Class core values

1. Be **respect**ful to yourself and others
2. Be **confident** and believe in yourself
3. Always do your **best**
4. Be **cooperative**
5. Be **creative**
6. Have **fun**
7. Be **patient** with yourself while you learn
8. Don’t be shy to **ask “stupid” questions**
9. Be **inclusive** and **accepting**

Week 2, Lecture 1

Trees, forests, and classification problems

Learning Objectives

1. Describe the basic concept of a decision tree
2. Apply computational coding to write a simple decision tree
3. Describe the basic concept behind a random forest
4. Apply knowledge of depth and number of trees to tune a random forest
5. Apply computational tools to write and employ random forests to a real dataset
6. Practice knowledge of data preparation and performance measurement

Decision trees are one of the simplest methods for binary classification

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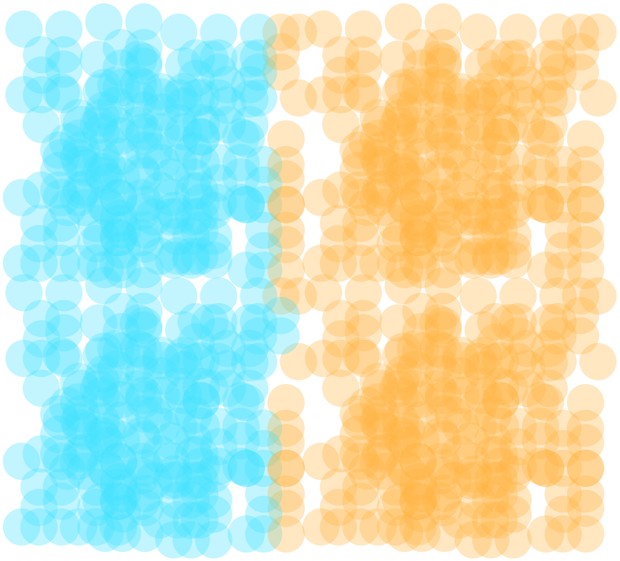

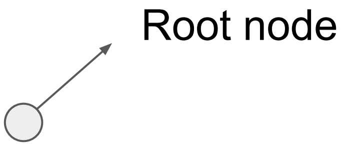

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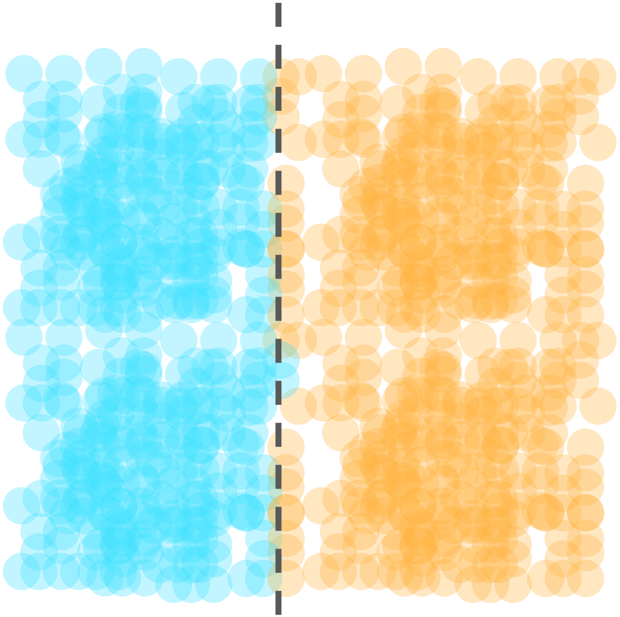
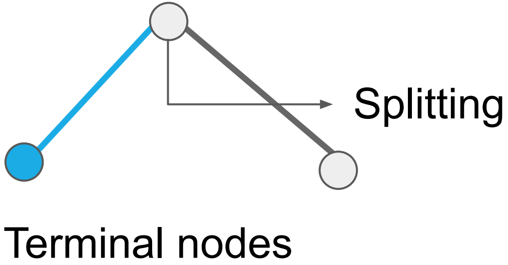
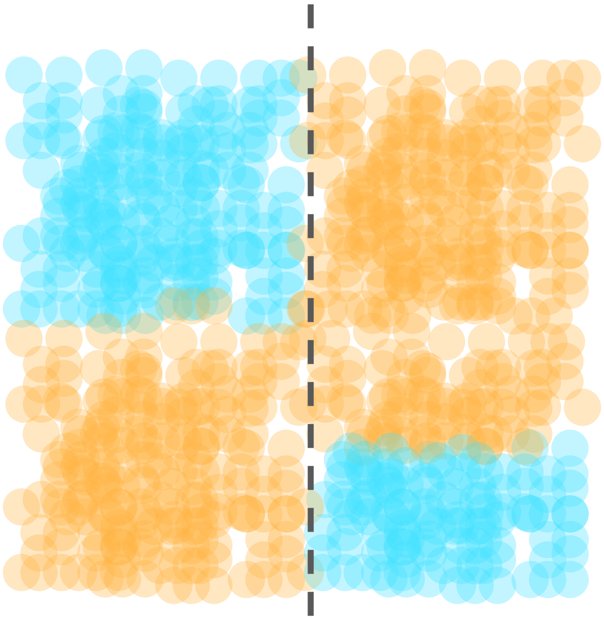
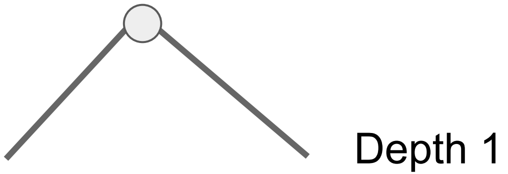




The depth of the decision tree can influence its performance





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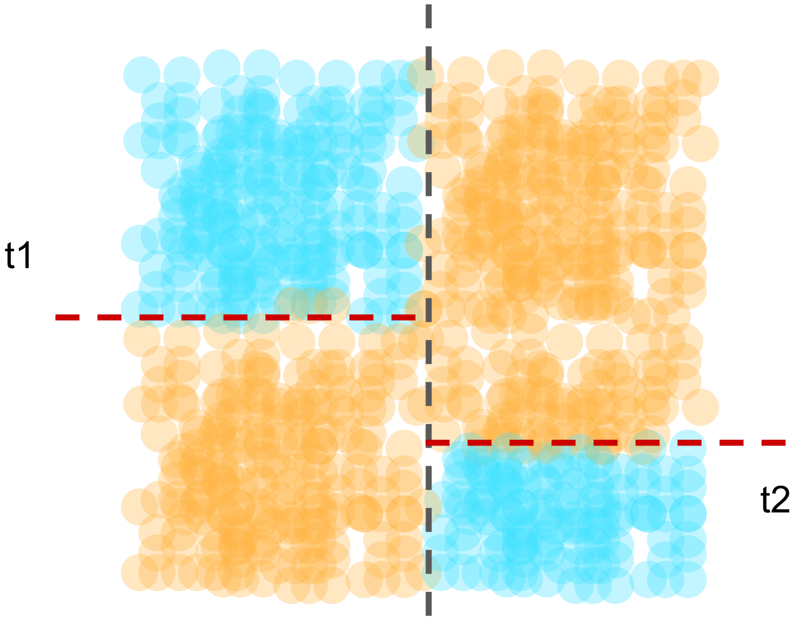

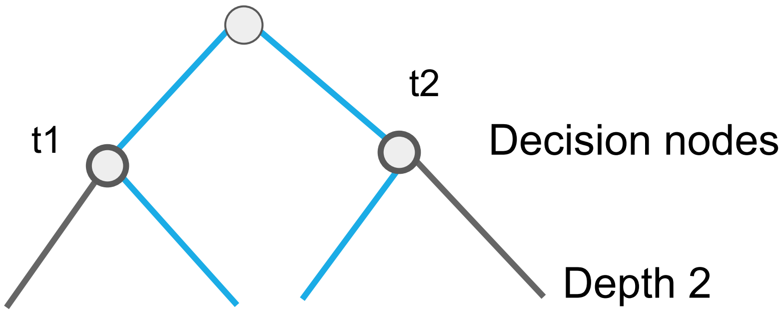

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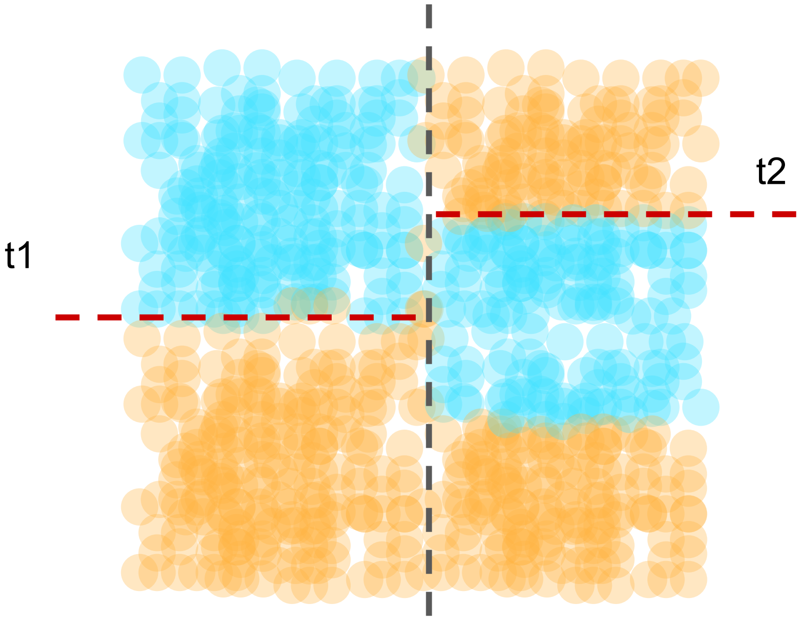

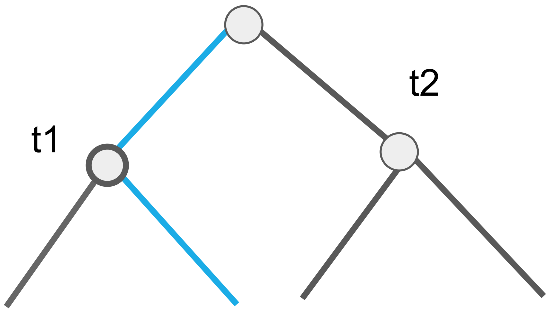

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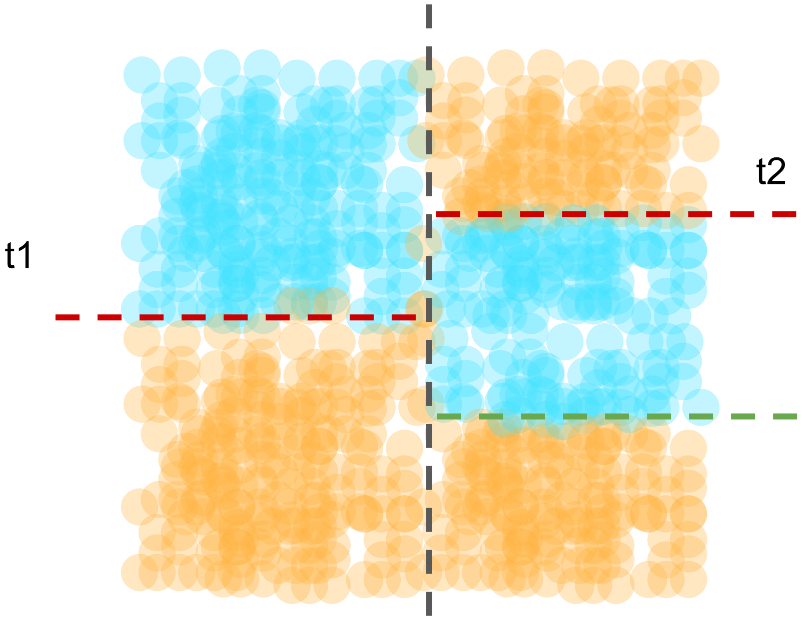
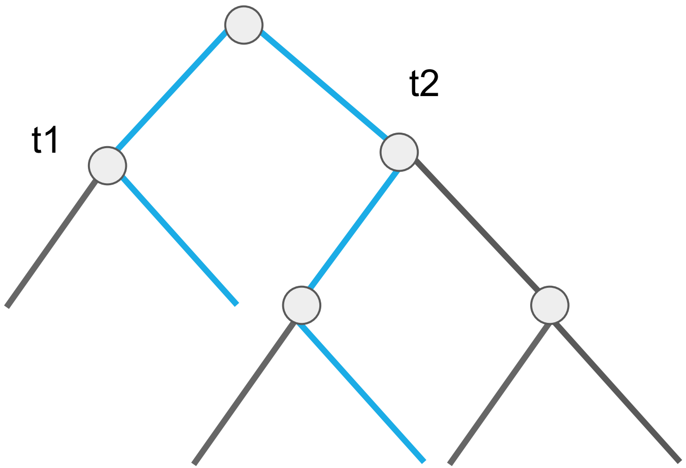
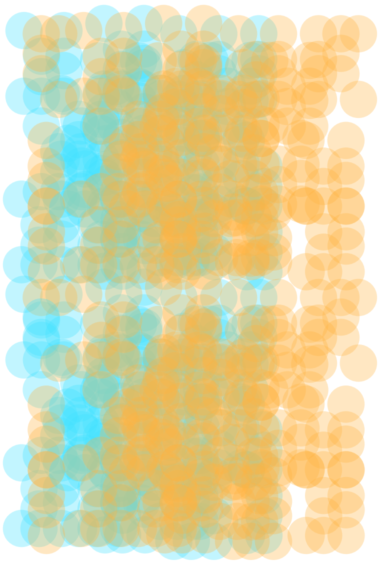
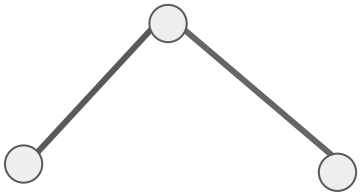


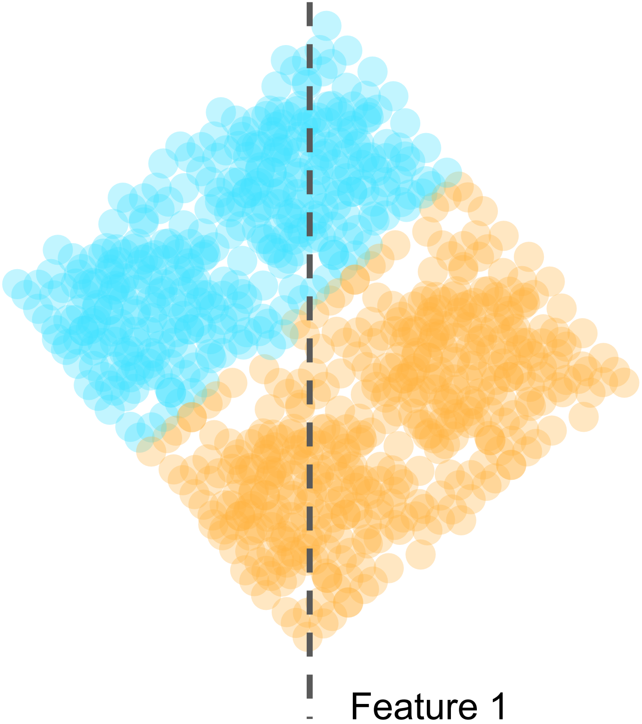


For decision trees to work, there needs to be an actual signal in the data





Feature engineering can help to find the best split



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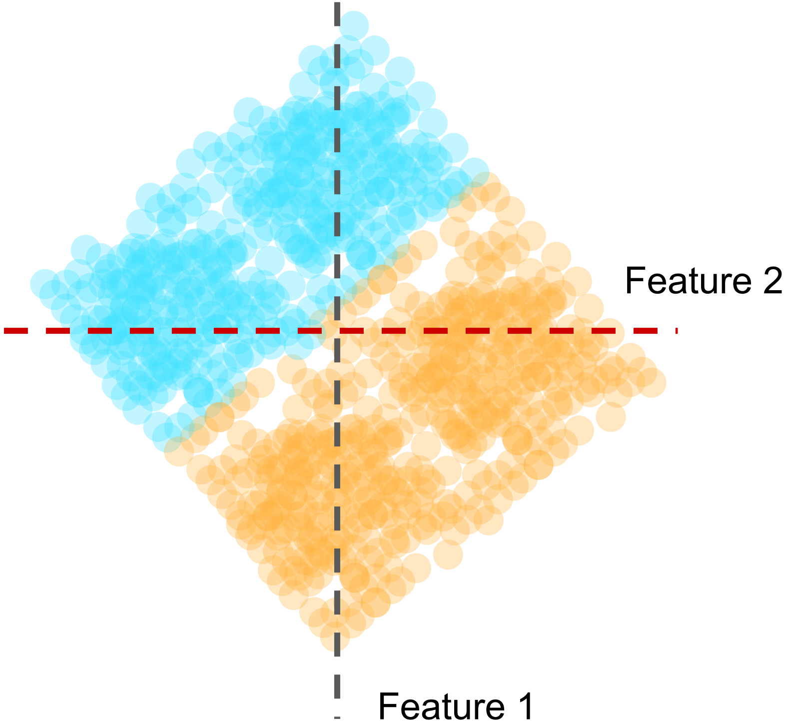

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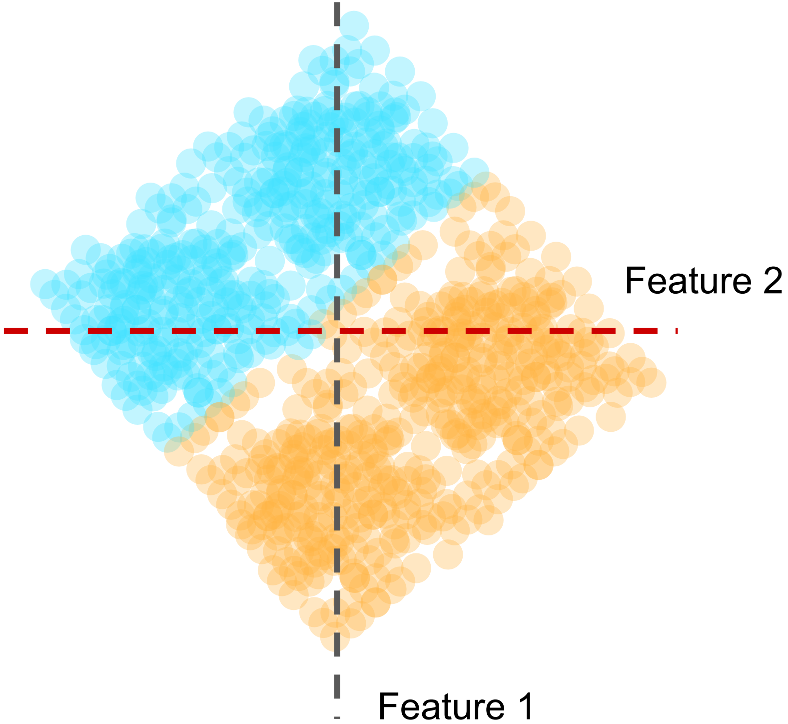
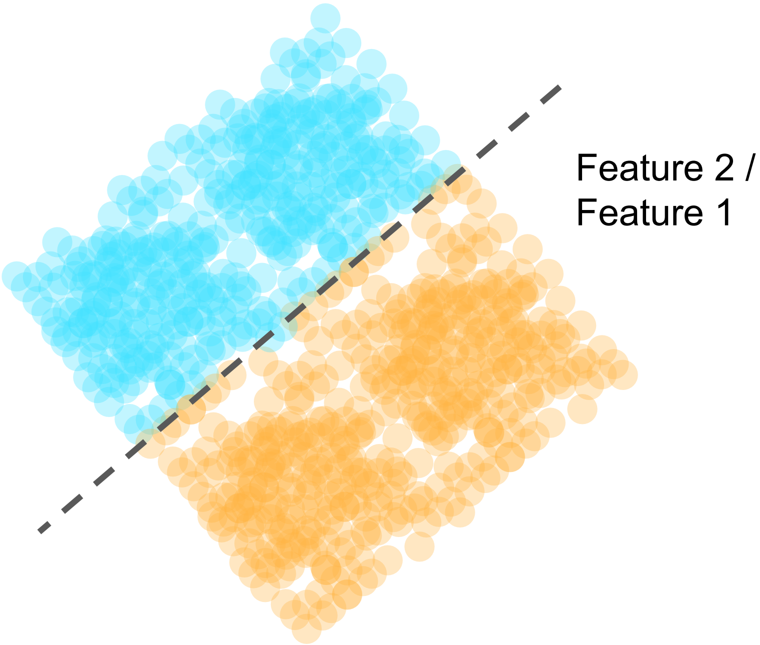
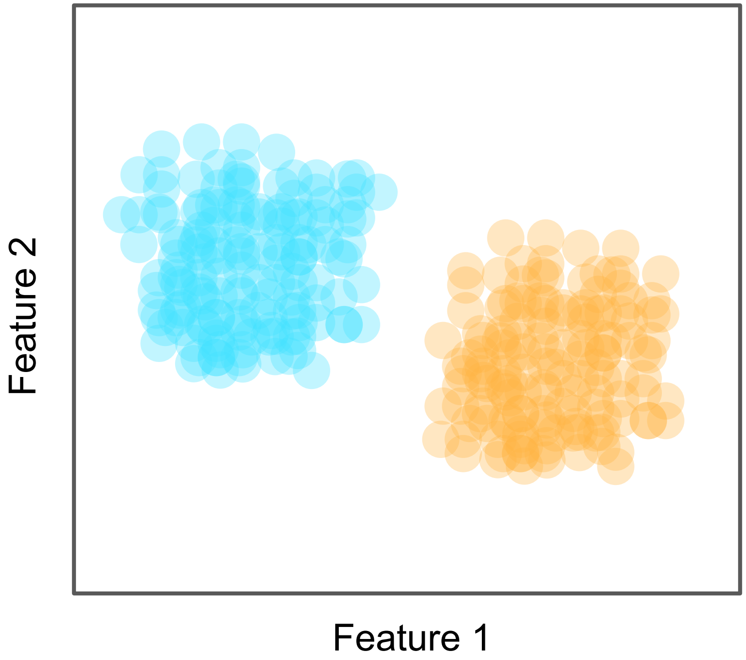




Decision trees optimize their decision to make the best split



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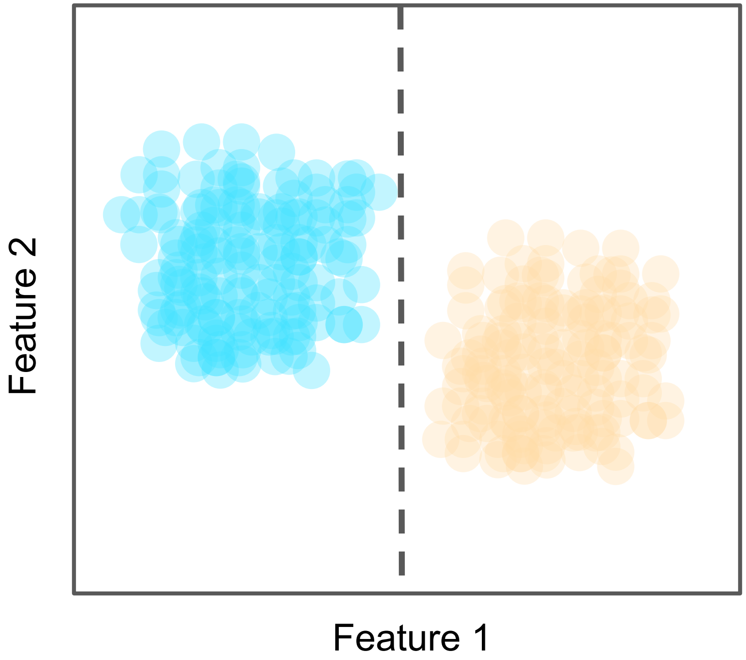

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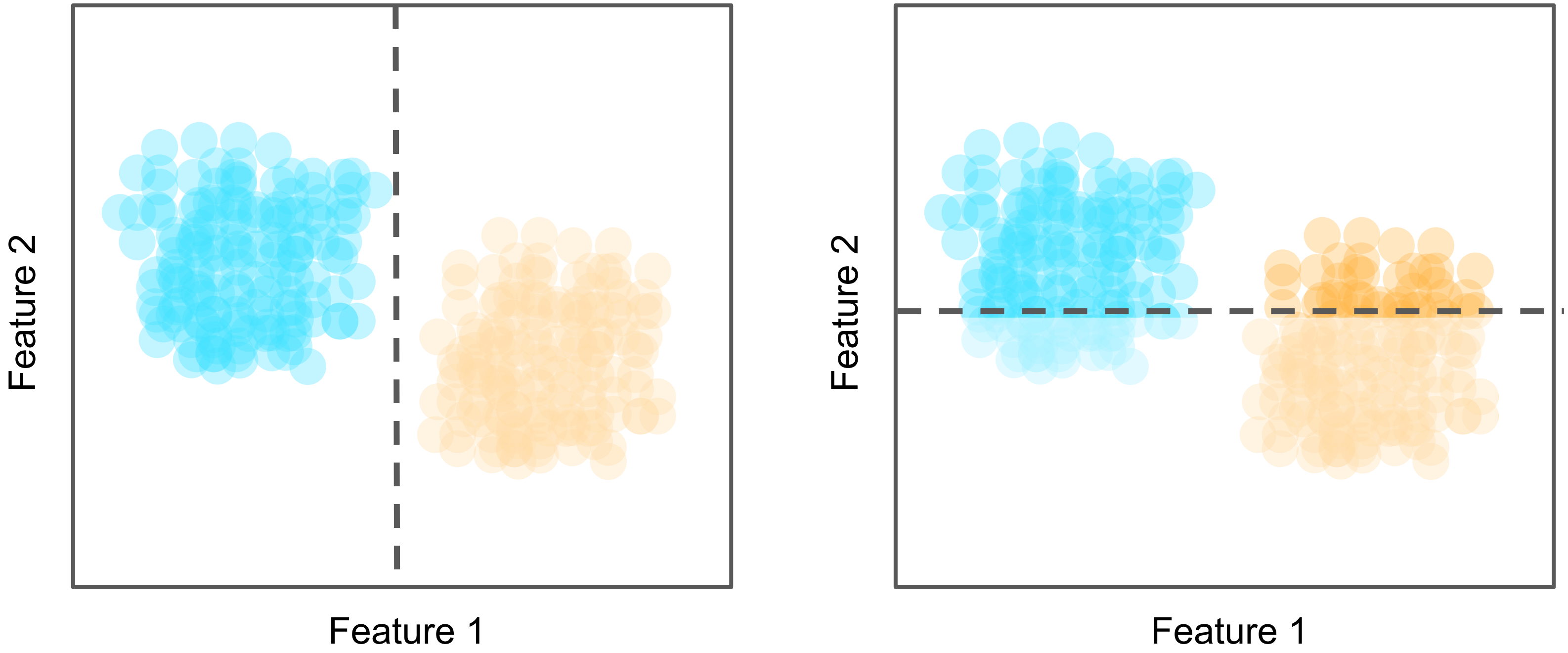
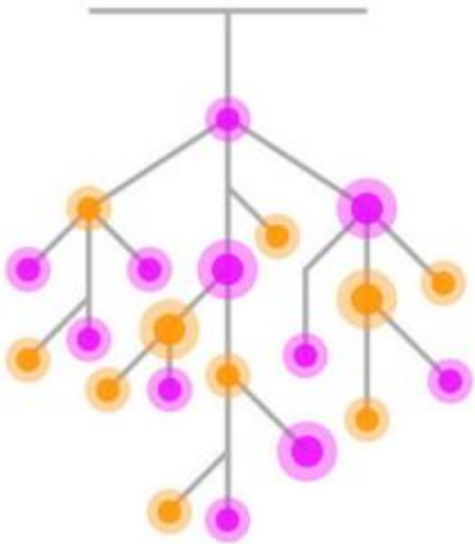
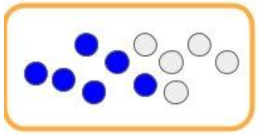


In-class activity

Writing a [very very] simple decision tree



Due to their optimization procedure, decision trees are prone to overfitting



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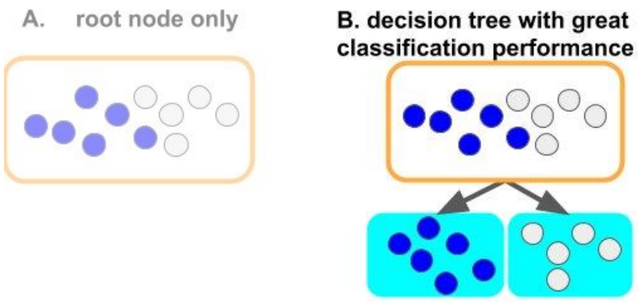

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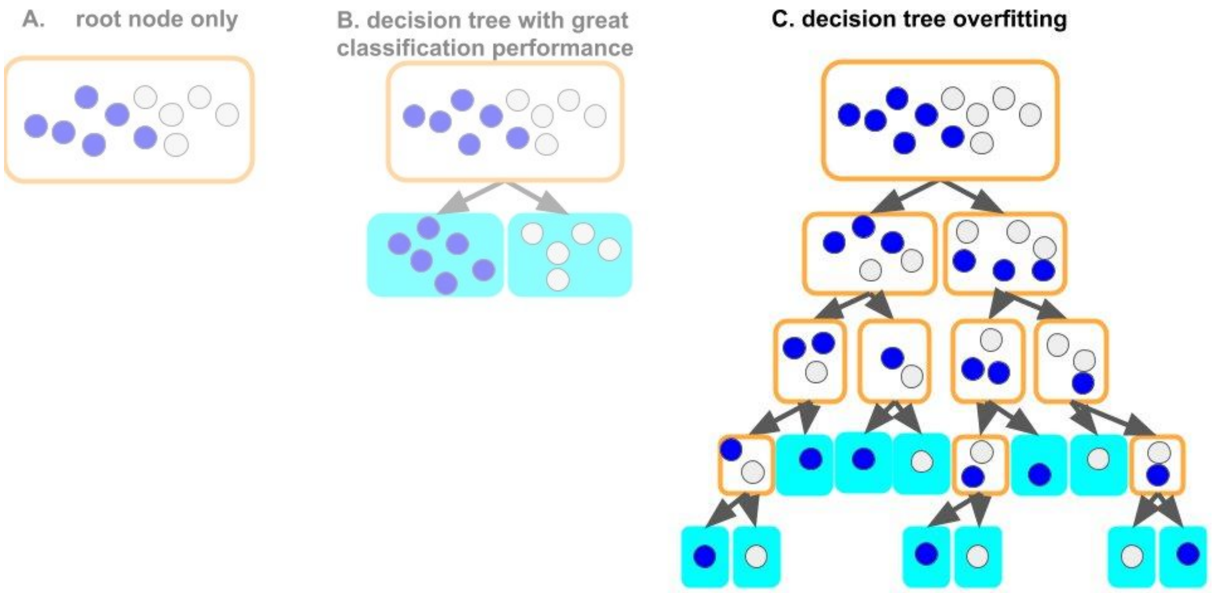
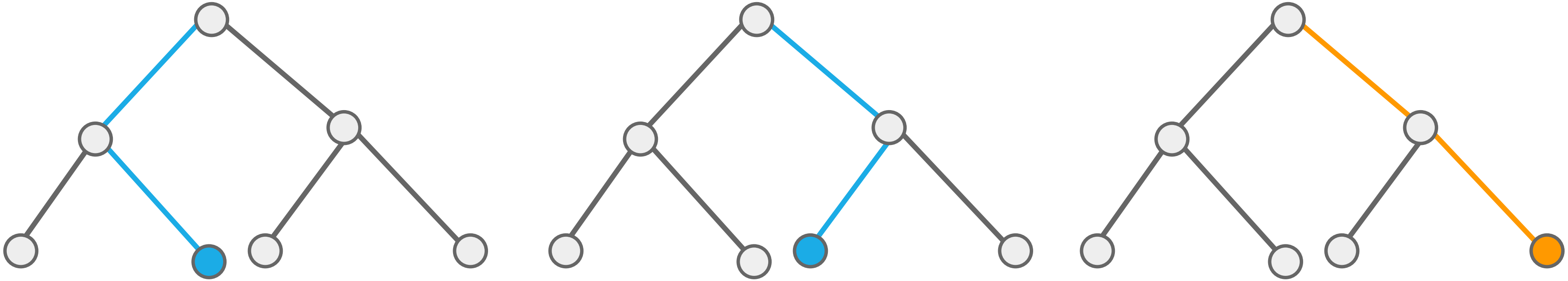


Combining different [shorter] trees (a forest) can result in a better performance

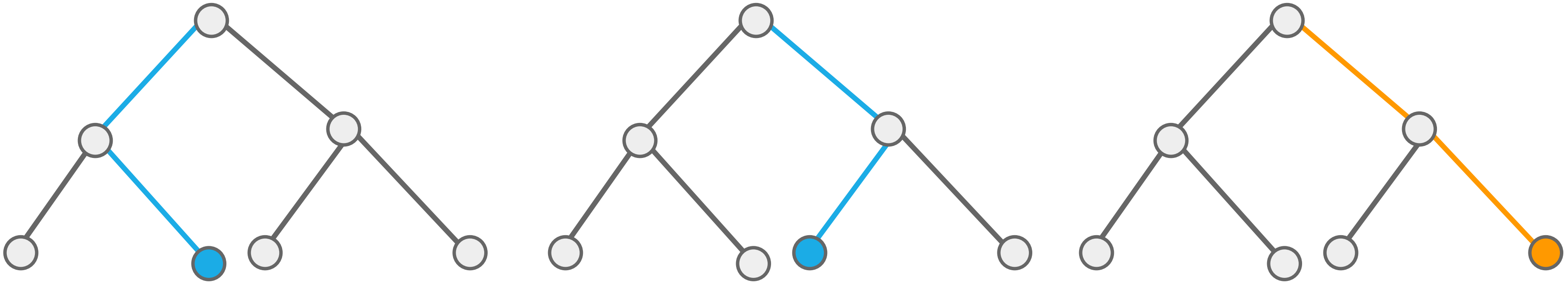


In-class activity

Voting

preg	plas	pres	skin	test	mass	pedi	age	Class
5	155	84	44	545	38.7	0.619	34	?
8	196	76	29	280	37.5	0.605	57	?
9	122	56	0	0	33.3	1.114	33	?
1	109	60	8	182	25.4	0.947	21	?
6	190	92	0	0	35.5	0.278	66	?

For random forests to work, the trees need to have low correlation



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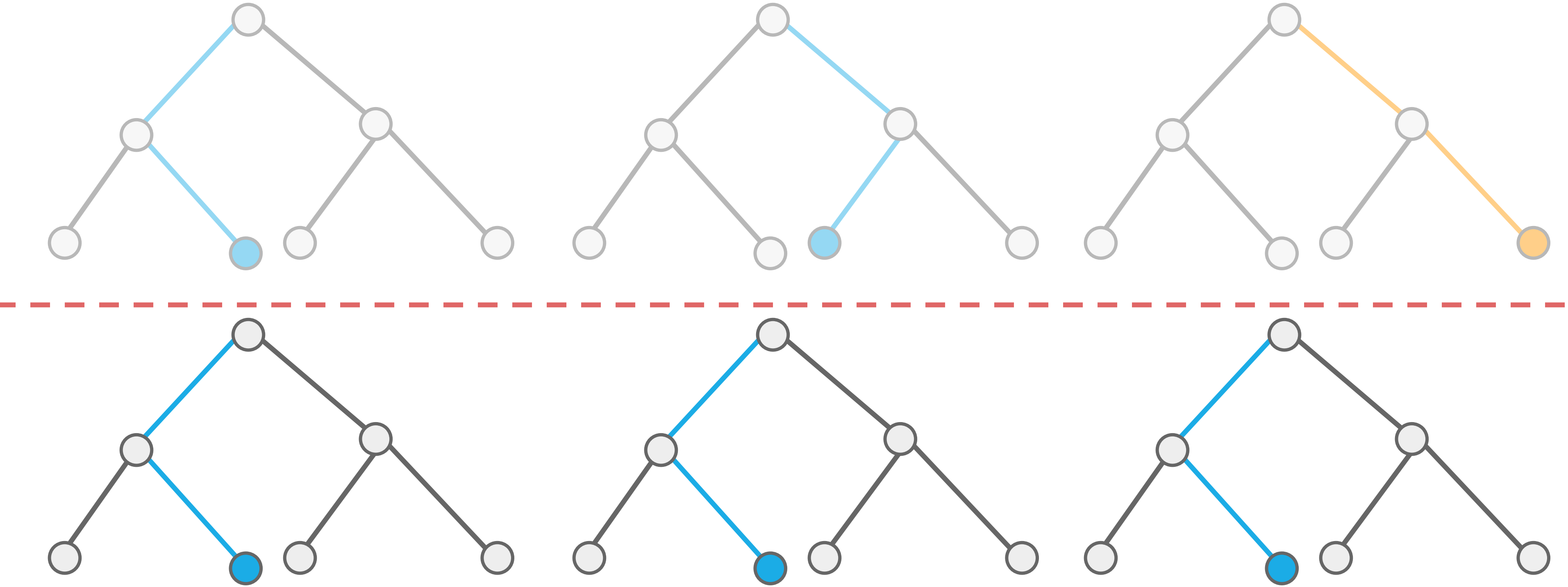
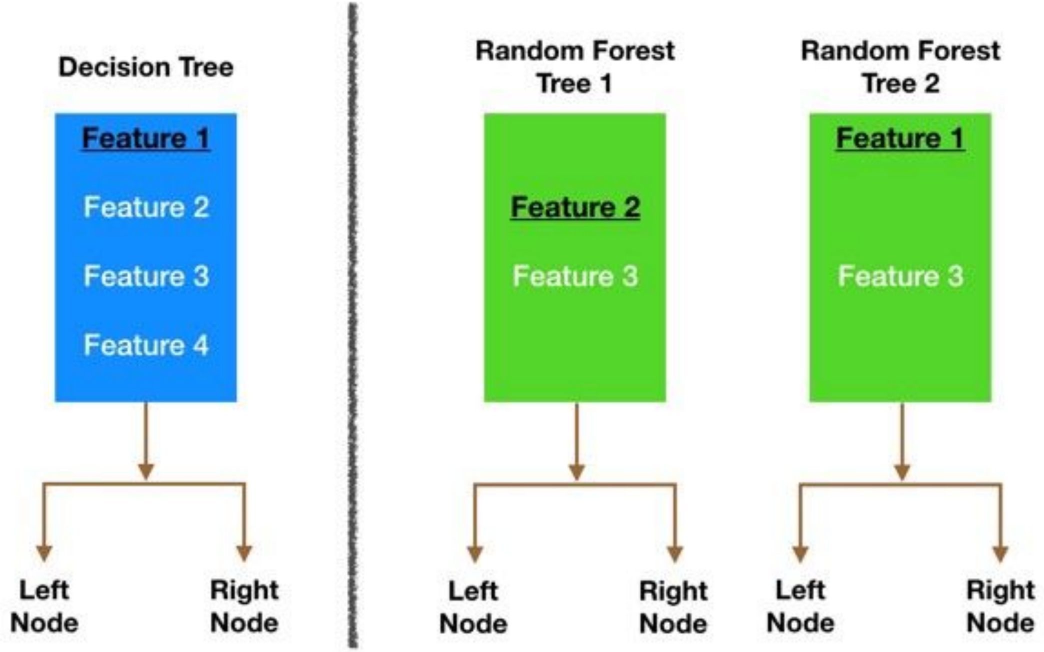


Feature randomness is one way to make sure trees diversify each other



Bagging (bootstrap aggregating) is another method to ensure diversity among trees

N

N-k

+ k

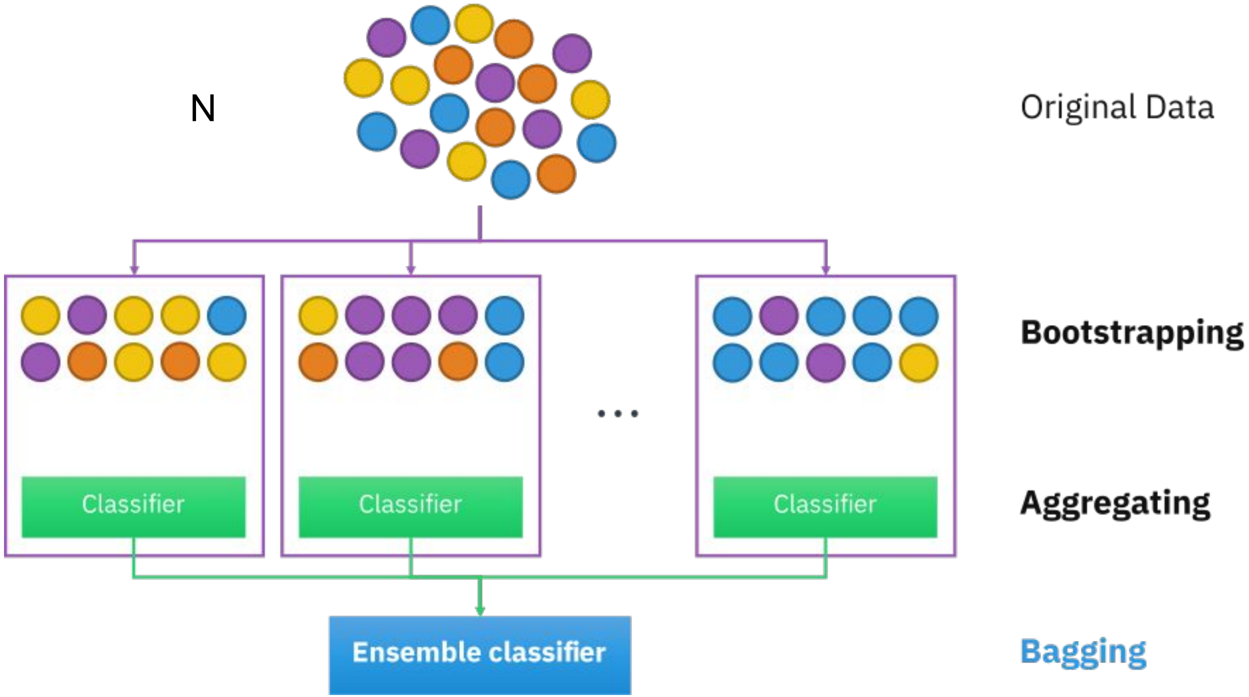


Image from Wikipedia: bootstrap aggregating

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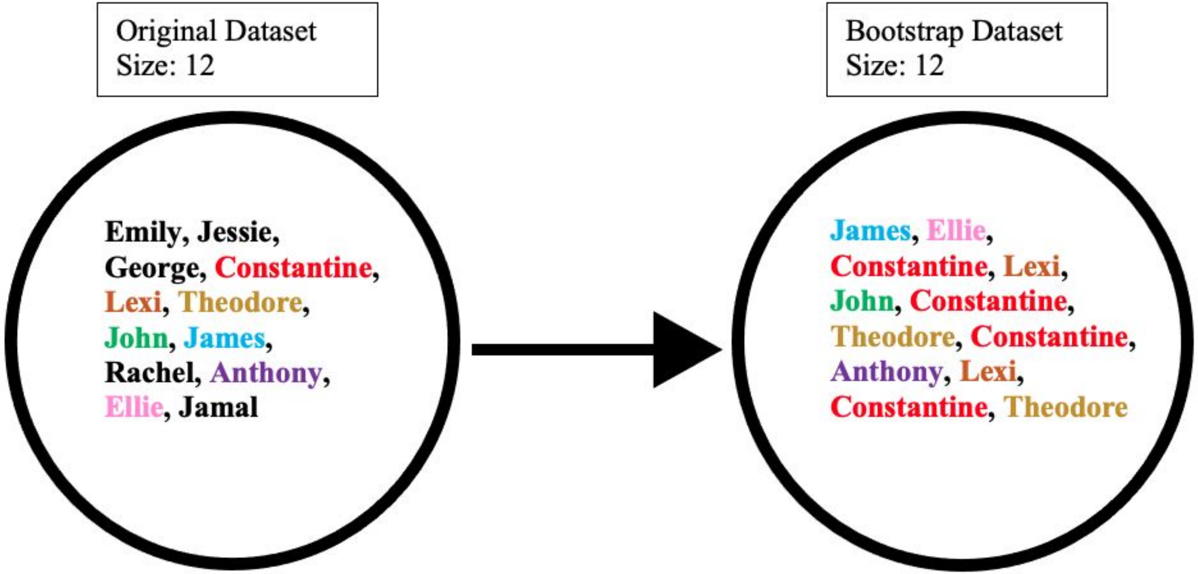


Random forests are similar to a wise crowd

5 important features:

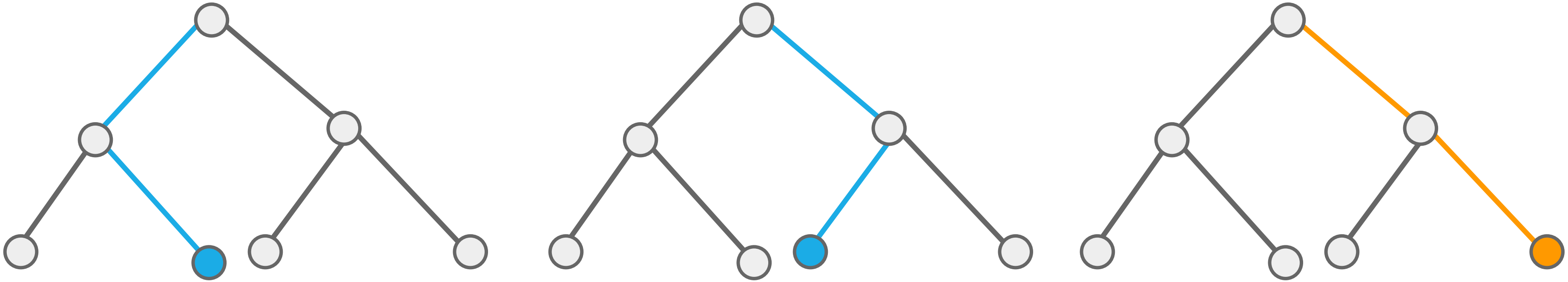
Random forests are similar to a wise crowd

5 important features:

1. Diversity of opinion
2. Independence
3. Decentralization
4. Aggregation
5. Trust

In-class activity

Building a random forest



Notes on random forests

Pros:

1. Lower variance than decision trees (slower risk of overfitting)
2. Easy to set-up and powerful
3. Works well with non-linear data
4. Easy preparation and deals well with missing/noisy data

Notes on random forests

Pros:

1. Lower variance than decision trees (slower risk of overfitting)
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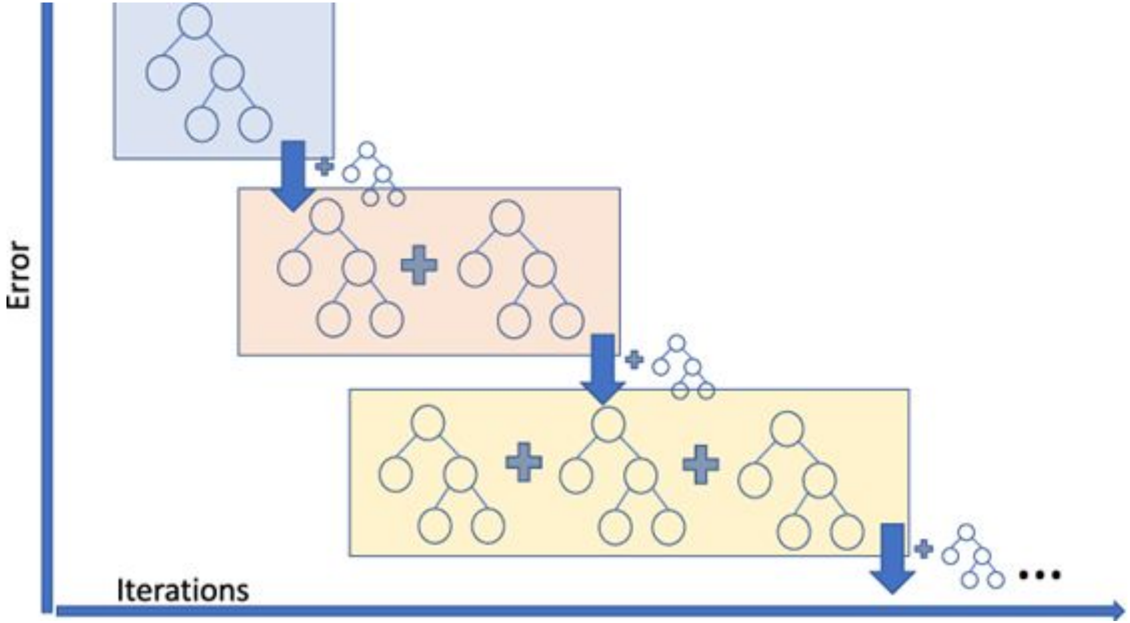
4. Easy preparation and deals well with missing/noisy data

Cons:

1. Slow
2. Very dependent on datasets
3. More complex → not as interpretable
4. Can't predict beyond the range of training data

Gradient boosting is another way to connect decision trees



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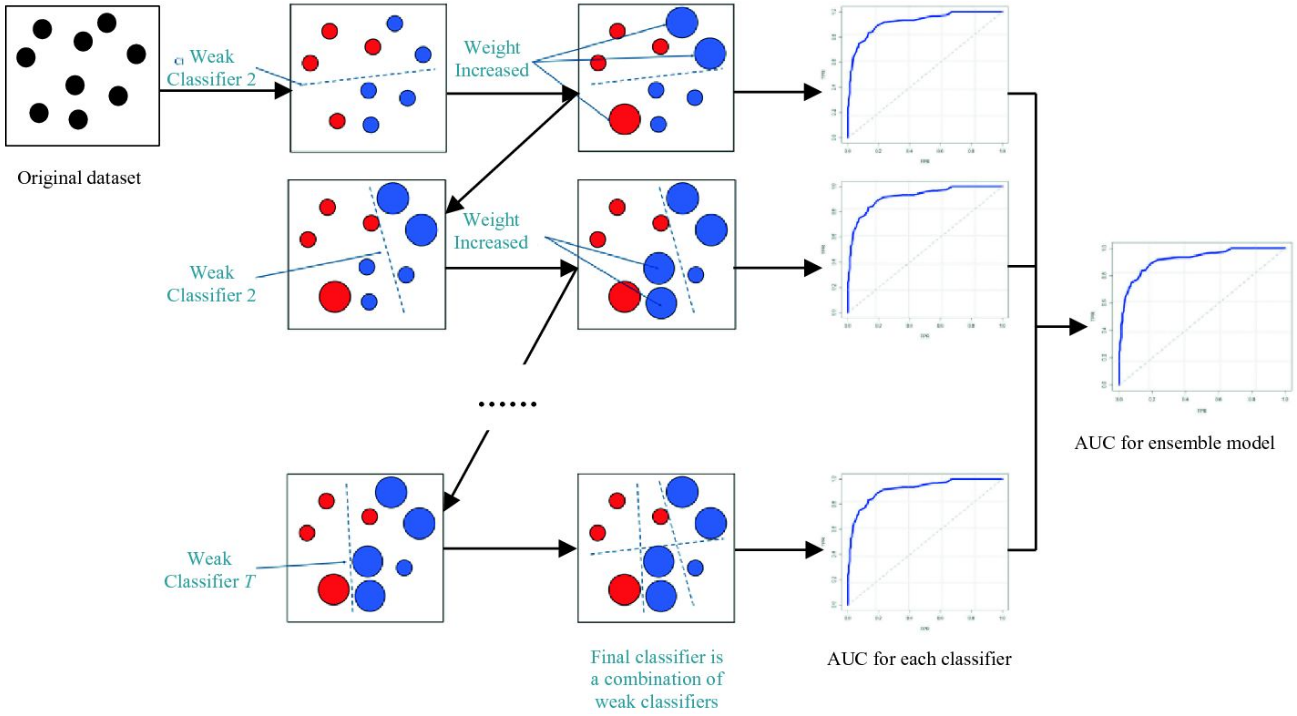

Some notes on gradient boosting

- Can perform better than RF if build properly
- Not appropriate for noisy data (overfitting)
- Harder to tune

Next lecture:

Simple methods can take you a long way!