



Imbalanced Classes

FinTech
Lesson 11.3



Class Objectives

By the end of class, you will be able to:



Define model evaluation metrics and understand the pros and cons of each metric as applied to different classification problems.



Define class imbalance and understand why it presents a problem for classification models.



Demonstrate the ability to under- and over-sample data with imbalanced classes.



Demonstrate the ability to plot a precision-recall curve and use it to compare different models.

Review of Classification Metrics

Confusion Matrix

A confusion matrix is a way to tally and visualize the errors of a classification model performance.

	Predicted True	Predicted False
Actually True	TP	FN
Actually False	FP	TN

Confusion Matrix

We can use our confusion matrix to calculate the model's overall **accuracy**.

- *Accuracy* is the proportion of correct calls
- It is calculated as $Acc = (TP+TN)/(TP+TN+FP+FN)$
- Treats FP and FNs equally—an issue for unbalanced data

	Predicted True	Predicted False
Actually True	TP	FN
Actually False	FP	TN

Confusion Matrix

We can use our confusion matrix to calculate the model's **precision**.

- *Precision* is the proportion of positive calls that were correct.
- It is calculated as $\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$, using the first column of the confusion matrix.
- A model with no FPs has perfect precision. All of its positive calls are correct!



If FPs are very undesirable, you want a high precision

	Predicted True	Predicted False
Actually True	TP	FN
Actually False	FP	TN

Confusion Matrix

We can use our confusion matrix to calculate the model's **recall**.

- Recall is the proportion of actually positive samples that were correct
- It is calculated as $\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$, using the first row of the confusion matrix
- Recall is a critical metric for optimizing a model with unbalanced data
- A model with no FNs has perfect recall. All of the positive samples are correctly identified!
- Recall is sometimes called sensitivity



If FNs are very undesirable, you want a model with high recall

	Predicted True	Predicted False
Actually True	TP	FN
Actually False	FP	TN



It is very rare that you will develop a model with high precision and recall. The two metrics are often opposition. When one goes up, the other often goes down.

Confusion Matrix

When evaluating a model, report both precision and recall.

Consider the credit example. The model predicts that an individual has good credit if its probability (from a logistic regression or SVM, for example) of good credit is ≥ 0.5 .

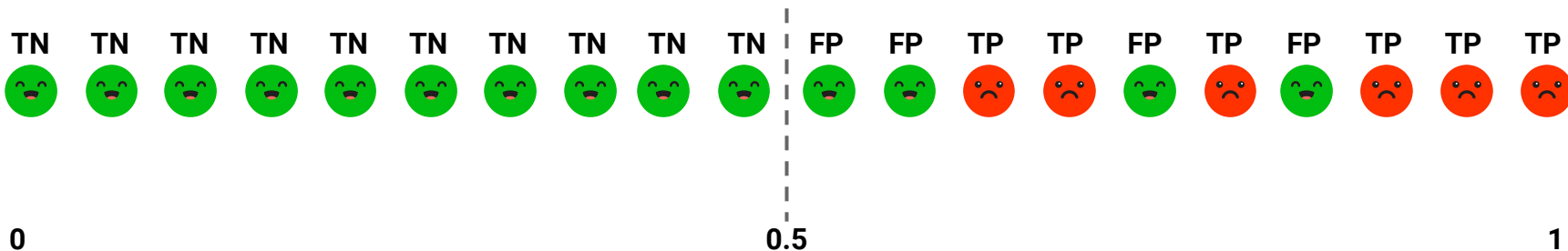
Probability a client has good credit



Client with truly good credit



Client with truly not good credit



Confusion Matrix

If we shift this probability threshold from 0.5 to 0.75, we may increase our FNs but decrease the FPs.

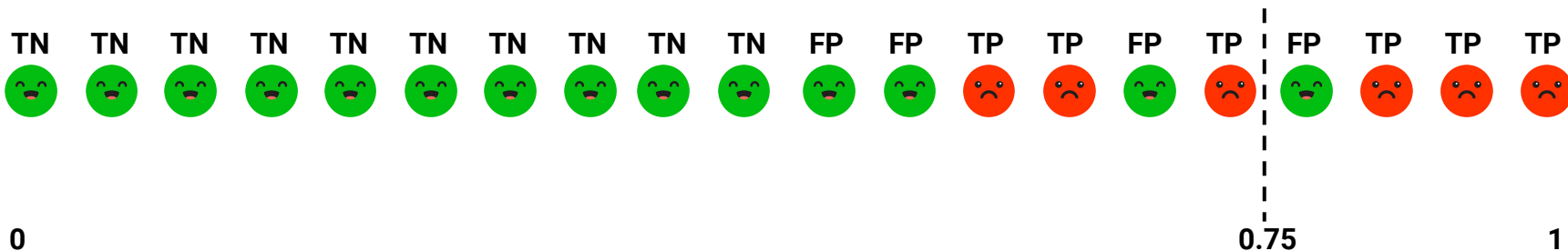
Probability a client has good credit



Client with truly good credit



Client with truly not good credit



Confusion Matrix

We can use our confusion matrix to calculate the model's **specificity**.

- *Specificity* is the proportion of actually negative samples that were correct.
- It is calculated as $\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$, using the second row of the confusion matrix.
- A model with no FPs has perfect specificity. All of the negative samples are correctly identified!
- Well-performing models with lots of TNs (>10,000) will often have very high specificity (>0.99).



If FPs are very undesirable, you want a highly specific model

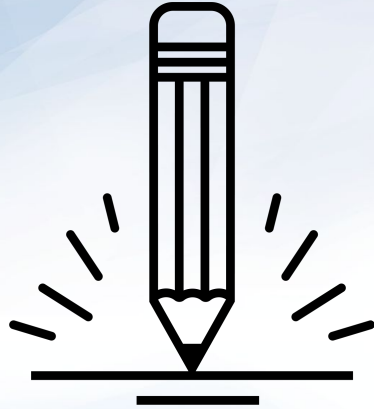
	Predicted True	Predicted False
Actually True	TP	FN
Actually False	FP	TN

Confusion Matrix

We can use our confusion matrix to calculate the model's **F1-score**.

- The *F1-score* (or F-measure) is another overall accuracy measure equivalent to the harmonic mean of the precision and recall
- It is calculated as $F1 = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$, using the first row and column of the confusion matrix.
- A model with perfect precision and recall has an F1-score of 1.0.
- The F1-score gives equal weight to precision and recall. Note that if either are 0, the score is 0 too.
- It is a good summary metric for comparing one model's performance to another.

	Predicted True	Predicted False
Actually True	TP	FN
Actually False	FP	TN



Activity:

Hypothetical Models

Suggested Time:
15 minutes





Time's Up! Let's Review.

Activity: Hypothetical Models

01

A company wants to block phishing messages:

Predict whether an email is spam or not spam.

02

Doctors want an objective second opinion on imaging results:

Predict whether or not an MRI shows cancerous growth.

03

A study looks at gender differences in writing:

Predict whether a student is a boy a girl based off their essays.

04

Improve weather forecasts:

Predict whether or not it will rain the next day.

05

A venture capital firm wants to optimize its investments:

Predict whether a company will file an IPO in the next 12 months.

Imbalanced Data

What's wrong with imbalanced classes?

Models are biased toward the majority class.

Evaluation metrics, such as accuracy, are misleading.



Dealing with imbalanced classes

Potential strategies:



Oversampling and undersampling



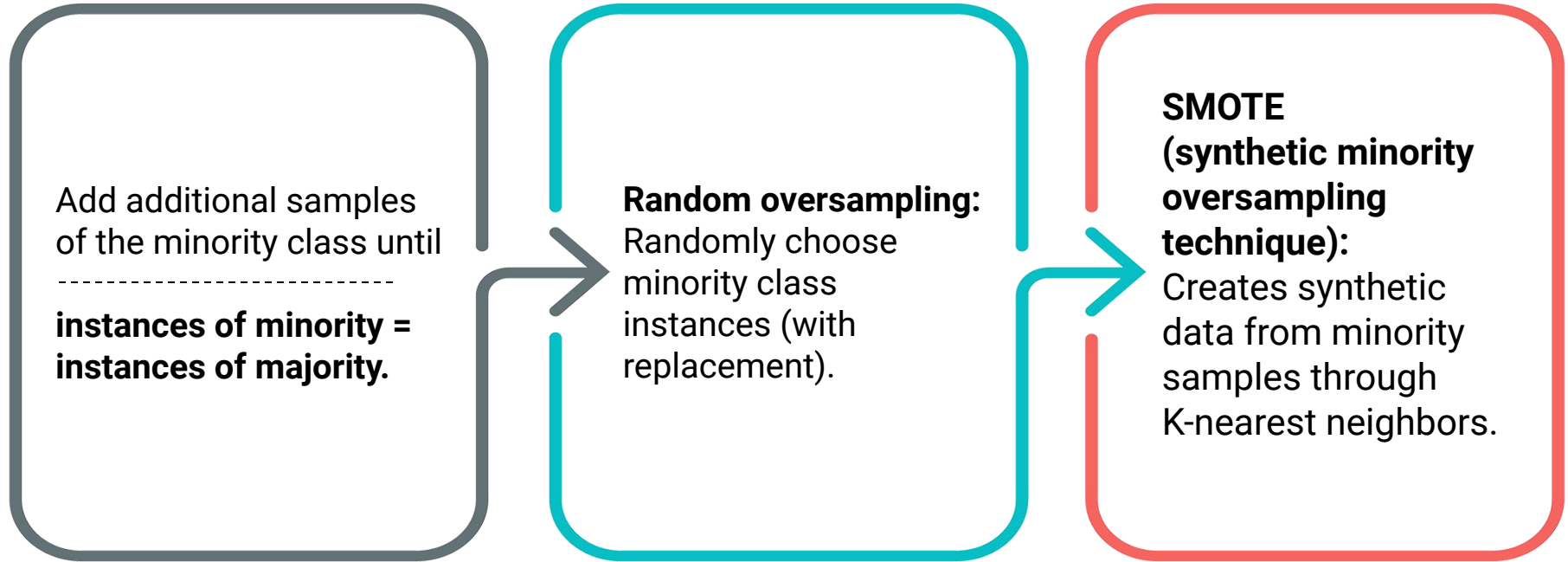
Use the right performance metrics for evaluation



Change your model

Oversampling

Potential strategies:





Activity: More Loans

In this activity, you will practice using random and SMOTE oversampling in combination with logistic regression to predict whether or not someone is likely to default on their credit card loans in a given month given demographic information.

Suggested Time:
15 minutes

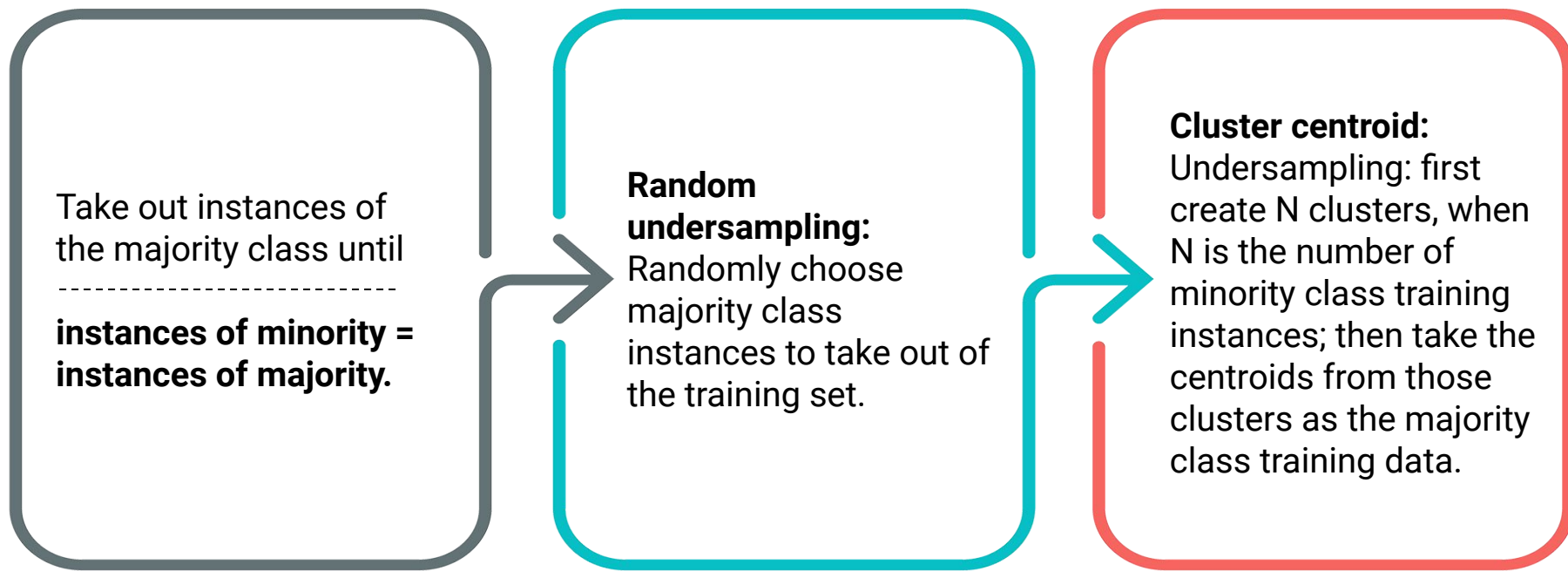




Time's Up! Let's Review.

Undersampling

Potential strategies:





Activity: Undersampling

In this activity, you will research and practice undersampling with the `imbalanced-learn` library.

Suggested Time:
15 minutes

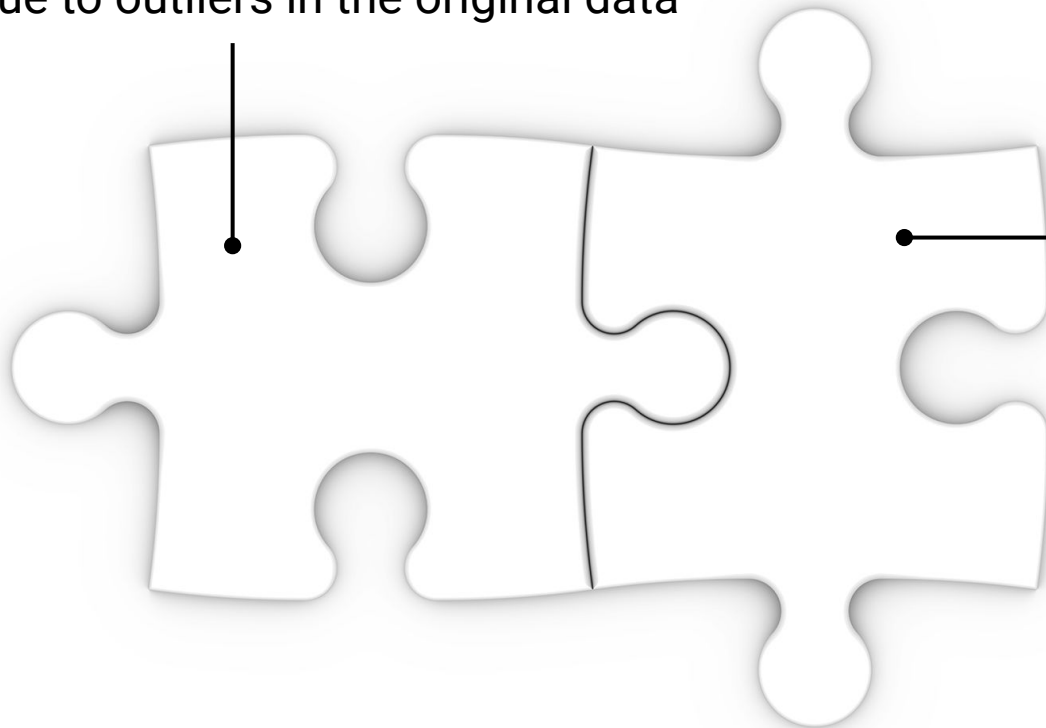




Time's Up! Let's Review.

Combination Sampling

Oversampling with **SMOTE** can result in noisy data due to outliers in the original data



Undersampling is not always realistic due to limited data

Combination Sampling

SMOTEENN “combines” the two methodologies

01

oversample

First, we oversample the minority class.

02

undersampling

Next, we “clean” the resulting data using an undersampling strategy: If a data points’ two nearest neighbors are in a different class, then we drop that data point.



Activity:

Combination Sampling

In this activity, you will practice combination sampling with the `imbalanced-learn` library.

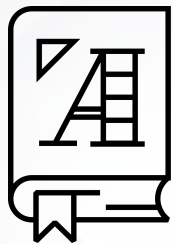
Suggested Time:
15 minutes





Time's Up! Let's Review.

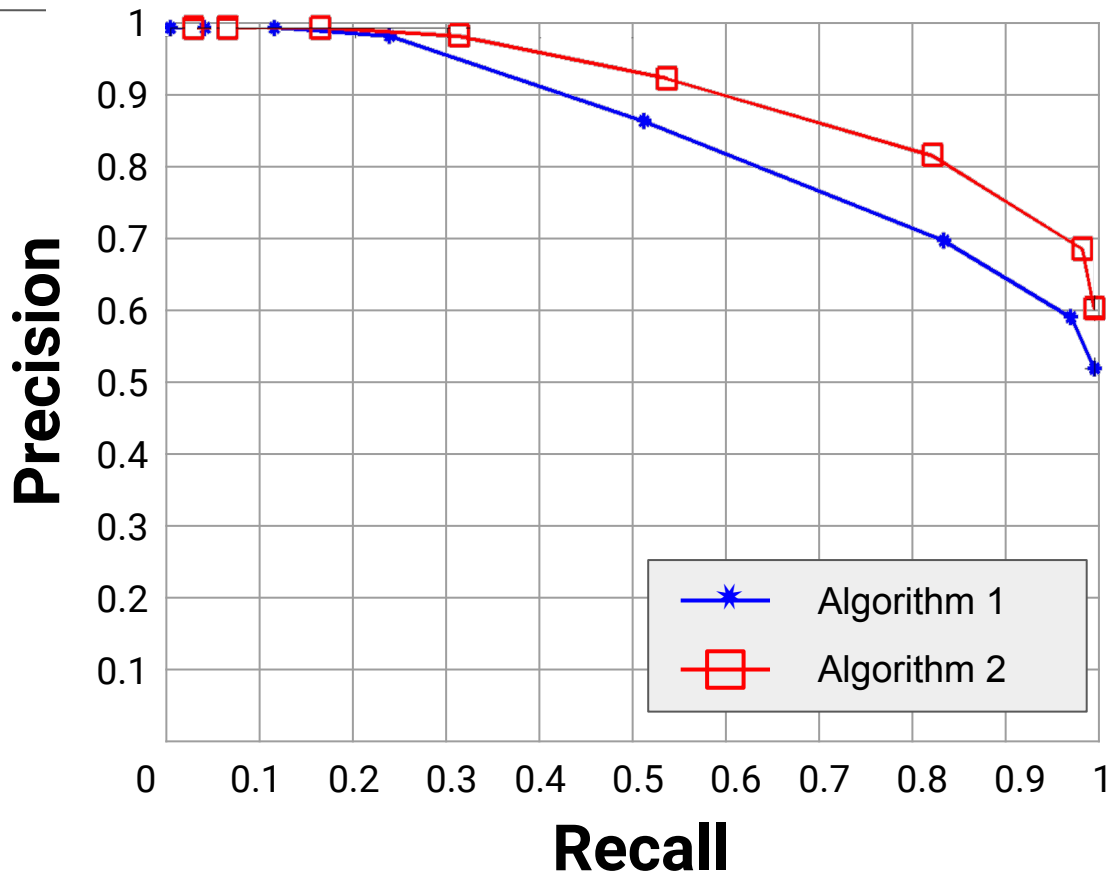
precision-recall curve



The balance between precision and recall can be visualized with a **precision-recall** curve.

precision-recall curve

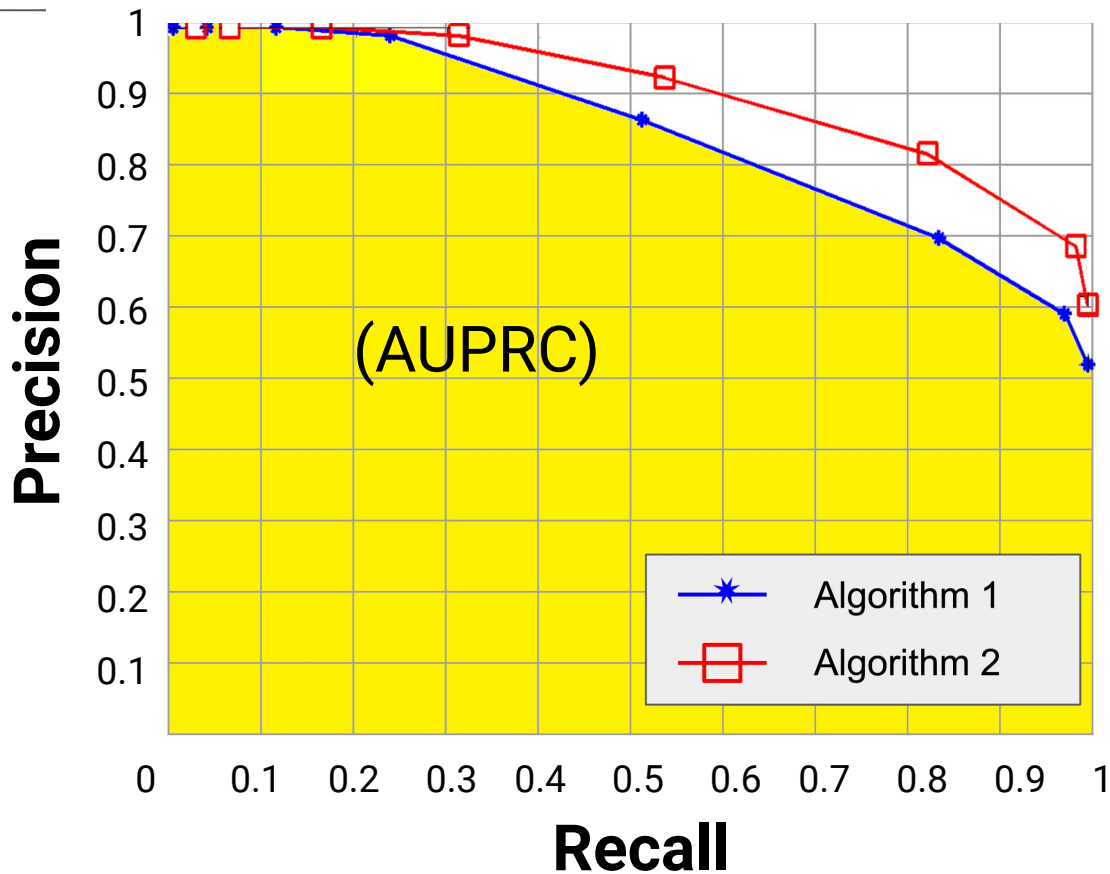
A PR curve plots recall (x-axis) versus precision (y-axis) at various classification thresholds to help visualize the balance between these metrics



precision-recall curve

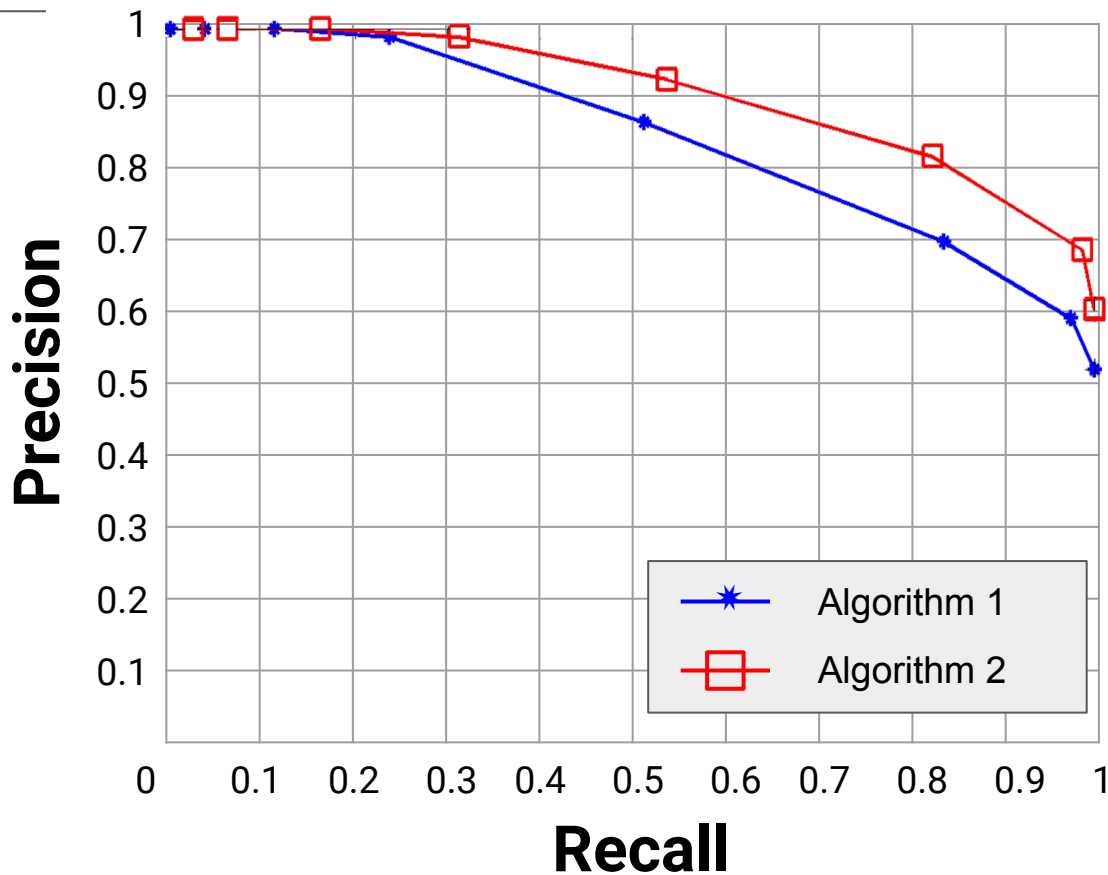
The area under the curve (AUPRC) is a metric for how good the model is in absolute terms.

It can be valuable when comparing one model to another.



precision-recall curve

Note how, in general, as the recall increases (right) the precision decreases (down).





Activity:

Credit Card Fraud

In this activity, you will practice combination sampling with the `imbalanced-learn` library.

Suggested Time:
15 minutes





Time's Up! Let's Review.



Questions?