Support Vector Machines

Contents

In this chapter you will learn all about the details of support vector machines. You'll learn about tuning hyperparameters for these models and using kernels to fit non-linear decision boundaries.

Support vectors

Support vector definition

Which of the following is a true statement about support vectors? To help you out, here's the picture of support vectors from the video (top), as well as the hinge loss from Chapter 2 (bottom).

- ☐ All support vectors are classified correctly.
- ☐ All support vectors are classified incorrectly.
- ☐ All correctly classified points are support vectors.
- ☑ All incorrectly classified points are support vectors.

Nice work, you got it!

Effect of removing examples

Support vectors are defined as training examples that influence the decision boundary. In this exercise, you'll observe this behavior by removing non support vectors from the training set.

The wine quality dataset is already loaded into `X` and `y` (first two features only). (Note: we specify `lims` in `plot_classifier()` so that the two plots are forced to use the same axis limits and can be compared directly.)

- Train a linear SVM on the whole data set.
- Create a new data set containing only the support vectors.
- Train a new linear SVM on the smaller data set.

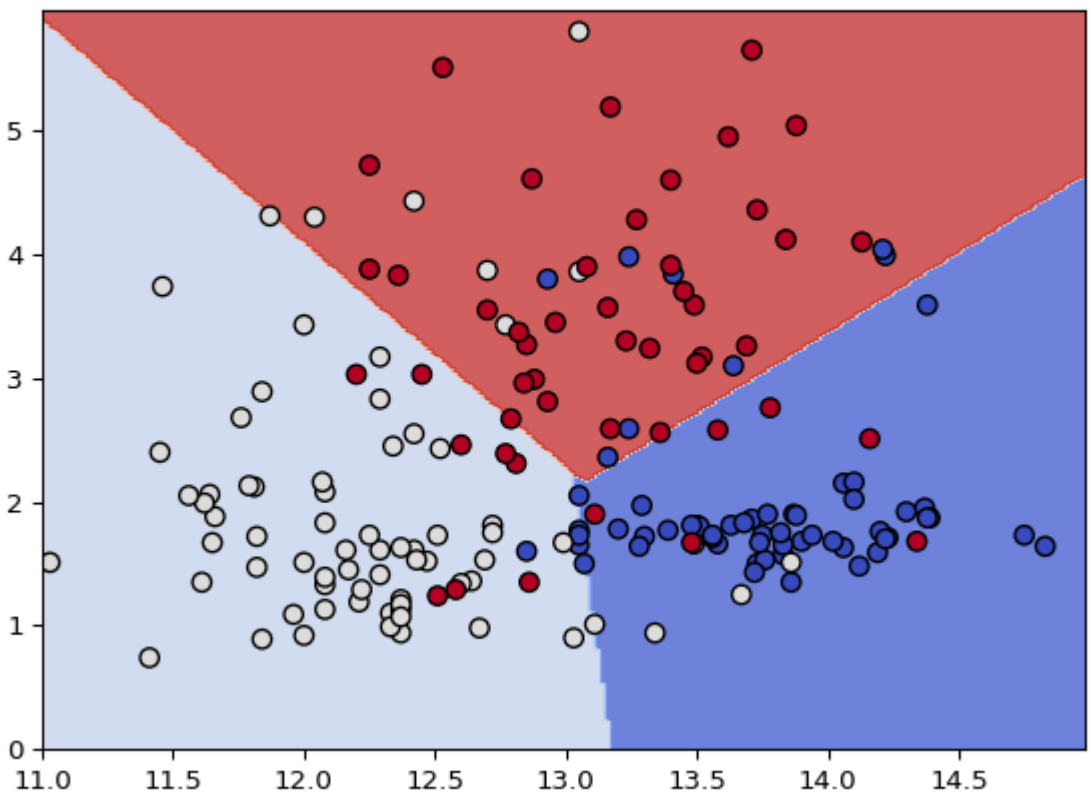
```
# edited/added
X = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/wine_X.csv').to_numpy()
y = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/wine_y.csv').to_numpy().ravel()

# Train a linear SVM
svm = SVC(kernel="linear")
svm.fit(X,y)
```

```
## SVC(kernel='linear')
```

```
plot_classifier(X, y, svm, lims=(11,15,0,6))

# Make a new data set keeping only the support vectors
```




```
print("Number of original examples", len(X))
```

```
## Number of original examples 178
```

```
print("Number of support vectors", len(svm.support_))
```

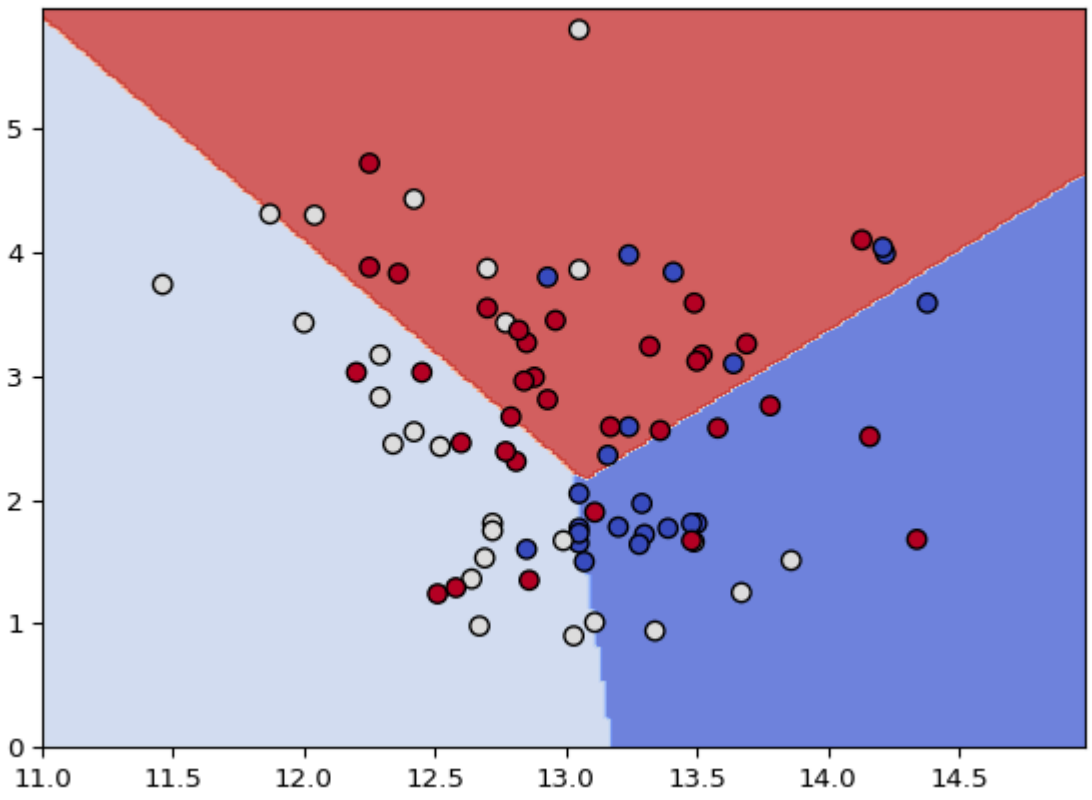
```
## Number of support vectors 81
```

```
X_small = X[svm.support_]
y_small = y[svm.support_]

# Train a new SVM using only the support vectors
svm_small = SVC(kernel="linear")
svm_small.fit(X_small, y_small)
```

```
## SVC(kernel='linear')
```

```
plot_classifier(X_small, y_small, svm_small, lims=(11,15,0,6))
```



Nice! Compare the decision boundaries of the two trained models: are they the same? By the definition of support vectors, they should be!

Kernel SVMs

GridSearchCV warm-up

In the video we saw that increasing the RBF kernel hyperparameter `gamma` increases training accuracy. In this exercise we'll search for the `gamma` that maximizes cross-validation accuracy using scikit-learn's `GridSearchCV`. A binary version of the handwritten digits dataset, in which you're just trying to predict whether or not an image is a "2", is already loaded into the variables `X` and `y`.

- Create a `GridSearchCV` object.
- Call the `fit()` method to select the best value of `gamma` based on cross-validation accuracy.

```
# edited/added
X = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/digits_2_X.csv').to_numpy()
y = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/digits_2_y.csv').astype('bool').to_numpy().ravel()

# Instantiate an RBF SVM
svm = SVC()

# Instantiate the GridSearchCV object and run the search
parameters = {'gamma':[0.00001, 0.0001, 0.001, 0.01, 0.1]}
searcher = GridSearchCV(svm, parameters)
searcher.fit(X, y)

# Report the best parameters
```

```
## GridSearchCV(estimator=SVC(),
##              param_grid={'gamma': [1e-05, 0.0001, 0.001, 0.01, 0.1]})
```

```
print("Best CV params", searcher.best_params_)
```

```
## Best CV params {'gamma': 0.001}
```

Great job! Larger values of `gamma` are better for training accuracy, but cross-validation helped us find something different (and better!).

Jointly tuning gamma and C with GridSearchCV

In the previous exercise the best value of `gamma` was 0.001 using the default value of `C`, which is 1. In this exercise you'll search for the best combination of `C` and `gamma` using `GridSearchCV`.

As in the previous exercise, the 2-vs-not-2 digits dataset is already loaded, but this time it's split into the variables `X_train`, `y_train`, `X_test`, and `y_test`. Even though cross-validation already splits the training set into parts, it's often a good idea to hold out a separate test set to make sure the cross-validation results are sensible.

- Run `GridSearchCV` to find the best hyperparameters using the training set.
- Print the best values of the parameters.
- Print out the accuracy on the test set, which was not used during the cross-validation procedure.

```
# edited/added
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y)

# Instantiate an RBF SVM
svm = SVC()

# Instantiate the GridSearchCV object and run the search
parameters = {'C':[0.1, 1, 10], 'gamma':[0.00001, 0.0001, 0.001, 0.01, 0.1]}
searcher = GridSearchCV(svm, parameters)
searcher.fit(X_train, y_train)

# Report the best parameters and the corresponding score
```

```
## GridSearchCV(estimator=SVC(),
##              param_grid={'C': [0.1, 1, 10],
##                          'gamma': [1e-05, 0.0001, 0.001, 0.01, 0.1]})
```

```
print("Best CV params", searcher.best_params_)
```

```
## Best CV params {'C': 1, 'gamma': 0.001}
```

```
print("Best CV accuracy", searcher.best_score_)

# Report the test accuracy using these best parameters
```

```
## Best CV accuracy 0.9970259812050857
```

```
print("Test accuracy of best grid search hypers:", searcher.score(X_test, y_test))
```

```
## Test accuracy of best grid search hypers: 1.0
```

You got it! Note that the best value of `gamma`, 0.0001, is different from the value of 0.001 that we got in the previous exercise, when we fixed `C=1`. Hyperparameters can affect each other!

Comparing logistic regression and SVM

- Logistic regression:
  - Is a linear classifier
  - Can use with kernels, but slow
  - Outputs meaningful probabilities
  - Can be extended to multi-class
  - All data points affect fit
  - L2 or L1 regularization
- Support Vector Machine (SVM)
  - Is a linear classifier
  - Can use with kernels, and fast

- Does not naturally output probabilities
- Can be extended to multi-class
- Only “support vectors” affect fit
- Conventionally just L2 regularization

An advantage of SVMs

Which of the following is an advantage of SVMs over logistic regression?

- [ ] They naturally output meaningful probabilities.
- [ ] They can be used with kernels.
- [x] They are computationally efficient with kernels.
- [ ] They learn sigmoidal decision boundaries.

That’s right! Having a limited number of support vectors makes kernel SVMs computationally efficient.

An advantage of logistic regression

Which of the following is an advantage of logistic regression over SVMs?

- [x] It naturally outputs meaningful probabilities.
- [ ] It can be used with kernels.
- [ ] It is computationally efficient with kernels.
- [ ] It learns sigmoidal decision boundaries.

You got it!

Using SGDClassifier

In this final coding exercise, you’ll do a hyperparameter search over the regularization strength and the loss (logistic regression vs. linear SVM) using `SGDClassifier()`.

- Instantiate an `SGDClassifier` instance with `random_state=0`.
- Search over the regularization strength and the `hinge` vs. `log_loss` losses.

```
# edited/added
from sklearn.linear_model import SGDClassifier
X, y = digits.data, digits.target
X_train, X_test, y_train, y_test = train_test_split(X, y)

# We set random_state=0 for reproducibility
linear_classifier = SGDClassifier(random_state=0)

# Instantiate the GridSearchCV object and run the search
parameters = {'alpha':[0.00001, 0.0001, 0.001, 0.01, 0.1, 1],
              'loss':['hinge', 'log_loss']}
searcher = GridSearchCV(linear_classifier, parameters, cv=10)
searcher.fit(X_train, y_train)

# Report the best parameters and the corresponding score
```

```
## GridSearchCV(cv=10, estimator=SGDClassifier(random_state=0),
##              param_grid={'alpha': [1e-05, 0.0001, 0.001, 0.01, 0.1, 1],
##                          'loss': ['hinge', 'log_loss']})
##
## /Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/model_selection/_validation.py:372: FitFailedWarning:
## 60 fits failed out of a total of 120.
## The score on these train-test partitions for these parameters will be set to nan.
## If these failures are not expected, you can try to debug them by setting
error_score='raise'.
##
## Below are more details about the failures:
## --------------------------------------------------------------------------------
## 60 fits failed with the following error:
## Traceback (most recent call last):
##   File "/Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/model_selection/_validation.py", line 681, in _fit_and_score
##     estimator.fit(X_train, y_train, **fit_params)
##   File "/Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 890, in fit
##     return self._fit(
##   File "/Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 649, in _fit
##     self._validate_params()
##   File "/Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/linear_model/_stochastic_gradient.py", line 162, in _validate_params
##     raise ValueError("The loss %s is not supported. " % self.loss)
## ValueError: The loss log_loss is not supported.
##
##   warnings.warn(some_fits_failed_message, FitFailedWarning)
## /Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/model_selection/_search.py:969: UserWarning: One or more of the test
scores are non-finite: [0.93391376        nan 0.94656716        nan 0.94062465
nan
##  0.94730238        nan 0.95101161        nan 0.95252626        nan]
##   warnings.warn(
```

```
print("Best CV params", searcher.best_params_)
```

```
## Best CV params {'alpha': 1, 'loss': 'hinge'}
```

```
print("Best CV accuracy", searcher.best_score_)
```

```
## Best CV accuracy 0.9525262576008844
```

```
print("Test accuracy of best grid search hypers:", searcher.score(X_test, y_test))
```

```
## Test accuracy of best grid search hypers: 0.9511111111111111
```

Congrats, you finished the last exercise in the course! One advantage of `SGDClassifier` is that it's very fast - this would have taken a lot longer with `LogisticRegression` or `LinearSVC`.

Conclusion

Conclusion

You made it - congratulations!

How does this course fit into data science?

You now have practice applying logistic regression and support vector machines to classification problems. How does this fit into a bigger picture? The way I see it, data science is the process of answering questions and making decisions based on data. The data science process usually combines several of the following pieces: data collection, data preparation, database design, visualization, communication, software engineering, machine learning, and more. In this course we focused on the machine learning portion. Machine learning has several branches like supervised learning, unsupervised learning, and reinforcement learning. We've been focusing on

supervised learning, which means trying to predict a target value from features given a labeled data set. Within supervised learning, we've focussed on classification, which means the thing we're trying to predict is categorical rather than a continuous in nature. Finally, we covered logistic regression and SVMs, the two most popular linear classifiers. So, while we've done a lot, there's so much more out there!

Congratulations & thanks!

Thanks for completing this journey with me. I hope you enjoyed it as much as I did. Congratulations again.
