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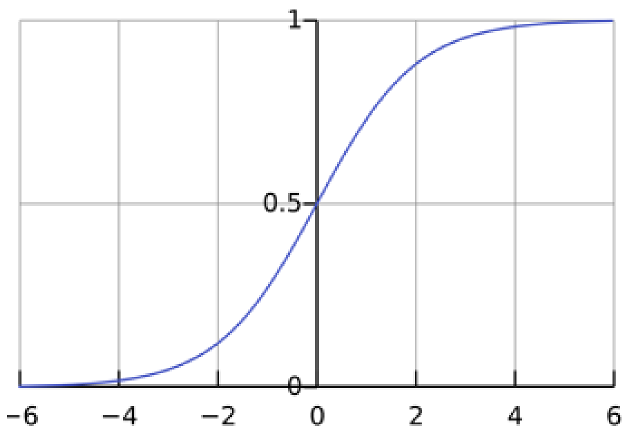
Probability of Default	Interpretation	Predicted loan status
0.4	Unlikely to default	0
0.90	Very likely to default	1
0.1	Very unlikely to default	0

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

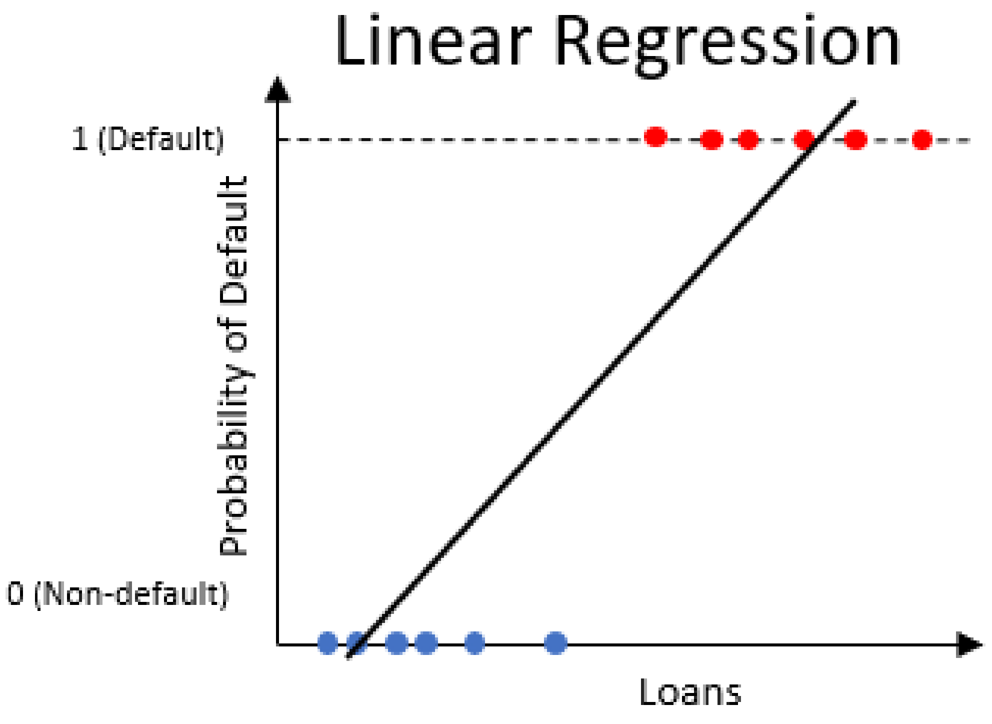
- Similar to the linear regression, but only produces values between `0` and `1`

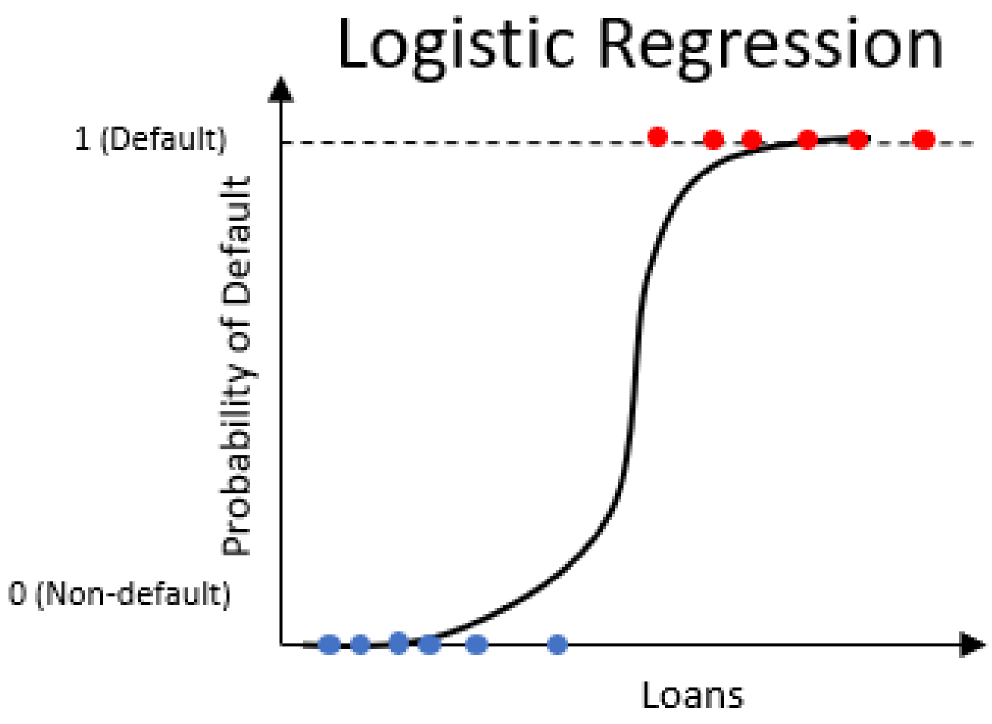
Linear Regression

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

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

Training and testing

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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]])
```

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

```
# 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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# Intercept
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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]])
```

Let's practice!

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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)
```

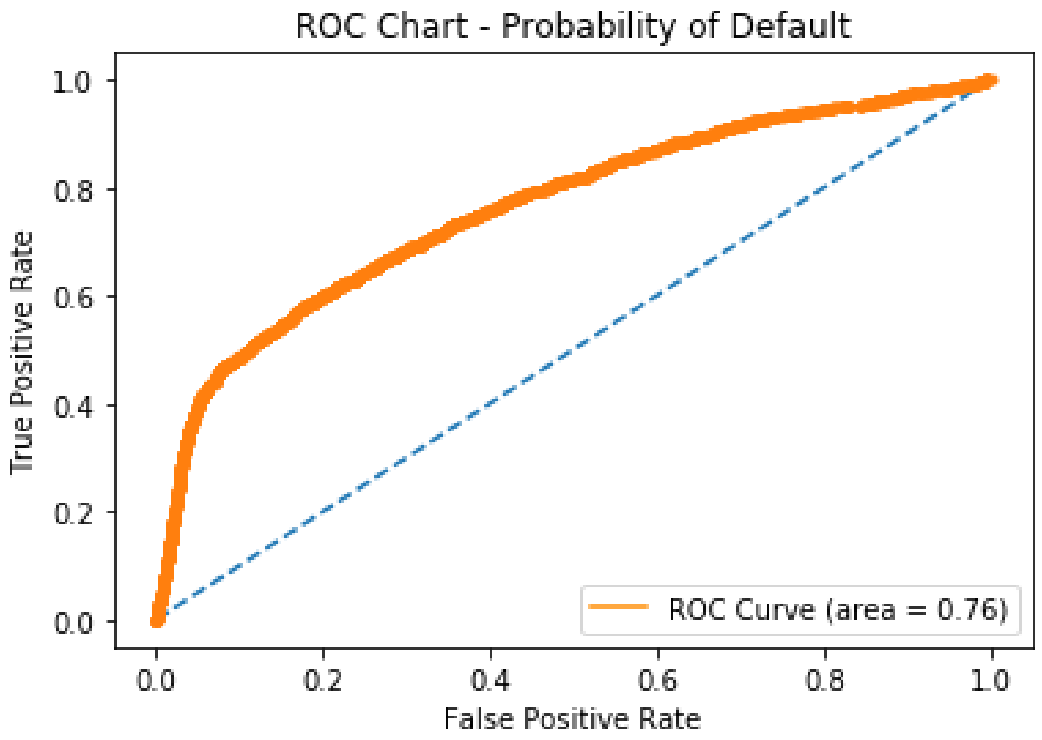
```
0.81
```

- 81% of values for `loan_status` predicted correctly

ROC curve charts

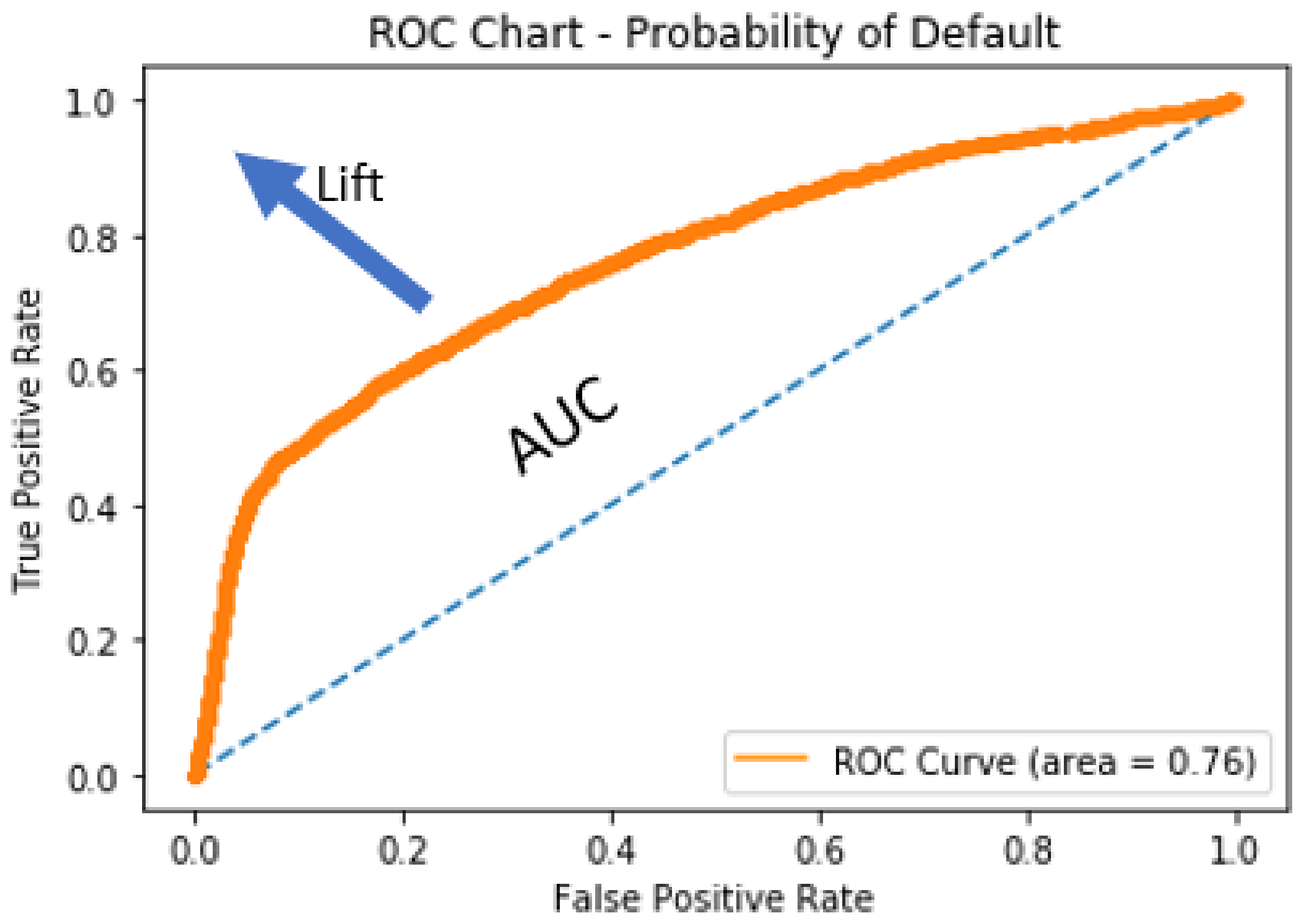
- Receiver Operating Characteristic curve
  - Plots true positive rate (sensitivity) against false positive rate (fall-out)

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



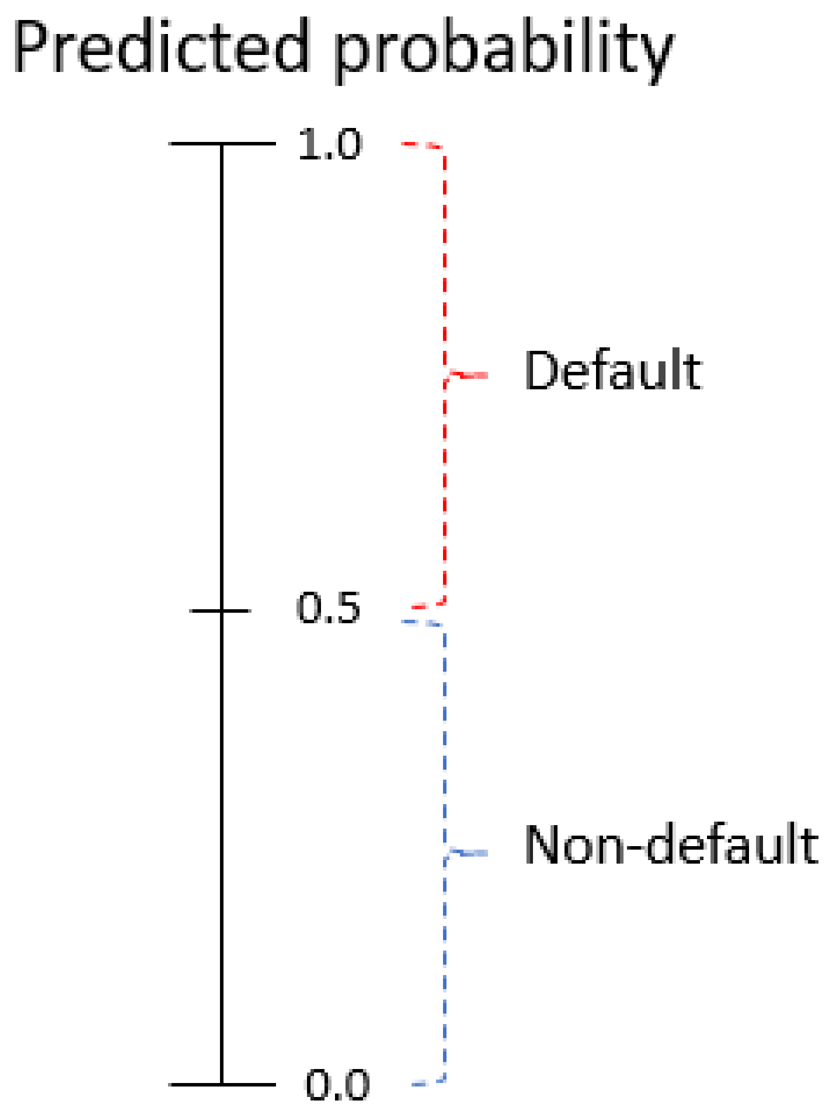
Analyzing ROC charts

- 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

	precision	recall	f1-score	support
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```
from sklearn.metrics import precision_recall_fscore_support
precision_recall_fscore_support(y_test,preds_df['loan_status'])[1][1]
```

Let's practice!

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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)

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

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

$$Recall(0) = \frac{TN}{TN + FP} \qquad Recall(1) = \frac{TP}{TP + FN}$$

Default recall for loan status

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

	precision	recall	f1-score	support
Non-Default	0.79	0.99	0.88	9198
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micro avg	0.78	0.78	0.78	11784
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$$Recall(1) = \frac{TP}{TP + FN}$$

Recall portfolio impact

- Classification report - Underperforming Logistic Regression model

	precision	recall	f1-score	support
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```
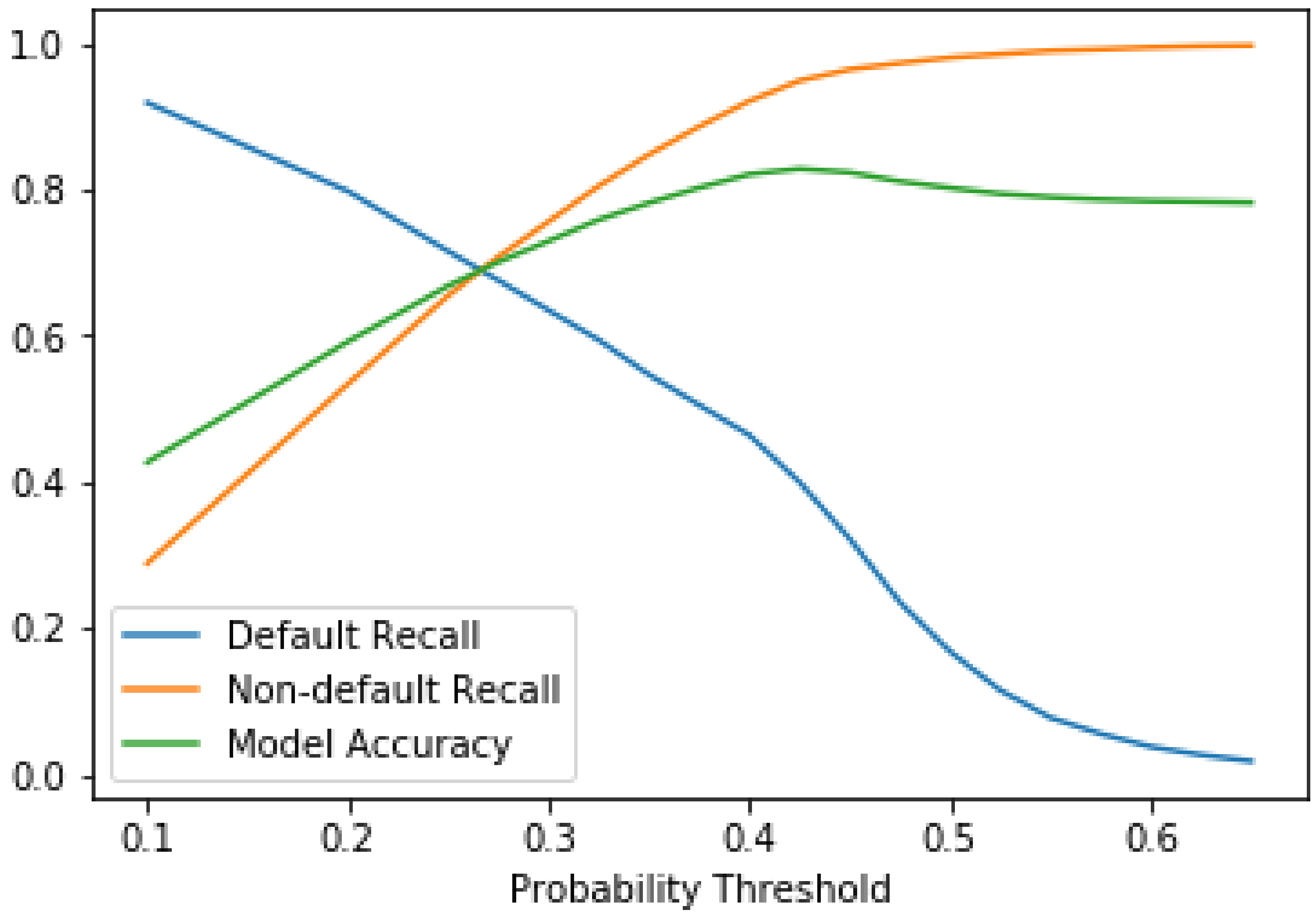

- Number of true defaults: 50,000

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



Let's practice!

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