Experimentaci?n Segment

January 10, 2019

Todo el proceso de experimentar con el dataset segment

```
In [1]: from demo_utils.demo0 import Demo0
        from demo_utils.demo3 import Demo3
        from sklearn.model_selection import GridSearchCV
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.linear_model import LogisticRegression
        from sklearn.svm import LinearSVC
        from demo_utils.general import get_data
        import warnings
        d = Demo0()
        testing_dataset = 'segment'
        run_mode = False
```

```
In [2]: warnings.filterwarnings('ignore')
        # warnings.filterwarnings('once')
        #warnings.filterwarnings(action='once')
```

1 Con los modelos simples

Ver cómo se comportan los modelos simples con este dataset

Habría que encontrar los mejores hiper-parámetros para cada uno de ellos

Los híper-parámetros que tienen son:

Decision Tree: - max_depth - min_samples_split - min_samples_leaf - min_weight_fraction_leaf - max_leaf_nodes - min_impurity_decrease

Logit: - C

Linear SVM: - C

1.0.1 HíperParámetros con DecisionTree

```
In [4]: if run_mode:
            tuned_parameters = [{
                'max_depth': [10, 100, 1000, 10000, 100000, None],
                'min_samples_split': [2, 3, 4, 5, 6, 7, 8, 9],
                'min_samples_leaf': [1, 2, 3, 4],
                'min_weight_fraction_leaf': [.0, .1, .3],
                'max_leaf_nodes': [10, 50, 100, 1000, None],
```

```
        'min_impurity_decrease': [.0, .2, .6],
    }]
    clf = GridSearchCV(DecisionTreeClassifier(), tuned_parameters, cv=10)
    data = get_data(testing_dataset)
    data_train = data['data_train']
    data_test = data['data_test']
    target_train = data['target_train']
    target_test = data['target_test']

    clf.fit(data_train, target_train)
    dt_best_params = clf.best_params_
    print('DecisionTree best params.')
    print(dt_best_params)
```

- **max_depth**: 100
- **max_leaf_nodes**: 1000
- **min_impurity_decrease**: 0.0
- **min_samples_leaf**: 1
- **min_samples_split**: 3
- **min_weight_fraction_leaf**: 0.0

1.0.2 HíperParámetros con Logit

```
In [5]: if run_mode:
    tuned_parameters = [{
        'C': [.1, .5, 1, 5, 10, 100, 500, 1000, 10000, 1000000],
    }]
    clf = GridSearchCV(LogisticRegression(multi_class='multinomial', solver='lbfgs'),
                       tuned_parameters, cv=10, iid=False)
    data = get_data(testing_dataset)
    data_train = data['data_train']
    data_test = data['data_test']
    target_train = data['target_train']
    target_test = data['target_test']

    clf.fit(data_train, target_train)
    print('LogisticRegression best params.')
    logit_best_params = clf.best_params_
    print(logit_best_params)
```

- **C**: 1000

(Tener en cuenta que da un convergence warning, que aquí se ignora)

1.0.3 HíperParámetros con LinearSVC

```
In [6]: if run_mode:
    tuned_parameters = [{
        'C': [.1, .5, 1, 5, 10, 100],
```

```
}]
clf = GridSearchCV(LinearSVC(), tuned_parameters, cv=10, iid=False)
data = get_data(testing_dataset)
data_train = data['data_train']
data_test = data['data_test']
target_train = data['target_train']
target_test = data['target_test']

clf.fit(data_train, target_train)
print('LinearSVC best params.')
linear_svc_best_params = clf.best_params_
print(linear_svc_best_params)
```

- **C**: 5

In [7]:
```
if not run_mode:
    # Para no tener que ejecutar el CV otra vez
    dt_best_params = {
        'max_depth': 100,
        'max_leaf_nodes': 1000,
        'min_impurity_decrease': 0.0,
        'min_samples_leaf': 1,
        'min_samples_split': 3,
        'min_weight_fraction_leaf': 0.0
    }
    logit_best_params = {'C': 1000}
    linear_svc_best_params = {'C': 5}
```

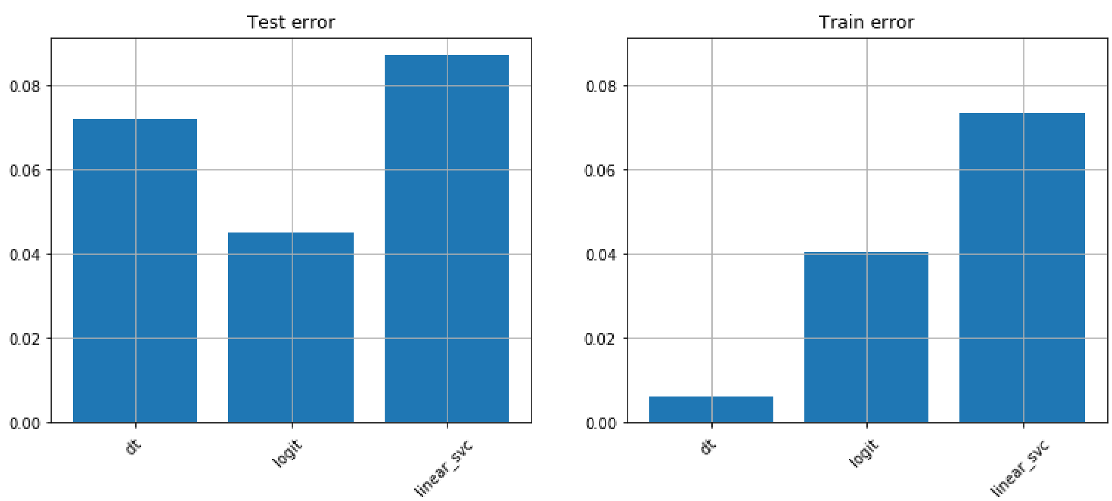
In [8]:
```
data = {
    'dts_name': testing_dataset,
    'dts_size': 1000,
    'features_range': (30, 100),
    'rbfsampler_gamma': 0.2,
    'nystroem_gamma': 0.2,
    'hparams': {
        'dt': dt_best_params,
        'logit': logit_best_params,
        'linearsvc': linear_svc_best_params,
    },
    'models': [
        {'model_name': 'dt',
         'sampler_name': 'identity',
         'box_type': 'none',
         'n_estim': None,
         'pca': False,
         'pca_first': False
        },
        {'model_name': 'logit',
```

```
                 'sampler_name': 'identity',
                 'box_type': 'none',
                 'n_estim': None,
                 'pca': False,
                 'pca_first': False
                },
                {'model_name': 'linear_svc',
                 'sampler_name': 'identity',
                 'box_type': 'none',
                 'n_estim': None,
                 'pca': False,
                 'pca_first': False
                }
            ]
        }
```

```
In [9]: d.non_interactive(**data)
```

2 Demo genérica

- Dataset: **segment**
- Size: **1000**



Como ya tienen un comportamiento muy bueno, no usaremos para nada PCA

2.1 Sampler con los modelos simples

```
In [10]: feature_range = (30, 800)
```

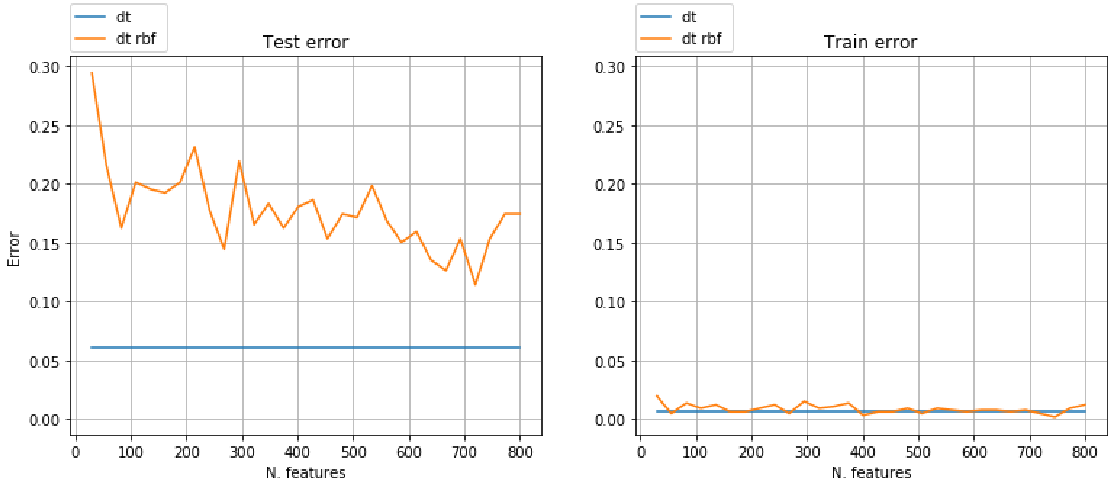
DT

```
In [11]: data = {
             'dts_name': testing_dataset,
             'dts_size': 1000,
             'features_range': feature_range,
             'rbfsampler_gamma': 0.2,
             'nystroem_gamma': 0.2,
             'hparams': {
                 'dt': {
                     'max_depth': 100,
                     'min_samples_split': 3,
                     'min_samples_leaf': 1,
                     'min_weight_fraction_leaf': 0.0,
                     'max_leaf_nodes': 1000,
                     'min_impurity_decrease': 0.0
                 },
                 'logit': {'C': 1000},
                 'linearsvc': {'C': 5}
             },
             'models': [
                 {'model_name': 'dt',
                  'sampler_name': 'identity',
                  'box_type': 'none',
                  'n_estim': None,
                  'pca': False,
                  'pca_first': False
                 },
                 {'model_name': 'dt',
                  'sampler_name': 'rbf',
                  'box_type': 'none',
                  'n_estim': None,
                  'pca': False,
                  'pca_first': False
                 }
             ]
         }
```

```
In [12]: d.non_interactive(**data)
```

3 Demo genérica

- Dataset: **segment**
- Size: **1000**



Logit

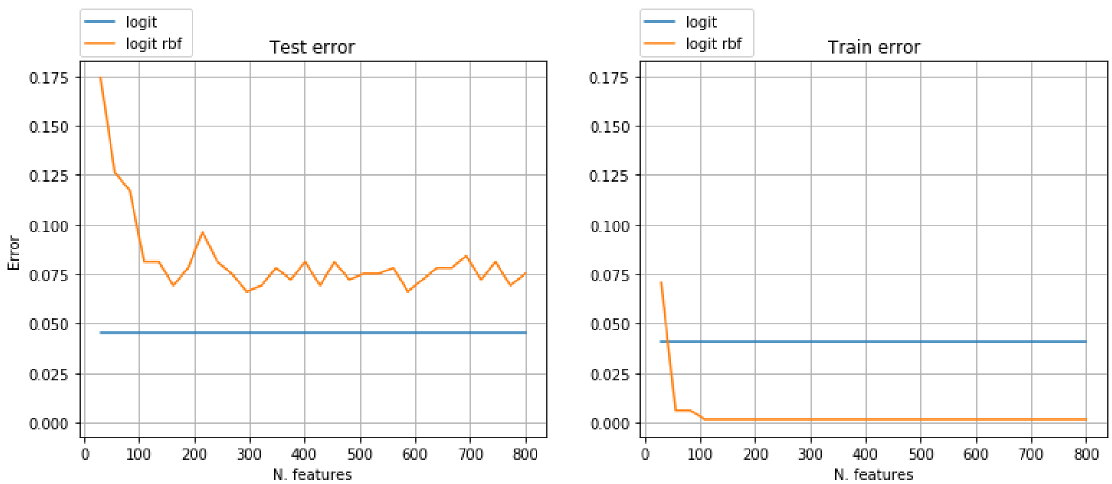
```
In [13]: data = {
             'dts_name': testing_dataset,
             'dts_size': 1000,
             'features_range': feature_range,
             'rbfsampler_gamma': 0.2,
             'nystroem_gamma': 0.2,
             'hparams': {
                 'dt': {
                     'max_depth': 100,
                     'min_samples_split': 3,
                     'min_samples_leaf': 1,
                     'min_weight_fraction_leaf': 0.0,
                     'max_leaf_nodes': 1000,
                     'min_impurity_decrease': 0.0
                 },
                 'logit': {'C': 1000},
                 'linearsvc': {'C': 5}
             },
             'models': [
                 {'model_name': 'logit',
                  'sampler_name': 'identity',
                  'box_type': 'none',
                  'n_estim': None,
                  'pca': False,
                  'pca_first': False
                 },
                 {'model_name': 'logit',
                  'sampler_name': 'rbf',
```

```
                  'box_type': 'none',
                  'n_estim': None,
                  'pca': False,
                  'pca_first': False
                 }
             ]
         }
```

```
In [14]: d.non_interactive(**data)
```

4 Demo genérica

- Dataset: **segment**
- Size: **1000**



LinearSVC

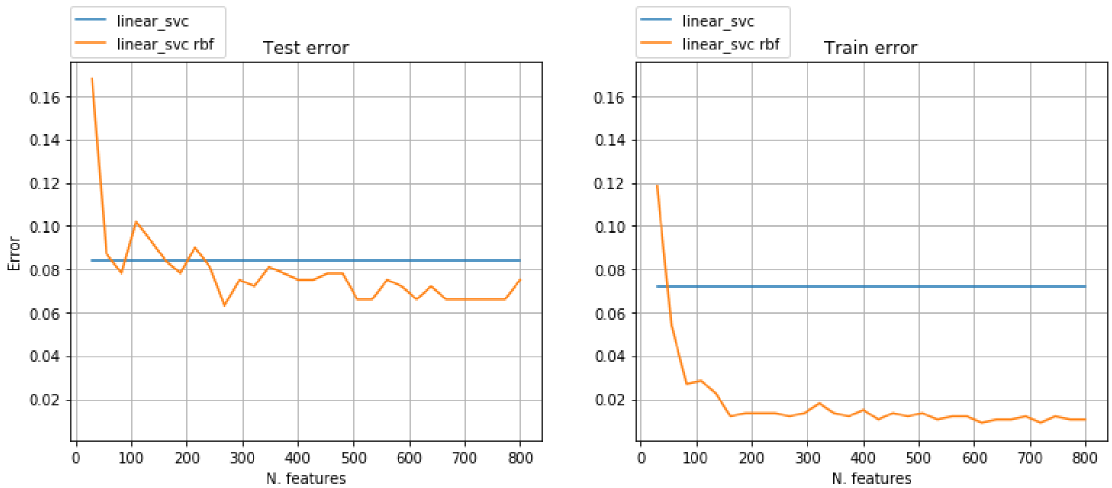
```
In [15]: data = {
             'dts_name': testing_dataset,
             'dts_size': 1000,
             'features_range': feature_range,
             'rbfsampler_gamma': 0.2,
             'nystroem_gamma': 0.2,
             'hparams': {
                 'dt': {
                     'max_depth': 100,
                     'min_samples_split': 3,
                     'min_samples_leaf': 1,
                     'min_weight_fraction_leaf': 0.0,
                     'max_leaf_nodes': 1000,
```

```
                'min_impurity_decrease': 0.0
            },
            'logit': {'C': 1000},
            'linearsvc': {'C': 5}
        },
        'models': [
            {'model_name': 'linear_svc',
             'sampler_name': 'identity',
             'box_type': 'none',
             'n_estim': None,
             'pca': False,
             'pca_first': False
            },
            {'model_name': 'linear_svc',
             'sampler_name': 'rbf',
             'box_type': 'none',
             'n_estim': None,
             'pca': False,
             'pca_first': False
            }
        ]
    }
```

```
In [16]: d.non_interactive(**data)
```

5 Demo genérica

- Dataset: **segment**
- Size: **1000**



Podemos observar comportamientos distintos con cada uno de los modelos simples: - DT parece que se beneficia de incrementar la cantidad de features, pero muy lentamente - Logit mejora muy rápidamente hasta cierto punto, donde se estanca. El error que obtiene es mayor que logit normal - LinearSVM mejora rápidamente hasta que se estanca, y saca un accuracy mejor que LinearSVM normal

5.1 £Qué gamma usar?

DT

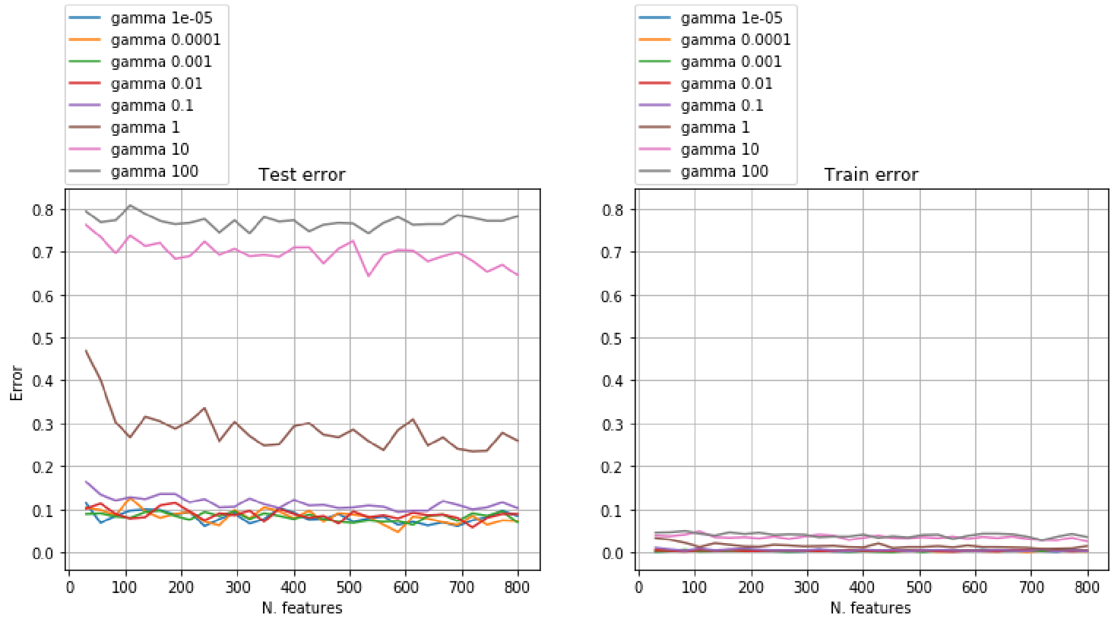
```
In [17]: d3 = Demo3()
```

```
In [19]: data = {
             'dts_name': testing_dataset,
             'model_data':
                 {'model_name': 'dt',
                  'sampler_name': 'rbf',
                  'pca_bool': False,
                  'n_estim': None,
                  'box_type': 'none'
                 },
             'hparams': {
                 'dt': dt_best_params,
                 'logit': logit_best_params,
                 'linearsvc': linear_svc_best_params,
             },
             'features_range': (30, 800)
         }
```

```
In [20]: d3.non_interactive(**data)
```

6 Diferencias entre los valores de gamma

- Model: **dt**
- Sampler: **rbf**
- Bagging: **none**
- N. estim.: **None**
- PCA: **False**



En general, cuanto más pequeña la gamma, mejor
Un valor de **gamma** = 0.001 ya es óptimo

Logit

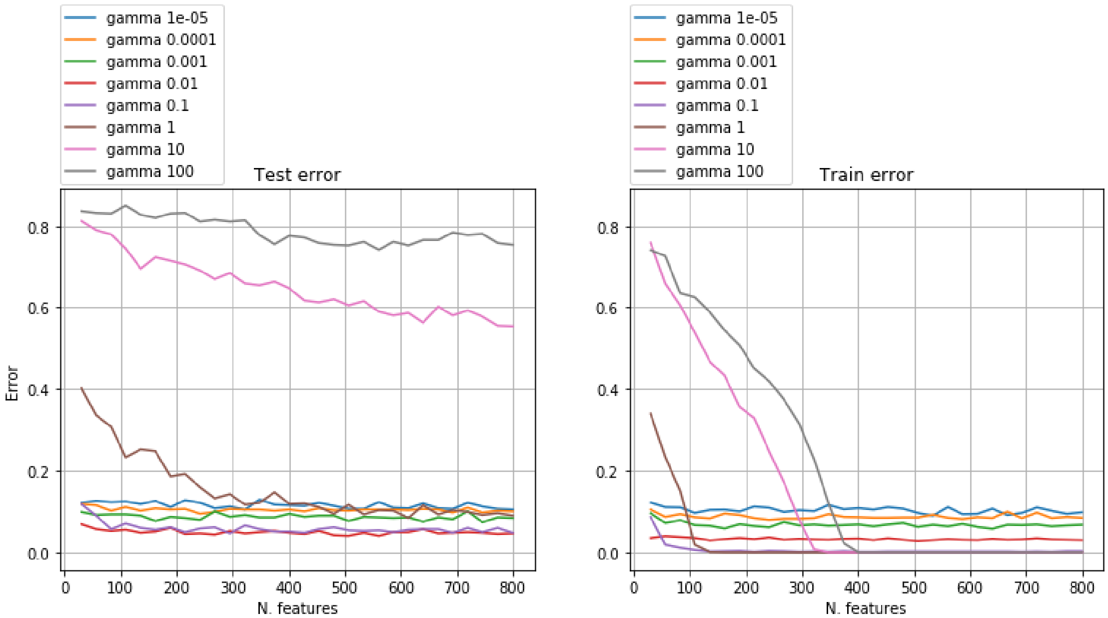
```
In [21]: data = {
             'dts_name': testing_dataset,
             'model_data':
                 {'model_name': 'logit',
                  'sampler_name': 'rbf',
                  'pca_bool': False,
                  'n_estim': None,
                  'box_type': 'none'
                 },
             'hparams': {
                 'dt': dt_best_params,
                 'logit': logit_best_params,
                 'linearsvc': linear_svc_best_params,
             },
             'features_range': (30, 800)
         }
```

```
In [22]: d3.non_interactive(**data)
```

7 Diferencias entre los valores de gamma

- Model: **logit**

- Sampler: **rbf**
- Bagging: **none**
- N. estim.: **None**
- PCA: **False**



Una valor de **gamma** = 0.01 parece ideal

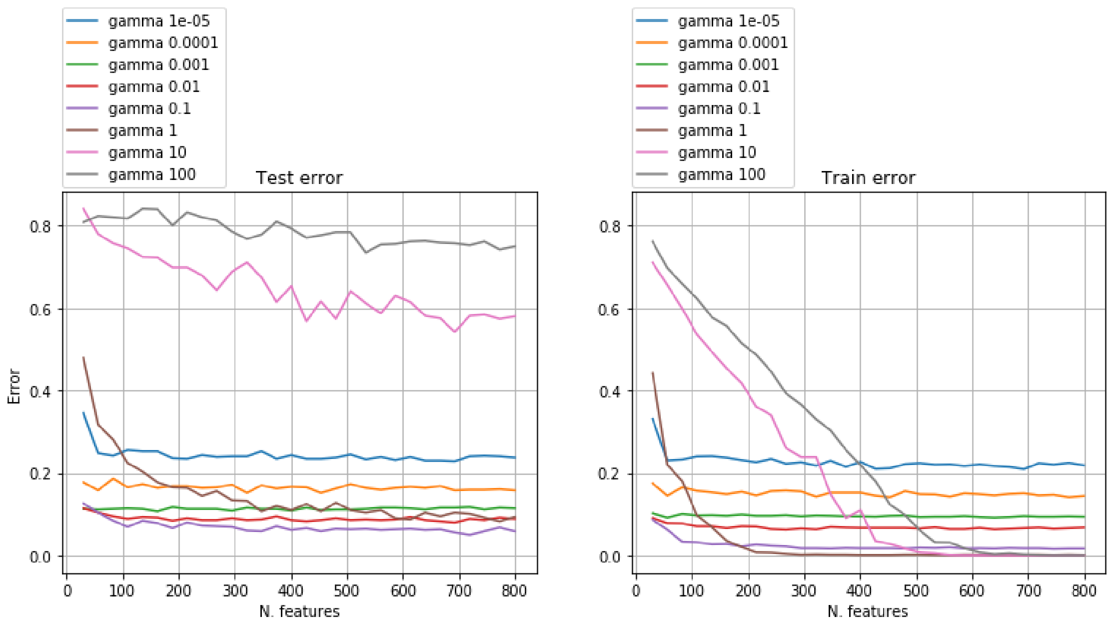
LinearSVC

```
In [23]: data = {
             'dts_name': testing_dataset,
             'model_data':
                 {'model_name': 'linear_svc',
                  'sampler_name': 'rbf',
                  'pca_bool': False,
                  'n_estim': None,
                  'box_type': 'none'
                 },
             'hparams': {
                 'dt': dt_best_params,
                 'logit': logit_best_params,
                 'linearsvc': linear_svc_best_params,
             },
             'features_range': (30, 800)
         }
```

```
In [24]: d3.non_interactive(**data)
```

8 Diferencias entre los valores de gamma

- Model: **linear_svc**
- Sampler: **rbf**
- Bagging: **none**
- N. estim.: **None**
- PCA: **False**



Una valor de **gamma** = 0.1 parece ideal