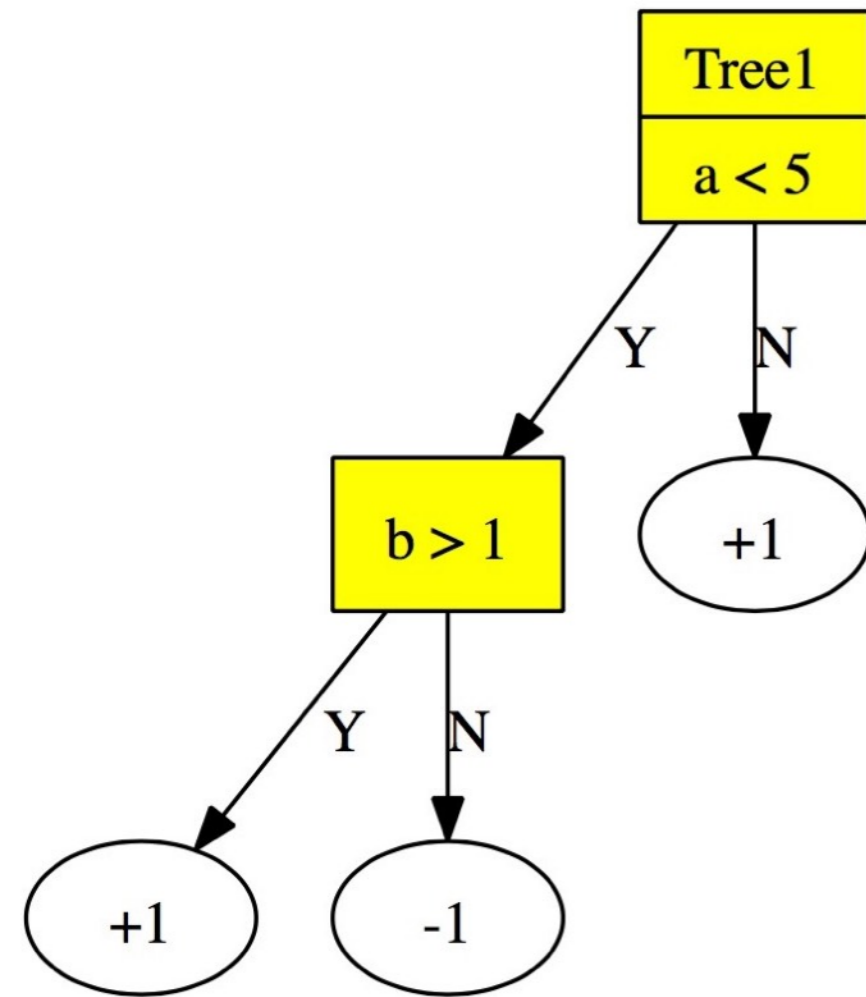
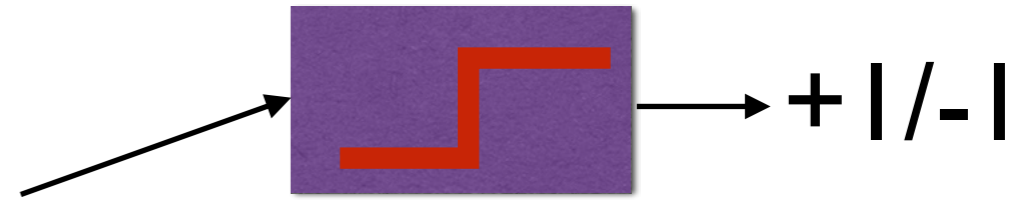


# Ensembles

# What are ensembles

- Ensembles are predictors defined as an average/vote over “base” or “weak” predictors.
- Ensembles come in two main flavors:
  - Boosting based Ensembles
  - Bootstrap based Ensembles.
- Any predictor can be used as a base predictor.
  - In this talk, and in Spark, the base predictors are decision trees.
  - We will restrict our attention to binary classification, but there are solutions for multi class and for regression.

# An Ensemble of trees



# The Bootstrap

1990

An  
Introduction  
to the  
Bootstrap

Bradley Efron

*Department of Statistics  
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and

Robert J. Tibshirani

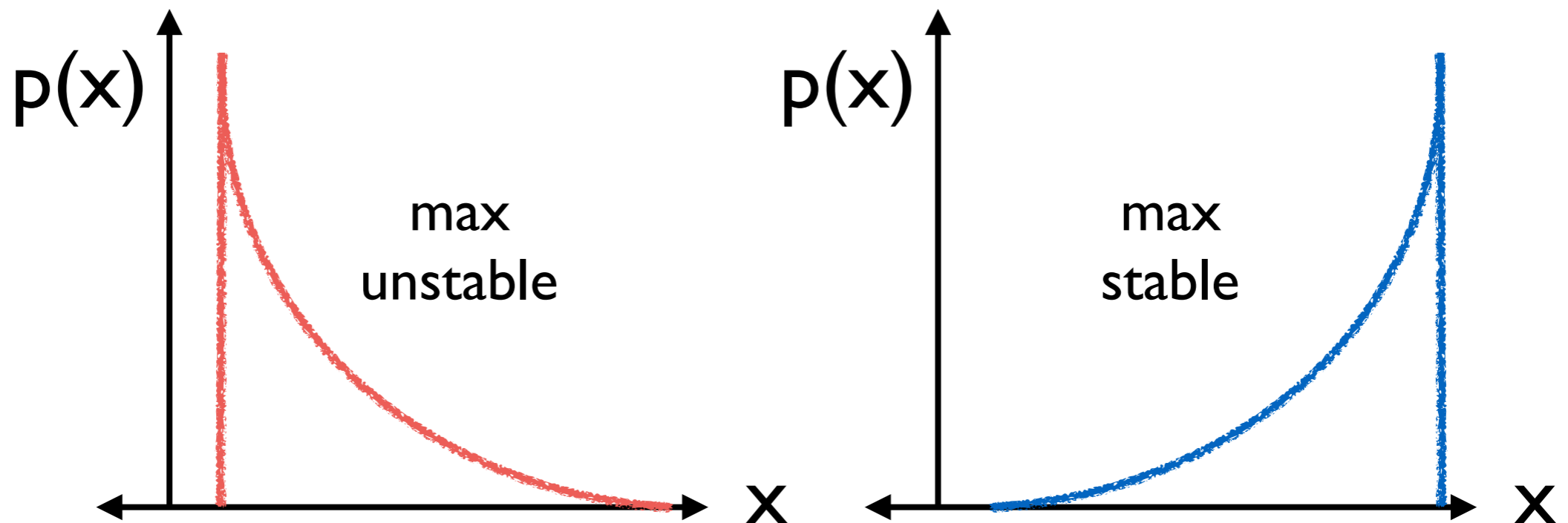
*Department of Preventative Medicine and Biostatistics  
and Department of Statistics, University of Toronto*

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# The Bootstrap

- A method for estimating out-of-sample variation
- Suppose that we estimate the maximum of of the distribution.
- Depending on the distribution, this estimate of max might be stable or not.



# How to estimate the variation

- In general - a hard question, we are trying to estimate a property of the true distribution, but we only have the sample.
- A Bootstrap sample: given a sample of size  $n$ , sample  $n$  times with replacement from this sample.
- Compute the estimator on each bootstrap sample and see how much it varies.
- Will work nicely for the max estimator.

# Bagging = bootstrap aggregation

- Decision trees have high data variation.
  - i.e. the generated tree is sensitive to small changes in the training set.
- To reduce the variation, we take a majority vote over several runs, each using an independent random resample of the training data.
- Running an algorithm over random resampling is called “The Bootstrap”
- Trees can be learned in parallel
- The result is a reduction in variation with no increase in the bias.



# Random Forests

- Based on bagging trees.
- Additional randomization: before choosing which leaf to split and how, choose a random subset of the features.
- Decreases the correlation between different trees.
- Speeds up the learning process.
- All trees get equal weight (1.0)
- All trees can be learned in parallel.

# Gradient Tree Boosting

- The trees are trained sequentially, one after the other.
- Each tree is trained using a **weighted** training set. The weights represent the gradient of the loss function.
- Each tree receives a different weight (corresponding to the alpha in adaboost)
- Stochastic gradient boosting: use random resampling of the training set a.k.a. Bagging.