Understanding Support Vector Machine via Examples

By Sadanand Singh — on 2017-07-08 in Machine Learning — 20 Comments

In the previous post on Support Vector Machines (SVM), we looked at the mathematical details of the algorithm. In this post, I will be discussing the practical implementations of SVM for classification as well as regression. I will be using the iris dataset as an example for the classification problem, and a randomly generated data as an example for the regression problem.

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In Python, scikit-learn is a widely used library for implementing machine learning algorithms, SVM is also available in scikit-learn library and follow the usual structure (Import library, object creation, fitting model and prediction). The sklearn.svm module provides mainly two classes: sklearn.svm.svc for classification and sklearn.svm.svr for regression.

Preparing Data for SVM Models

As pointed out by **Admiral deblue** in the comments below, all practical implementations of SVMs have strict requirements for training and testing (prediction). The first requirement is that all data should be numerical. Therefore, if you have categorical features, they need to be converted to numerical values using variable transformation techniques like one-hot-encoding, label-encoding etc. SVM model implementations in python also do not support missing values, hence you need to either remove data with missing values or use some form of data imputing. The sklearn.preprocessing.Imputer module can be quite helpful for this exercise. Furthermore, since SVMs assume that the data it works with is in a standard range, usually either 0 to 1, or -1 to 1 etc. (so that all feature variables are treated equally), it would be best served to use the feature "normalization" before training the model. The sklearn.preprocessing.StandardScaler module can use used for such normalization.

In general, sklearn models require training data (X) to be numpy nd-array and dependent variable (y) as numpy 1-d array. With newer versions of Pandas, Pandas data-frame and series can also be used for providing X and y to sklearn models.

sklearn.pipeline provides an impressive set of tools to deal with various aspects of data preparation for training different models in a coherent manner. This will be a topic of discussion for a post in near future.

SVM for Classification Problems

The iris dataset is a simple dataset of contains 3 classes of 50 instances each, where each class refers to a type of iris plant. One class is linearly separable from the other two; the latter are NOT linearly separable from each other. Each instance has 4 features:

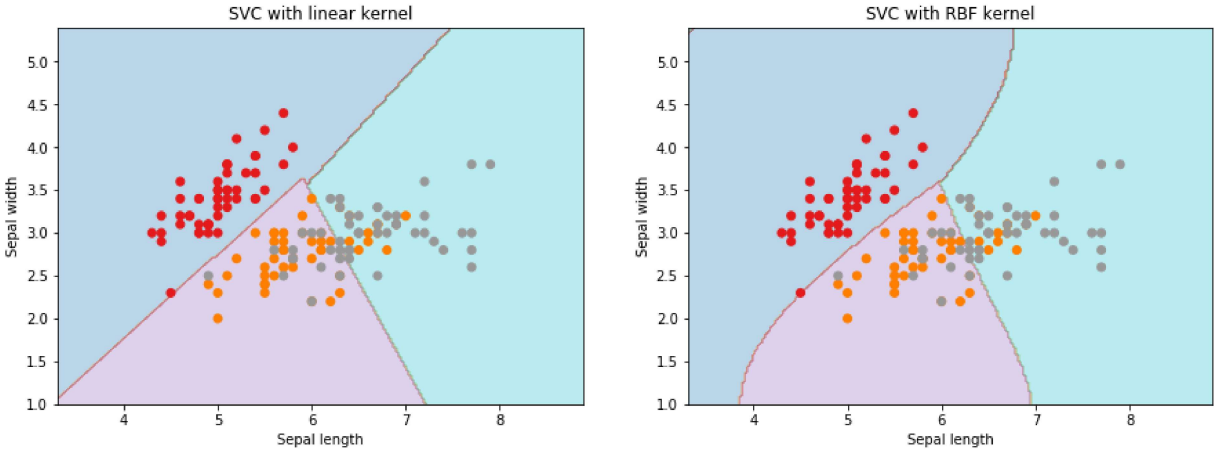
1. sepal length
2. sepal width
3. petal length
4. petal width

A typical problem to solve is to predict the *class* of the iris plant based on these 4 features. For brevity and visualization, in this example we will be using only the first two features.

Setup

Below is the simplest implementation of a SVM for this problem. In this example, we see the simplest implementation of SVM classifier with the linear and the radial basis function (rbf) kernels.

```
import pandas as pd
import numpy as np
from sklearn import svm, datasets
import matplotlib.pyplot as plt
%matplotlib inline

iris = datasets.load_iris()
X = iris.data[:, :2]  # we only take the first two features.
y = iris.target

# Plot resulting Support Vector boundaries with original data
# Create fake input data for prediction that we will use for plotting
# create a mesh to plot in
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
h = (x_max / x_min)/100
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
 np.arange(y_min, y_max, h))
X_plot = np.c_[xx.ravel(), yy.ravel()]

# Create the SVC model object
C = 1.0  # SVM regularization parameter
svc = svm.SVC(kernel='linear', C=C, decision_function_shape='ovr').fit(X, y)
Z = svc.predict(X_plot)
Z = Z.reshape(xx.shape)

plt.figure(figsize=(15, 5))
plt.subplot(121)
plt.contourf(xx, yy, Z, cmap=plt.cm.tab10, alpha=0.3)
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Set1)
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')
plt.xlim(xx.min(), xx.max())
plt.title('SVC with linear kernel')

# Create the SVC model object
C = 1.0  # SVM regularization parameter
svc = svm.SVC(kernel='rbf', C=C, decision_function_shape='ovr').fit(X, y)

Z = svc.predict(X_plot)
Z = Z.reshape(xx.shape)

plt.subplot(122)
plt.contourf(xx, yy, Z, cmap=plt.cm.tab10, alpha=0.3)
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Set1)
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')
plt.xlim(xx.min(), xx.max())
plt.title('SVC with RBF kernel')

plt.show()
```



Parameter Tuning

Similar to any machine learning algorithm, we need to choose/tune hyper-parameters for these models. The important parameters to tune are: C (the penalty parameter or the error term. Remember from our last post, this acts as a regularization parameter for SVM) and γ (Kernel coefficient for 'rbf', 'poly' and 'sigmoid' kernels). In above example, we used a default value of $\gamma = \frac{1}{n_{features}} = 0.5$.

Multi-class Classification

SVM by definition is well suited for binary classification. In order to perform multi-class classification, the problem needs to be transformed into a set of binary classification problems.

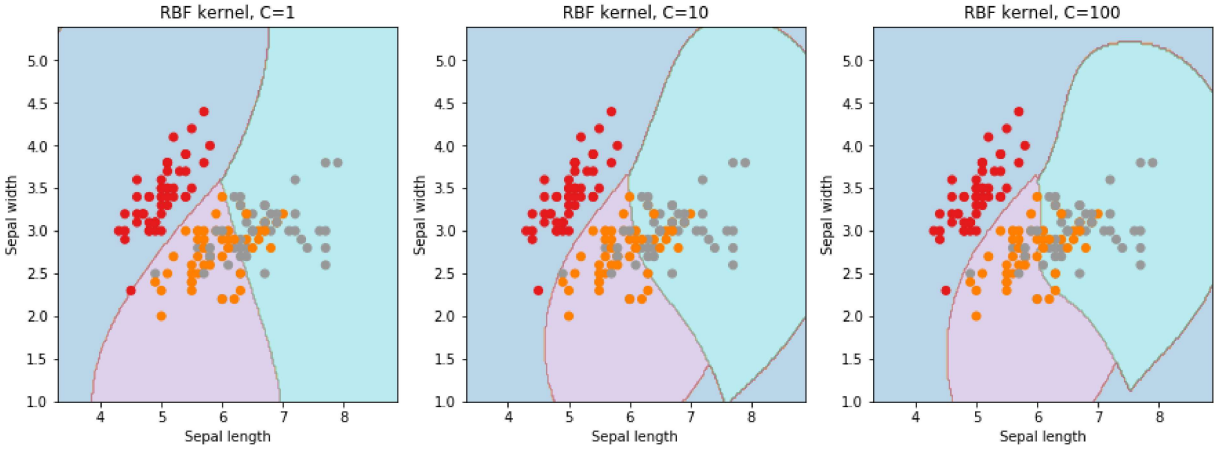
There are two approaches to do this:

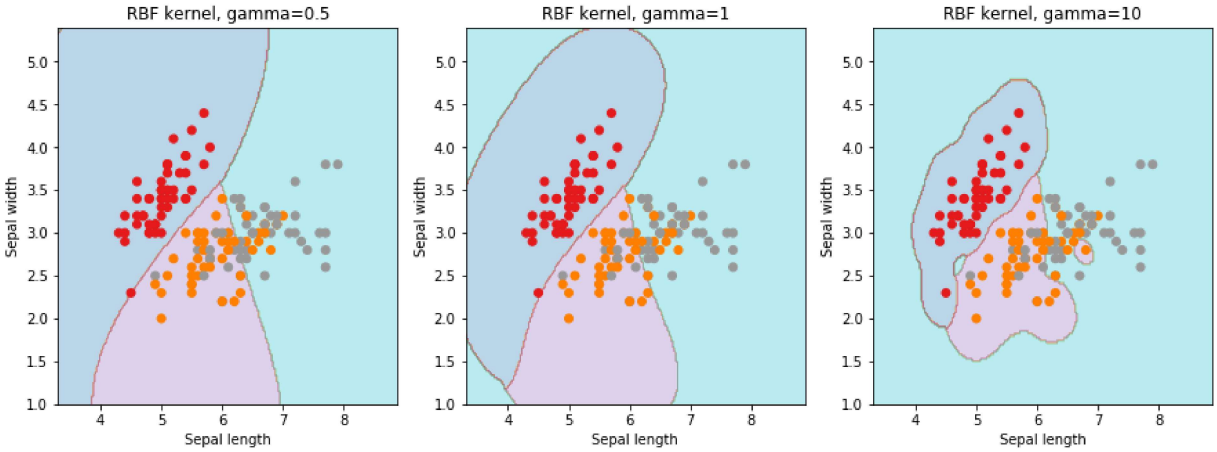
One vs. Rest Approach (OvR): This strategy involves training a single classifier per class, with the samples of that class as positive samples and all other samples as negatives. This strategy requires the base classifiers to produce a real-valued confidence score for its decision, rather than just a class label; discrete class labels alone can lead to ambiguities, where multiple classes are predicted for a single sample.

One vs. One Approach (OvO): In the one-vs.-one (OvO) strategy, one trains K(K − 1)/2 binary classifiers for a K-way multi-class problem; each receives the samples of a pair of classes from the original training set, and must learn to distinguish these two classes. At prediction time, a voting scheme is applied: all K(K − 1)/2 classifiers are applied to an unseen sample and the class that got the highest number of "+1" predictions gets predicted by the combined classifier. Like OvR, OvO suffers from ambiguities in that some regions of its input space may receive the same number of votes.

In svm.svc implementation, `decision_function_shape` parameter provides the option to choose one of two strategy. Although, by default OvO strategy is chosen for historical reasons, it is always recommended to switch to the OvR approach.

Let us first understand what effects C and γ parameters have on SVM models. As seen below, we find that higher the value of γ, it will try to exact fit the as per training data set i.e. generalization error and cause over-fitting problem. C controls the trade off between smooth decision boundary and classifying the training points correctly.





We will be using 5-fold cross validation to perform grid search to calculate optimal hyper-parameters. This is easily achieved in scikit-learn using the sklearn.model_selection.GridSearchCV class.

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.utils import shuffle

# shuffle the dataset
X, y = shuffle(X, y, random_state=0)

# Split the dataset in two equal parts
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.25, random_state=0)

# Set the parameters by cross-validation
parameters = [{'kernel': ['rbf'],
                    'gamma': [1e-4, 1e-3, 0.01, 0.1, 0.2, 0.5],
                     'C': [1, 10, 100, 1000]},
                   {'kernel': ['linear'], 'C': [1, 10, 100, 1000]}]

print("# Tuning hyper-parameters")
print()

clf = GridSearchCV(svm.SVC(decision_function_shape='ovr'), parameters, cv=5)
clf.fit(X_train, y_train)

print("Best parameters set found on development set:")
print()
print(clf.best_params_)
print()
print("Grid scores on training set:")
print()
means = clf.cv_results_['mean_test_score']
stds = clf.cv_results_['std_test_score']
for mean, std, params in zip(means, stds, clf.cv_results_['params']):
    print("%0.3f (+/-%0.03f) for %r"
          % (mean, std * 2, params))
print()
```

Output:

```
# Tuning hyper-parameters

Best parameters set found on development set:

{'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}

Grid scores on training set:

0.634 (+/-0.066) for {'C': 1, 'gamma': 0.0001, 'kernel': 'rbf'}
0.634 (+/-0.066) for {'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}
0.634 (+/-0.066) for {'C': 1, 'gamma': 0.01, 'kernel': 'rbf'}
0.768 (+/-0.168) for {'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}
0.768 (+/-0.161) for {'C': 1, 'gamma': 0.2, 'kernel': 'rbf'}
0.768 (+/-0.173) for {'C': 1, 'gamma': 0.5, 'kernel': 'rbf'}
0.634 (+/-0.066) for {'C': 10, 'gamma': 0.0001, 'kernel': 'rbf'}
0.634 (+/-0.066) for {'C': 10, 'gamma': 0.001, 'kernel': 'rbf'}
0.768 (+/-0.168) for {'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
0.750 (+/-0.193) for {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
0.750 (+/-0.193) for {'C': 10, 'gamma': 0.2, 'kernel': 'rbf'}
0.732 (+/-0.183) for {'C': 10, 'gamma': 0.5, 'kernel': 'rbf'}
0.634 (+/-0.066) for {'C': 100, 'gamma': 0.0001, 'kernel': 'rbf'}
0.768 (+/-0.168) for {'C': 100, 'gamma': 0.001, 'kernel': 'rbf'}
0.759 (+/-0.178) for {'C': 100, 'gamma': 0.01, 'kernel': 'rbf'}
0.741 (+/-0.164) for {'C': 100, 'gamma': 0.1, 'kernel': 'rbf'}
0.723 (+/-0.175) for {'C': 100, 'gamma': 0.2, 'kernel': 'rbf'}
0.732 (+/-0.183) for {'C': 100, 'gamma': 0.5, 'kernel': 'rbf'}
0.768 (+/-0.168) for {'C': 1000, 'gamma': 0.0001, 'kernel': 'rbf'}
0.759 (+/-0.178) for {'C': 1000, 'gamma': 0.001, 'kernel': 'rbf'}
0.750 (+/-0.193) for {'C': 1000, 'gamma': 0.01, 'kernel': 'rbf'}
0.732 (+/-0.183) for {'C': 1000, 'gamma': 0.1, 'kernel': 'rbf'}
0.732 (+/-0.183) for {'C': 1000, 'gamma': 0.2, 'kernel': 'rbf'}
0.696 (+/-0.164) for {'C': 1000, 'gamma': 0.5, 'kernel': 'rbf'}
0.768 (+/-0.173) for {'C': 1, 'kernel': 'linear'}
0.759 (+/-0.178) for {'C': 10, 'kernel': 'linear'}
0.759 (+/-0.178) for {'C': 100, 'kernel': 'linear'}
0.759 (+/-0.178) for {'C': 1000, 'kernel': 'linear'}
```

We have done a few things in above code. Let us break down these in steps.

First, if you pay attention to the input dataset, it lists three different class of iris plants in order. In order for models to be forgetful about such an order, its safer to first shuffle the dataset. This is achieved using the shuffle() method. We also want to take aside a fraction of dataset for final testing of our algorithms success. This is done using the train_test_split() method. In this particular case, we have kept aside about $^1/_4$ th of the dataset for testing.

Moving to the main part of the code: tuning of hyper-parameters for SVM. It is done using the `GridSearchCV()` class (The highlighted lines in the above code blocks). At the end, we are also printing out the accuracy score for different set of parameters. We can find the best set of parameters by the `clf.best_params_` property.

Classification Scoring

By default scikit-learn uses accuracy as score for classification tasks. GridSearchCV() provides option to use alternative scoring metrics via the `scoring` parameter. Some common alternatives are, precision, recall, auc with different averaging strategies like micro, macro, weighted etc.

Finally, we can test our model on the test dataset and evaluate various classification metrics using the `classification_report()` method.

```
print("Detailed classification report:")
print()
print("The model is trained on the full development set.")
print("The scores are computed on the full evaluation set.")
print()
y_true, y_pred = y_test, clf.predict(X_test)
print(classification_report(y_true, y_pred))
print()
```

Output:

```
Detailed classification report:


The model is trained on the full development set.
The scores are computed on the full evaluation set.

             precision    recall  f1-score   support

          0       1.00      1.00      1.00        12
          1       0.73      0.92      0.81        12
          2       0.91      0.71      0.80        14

avg / total       0.88      0.87      0.87        38
```

Apart from accuracy, three major metrics to understand the task for classification are: precision, recall and f1-score.

Precision: The precision is the ratio `tp / (tp + fp)` where `tp` is the number of true positives and `fp` the number of false positives. The precision is intuitively the ability of the classifier not to label as positive a sample that is negative.

Recall: The recall is the ratio `tp / (tp + fn)` where `tp` is the number of true positives and `fn` the number of false negatives. The recall is intuitively the ability of the classifier to find all the positive samples.

F_1-Score: It can be interpreted as a weighted harmonic mean of the precision and recall, where an f1-score reaches its best value at 1 and worst score at 0.

Support: Although not a scoring metric, it is an important quantity when looking at different metrics. It is the number of occurrences of each class in `y_true`.

SVM for Regression Problems

Let us first generate a random dataset where we want to generate a regression model. In order to have a good visualization of our results, it would be best to use a single feature as an example. In order to study effect of non-linear models, we will be generating our data from the `sin()` function.

```
X = np.sort(5 * np.random.rand(200, 1), axis=0)
y = np.sin(X).ravel()
y[::5] += 3 * (0.5 - np.random.rand(40))
```

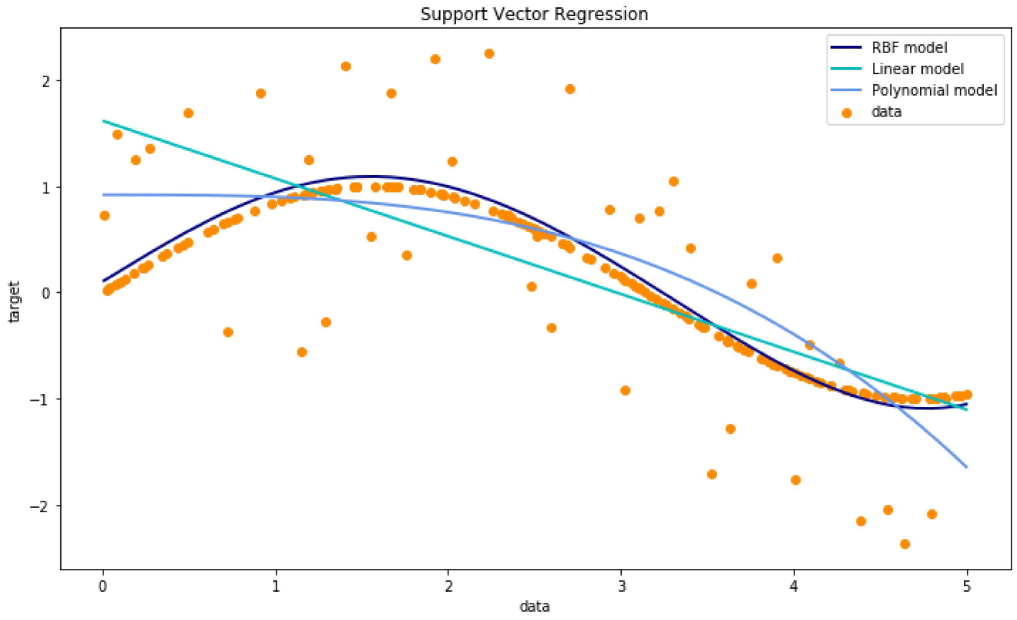
Setup

Below is the simplest implementation of a SVM for this regression problem. In sci-kit learn SVM regression models are implemented using the svm.SVR class.

In this example, we see the simplest implementation of SVM regressors with the linear, polynomial of degree 3 and the radial basis function (rbf) kernels.

```
from sklearn.svm import SVR
svr_rbf = SVR(kernel='rbf', C=1e3, gamma=0.1)
svr_lin = SVR(kernel='linear', C=1e3)
svr_poly = SVR(kernel='poly', C=1e3, degree=3)
y_rbf = svr_rbf.fit(X, y).predict(X)
y_lin = svr_lin.fit(X, y).predict(X)
y_poly = svr_poly.fit(X, y).predict(X)

lw = 2
plt.figure(figsize=(12, 7))
plt.scatter(X, y, color='darkorange', label='data')
plt.plot(X, y_rbf, color='navy', lw=lw, label='RBF model')
plt.plot(X, y_lin, color='c', lw=lw, label='Linear model')
plt.plot(X, y_poly, color='cornflowerblue', lw=lw, label='Polynomial model')
plt.xlabel('data')
plt.ylabel('target')
plt.title('Support Vector Regression')
plt.legend()
plt.show()
```

Output:



Parameter Tuning

The common hyper-parameters in the case of SVM regressors are: C (the error term), ϵ (specifies the epsilon-tube within which no penalty is associated in the training loss function with points predicted within a distance epsilon from the actual value) and γ (Kernel coefficient for 'rbf', 'poly' and 'sigmoid' kernels). Given our example is extremely simplified, we won't be able to observe any significant impact of any of these parameters. In general, similar to classification case, `GridSearchCV` can be used to tune SVM regression models as well.

Concluding Remarks

So that brings us to an end to the different aspects of Support Vector Machine algorithms. In the first post on the topic, I described the theory and the mathematical formulation of the algorithm. In this post, I discussed the implementation details in Python and ways to tune various hyper-parameters in both classification and regression cases. From practical experience, SVMs are great for:

- Small to medium data sets only. Training becomes extremely slow in the case of larger datasets.
- Data sets with low noise. When the data set has more noise i.e. target classes are overlapping, SVM perform very poorly.
- When feature dimensions are very large. SVMs are extremely helpful specially when no. of features is larger than no. of samples.
- Since only a subset of training points are used in the decision function (called support vectors), it is quite memory efficient. This also leads to extremely fast prediction.

An important point to note is that the SVM doesn't directly provide probability estimates, these are calculated using an expensive cross-validation in scikit-learn implementation.

Finally, as would be the case with any machine learning algorithm, I would suggest you to use SVM and analyze the power of SVMs by tuning various hyper-parameters. I want to hear your experience with SVM, how have you tuned SVM models to avoid over-fitting and reduce the training time? Please share your views and experiences in the comments below.

TAGGED IN: Machine Learning Python

Previous post Next post

sadanandsingh Admin ➚ KK • 6 months ago

The following quora answer is a very good and simple explanation of support vector regression.
https://www.quora.com/How-c...

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KK ➚ sadanandsingh • 6 months ago

Thanks Sadanand. I will have a look and update you.

▲ | ▼ • Reply • Share ›

ottoh hidayatullah • 7 months ago

Hi Sadanand,
im new learner Machine Learning my question is i try using LinearSVC and the result is different with svm.SVC with kernel Linear, why? and i cant use svm.SVC as my model to predict new input data error coming up

ValueError: cannot use sparse input in 'SVC' trained on dense data

can you help me to explain this?

▲ | ▼ • Reply • Share ›

sadanandsingh Admin ➚ ottoh hidayatullah • 7 months ago

Hi Ottoh,
The reason for differences in LinearSVC vs svm.SVC is the use of underlying libraries in two. LinearSVC uses liblinear library where as svm.SVC uses the libsvm library. The two libraries have quite different default settings including loss functions, and that can lead to quite different results.

For your second problem, it basically means that your testing set is not in the same format as your training set. Since it cannot used sparse input on dense data, either convert your dense data to sparse data (recommended) or your sparse data to dense data. Use SciPy to create a sparse matrix from a dense one.

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achyuta • 8 months ago

Hi sadanand,
Thanks for such a great explanation.

I am using structural SVM multi class linear classifier to do NER (named entity recognition) opt.

Training is taking huge time.
Input parameters are :
Sample size : 1470
C = 200
Epsilon= 0.0001
Max iterations: 2000
Cross validation = true
max_C = 5000
min_C = 0.0001

Does max iterations impact performance ? If so , can I take small value of max iterations?

C parameter makes impact on performance (time complexity and accuracy) right !!. So I tried different values of C and got some time difference. But problem is every time I change C value I am getting different best C value. Why ? Yes I am doing cross validation. Where

see more

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boy boy • 8 months ago

hi how to display grid score on testing set,the score are only displayed for training set which makes it unable to verify which parameter gives the best fit.High accuracy on training data does not necessarily mean it is the best parameter so it will be help full to verify the score with testing set.
regards,
Yumlembam Rahul

▲ | ▼ • Reply • Share ›

sadanandsingh Admin ➚ boy boy • 8 months ago

Hi,
The score you get on training set is cross validation score, so its not as bad as using training data fully for hyperparameter tuning. Ideally, we should have another validation set just for hyper parameters tuning. I don't think Gridsearch API provides any interface for that though. You will have write your own pipeline to achieve that.

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boy boy ➚ sadanandsingh • 8 months ago

Thank you for your reply appreciate it

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Martine • 9 months ago

Hi Sadanand,

I am currently using Support Vector Regression on a data set. I am trying to figure out what exactly it is that is passed on from training the model in order to predict the y-values in the test set. Are the support vectors from the trained model used on the training set? And how are they used? Or is it something else?
Hope you can help out!

regards, Martine

Reply • Share ›

sadanandsingh Admin ➚ Martine • 9 months ago

Hi Martin,
If I understand your question, you are asking about the functional form of the model. Briefly, the function f(x) = y for SVM is of the form f(x) = x'W+b [where x' is trasnpose of vector x], W is given by \sum_{i=1}^{m} \alpha_i y_i x_i [where m is no. of support vectors, \alpha_i are coefficients determined during training and b are bias terms for corresponding support vectors.]

If you look at my previous post (https://sadanand-singh.gith..., you can find answer to these in more mathematical detail.

Hope this helps.

Reply • Share ›

Rongzhen Chen • a year ago

Hi Sadanand,

I am a new learner on machine learning. Just wondering something regarding your code. I am testing how the feature scaling affects performance. I did the test:

1. X[:,0]=X[:,0]*10; X[:,1]=X[:,1]/10 # here I have changed the original data in a bad way *10 and /10, respecitvely.

The result is

precision recall f1-score support

0 1.00 1.00 1.00 11

1 0.62 0.73 0.67 11

2 0.79 0.69 0.73 16

avg / total 0.80 0.79 0.79 38

2. I am expecting the result will be improved if I did the feature scaling: from sklearn import preprocessing; X[:,0]=X[:,0]*10;

see more

1 Reply • Share ›

sadanandsingh Admin ➚ Rongzhen Chen • a year ago

Hi Rongzhen,
The reason you are not able to see much impact of such a scaling, for this particular problem is actually related to the nature of this particular problem, not 5-fold cross validation. Suppose, just for simplicity, we assume support vector decision boundary is linear. Then the slope of linear decision boundary will not depend on the range of X1 and X2, instead it should depend upon distribution of points. However, given the three classes are already quite well separated in this problem, by scaling the data, the way you did, you really have not made any significant change in the distribution of the data and hence SVC is able to still extract correct decision boundary for the problem.

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Barbarian Blue • a year ago

This is nice. But since most would be using on their own data, it would be nice to know how the data should be formatted in order to import.

Reply • Share ›

sadanandsingh Admin ➚ Barbarian Blue • a year ago

Thanks. I can add a bit about data formatting as well. In general though, one will need numbers-only columns for SVM to work. So, if you have categorical features in your data, they need to be transformed into numbers using transformations like "one-hot-encoding","label-encoding" etc. Furthermore, since SVMs assume that the data it works with is in a standard range, usually either 0 to 1, or -1 to 1 etc., it would be best served to use the feature "normalization" before training the model.

Thanks for pointing this out. I will add this little bit in more detail in the post. Data transformation is though a full topic in itself, I should consider doing a post on that itself in near future.

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sadanandsingh — Interesting article! However I have deep reservations about IBM and Watson. They are never clear about details and just use some …

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hp — Thanks.

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sadanandsingh — If we consider function stack, the first method is O(n) in space, fibN2() is O(1) in space as we are saving a constant

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sadanandsingh — What version of R you are using?