Divisione fra regioni

In questo notebook si analizza se possa essere sensato splittare il dataset di lavoro a seconda della regione di appartenza (feature `regionidcounty`).

In [1]:
```
# Libraries
import pandas as pd
import numpy  as np
import re
import warnings
import matplotlib.pyplot  as plt
import matplotlib.patches as mpatches

from sklearn.preprocessing import StandardScaler
from sklearn.cluster       import KMeans
from sklearn.cluster       import AgglomerativeClustering
from sklearn.cluster       import DBSCAN
from sklearn.metrics       import accuracy_score
from sklearn.metrics       import confusion_matrix
from sklearn.metrics       import plot_confusion_matrix
from sklearn.decomposition import PCA
from sklearn.ensemble      import RandomForestClassifier
from sklearn.utils         import resample

warnings.filterwarnings('ignore')
```

Lettura dei dati

In [2]:
```
# local file paths
dir_name = 'preparazione'

fp_xtrain = dir_name + "/X_train.csv"
fp_ytrain = dir_name + "/y_train.csv"
fp_xval   = dir_name + "/X_val.csv"
fp_yval   = dir_name + "/y_val.csv"
fp_xtest  = dir_name + "/X_test.csv"
fp_ytest  = dir_name + "/y_test.csv"
```

Lettura dei dati preprocessati:

In [3]:
```
# Reading dataframes
X_train = pd.read_csv(fp_xtrain, low_memory=False)
y_train = pd.read_csv(fp_ytrain, low_memory=False)
X_val   = pd.read_csv(fp_xval,   low_memory=False)
y_val   = pd.read_csv(fp_yval,   low_memory=False)
X_test  = pd.read_csv(fp_xtest,  low_memory=False)
y_test  = pd.read_csv(fp_ytest,  low_memory=False)
```

In [4]:
```
# Removes from the given dataframe the column with the given name
def remove_column(df, col_names):
    df.drop(col_names, axis=1, inplace=True)
    return df
```

In [5]:
```
for X in [X_train, X_val, X_test]:
    X = remove_column(X, ['parcelid'])
```

In [6]:
```
# Prints all dataframes shape
def dimensionality(y=False):
    print(f'X_train {  X_train.shape}')
    print(f'X_val   {    X_val.shape}')
    print(f'X_test  {   X_test.shape}')
    if y:
        print(f'y_train { y_train.shape}')
        print(f'y_val   {   y_val.shape}')
        print(f'y_test  {  y_test.shape}')
```

In [7]:
```
dimensionality(y=True)
```

```
X_train (99709, 72)
X_val   (33572, 72)
X_test  (33567, 72)
y_train (99709, 1)
y_val   (33572, 1)
y_test  (33567, 1)
```

In [8]:
```
print(*X_train.columns, sep='\n')
```

```
bathroomcnt
bedroomcnt
buildingqualitytypeid
calculatedbathnbr
calculatedfinishedsquarefeet
finishedsquarefeet12
fireplacecnt
latitude
longitude
lotsizesquarefeet
rawcensustractandblock
regionidcity
regionidzip
roomcnt
unitcnt
yearbuilt
structuretaxvaluedollarcnt
taxvaluedollarcnt
landtaxvaluedollarcnt
taxamount
int_transactiondate
period_mean_price
neighborhood_mean_price
living_area_prop
tax_ratio
tax_prop
buildingqualitytypeid_na_flag
unitcnt_na_flag
assessmentyear_2015.0
fips_6037.0
fips_6059.0
fips_6111.0
heatingorsystemtypeid_1.0
heatingorsystemtypeid_2.0
heatingorsystemtypeid_6.0
heatingorsystemtypeid_7.0
heatingorsystemtypeid_10.0
heatingorsystemtypeid_11.0
heatingorsystemtypeid_12.0
heatingorsystemtypeid_13.0
heatingorsystemtypeid_18.0
heatingorsystemtypeid_20.0
heatingorsystemtypeid_24.0
poolcnt_1.0
propertycountylandusecode_0100
propertycountylandusecode_0101
propertycountylandusecode_010C
propertycountylandusecode_122
propertycountylandusecode_34
propertycountylandusecode_rare
propertylandusetypeid_31.0
propertylandusetypeid_246.0
propertylandusetypeid_247.0
propertylandusetypeid_248.0
propertylandusetypeid_260.0
propertylandusetypeid_261.0
propertylandusetypeid_263.0
propertylandusetypeid_264.0
propertylandusetypeid_265.0
propertylandusetypeid_266.0
propertylandusetypeid_267.0
propertylandusetypeid_269.0
propertylandusetypeid_275.0
propertyzoningdesc_LAR1
propertyzoningdesc_LAR3
propertyzoningdesc_LARD1.5
propertyzoningdesc_LARS
propertyzoningdesc_LBR1N
propertyzoningdesc_rare
regionidcounty_1286.0
regionidcounty_2061.0
regionidcounty_3101.0
```

Colonne che discriminino la regione:

In [9]:
```
regionids = ['regionidcounty_1286.0', 'regionidcounty_2061.0', 'regionidcounty_3101.0']

region_names = np.array([   'A',    'B',    'C'])
region_ids   = np.array(['1286', '2061', '3101'])
```

Clustering

Verifica se un algoritmo di clustering sia in grado di individuare le differenti regioni

Per farlo lavoro esclusivamente sul dataset di train: costruendo un nuova dataset:

- `X'`, ossia il dataset X_train senza le tre colonne `regioid_county`
- `y'`, che sfrutta un label encoding con etichette 0, 1 e 2 a seconda della regione di appartenenza

In [10]:
```
# Returns a new dataframe X without region infos, which are returned in y vector in 0, 1, 2 encoding
def get_X_y(X):
    X_ = X.copy()
    y_ = X_.loc[:, regionids]
    y_.loc[:,['region']] =\
        y_.loc[:,regionids[0]] * 0 +\
        y_.loc[:,regionids[1]] * 1 +\
        y_.loc[:,regionids[2]] * 2
    X_ = remove_column(X_, regionids)
    y_ = remove_column(y_, regionids)
    y_ = y_.values.ravel().astype(np.int64)
    return X_, y_
```

k-means

Utilizzo di un algoritmo di clustering k-means

In [11]:
```
def kmeans_clustering(X):
    kmeans = KMeans(n_clusters=3).fit(X)
    print(kmeans.labels_)
    return kmeans, kmeans.labels_
```

In [12]:
```
# Returns the accuracy score given actual values and predictions
def accuracy(y_true, y_pred, verbose = False):
    acc = accuracy_score(y_true, y_pred)
    if verbose:
        print(y_pred [:35])
        print(y_true [:35])
        print('Accuracy: ', acc)
    return acc
```

In [13]:
```
X_clu, y_true = get_X_y(X_train)
```

In [14]:
```
_, y_pred = kmeans_clustering(X_clu)
```

```
[0 0 0 ... 0 0 0]
```

In [15]:
```
print('True     ', y_true[:35],)
print('Predicted', y_pred[:35],)
```

```
True      [0 2 2 0 2 0 1 0 0 2 0 0 2 2 2 2 2 1 2 2 2 0 2 2 2 2 1 2 2 0 2 2 0 2 2]
Predicted [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

Sembra che l'algoritmo abbia individuato un cluster molto grande rispetto agli altri

In [16]:
```
for i in range(3):
    print(f'Occorrenze Regione{region_names[i]} : {np.bincount(y_true)[i]}')
print()

for i in range(3):
    print(f'Occorrenze Cluster{i} : {np.bincount(y_pred)[i]}')
```

```
Occorrenze RegioneA : 26819
Occorrenze RegioneB : 8119
Occorrenze RegioneC : 64771

Occorrenze Cluster0 : 91812
Occorrenze Cluster1 : 257
Occorrenze Cluster2 : 7640
```

Quasi tutte le instanze infatti sono nel cluster 1, le proporzioni tra cluster non sono quelle attese. L'algoritmo trova un cluster molto grande.

Per indagarne meglio il fenomeno, riduco la dimensionalità a 2 usando una Principal Componenet Analysis.

Principal Componenet Analysis

In [17]:
```
X_pca, y_pca = get_X_y(X_train)
```

In [18]:
```
X_train.shape
```

Out[18]:
```
(99709, 72)
```

In [19]:
```
X_pca.shape
```

Out[19]:
```
(99709, 69)
```

In [20]:
```
y_pca.shape
```

Out[20]:
```
(99709,)
```

Riduco X a due dimensioni.

In [21]:
```
X_pca_2 = PCA(n_components=2).fit_transform(X_pca)
```

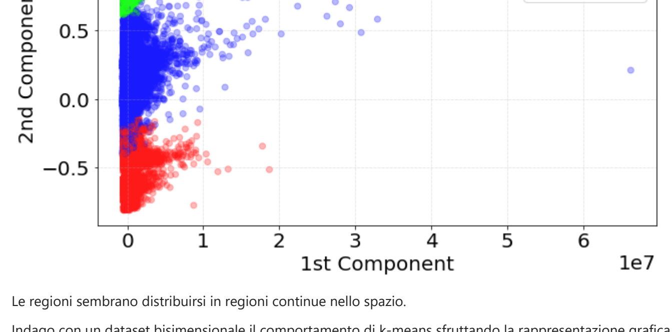
In [22]:
```
X_pca_2.shape
```

Out[22]:
```
(99709, 2)
```

Sfrutto la bidimensionalità per ottenere una rappresentazione grafica.

In [23]:
```
def plot_regions(X, y, title="", file_name=''):

    plt.rcParams.update({'font.size': 20})
    fig, ax = plt.subplots(figsize=(10,6))

    colors = np.array([
        (1., .1, .1, .3),
        (.1, 1., .1, .3),
        (.1, .1, 1., .3)]
    )

    # scatter is ismilar to plot, additionally a color per point is provided
    scatter = ax.scatter(X[:,0],X[:,1], c=colors[y], label=region_ids[y])

    handles = []
    for c,l in zip(colors, region_ids):
        handles.append(mpatches.Patch(color=c, label=l))
    plt.legend(handles=handles)

    ax.set_xlabel("1st Component")
    ax.set_ylabel("2nd Component")
    ax.set_title(title, fontsize=20)
    ax.grid(linestyle=':', linewidth=.5)

    if file_name != '':
        fig.savefig('images/' + file_name + '.jpg')
```

In [24]:
```
plot_regions(X_pca_2, y_pca, title="PCA", file_name='regioni')
```



Le regioni sembrano distribuirsi in regioni continue nello spazio.

Indago con un dataset bisimensionale il comportamento di k-means sfruttando la rappresentazione grafica

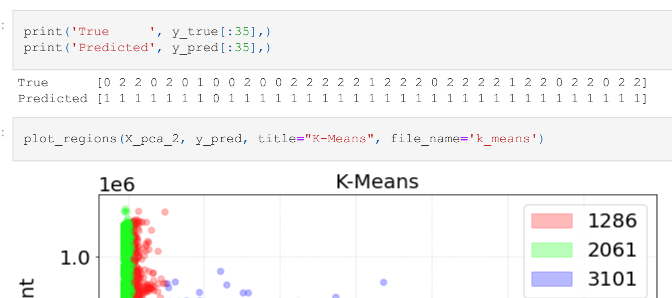
In [25]:
```
est, y_pred = kmeans_clustering(X_pca_2)
```

```
[1 1 1 ... 1 1 1]
```

In [26]:
```
print('True     ', y_true[:35],)
print('Predicted', y_pred[:35],)
```

```
True      [0 2 2 0 2 0 1 0 0 2 0 0 2 2 2 2 2 1 2 2 2 0 2 2 2 2 1 2 2 0 2 2 0 2 2]
Predicted [1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

In [27]:
```
plot_regions(X_pca_2, y_pred, title="K-Means", file_name='k_means')
```



Il clustering con k_means non individua in maniera precisa i tre cluster, poiché ha il limite di individuare specialmente cluster circolari, differenti da questo particolare caso.

Un algoritmo di clustering come DBSCAN non risulterebbe vantaggioso: l'algoritmo individuerebbe alcuni outlier e non sarebbe in grado di seprare le regioni; questo perché DBSCAN si basa sulla distanza euclidea e le regioni non sono ben distanziate nello spazio, DBSCAN non sarebbe in grado di separarli.

Algoritmo di classificazione

Provo con un algoritmo di Classificazione dividendo il mio dataset di Train a in Train e Test con rapporto 2:1

In [28]:
```
half = int(len(X_pca)*2/3)
```

Studio sia il dataset completo che quello ridotto con la PCA

In [29]:
```
X_class_train   = X_pca  [:half]
X_class_train_2 = X_pca_2[:half]
y_class_train   = y_pca  [:half]


X_class_test    = X_pca  [half:]
X_class_test_2  = X_pca_2[half:]
y_class_test    = y_pca  [half:]
```

In [30]:
```
def classifier(X_train, y_train, X_test, y_test):
    rfc = RandomForestClassifier(n_estimators=100, n_jobs=-1)
    rfc.fit(X_train, y_train)
    y_pred = rfc.predict(X_test)
    acc = accuracy_score(y_pred, y_test)
    print(f'Accuracy: {acc}')
    plot_confusion_matrix(rfc, X_test, y_test)
```

Usando il dataset con PCA:

In [31]:
```
classifier(X_class_train_2, y_class_train, X_class_test_2, y_class_test)
```

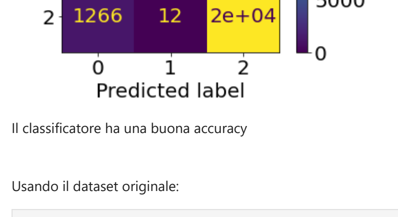
```
Accuracy: 0.9316424466708788
```

Il classificatore ha una buona accuracy

Usando il dataset originale:

In [32]:
```
# X con le feature originali
classifier(X_class_train, y_class_train, X_class_test, y_class_test)
```

```
Accuracy: 1.0
```



La classificazione ha la massima precisione.
Forse nella PCA sono stati inevitabilmente compressi dei dati, che però nelle feature originali portano in maniera silente informazione delle regioni (ad esempio `propertycountylandusecode`, `propertyzoningdesc` o `propertylandusetypeid` potrebbero avere dei codici specifici della regione; oppure `latitude` e `longitude` potrebbero riuscire a separare geograficamente le tre regioni)

Provo la classificazione non considerando esplicitamente colonne legate alla regione.

In [33]:
```
def classifier_remove_col(X_train, y_train, X_test, y_test, rem_col):
    X_tr = X_train.copy()
    X_te = X_test.copy()
    X_tr = remove_column(X_tr, rem_col)
    X_te = remove_column(X_te, rem_col)
    classifier(X_tr, y_train, X_te, y_test)
```

In [34]:
```
prop_lti = list(filter(re.compile("^propertylandusetypeid_.*$").match, list(X_train.columns)))
prop_lti
```

Out[34]:
```
['propertylandusetypeid_31.0',
 'propertylandusetypeid_246.0',
 'propertylandusetypeid_247.0',
 'propertylandusetypeid_248.0',
 'propertylandusetypeid_260.0',
 'propertylandusetypeid_261.0',
 'propertylandusetypeid_263.0',
 'propertylandusetypeid_264.0',
 'propertylandusetypeid_265.0',
 'propertylandusetypeid_266.0',
 'propertylandusetypeid_267.0',
 'propertylandusetypeid_269.0',
 'propertylandusetypeid_275.0']
```

In [35]:
```
prop_clc = list(filter(re.compile("^propertycountylandusecode_.*$").match, list(X_train.columns)))
prop_clc
```

Out[35]:
```
['propertycountylandusecode_0100',
 'propertycountylandusecode_0101',
 'propertycountylandusecode_010C',
 'propertycountylandusecode_122',
 'propertycountylandusecode_34',
 'propertycountylandusecode_rare']
```

In [36]:
```
prop_zid = list(filter(re.compile("^propertyzoningdesc_.*$").match, list(X_train.columns)))
prop_zid
```

Out[36]:
```
['propertyzoningdesc_LAR1',
 'propertyzoningdesc_LAR3',
 'propertyzoningdesc_LARD1.5',
 'propertyzoningdesc_LARS',
 'propertyzoningdesc_LBR1N',
 'propertyzoningdesc_rare']
```

In [37]:
```
regions = ['regionidcity', 'regionidzip', 'rawcensustractandblock', 'latitude', 'longitude']
regions
```

Out[37]:
```
['regionidcity',
 'regionidzip',
 'rawcensustractandblock',
 'latitude',
 'longitude']
```

In [38]:
```
fips = list(filter(re.compile("^fips_.*$").match, list(X_train.columns)))
fips
```

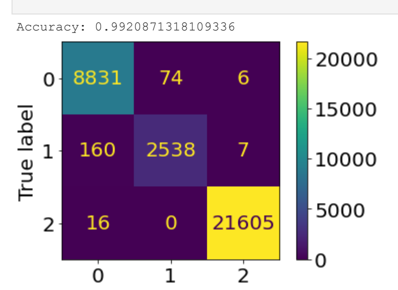
Out[38]:
```
['fips_6037.0', 'fips_6059.0', 'fips_6111.0']
```

In [39]:
```
region_about = prop_lti + prop_clc + prop_zid +regions + fips
region_about
```

Out[39]:
```
['propertylandusetypeid_31.0',
 'propertylandusetypeid_246.0',
 'propertylandusetypeid_247.0',
 'propertylandusetypeid_248.0',
 'propertylandusetypeid_260.0',
 'propertylandusetypeid_261.0',
 'propertylandusetypeid_263.0',
 'propertylandusetypeid_264.0',
 'propertylandusetypeid_265.0',
 'propertylandusetypeid_266.0',
 'propertylandusetypeid_267.0',
 'propertylandusetypeid_269.0',
 'propertylandusetypeid_275.0',
 'propertycountylandusecode_0100',
 'propertycountylandusecode_0101',
 'propertycountylandusecode_010C',
 'propertycountylandusecode_122',
 'propertycountylandusecode_34',
 'propertycountylandusecode_rare',
 'propertyzoningdesc_LAR1',
 'propertyzoningdesc_LAR3',
 'propertyzoningdesc_LARD1.5',
 'propertyzoningdesc_LARS',
 'propertyzoningdesc_LBR1N',
 'propertyzoningdesc_rare',
 'regionidcity',
 'regionidzip',
 'rawcensustractandblock',
 'latitude',
 'longitude',
 'fips_6037.0',
 'fips_6059.0',
 'fips_6111.0']
```

In [40]:
```
classifier_remove_col(X_class_train, y_class_train, X_class_test, y_class_test, region_about)
```

```
Accuracy: 0.9920871318109336
```



La classificazione ha comunque una precisione molto alta. Questo significa che pur rimuovendo le colonne esplicitamente collegate alla regione di appartenenza è comunque possibile individuare un pattern nei dati specifico di una certa regione.

Split

Divisoine del Dataset per del suo `regionidcounty`.

In [41]:
```
# Returns the X, y dataframes splitted throught regions
def split_regionid(X, y):
    A = X.loc[:,regionids[0]] == 1
    B = X.loc[:,regionids[1]] == 1
    C = X.loc[:,regionids[2]] == 1
    return X[A], X[B], X[C], y[A], y[B], y[C]
```

In [42]:
```
X_trainA, X_trainB, X_trainC, y_trainA, y_trainB, y_trainC = split_regionid(X_train, y_train)
X_valA,   X_valB,   X_valC,   y_valA,   y_valB,   y_valC   = split_regionid(X_val,   y_val  )
X_testA,  X_testB,  X_testC,  y_testA,  y_testB,  y_testC  = split_regionid(X_test,  y_test )
```

Mantengo i dataframe in un array.

In [43]:
```
X_train = np.array([X_trainA, X_trainB, X_trainC], dtype=object)
X_val   = np.array([X_valA,   X_valB,   X_valC  ], dtype=object)
X_test  = np.array([X_testA,  X_testB,  X_testC ], dtype=object)
y_train = np.array([y_trainA, y_trainB, y_trainC], dtype=object)
y_val   = np.array([y_valA,   y_valB,   y_valC  ], dtype=object)
y_test  = np.array([y_testA,  y_testB,  y_testC ], dtype=object)
```

In [44]:
```
for X in [X_train, X_val, X_test]:
    for x in X:
        x = remove_column(x, regionids)
```

In [45]:
```
def dimensionality(y=False):
    for i in range(3):
        print(f'X_train{region_names[i]}: {X_train[i].shape}')
        print(f'X_val{region_names[i]}:   {X_val  [i].shape}')
        print(f'X_test{region_names[i]}:  {X_test [i].shape}')
        if y:
            print(f'y_train{region_names[i]}: {y_train[i].shape}')
            print(f'y_val{region_names[i]}:   {y_val  [i].shape}')
            print(f'y_test{region_names[i]}:  {y_test [i].shape}')
            print()
```

In [46]:
```
dimensionality(y=True)
```

```
X_trainA: (26819, 69)
X_valA:   (9006, 69)
X_testA:  (9085, 69)
y_trainA: (26819, 1)
y_valA:   (9006, 1)
y_testA:  (9085, 1)

X_trainB: (8119, 69)
X_valB:   (2658, 69)
X_testB:  (2606, 69)
y_trainB: (8119, 1)
y_valB:   (2658, 1)
y_testB:  (2606, 1)

X_trainC: (64771, 69)
X_valC:   (21908, 69)
X_testC:  (21876, 69)
y_trainC: (64771, 1)
y_valC:   (21908, 1)
y_testC:  (21876, 1)
```

Le proporzioni fra regioni sono circa 3:1:8.

Salvataggio dei dati

Salvo i dati in una dataset apposito con già lo split per regione.

In [47]:
```
dir_name = 'regioni'

for i in range(3):
    X_train[i].to_csv( dir_name + f'/X_train{region_names[i]}.csv',  index=False)
    X_val  [i].to_csv( dir_name + f'/X_val{  region_names[i]}.csv',  index=False)
    X_test [i].to_csv( dir_name + f'/X_test{ region_names[i]}.csv',  index=False)
    y_train[i].to_csv( dir_name + f'/y_train{region_names[i]}.csv',  index=False)
    y_val  [i].to_csv( dir_name + f'/y_val{  region_names[i]}.csv',  index=False)
    y_test [i].to_csv( dir_name + f'/y_test{ region_names[i]}.csv',  index=False)
```