

Centralizando com HTML

EFC 3

html inicio

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fim html

Parte I - Devivação

Z = Camada intermediária da rede.

$out Z$ = Saída da camada Z (de acordo com a função de ativação).

$inp Z$ = Entrada da camada Z (amostras de entrada).

\hat{y} = Ground true

De forma geral temos a seguinte derivação para a retropropagação do erro para qualquer v_n .

$$\frac{\partial J}{\partial v_n} = \frac{\partial J}{\partial out Z} \frac{\partial out Z}{\partial inp Z} \frac{\partial inp Z}{\partial v_n}$$

No caso específico para v_{12} temos:

$$\frac{\partial J}{\partial v_{12}} = \frac{\partial J}{\partial out Z} \frac{\partial out Z}{\partial inp Z} \frac{\partial inp Z}{\partial v_{12}}$$

Realizando as derivadas expostas acima:

$$\frac{\partial J}{\partial out Z} = \sum_{n=1}^N (\hat{y} - y) w_n$$

$$\frac{\partial out Z}{\partial inp Z} = f(.)$$

$$\frac{\partial inp Z}{\partial v_n} = x_n$$

Então para v_{12} :

$$\frac{\partial J}{\partial out Z} = (\hat{y}_1 - y_1) w_{30} + (\hat{y}_2 - y_2) w_{31}$$

$$\frac{\partial out Z}{\partial inp Z} = f(.)$$

$$\frac{\partial inp Z}{\partial v_{12}} = x_1$$

Finalmente:

$$\frac{\partial J}{\partial v_{12}} = ((\hat{y}_1 - y_1) w_{30} + (\hat{y}_2 - y_2) w_{31}) \times f(.) \times x_1$$

Parte II – Classificação binária com redes MLP e SVMs

Utilizando MLP, testou-se dois métodos de estimação: batch e online, dentre eles, pode-se observar que a melhor acurácia e também, convergiu mais rapidamente, em comparação ao batch, ocorreu quando usou-se o método de estimação batch, com as configurações:

- Épocas = 200.
- Camada oculta com 50 neurônios, com função de ativação ReLU.
- Entropia cruzada para a função custo.
- Os parâmetros foram calculados utilizando o método Adam.

Onde observou-se que o melhor resultado foi 86% de acurácia nos testes, utilizando a validação cruzada nos testes de validação, foram testados os valores 5, 10, 15, 30, 50 para a camada oculta, a que apresentou o melhor resultado foi a rede com 50 neurônios, resultado esse, pouco melhor do que quando utilizado o valor de 30 neurônios para a camada oculta, o resultado pode ser visto na figura 1.

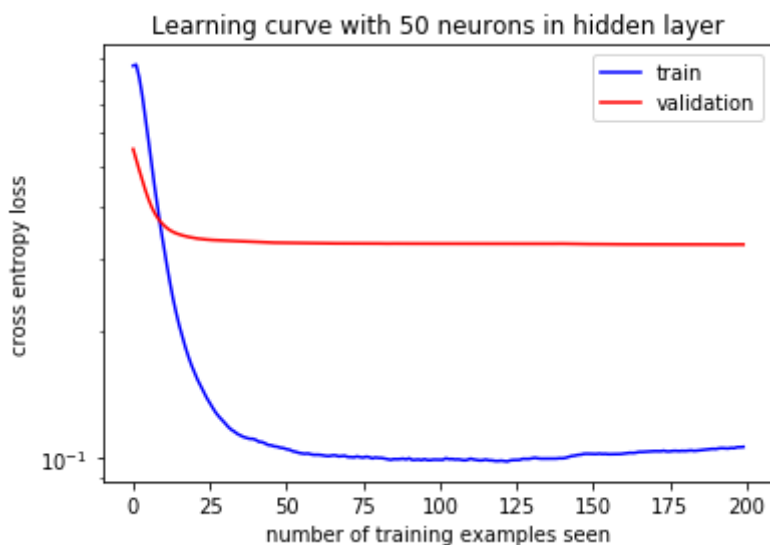


Figura 1: Curva de aprendizado.

Na figura 3, é possível analisar melhor as regiões de decisão e as classes de cada amostra, bastante parecida com a figura mostrada no enunciado utilizando o estimador MAP

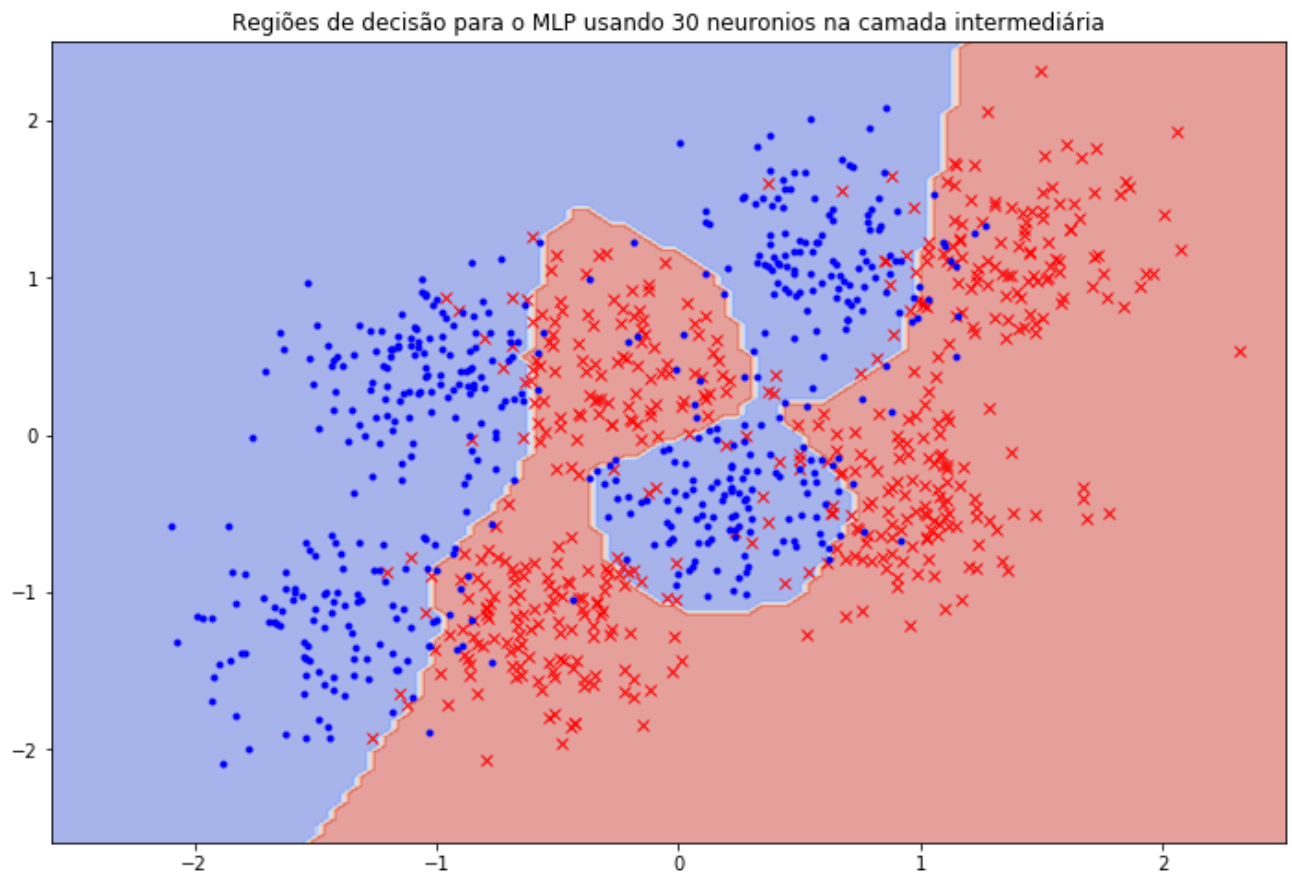
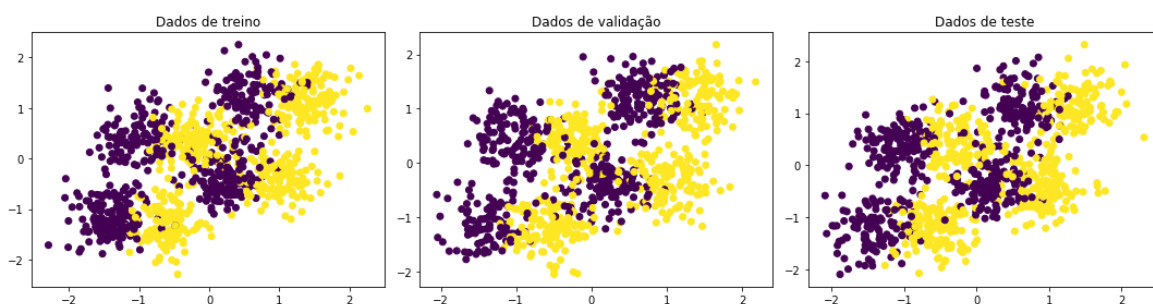


Figura 2: Regiões de decisão e classes

SVM - foi utilizada a biblioteca `sklearn.svm` para as máquinas de vetores de suporte, os hiperparâmetros foram escolhidos com validação cruzada, igual feito no MLP. O melhor resultado obtido com nos testes foi com o kernel RBF e taxa de penalidade do erro = 50, a melhor acurácia foi de 0.867, o gráfico plotado pode ser visto na figura 3



Aplicando a MLP

usando batch

Out[197]:

```
MLPClassifier(activation='relu', alpha=0.0001, batch_size=36, beta_1=0.9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
              hidden_layer_sizes=(100,), learning_rate='constant',
              learning_rate_init=0.0001, max_iter=1000, momentum=0.9,
              n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
              random_state=1, shuffle=True, solver='adam', tol=0.0001,
              validation_fraction=0.1, verbose=False, warm_start=False)
```

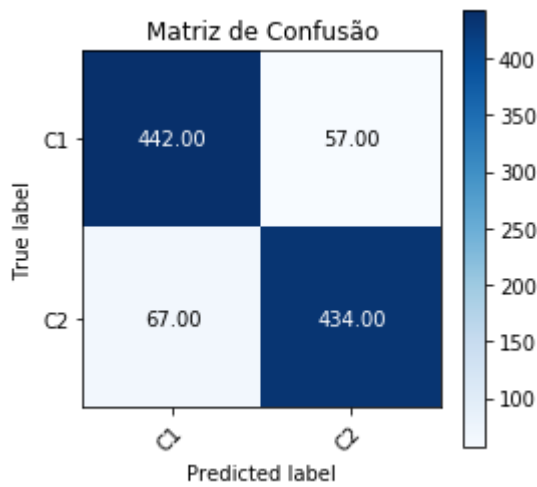
Acurácia:
87.6%

Classification report:

	precision	recall	f1-score	support
C1	0.87	0.89	0.88	499
C2	0.88	0.87	0.88	501
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000

Out[198]:

(1.5, -0.5)



Out[200]:

```
GridSearchCV(cv=3, error_score='raise-deprecating',
             estimator=MLPClassifier(activation='relu', alpha=0.0001,
                                     batch_size='auto', beta_1=0.9,
                                     beta_2=0.999, early_stopping=False,
                                     epsilon=1e-08, hidden_layer_sizes=(100,),
                                     learning_rate='constant',
                                     learning_rate_init=0.001, max_iter=500,
                                     momentum=0.9, n_iter_no_change=10,
                                     nesterovs_momentum=True, power_t=0.5,
                                     random_state=None, solver='adam', tol=0.0001,
                                     validation_fraction=0.1, verbose=False,
                                     warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'activation': ['tanh', 'relu'],
                         'alpha': [0.0001, 0.05],
                         'hidden_layer_sizes': [(50, 50, 50), (50, 100, 50),
                                                (100,)],
                         'learning_rate': ['constant', 'adaptive'],
                         'solver': ['sgd', 'adam']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

Resultados usando

----- Melhores parametros-----

Best parameters found:

{'activation': 'relu', 'alpha': 0.05, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'adam'}

----- Melhores parametros-----

0.663 (+/-0.036) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.878 (+/-0.044) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.664 (+/-0.027) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.872 (+/-0.037) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.664 (+/-0.033) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.868 (+/-0.021) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.661 (+/-0.026) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.874 (+/-0.038) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.651 (+/-0.038) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (100,), 'learning_rate': 'constant', 'solver': 'sgd'}

0.666 (+/-0.029) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (100,), 'learning_rate': 'constant', 'solver': 'adam'}

0.650 (+/-0.036) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (100,), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.666 (+/-0.029) for {'activation': 'tanh', 'alpha': 0.0001, 'hidden_layer_sizes': (100,), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.668 (+/-0.024) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.870 (+/-0.044) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.666 (+/-0.034) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.878 (+/-0.024) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.657 (+/-0.026) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.878 (+/-0.030) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.668 (+/-0.034) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.867 (+/-0.020) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.651 (+/-0.029) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (100,), 'learning_rate': 'constant', 'solver': 'sgd'}

0.657 (+/-0.014) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_size': (100,), 'learning_rate': 'constant', 'solver': 'adam'}

0.654 (+/-0.039) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_size': (100,), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.669 (+/-0.029) for {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_size': (100,), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.709 (+/-0.022) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.878 (+/-0.037) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.719 (+/-0.041) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.874 (+/-0.035) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.754 (+/-0.085) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.875 (+/-0.050) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.706 (+/-0.042) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.875 (+/-0.029) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.671 (+/-0.028) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (100,), 'learning_rate': 'constant', 'solver': 'sgd'}

0.872 (+/-0.049) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (100,), 'learning_rate': 'constant', 'solver': 'adam'}

0.664 (+/-0.041) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (100,), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.872 (+/-0.037) for {'activation': 'relu', 'alpha': 0.0001, 'hidden_layer_size': (100,), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.711 (+/-0.018) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.882 (+/-0.034) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.712 (+/-0.031) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.879 (+/-0.034) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 50, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.713 (+/-0.026) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'sgd'}

0.872 (+/-0.039) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'constant', 'solver': 'adam'}

0.719 (+/-0.036) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.880 (+/-0.039) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (50, 100, 50), 'learning_rate': 'adaptive', 'solver': 'adam'}

0.674 (+/-0.029) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (100,), 'learning_rate': 'constant', 'solver': 'sgd'}

0.867 (+/-0.041) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (100,), 'learning_rate': 'constant', 'solver': 'adam'}

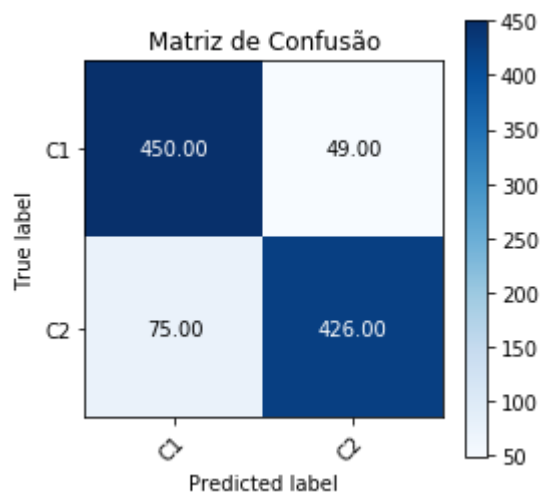
0.670 (+/-0.036) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (100,), 'learning_rate': 'adaptive', 'solver': 'sgd'}

0.871 (+/-0.040) for {'activation': 'relu', 'alpha': 0.05, 'hidden_layer_size': (100,), 'learning_rate': 'adaptive', 'solver': 'adam'}

Results on the test set:

	precision	recall	f1-score	support
-1.0	0.86	0.90	0.88	499
1.0	0.90	0.85	0.87	501
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000

Out[203]:
(1.5, -0.5)

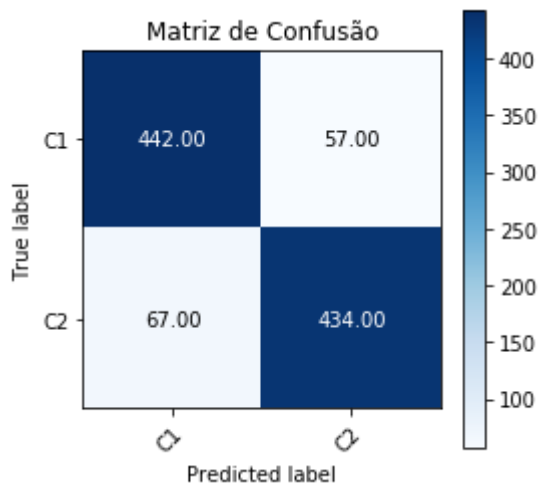


Acurácia:
87.6%

Classification report:

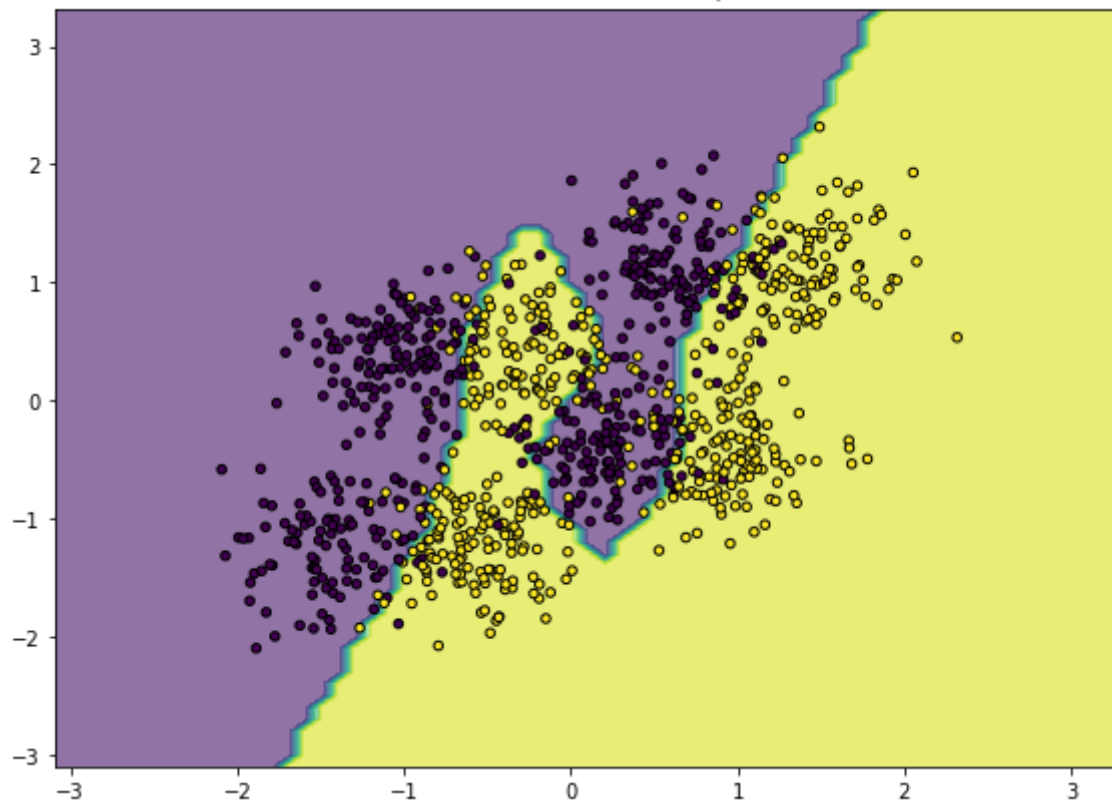
	precision	recall	f1-score	support
C1	0.87	0.89	0.88	499
C2	0.88	0.87	0.88	501
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000

Out[204]:
(1.5, -0.5)



Fronteiras de decisão

Fronteiras de Decisão)



Model: "Multi Layer Perceptron"

Layer (type)	Output Shape	Param #
Input_Layer (Dense)	(None, 100)	300
Output_Layer (Dense)	(None, 2)	202

Total params: 502
Trainable params: 502
Non-trainable params: 0

None

Optimizer:

- learning_rate: 0.001
- beta_1: 0.9
- beta_2: 0.999
- decay: 0.0
- epsilon: 0.0
- amsgrad: False

```
-----  
NameError                                Traceback (most recent call last)  
<ipython-input-10-684d061c2c1b> in <module>  
----> 1 plt.figure(figsize=(13, 4))  
      2 plt.subplot(1, 2, 1)  
      3 plt.plot(history.history["loss"], label="Loss", color='red')  
      4 plt.plot(history.history["accuracy"], label="Accuracy")  
      5 plt.legend()
```

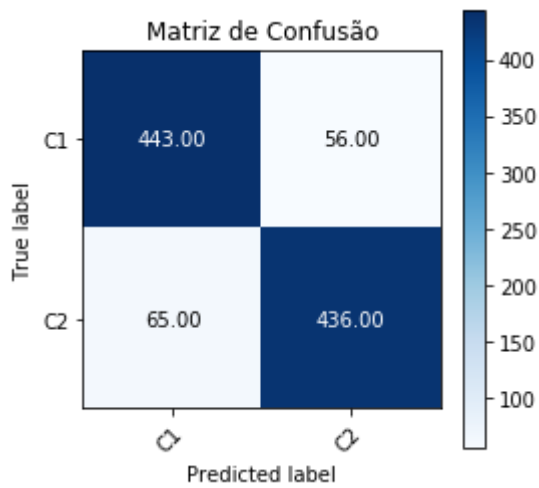
NameError: name 'plt' is not defined

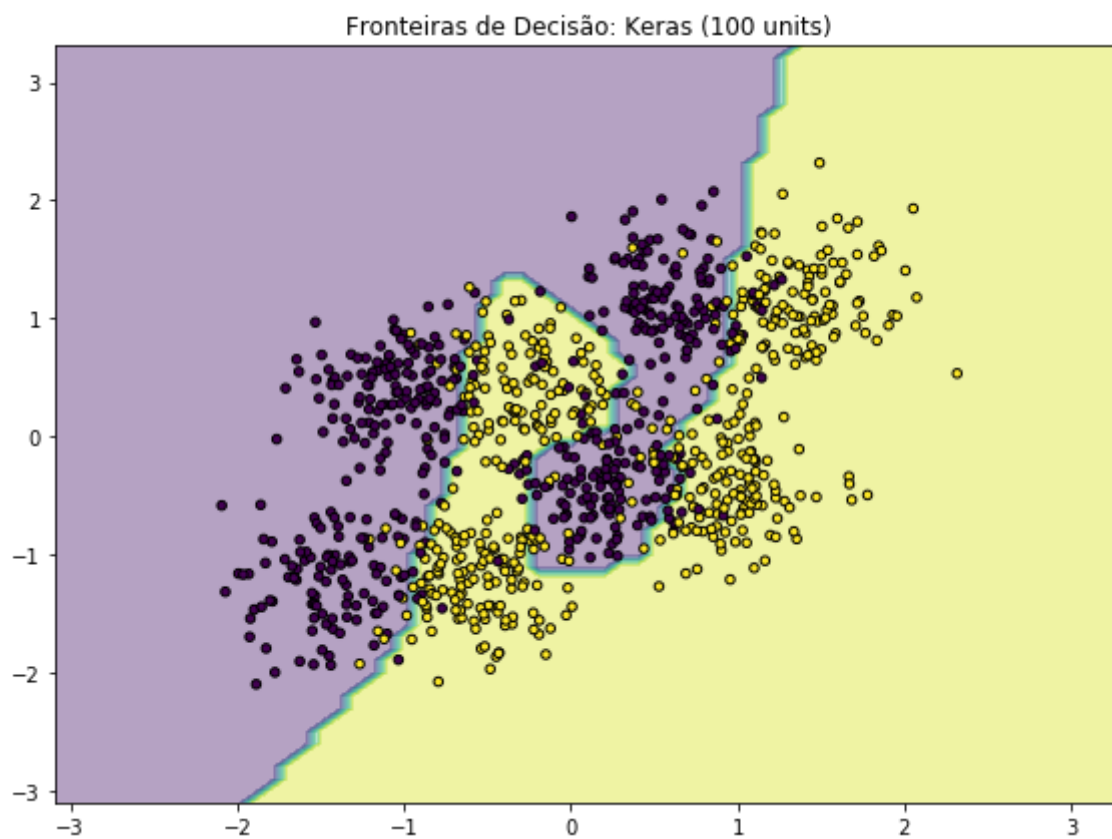
Acurácia:
87.9%

Classification report:

	precision	recall	f1-score	support
C1	0.87	0.89	0.88	499
C2	0.89	0.87	0.88	501
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000

Out[217]:
(1.5, -0.5)





com Keras, mais neuronios

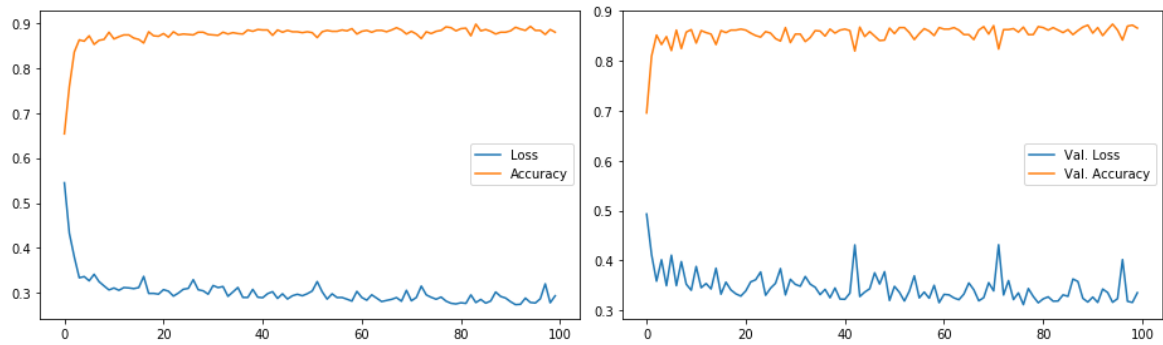
Model: "Multi Layer Perceptron"

Layer (type)	Output Shape	Param #
Input_Layer (Dense)	(None, 32768)	98304
Output_Layer (Dense)	(None, 2)	65538

Total params: 163,842
Trainable params: 163,842
Non-trainable params: 0

None

- Optimizer:
- learning_rate: 0.001
 - beta_1: 0.9
 - beta_2: 0.999
 - decay: 0.0
 - epsilon: 0.0
 - amsgrad: True

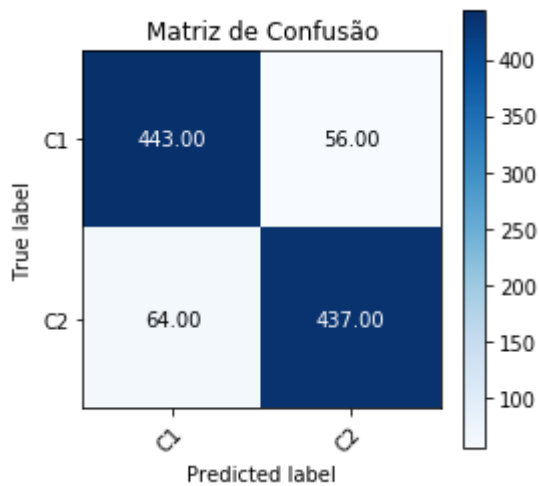


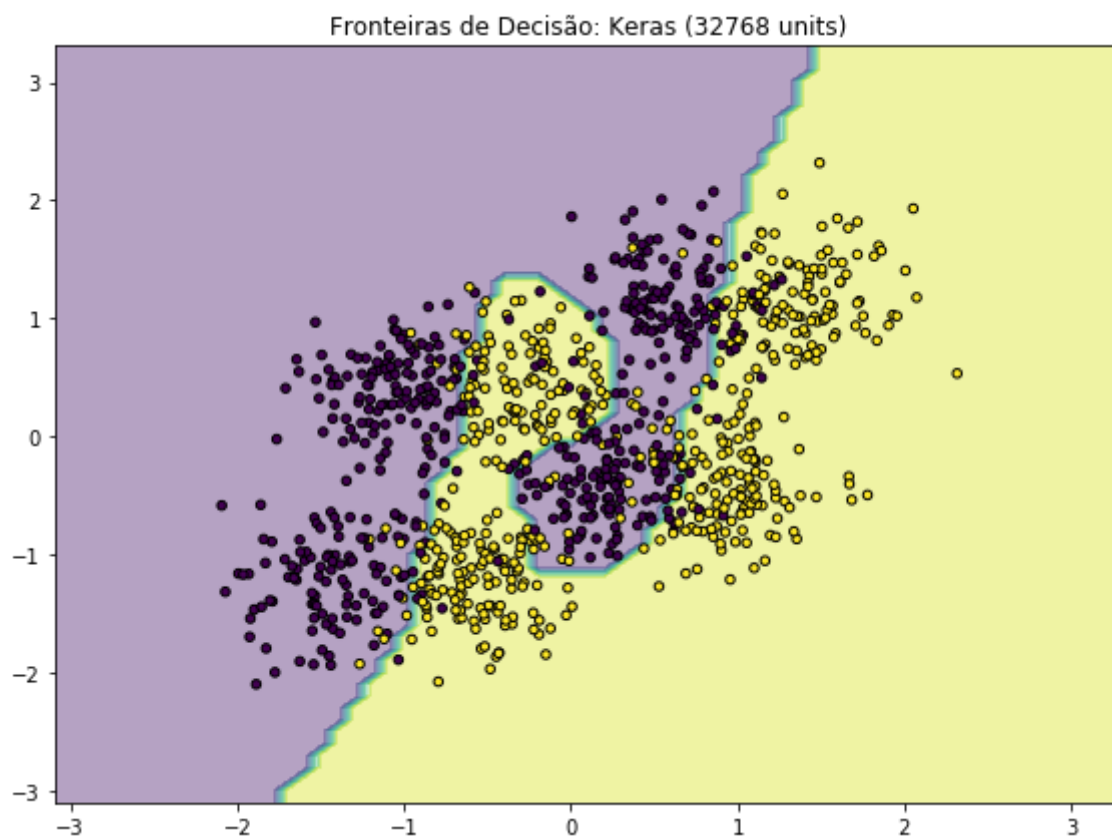
Acurácia:
88.0%

Classification report:

	precision	recall	f1-score	support
C1	0.87	0.89	0.88	499
C2	0.89	0.87	0.88	501
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000

Out[222]:
(1.5, -0.5)





Mais camadas densas

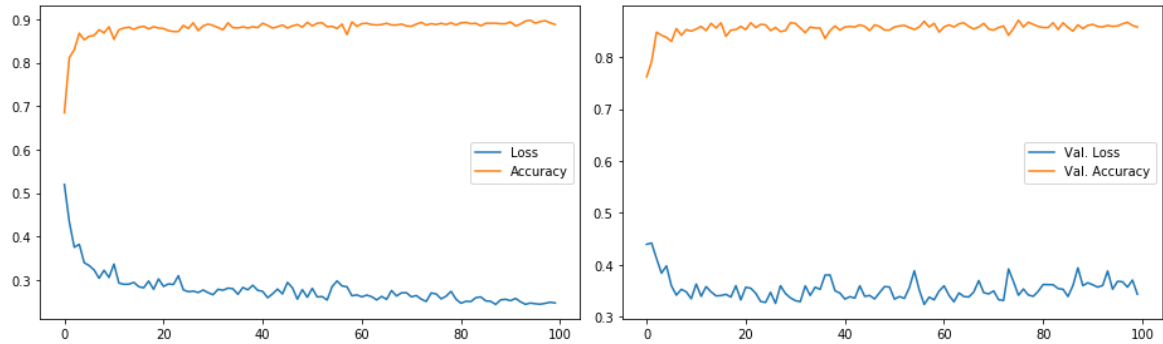
Model: "Multi Layer Perceptron"

Layer (type)	Output Shape	Param #
Input_Layer_1 (Dense)	(None, 1024)	3072
Input_Layer_2 (Dense)	(None, 1024)	1049600
Input_Layer_3 (Dense)	(None, 1024)	1049600
Input_Layer_4 (Dense)	(None, 1024)	1049600
Input_Layer_5 (Dense)	(None, 1024)	1049600
Input_Layer_6 (Dense)	(None, 1024)	1049600
Output_Layer (Dense)	(None, 2)	2050

Total params: 5,253,122
Trainable params: 5,253,122
Non-trainable params: 0

None

- Optimizer:
- learning_rate: 0.001
 - beta_1: 0.9
 - beta_2: 0.999
 - decay: 0.0
 - epsilon: 0.0
 - amsgrad: True



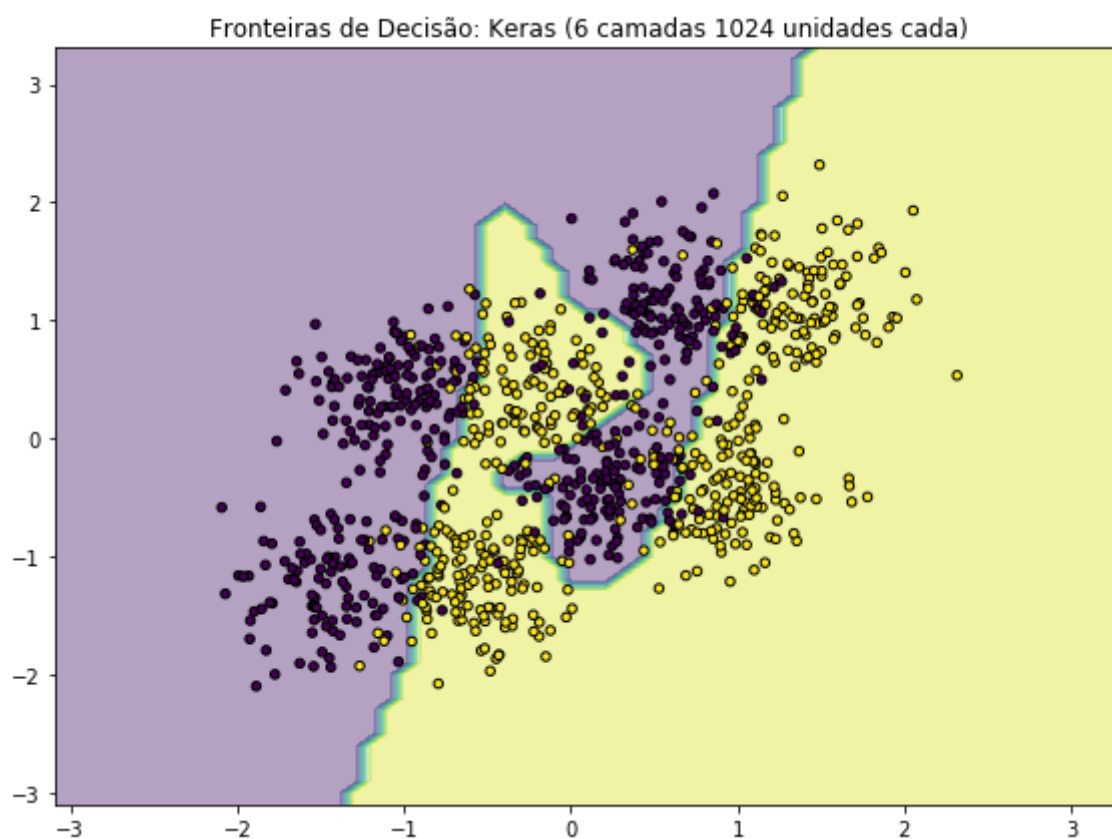
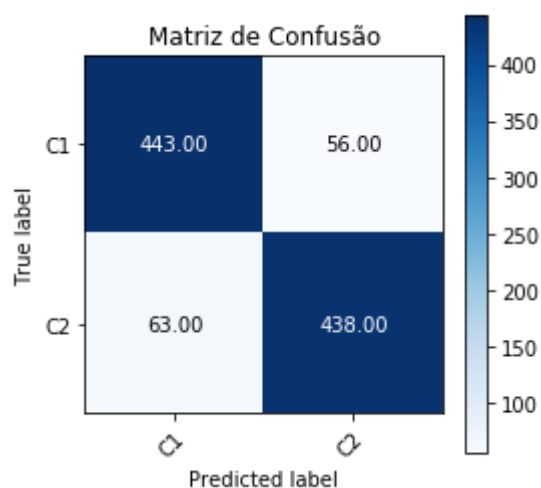
Acurácia:
88.1%

Classification report:

	precision	recall	f1-score	support
C1	0.88	0.89	0.88	499
C2	0.89	0.87	0.88	501
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000

Out[227]:

(1.5, -0.5)



Minima quantidade de neuronios

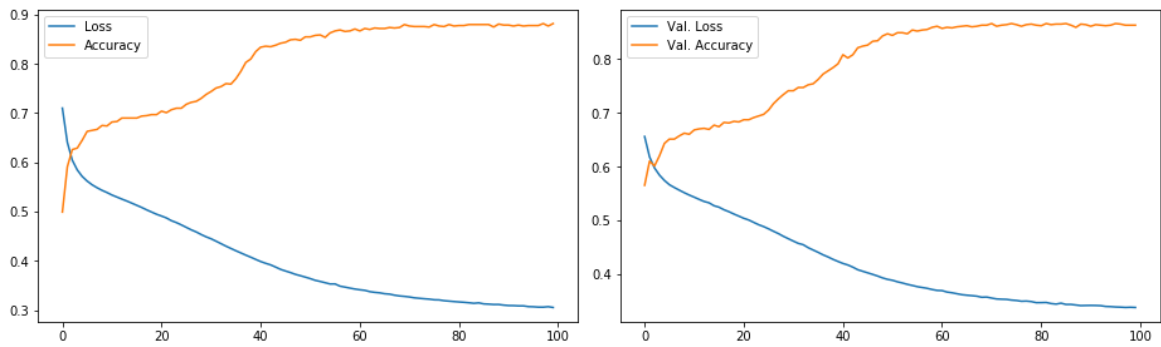
Model: "Multi Layer Perceptron"

Layer (type)	Output Shape	Param #
Input_Layer_1 (Dense)	(None, 30)	90
Output_Layer (Dense)	(None, 2)	62

Total params: 152
Trainable params: 152
Non-trainable params: 0

None

- Optimizer:
- learning_rate: 0.001
 - beta_1: 0.9
 - beta_2: 0.999
 - decay: 0.0
 - epsilon: 0.0
 - amsgrad: True

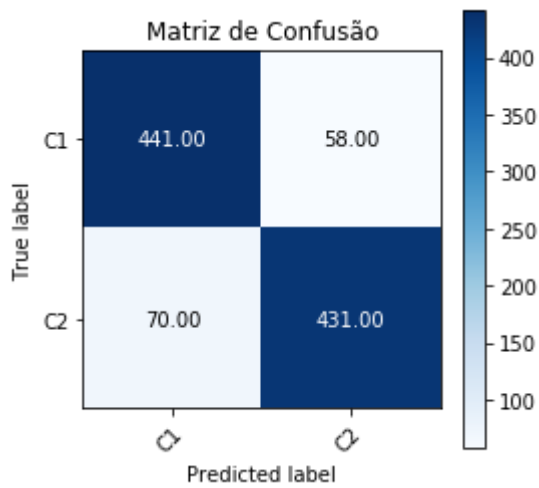


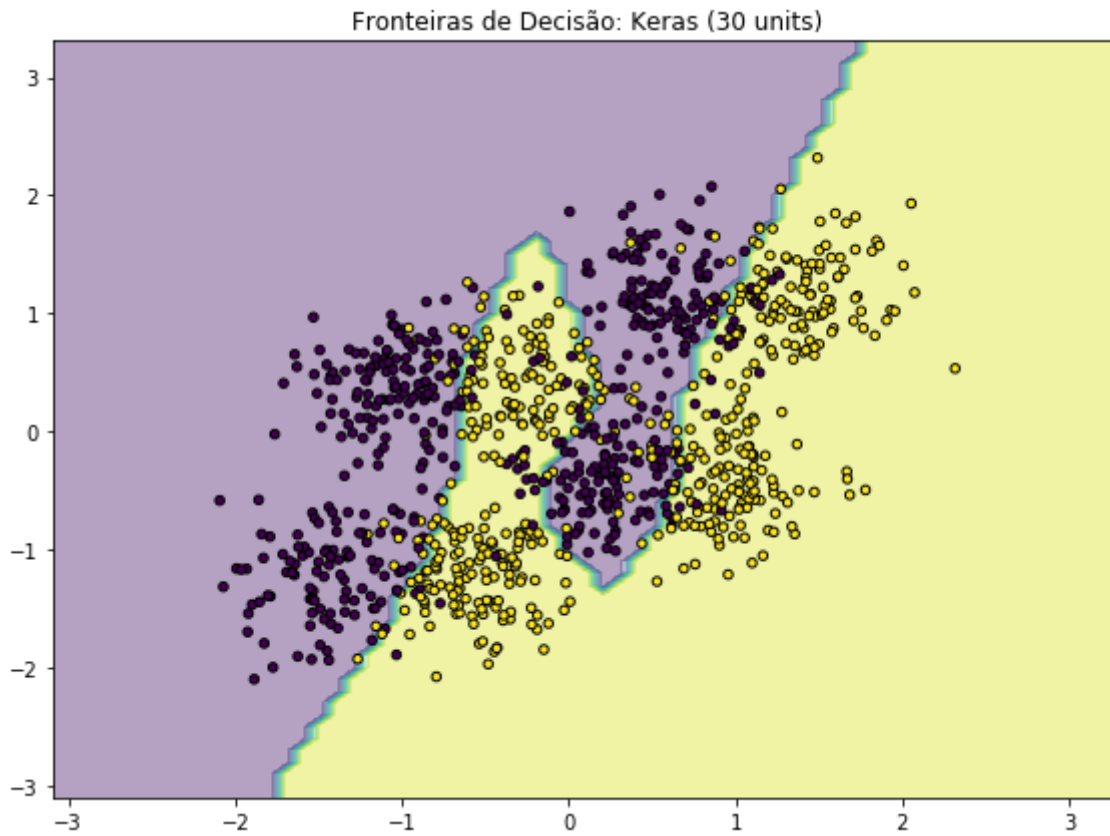
Acurácia:
87.2%

Classification report:

	precision	recall	f1-score	support
C1	0.86	0.88	0.87	499
C2	0.88	0.86	0.87	501
accuracy			0.87	1000
macro avg	0.87	0.87	0.87	1000
weighted avg	0.87	0.87	0.87	1000

Out[231]:
(1.5, -0.5)





SVM

Out[233]:

```
SVC(C=5, cache_size=200, class_weight=None, coef0=0.0,  
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',  
    max_iter=-1, probability=False, random_state=1, shrinking=True, tol=0.001,  
    verbose=False)
```

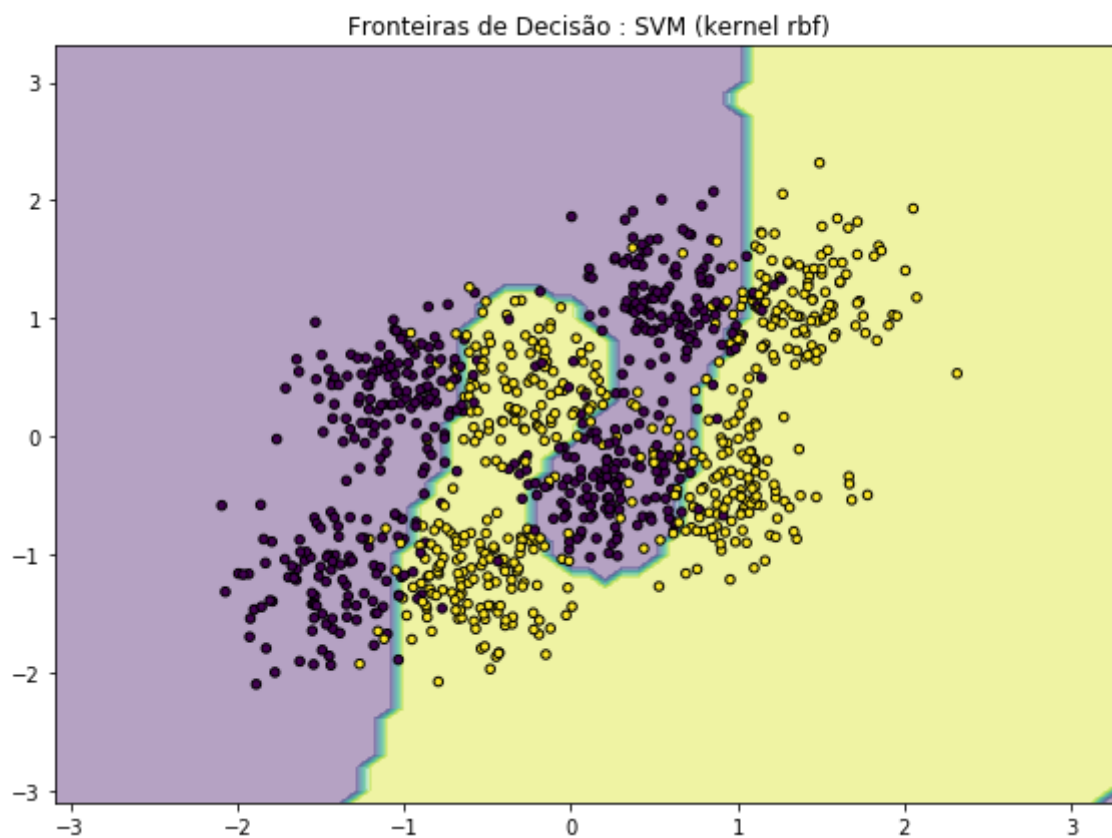
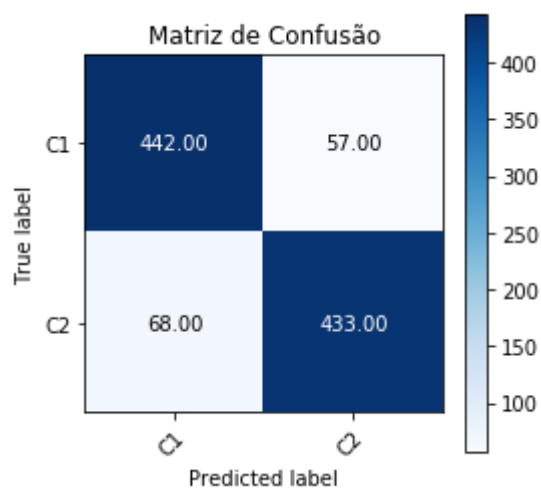
Acurácia:
87.5%

Classification report:

	precision	recall	f1-score	support
C1	0.87	0.89	0.88	499
C2	0.88	0.86	0.87	501
accuracy			0.88	1000
macro avg	0.88	0.88	0.87	1000
weighted avg	0.88	0.88	0.87	1000

Out[234]:

(1.5, -0.5)



SVM diferente

Out[236]:

```
SVC(C=5, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='poly',
    max_iter=-1, probability=False, random_state=1, shrinking=True, tol=0.001,
    verbose=False)
```

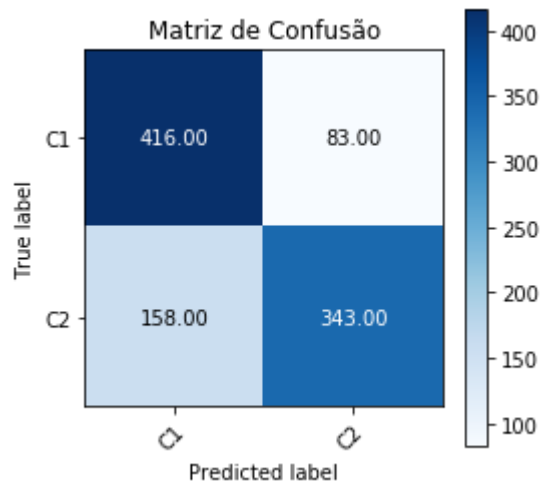
Acurácia:
75.9%

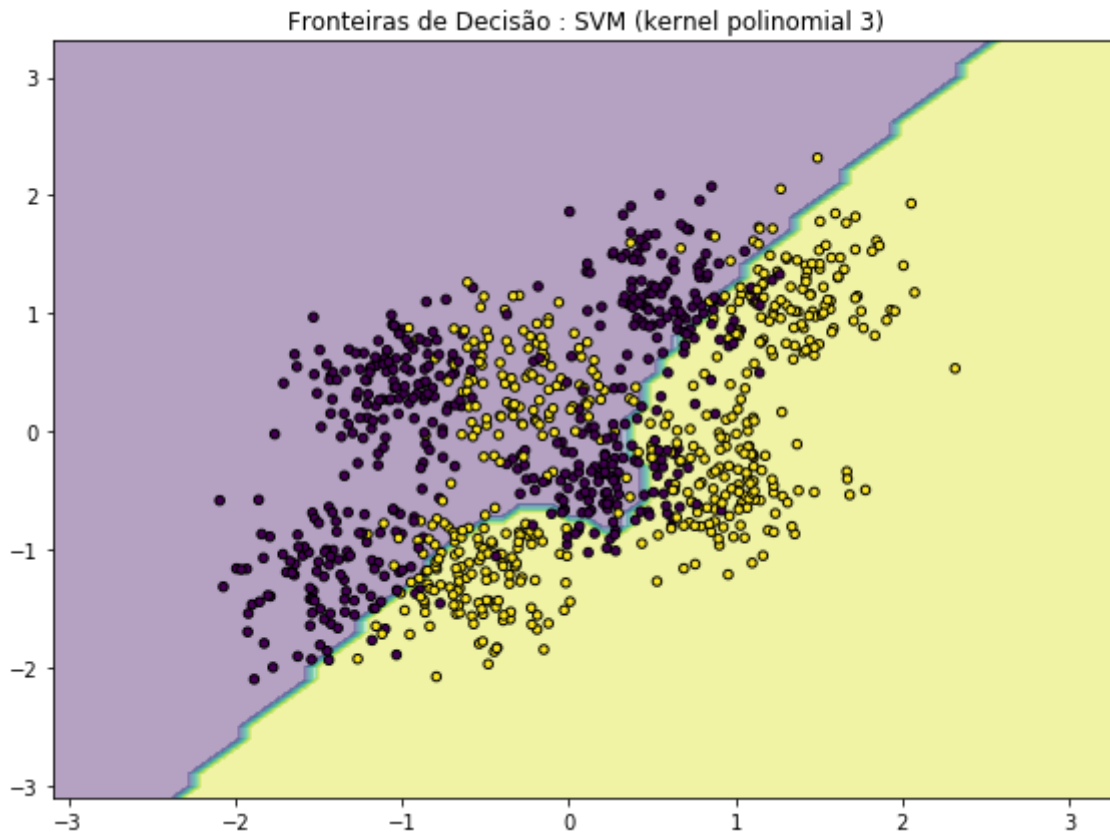
Classification report:

	precision	recall	f1-score	support
C1	0.72	0.83	0.78	499
C2	0.81	0.68	0.74	501
accuracy			0.76	1000
macro avg	0.76	0.76	0.76	1000
weighted avg	0.77	0.76	0.76	1000

Out[237]:

(1.5, -0.5)





SVM 9

Out[239]:

```
SVC(C=5, cache_size=200, class_weight=None, coef0=0.0,  
    decision_function_shape='ovr', degree=9, gamma='scale', kernel='poly',  
    max_iter=-1, probability=False, random_state=1, shrinking=True, tol=0.001,  
    verbose=False)
```

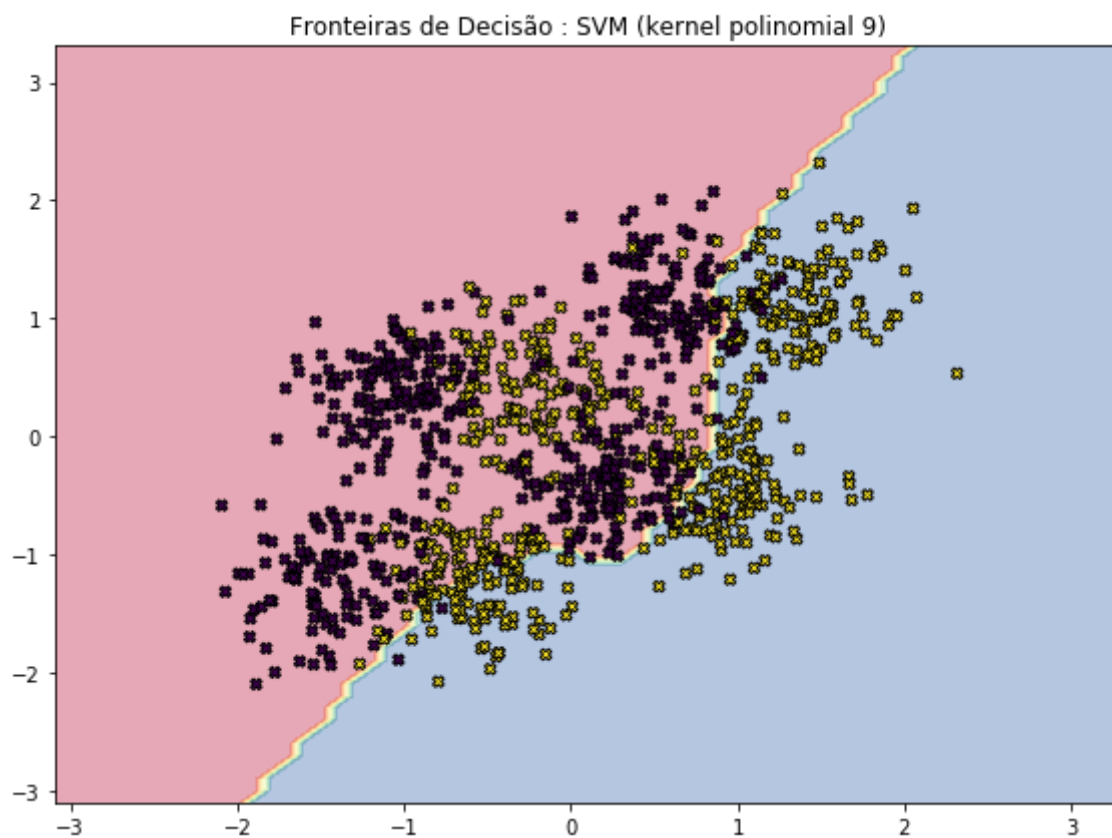
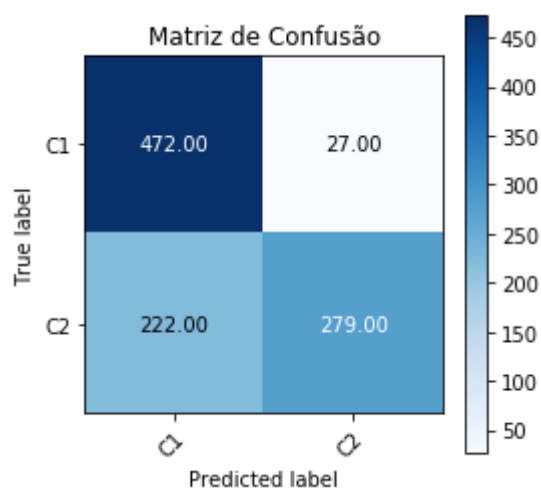
Acurácia:
75.1%

Classification report:

	precision	recall	f1-score	support
C1	0.68	0.95	0.79	499
C2	0.91	0.56	0.69	501
accuracy			0.75	1000
macro avg	0.80	0.75	0.74	1000
weighted avg	0.80	0.75	0.74	1000

Out[240]:

(1.5, -0.5)



H = 5

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:17: UserWarning: Using a target size (torch.Size([1000, 2])) that is different to the input size (torch.Size([1000, 1])) is deprecated. Please ensure they have the same size.

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-74-823fb79200a5> in <module>
     15         otimizador.zero_grad()
     16         saida = modelo(X_treino_tmp)
--> 17         perda = F.binary_cross_entropy(saida, y_treino_tmp)
     18         perda.backward()
     19         otimizador.step()

~/local/lib/python3.7/site-packages/torch/nn/functional.py in binary_cross_entropy(input, target, weight, size_average, reduce, reduction)
    2056     if input.numel() != target.numel():
    2057         raise ValueError("Target and input must have the same number of
elements. target nelement ({})"
-> 2058                                "!= input nelement ({}).format(target.numel(),
input.numel()))
    2059
    2060     if weight is not None:
```

ValueError: Target and input must have the same number of elements. target nelement (2000) != input nelement (1000)

online (padrão-a-padrão)

H = 5

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:24: UserWarning: Using a target size (torch.Size([2])) that is different to the input size (torch.Size([1])) is deprecated. Please ensure they have the same size.

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-75-40a65456c008> in <module>
     22         otimizador.zero_grad()
     23         saida = modelo(data)
--> 24         perda = F.binary_cross_entropy(saida, target)
     25         perda.backward()
     26         otimizador.step()

~/local/lib/python3.7/site-packages/torch/nn/functional.py in binary_cross_entropy(input, target, weight, size_average, reduce, reduction)
    2056     if input.numel() != target.numel():
    2057         raise ValueError("Target and input must have the same number of
elements. target nelement ({})"
-> 2058                                "!= input nelement ({}).format(target.numel(),
input.numel()))
    2059
    2060     if weight is not None:
```

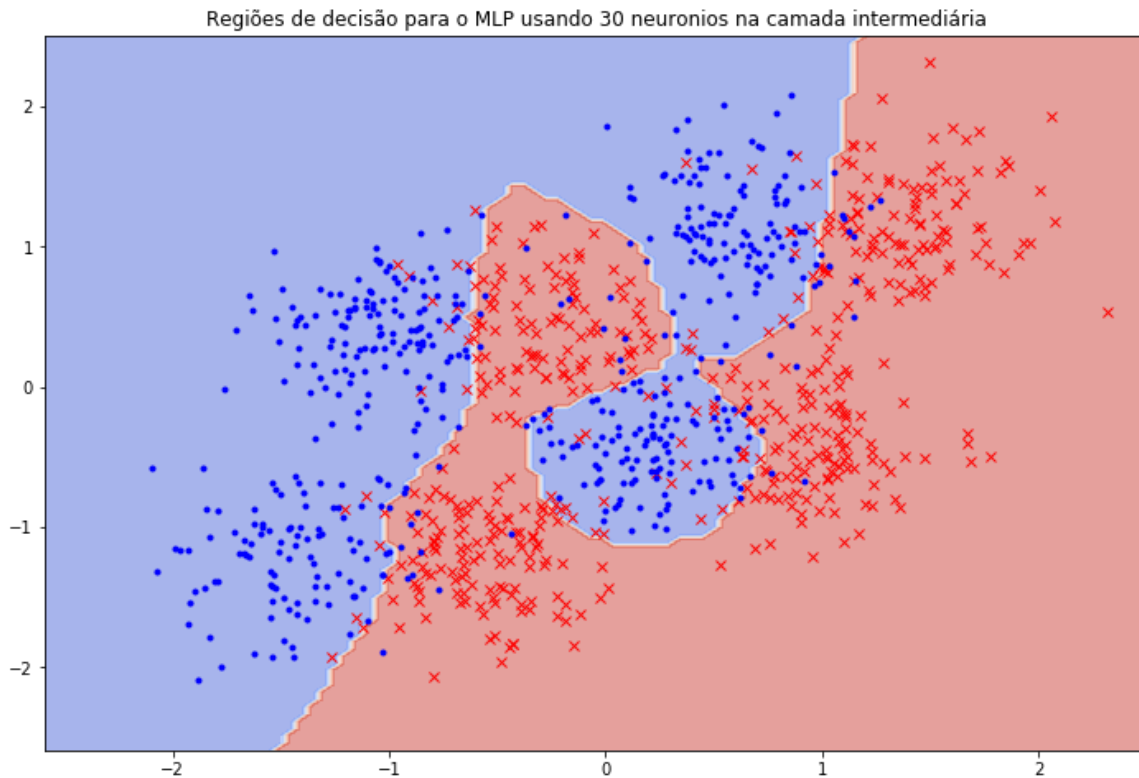
ValueError: Target and input must have the same number of elements. target nelement (2) != input nelement (1)

Dados de teste: Avg. loss: 0.3240, Accuracy: 881/1000 (88%)

```
/usr/local/lib/python3.7/dist-packages/torch/nn/_reduction.py:46: UserWarning: size_average and reduce args will be deprecated, please use reduction='sum' instead.
```

```
warnings.warn(warning.format(ret))
```

Acurácia de teste 0.88



SVM

Out[61]:

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

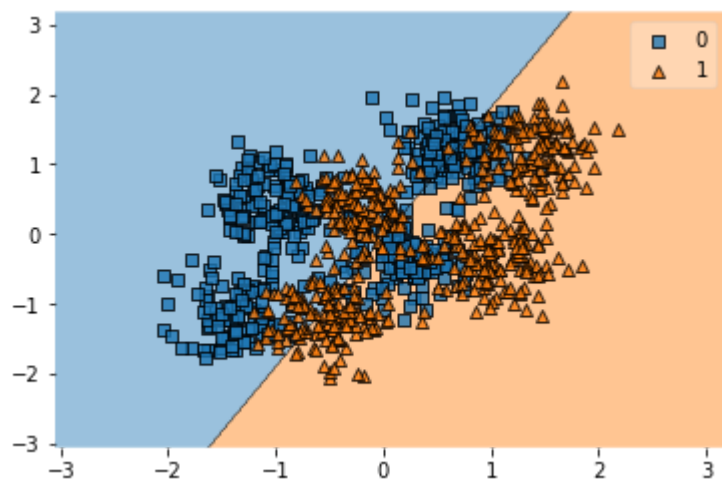
Out[62]:

0.853

===

SVM com $C = 1$ e kernel = linear

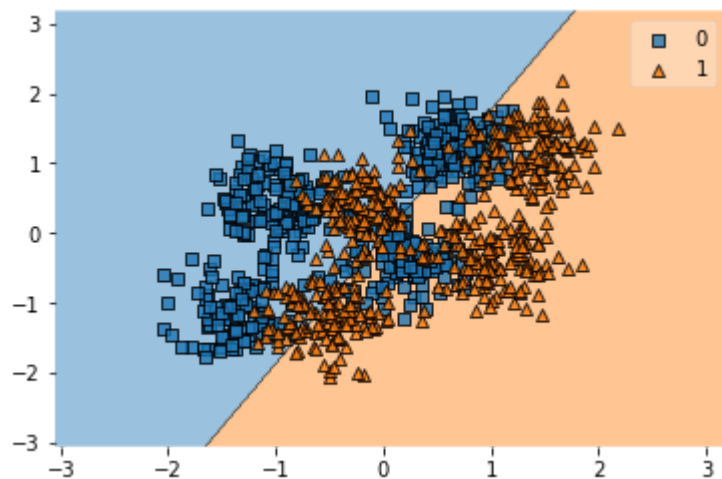
Acurácia: 0.658, F1-score: 0.667, AUC: 0.658



===

SVM com $C = 10$ e kernel = linear

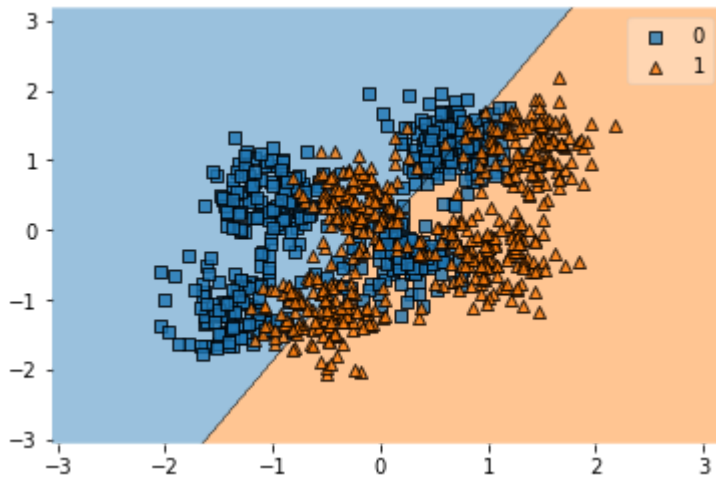
Acurácia: 0.661, F1-score: 0.670, AUC: 0.661



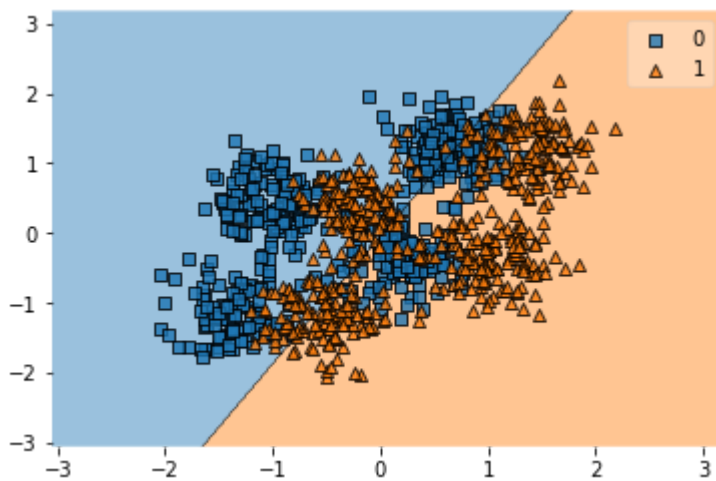
===

SVM com $C = 50$ e kernel = linear

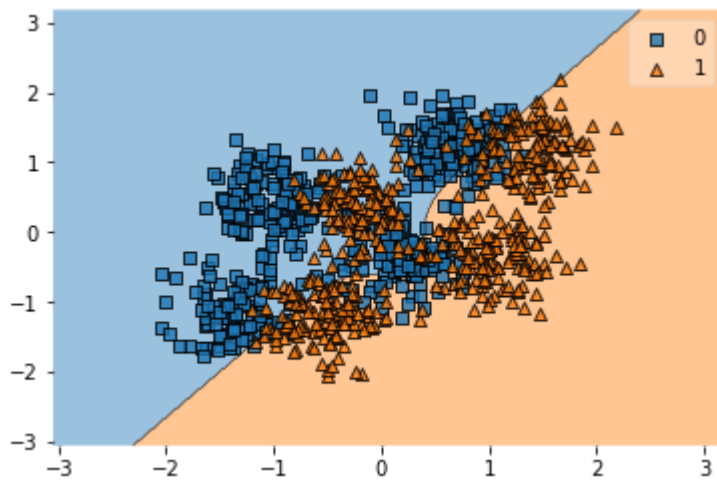
Acurácia: 0.661, F1-score: 0.670, AUC: 0.661



===
SVM com $C = 100$ e kernel = linear
Acurácia: 0.661, F1-score: 0.670, AUC: 0.661



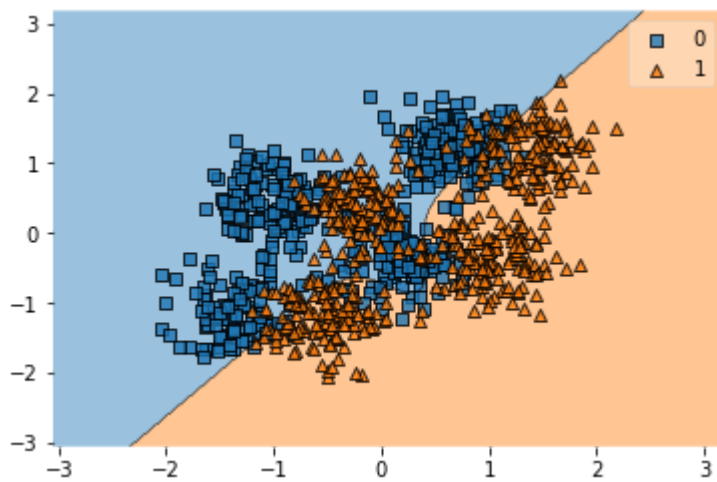
===
SVM com $C = 1$ e kernel = poly
Acurácia: 0.743, F1-score: 0.726, AUC: 0.746



===

SVM com $C = 10$ e kernel = poly

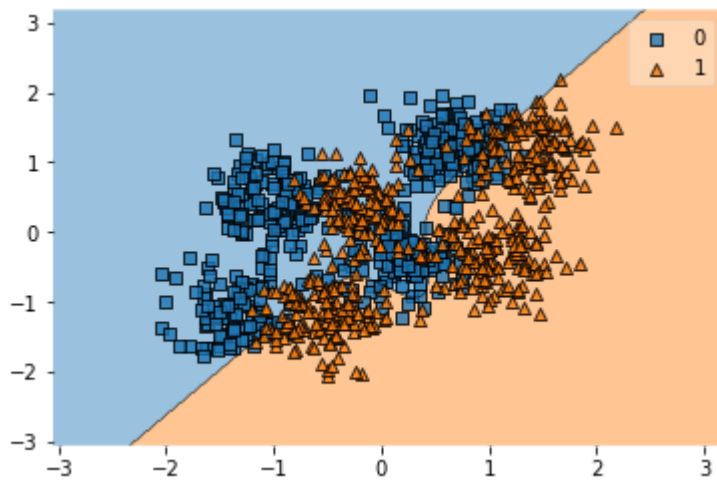
Acurácia: 0.75, F1-score: 0.731, AUC: 0.754



===

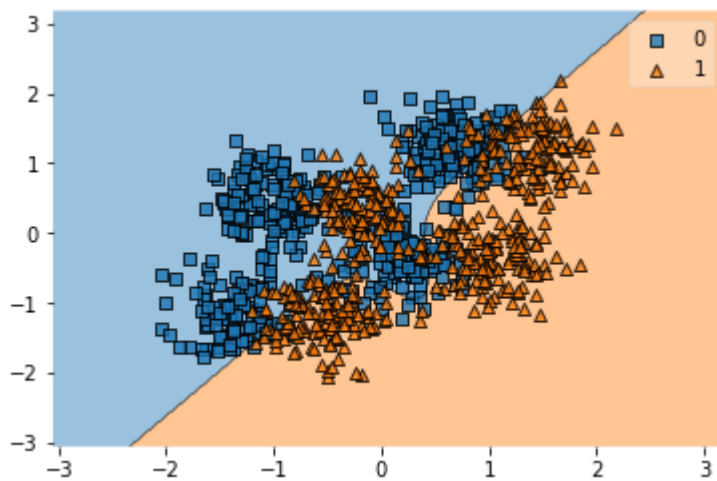
SVM com $C = 50$ e kernel = poly

Acurácia: 0.752, F1-score: 0.732, AUC: 0.756



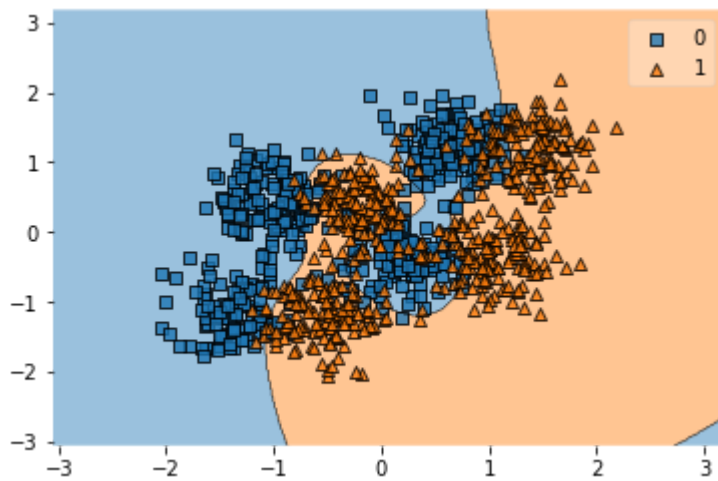
===

SVM com $C = 100$ e `kernel = poly`
Acurácia: 0.752, F1-score: 0.732, AUC: 0.756



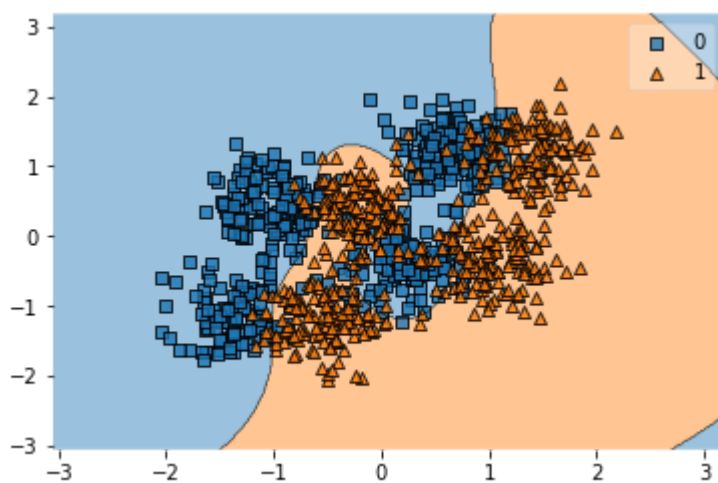
===

SVM com $C = 1$ e `kernel = rbf`
Acurácia: 0.853, F1-score: 0.858, AUC: 0.853



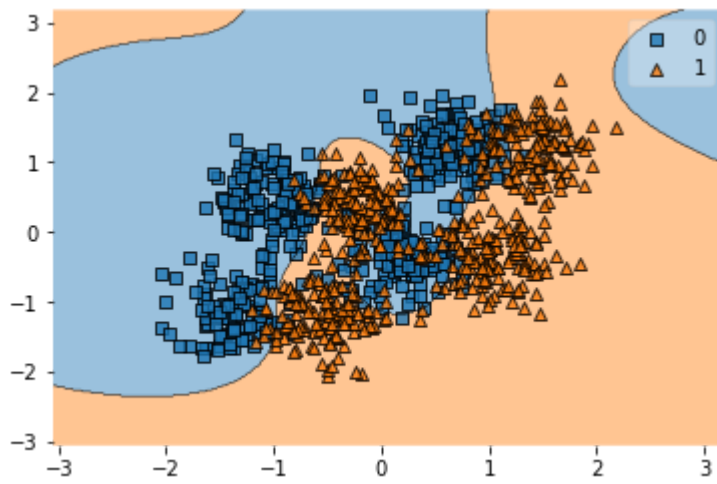
===

SVM com $C = 10$ e kernel = rbf
Acurácia: 0.864, F1-score: 0.868, AUC: 0.864



===

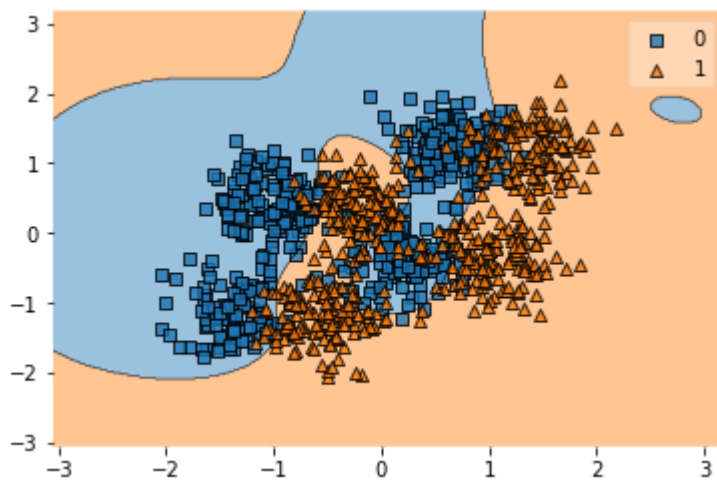
SVM com $C = 50$ e kernel = rbf
Acurácia: 0.867, F1-score: 0.871, AUC: 0.867



===

SVM com $C = 100$ e kernel = rbf

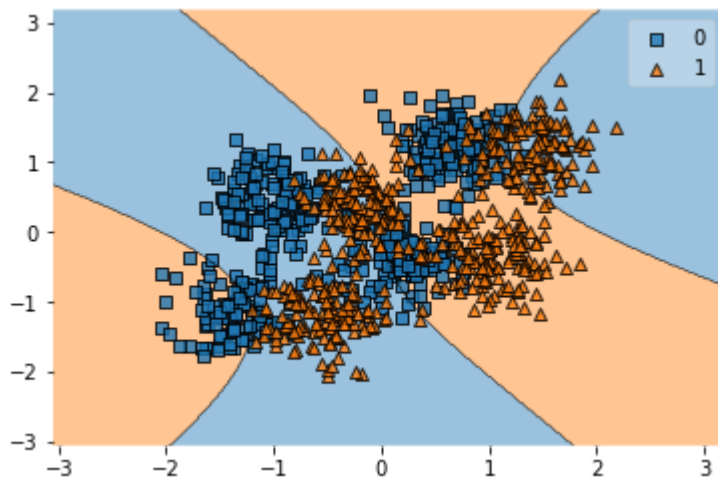
Acurácia: 0.866, F1-score: 0.870, AUC: 0.866



===

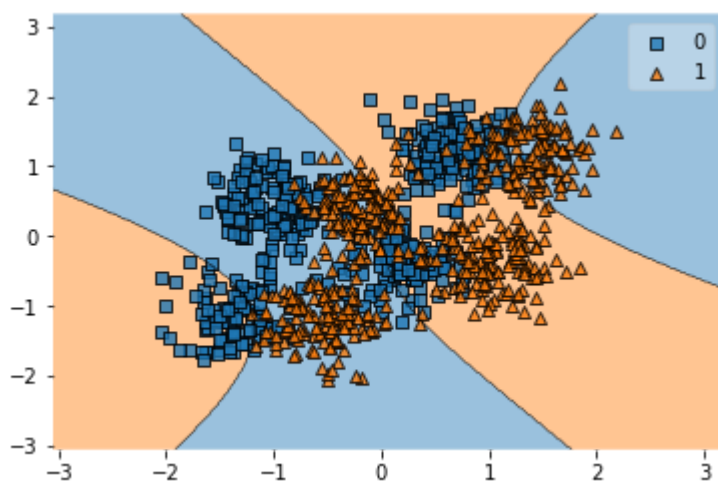
SVM com $C = 1$ e kernel = sigmoid

Acurácia: 0.415, F1-score: 0.421, AUC: 0.415



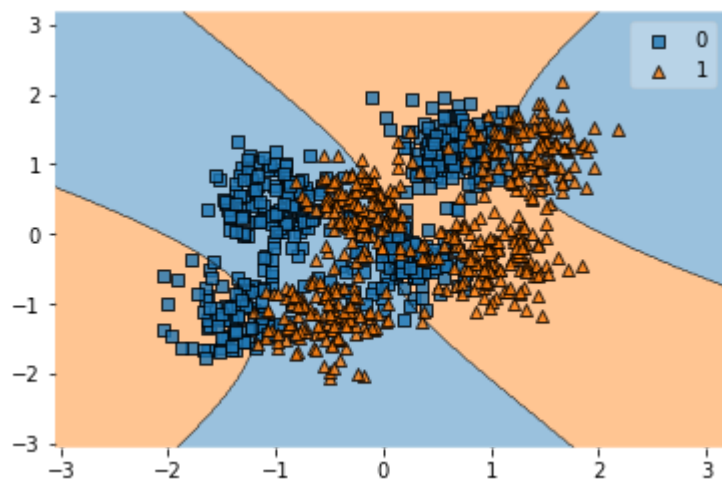
===

SVM com $C = 10$ e kernel = sigmoid
Acurácia: 0.413, F1-score: 0.421, AUC: 0.413



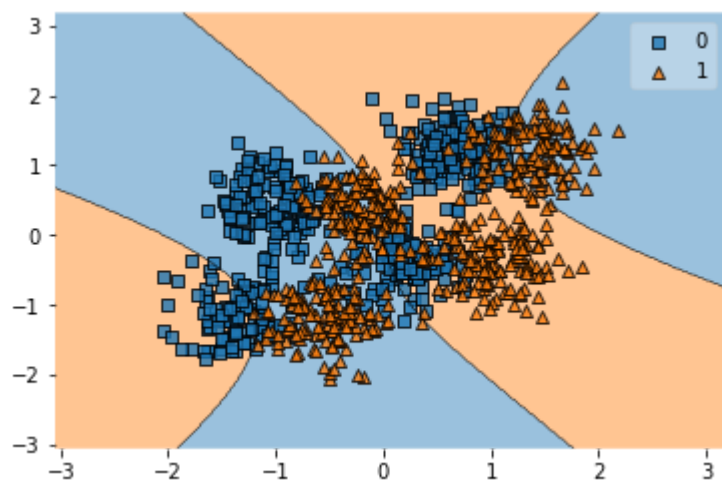
===

SVM com $C = 50$ e kernel = sigmoid
Acurácia: 0.414, F1-score: 0.422, AUC: 0.414



===

SVM com $C = 100$ e kernel = sigmoid
Acurácia: 0.414, F1-score: 0.422, AUC: 0.414



===

SVM com $C = 50$ e kernel = rbf

Acurácia: 0.874, F1-score: 0.873, AUC: 0.874

