefficient value and pick top 10
top_10 = pd.Series(lasso.coef_, index=X.columns)[selected_mask].abs().
↪sort_values(ascending=False).head(10).index.tolist()

print("Top 10 features selected by Lasso:", top_10)
model_metrics(target,top_10)

X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

# Use your selected top 10 features
X_top10_scaled = X_scaled_df[top_10]
```

```python
# View the first few rows
X_top10_scaled.head()
```

```
Median Center Cost Under 6
(35257, 8) 8
R-Squared: 0.5301561945775557
Adjusted R-Squared: 0.529622508585311
Root Mean Squared Error (RMSE): 32.08337680999944
Mean Absolute Error (MAE): 23.774043139737383
(35257, 8)
                                              Feature  Coefficient  Positive
5                           MFI Median family income    31.322507      True
0  EMP_M Civilian Employed Pop. (16+) Management,…   16.479877     False
4  EMP_P Civilian Employed Pop. (16+) Production,…   15.738873     False
3  EMP_N Civilian Employed Pop. (16+) Natural res…   13.849940     False
2  EMP_SALES Civilian Employed Pop. (16+) Sales a…    9.171941     False
6                    HOUSEHOLDS Number of Households     8.305114      True
7  H_6TO17_PERC Percent Households with Children …    2.911146     False
1  EMP_SERVICE Civilian Employed Pop. (16+) Servi…    1.887960     False
(35257, 8) 8
R-Squared: 0.5301561945775557
Adjusted R-Squared: 0.529622508585311
Root Mean Squared Error (RMSE): 32.08337680999944
Mean Absolute Error (MAE): 23.774043139737383
(35257, 8)
                                              Feature  Coefficient  Positive
0                           MFI Median family income    31.322507      True
1  EMP_M Civilian Employed Pop. (16+) Management,…   16.479877     False
2  EMP_P Civilian Employed Pop. (16+) Production,…   15.738873     False
3  EMP_N Civilian Employed Pop. (16+) Natural res…   13.849940     False
4  EMP_SALES Civilian Employed Pop. (16+) Sales a…    9.171941     False
5                    HOUSEHOLDS Number of Households     8.305114      True
6  H_6TO17_PERC Percent Households with Children …    2.911146     False
7  EMP_SERVICE Civilian Employed Pop. (16+) Servi…    1.887960     False
Top 10 features selected by Lasso: ['MFI', 'HOUSEHOLDS', 'EMP_SERVICE', 'EMP_N',
'H_6TO17_PERC', 'EMP_M', 'EMP_P']
(35257, 7) 7
R-Squared: 0.5302049587964041
Adjusted R-Squared: 0.5297380983068491
Root Mean Squared Error (RMSE): 32.08171182965184
Mean Absolute Error (MAE): 23.77412082047385
(35257, 7)
                                              Feature  Coefficient  Positive
0                           MFI Median family income    31.340616      True
1                    HOUSEHOLDS Number of Households     8.301470      True
2  EMP_SERVICE Civilian Employed Pop. (16+) Servi…    7.950468      True
4  H_6TO17_PERC Percent Households with Children …    2.915228     False
```

```
3  EMP_N Civilian Employed Pop. (16+) Natural res…     2.269542     False
5  EMP_M Civilian Employed Pop. (16+) Management,…     1.774478      True
6  EMP_P Civilian Employed Pop. (16+) Production,…     0.278761     False
```

[146]:

```
        MFI  HOUSEHOLDS  EMP_SERVICE     EMP_N  H_6TO17_PERC     EMP_M  \
0 -0.043121   -0.178951    -0.220520  0.084896      1.250912 -0.623473
1  0.085493   -0.179642    -0.577832 -0.220056      1.696881 -0.311137
2  0.133043   -0.168012    -0.275491 -0.290430      1.613266 -0.340883
3  0.216973   -0.165735    -0.467890 -0.501551      1.576295 -0.058293
4  0.287743   -0.166255    -0.495376 -0.900334      1.549568  0.075565

      EMP_P
0 -0.516622
1 -0.376020
2 -0.534198
3 -0.305718
4 -0.305718
```

[161]:

```
#possible = ['MFI','MFI_2022', 'FME_2022', 'HOUSEHOLDS', 'FEMP_SALES',␣
 ↪'UNR_20TO64', 'FEMP_N', 'EMP_SERVICE', 'MEMP_SERVICE', 'EMP_N',␣
 ↪'H_6TO17_PERC']
#for column in possible:
    #print("\n\n",column)
    #model_metrics(target,[column])
```

[163]:

```
#corr_matrix = X.corr().abs()
#high_corr = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).
 ↪astype(bool))
#collinear_pairs = [(col1, col2) for col1 in high_corr.columns for col2 in␣
 ↪high_corr.index if high_corr.loc[col2, col1] > 0.9]
#collinear_pairs
```

[164]:

```
data[predictors].isnull().sum()
```

[164]:

```
MFI                   0
FME                   0
HOUSEHOLDS            0
EMP_SERVICE           0
FEMP_SALES            0
FEMP_N                0
UNR_20TO64            0
EMP_N                 0
H_6TO17_PERC          1
FLFPR_20TO64_6TO17    0
dtype: int64
```

[165]:

```python
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression

predictors = ['MFI', 'FME', 'HOUSEHOLDS', 'EMP_SERVICE', 'FEMP_SALES', 'FEMP_N', 'UNR_20T064', 'EMP_N', 'H_6T017_PERC', 'FLFPR_20T064_6T017']
target = 'MCUNDER6'

df_clean = data.dropna(subset=predictors)


df_known = df_clean[df_clean[target].notnull()]
df_unknown = df_clean[df_clean[target].isnull()]

X_train = df_known[predictors]
y_train = df_known[target]
model = LinearRegression()
model.fit(X_train, y_train)

X_unknown = df_unknown[predictors]
df_clean.loc[df_clean[target].isnull(), target] = model.predict(X_unknown)
temp = df_clean.copy()
temp[target+'_PERC']=temp[target]*52/data['MFI'] # 52 weeks full-time

from sklearn.preprocessing import MinMaxScaler

temp['MCUNDER6_IMPACT'] = temp['MCUNDER6_PERC']*temp['H_UNDER6_PERC']
scaler = MinMaxScaler(feature_range=(0, 100))  # Set custom range
temp['MCUNDER6_IMPACT_SCALED'] = scaler.fit_transform(temp[['MCUNDER6_IMPACT']])

df_clean = temp
df_clean.to_csv('ndcp_imputed.csv')
```