In [91]:
```
"""
Universidade Federal de Pernambuco - CIn
Pós-graduação em Ciência da Computação
Disciplina: Aprendizagem de Máquina
Professor: Leandro Maciel Almeida
Estudantes: Carlos Antônio Alves Junior,
            Matheus Johann Araújo e
            Marcos de Souza Oliveira.
Atividade: Missão 05 - SVM
Data: 20/07/2021

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Referências:
    https://scikit-learn.org/stable/modules/svm.html
    https://scikit-learn.org/stable/modules/multiclass.html
    https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html
    https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RepeatedStratifiedKFold.html
    https://archive.ics.uci.edu/ml/datasets/glass+identification
    https://www.vebuso.com/2020/03/svm-hyperparameter-tuning-using-gridsearchcv/
    https://www.youtube.com/watch?v=Zj1CoJk2feE
"""

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.model_selection import RepeatedStratifiedKFold
```

In [92]:
```
# Reading database
dt = pd.read_csv('./glass.data')
dt.columns = ['ID', 'RI', 'NA', 'MG', 'AL', 'SI', 'K', 'CA', 'BA', 'FE', 'class']
```

In [93]:
```
# Removing ID column
dt = dt.drop('ID', 1)
```

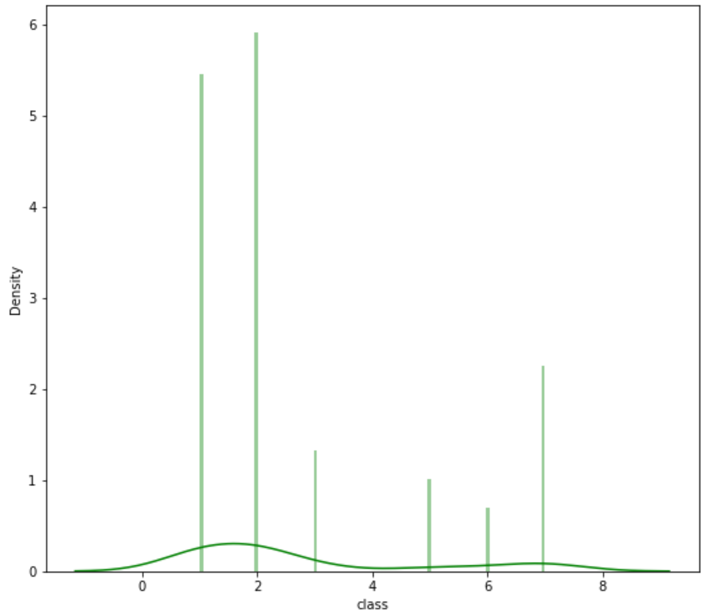
In [94]:
```
# Displaying existing columns
print(dt.columns)
```

```
Index(['RI', 'NA', 'MG', 'AL', 'SI', 'K', 'CA', 'BA', 'FE', 'class'], dtype='object')
```

In [95]:
```
print(dt['class'].describe())
plt.figure(figsize=(9, 8))
sns.distplot(dt['class'], color='g', bins=100, hist_kws={'alpha': 0.4});
plt.show()
```

```
count    214.000000
mean       2.780374
std        2.103739
min        1.000000
25%        1.000000
50%        2.000000
75%        3.000000
max        7.000000
Name: class, dtype: float64
```

```
c:\program files\python36\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

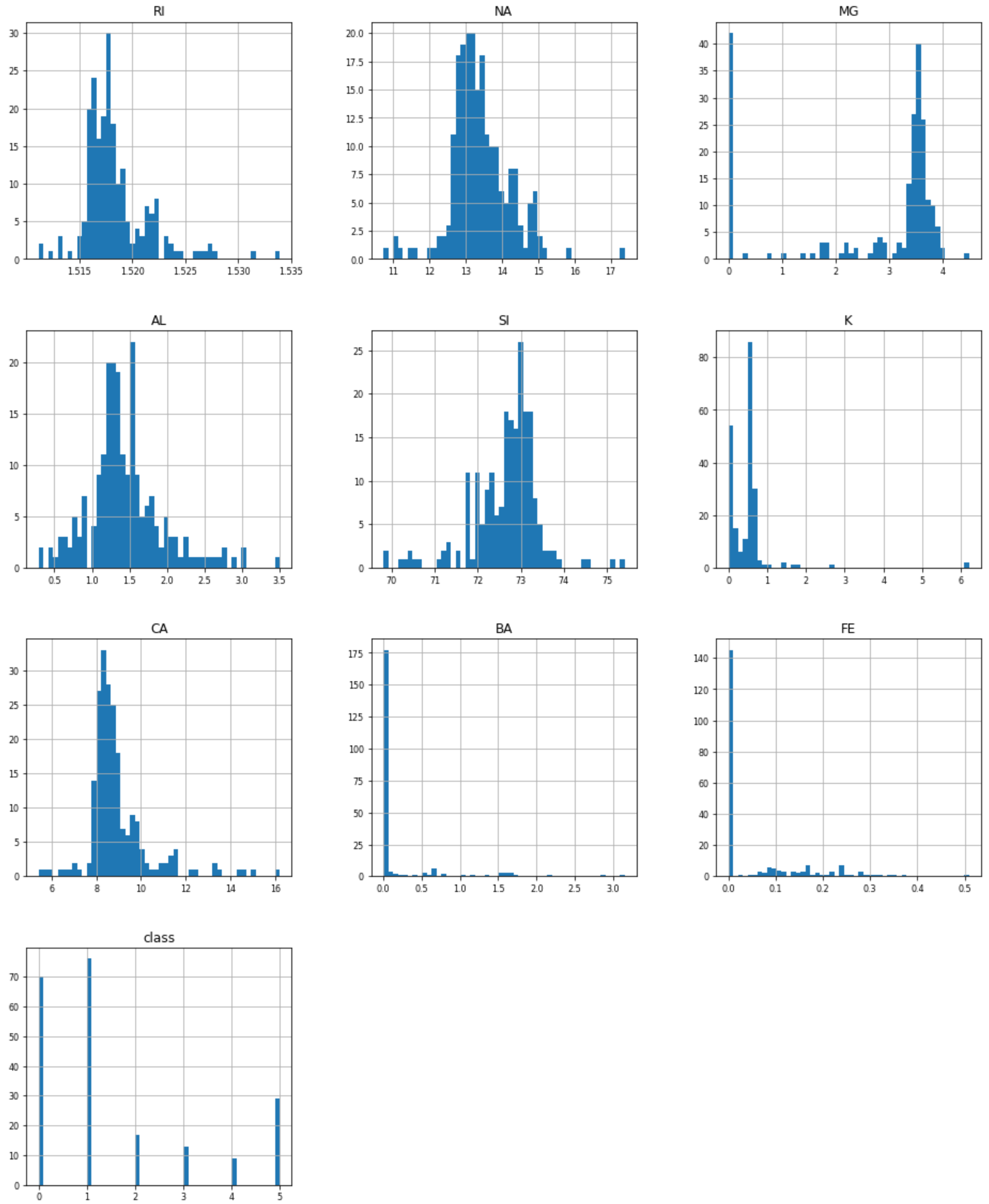


In [96]:

```
dt['class'] = dt['class'] - 1
dt['class'] = dt['class'].mask(dt['class'] > 3, dt['class'] - 1)
```

In [97]:

```
dt.hist(figsize=(16, 20), bins=50, xlabelsize=8, ylabelsize=8);
```



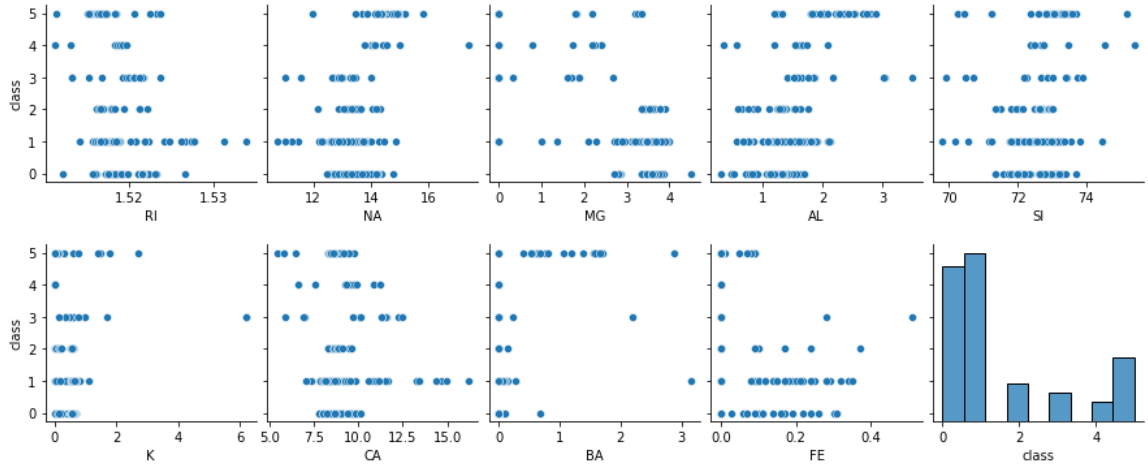
In [98]:

```
df_num_corr = dt.corr()['class'][:-1]
golden_features_list = df_num_corr[abs(df_num_corr) > 0.5].sort_values(ascending=False)
print("There is {} strongly correlated values with Class:\n{}".format(len(golden_features_list), golden_features_list))
```

```
There is 4 strongly correlated values with Class:
AL    0.591198
BA    0.577676
NA    0.506424
MG   -0.728160
Name: class, dtype: float64
```

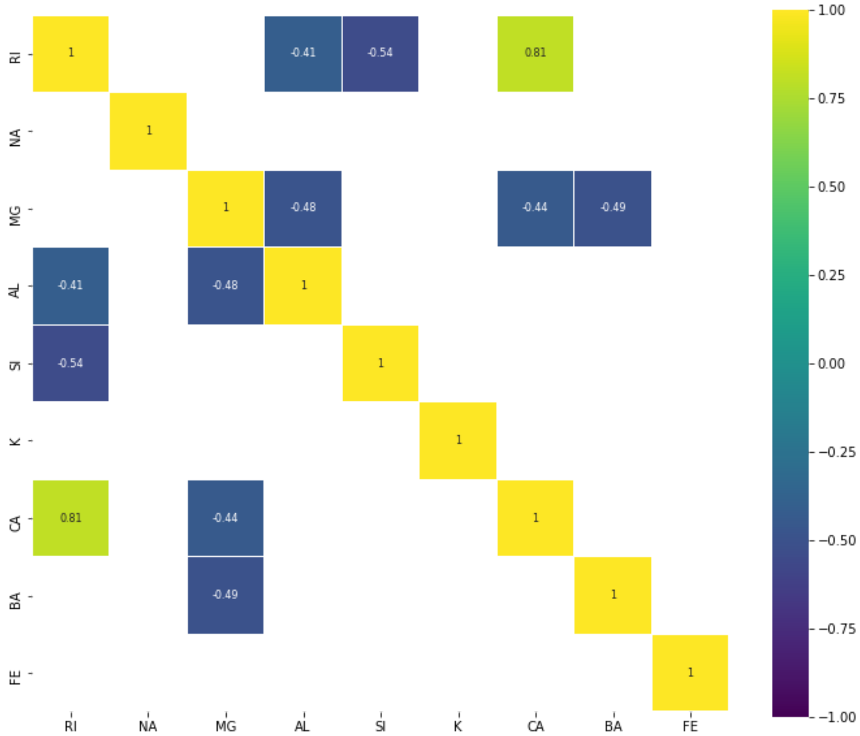
In [99]:

```
for i in range(0, len(dt.columns), 5):
    sns.pairplot(data=dt,
                 x_vars=dt.columns[i:i+5],
                 y_vars=['class'])
    plt.show()
```



In [100…

```
corr = dt.drop('class', axis=1).corr() # We already examined class correlations
plt.figure(figsize=(12, 10))
sns.heatmap(corr[(corr >= 0.5) | (corr <= -0.4)],
            cmap='viridis', vmax=1.0, vmin=-1.0, linewidths=0.1,
            annot=True, annot_kws={"size": 8}, square=True);
plt.show()
```



In [101…

```
dt.describe(percentiles=[0.5])
```

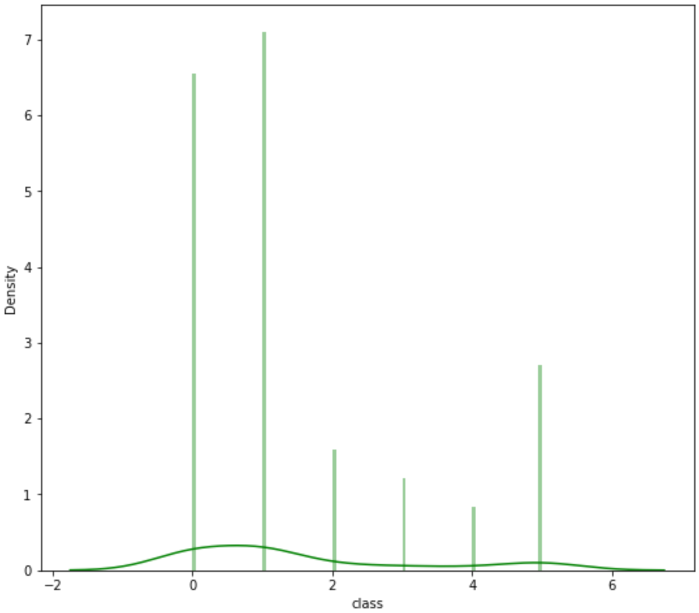
Out[101…

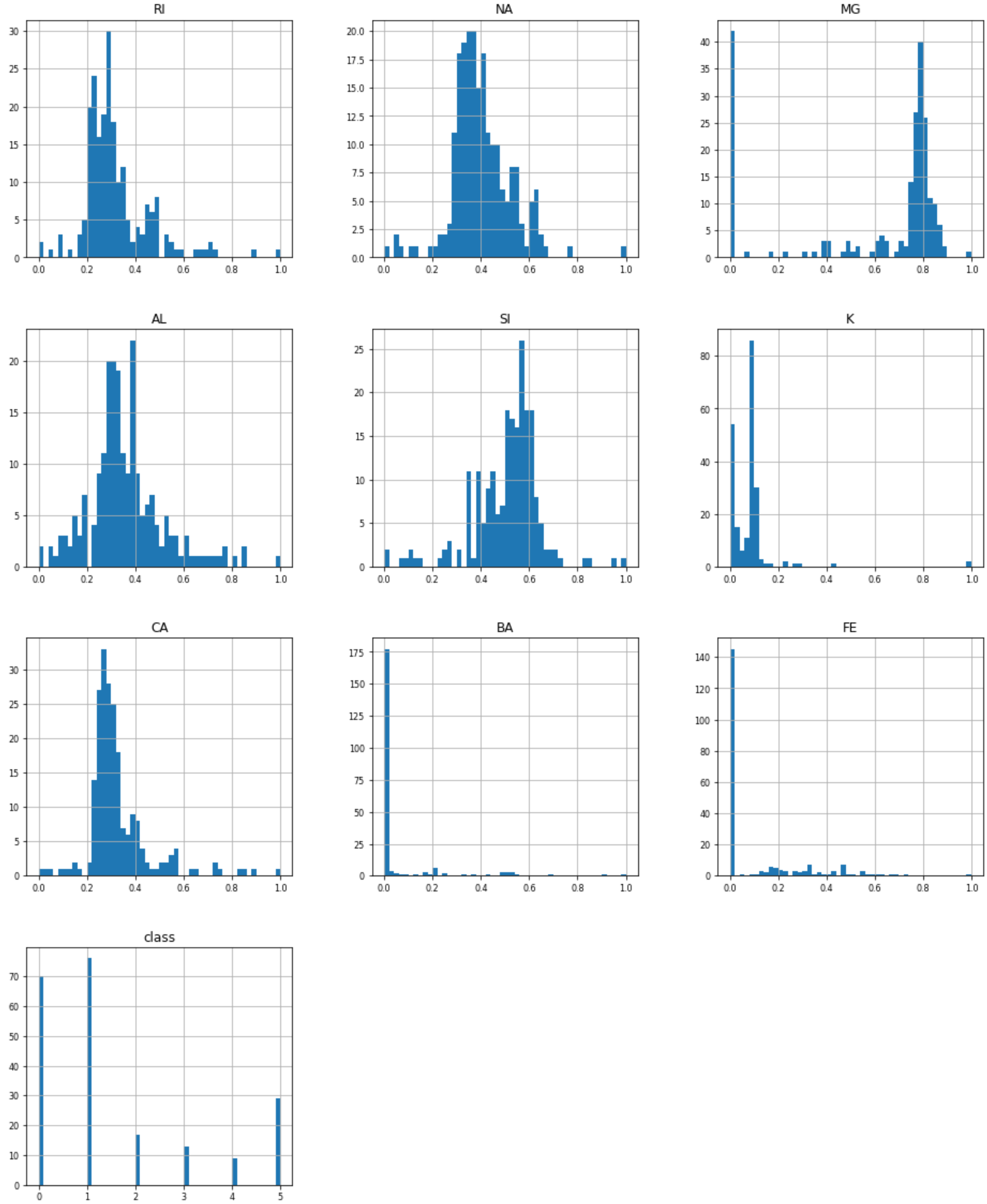
	RI	NA	MG	AL	SI	K	CA	BA	FE	class
count	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000	214.000000
mean	1.518365	13.407850	2.684533	1.444907	72.650935	0.497056	8.956963	0.175047	0.057009	1.542056
std	0.003037	0.816604	1.442408	0.499270	0.774546	0.652192	1.423153	0.497219	0.097439	1.707648
min	1.511150	10.730000	0.000000	0.290000	69.810000	0.000000	5.430000	0.000000	0.000000	0.000000
50%	1.517680	13.300000	3.480000	1.360000	72.790000	0.555000	8.600000	0.000000	0.000000	1.000000
max	1.533930	17.380000	4.490000	3.500000	75.410000	6.210000	16.190000	3.150000	0.510000	5.000000

In [102…

```
norm_min_max = lambda x: (x - np.min(x))/(np.max(x) - np.min(x))
dt = dt.copy()
dt.iloc[:,0:9] = dt.iloc[:,0:9].apply(norm_min_max, axis=0)
dt.describe(percentiles=[0.5])
plt.figure(figsize=(9, 8))
sns.distplot(dt['class'], color='g', bins=100, hist_kws={'alpha': 0.4});
plt.show()
dt.hist(figsize=(16, 20), bins=50, xlabelsize=8, ylabelsize=8);
plt.show()
```

```
c:\program files\python36\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplo
t` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```


Density
class
0
1
2
3
4
5
6
7
−2
0
2
4
6



In [103…

```
# A function which returns the corresponding SVC model
# Kernels: poly = 0, rbf = 1, sigmoid = 2, linear = 3
def getClassifier(ktype):
  # Polynomial kernal
  if ktype == 0 or ktype == 'poly':
    return svm.SVC(kernel='poly', degree=8, gamma="auto")
  # Radial Basis Function kernal
  elif ktype == 1 or ktype == 'rbf':
    return svm.SVC(kernel='rbf', gamma="auto")
  # Sigmoid kernal
  elif ktype == 2 or ktype == 'sigmoid':
    return svm.SVC(kernel='sigmoid', gamma="auto")
  # Linear kernal
  elif ktype == 3 or ktype == 'linear':
    return svm.SVC(kernel='linear', gamma="auto")

# SVM get Accuracy Score and Best Params
def getAccuracyScoreAndBestParams(x, y, kernel, svclassifier = None, test_size=0.2, random_state=40, verbose=1):
    # Separate data into test and training sets
    X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=test_size, random_state=random_state)
    # Set svclassifier
    if svclassifier == None:
        svclassifier = getClassifier(kernel)
    # Make prediction
    svclassifier.fit(X_train, y_train)
    # Evaluate our model
    y_pred = svclassifier.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
```

```
    param_grid = {
        'C': [0.1, 1, 10, 100, 1000],
        'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
        'kernel': [kernel]
    }
    grid = GridSearchCV(svm.SVC(), param_grid, refit=True, verbose=verbose)
    grid.fit(X_train, y_train)
    #be = grid.best_estimator_
    bp = grid.best_params_
    grid_predictions = grid.predict(X_test)
    print(f'Accuracy Score ({kernel}): {acc}')
    #print(f'Grid Best Estimator: {be}')
    print(f'Grid Best Params: {bp}')
    if verbose == 2:
        print(f'Confusion Matrix:\r\n{confusion_matrix(y_test, grid_predictions)}')
        print(f'Classification Report:\r\n{classification_report(y_test, grid_predictions)}')
    print()
    return {'acc': acc, 'bp': bp}

# Role that trains the model
def smv_model_run_kernel(kernel, x_train, y_train, C=1.0, gamma='scale'):
    # Definindo o modo de funcionamento do modelo
    model = svm.SVC(
        kernel=kernel, # Kernels possíveis: linear, poly, rbf, sigmoid, precomputed
        C=C, # Termo de regularização
        gamma=gamma
    )
    # Inserindo os dados de treinamento no modelo
    model.fit(x_train, y_train)
    return model

# Remove empty data
dt = dt.dropna()

# Y contains only classes (target)
y = dt['class']

# X contains only attributes
X = dt.drop('class', 1)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=40)

# Removing columns
x_test_cor = X_test.drop(columns=['AL','BA', 'NA', 'MG'])

# Selecting the best hyperparameters
sel_poly = getAccuracyScoreAndBestParams(X, y, 'poly')['bp']
sel_rbf = getAccuracyScoreAndBestParams(X, y, 'rbf')['bp']
sel_sigmoid = getAccuracyScoreAndBestParams(X, y, 'sigmoid')['bp']
sel_linear = getAccuracyScoreAndBestParams(X, y, 'linear')['bp']

rskf = RepeatedStratifiedKFold(n_splits=10, n_repeats=5)

scores_train = [[], [], [], []]
scores_val = [[], [], [], []]

scores_train_cor = [[], [], [], []]
scores_val_cor = [[], [], [], []]

for train_index, test_index in rskf.split(X_train, y_train):
    X_train_k, X_test_k = X_train.iloc[train_index], X_train.iloc[test_index]
    y_train_k, y_test_k = y_train.iloc[train_index], y_train.iloc[test_index]

    x_train_k_cor, x_test_k_cor = X_train_k.drop(columns=['AL','BA', 'NA', 'MG']), X_test_k.drop(columns=['AL','BA', 'NA', 'MG'])

    # Model training with hyperparameter adjustment - Using (X_train_k, y_train_k)
    model_poly = smv_model_run_kernel('poly', X_train_k, y_train_k, C=sel_poly['C'], gamma=sel_poly['gamma'])
    model_rbf = smv_model_run_kernel('rbf', X_train_k, y_train_k, C=sel_rbf['C'], gamma=sel_rbf['gamma'])
    model_sigmoid = smv_model_run_kernel('sigmoid', X_train_k, y_train_k, C=sel_sigmoid['C'], gamma=sel_sigmoid['gamma'])
    model_linear = smv_model_run_kernel('linear', X_train_k, y_train_k, C=sel_linear['C'], gamma=sel_linear['gamma'])

    # Model training with hyperparameter adjustment - Using (x_train_k_cor, y_train_k)
    model_poly_cor = smv_model_run_kernel('poly', x_train_k_cor, y_train_k, C=sel_poly['C'], gamma=sel_poly['gamma'])
    model_rbf_cor = smv_model_run_kernel('rbf', x_train_k_cor, y_train_k, C=sel_rbf['C'], gamma=sel_rbf['gamma'])
    model_sigmoid_cor = smv_model_run_kernel('sigmoid', x_train_k_cor, y_train_k, C=sel_sigmoid['C'], gamma=sel_sigmoid['gamma'])
    model_linear_cor = smv_model_run_kernel('linear', x_train_k_cor, y_train_k, C=sel_linear['C'], gamma=sel_linear['gamma'])

    # Assessing accuracy and storing each model's score
    scores_train[0].append(model_poly.score(X_train_k, y_train_k))
    scores_train[1].append(model_rbf.score(X_train_k, y_train_k))
    scores_train[2].append(model_sigmoid.score(X_train_k, y_train_k))
    scores_train[3].append(model_linear.score(X_train_k, y_train_k))

    scores_train_cor[0].append(model_poly_cor.score(x_train_k_cor, y_train_k))
    scores_train_cor[1].append(model_rbf_cor.score(x_train_k_cor, y_train_k))
    scores_train_cor[2].append(model_sigmoid_cor.score(x_train_k_cor, y_train_k))
    scores_train_cor[3].append(model_linear_cor.score(x_train_k_cor, y_train_k))

    scores_val[0].append(model_poly.score(X_test_k, y_test_k))
    scores_val[1].append(model_rbf.score(X_test_k, y_test_k))
    scores_val[2].append(model_sigmoid.score(X_test_k, y_test_k))
    scores_val[3].append(model_linear.score(X_test_k, y_test_k))

    scores_val_cor[0].append(model_poly_cor.score(x_test_k_cor, y_test_k))
    scores_val_cor[1].append(model_rbf_cor.score(x_test_k_cor, y_test_k))
    scores_val_cor[2].append(model_sigmoid_cor.score(x_test_k_cor, y_test_k))
    scores_val_cor[3].append(model_linear_cor.score(x_test_k_cor, y_test_k))

kernels = ["poly", "rbf", "sigmoid", "linear"]
models = [model_poly, model_rbf, model_sigmoid, model_linear]
```

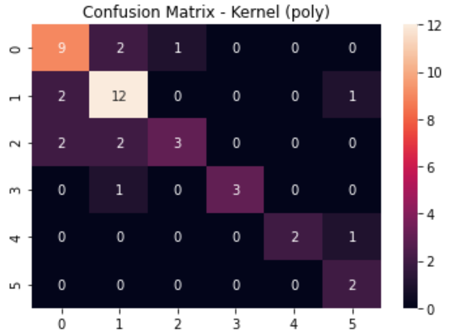
```python
def print_mean_acc(kernel, scores_train, scores_val, scores_train_cor, scores_val_cor):
    kernel = kernel.upper()
    print("Média de acurácia para kernel", kernel)
    print("Treino: ", np.mean(scores_train))
    print("Validação: ", np.mean(scores_val))
    print()
    print("Média de acurácia para kernel", kernel, "(sem atributos correlacionados)")
    print("Treino: ", np.mean(scores_train_cor))
    print("Validação: ", np.mean(scores_val_cor))
    print()

print("-" * 100)
print("Acurácia do conjunto de treinamento: ")
print("-" * 100)
for i in range(4):
    print_mean_acc(
        kernels[i],
        scores_train[i],
        scores_val[i],
        scores_train_cor[i],
        scores_val_cor[i]
    )


print("-" * 100)
print("Acurácia do conjunto de testes: ")
print("-" * 100)
print("Kernel POLY")
print("Score:", model_poly.score(X_test, y_test))
print("Score (sem atributos correlacionados):", model_poly_cor.score(x_test_cor, y_test))
print()
print("Kernel RBF")
print("Score:", model_rbf.score(X_test, y_test))
print("Score (sem atributos correlacionados):", model_rbf_cor.score(x_test_cor, y_test))
print()
print("Kernel SIGMOID")
print("Score:", model_sigmoid.score(X_test, y_test))
print("Score (sem atributos correlacionados):", model_sigmoid_cor.score(x_test_cor, y_test))
print()
print("Kernel LINEAR")
print("Score:", model_linear.score(X_test, y_test))
print("Score (sem atributos correlacionados):", model_linear_cor.score(x_test_cor, y_test))
print()

i = 0
for kernel in kernels:
  ax = plt.subplot()
  ax.set_title(f"Confusion Matrix - Kernel ({kernel})")
  predict_results = models[i].predict(X_test)
  cm = confusion_matrix(predict_results, y_test)
  sns.heatmap(cm, annot=True, ax=ax)
  plt.show()
  i += 1
```

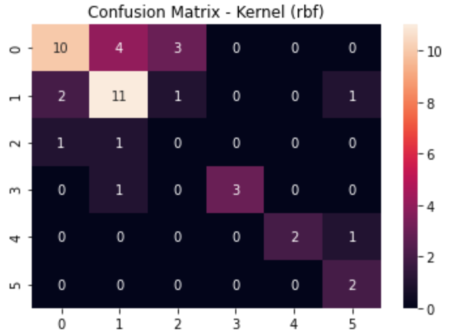
```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
Accuracy Score (poly): 0.3953488372093023
Grid Best Params: {'C': 1000, 'gamma': 1, 'kernel': 'poly'}

Fitting 5 folds for each of 25 candidates, totalling 125 fits
Accuracy Score (rbf): 0.5116279069767442
Grid Best Params: {'C': 100, 'gamma': 1, 'kernel': 'rbf'}

Fitting 5 folds for each of 25 candidates, totalling 125 fits
Accuracy Score (sigmoid): 0.4418604651162791
Grid Best Params: {'C': 1000, 'gamma': 0.1, 'kernel': 'sigmoid'}

Fitting 5 folds for each of 25 candidates, totalling 125 fits
Accuracy Score (linear): 0.4883720930232558
Grid Best Params: {'C': 100, 'gamma': 1, 'kernel': 'linear'}
```

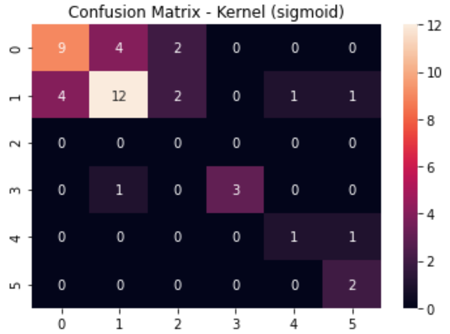
```
c:\program files\python36\lib\site-packages\sklearn\model_selection\_split.py:668: UserWarning: The least populated class in y has only 7
members, which is less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)
c:\program files\python36\lib\site-packages\sklearn\model_selection\_split.py:668: UserWarning: The least populated class in y has only 7
members, which is less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)
c:\program files\python36\lib\site-packages\sklearn\model_selection\_split.py:668: UserWarning: The least populated class in y has only 7
members, which is less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)
c:\program files\python36\lib\site-packages\sklearn\model_selection\_split.py:668: UserWarning: The least populated class in y has only 7
members, which is less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)
c:\program files\python36\lib\site-packages\sklearn\model_selection\_split.py:668: UserWarning: The least populated class in y has only 7
members, which is less than n_splits=10.
  % (min_groups, self.n_splits)), UserWarning)
```

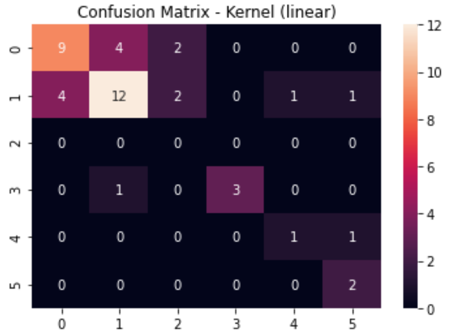
```
----------------------------------------------------------------------------------------------------
Acurácia do conjunto de treinamento: 
----------------------------------------------------------------------------------------------------
Média de acurácia para kernel POLY
Treino:  0.9481478652066886
Validação:  0.720392156862745

Média de acurácia para kernel POLY (sem atributos correlacionados)
Treino:  0.7966148883795942
Validação:  0.6233986928104575

Média de acurácia para kernel RBF
Treino:  0.8831686614039553
Validação:  0.6983006535947712

Média de acurácia para kernel RBF (sem atributos correlacionados)
Treino:  0.7733587980646806
```

```
Validação:  0.6256209150326797

Média de acurácia para kernel SIGMOID
Treino:  0.7372302860538152
Validação:  0.6419607843137256

Média de acurácia para kernel SIGMOID (sem atributos correlacionados)
Treino:  0.6010440539852304
Validação:  0.5591503267973857

Média de acurácia para kernel LINEAR
Treino:  0.7467184449537392
Validação:  0.6513071895424838

Média de acurácia para kernel LINEAR (sem atributos correlacionados)
Treino:  0.610398947457771
Validação:  0.5696732026143791

-----------------------------------------------------------------------------------------------------
Acurácia do conjunto de testes:
-----------------------------------------------------------------------------------------------------
Kernel POLY
Score: 0.7209302325581395
Score (sem atributos correlacionados): 0.6046511627906976

Kernel RBF
Score: 0.6511627906976745
Score (sem atributos correlacionados): 0.6511627906976745

Kernel SIGMOID
Score: 0.627906976744186
Score (sem atributos correlacionados): 0.4883720930232558

Kernel LINEAR
Score: 0.627906976744186
Score (sem atributos correlacionados): 0.4883720930232558
```





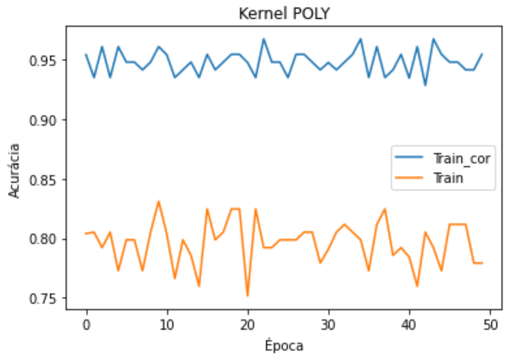




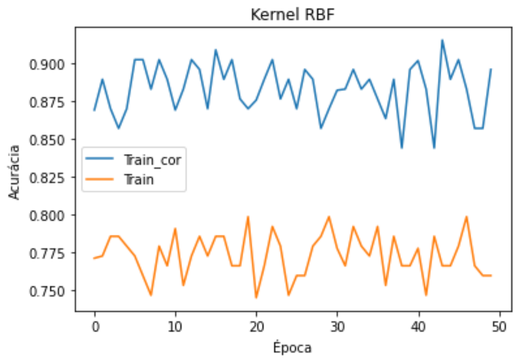
In [104…

```
for i in range(4):
    print_mean_acc(
        kernels[i],
        scores_train[i],
        scores_val[i],
        scores_train_cor[i],
        scores_val_cor[i]
    )
    plt.plot(range(50), scores_train[i], label = "Train_cor")
    plt.plot(range(50), scores_train_cor[i], label = "Train")
    plt.xlabel('Época')
    # Set the y axis label of the current axis.
    plt.ylabel('Acurácia')
    # Set a title of the current axes.
    plt.title("Kernel " + kernels[i].upper())
    plt.legend()
    # Display a figure.
    plt.show()
```

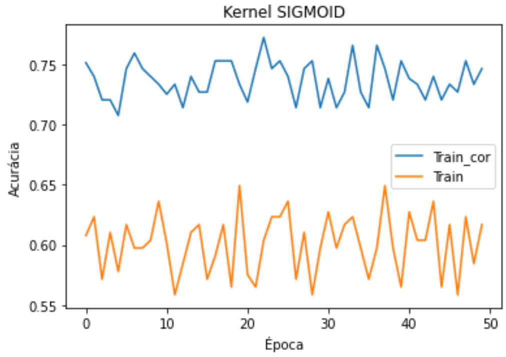
```
Média de acurácia para kernel POLY
Treino:  0.9481478652066886
Validação:  0.720392156862745

Média de acurácia para kernel POLY (sem atributos correlacionados)
Treino:  0.7966148883795942
Validação:  0.6233986928104575
```



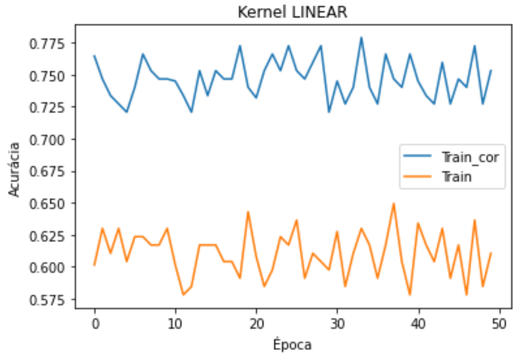

```
Média de acurácia para kernel RBF
Treino:  0.8831686614039553
Validação:  0.6983006535947712

Média de acurácia para kernel RBF (sem atributos correlacionados)
Treino:  0.7733587980646806
Validação:  0.6256209150326797
```




```
Média de acurácia para kernel SIGMOID
Treino:  0.7372302860538152
Validação:  0.6419607843137256

Média de acurácia para kernel SIGMOID (sem atributos correlacionados)
Treino:  0.6010440539852304
Validação:  0.5591503267973857
```

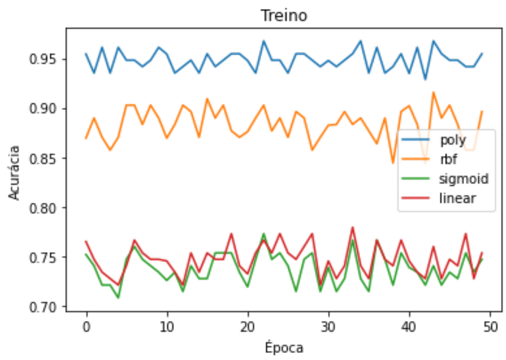


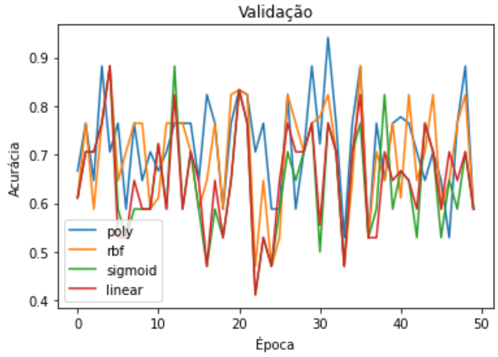

```
Média de acurácia para kernel LINEAR
Treino:  0.7467184449537392
Validação:  0.6513071895424838

Média de acurácia para kernel LINEAR (sem atributos correlacionados)
Treino:  0.610398947457771
Validação:  0.5696732026143791
```



In [105…

```
plt.plot(range(50), scores_train[0], label = "poly")
plt.plot(range(50), scores_train[1], label = "rbf")
plt.plot(range(50), scores_train[2], label = "sigmoid")
plt.plot(range(50), scores_train[3], label = "linear")

plt.xlabel('Época')
# Set the y axis label of the current axis.
plt.ylabel('Acurácia')
# Set a title of the current axes.
plt.title("Treino")
plt.legend()
# Display a figure.
plt.show()

plt.plot(range(50), scores_val[0], label = "poly")
plt.plot(range(50), scores_val[1], label = "rbf")
plt.plot(range(50), scores_val[2], label = "sigmoid")
plt.plot(range(50), scores_val[3], label = "linear")

plt.xlabel('Época')
# Set the y axis label of the current axis.
plt.ylabel('Acurácia')
# Set a title of the current axes.
plt.title("Validação")
plt.legend()
# Display a figure.
plt.show()

print("END OF CODE")
```




Validação
Acurácia
Época
poly
rbf
sigmoid
linear
0.9
0.8
0.7
0.6
0.5
0.4
0
10
20
30
40
50

```
END OF CODE
```