Logistic regression

Contents

In this chapter you will delve into the details of logistic regression. You'll learn all about regularization and how to interpret model output.

Logistic regression and regularization

Regularized logistic regression

Regularized logistic regression

- Hyperparameter *C* is the inverse of the regularization strength,
  - Larger *C*: less regularization,
  - Smaller *C*: more regularization,
- Regularized loss = original loss + large coefficient penalty
  - More regularization: lower training accuracy,
  - More regularization: (almost always) higher test accuracy

L1 vs. L2 regularization

*Lasso = linear regression with L1 regularization, *Ridge = linear regression with L2 regularization,

In Chapter 1, you used logistic regression on the handwritten digits data set. Here, we'll explore the effect of L2 regularization.

The handwritten digits dataset is already loaded, split, and stored in the variables `X_train`, `y_train`, `X_valid`, and `y_valid`. The variables `train_errs` and `valid_errs` are already initialized as empty lists.

- Loop over the different values of `C_value`, creating and fitting a `LogisticRegression` model each time.
- Save the error on the training set and the validation set for each model.
- Create a plot of the training and testing error as a function of the regularization parameter, `C`.
- Looking at the plot, what's the best value of `C`?

```
# edited/added
from sklearn.datasets import load_digits

digits = load_digits()
X_train, X_valid, y_train, y_valid = train_test_split(digits.data, digits.target)
C_values = [0.001, 0.01, 0.1, 1, 10, 100, 1000]

# Train and validaton errors initialized as empty list
train_errs = list()
valid_errs = list()

# Loop over values of C_value
for C_value in [0.001, 0.01, 0.1, 1, 10, 100, 1000]:
    # Create LogisticRegression object and fit
    lr = LogisticRegression(C=C_value)
    lr.fit(X_train, y_train)

    # Evaluate error rates and append to lists
    train_errs.append( 1.0 - lr.score(X_train, y_train) )
    valid_errs.append( 1.0 - lr.score(X_valid, y_valid) )

# Plot results
```

```
## LogisticRegression(C=0.001)
## LogisticRegression(C=0.01)
## LogisticRegression(C=0.1)
## LogisticRegression(C=1)
## LogisticRegression(C=10)
## LogisticRegression(C=100)
## LogisticRegression(C=1000)
##
## /Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed to
converge (status=1):
## STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
##
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## Please also refer to the documentation for alternative solver options:
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##   n_iter_i = _check_optimize_result(
```
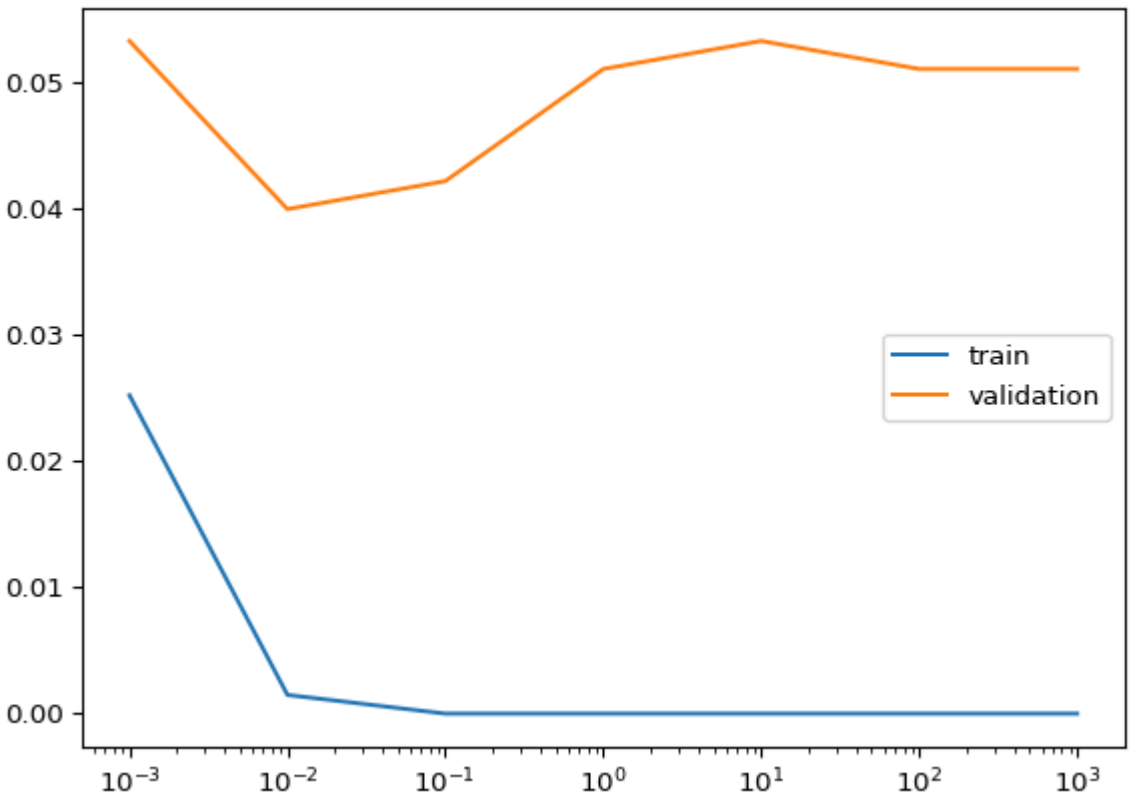

```
plt.semilogx(C_values, train_errs, C_values, valid_errs)
plt.legend(("train", "validation"))
plt.show()
```



Congrats! As you can see, too much regularization (small `C`) doesn't work well - due to underfitting - and too little regularization (large `C`) doesn't work well either - due to overfitting.

Logistic regression and feature selection

In this exercise we'll perform feature selection on the movie review sentiment data set using L1 regularization. The features and targets are already loaded for you in `X_train` and `y_train`.

We'll search for the best value of `C` using scikit-learn's `GridSearchCV()`, which was covered in the prerequisite course.

- Instantiate a logistic regression object that uses L1 regularization.
- Find the value of `C` that minimizes cross-validation error.
- Print out the number of selected features for this value of `C`.

```
# edited/added
from sklearn.datasets import load_svmlight_file
from sklearn.model_selection import GridSearchCV

# edited/added
import numpy as np
from sklearn.datasets import load_svmlight_file
X_train, y_train = load_svmlight_file('archive/Linear-Classifiers-in-
Python/datasets/train_labeledBow.feat')
X_train = X_train[11000:13000,:2500]
y_train = y_train[11000:13000]
y_train[y_train < 5] = -1.0
y_train[y_train >= 5] = 1.0

# Specify L1 regularization
lr = LogisticRegression(solver='liblinear', penalty='l1')

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

# Report the best parameters
```

```
## GridSearchCV(estimator=LogisticRegression(penalty='l1', solver='liblinear'),
##              param_grid={'C': [0.001, 0.01, 0.1, 1, 10]})
```

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

# Find the number of nonzero coefficients (selected features)
```

```
## Best CV params {'C': 0.1}
```

```
best_lr = searcher.best_estimator_
coefs = best_lr.coef_
print("Total number of features:", coefs.size)
```

```
## Total number of features: 2500
```

```
print("Number of selected features:", np.count_nonzero(coefs))
```

```
## Number of selected features: 143
```

Great job! As you can see, a whole lot of features were discarded here.

Identifying the most positive and negative words

In this exercise we'll try to interpret the coefficients of a logistic regression fit on the movie review sentiment dataset. The model object is already instantiated and fit for you in the variable `lr`.

In addition, the words corresponding to the different features are loaded into the variable `vocab`. For example, since `vocab\[100\]` is "think", that means feature 100 corresponds to the number of times the word "think" appeared in that movie review.

- Find the words corresponding to the 5 largest coefficients.
- Find the words corresponding to the 5 smallest coefficients.

```
# edited/added
vocab = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/vocab.csv').to_numpy()

# Get the indices of the sorted cofficients
inds_ascending = np.argsort(best_lr.coef_.flatten())
inds_descending = inds_ascending[::-1]

# Print the most positive words
print("Most positive words: ", end="")
```

```
## Most positive words:
```

```
for i in range(5):
    print(vocab[inds_descending[i]], end=", ")
```

```
## ['great'], ['best'], ['our'], ['may'], ['enjoy'],
```

```
print("\n")

# Print most negative words
```

```
print("Most negative words: ", end="")
```

```
## Most negative words:
```

```
for i in range(5):
    print(vocab[inds_ascending[i]], end=", ")
```

```
## ['worst'], ['boring'], ['bad'], ['waste'], ['annoying'],
```

```
print("\n")
```

You got it! The answers sort of make sense, don't they?

Logistic regression and probabilities

Getting class probabilities

Which of the following transformations would make sense for transforming the raw model output of a linear classifier into a class probability?

- ☐ (1)
- ☐ (2)
- ☑ (3)
- ☐ (4)

That's right! The function in the picture is fairly similar to the logistic function used by logistic regression.

Regularization and probabilities

In this exercise, you will observe the effects of changing the regularization strength on the predicted probabilities.

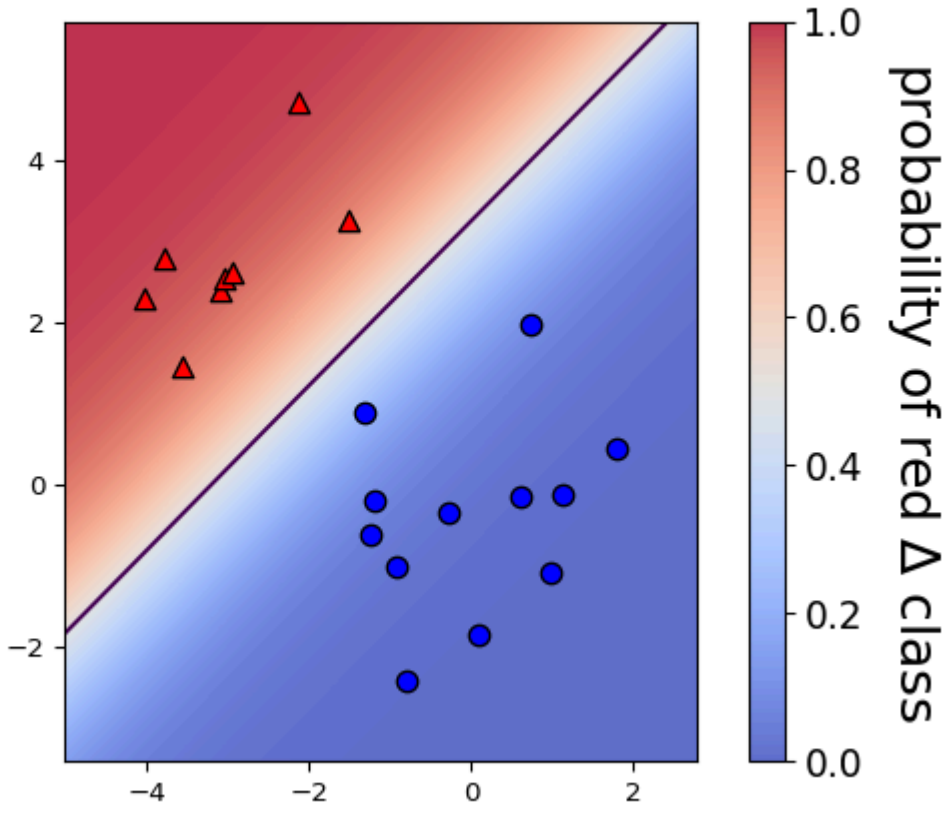
A 2D binary classification dataset is already loaded into the environment as `X` and `y`.

- Compute the maximum predicted probability.
- Run the provided code and take a look at the plot.
- Create a model with `C=0.1` and examine how the plot and probabilities change.

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

# Set the regularization strength
model = LogisticRegression(C=1)

# Fit and plot
model.fit(X,y)
```

```
## LogisticRegression(C=1)
```

```
plot_classifier(X,y,model,proba=True)

# Predict probabilities on training points
```



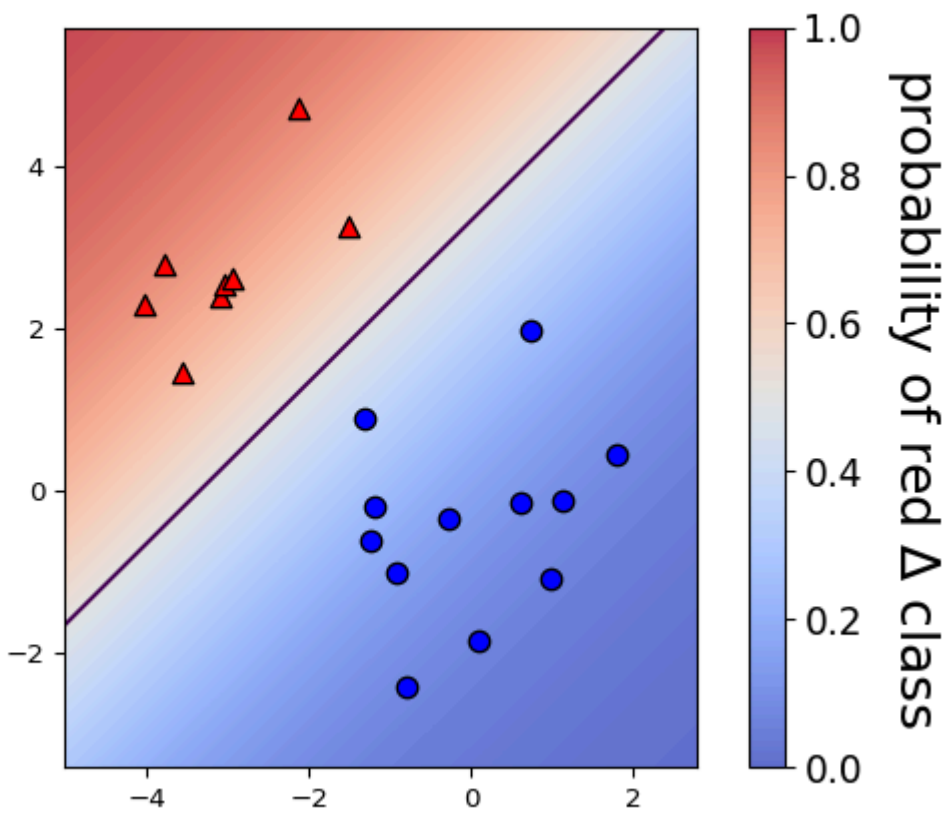

```
prob = model.predict_proba(X)
print("Maximum predicted probability", np.max(prob))

# Set the regularization strength
```

```
## Maximum predicted probability 0.9973143426900802
```

```
model = LogisticRegression(C=0.1)

# Fit and plot
model.fit(X,y)
```

```
## LogisticRegression(C=0.1)
```

```
plot_classifier(X,y,model,proba=True)

# Predict probabilities on training points
```




```
prob = model.predict_proba(X)
print("Maximum predicted probability", np.max(prob))
```

```
## Maximum predicted probability 0.9352061680350906
```

You got it! As you probably noticed, smaller values of `C` lead to less confident predictions. That's because smaller `C` means more regularization, which in turn means smaller coefficients, which means raw model outputs closer to zero and, thus, probabilities closer to 0.5 after the raw model output is squashed through the sigmoid function. That's quite a chain of events!

Visualizing easy and difficult examples

In this exercise, you'll visualize the examples that the logistic regression model is most and least confident about by looking at the largest and smallest predicted probabilities.

The handwritten digits dataset is already loaded into the variables `X` and `y`. The `show_digit` function takes in an integer index and plots the corresponding image, with some extra information displayed above the image.

- Fill in the first blank with the *index* of the digit that the model is most confident about.
- Fill in the second blank with the *index* of the digit that the model is least confident about.
- Observe the images: do you agree that the first one is less ambiguous than the second?

```
# edited/added
def show_digit(i, lr=None):
    plt.imshow(np.reshape(X[i], (8,8)), cmap='gray',
               vmin = 0, vmax = 16, interpolation=None)
    plt.xticks(())
    plt.yticks(())
    if lr is None:
        plt.title("class label = %d" % y[i])
    else:
        pred = lr.predict(X[i][None])
        pred_prob = lr.predict_proba(X[i][None])[0,pred]
        plt.title("label=%d, prediction=%d, proba=%.2f" % (y[i], pred, pred_prob))
        plt.show()

X, y = digits.data, digits.target

lr = LogisticRegression()
lr.fit(X,y)

# Get predicted probabilities
```

```
## LogisticRegression()
##
## /Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed to
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## Please also refer to the documentation for alternative solver options:
##     https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
##   n_iter_i = _check_optimize_result(
```
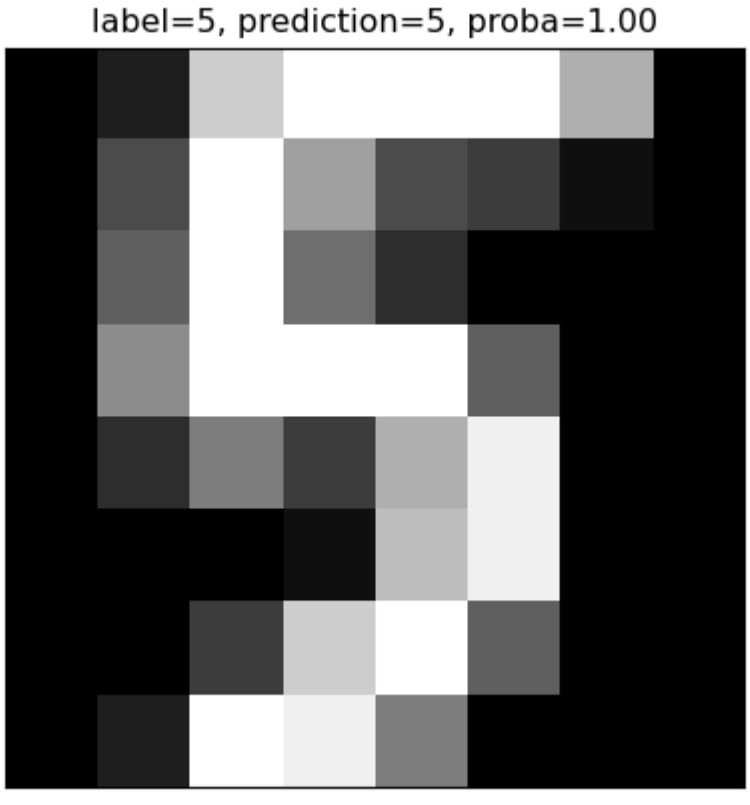
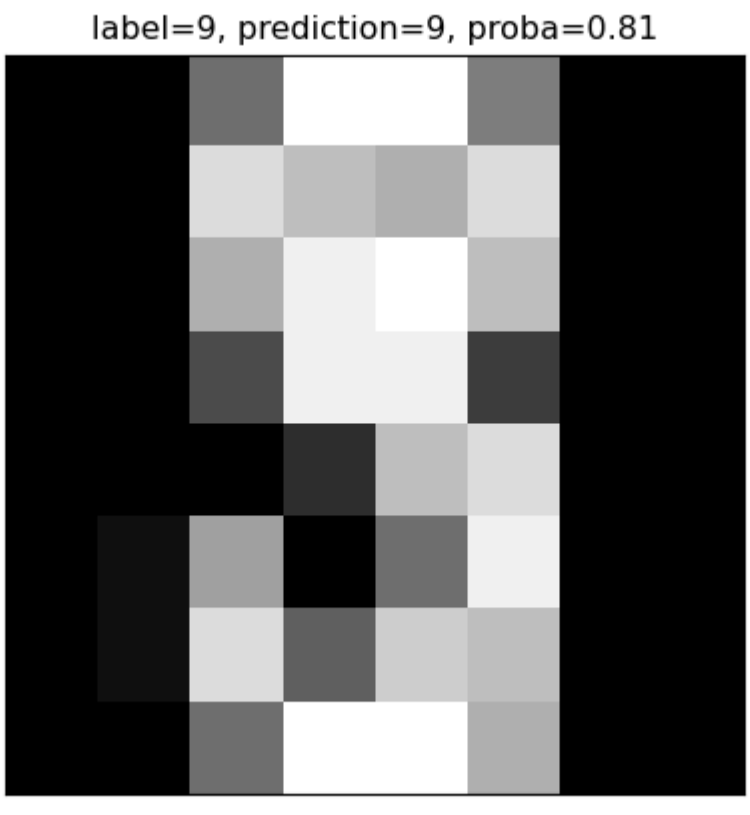

```
proba = lr.predict_proba(X)

# Sort the example indices by their maximum probability
proba_inds = np.argsort(np.max(proba,axis=1))

# Show the most confident (least ambiguous) digit
show_digit(proba_inds[-1], lr)

# Show the least confident (most ambiguous) digit
```




```
show_digit(proba_inds[0], lr)
```



Great job! As you can see, the least confident example looks like a weird 9, and the most confident example looks like a very typical 5.

Multi-class logistic regression

Counting the coefficients

If you fit a logistic regression model on a classification problem with 3 classes and 100 features, how many coefficients would you have, including intercepts?

- [ ] 101
- [ ] 103
- [ ] 301
- [x] 303

Nicely done! Feel free to test this out with scikit-learn!

Fitting multi-class logistic regression

In this exercise, you'll fit the two types of multi-class logistic regression, one-vs-rest and softmax/multinomial, on the handwritten digits data set and compare the results. The handwritten digits dataset is already loaded and split into `X_train`, `y_train`, `X_test`, and `y_test`.

- Fit a one-vs-rest logistic regression classifier by setting the `multi_class` parameter and report the results.
- Fit a multinomial logistic regression classifier by setting the `multi_class` parameter and report the results.

```
# edited/added
X_train, X_test, y_train, y_test = train_test_split(digits.data, digits.target)

# Fit one-vs-rest logistic regression classifier
lr_ovr = LogisticRegression(multi_class="ovr")
lr_ovr.fit(X_train, y_train)
```

```
## LogisticRegression(multi_class='ovr')
##
## /Users/macos/Library/r-miniconda/envs/r-reticulate/lib/python3.8/site-
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##   n_iter_i = _check_optimize_result(
```

```
print("OVR training accuracy:", lr_ovr.score(X_train, y_train))
```

```
## OVR training accuracy: 0.9985152190051967
```

```
print("OVR test accuracy    :", lr_ovr.score(X_test, y_test))

# Fit softmax classifier
```

```
## OVR test accuracy    : 0.9622222222222222
```

```
lr_mn = LogisticRegression(multi_class="multinomial")
lr_mn.fit(X_train, y_train)
```

```
## LogisticRegression(multi_class='multinomial')
##
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packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed to
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## STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
##
## Increase the number of iterations (max_iter) or scale the data as shown in:
##     https://scikit-learn.org/stable/modules/preprocessing.html
## Please also refer to the documentation for alternative solver options:
##     https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
##   n_iter_i = _check_optimize_result(
```

```
print("Softmax training accuracy:", lr_mn.score(X_train, y_train))
```

```
## Softmax training accuracy: 1.0
```

```
print("Softmax test accuracy    :", lr_mn.score(X_test, y_test))
```

```
## Softmax test accuracy    : 0.9622222222222222
```

Nice work! As you can see, the accuracies of the two methods are fairly similar on this data set.

Visualizing multi-class logistic regression

In this exercise we'll continue with the two types of multi-class logistic regression, but on a toy 2D data set specifically designed to break the one-vs-rest scheme.

The data set is loaded into `X_train` and `y_train`. The two logistic regression objects,`lr_mn` and `lr_ovr`, are already instantiated (with `C=100`), fit, and plotted.

Notice that `lr_ovr` never predicts the dark blue class... yikes! Let's explore why this happens by plotting one of the binary classifiers that it's using behind the scenes.

- Create a new logistic regression object (also with `C=100`) to be used for binary classification.
- Visualize this binary classifier with `plot_classifier`... does it look reasonable?

```
# edited/added
X_train = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/toy_X_train.csv').to_numpy()
y_train = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/toy_y_train.csv').to_numpy().ravel()

lr_ovr = LogisticRegression(max_iter=10000, C=100)
lr_ovr.fit(X_train, y_train)
```

```
## LogisticRegression(C=100, max_iter=10000)
```

```
fig, ax = plt.subplots();
ax.set_title("lr_ovr (one-vs-rest)");
plot_classifier(X_train, y_train, lr_ovr, ax=ax);

lr_mn = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=10000)
lr_mn.fit(X_train, y_train)
```

```
## LogisticRegression(max_iter=10000, multi_class='multinomial')
```

```
fig, ax = plt.subplots();
ax.set_title("lr_mn (softmax)");
plot_classifier(X_train, y_train, lr_ovr, ax=ax);

# Print training accuracies
print("Softmax training accuracy:", lr_mn.score(X_train, y_train))
```

```
## Softmax training accuracy: 0.952
```

```
print("One-vs-rest training accuracy:", lr_ovr.score(X_train, y_train))

# Create the binary classifier (class 1 vs. rest)
```

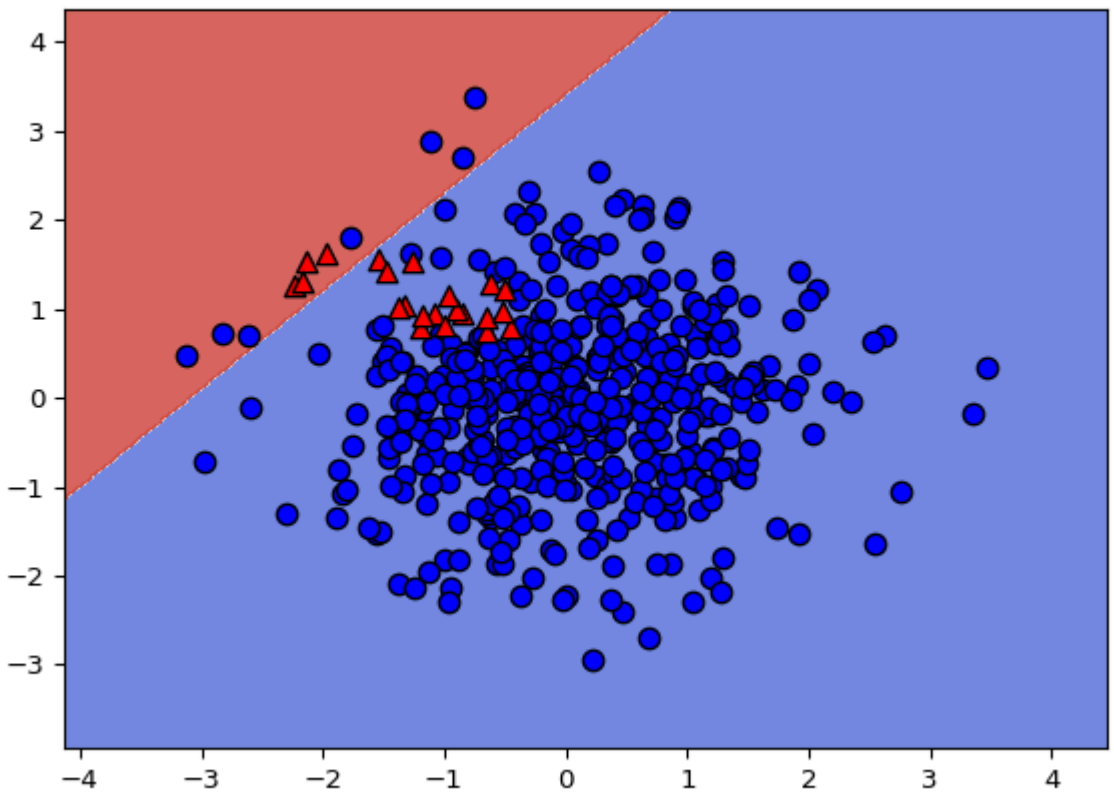
```
## One-vs-rest training accuracy: 0.996
```

```
lr_class_1 = LogisticRegression(C=100)
lr_class_1.fit(X_train, y_train==1)

# Plot the binary classifier (class 1 vs. rest)
```

```
## LogisticRegression(C=100)
```

```
plot_classifier(X_train, y_train==1, lr_class_1)
```



Nice work! As you can see, the binary classifier incorrectly labels almost all points in class 1 (shown as red triangles in the final plot)! Thus, this classifier is not a very effective component of the one-vs-rest classifier. In general, though, one-vs-rest often works well.

One-vs-rest SVM

As motivation for the next and final chapter on support vector machines, we'll repeat the previous exercise with a non-linear SVM. Once again, the data is loaded into `X_train`, `y_train`, `X_test`, and `y_test` .

Instead of using `LinearSVC`, we'll now use scikit-learn's `SVC` object, which is a non-linear "kernel" SVM (much more on what this means in Chapter 4!). Again, your task is to create a plot of the binary classifier for class 1 vs. rest.

- Fit an `SVC` called `svm_class_1` to predict class 1 vs. other classes.
- Plot this classifier.

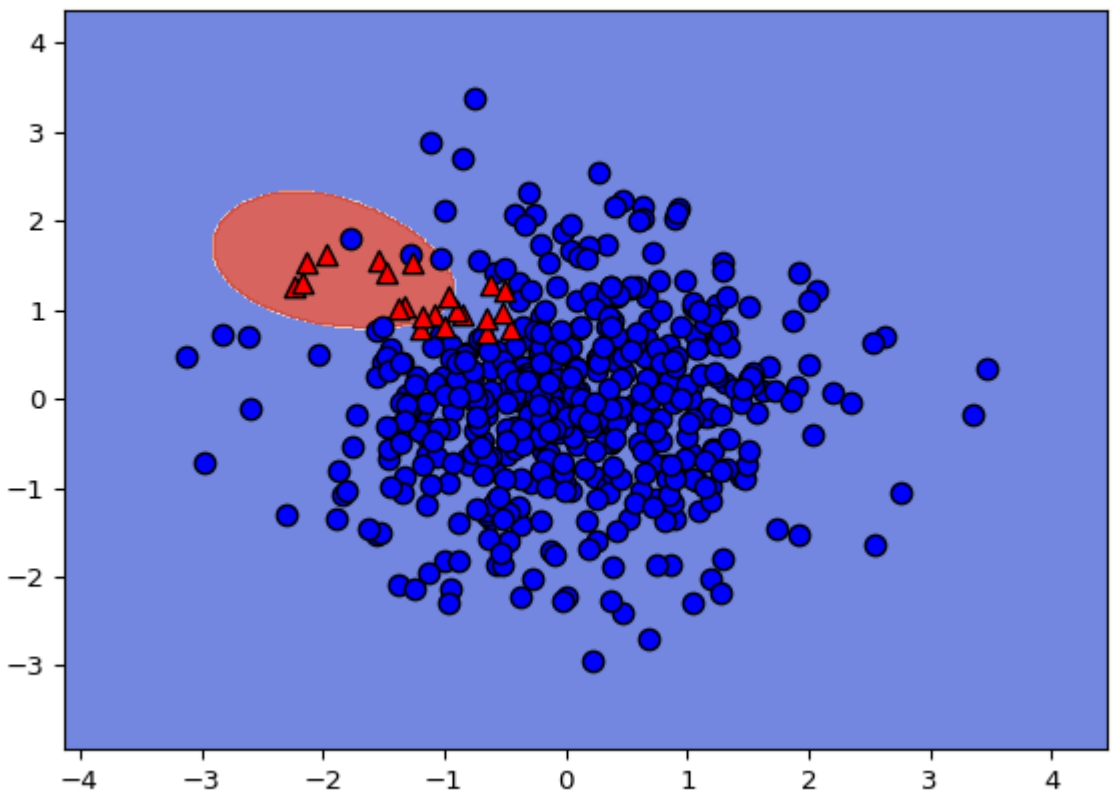
```
# edited/added
X_test = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/toy_X_test.csv').to_numpy()
y_test = pd.read_csv('archive/Linear-Classifiers-in-
Python/datasets/toy_y_test.csv').to_numpy().ravel()

# We'll use SVC instead of LinearSVC from now on
from sklearn.svm import SVC

# Create/plot the binary classifier (class 1 vs. rest)
svm_class_1 = SVC()
svm_class_1.fit(X_train, y_train==1)
```

```
## SVC()
```

```
plot_classifier(X_train, y_train==1, svm_class_1)
```



Cool, eh?! The non-linear SVM works fine with one-vs-rest on this dataset because it learns to "surround" class 1.