First import all libraries

In [71]:
```
%pylab
%matplotlib inline
import pandas as pd
import seaborn as sns
sns.set(style="white")

# import library for ML
import sklearn
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier
from sklearn import tree
```

```
Using matplotlib backend: MacOSX
Populating the interactive namespace from numpy and matplotlib

/Users/ashrafulislam/anaconda3/lib/python3.7/site-packages/IPython/core/magic
s/pylab.py:160: UserWarning: pylab import has clobbered these variables:
['f', 'clf']
`%matplotlib` prevents importing * from pylab and numpy
  "\n`%matplotlib` prevents importing * from pylab and numpy"
```

Data Acquision and Cleaning

We will describe data collection and cleaning part here. We have collected two datasets, one for **heart-disease-death** and another one for **Social Vulnerability Index (SVI)**.

Heart rate disease dataset

Read data

This data has several columns. However, for our purpose, the final data will have three columns: `COUNTY` , `STATE` , `RATE` (death rate from heart disease per 10,000 people)

In [72]:
```
hd_filename = "./Heart_Disease_Mortality_Data_Among_US_Adults__35___by_State_T
erritory_and_County.xls"
df_xls = pd.read_excel(hd_filename)  # original dataset
# get data for 'overall' gender and 'overall' ethnicity
df_xls = df_xls[(df_xls['Stratification1']=='Overall') & (df_xls['Stratificati
on2']=='Overall')]
print("Column names in the original dataset")
print(df_xls.columns)
```

```
Column names in the original dataset
Index(['Year', 'LocationAbbr', 'LocationDesc', 'GeographicLevel', 'DataSourc
e',
       'Class', 'Topic', 'Data_Value', 'Data_Value_Unit', 'Data_Value_Type',
       'Data_Value_Footnote_Symbol', 'Data_Value_Footnote',
       'StratificationCategory1', 'Stratification1', 'StratificationCategory
2',
       'Stratification2', 'TopicID', 'LocationID', 'Location 1'],
      dtype='object')
```

Clean data

In [73]:
```
df = pd.DataFrame()
df['COUNTY'] = df_xls.LocationDesc.apply(lambda name: name.lower().replace("co
unty", "").strip())
df['STATE'] = df_xls.LocationAbbr
df['RATE'] = df_xls.Data_Value
df_hr = df.dropna()  # clean data
df_hr = df_hr.sort_values(by=['STATE', 'COUNTY'])
df.head()
```

Out[73]:

	COUNTY	STATE	RATE
0	aleutians east	AK	105.3
1	aleutians west	AK	211.9
2	anchorage	AK	257.9
3	bethel	AK	351.6
4	bristol bay	AK	NaN

SVI data

Read data

In [74]:
```
svi_filename = "./SVI2014_US_CNTY.csv"
df_xls_svi = pd.read_csv(svi_filename)
```

Clean Data

This is a large dataset. The metrics that will be in the analysis:

1. EP_POV (person below povert estimate),
2. EP_UNEMP (civilian unemployed),
3. EP_PCI (per capita income),
4. EP_NOHSDP (person with no high school diploma),
5. EP_AGE65 (person age 65+),
6. EP_AGE17 (17+),
7. EP_SNGPNT (single parent household with one children),
8. EP_MINRTY (minority estimate except white, non-hispanic),
9. EP_LIMENG (person who speaks English less than well),
10. EP_NOVEH (household with no vehicle),
11. EP_GROUPQ (person in group quarters),
12. E_TOTPOP (total population).

All values are in percentage [0-100] except E_TOTPOP and EP_PCI .

In [75]:

```
columns_to_chose = ["ST_ABBR", "COUNTY", "E_TOTPOP", "EP_POV", "EP_UNEMP", "EP
_PCI", "EP_NOHSDP", "EP_AGE65", "EP_AGE17", "EP_SNGPNT", "EP_MINRTY", "EP_LIME
NG", "EP_NOVEH", "EP_GROUPQ"]
df_svi = df_xls_svi.filter(columns_to_chose).dropna()
df_svi['COUNTY'] = df_xls_svi.COUNTY.apply(lambda name: name.lower().replace(
"county", "").strip())
df_svi = df_svi.rename(columns={"ST_ABBR": "STATE"})
df_svi = df_svi.sort_values(by=['STATE', 'COUNTY'])
df_svi.head()
```

Out[75]:

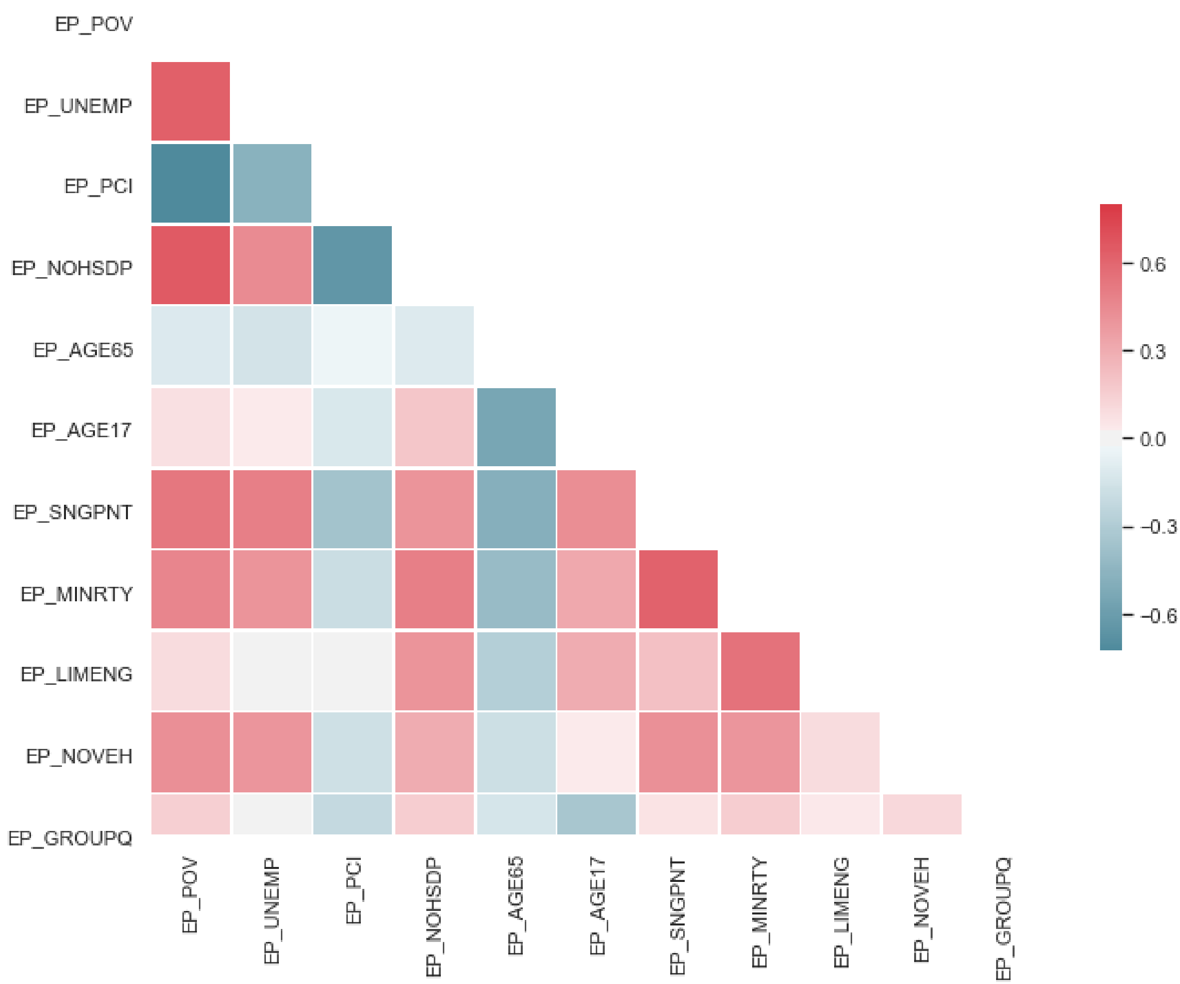
	STATE	COUNTY	E_TOTPOP	EP_POV	EP_UNEMP	EP_PCI	EP_NOHSDP	EP_AGE65	EP_
67	AK	aleutians east	3296.0	16.4	2.2	27122.0	20.5	5.1	
68	AK	aleutians west	5650.0	8.9	2.7	32700.0	14.5	5.7	
69	AK	anchorage	298178.0	8.3	6.9	36508.0	7.5	8.1	
70	AK	bethel	17576.0	23.7	17.3	18875.0	19.8	6.2	
71	AK	bristol bay	995.0	7.2	5.5	37012.0	8.8	6.7	

Show correlation among different metrics

Here, we show correlation among different columns of the dataset

In [76]:
```
df_svi_ep = df_svi.filter(regex='EP') / 100.  # normalize
corr = df_svi_ep.corr()
# plot correlation matrix
# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))
# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)
# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
# Draw the heatmap with the mask and correct aspect ratio
plt.figure(1)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.8, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[76]: <matplotlib.axes._subplots.AxesSubplot at 0x1a226b92d0>



From the heatmap, we can have some interesting findings:

- There is high correlation between EP_UNEMP and EP_POV, *i.e.*, poverty and unemploymet rate highly correlates. Same goes for poverty vs no-high-school-diploma.
- High correlation between minority population (EP_MINRTY) and limited English (EP_LIMENG), minority population and no vehicle in household(EP_NOVEH), minority population and single parent household (EP_SNGPNT)
- High correlation between single parent household and poverty, which is interesting, as this is generally reversed in developing nations.

Merge two datasets

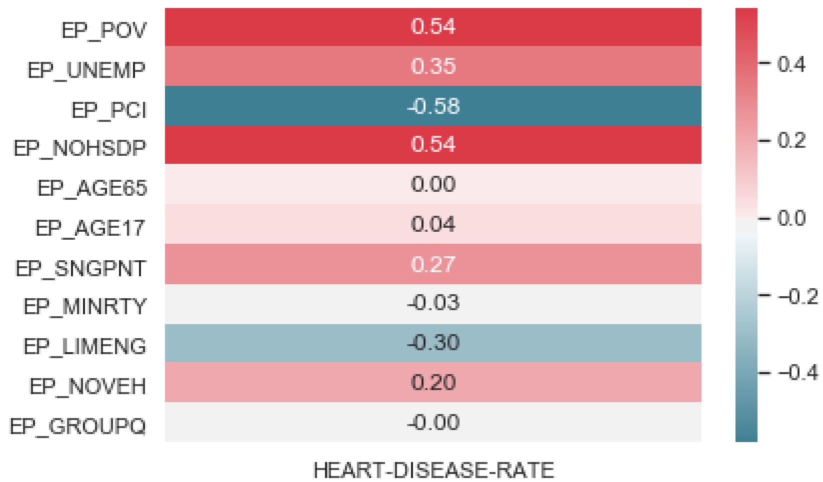
In this section, we merge two datasets together. We only filter those values that are common in both datasets.

In [77]:
```
# Merge two different datasets along 'STATE' and 'COUNTY'
df_merge = pd.merge(df_hr, df_svi, on=['COUNTY', 'STATE'])
df_merge = df_merge.dropna()
```

Correlation with Heart-disease-death-rate

Here, we show the correlation between different factors in SVI with heart-disease-death-rate

In [78]:
```python
# Plot heatmap of heart-rate disease vs EP_*

df_merge_ep = df_merge.filter(regex='EP') / 100.  # normalize
corr = df_merge_ep.corrwith(df_merge.RATE)
f, ax = plt.subplots()
# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)
# Draw the heatmap with the mask and correct aspect ratio
corr = pd.DataFrame(corr, columns=["HEART-DISEASE-RATE"])
cmap = sns.diverging_palette(220, 10, as_cmap=True)

sns.heatmap(corr, annot=True, fmt=".2f", cmap=cmap, ax=ax)
plt.autoscale()
```



Some findings from the heat-map:

- Heart-disease-death-rate highly correlates with **poverty** and **no-high-school-diploma-household**
- Heart-disease-death-rate inversely correlates with **per-capita-income** and **limited-English-speaking-ability**

Machine Learning Part

Data Preprocessing

In [79]:
```
# Convert heart rate disease values to categorical values
df_merge['RATE_CAT'] = pd.cut(df_merge.RATE.values, bins=[0, 320, 420, 800],
            labels=["low", "medium", "high"])
df_merge['RATE_CAT'].value_counts(sort=False)
```

Out[79]:
```
low       373
medium    483
high      254
Name: RATE_CAT, dtype: int64
```

In [80]:
```
# get feature and target
feature_columns = ["E_TOTPOP", "EP_POV", "EP_UNEMP", "EP_PCI", "EP_NOHSDP", "EP_AGE65", "EP_AGE17", "EP_SNGPNT", "EP_MINRTY", "EP_LIMENG", "EP_NOVEH", "EP_GROUPQ"]
target_column = ["RATE_CAT"]
X = df_merge.loc[:, feature_columns]
X_scale = preprocessing.scale(X)
Y = df_merge.loc[:, target_column].values.ravel()
le = preprocessing.LabelEncoder()
Y = le.fit_transform(Y)
n_target = len(np.unique(Y))
```

In [81]:
```
# test train split
X_train, X_test, Y_train, Y_test = train_test_split(X_scale, Y, test_size=0.3, random_state=1)
print("train sample: ", X_train.shape[0])
print("test sample: ", X_test.shape[0])
```

```
train sample:  777
test sample:  333
```

SVM Classification

In [82]:
```
## SVM model

clf = svm.SVC(gamma='scale', decision_function_shape='ovo')
clf.fit(X_train, Y_train)
```

Out[82]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovo', degree=3, gamma='scale', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

In [83]:
```
y_pred = clf.predict(X_test)
_score = accuracy_score(Y_test, y_pred, normalize=True)
print("Accuracy :", _score)
```

```
Accuracy : 0.6636636636636637
```

From SVM classifier, we can get around **67%** classification accuracy

In [84]:

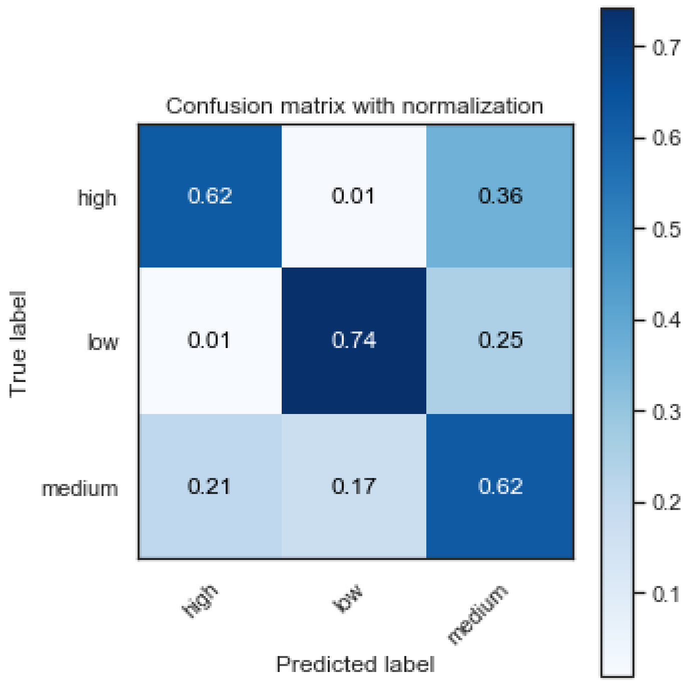
```python
# helper function

from sklearn.utils.multiclass import unique_labels
def plot_confusion_matrix(y_true, y_pred, classes,
                          normalize=False,
                          title=None,
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if not title:
        if normalize:
            title = 'Normalized confusion matrix'
        else:
            title = 'Confusion matrix, without normalization'

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    # Only use the labels that appear in the data
    classes = classes[unique_labels(y_true, y_pred)]
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    fig, ax = plt.subplots(figsize=(5,5))
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # We want to show all ticks...
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # ... and label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')

    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")

    # Loop over data dimensions and create text annotations.
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    plt.autoscale()
    return ax
```

Plot Confusion-matrix

In [85]:
```
plot_confusion_matrix(y_pred, Y_test, classes=le.classes_, normalize=True,
                      title='Confusion matrix with normalization')
```

```
Normalized confusion matrix
[[0.62162162 0.01351351 0.36486486]
 [0.00884956 0.74336283 0.24778761]
 [0.20547945 0.17123288 0.62328767]]
```

Out[85]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a21abe510>
```



K-NN Classifier

In [86]:
```
clf = KNeighborsClassifier(n_neighbors=10)
clf.fit(X_train, Y_train)

y_pred = clf.predict(X_test)
_score = accuracy_score(Y_test, y_pred, normalize=True)
print("Accuracy : ", _score)
```

```
Accuracy :  0.6636636636636637
```

In [87]:
```
clf = tree.DecisionTreeClassifier()
clf.fit(X_train, Y_train)

y_pred = clf.predict(X_test)
_score = accuracy_score(Y_test, y_pred, normalize=True)
print("Accuracy : ", _score)
```

```
Accuracy :  0.5255255255255256
```

SVM and K-NN seem to work best for this problem