Train In Data

# Precision-Recall Curve

# Precision and Recall

- **Recall** = TP / (TP + FN)
  - Fraction of minority samples identified
- **Precision** = TP / (TP + FP)
  - Fraction of positive predictions that are indeed minority class

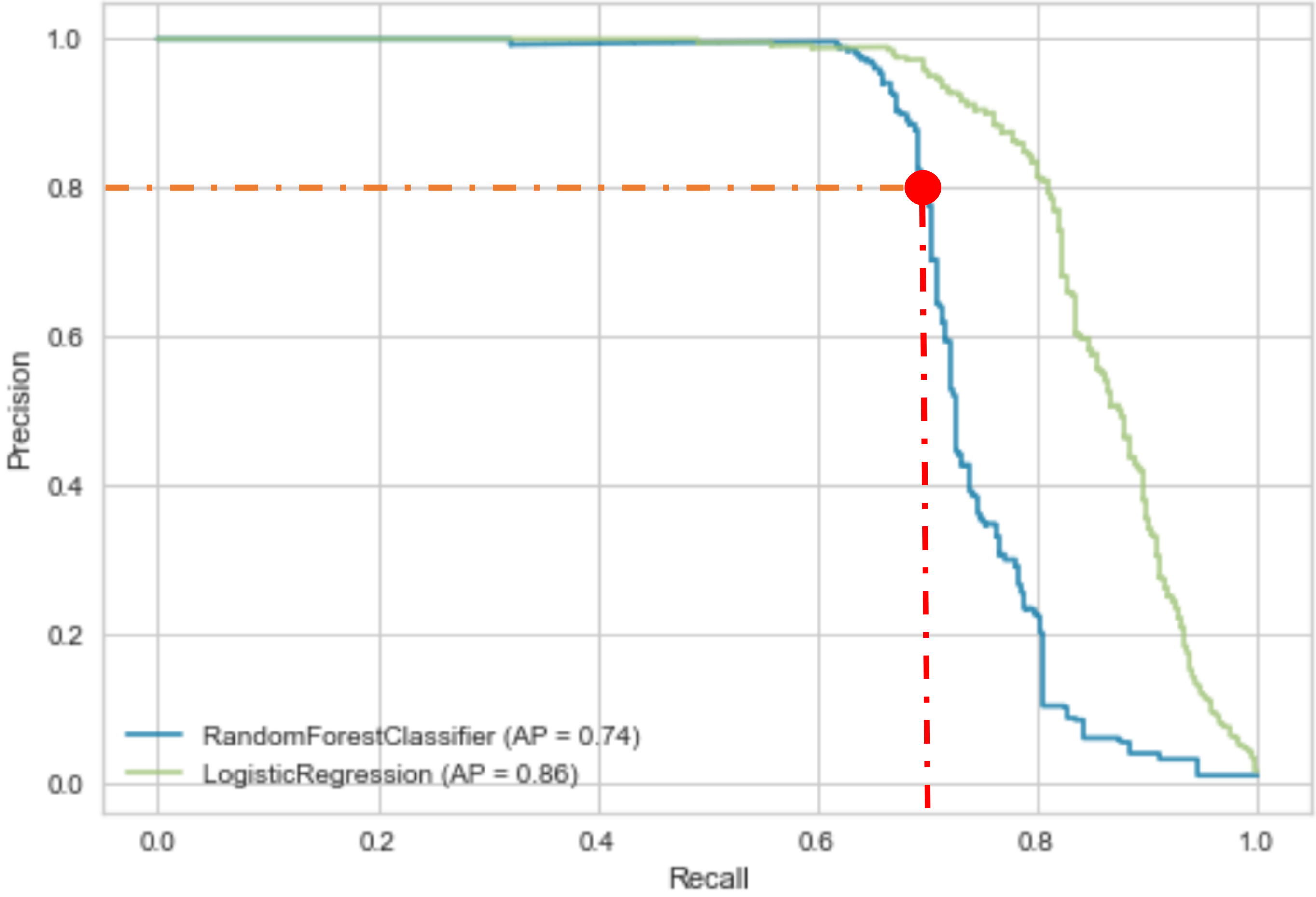
# Precision-Recall Curve

- The Precision-Recall Curve shows the relationship between precision and recall for every cut-off / Discriminant Probability Threshold.

- The PRC is a graph with:
  - ✓ Recall in the x-axis
  - ✓ Precision in the y-axis

- Every point on the PRC represents a chosen cut-off. Every point provides the precision and the recall for a certain cut-off / threshold.

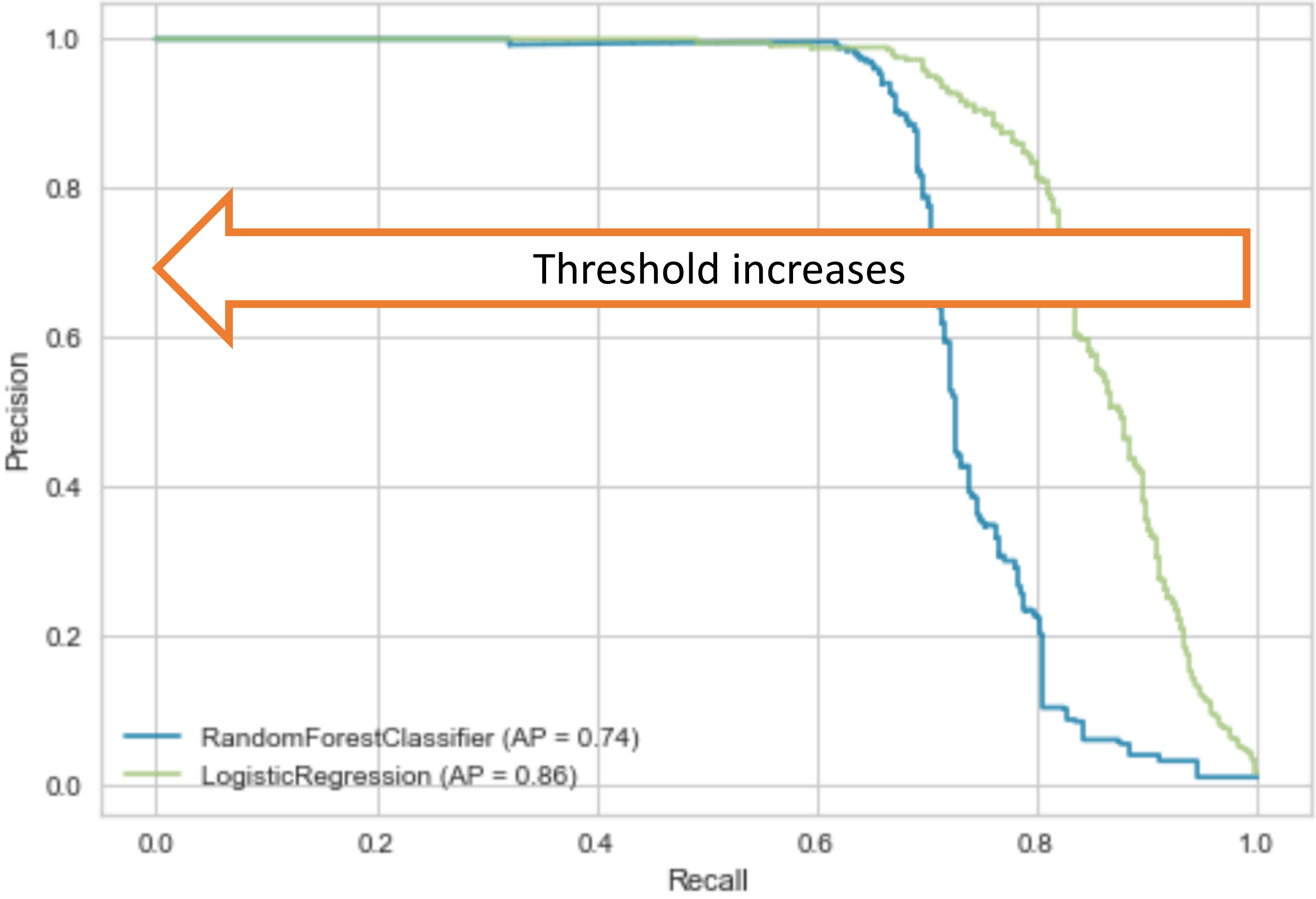
# Precision-Recall Curve




For the threshold at ●:

- Precision = 0.8
- Recall = 0.7

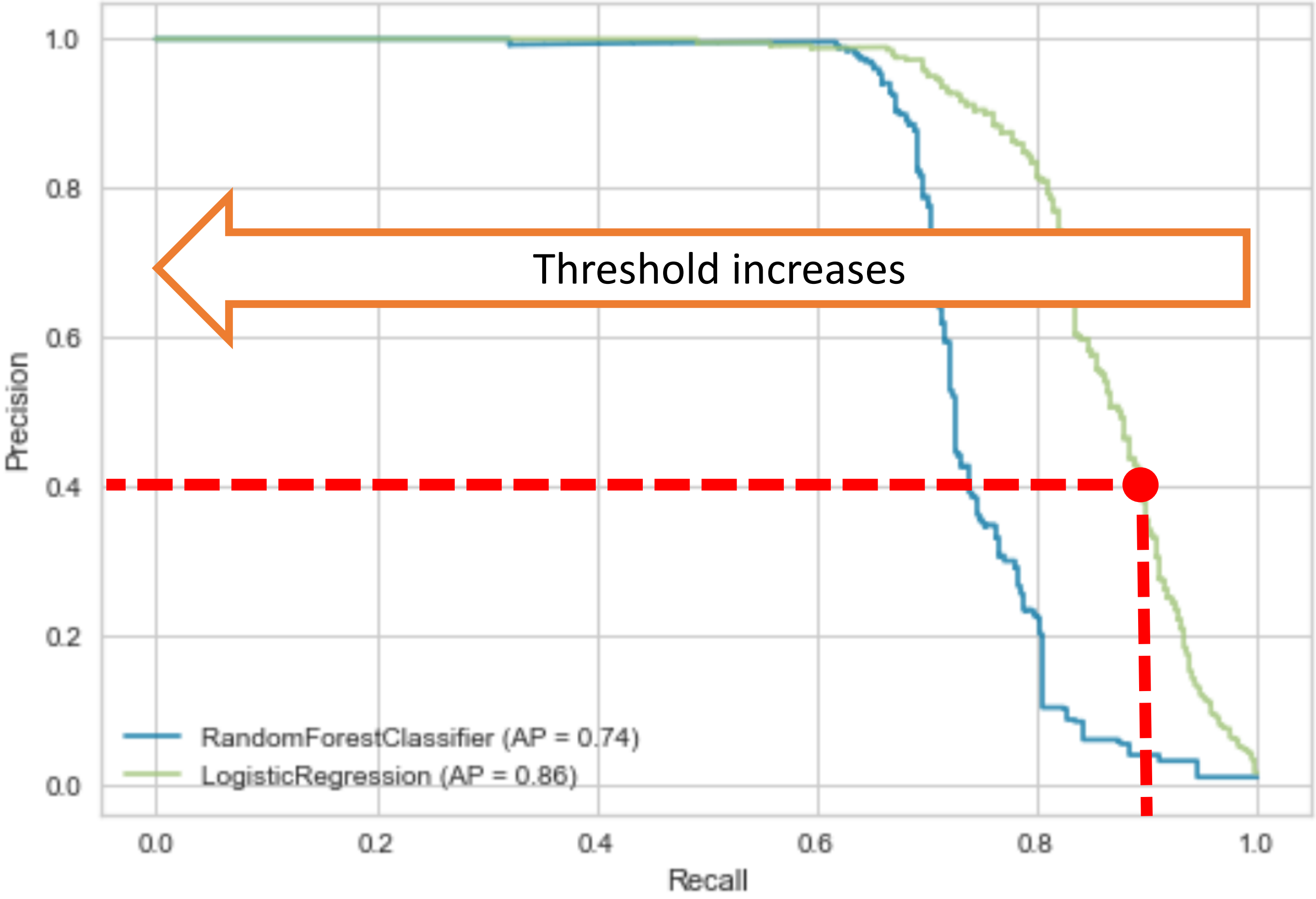
# Precision-Recall Curve




As threshold increases:

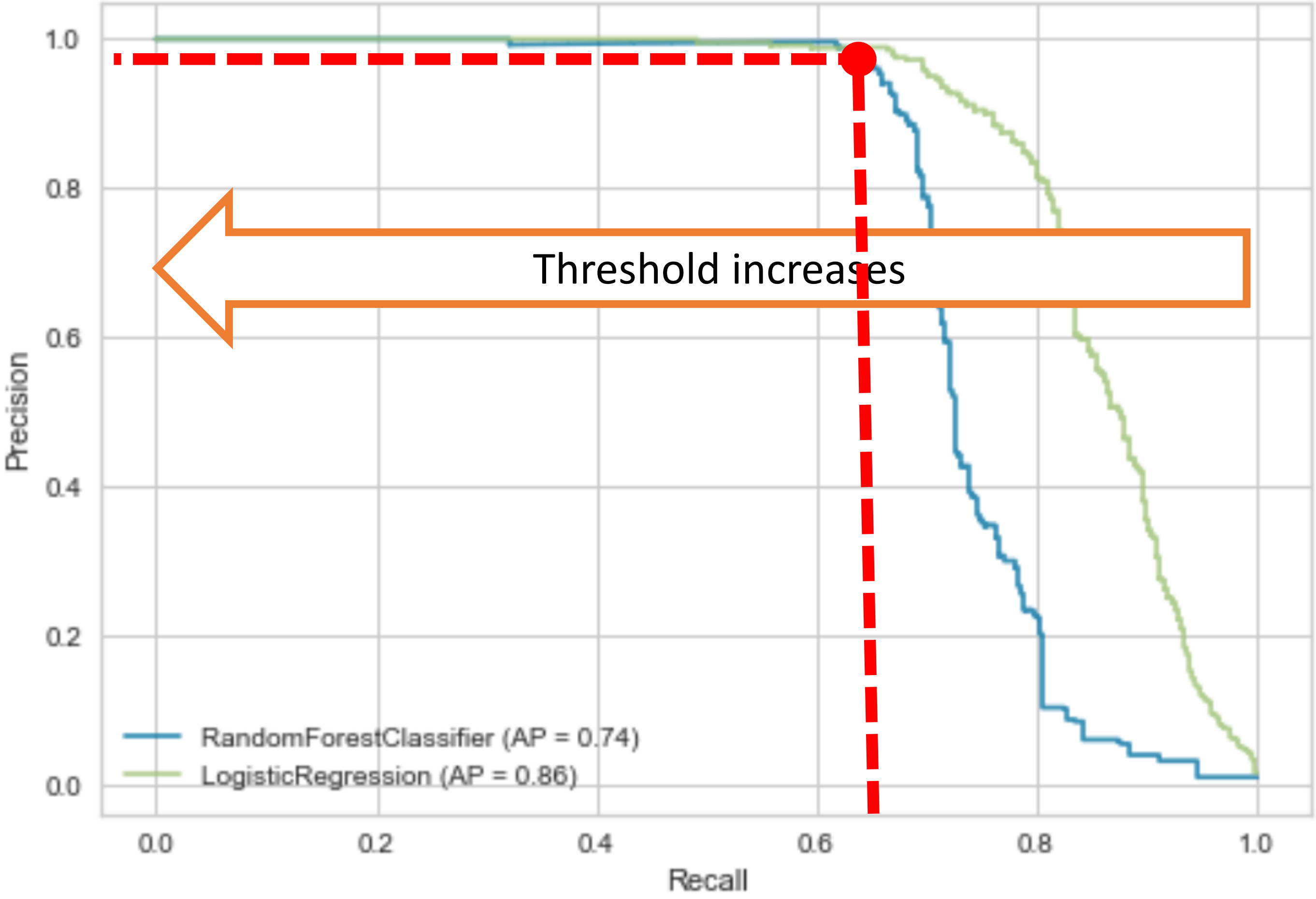
- Precision increases
  - TP / (TP + FP)
- Recall decreases
  - (TP / (TP + FN) )

# Precision-Recall Curve



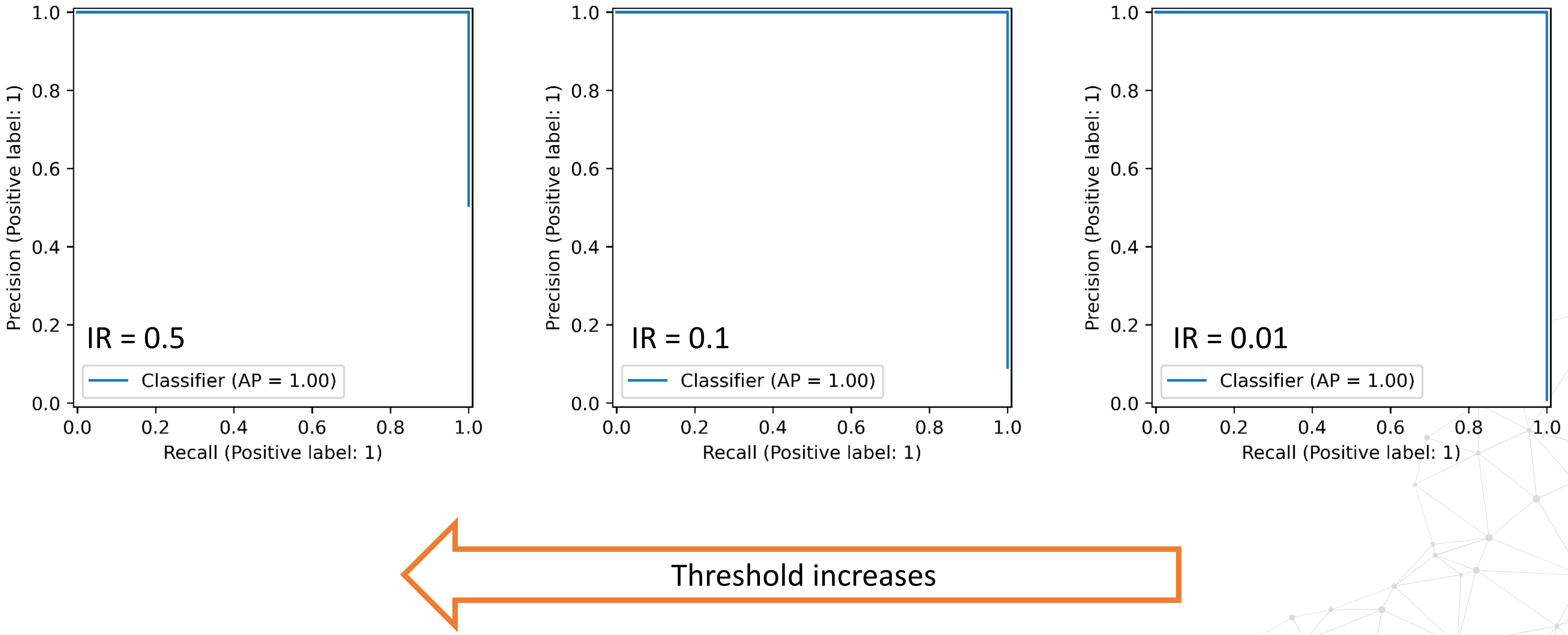

- Low probability threshold ~ 0.2
  - Recall = 0.9
  - Precision = 0.4

# Precision-Recall Curve

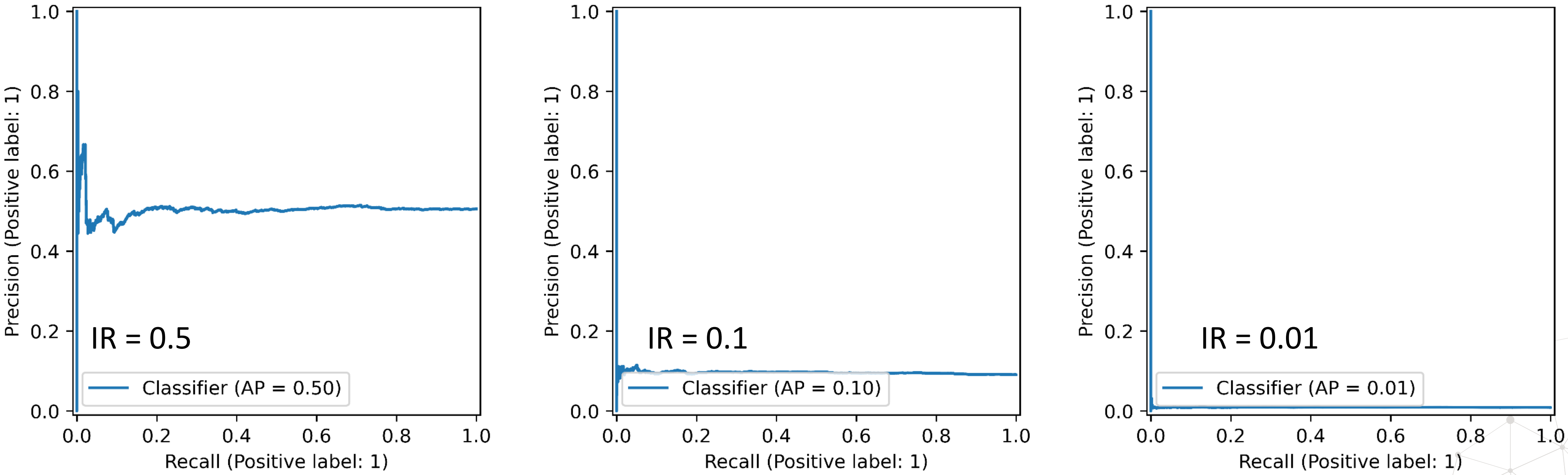



- High probability threshold ~ 0.8
  - Recall = 0.62
  - Precision = 0.9

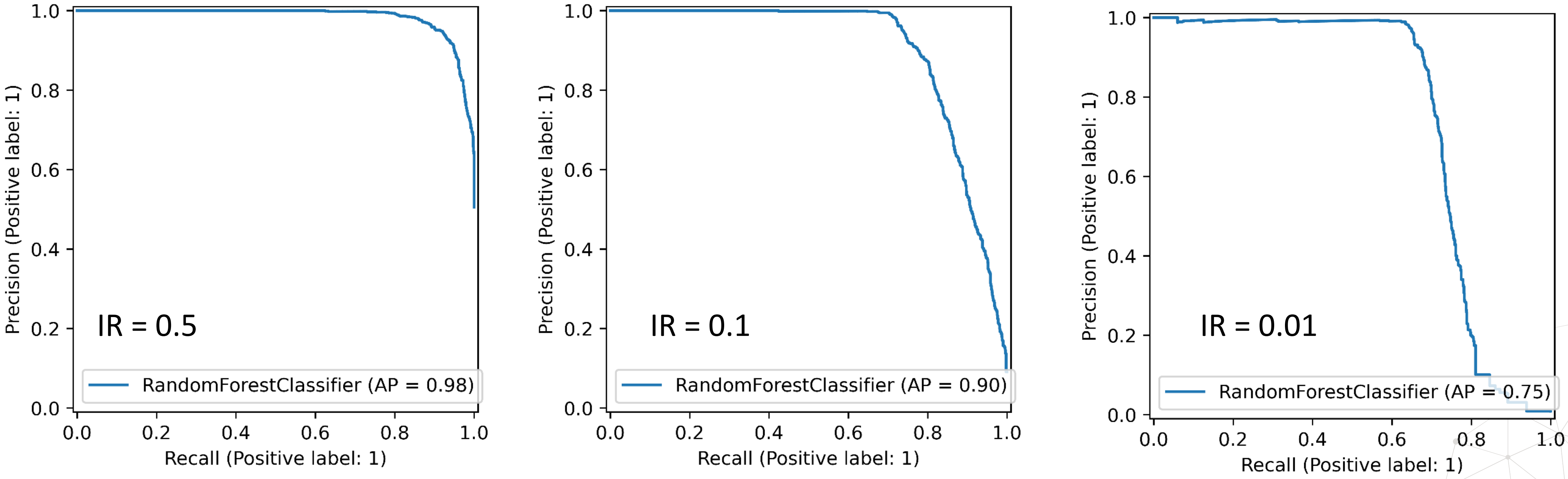
# PRC: Perfect model



# PRC: Random model

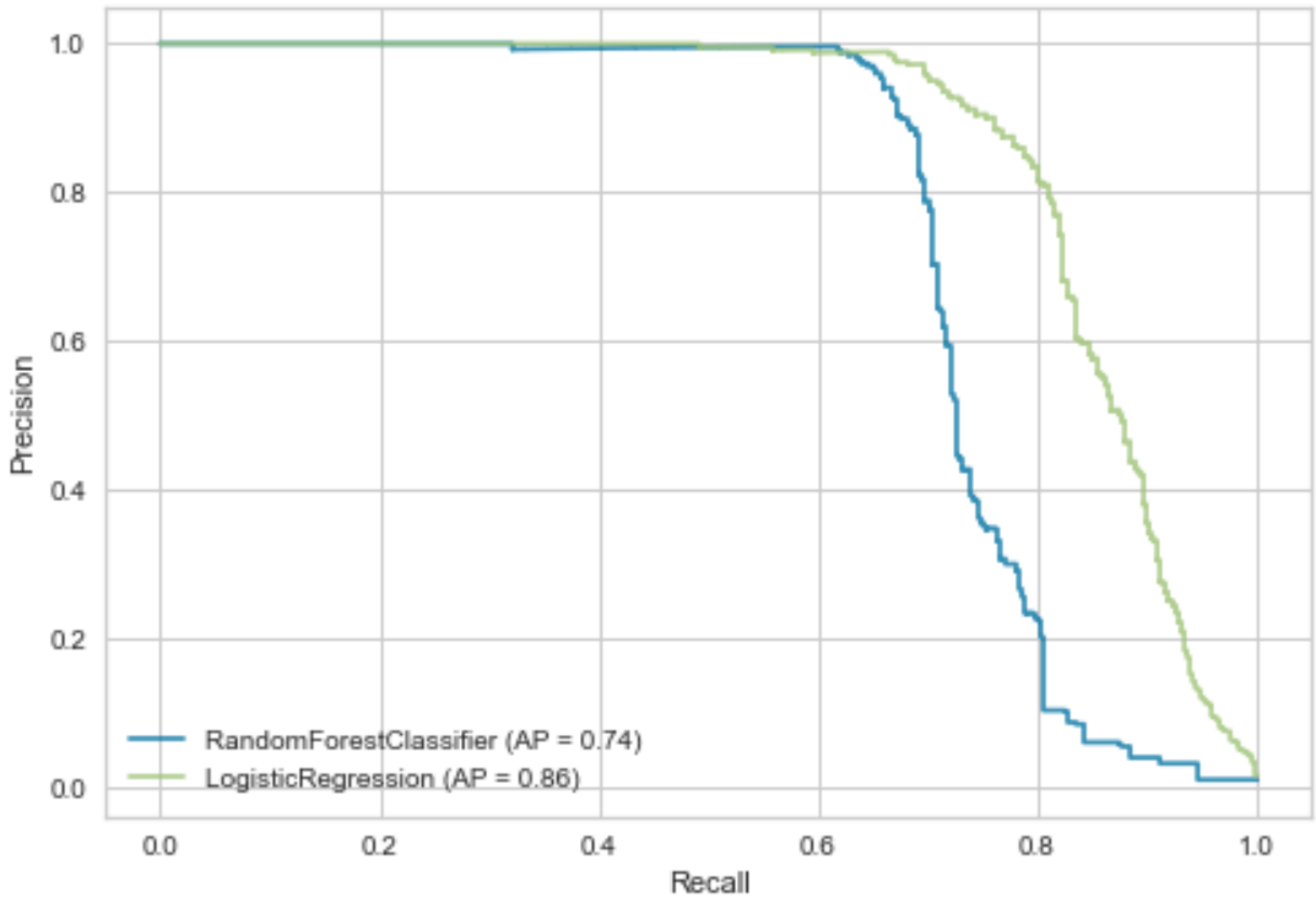



# Precision-Recall Curve: Random




Threshold increases

# Precision-Recall Curve




- The area under the PRC provides an aggregate measure of performance across all possible classification thresholds.
- Larger area indicates better model performance

# PRC vs ROC Curve

## The Relationship Between Precision-Recall and ROC Curves

**Jesse Davis** JDAVIS@CS.WISC.EDU
**Mark Goadrich** RICHM@CS.WISC.EDU
Department of Computer Sciences and Department of Biostatistics and Medical Informatics, University of Wisconsin-Madison, 1210 West Dayton Street, Madison, WI, 53706 USA

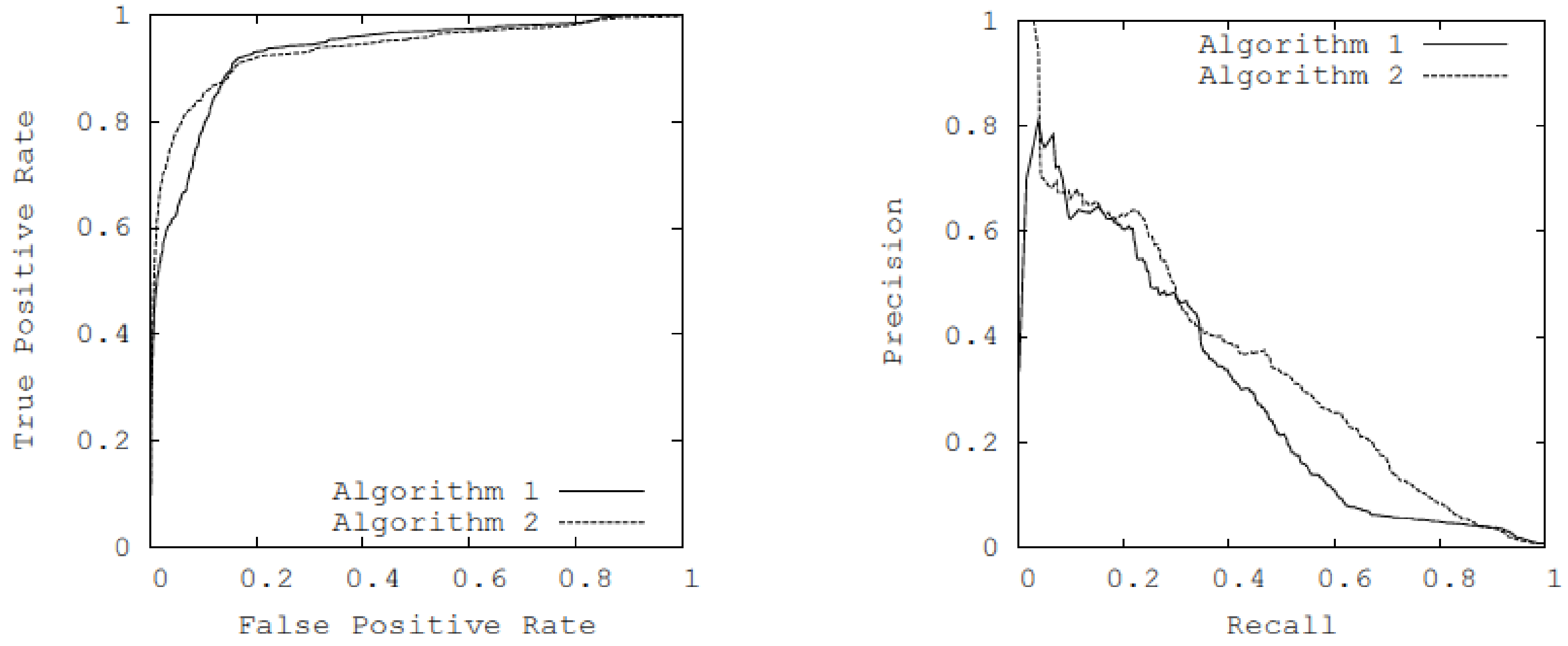
### Abstract

Receiver Operator Characteristic (ROC) curves are commonly used to present results for binary decision problems in machine learning. However, when dealing with highly skewed datasets, Precision-Recall (PR) curves give a more informative picture of an algorithm's performance. We show that a deep connection exists between ROC space and PR space, such that a curve dominates in ROC space if and only if it dominates in PR space. A corollary is the notion of an achievable PR curve, which has properties much like the convex hull in ROC space;

in the class distribution. Drummond and Holte (2000; 2004) have recommended using cost curves to address this issue. Cost curves are an excellent alternative to ROC curves, but discussing them is beyond the scope of this paper.

Precision-Recall (PR) curves, often used in Information Retrieval (Manning & Schutze, 1999; Raghavan et al., 1989), have been cited as an alternative to ROC curves for tasks with a large skew in the class distribution (Bockhorst & Craven, 2005; Bunescu et al., 2004; Davis et al., 2005; Goadrich et al., 2004; Kok & Domingos, 2005; Singla & Domingos, 2005). An important difference between ROC space and PR space is the visual representation of the curves. Looking

# PRC vs ROC Curve




(a) Comparison in ROC space



(b) Comparison in PR space

*Figure 1.* The difference between comparing algorithms in ROC vs PR space

It is harder to discriminate between ROC curves with large areas under the curve.

# THANK YOU

www.trainindata.com