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README.md

# Evaluating Logistic Regression Models - Lab

## Introduction

In regression, you are predicting continous values so it makes sense to discuss error as a distance of how far off our estimates were. When classifying a binary variable, however, a model is either correct or incorrect. As a result, we tend to quantify this in terms of how many false positives versus false negatives we come across. In particular, we examine a few different specific measurements when evaluating the performance of a classification algorithm. In this lab, you'll review precision, recall, accuracy, and F1 score in order to evaluate our logistic regression models.

## Objectives

In this lab you will:

- Implement evaluation metrics from scratch using Python

## Terminology review

Let's take a moment and review some classification evaluation metrics:

$$\text{Precision} = \frac{\text{Number of True Positives}}{\text{Number of Predicted Positives}}$$

$$\text{Recall} = \frac{\text{Number of True Positives}}{\text{Number of Actual Total Positives}}$$

$$\text{Accuracy} = \frac{\text{Number of True Positives + True Negatives}}{\text{Total Observations}}$$

$$\text{F1 score} = 2 * \frac{\text{Precision * Recall}}{\text{Precision + Recall}}$$

At times, it may be best to tune a classification algorithm to optimize against precision or recall rather than overall accuracy. For example, imagine the scenario of predicting whether or not a patient is at risk for cancer and should be brought in for additional testing. In cases such as this, we often may want to cast a slightly wider net, and it is preferable to optimize for recall, the number of cancer positive cases, than it is to optimize precision, the percentage of our predicted cancer-risk patients who are indeed positive.

## Split the data into training and test sets

```
import pandas as pd
df = pd.read_csv('heart.csv')
df.head()
```

<style scoped> .dataframe tbody tr th:only-of-type { vertical-align: middle; }

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    vertical-align: top;
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```

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| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | olc |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 63 | 1 | 3 | 145 | 233 | 1 | 0 | 150 | 0 | 2.3 |
| **1** | 37 | 1 | 2 | 130 | 250 | 0 | 1 | 187 | 0 | 3.5 |

| | age | sex | cp | trestbps | chol | fbs | restecg | thalach | exang | olc |
|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 41 | 0 | 1 | 130 | 204 | 0 | 0 | 172 | 0 | 1.4 |
| 3 | 56 | 1 | 1 | 120 | 236 | 0 | 1 | 178 | 0 | 0.8 |
| 4 | 57 | 0 | 0 | 120 | 354 | 0 | 1 | 163 | 1 | 0.6 |

Split the data first into `X` and `y`, and then into training and test sets. Assign 25% to the test set and set the `random_state` to 0.

```
# Import train_test_split
from sklearn.model_selection import train_test_split

# Split data into X and y
y = df['target']
X = df.drop(columns=['target'], axis=1)

# Split the data into a training and a test set
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

## Build a vanilla logistic regression model

- Import and instantiate `LogisticRegression`
- Make sure you do not use an intercept term and use the `'liblinear'` solver
- Fit the model to training data

```
# Import LogisticRegression
from sklearn.linear_model import LogisticRegression

# Instantiate LogisticRegression
logreg = LogisticRegression(fit_intercept=False, C=1e12, solver='liblinear')

# Fit to training data
model_log = logreg.fit(X_train, y_train)
model_log
```

```
LogisticRegression(C=1000000000000.0, class_weight=None, dual=False,
                   fit_intercept=False, intercept_scaling=1, l1_ratio=None,
                   max_iter=100, multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001,
```

```
verbose=0,
                   warm_start=False)
```

## Write a function to calculate the precision

```python
def precision(y, y_hat):
    # Could also use confusion matrix
    y_y_hat = list(zip(y, y_hat))
    tp = sum([1 for i in y_y_hat if i[0] == 1 and i[1] == 1])
    fp = sum([1 for i in y_y_hat if i[0] == 0 and i[1] == 1])
    return tp / float(tp + fp)
```

## Write a function to calculate the recall

```python
def recall(y, y_hat):
    # Could also use confusion matrix
    y_y_hat = list(zip(y, y_hat))
    tp = sum([1 for i in y_y_hat if i[0] == 1 and i[1] == 1])
    fn = sum([1 for i in y_y_hat if i[0] == 1 and i[1] == 0])
    return tp / float(tp + fn)
```

## Write a function to calculate the accuracy

```python
def accuracy(y, y_hat):
    # Could also use confusion matrix
    y_y_hat = list(zip(y, y_hat))
    tp = sum([1 for i in y_y_hat if i[0] == 1 and i[1] == 1])
    tn = sum([1 for i in y_y_hat if i[0] == 0 and i[1] == 0])
    return (tp + tn) / float(len(y_hat))
```

## Write a function to calculate the F1 score

```python
def f1(y, y_hat):
    precision_score = precision(y, y_hat)
    recall_score = recall(y, y_hat)
    numerator = precision_score * recall_score
```

```
    denominator = precision_score + recall_score
    return 2 * (numerator / denominator)
```

## Calculate the precision, recall, accuracy, and F1 score of your classifier

Do this for both the training and test sets.

```
y_hat_train = logreg.predict(X_train)
y_hat_test = logreg.predict(X_test)

print('Training Precision: ', precision(y_train, y_hat_train))
print('Testing Precision: ', precision(y_test, y_hat_test))
print('\n\n')

print('Training Recall: ', recall(y_train, y_hat_train))
print('Testing Recall: ', recall(y_test, y_hat_test))
print('\n\n')

print('Training Accuracy: ', accuracy(y_train, y_hat_train))
print('Testing Accuracy: ', accuracy(y_test, y_hat_test))
print('\n\n')

print('Training F1-Score: ', f1(y_train, y_hat_train))
print('Testing F1-Score: ', f1(y_test, y_hat_test))
```

```
Training Precision:  0.8396946564885496
Testing Precision:  0.8125



Training Recall:  0.9016393442622951
Testing Recall:  0.9069767441860465



Training Accuracy:  0.8546255506607929
Testing Accuracy:  0.8289473684210527



Training F1-Score:  0.8695652173913043
Testing F1-Score:  0.8571428571428572
```

Great job! Now it's time to check your work with `sklearn`.

## Calculate metrics with `sklearn`

Each of the metrics we calculated above is also available inside the `sklearn.metrics` module.

In the cell below, import the following functions:

- `precision_score`
- `recall_score`
- `accuracy_score`
- `f1_score`

Compare the results of your performance metrics functions above with the `sklearn` functions. Calculate these values for both your train and test set.

```python
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score

print('Training Precision: ', precision_score(y_train, y_hat_train))
print('Testing Precision: ', precision_score(y_test, y_hat_test))
print('\n\n')

print('Training Recall: ', recall_score(y_train, y_hat_train))
print('Testing Recall: ', recall_score(y_test, y_hat_test))
print('\n\n')

print('Training Accuracy: ', accuracy_score(y_train, y_hat_train))
print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
print('\n\n')

print('Training F1-Score: ', f1_score(y_train, y_hat_train))
print('Testing F1-Score: ', f1_score(y_test, y_hat_test))
```

```
Training Precision:  0.8396946564885496
Testing Precision:  0.8125



Training Recall:  0.9016393442622951
Testing Recall:  0.9069767441860465
```

```
Training Accuracy:  0.8546255506607929
Testing Accuracy:  0.8289473684210527
```

```
Training F1-Score:  0.8695652173913043
Testing F1-Score:  0.8571428571428572
```

Nicely done! Did the results from `sklearn` match that of your own?

## Compare precision, recall, accuracy, and F1 score for train vs test sets

Calculate and then plot the precision, recall, accuracy, and F1 score for the test and training splits using different training set sizes. What do you notice?

```
import matplotlib.pyplot as plt
%matplotlib inline
```

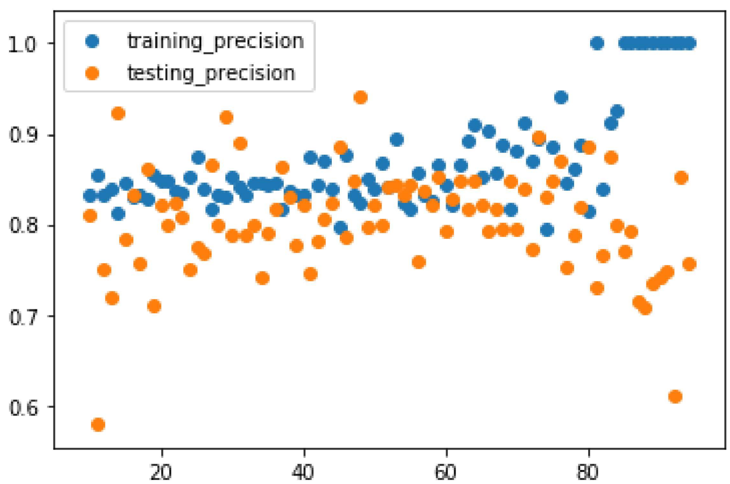
```
training_precision = []
testing_precision = []
training_recall = []
testing_recall = []
training_accuracy = []
testing_accuracy = []
training_f1 = []
testing_f1 = []

for i in range(10, 95):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=i/100.0)
    logreg = LogisticRegression(fit_intercept=False, C=1e25, solver='liblinear')
    model_log = logreg.fit(X_train, y_train)
    y_hat_test = logreg.predict(X_test)
    y_hat_train = logreg.predict(X_train)

    training_precision.append(precision(y_train, y_hat_train))
    testing_precision.append(precision(y_test, y_hat_test))
    training_recall.append(recall(y_train, y_hat_train))
    testing_recall.append(recall(y_test, y_hat_test))
    training_accuracy.append(accuracy(y_train, y_hat_train))
    testing_accuracy.append(accuracy(y_test, y_hat_test))
    training_f1.append(f1(y_train, y_hat_train))
```

```
    testing_f1.append(f1(y_test, y_hat_test))
```

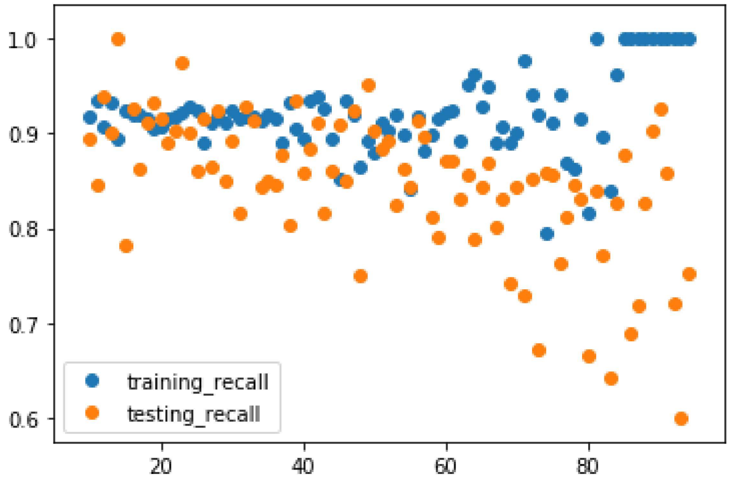
Create four scatter plots looking at the train and test precision in the first one, train and test recall in the second one, train and test accuracy in the third one, and train and test F1 score in the fourth one.

We already created the scatter plot for precision:

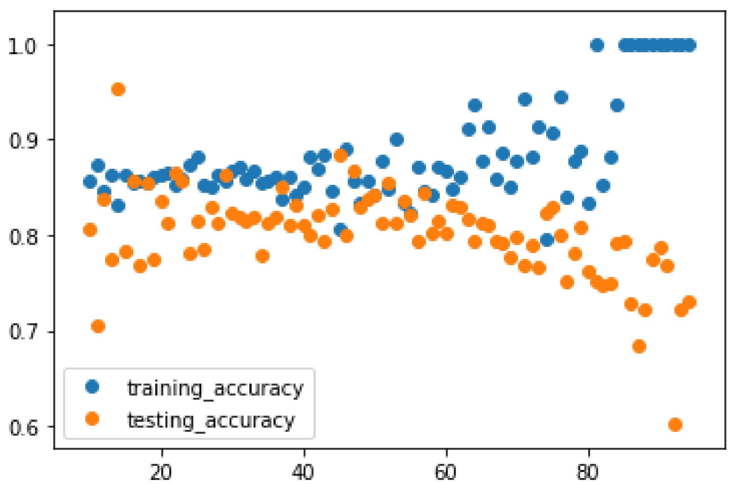
```
# Train and test precision
plt.scatter(list(range(10, 95)), training_precision, label='training_precision')
plt.scatter(list(range(10, 95)), testing_precision, label='testing_precision')
plt.legend()
plt.show()
```




```
# Train and test recall
plt.scatter(list(range(10, 95)), training_recall, label='training_recall')
plt.scatter(list(range(10, 95)), testing_recall, label='testing_recall')
plt.legend()
plt.show()
```




```
# Train and test accuracy
plt.scatter(list(range(10, 95)), training_accuracy, label='training_accuracy')
plt.scatter(list(range(10, 95)), testing_accuracy, label='testing_accuracy')
plt.legend()
plt.show()
```




```
# Train and test F1 score
plt.scatter(list(range(10, 95)), training_f1, label='training_f1')
plt.scatter(list(range(10, 95)), testing_f1, label='testing_f1')
plt.legend()
plt.show()
```


## Summary

Nice! In this lab, you calculated evaluation metrics for classification algorithms from scratch in Python. Going forward, continue to think about scenarios in which you might prefer to optimize one of these metrics over another.

### Releases

No releases published

### Packages

No packages published

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- **Jupyter Notebook** 100.0%