Logistic regression for probability of default

CREDIT RISK MODELING IN PYTHON

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Probability of default

- The likelihood that someone will default on a loan is the probability of default
- A probability value between 0 and 1 like `0.86`
- `loan_status` of `1` is a default or `0` for non-default

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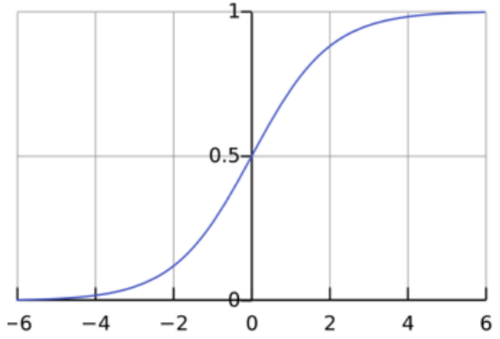
Probability of Default	Interpretation	Predicted loan status
0.4	Unlikely to default	0
0.90	Very likely to default	1
0.1	Very unlikely to default	0

Predicting probabilities

- Probabilities of default as an outcome from machine learning
  - Learn from data in columns (features)
- Classification models (default, non-default)
- Two most common models:
  - Logistic regression
  - Decision tree

Logistic Regression



Decision Tree

Logistic regression

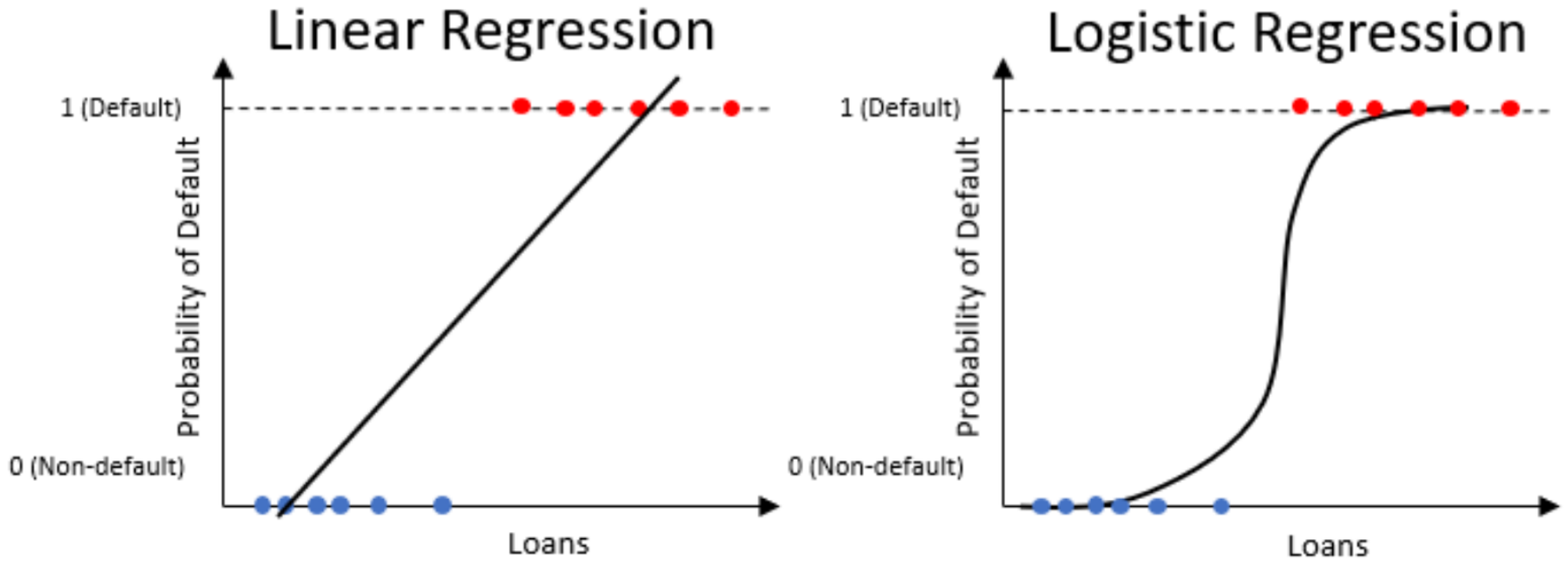
- Similar to the linear regression, but only produces values between `0` and `1`

Linear Regression

$$Y = \beta_0 + (\beta_1 * X_1) + (\beta_2 * X_2) \ldots$$

Logistic Regression

$$P(loan\_status = 1) = \frac{1}{1 + e^{-Y}}$$



Training a logistic regression

- Logistic regression available within the scikit-learn package

```
from sklearn.linear_model import LogisticRegression
```

- Called as a function with or without parameters

```
clf_logistic = LogisticRegression(solver='lbfgs')
```

- Uses the method `.fit()` to train

```
clf_logistic.fit(training_columns, np.ravel(training_labels))
```

- Training Columns: all of the columns in our data **except** `loan_status`
- Labels: `loan_status` (0,1)

Training and testing

- Entire data set is usually split into two parts

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Data Subset	Usage	Portion
Train	Learn from the data to generate predictions	60%
Test	Test learning on new unseen data	40%

Creating the training and test sets

- Separate the data into training columns and labels

```
X = cr_loan.drop('loan_status', axis = 1)
y = cr_loan[['loan_status']]
```

- Use `train_test_split()` function already within sci-kit learn

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.4, random_state=123)
```

- `test_size` : percentage of data for test set
- `random_state` : a random seed value for reproducibility

Let's practice!

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Predicting the probability of default

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Logistic regression coefficients

```
# Model Intercept
array([-3.30582292e-10])
# Coefficients for ['loan_int_rate','person_emp_length','person_income']
array([[ 1.28517496e-09, -2.27622202e-09, -2.17211991e-05]])
```

$$P(loan\_status = 1) = \frac{1}{1 + e^{-\left(-3.3e^{-10} + (1.29e^{-9} * Int\ Rate) + (-2.28e^{-9} * Emp\ Length) + (-2.17e^{-5} * Income)\right)}}$$

```
# Calculating probability of default
int_coef_sum = -3.3e-10 +
    (1.29e-09 * loan_int_rate) + (-2.28e-09 * person_emp_length) + (-2.17e-05 * person_income)
prob_default = 1 / (1 + np.exp(-int_coef_sum))
prob_nondefault = 1 - (1 / (1 + np.exp(-int_coef_sum)))
```

Interpreting coefficients

```
# Intercept
intercept = -1.02
# Coefficient for employment length
person_emp_length_coef = -0.056
```

- For every 1 year increase in `person_emp_length` , the person is less likely to default

Interpreting coefficients

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- For every 1 year increase in `person_emp_length` , the person is less likely to default

intercept	person_emp_length	value * coef	probability of default
`-1.02`	10	(10 * `-0.06`)	.17
`-1.02`	11	(11 * `-0.06`)	.16
`-1.02`	12	(12 * `-0.06`)	.15

Using non-numeric columns

- Numeric: `loan_int_rate`, `person_emp_length`, `person_income`
- Non-numeric:

```
cr_loan_clean['loan_intent']
```

```
EDUCATION
MEDICAL
VENTURE
PERSONAL
DEBTCONSOLIDATION
HOMEIMPROVEMENT
```

- Will cause errors with machine learning models in Python unless processed

One-hot encoding

- Represent a string with a number

	person_age	person_income	loan_intent
0	21	9600	EDUCATION
1	25	9600	MEDICAL
2	23	65500	MEDICAL
3	24	54400	MEDICAL
4	21	9900	VENTURE

One-hot encoding

- Represent a string with a number
- `0` or `1` in a new column `column_VALUE`

	person_age	person_income	loan_intent
0	21	9600	EDUCATION
1	25	9600	MEDICAL
2	23	65500	MEDICAL
3	24	54400	MEDICAL
4	21	9900	VENTURE

	person_age	person_income	loan_intent_EDUCATION	loan_intent_MEDICAL	loan_intent_VENTURE
0	21	9600	1	0	0
1	25	9600	0	1	0
2	23	65500	0	1	0
3	24	54400	0	1	0
4	21	9900	0	0	1

Get dummies

- Utilize the `get_dummies()` within `pandas`

```
# Separate the numeric columns
cred_num = cr_loan.select_dtypes(exclude=['object'])
# Separate non-numeric columns
cred_cat = cr_loan.select_dtypes(include=['object'])
# One-hot encode the non-numeric columns only
cred_cat_onehot = pd.get_dummies(cred_cat)
# Union the numeric columns with the one-hot encoded columns
cr_loan = pd.concat([cred_num, cred_cat_onehot], axis=1)
```

Predicting the future, probably

- Use the `.predict_proba()` method within scikit-learn

```
# Train the model
clf_logistic.fit(X_train, np.ravel(y_train))
# Predict using the model
clf_logistic.predict_proba(X_test)
```

- Creates array of probabilities of default

```
# Probabilities: [[non-default, default]]
array([[0.55, 0.45]])
```

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Credit model performance

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Model accuracy scoring

- Calculate accuracy

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Number\ of\ predictions}$$

- Use the `.score()` method from scikit-learn

```
# Check the accuracy against the test data
clf_logistic1.score(X_test,y_test)
```

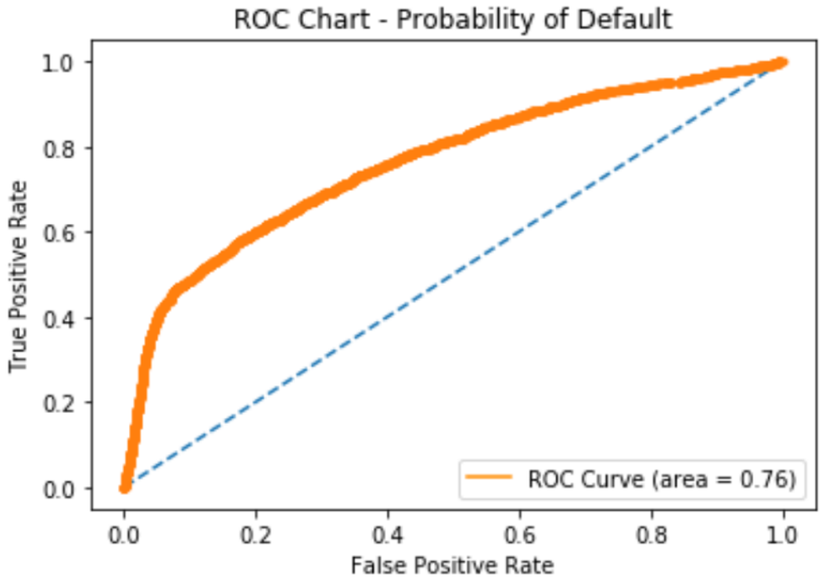
```
0.81
```

- 81% of values for `loan_status` predicted correctly

ROC curve charts

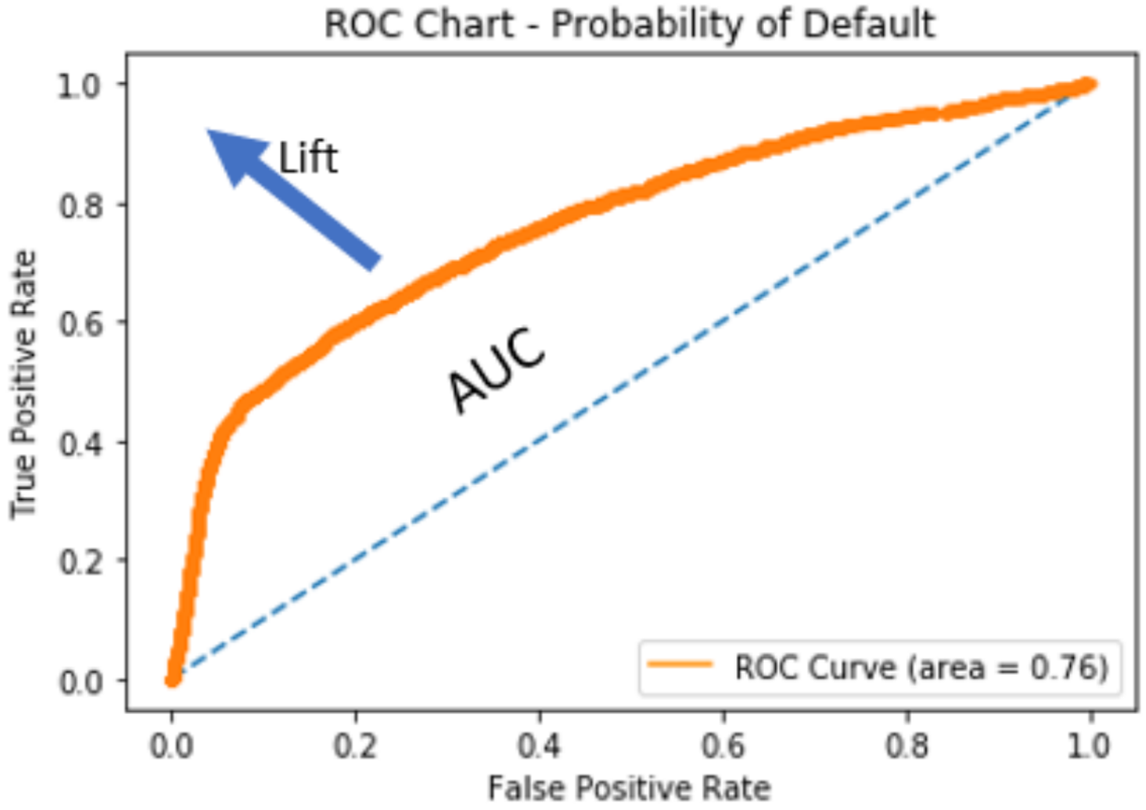
- Receiver Operating Characteristic curve
  - Plots true positive rate (sensitivity) against false positive rate (fall-out)

```
fallout, sensitivity, thresholds = roc_curve(y_test, prob_default)
plt.plot(fallout, sensitivity, color = 'darkorange')
```



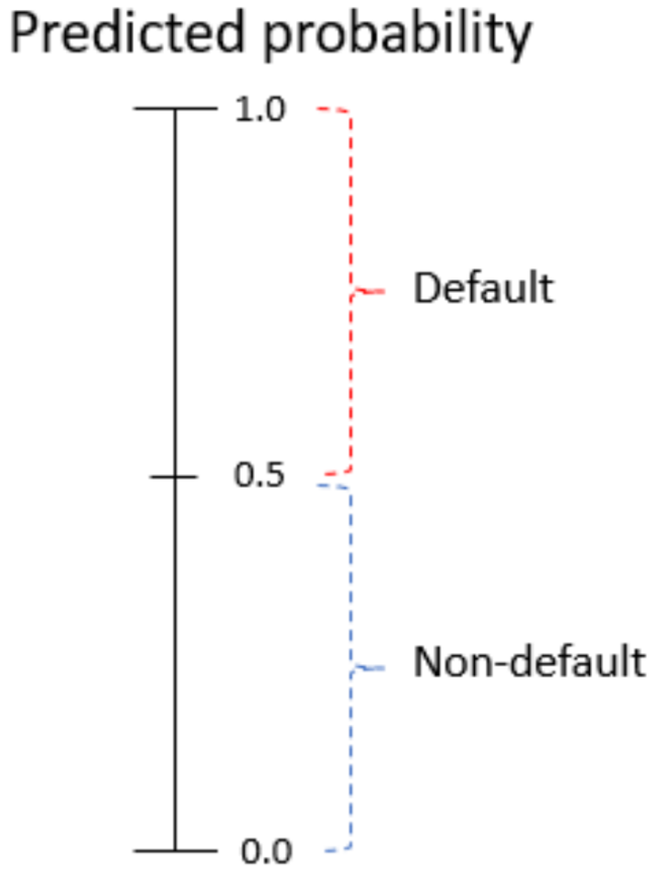
Analyzing ROC charts

- Area Under Curve (AUC): area between curve and random prediction



Default thresholds

- Threshold: at what point a probability is a default



Predicted probability	New loan_status
0.45	0 (non-default
0.87	1 (default)

Setting the threshold

- Relabel loans based on our threshold of `0.5`

```
preds = clf_logistic.predict_proba(X_test)
preds_df = pd.DataFrame(preds[:,1], columns = ['prob_default'])
preds_df['loan_status'] = preds_df['prob_default'].apply(lambda x: 1 if x > 0.5 else 0)
```

	prob_default	loan_status
11779	0.079626	0
11780	0.051979	0
11781	0.522450	1
11782	0.370478	0
11783	0.123786	0

Credit classification reports

- `classification_report()` within scikit-learn

```
from sklearn.metrics import classification_report
classification_report(y_test, preds_df['loan_status'], target_names=target_names)
```

	precision	recall	f1-score	support
Non-Default	0.79	0.99	0.88	9198
Default	0.67	0.04	0.07	2586
micro avg	0.78	0.78	0.78	11784
macro avg	0.73	0.52	0.47	11784
weighted avg	0.76	0.78	0.70	11784

Selecting classification metrics

- Select and store specific components from the `classification_report()`
- Use the `precision_recall_fscore_support()` function from scikit-learn

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```
from sklearn.metrics import precision_recall_fscore_support
precision_recall_fscore_support(y_test,preds_df['loan_status'])[1][1]
```

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Model discrimination and impact

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Confusion matrices

- Shows the number of correct and incorrect predictions for each `loan_status`

True Negatives (Predicted = 0, Actual = 0)	**False Positives** (Predicted = 1, Actual = 0)
False Negatives (Predicted = 0, Actual = 1)	**True Positives** (Predicted = 1, Actual = 1)

$$Precision(0) = \frac{TN}{TN + FN}$$

$$Precision(1) = \frac{TP}{TP + FP}$$

$$Recall(0) = \frac{TN}{TN + FP}$$

$$Recall(1) = \frac{TP}{TP + FN}$$

Default recall for loan status

- Default recall (or sensitivity) is the proportion of true defaults predicted

	precision	recall	f1-score	support
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$$Recall(1) = \frac{TP}{TP + FN}$$

Recall portfolio impact

- Classification report - Underperforming Logistic Regression model

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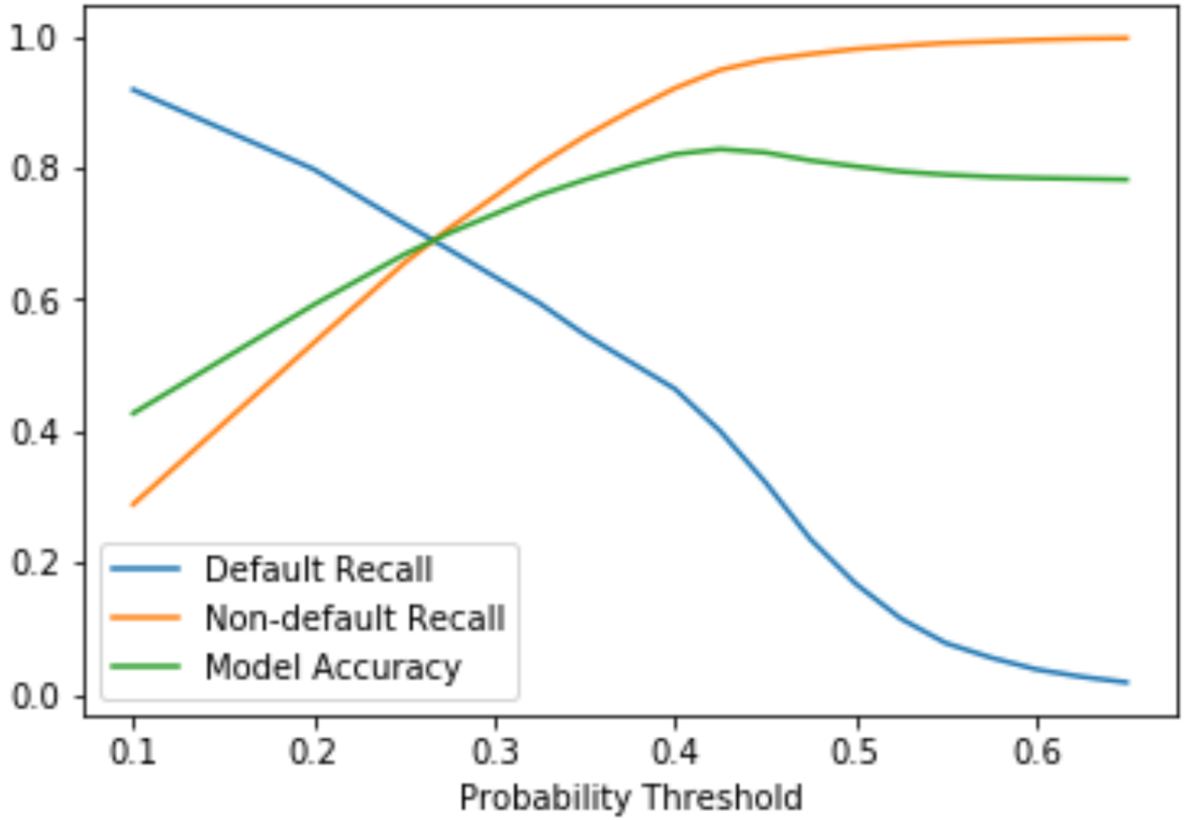
- Number of true defaults: 50,000

Loan Amount	Defaults Predicted / Not Predicted	Estimated Loss on Defaults
$50	.04 / .96	(50000 x .96) x 50 = $2,400,000

Recall, precision, and accuracy

- Difficult to maximize all of them because there is a trade-off



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