How good is your model?

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Classification metrics

- Measuring model performance with accuracy:
 - Fraction of correctly classified samples
 - Not always a useful metric



Class imbalance

- Classification for predicting fraudulent bank transactions
 - 99% of transactions are legitimate; 1% are fraudulent
- Could build a classifier that predicts NONE of the transactions are fraudulent
 - 99% accurate!
 - But terrible at actually predicting fraudulent transactions
 - Fails at its original purpose
- Class imbalance: Uneven frequency of classes
- Need a different way to assess performance

Confusion matrix for assessing classification performance

Confusion matrix

Predicted:	Predicted:
Legitimate	Fraudulent

Actual: Legitimate

True Negative	False Positive	
False Negative	True Positive	

Predicted: Predicted: Legitimate Fraudulent

Actual: Legitimate

True Negative	False Positive	
False Negative	True Positive	

Predicted: Predicted: Legitimate Fraudulent

Actual: Legitimate

True Negative	False Positive	
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Predicted: Predicted: Legitimate Fraudulent

Actual: Legitimate

True Negative	False Positive
False Negative	True Positive

Predicted:	Predicted:
Legitimate	Fraudulent

Actual: Legitimate

Actual: Fraudulent

True Negative	False Positive	
False Negative	True Positive	

Accuracy:

$$\frac{tp+tn}{tp+tn+fp+fn}$$

Precision

Predicted: Predicted: Legitimate Fraudulent

Actual: Legitimate

Actual: Fraudulent

True Negative False Positive
False Negative True Positive

Precision

$$\frac{true\ positives}{true\ positives + false\ positives}$$

- High precision = lower false positive rate
- High precision: Not many legitimate transactions are predicted to be fraudulent

Recall

Predicted: Predicted: Legitimate Fraudulent

Actual: Legitimate

Actual: Fraudulent

True Negative False Positive
False Negative True Positive

Recall

$$\frac{true\ positives}{true\ positives + false\ negatives}$$

- High recall = lower false negative rate
- High recall: Predicted most fraudulent transactions correctly

F1 score

• F1 Score: $2*\frac{precision*recall}{precision+recall}$

Confusion matrix in scikit-learn

Confusion matrix in scikit-learn

```
print(confusion_matrix(y_test, y_pred))
```

```
[[1106 11]
[ 183 34]]
```



Classification report in scikit-learn

print(classification_report(y_test, y_pred))

	precision	recall	f1-score	support
0	0.86	0.99	0.92	1117
1	0.76	0.16	0.26	217
accuracy			0.85	1334
macro avg	0.81	0.57	0.59	1334
weighted avg	0.84	0.85	0.81	1334



Let's practice!

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Logistic regression and the ROC curve

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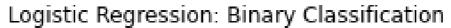
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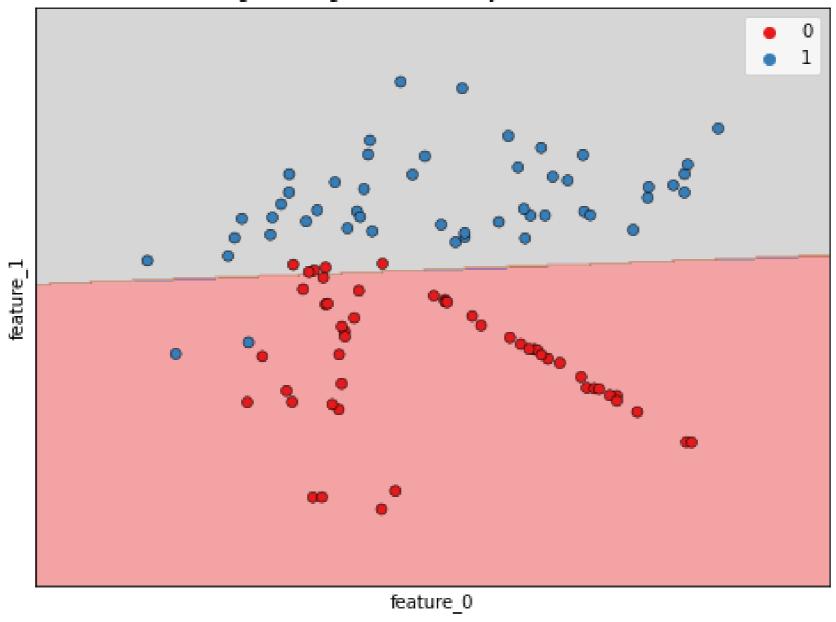


Logistic regression for binary classification

- Logistic regression is used for classification problems
- Logistic regression outputs probabilities
- ullet If the probability, $\,p>0.5$:
 - The data is labeled 1
- If the probability, $\,p < 0.5$:
 - The data is labeled 0

Linear decision boundary





Logistic regression in scikit-learn

Predicting probabilities

```
y_pred_probs = logreg.predict_proba(X_test)[:, 1]
print(y_pred_probs[0])
```

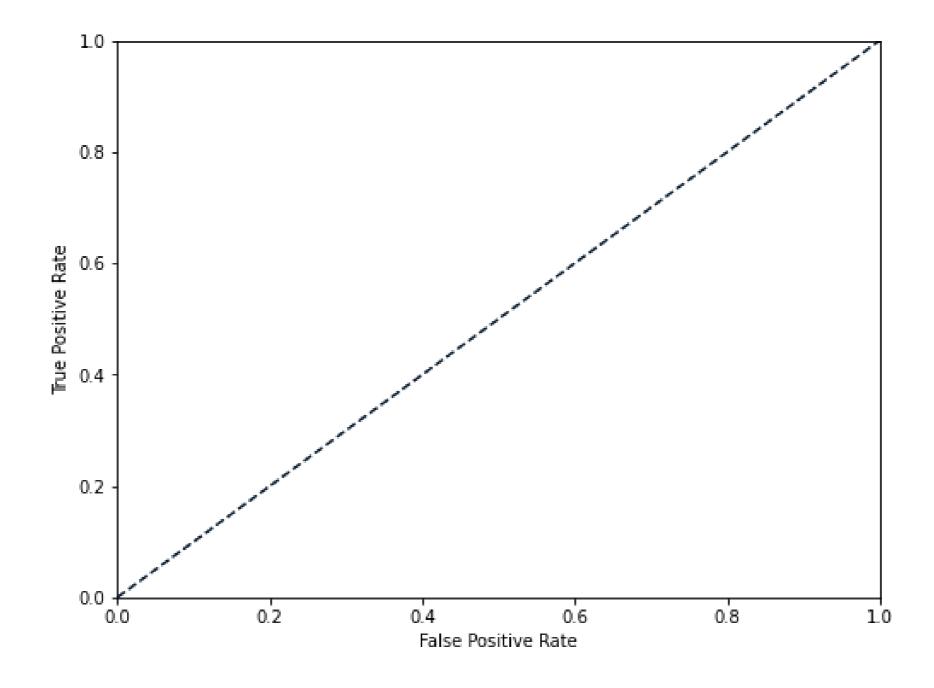
[0.08961376]



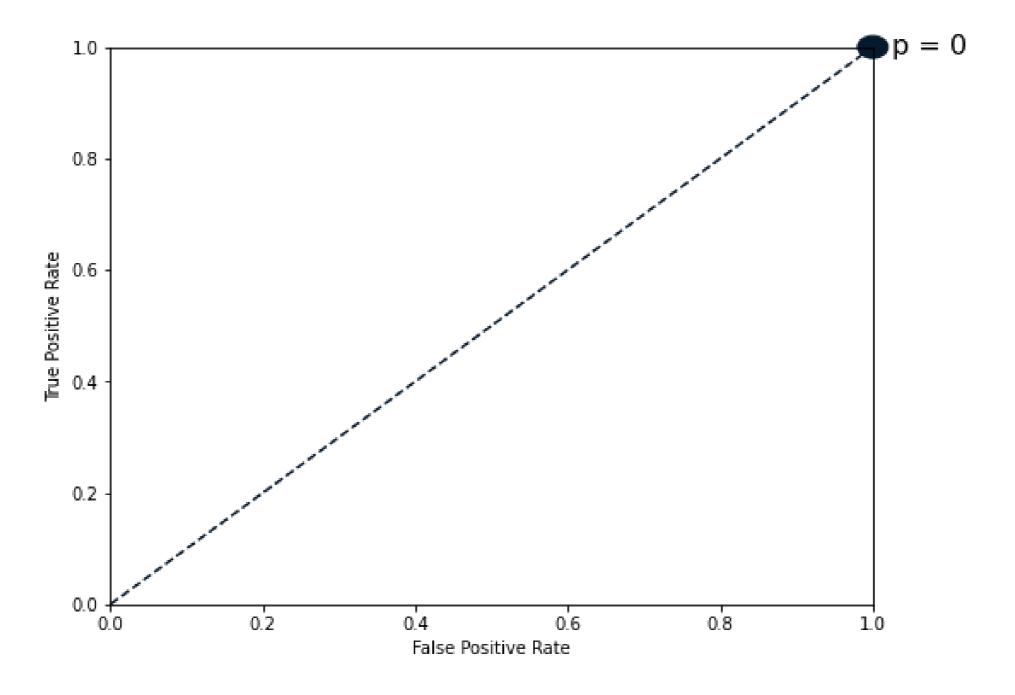
Probability thresholds

- By default, logistic regression threshold = 0.5
- Not specific to logistic regression
 - KNN classifiers also have thresholds
- What happens if we vary the threshold?

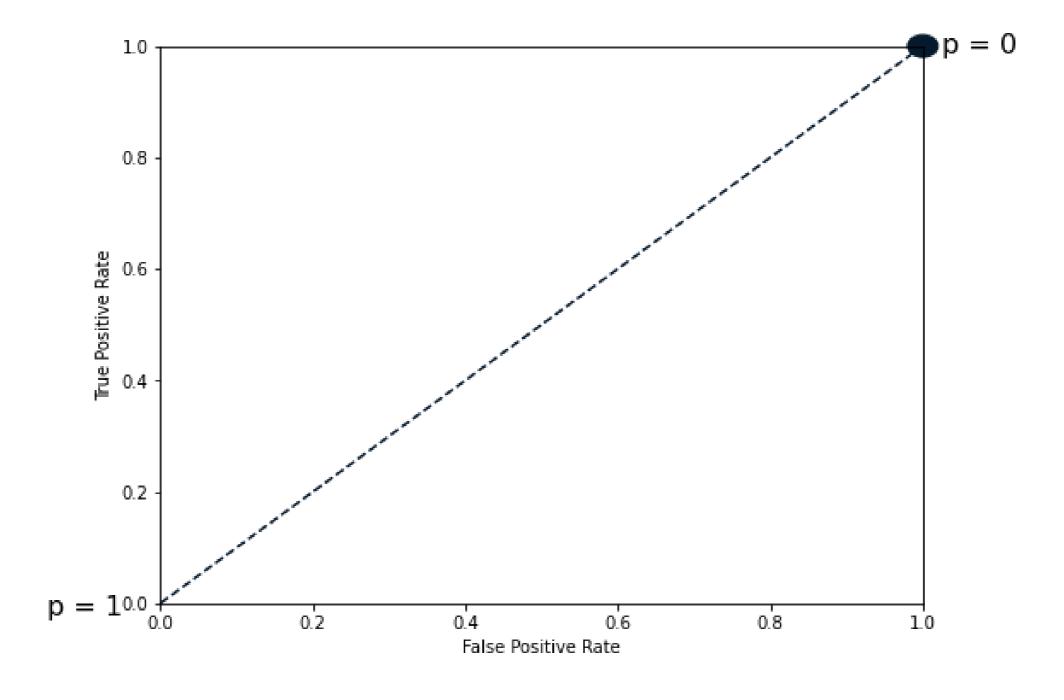




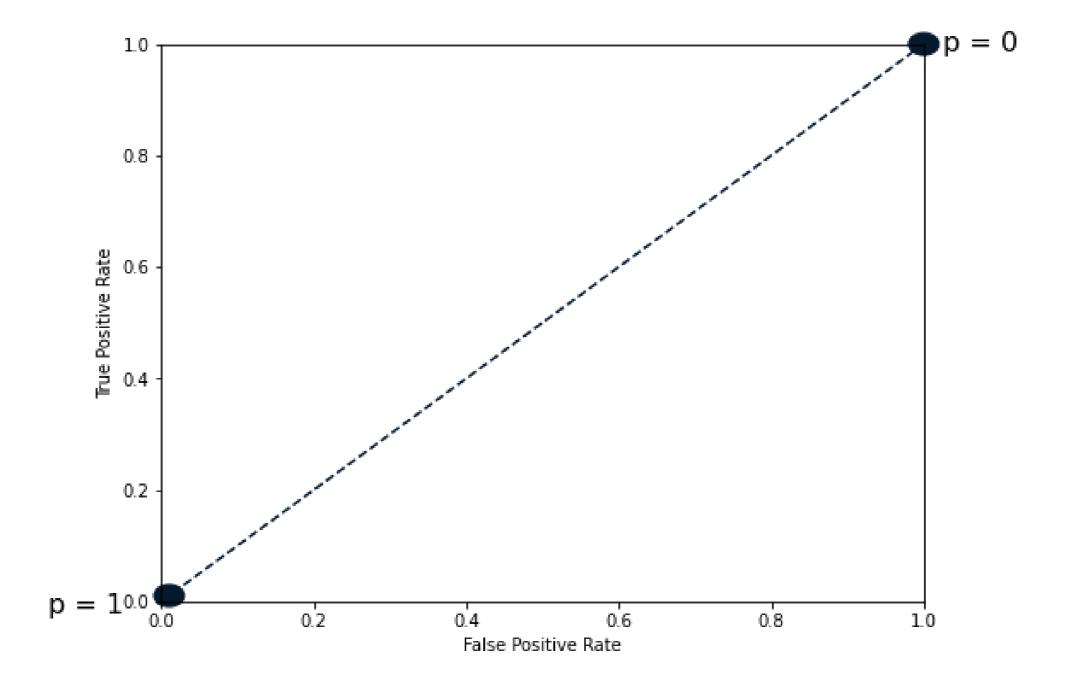




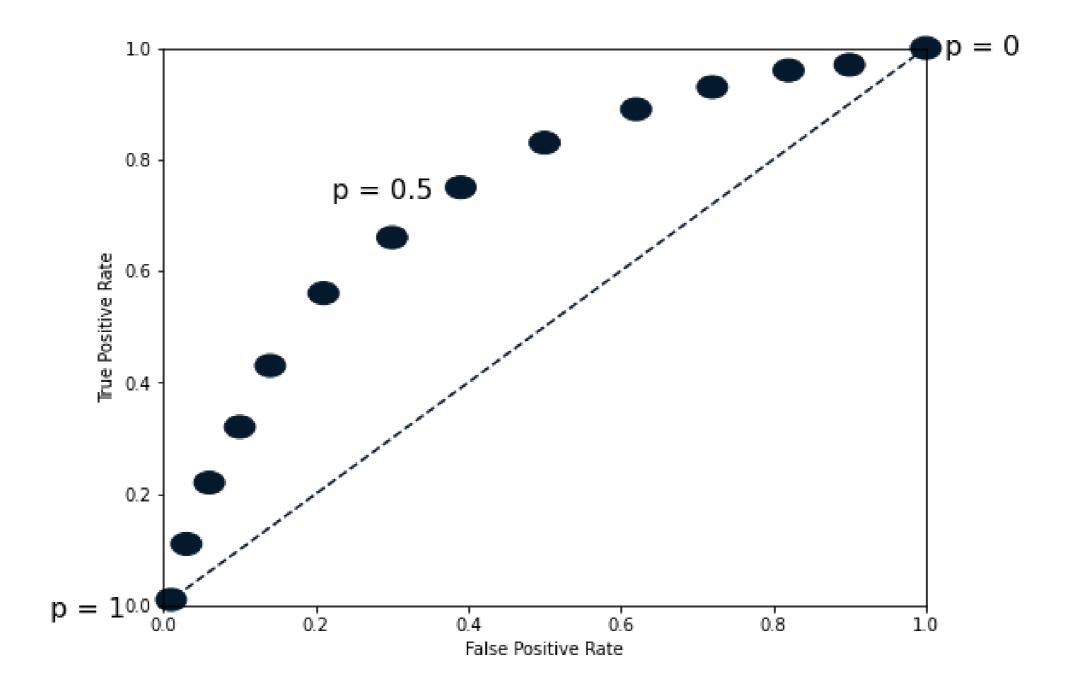




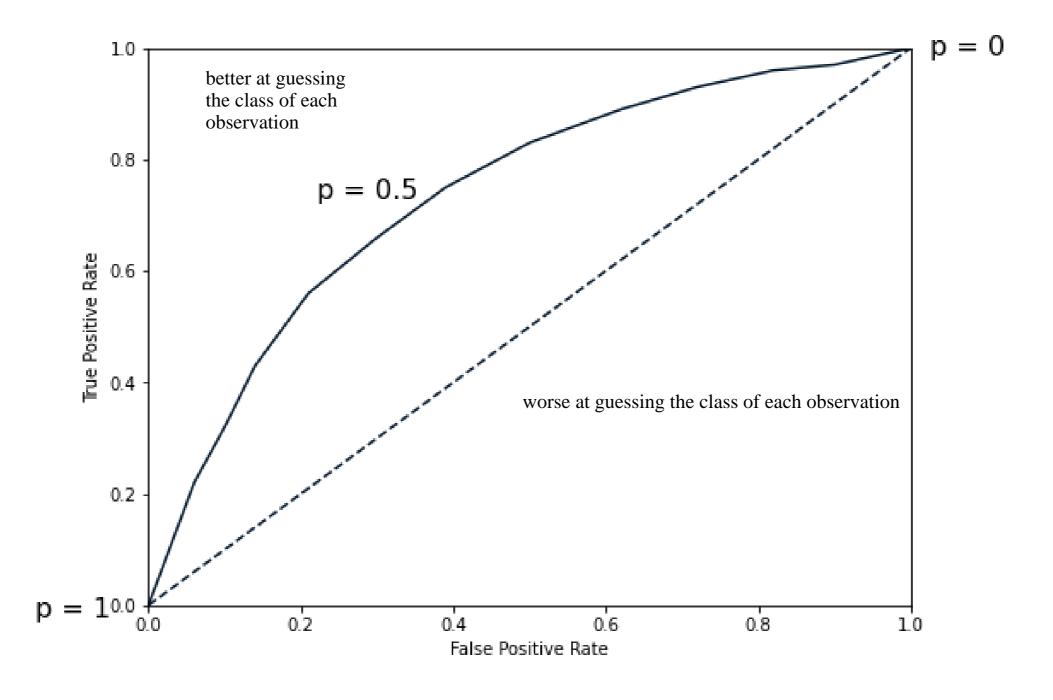








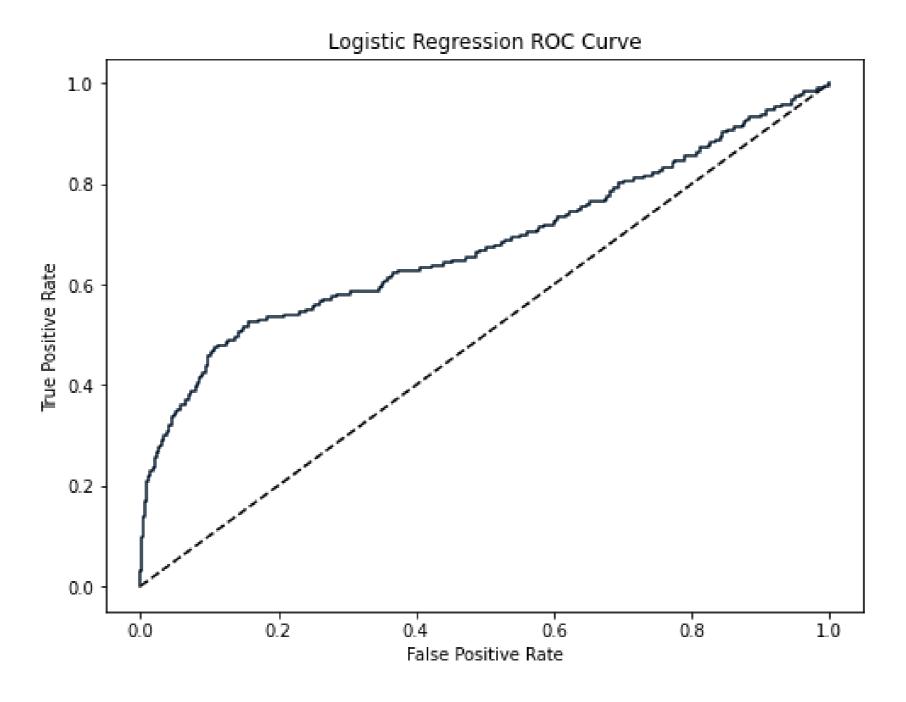




Plotting the ROC curve

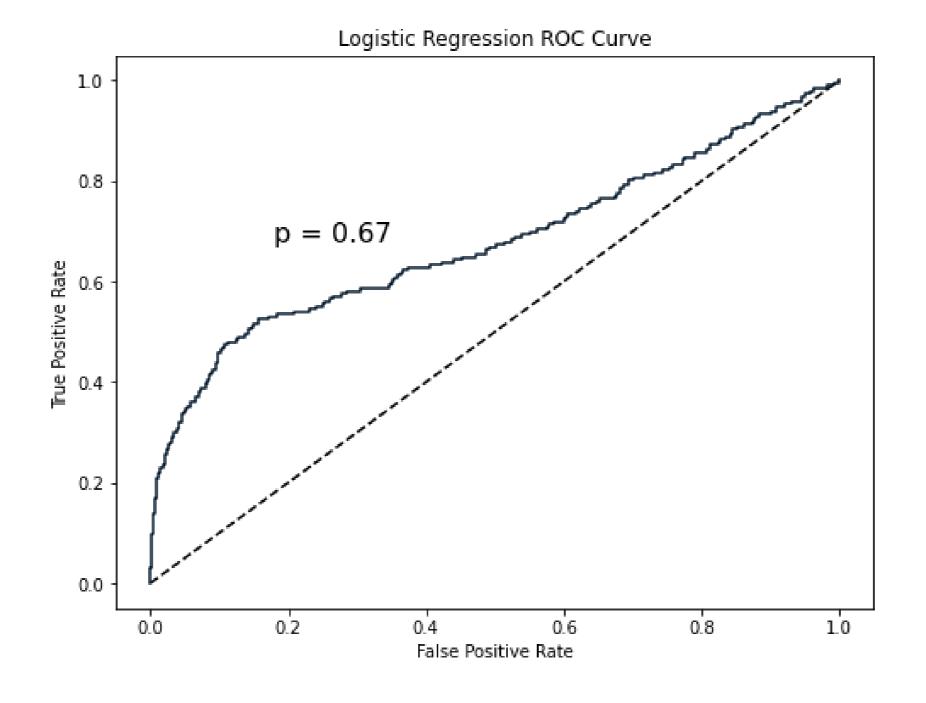
```
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_probs)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve')
plt.show()
```

Plotting the ROC curve





ROC AUC



ROC AUC in scikit-learn

```
from sklearn.metrics import roc_auc_score
print(roc_auc_score(y_test, y_pred_probs))
```

0.6700964152663693



Let's practice!

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Hyperparameter tuning

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Hyperparameter tuning

- Ridge/lasso regression: Choosing alpha
- KNN: Choosing n_neighbors
- Hyperparameters: Parameters we specify before fitting the model
 - Like alpha and n_neighbors

Choosing the correct hyperparameters

- 1. Try lots of different hyperparameter values
- 2. Fit all of them separately
- 3. See how well they perform
- 4. Choose the best performing values

- This is called hyperparameter tuning
- It is essential to use cross-validation to avoid overfitting to the test set
- We can still split the data and perform cross-validation on the training set
- We withhold the test set for final evaluation

Grid search cross-validation

		euclidean	manhattan etric
n_neighbors	2		
	5		
	8		
	11		

Grid search cross-validation

		metric	
		euclidean	manhattan
n_neighbors	2	0.8634	0.8646
	G	0.8748	0.8714
	8	0.8704	0.8688
	11	0.8716	0.8692

Grid search cross-validation

		metric	
		euclidean	manhattan
n_neighbors	2	0.8634	0.8646
	5	0.8748	0.8714
	8	0.8704	0.8688
	11	0.8716	0.8692

GridSearchCV in scikit-learn

```
{'alpha': 0.0001, 'solver': 'sag'}
0.7529912278705785
```

Limitations and an alternative approach

- 3-fold cross-validation, 1 hyperparameter, 10 total values = 30 fits
- 10 fold cross-validation, 3 hyperparameters, 30 total values = 900 fits

RandomizedSearchCV

```
{'solver': 'sag', 'alpha': 0.0001}
0.7529912278705785
```

Evaluating on the test set

```
test_score = ridge_cv.score(X_test, y_test)
print(test_score)
```

0.7564731534089224



Let's practice!

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