Decision Forest

After Twenty Years

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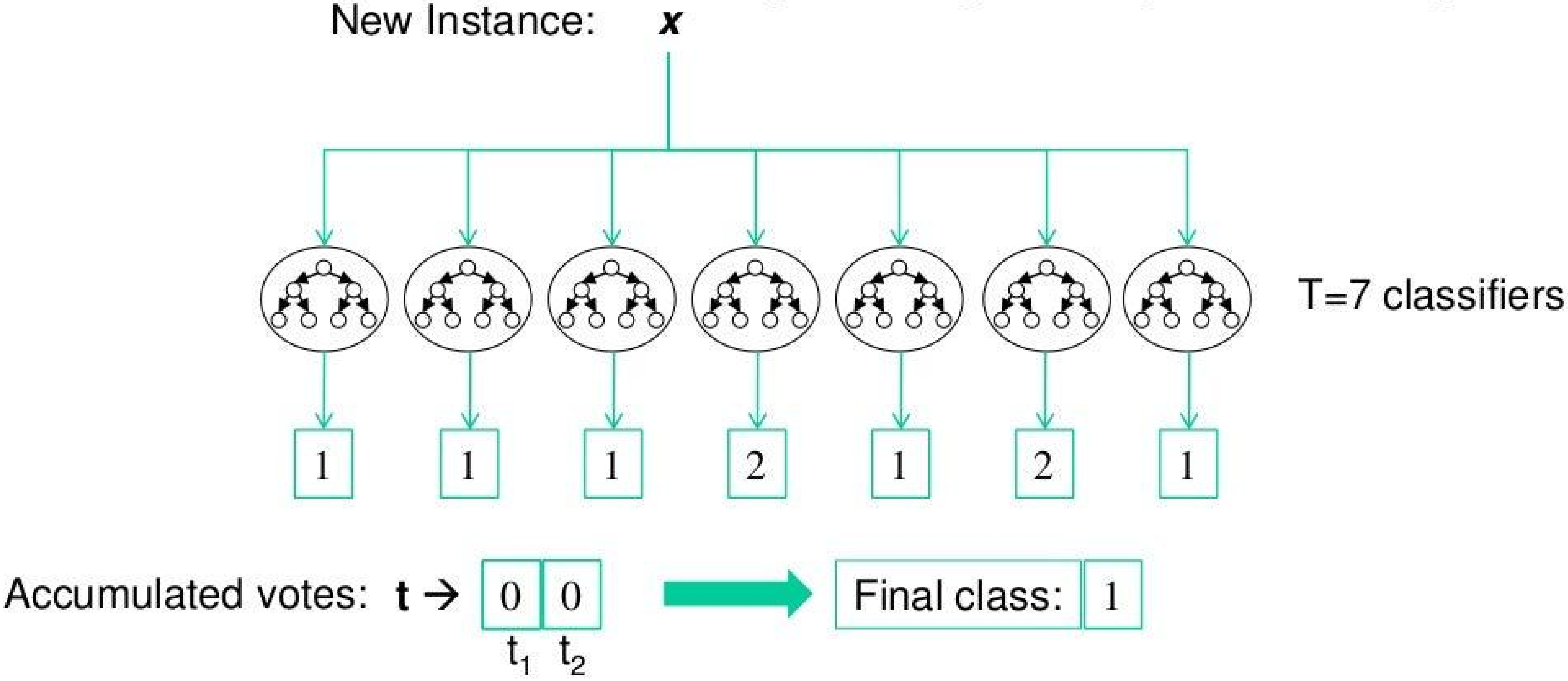
Do we need hundreds of classifiers to solve real world classification problems? (Fernández-Delgado *et al.*, 2014)

Empirically comparing
179 classification algorithms
over 121 datasets

“The classifier most likely to be the best is random forest (achieves 94.1% of the maximum accuracy overcoming 90% in the 84.3% of the data sets)”

Classification by majority voting



New Instance: ***x***

T=7 classifiers

Accumulated votes: **t** → 0 0

t_1 t_2

Final class: 1

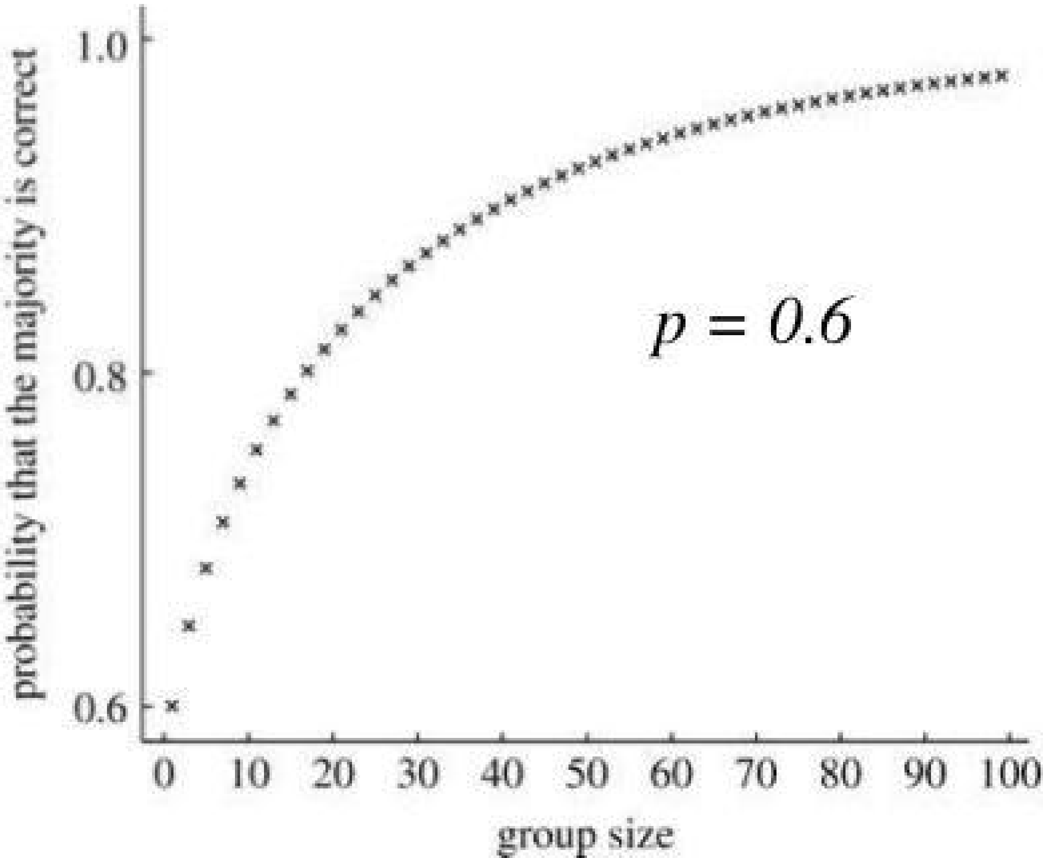
Obtained from Alberto Suárez, 2012

The Condorcet's Jury Theorem (Marquis of Condorcet,1784)

- The most basic jury theorem in social choice
- N = the number of jurors
- p = the probability of an individual juror being right
- μ= the probability that a jury gives the correct answer

$$\mu = \sum_{i=m}^{N} \left(\frac{N!}{(N-i)!\,i!} \right) (p)^{i} (1-p)^{N-i}$$

- $p > 0.5$ implies $\mu > p$.
- and μ → 1 when N→∞.



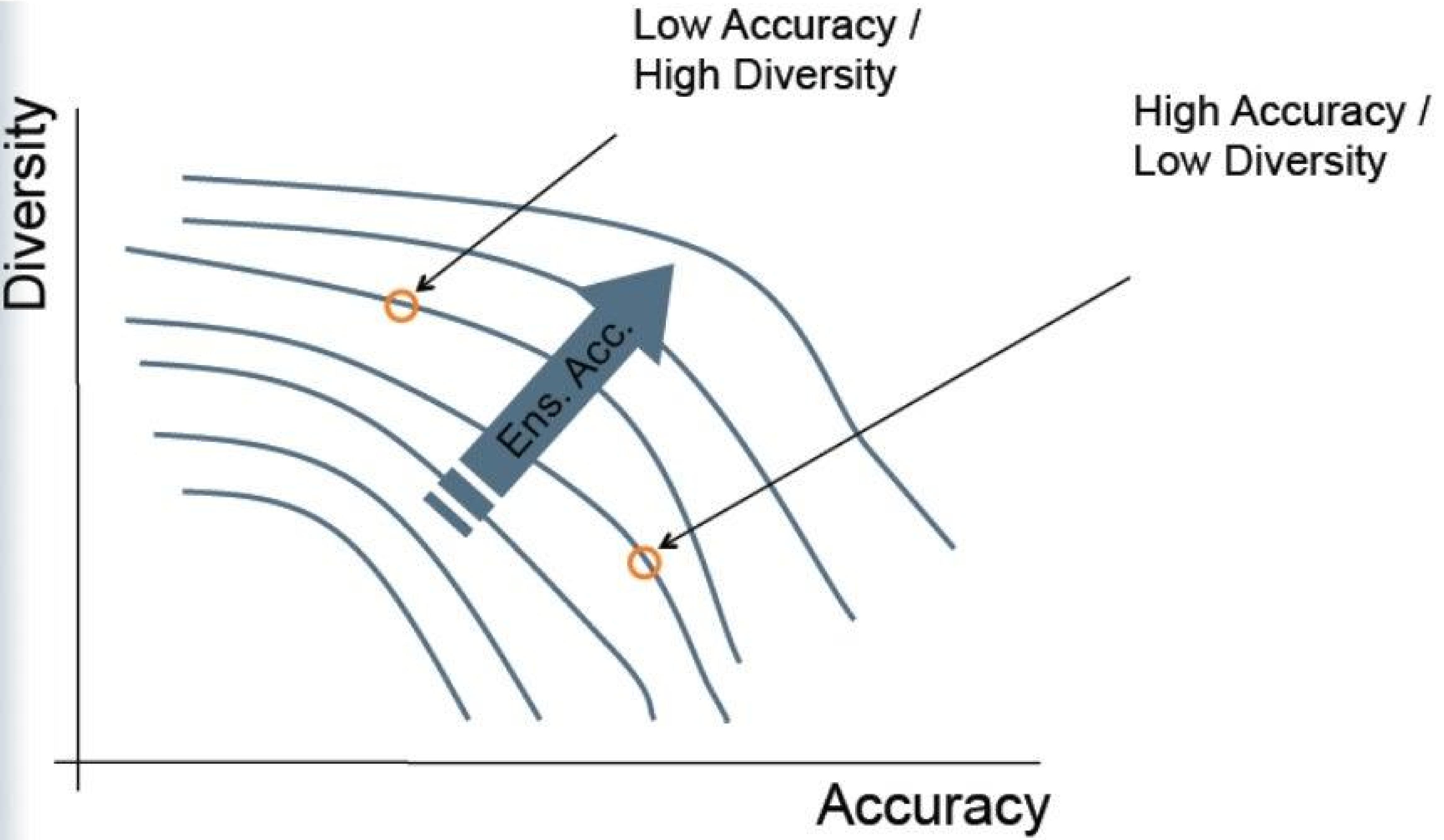
The Wisdom of Crowds

- Francis Galton promoted statistics and invented the concept of correlation.
- In 1906 Galton visited a livestock fair and stumbled upon an intriguing contest.
- An ox was on display, and the villagers were invited to guess the animal's weight.
- Nearly 800 gave it a go and, not surprisingly, not one hit the exact mark: 1,198 pounds.
- Astonishingly, however, the average of those 800 guesses came close - very close indeed. It was 1,197 pounds.

Key Criteria for Crowd to be Wise

- Diversity of opinion
  - Each person should have private information even if it's just an eccentric interpretation of the known facts.
- Independence
  - People's opinions aren't determined by the opinions of those around them.
- Decentralization
  - People are able to specialize and draw on local knowledge.
- Aggregation
  - Some mechanism exists for turning private judgments into a collective decision.

The Diversity Tradeoff

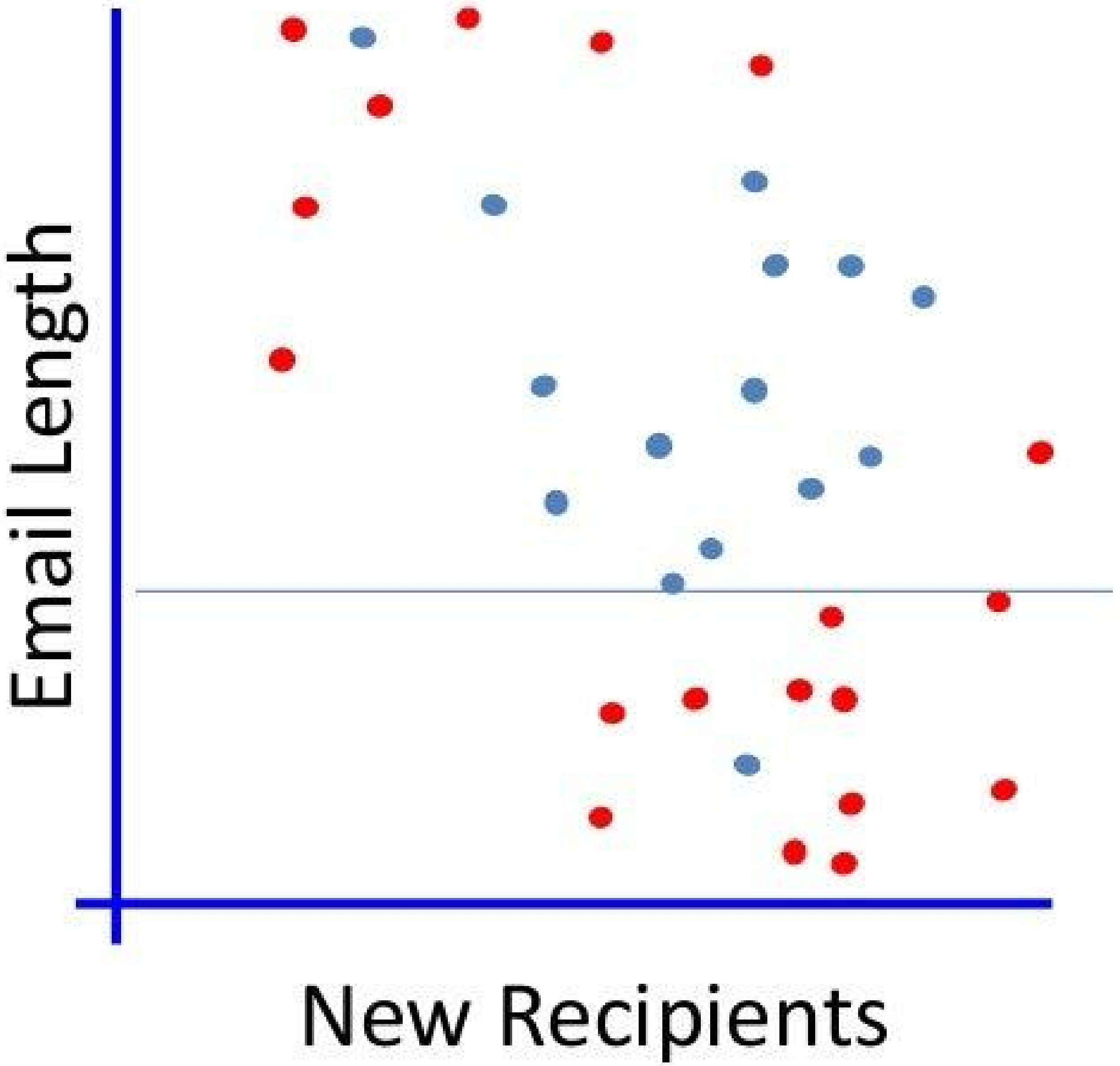


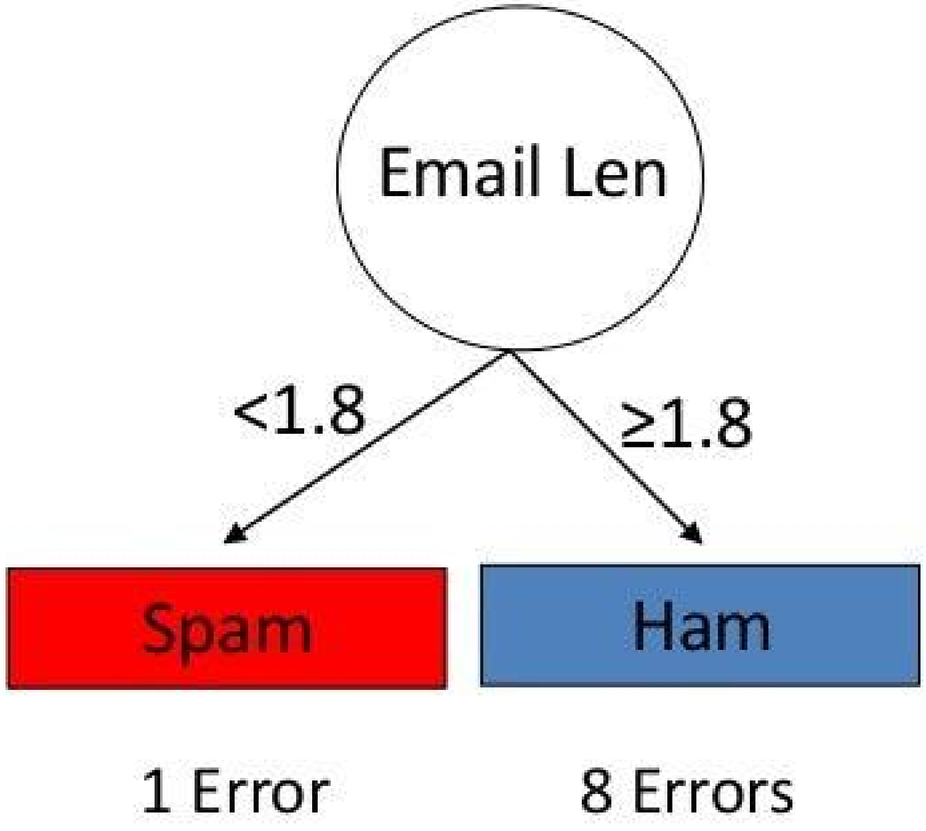
of individual trees

There’s no Real Tradeoff…

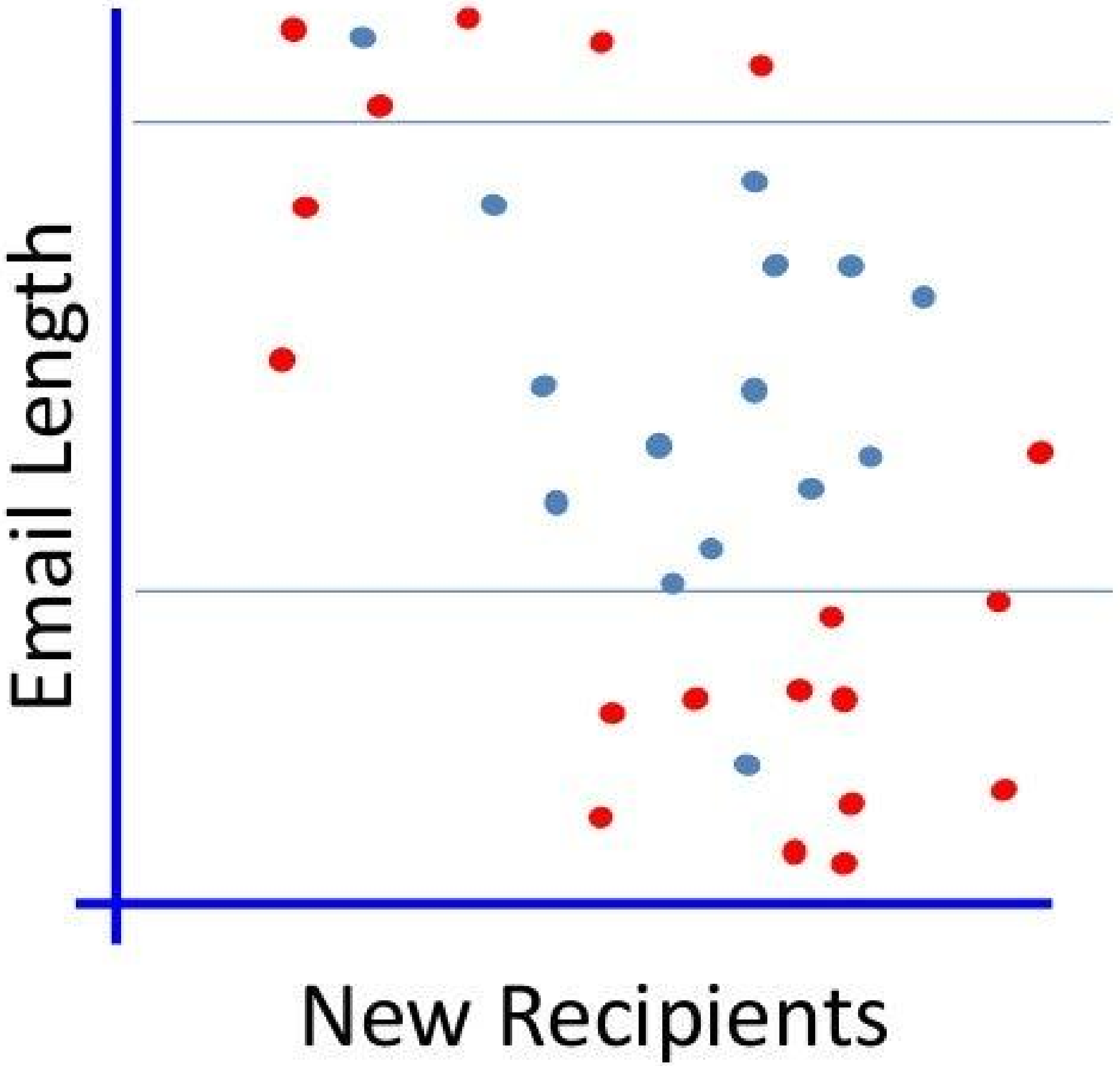
- Ideally, all trees would be right about everything!
- If not, they should be wrong about different cases.

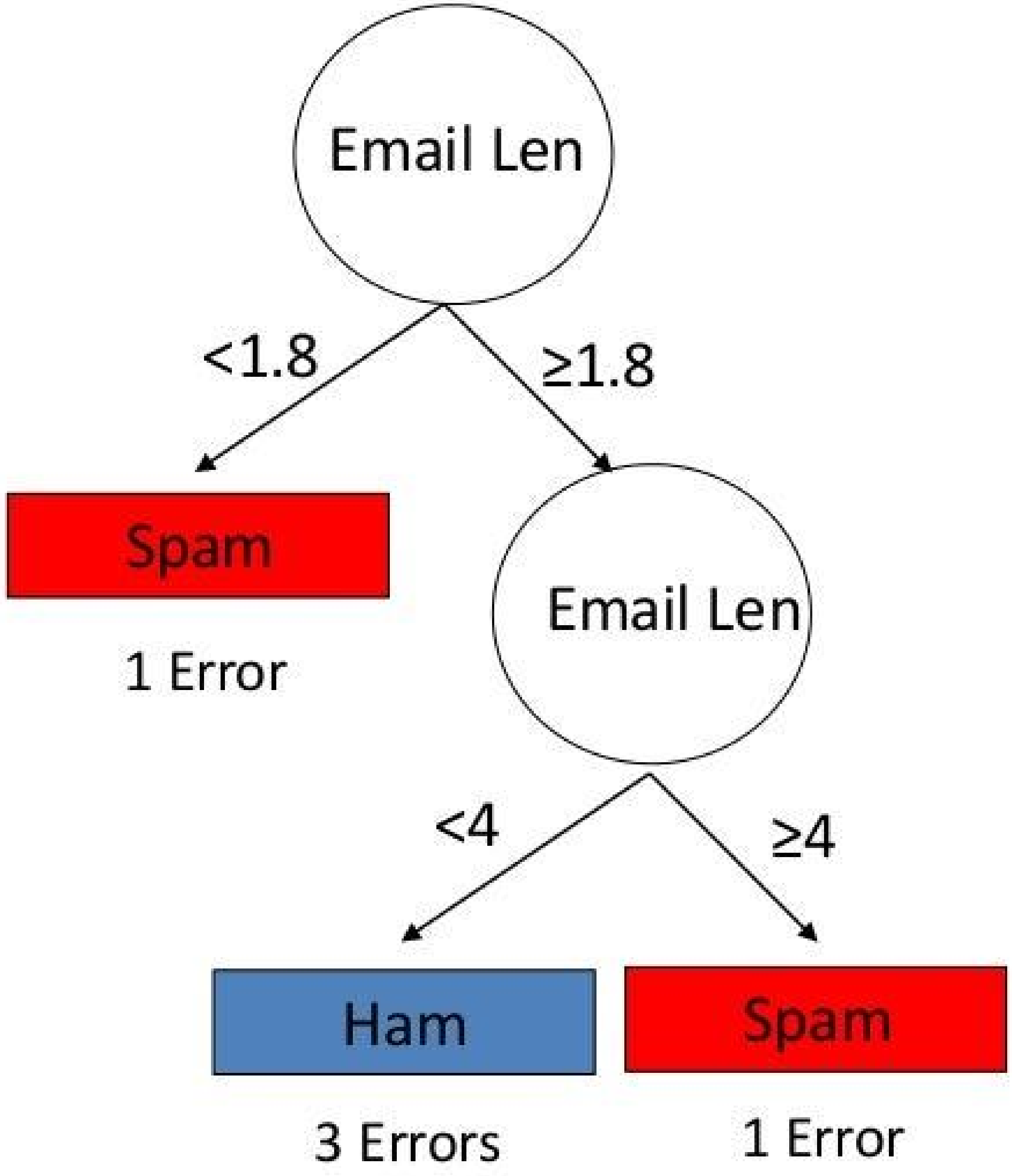
Top Down Induction of Decision Trees



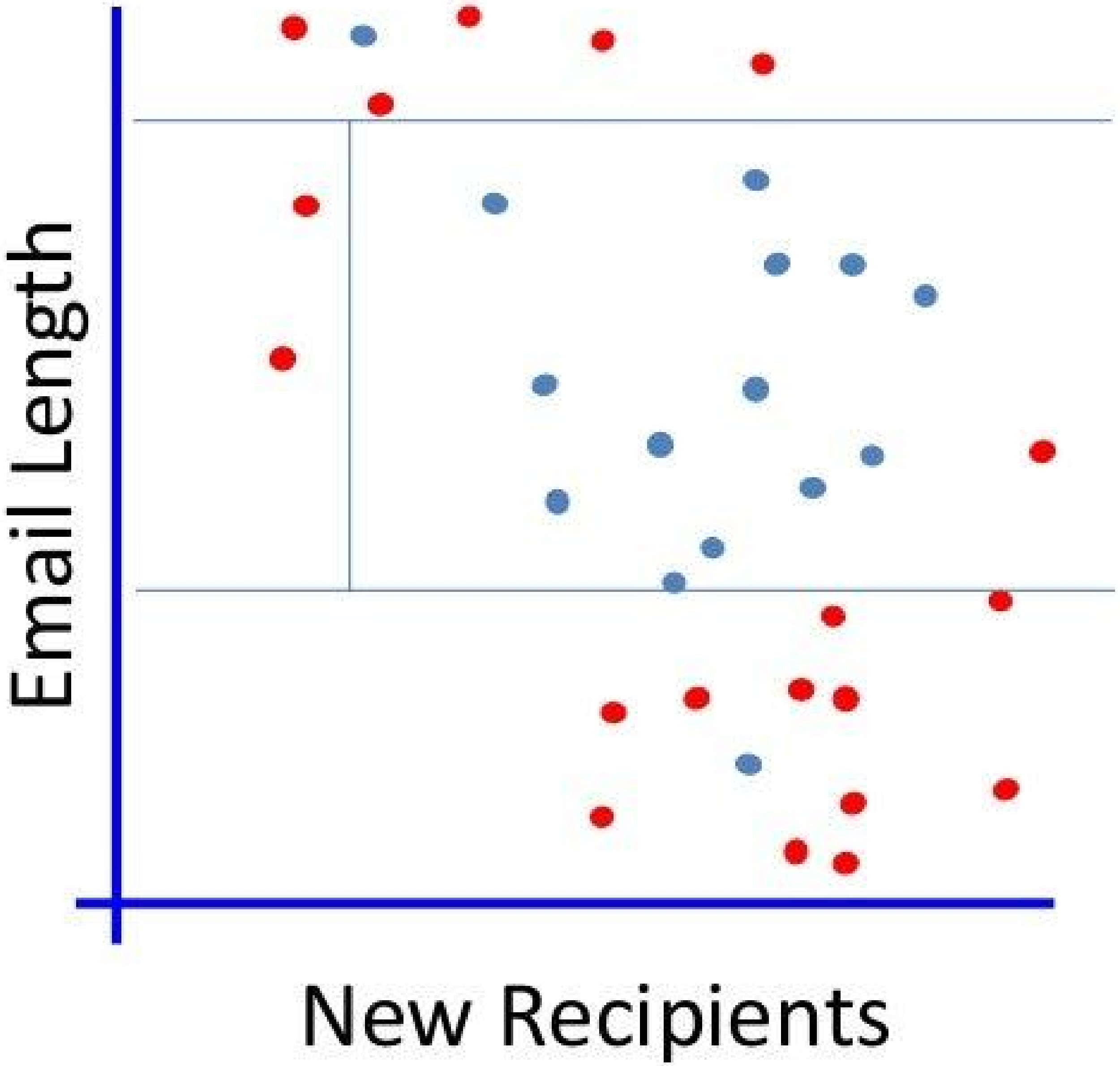


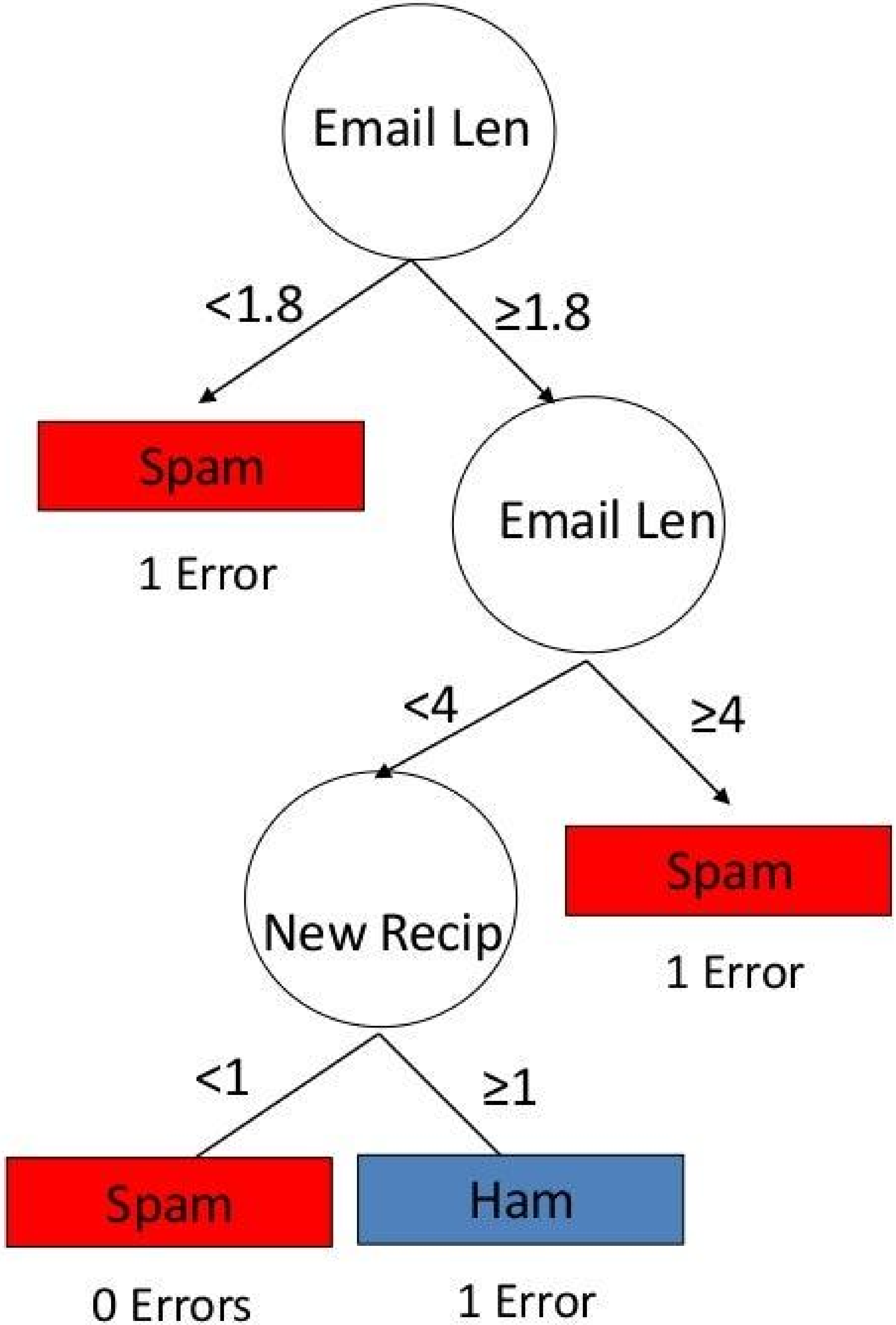
Top Down Induction of Decision Trees





Top Down Induction of Decision Trees





Email Len

<1.8

≥1.8

Spam

1 Error

Email Len

<4

≥4

New Recip

Spam

1 Error

<1

≥1

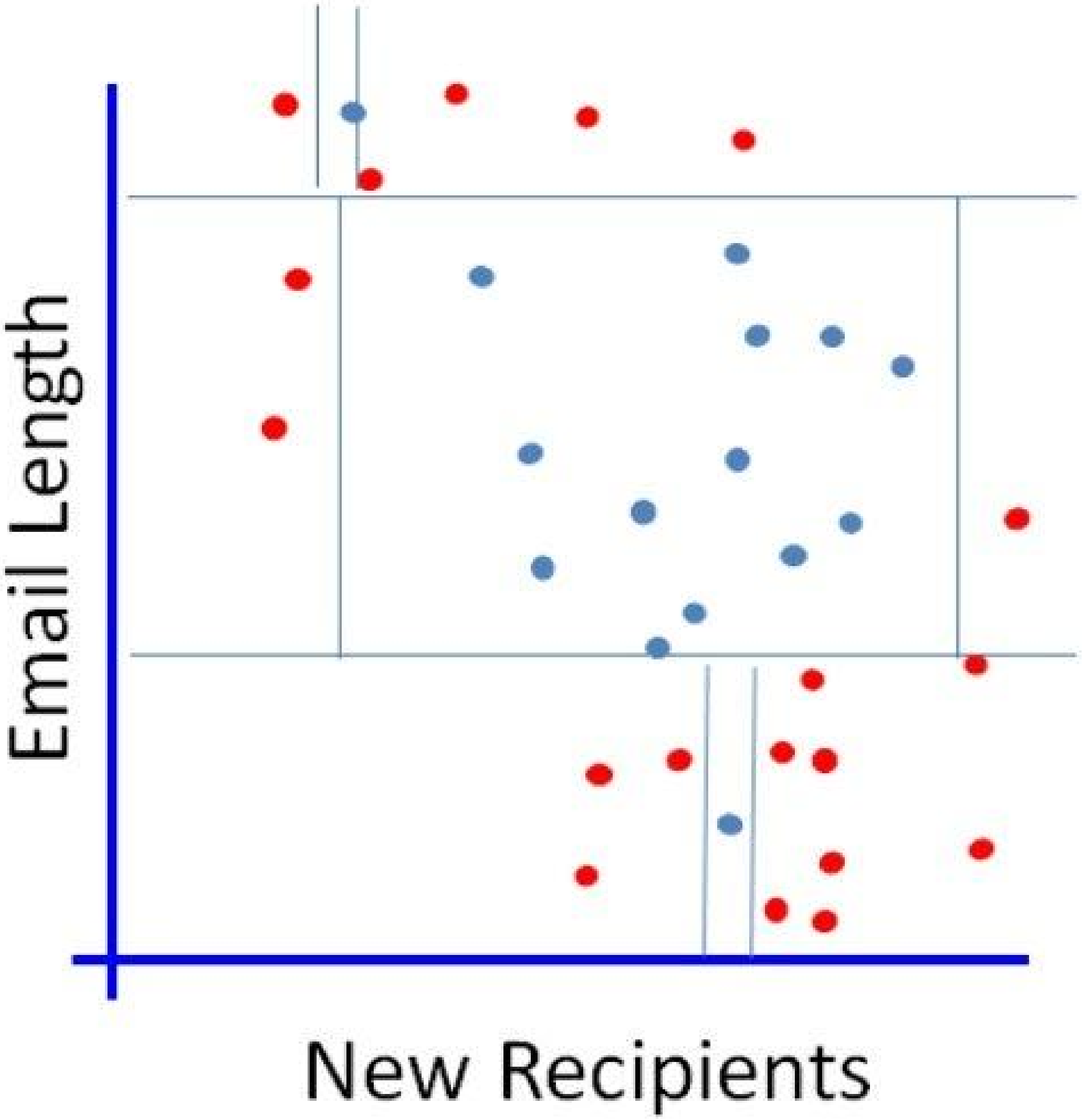
Spam

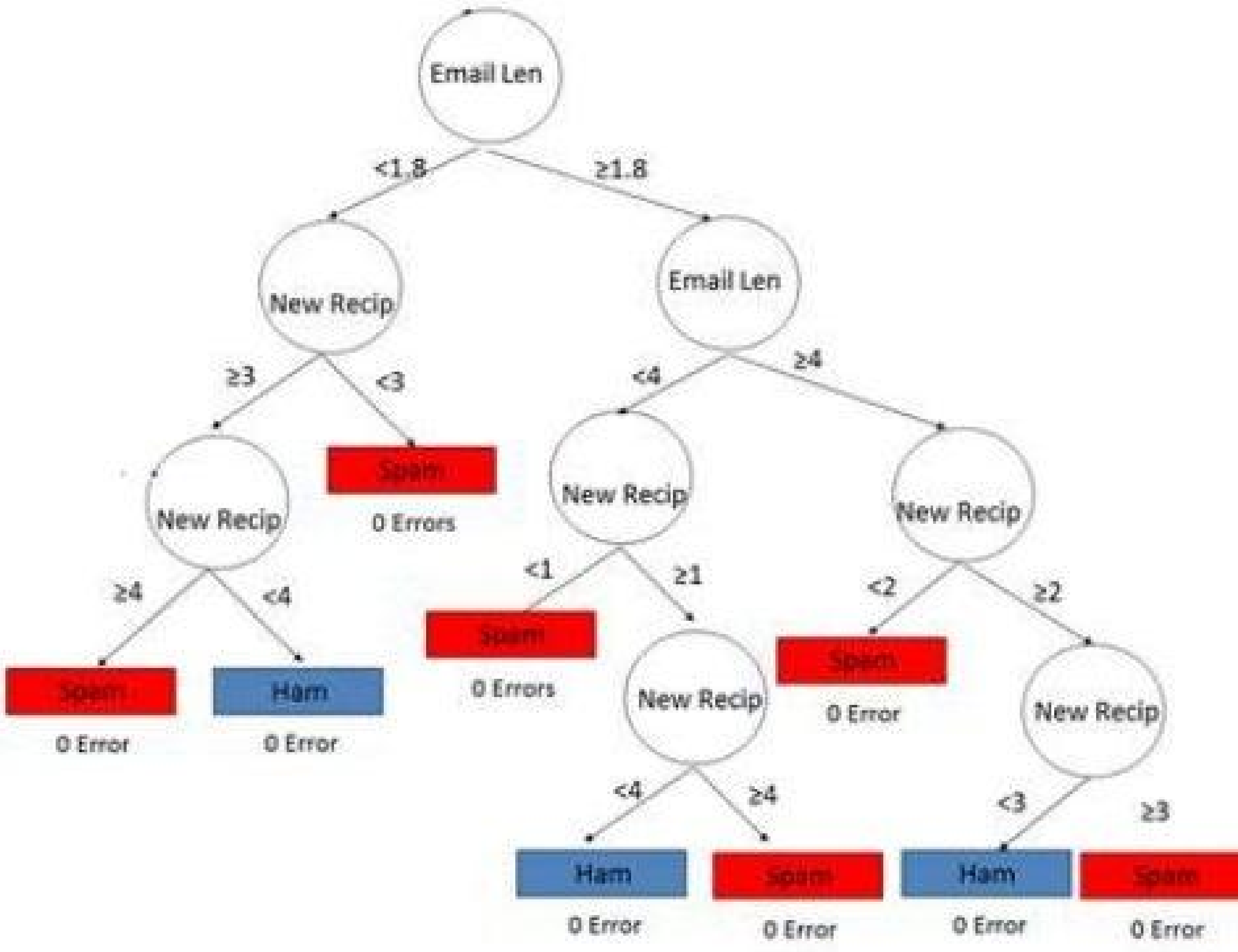
Ham

0 Errors

1 Error

Top Down Induction of Decision Trees





Why Does Decision Forest Work?

- Local minima
- Lack of sufficient data
- Limited Representation

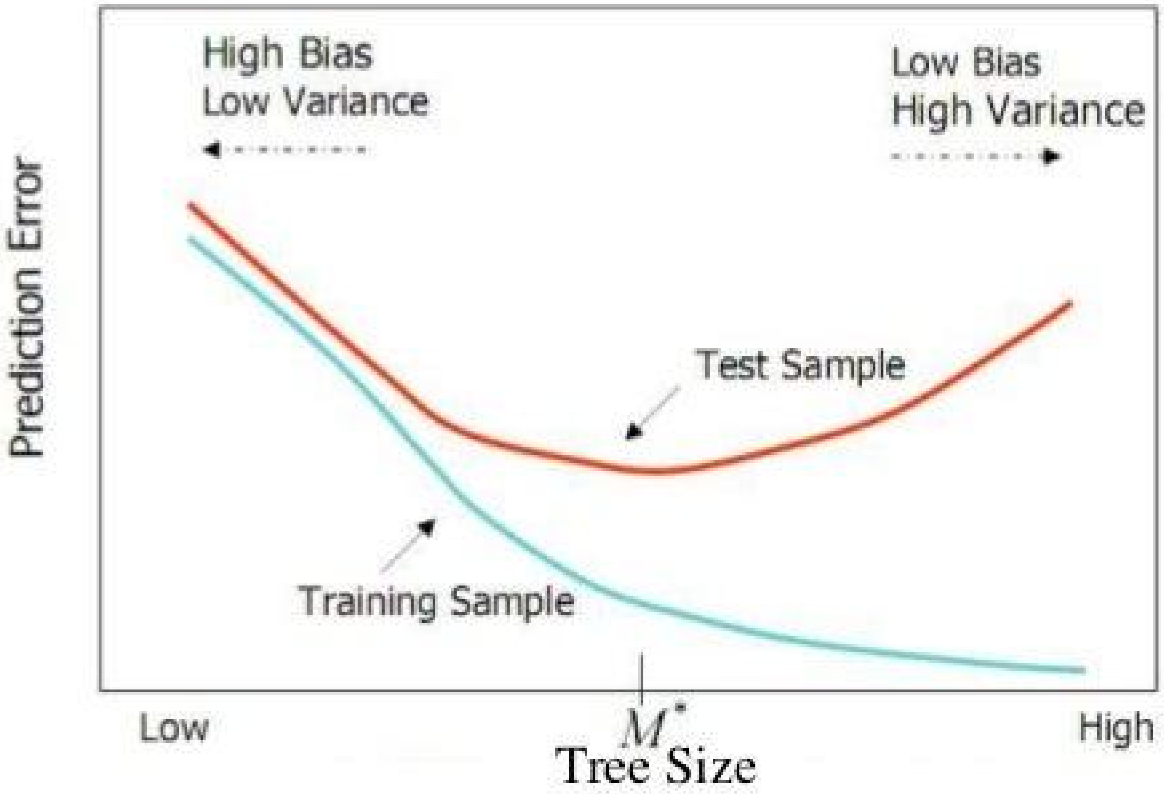
Bias and Variance Decomposition

Bias

- The tendency to consistently learn the same wrong thing because the hypothesis space considered by the learning algorithm does not include sufficient hypotheses

Variance

- The tendency to learn random things irrespective of the real signal due to the particular training set used



It all started about two years ago …

Iterative Methods

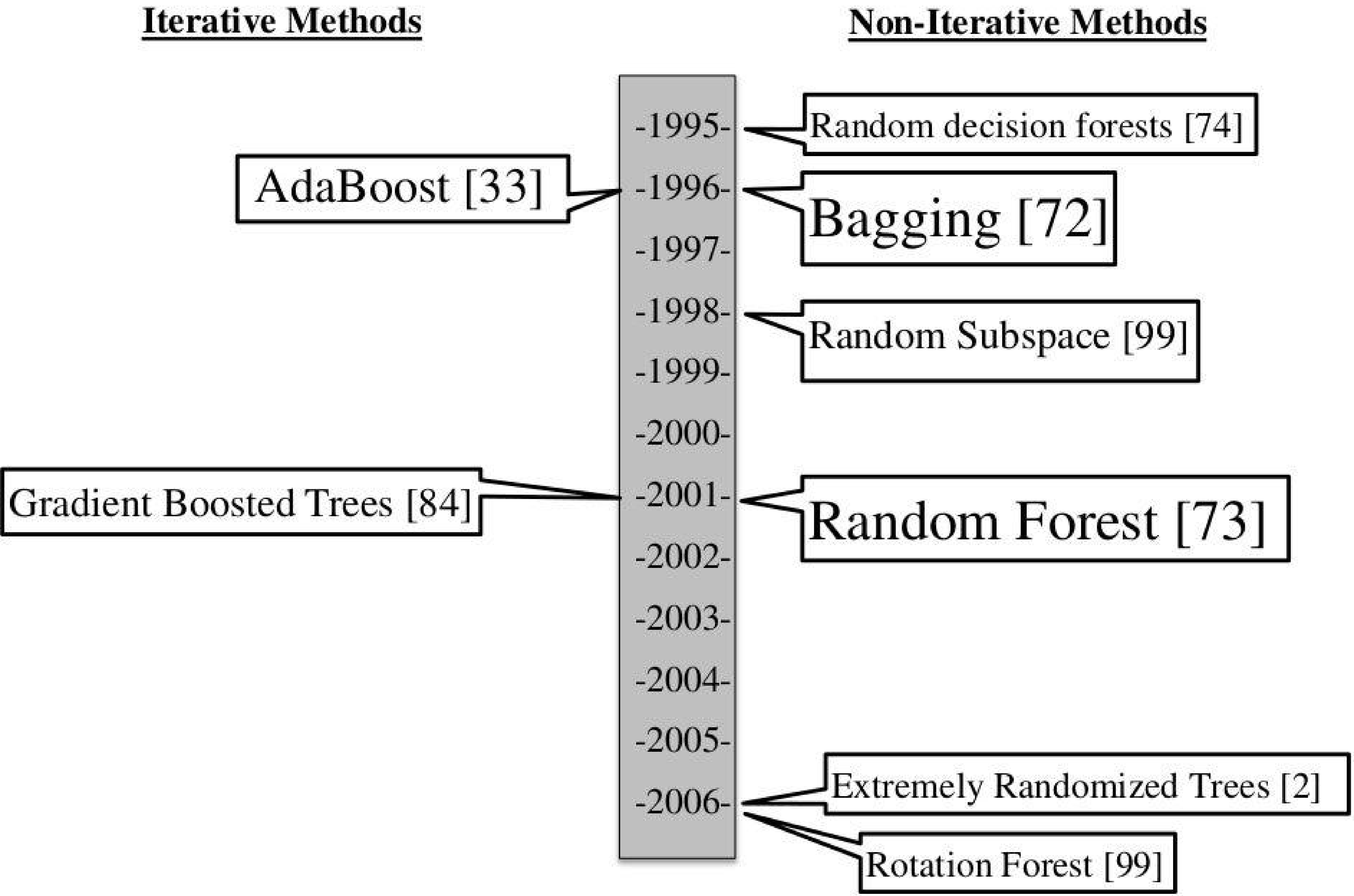
- Reduce both Bias and Variance errors
- Hard to parallelize

- AdaBoost (Freund & Schapire, 1996)
- Gradient Boosted Trees (Friedman, 1999)
- Feature-based Partitioned Trees (Rokach, 2008)
- Stochastic gradient boosted distributed decision trees (Ye et al., 2009)
- Parallel Boosted Regression Trees (Tyree et al., 2011)

Non-Iterative Methods

- Mainly reduce variance error
- Embarrassingly parallel

- Random decision forests (Ho, 1995)
- Bagging (Bootstrap aggregating) (Breiman, 1996)
- Random Subspace Decision Forest (Ho, 1998)
- Randomized Tree (Dietterich, 2000)
- Random Forest (Breiman, 2001)
- Switching Classes (Martínez-Muñoz and Suárez, 2005)
- Rotation Forest (Rodríguez et al., 2006)
- Extremely Randomized Trees (Geurts et al., 2006)
- Randomly Projected Trees (Schclar and Rokach, 2009)



Iterative Methods

Non-Iterative Methods

-1995- Random decision forests [74]

-1996- AdaBoost [33] | Bagging [72]

-1997-

-1998- Random Subspace [99]

-1999-

-2000-

-2001- Gradient Boosted Trees [84] | Random Forest [73]

-2002-

-2003-

-2004-

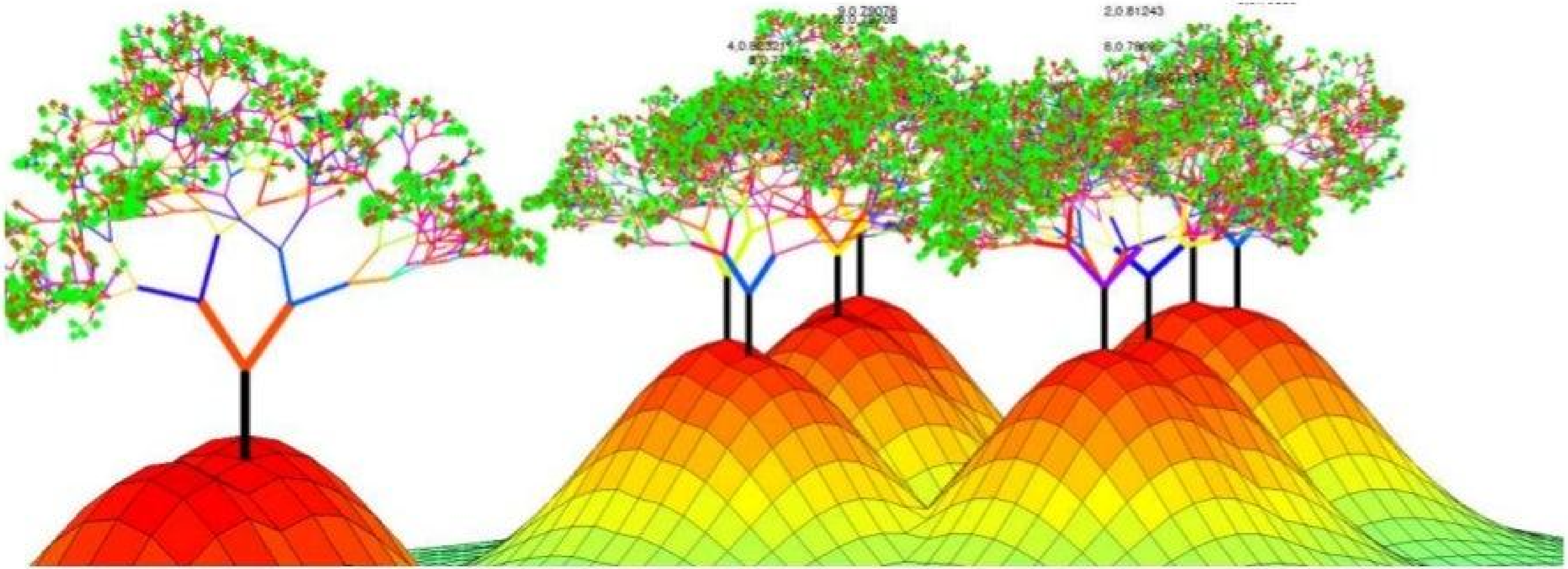
-2005-

-2006- Extremely Randomized Trees [2] | Rotation Forest [99]

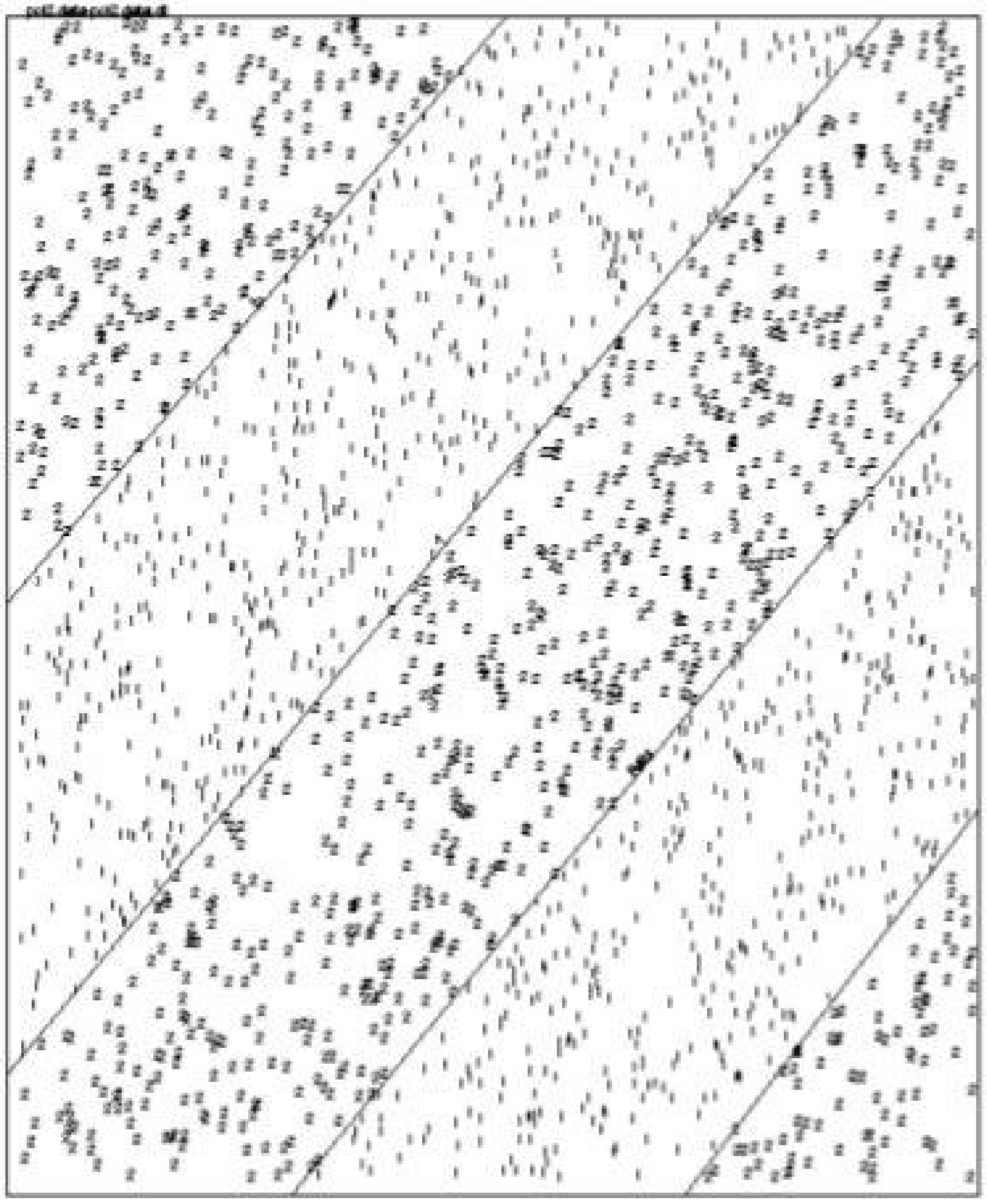
Random Forests

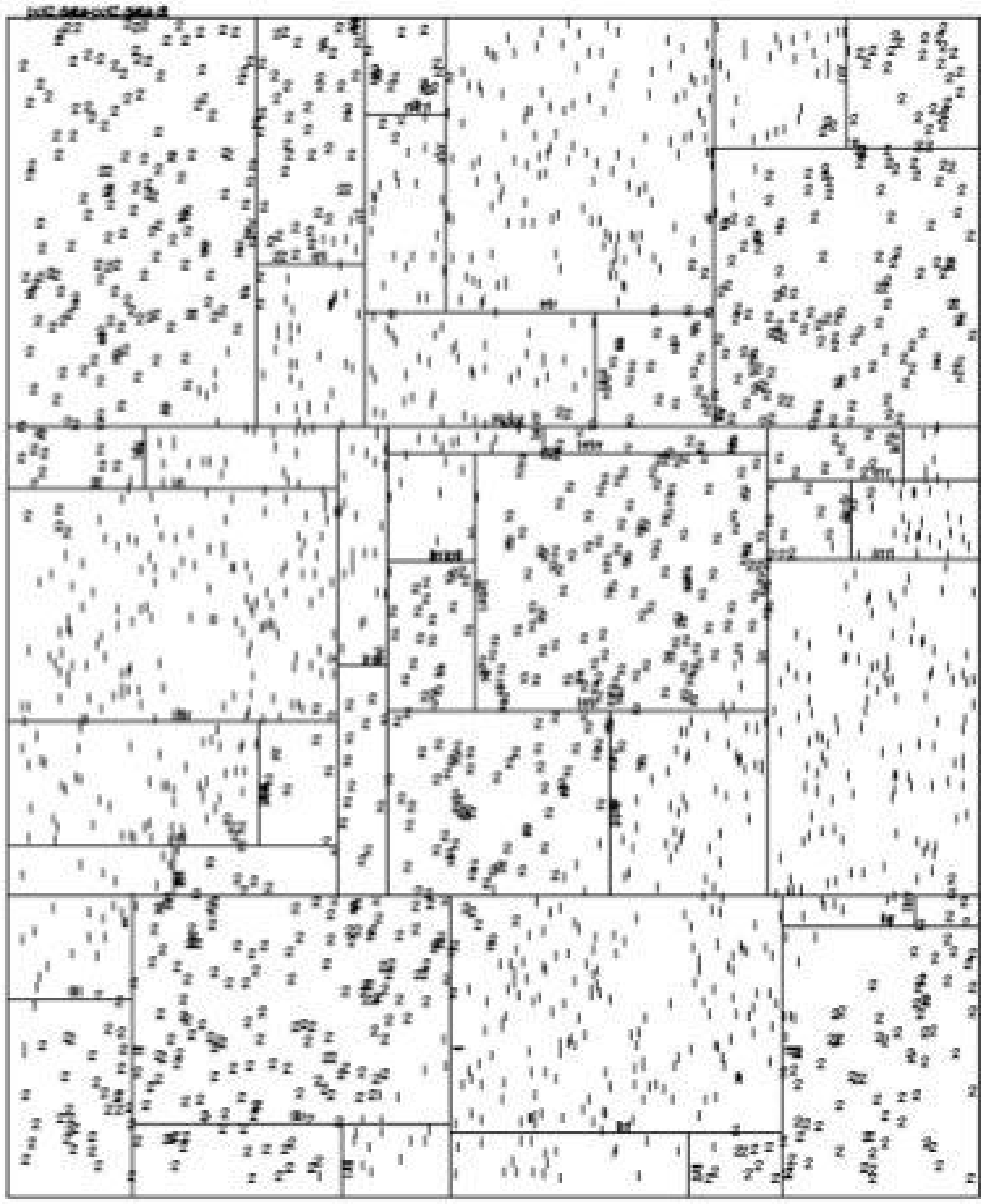
(Breiman, 2001)

1. A bootstrap ***random*** sample of size *n* sampled from training set ***with replacement***
2. Evaluate a node split on a ***random*** subset of variables
3. No pruning.



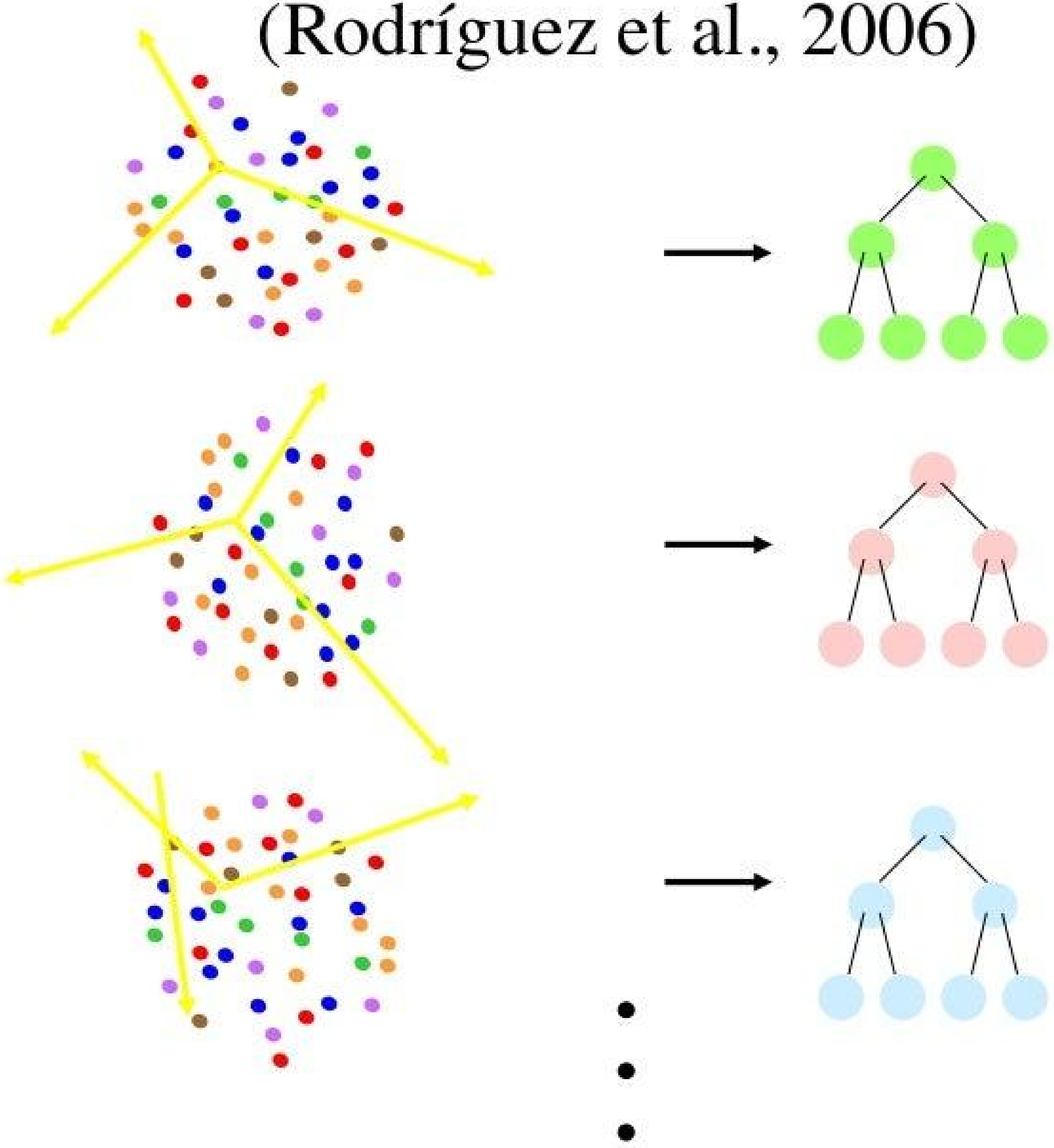
Limited Representation





Rotation Forest

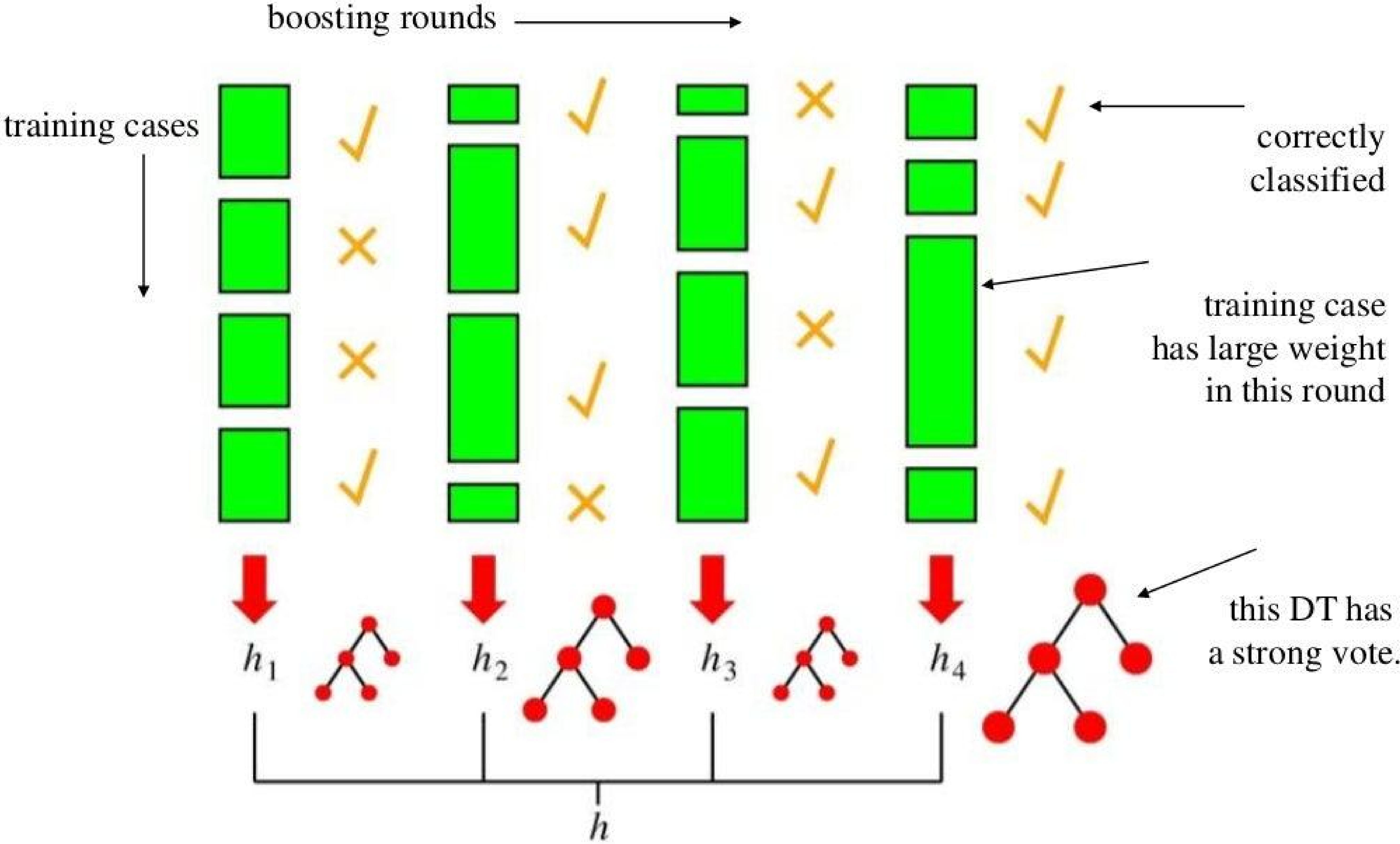
(Rodríguez et al., 2006)



AdaBoost

(Freund & Schapire, 1996)

"Best off-the-shelf classifier in the world" – Breiman (1996)


boosting rounds
training cases
correctly classified
training case has large weight in this round
this DT has a strong vote.
h_1
h_2
h_3
h_4
h