Carnegie Mellon University
Heinz College

Unstructured Data Analysis

Lecture 11: Wrap-up predictive model evaluation, classical classifiers

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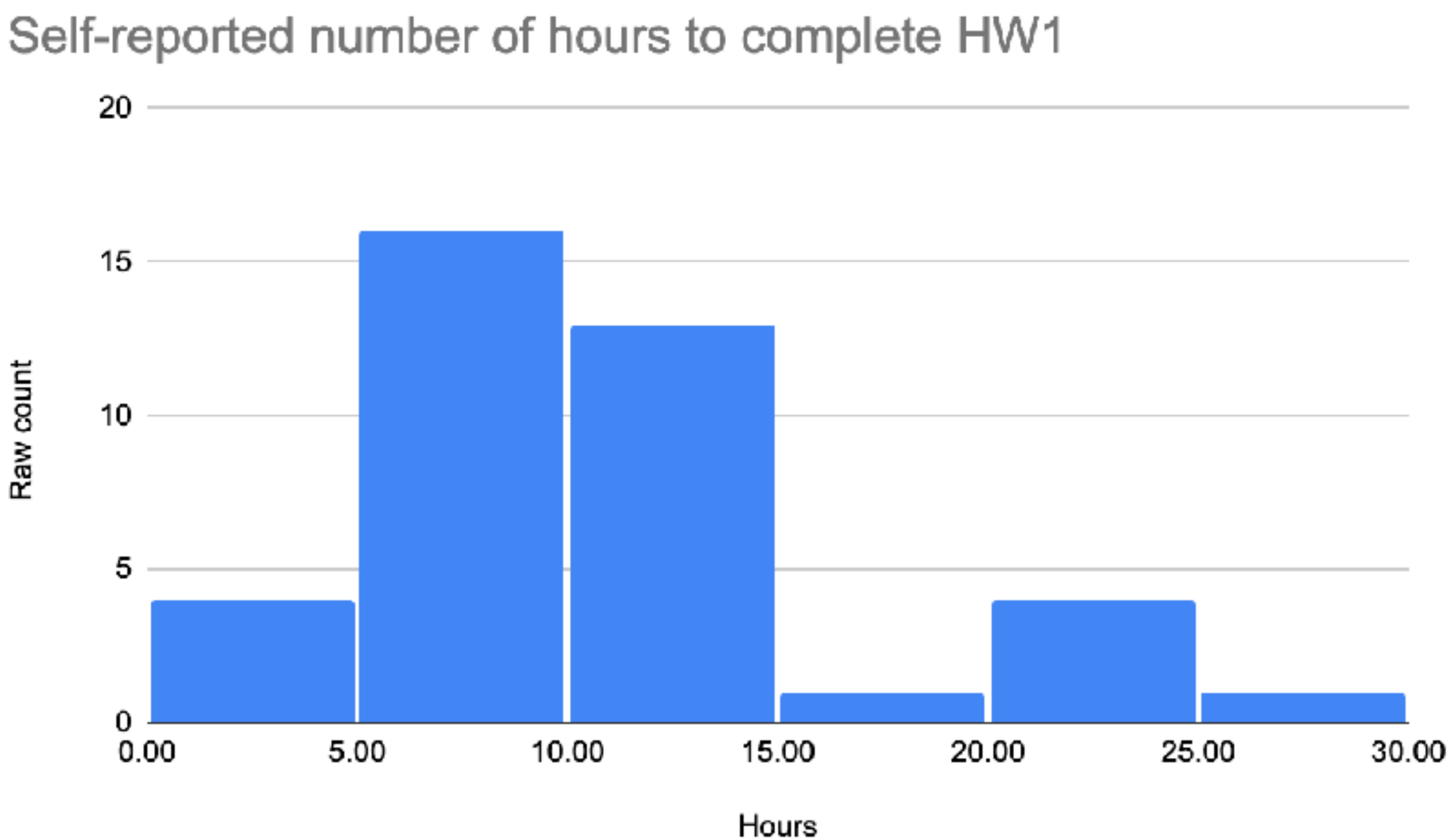
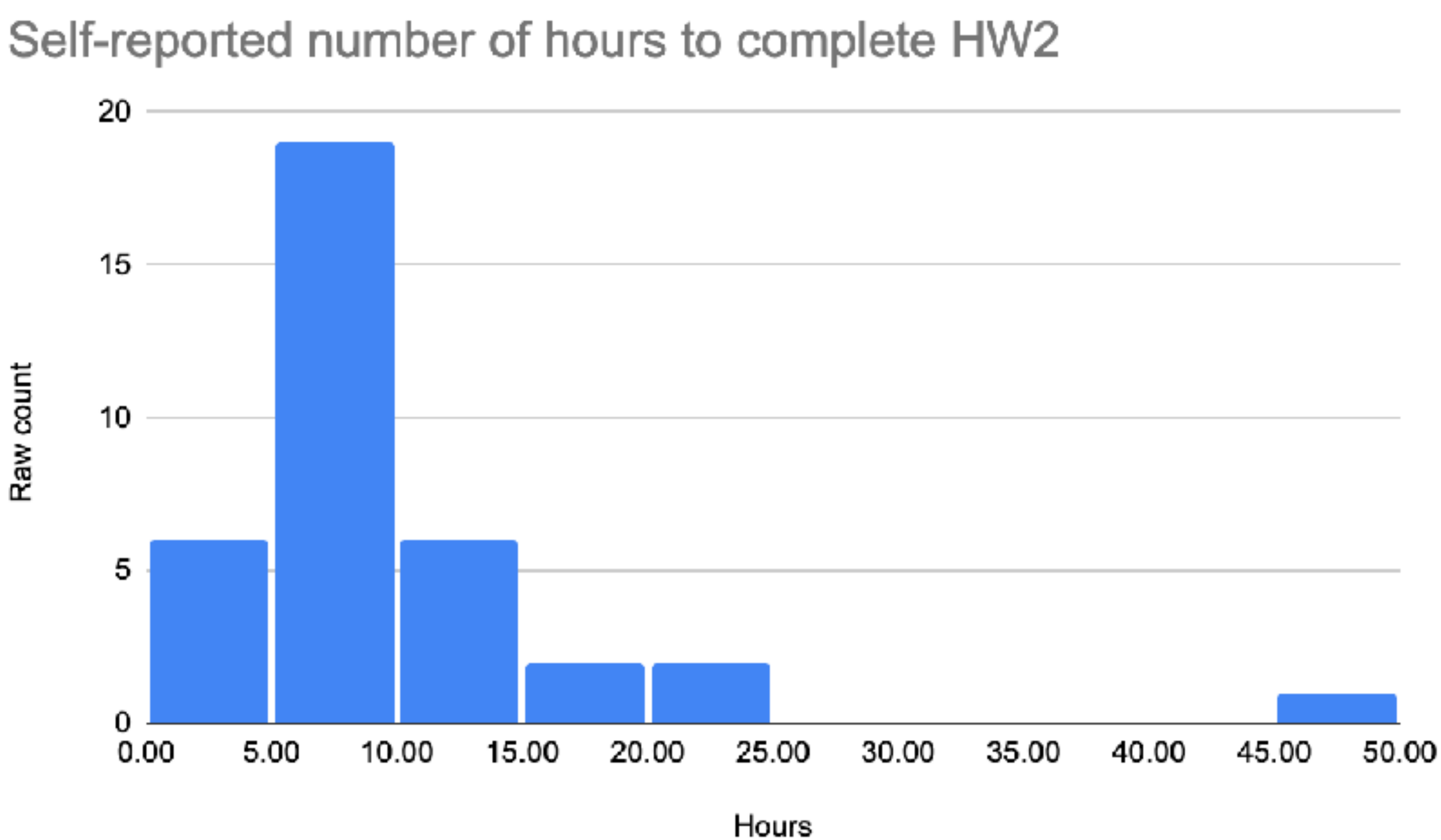
Belated Questionnaire Results

- Lots of comments regarding the coding aspect of the course
  - Some want more explanation of the code
  - Some want code in lecture to be much closer to what you're expected to write for code in HW
- Some comments on the course not being technical enough (e.g., not enough math, not enough details on models)
- Try using Kahoot (I've never heard of this before)

Questionnaire: HW1 time

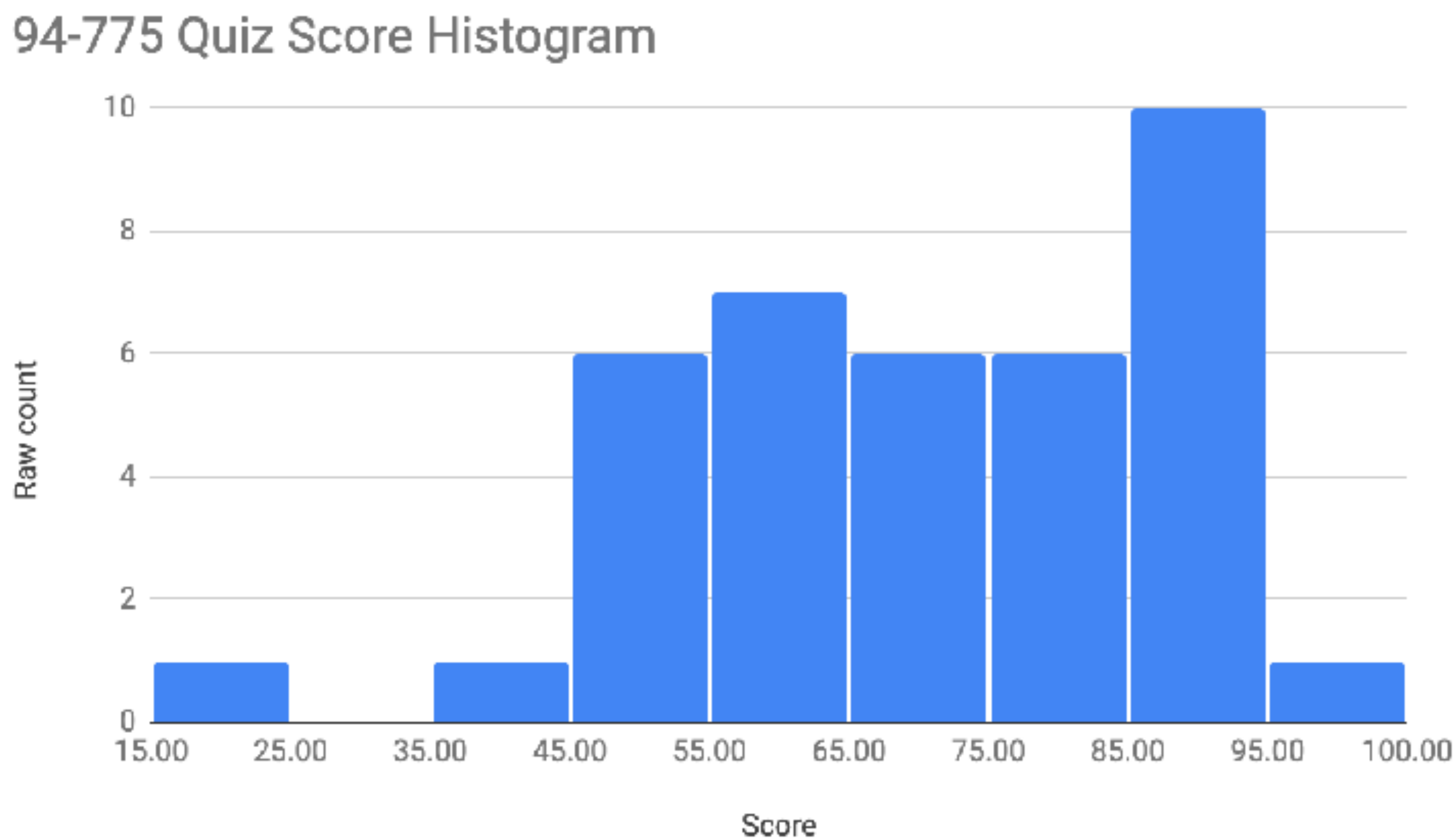


Questionnaire: HW2 time



HW3 is out! It’s short.

Quiz Results



Mean: 70.8, std dev: 18.5, median: 72
1 student did get a perfect score

Quiz Regrade

- First look over solutions very carefully
- If you think there is a genuine grading error, email me with:
  - An explanation of what was incorrectly graded
  - How many points are at stake
- We will regrade your exam and your score can go up, stay the same, or go down
- Due this Thursday 11:59pm Pittsburgh time

Other Announcements

- Projects: due next Friday (gasp)
  - This semester, because of the random CMU break days, the second half of my usual schedule got shifted…
  - We are *not* expecting as thorough/polished projects as in previous semesters, so don't panic if your analysis ends up looking a bit "preliminary"
- **Thursday lecture is remote**
- I will hold OH specifically for 94-775 students 3pm-4pm after class on Thursday (to discuss course performance/projects/HW3/etc) — use my usual OH Zoom link

Today

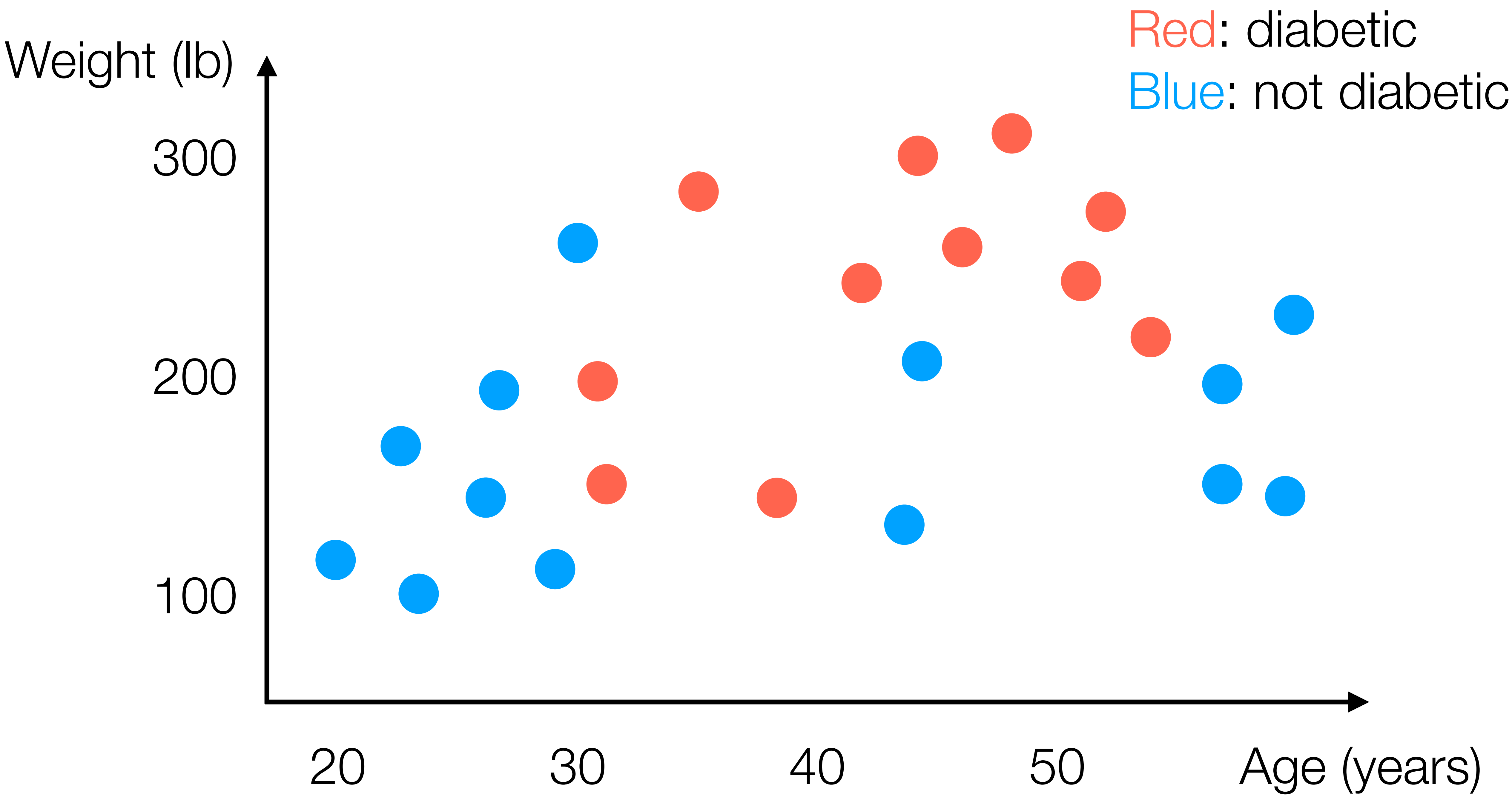
- Wrap-up coverage of how to evaluate whether a predictive model is good & classical classifiers
    - In many datasets (especially small, structured ones), neural nets & deep learning could work poorly… in such cases, often decision-tree-based methods can work well

      random forests, gradient boosting (e.g., XGBoost)

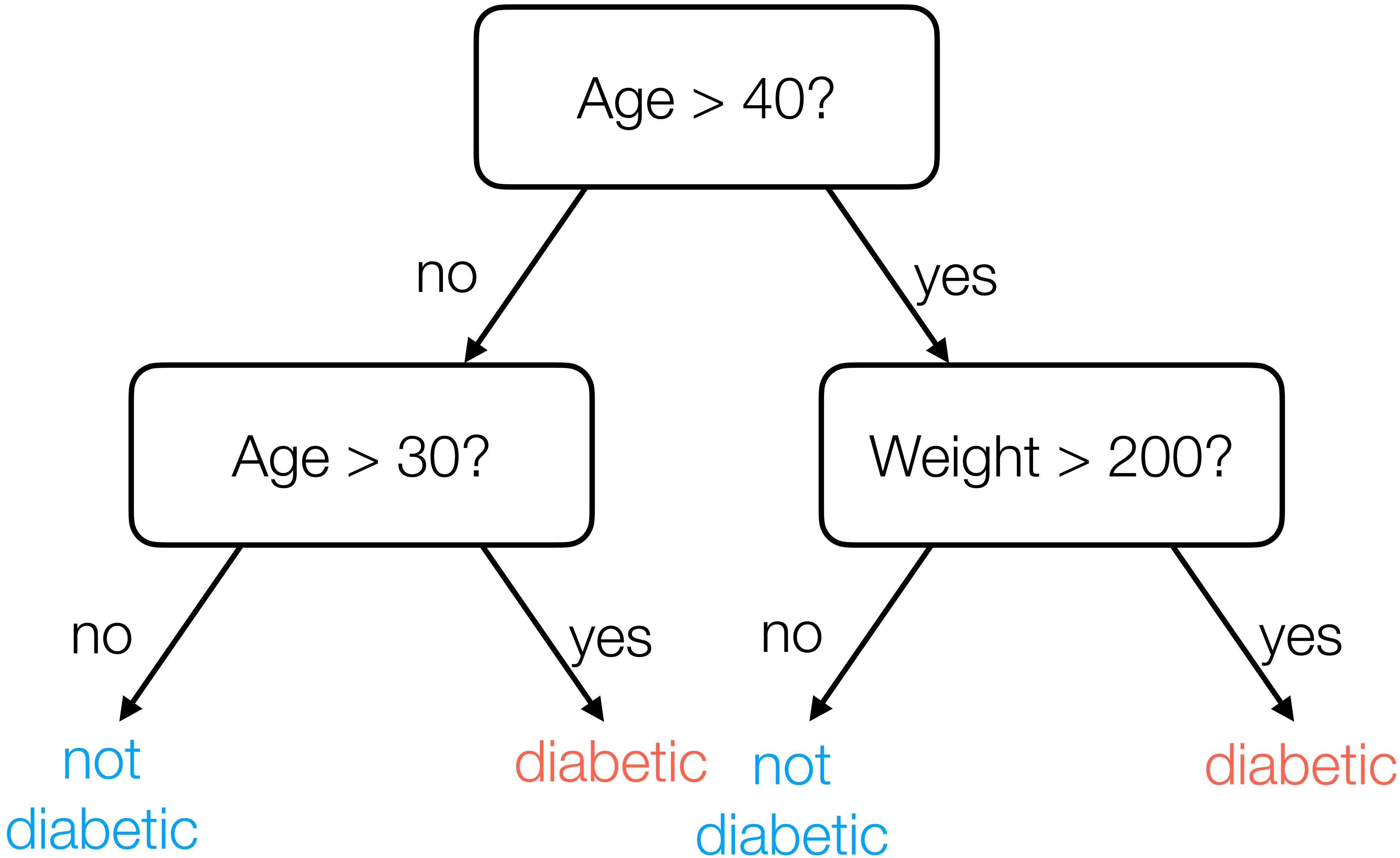
- Start coverage of neural nets & deep learning

Decision Trees & Forests

Example Made-Up Data



Example Decision Tree

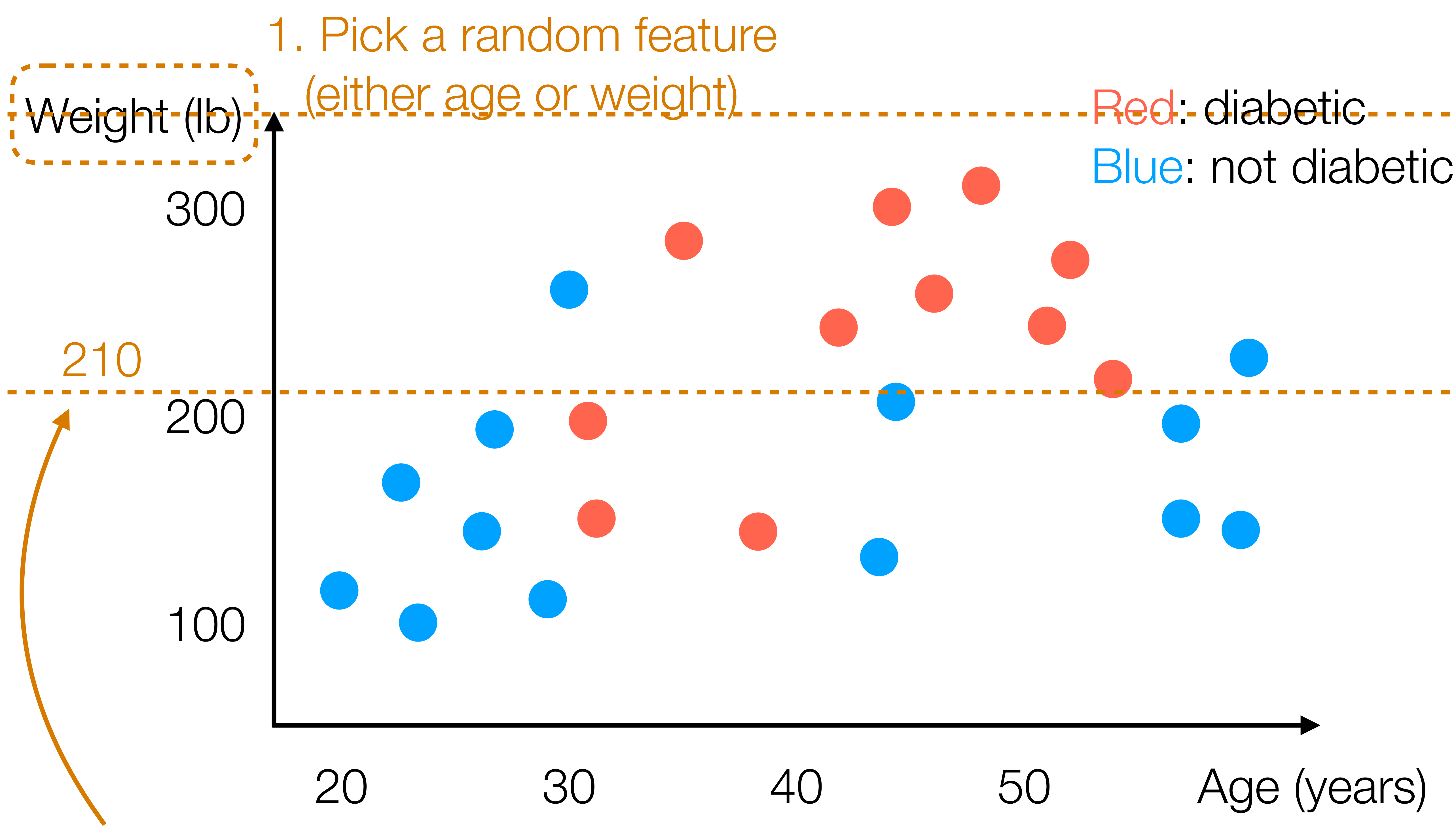


Learning a Decision Tree

- Many ways: general approach actually looks a lot like divisive clustering *but accounts for label information*

- I'll show one way (that nobody actually uses in practice) but it's easy to explain

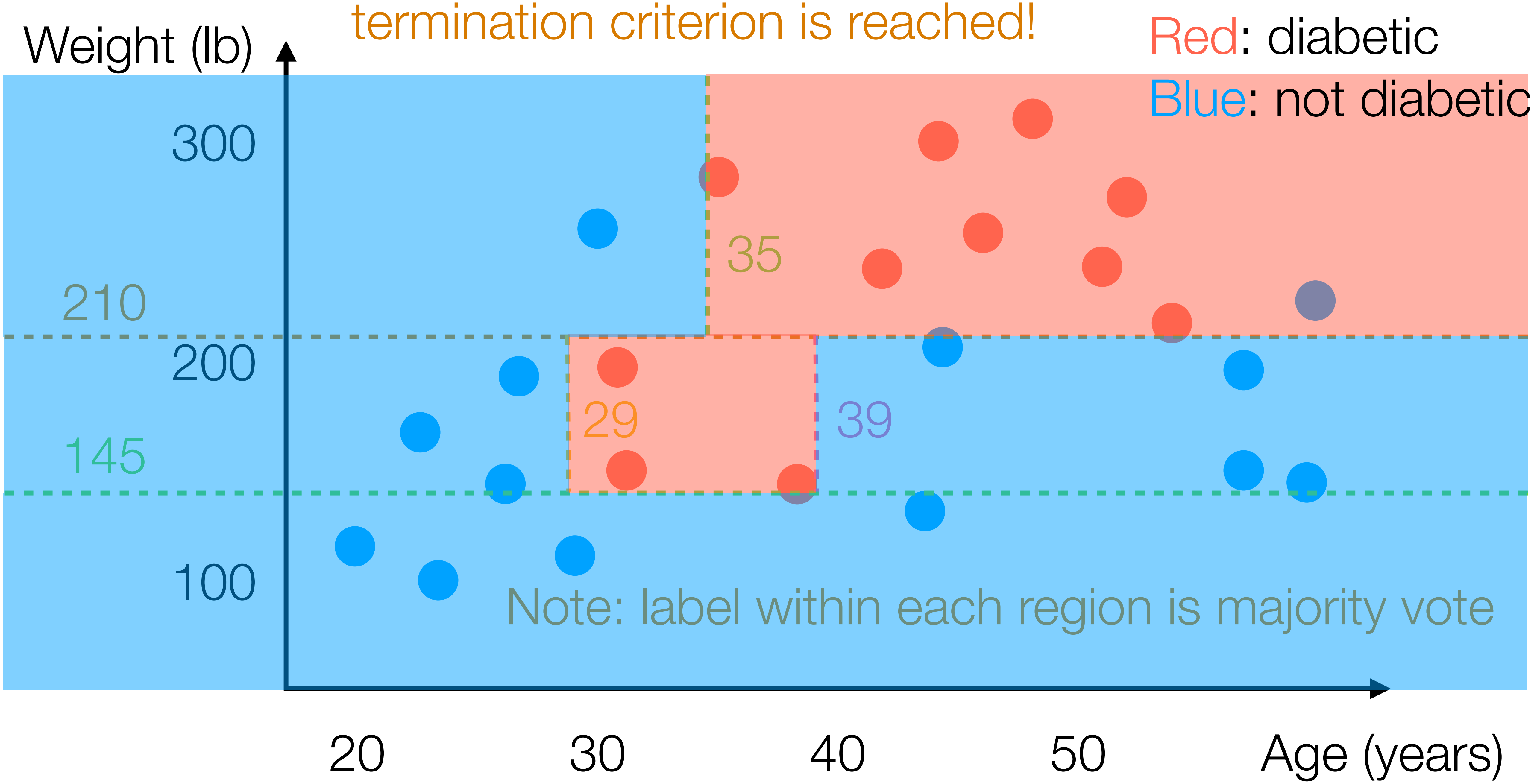
Learning a Decision Tree



2. Find threshold for which red and blue are as "separate as possible" (on one side, mostly red; on other side, mostly blue)

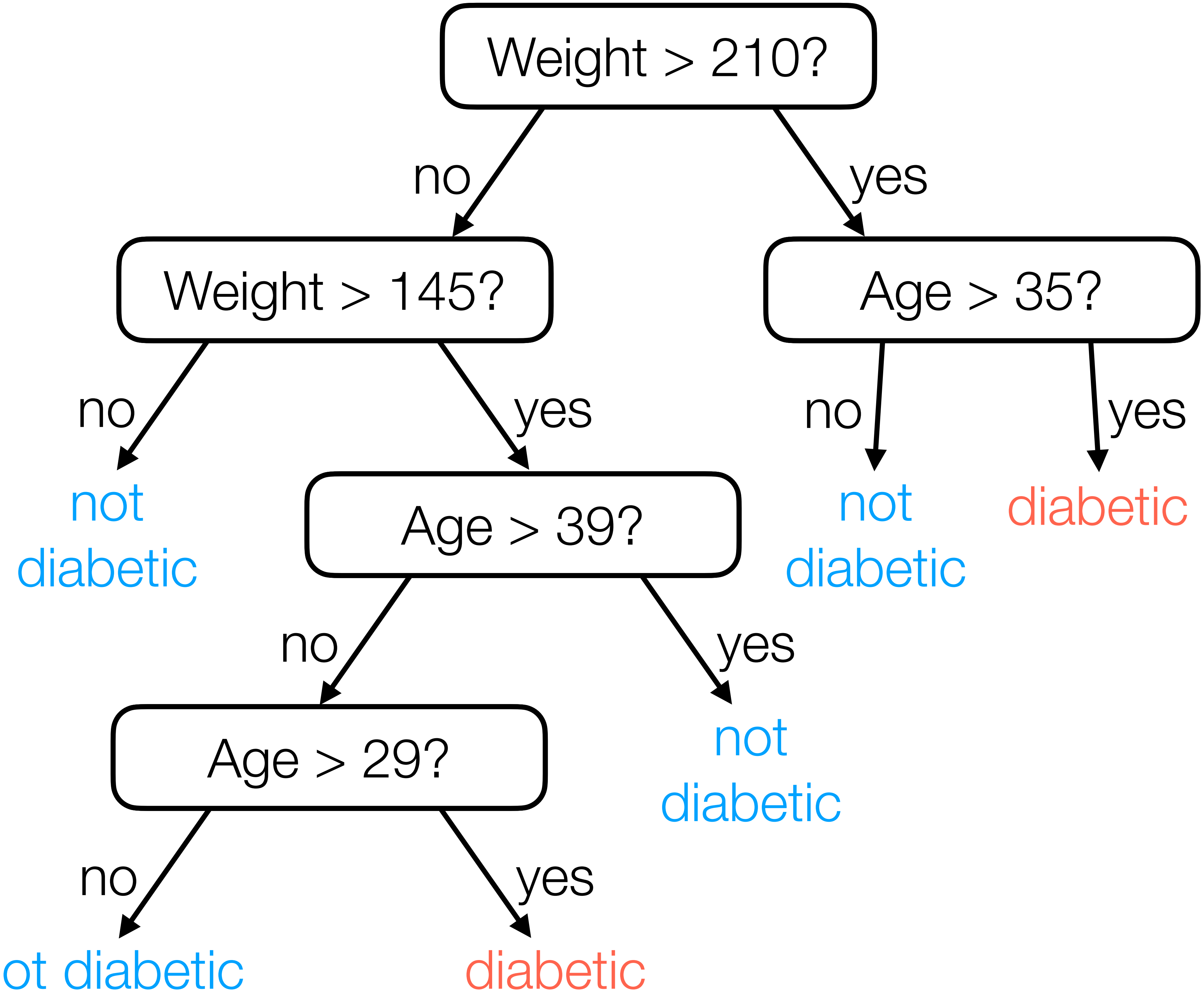
Learning a Decision Tree

Within each side, recurse until a termination criterion is reached!



Example termination criteria: ≥90% points within region has same label, number of points within region is <5

Decision Tree Learned



For a new person with feature vector (age, weight), easy to predict!

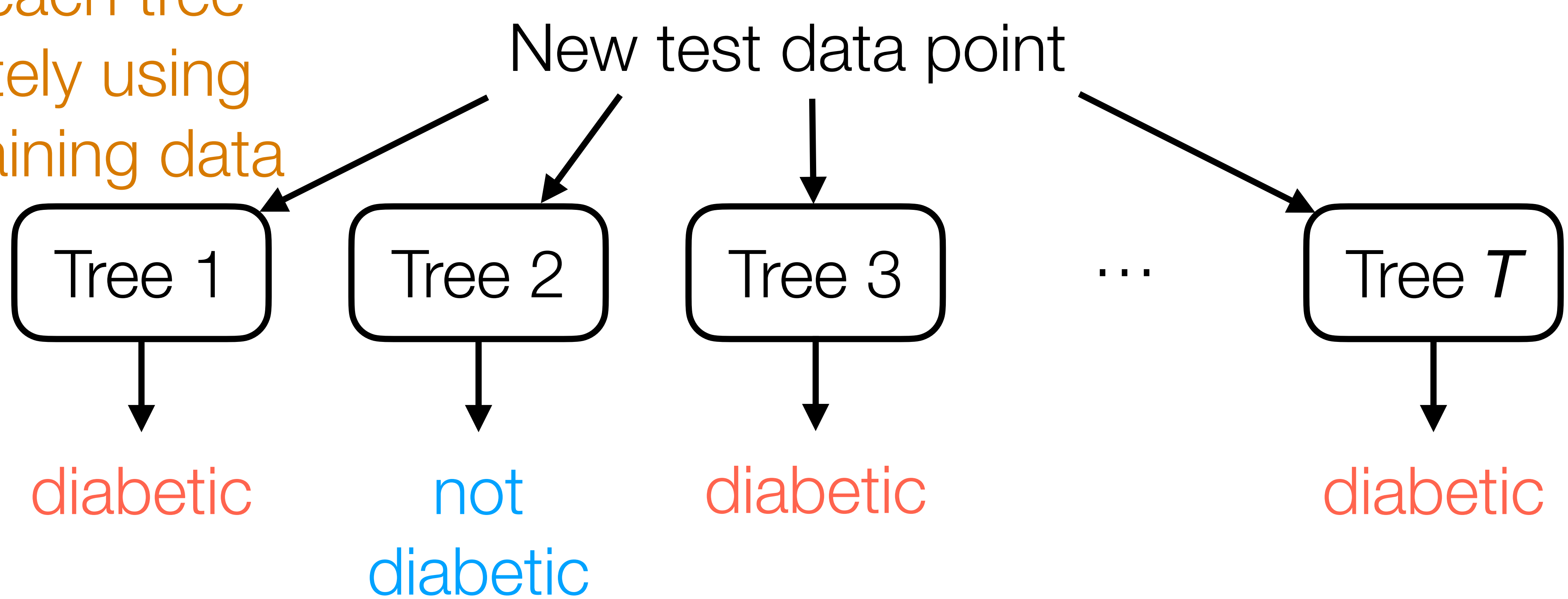
Decision Forest for Classification

- Typically, a decision tree is learned with randomness (e.g., we randomly chose which feature to threshold)

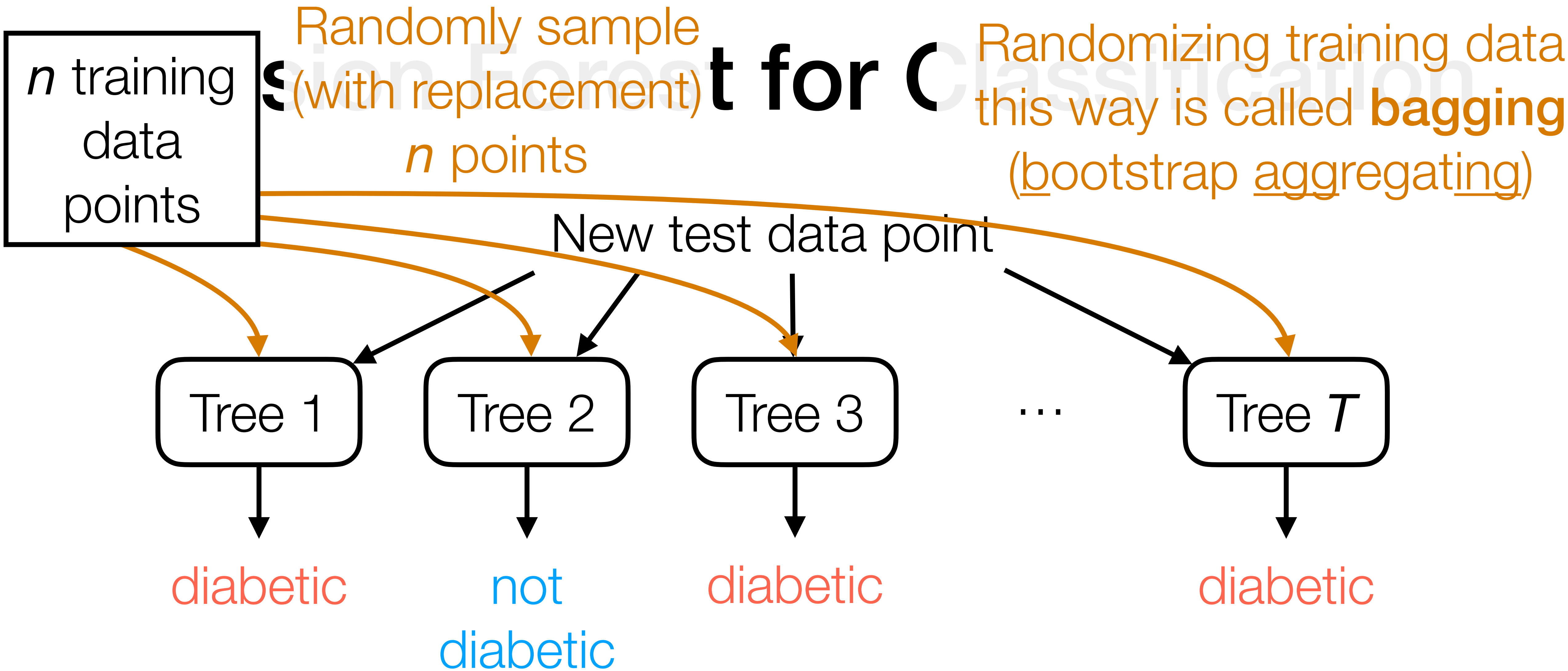
  ➔ by re-running the same learning procedure, we can get different decision trees that make different predictions!

- For a more stable prediction, use many decision trees

Learn each tree separately using same training data



Final prediction: majority vote of the different trees' predictions



Question: What happens if all the trees are the same?

Adding randomness can make trees more different!

- **Random Forest:** randomize training data used for each tree, randomly choose a few features to try to split on (and among these features, choose the best one to split on)

Back to the demo

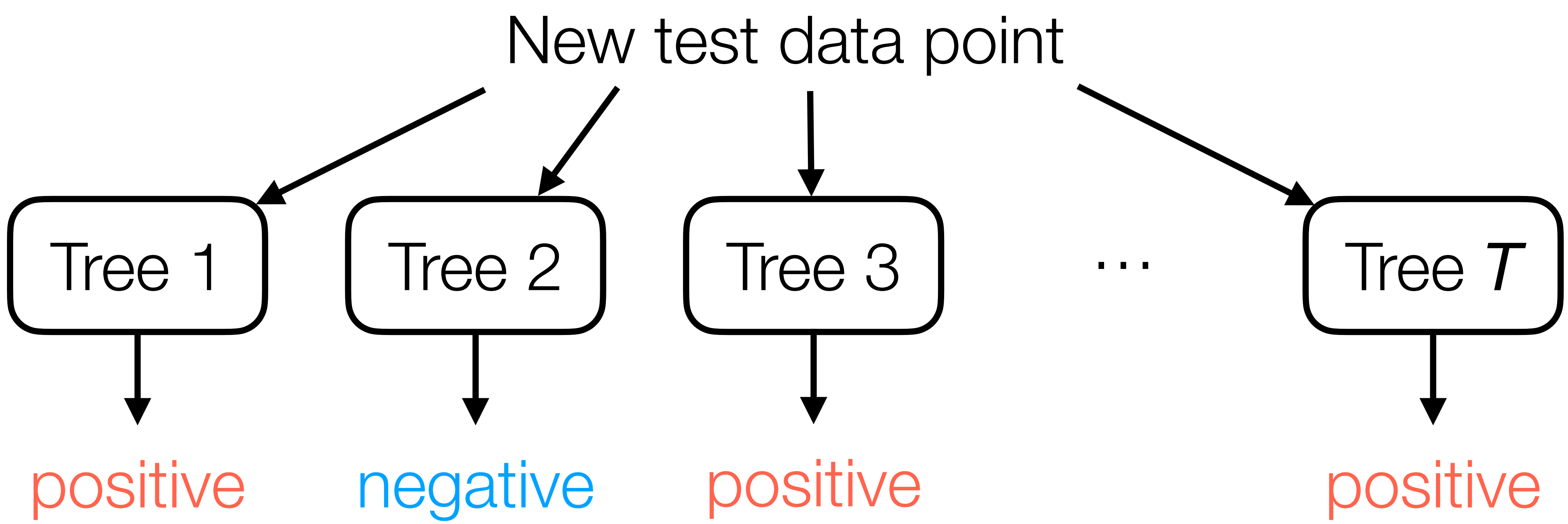
Another Way to Benchmark

- In the demo: we just saw that we can compare test set prediction accuracy across different algorithms and also look at confusion matrices

- For <u>binary</u> classification, we can do a more detailed analysis

Binary Classification: ROC Curves

For simplicity, think of the random forest for now

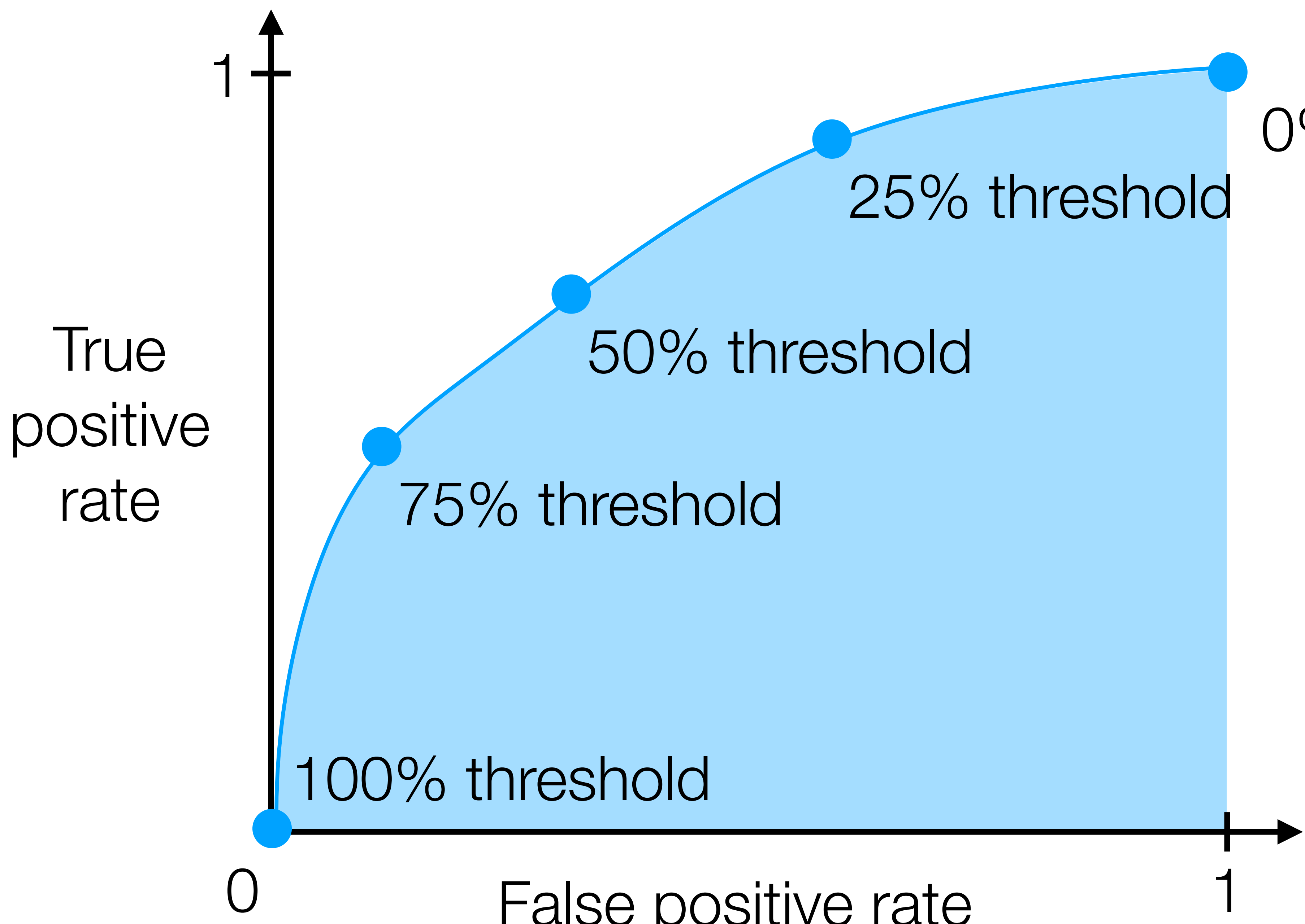


Final prediction: majority vote of the different trees' predictions

≥ 50% of trees need to say **positive** for final prediction to be **positive**

We can vary this 50% threshold!

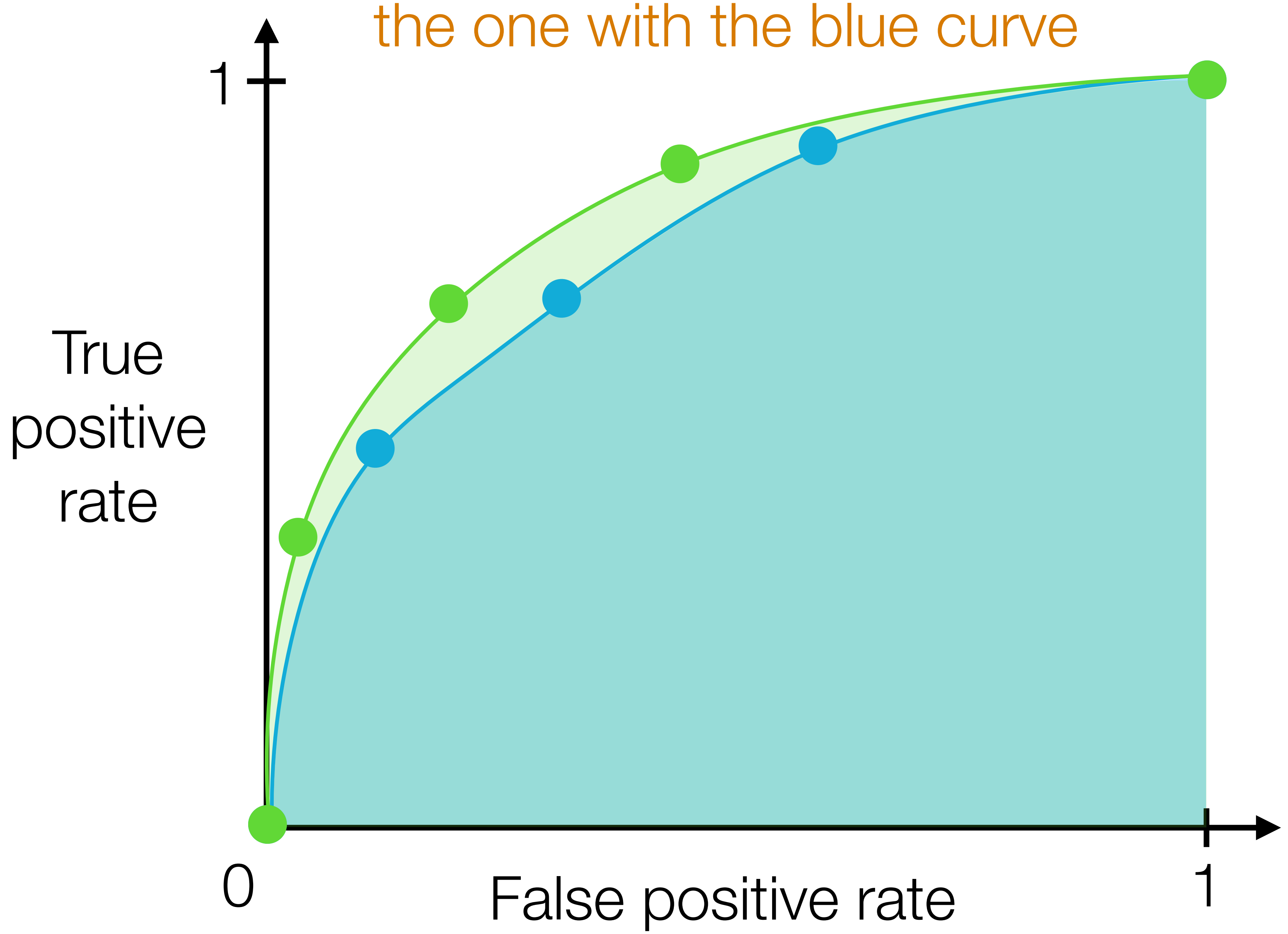
Binary Classification: ROC Curves



Error rates are computed on test data

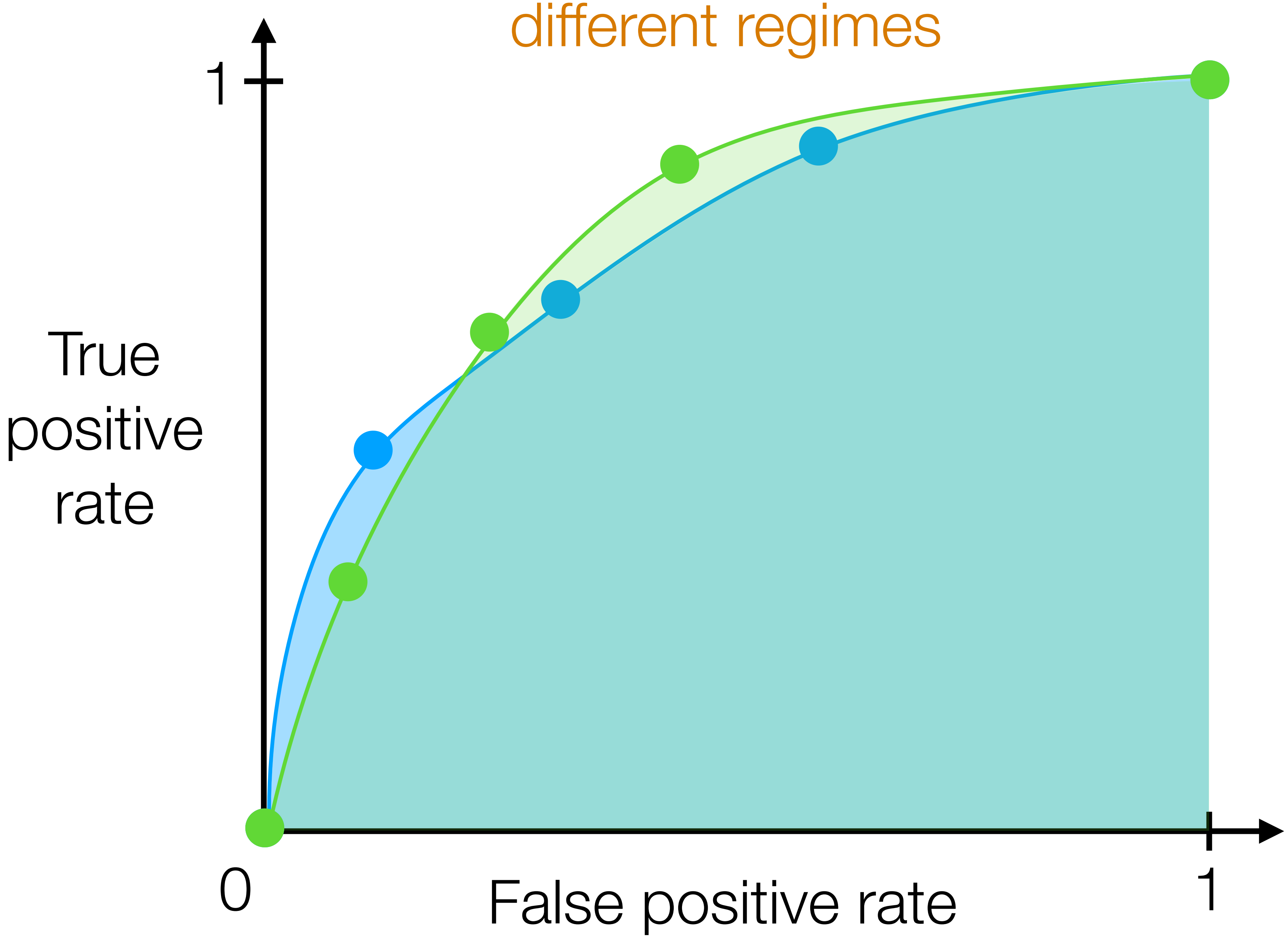
Binary Classification: ROC Curves

A classifier with the green curve is better than the one with the blue curve

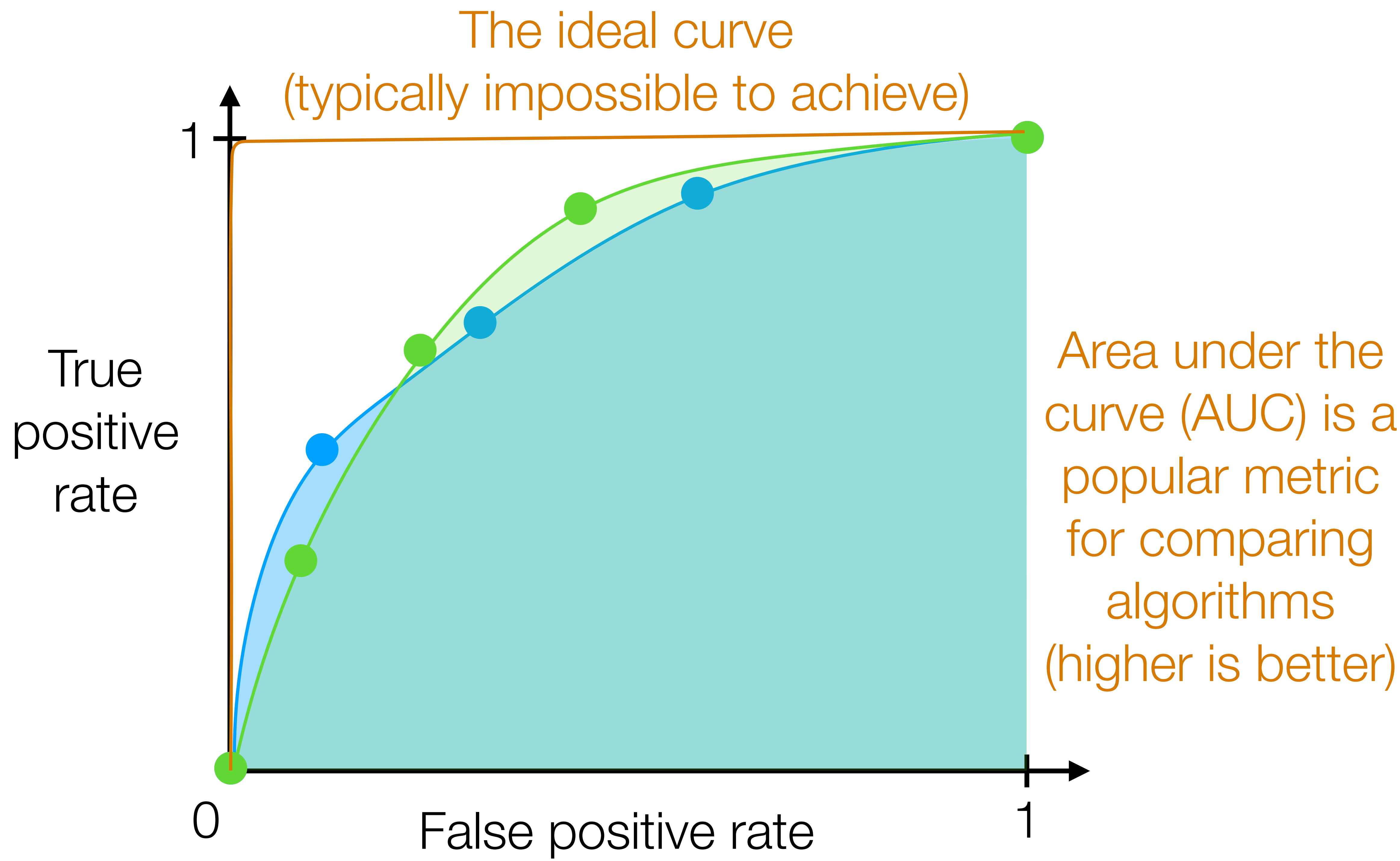


Binary Classification: ROC Curves

It's possible that algorithms are better in different regimes



Binary Classification: ROC Curves



Binary Classification: ROC Curves

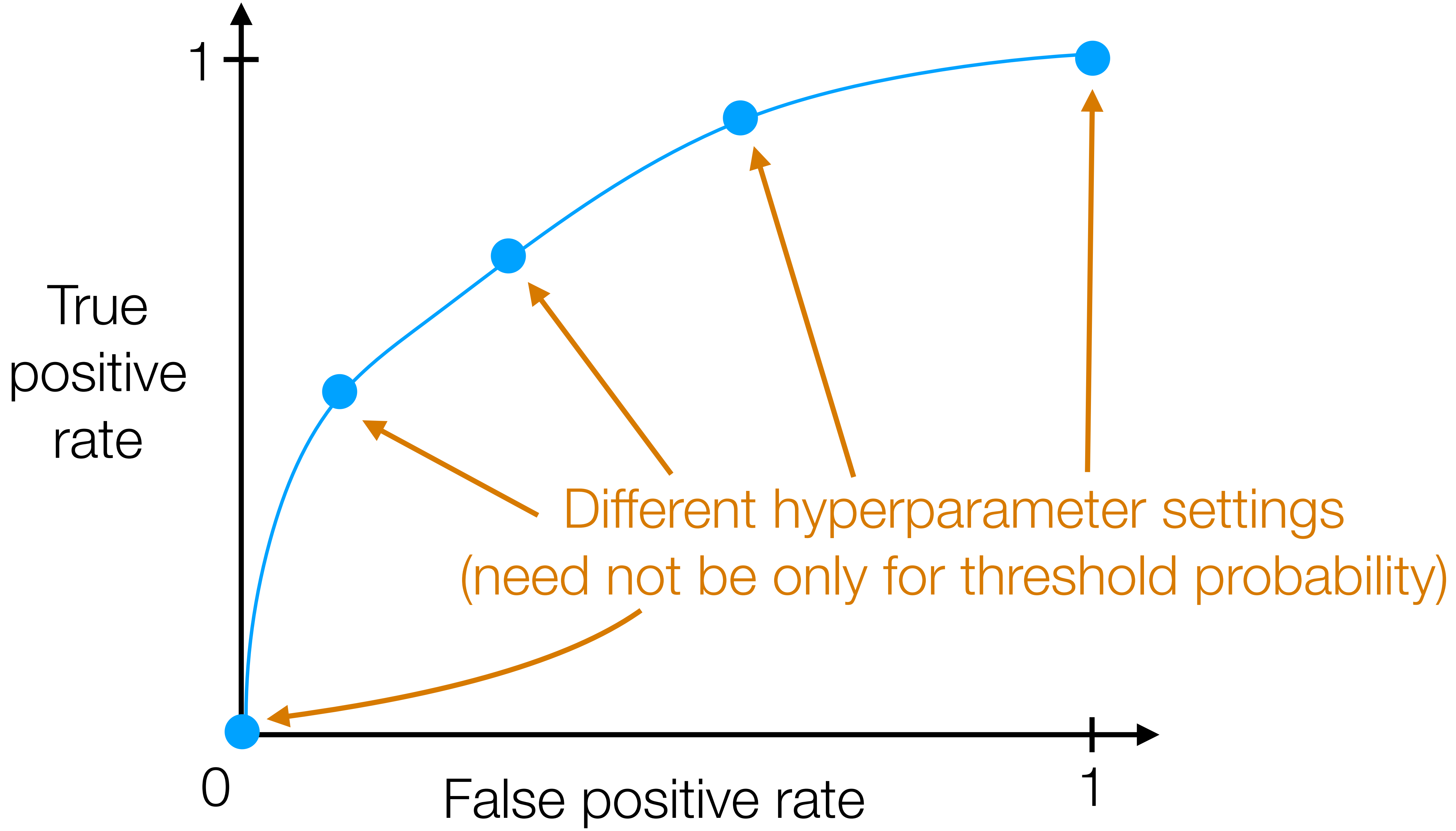
What we just saw:

- For a classifier that we can set the threshold probability to different values, we can plot an ROC curve
- True positive rate (TPR) and false positive rate (FPR) are evaluated on test data

Other variants are possible:

- Plot precision vs recall instead of TPR vs FPR
- Can actually plot ROC/precision-recall curves sweeping over hyperparameters aside from threshold probability!
- For ROC/precision-recall, rather than evaluating on test data, can evaluate on validation data during training *to help choose hyperparameters*

Binary Classification: ROC Curves



Can also be computed on validation data instead of test data!