

Lecture 8: 17 February 2022

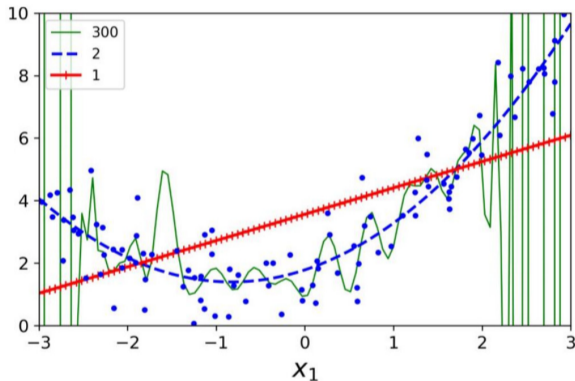
Madhavan Mukund

<https://www.cmi.ac.in/~madhavan>

Data Mining and Machine Learning
January–May 2022

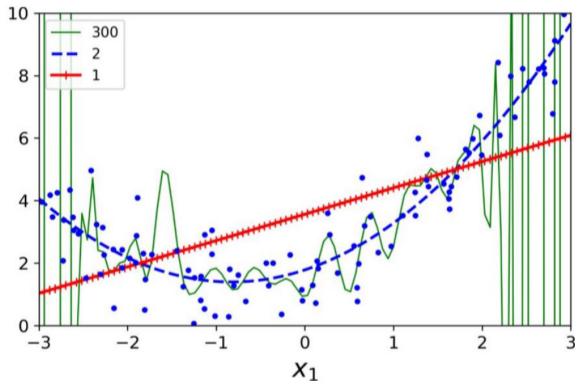
Overfitting

- Overfitting: model too specific to training data, does not generalize well



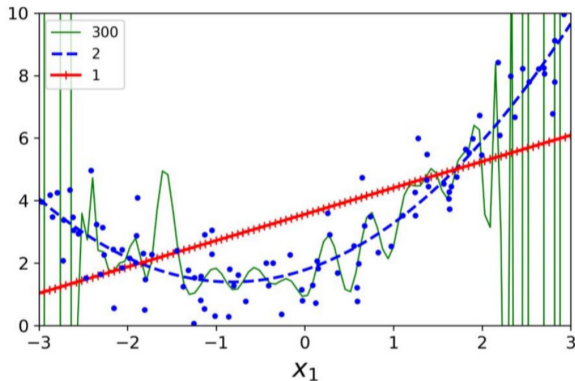
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- Regression — use regularization to penalize model complexity



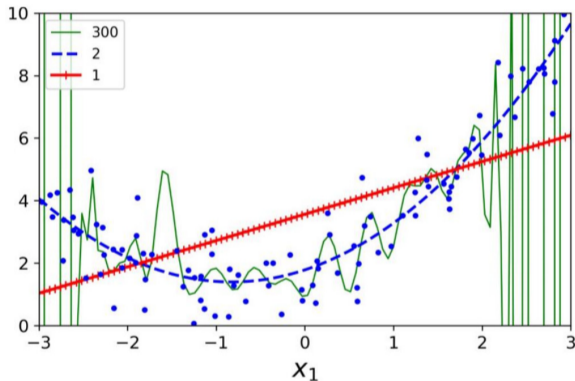
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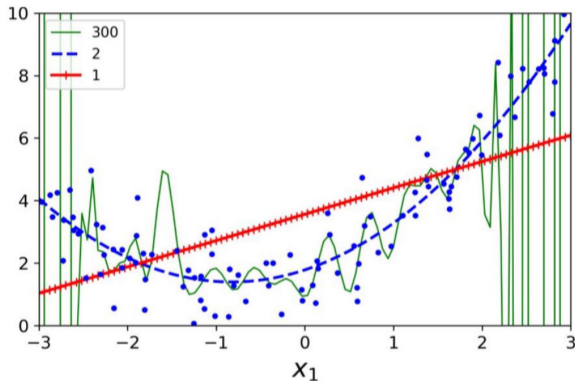
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- Deep, complex trees ask too many questions



Overfitting

- Overfitting: model too specific to training data, does not generalize well
- Regression — use regularization to penalize model complexity
- What about decision trees?
- Deep, complex trees ask too many questions
- Prefer shallow, simple trees



Tree pruning

- Remove leaves to improve generalization

Tree pruning

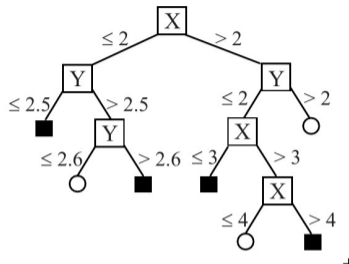
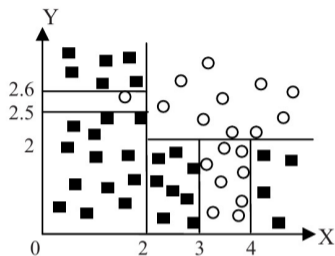
- Remove leaves to improve generalization
- Top-down pruning
 - Fix a maximum depth when building the tree
 - How to decide the depth in advance?

Tree pruning

- Remove leaves to improve generalization
- Top-down pruning
 - Fix a maximum depth when building the tree
 - How to decide the depth in advance?
- Bottom-up pruning
 - Build the full tree
 - Remove a leaf if the reduced tree generalizes better
 - How do we measure this?

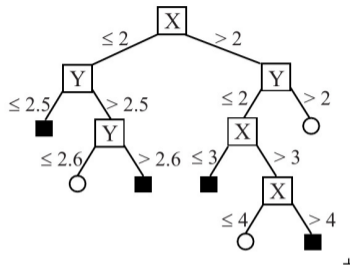
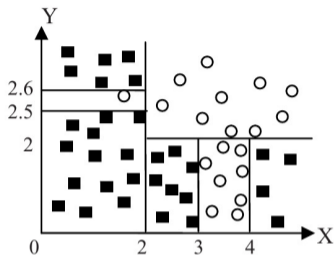
Tree pruning

Overfitted tree

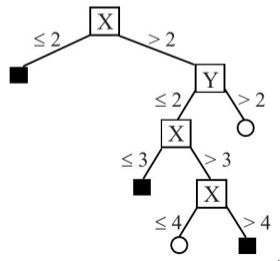
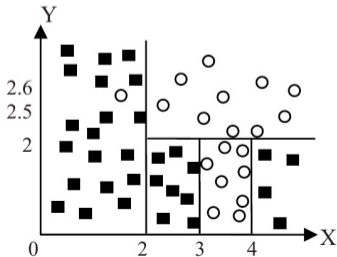


Tree pruning

Overfitted tree



Pruned tree



Bottom up tree pruning

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- Does the confidence interval decrease (improve)?

Example: Predict party from voting pattern [Quinlan]

- Predict party affiliation of US legislators based on voting pattern
 - Read the tree from left to right

physician fee freeze = n:

adoption of the budget resolution = y: democrat (151)

adoption of the budget resolution = u: democrat (1)

adoption of the budget resolution = n:

education spending = n: democrat (6)

education spending = y: democrat (9)

education spending = u: republican (1)

physician fee freeze = y:

synfuels corporation cutback = n: republican (97/3)

synfuels corporation cutback = u: republican (4)

synfuels corporation cutback = y:

duty free exports = y: democrat (2)

duty free exports = u: republican (1)

duty free exports = n:

education spending = n: democrat (5/2)

education spending = y: republican (13/2)

education spending = u: democrat (1)

physician fee freeze = u:

water project cost sharing = n: democrat (0)

water project cost sharing = y: democrat (4)

water project cost sharing = u:

mx missile = n: republican (0)

mx missile = y: democrat (3/1)

mx missile = u: republican (2)

Example: Predict party from voting pattern [Quinlan]

- Predict party affiliation of US legislators based on voting pattern
 - Read the tree from left to right
- After pruning, drastically simplified tree

```
physician fee freeze = n: democrat (168/2.6)
physician fee freeze = y: republican (123/13.9)
physician fee freeze = u:
|
| mx missile = n: democrat (3/1.1)
| mx missile = y: democrat (4/2.2)
| mx missile = u: republican (2/1)
```

Example: Predict party from voting pattern [Quinlan]

- Predict party affiliation of US legislators based on voting pattern
 - Read the tree from left to right
- After pruning, drastically simplified tree
- Quinlan's comment on his use of sampling theory for post-pruning

Now, this description does violence to statistical notions of sampling and confidence limits, so the reasoning should be taken with a large grain of salt. Like many heuristics with questionable underpinnings, however, the estimates it produces seem frequently to yield acceptable results.

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