Choosing C Hyperparameter for SVM Classifiers: Examples with Scikit-Learn

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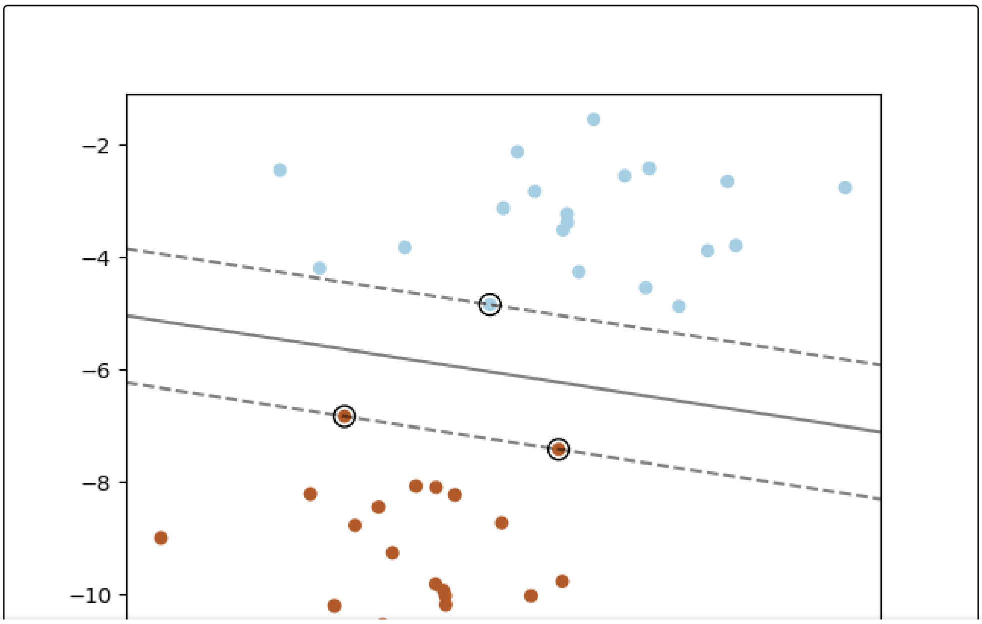
> ***TL;DR:*** *Use a lower setting for* `C` *(e.g. 0.001) if your training data is very noisy. For polynomial and RBF kernels, this makes a lot of difference. Not so much for linear kernels.*

View all code on this **jupyter notebook (https://github.com/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb)**

SVM tries to find separating planes

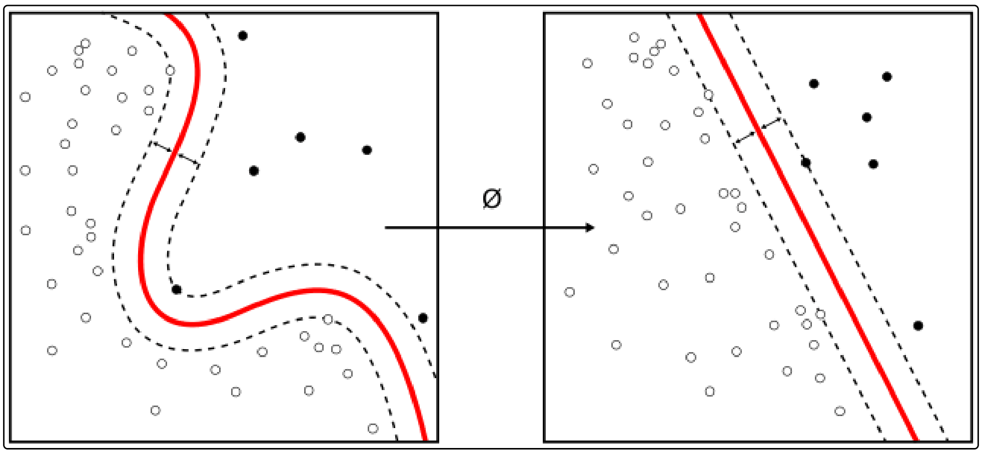
In other words, it tries to find planes that separate Positive from Negative points



The solid line in the middle represents the best possible line for separating positive from negative samples.
The circled points are the support vectors.
Source: Sklearn Guide on SVMs

Kernel methods

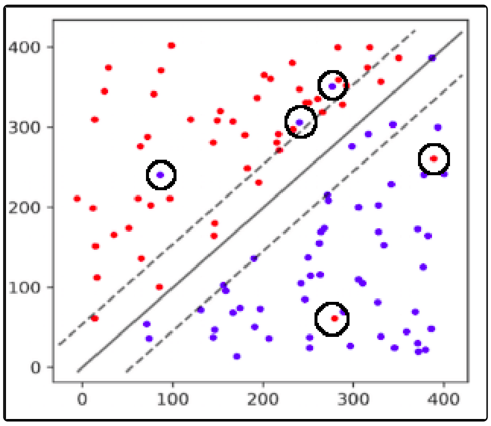
SVM can also find surfaces other than simple planes if you employ **kernel methods**



Kernels (transformation functions) can be used to transform the points such that hyperplanes can be found even for points that are not linearly separable
Source: [Wikipedia Article on Kernel Methods (https://en.wikipedia.org/wiki/Kernel_method)](https://en.wikipedia.org/wiki/Kernel_method)

Noisy points

Real-life data is noisy, so a robust SVM classifier must be able to ignore noisy, outlier points to discover a generalizable plane.



A separating plane that ignores some (probably noisy) points.
Source: **[Learn OpenCV (https://www.learnopencv.com/svm-using-scikit-learn-in-python/)](https://www.learnopencv.com/svm-using-scikit-learn-in-python/)**

Soft-margin vs hard-margin

Hard-margin SVM	**Soft-Margin SVM**
Try to find a hyperplane that best separates positive from negative points, **such that no point is misclassified.**	Try to find a hyperplane that best separates positive from negative points, but **allows for some points to be misclassified**, in which case the objective function is punished proportionally to degree of misclassification

By default, most packages like scikit-learn implement a *soft-margin* SVM.

This means that a separating hyperplane that separates positive from negative points will still be considered *even if* some points are misclassified.

The C parameter

> *The lower the* ***C*** *parameters, the softer the margin*

The `C` parameter controls how much you want to punish your model for each misclassified point for a given curve:

Large values of C	Small Values of C
Large effect of noisy points.	Low effect of noisy points.
A plane with very few misclassifications will be given precedence.	Planes that separate the points well will be found, even if there are some misclassifications

In other words, `C` is a **regularization parameter** for SVMs.

Examples: Generating synthetic datasets for the examples

> *More information on creating synthetic datasets here:* [Scikit-Learn examples: Making Dummy Datasets (http://queirozf.com/entries/scikit-learn-examples-making-dummy-dataset)](http://queirozf.com/entries/scikit-learn-examples-making-dummy-dataset)

For all the following examples, a **noisy** classification problem was created as follows:

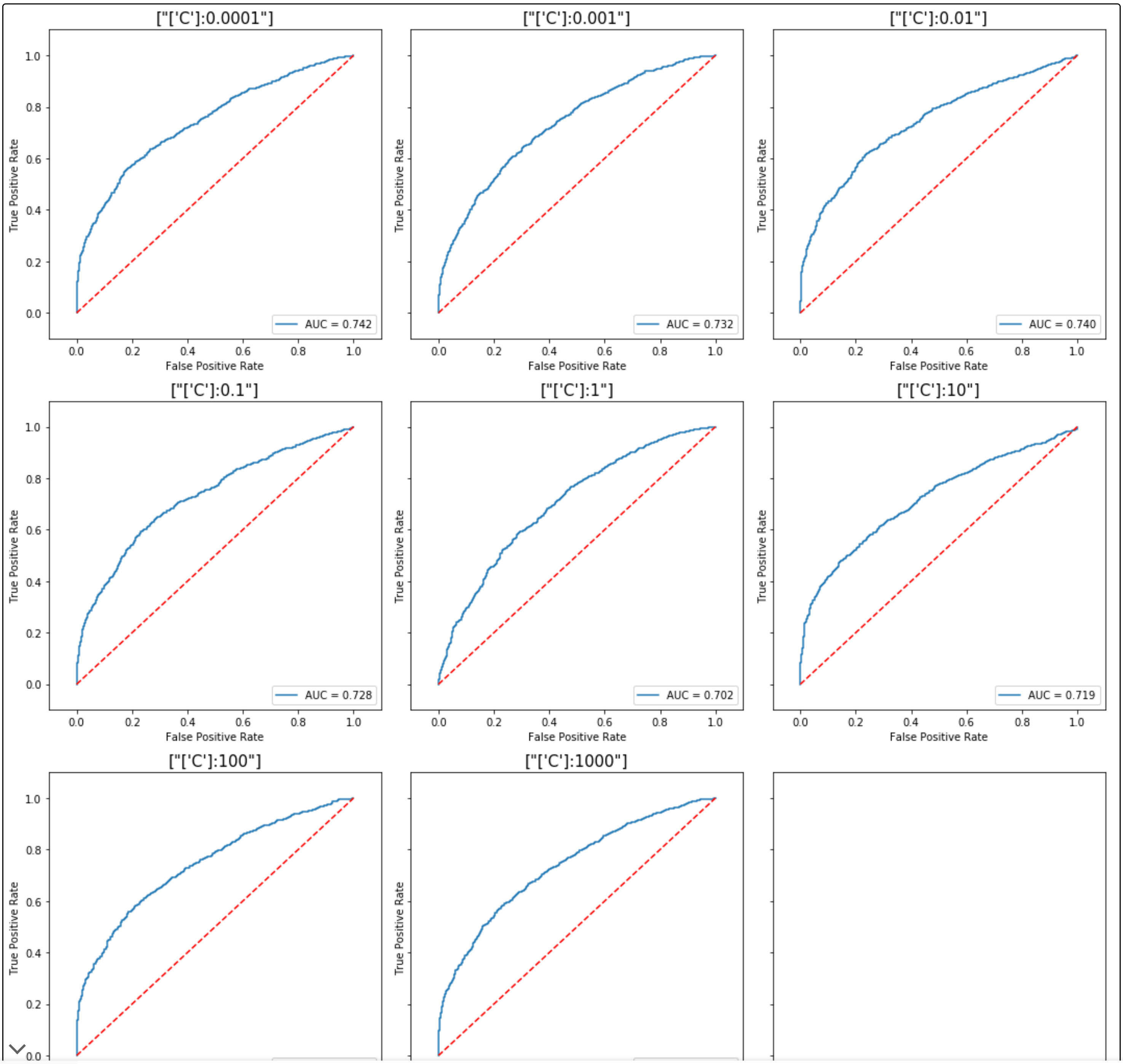
- We generated a dummy **training** dataset setting `flip_y` to 0.35, which means that in this dataset, 35% of the targets are *flipped*, i.e. a 1 where a 0 should be and a 0 where there should be a 1
- We generated a dummy **test** dataset with the same settings as the training dataset, except for the noise parameter (`flip_y`). There is no noise in the test dataset because we want to ascertain how much a model *trained* on noisy data performs with respect to the choice of C.

```
np.random.seed(222)
# train dataset
X, y = make_classification(
    n_samples=10000,
    n_features=10,
    n_informative=10,
    n_redundant=0,
    weights=[0.3,0.7],
    class_sep=0.7,
    flip_y=0.35) # the default value for flip_y is 0.01, or 1%
X_train, _ , y_train, _ = train_test_split(X, y, test_size=0.25)

np.random.seed(222)
# test dataset
X, y = make_classification(
    n_samples=10000,
    n_features=10,
    n_informative=10,
    n_redundant=0,
    weights=[0.3,0.7],
```

Examples: Choice of C for SVM Linear Kernel

For a linear kernel, the choice of `C` does not seem to affect performance very much:

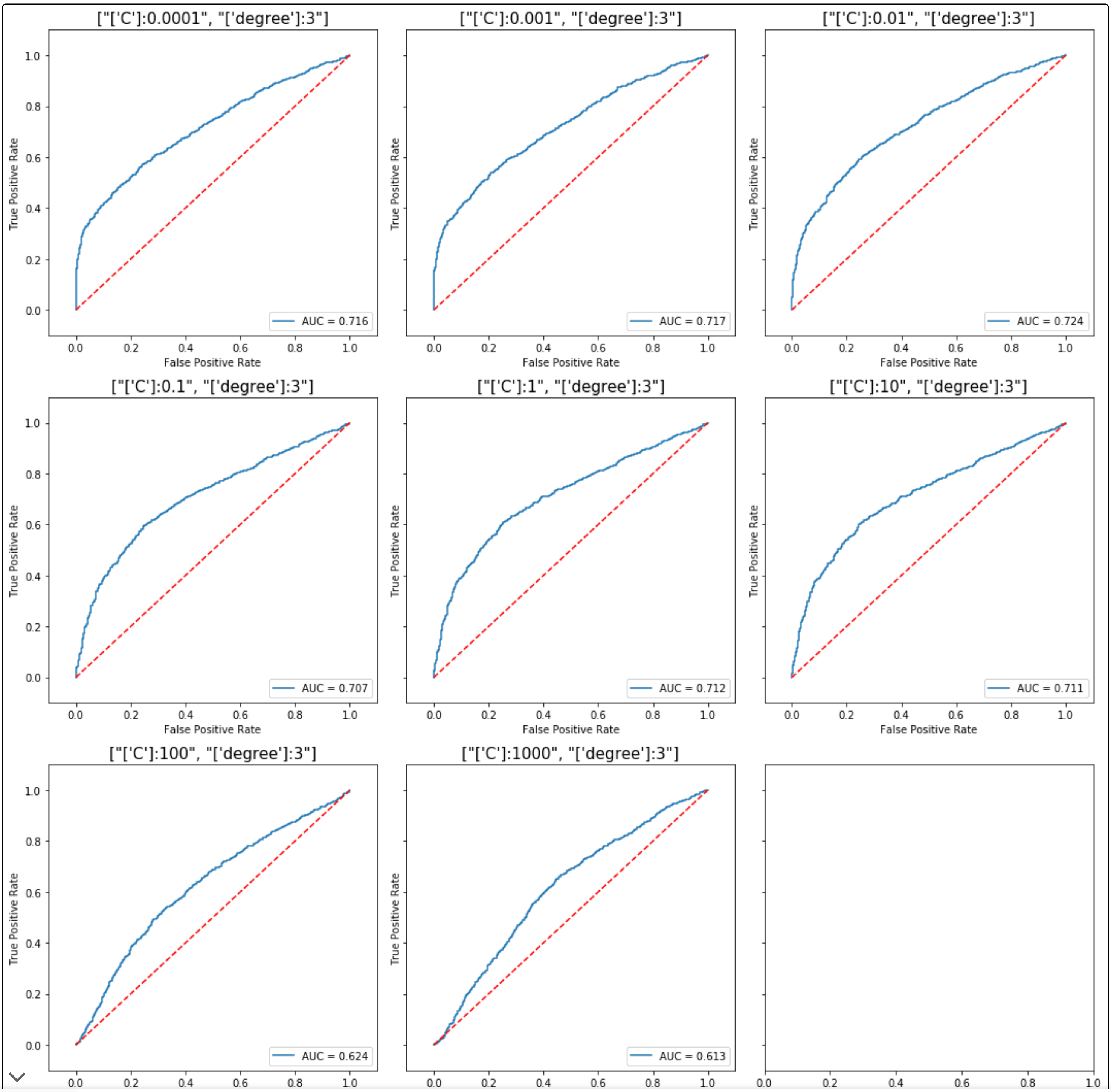


For a linear kernel, varying the C parameter doesn't make much difference even though we are using a highly noisy dataset.

View the full code here: ***[linear-kernel (https://nbviewer.jupyter.org/github/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb?flush_cache=true#linear-kernel)](https://nbviewer.jupyter.org/github/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb?flush_cache=true#linear-kernel)***

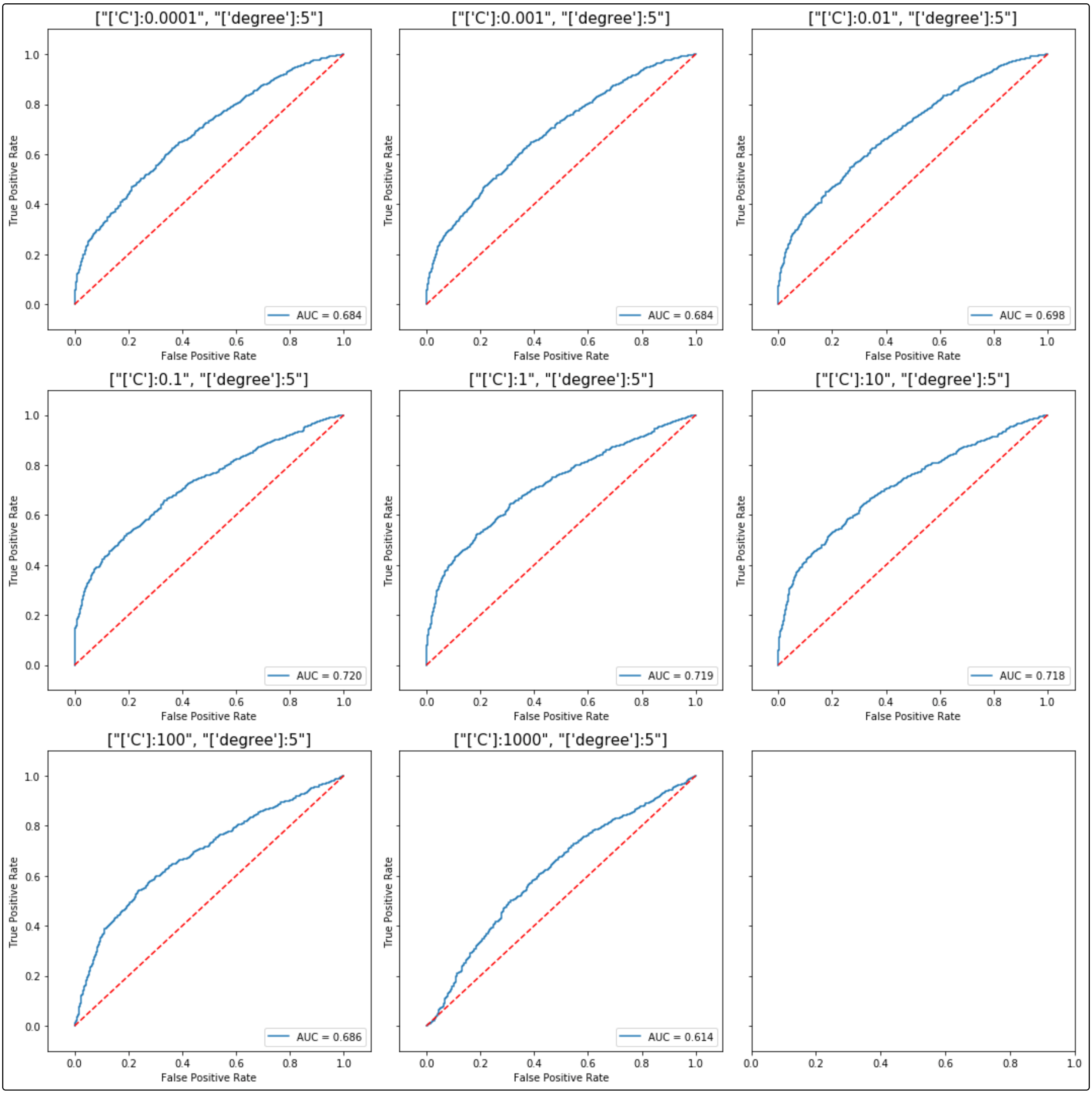
Examples: Choice of C for SVM, Polynomial Kernel

For polynomial kernels, the choice of C does affect the out-of-sample performance, but the optimal value for C may not necessarily be the lowest one.



score was not achieved at the minimum C, but with C=0.01.

View the full code here: **[polynomial kernel, degree=3 (https://nbviewer.jupyter.org/github/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb?flush_cache=true#polynomial-kernel,-degree=3)](https://nbviewer.jupyter.org/github/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb?flush_cache=true#polynomial-kernel,-degree=3)**

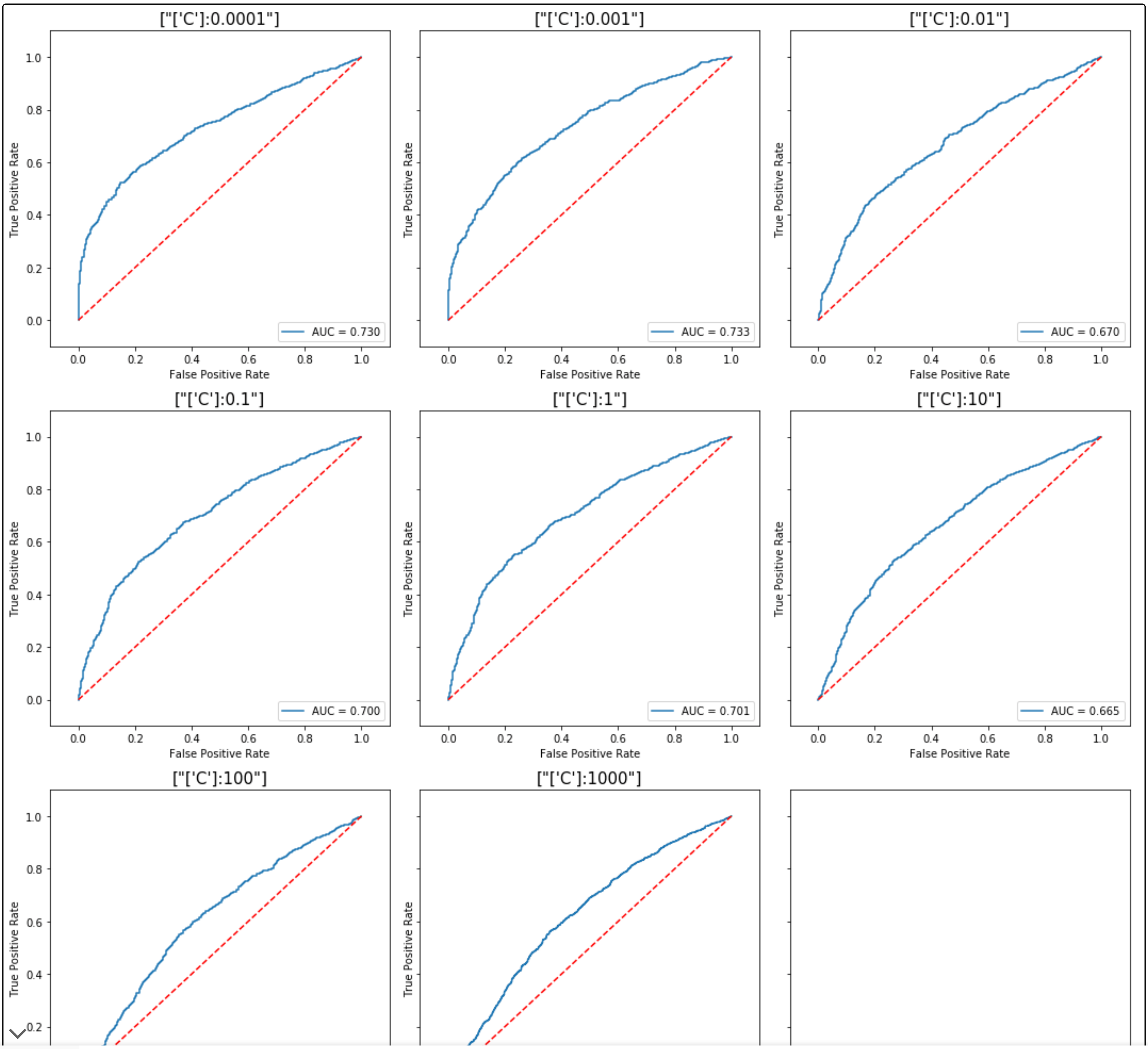


Again, for a polynomial kernel with degree 5, the optimal value for out-of-sample score was not achieved at the minimum C, but with C=1.0.

View the full code here: **[polynomial kernel, degree=5 (https://nbviewer.jupyter.org/github/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb?flush_cache=true#polynomial-kernel,-degree=5)](https://nbviewer.jupyter.org/github/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb?flush_cache=true#polynomial-kernel,-degree=5)**

Examples: Choice of C for SVM, RBF Kernel

For an SVM model with the RBF kernel, it is once more easy to see that lower values of the C parameter allow the classifier to learn better under noisy data.



Difference in performance for a SVM trained using the RBF kernel, with varying choice of C.
View the full code here: ***RBF kernel (https://nbviewer.jupyter.org/github/queirozfcom/python-sandbox/blob/master/python3/notebooks/svm-c/svm-c.ipynb?flush_cache=true#rbf-kernel)***

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