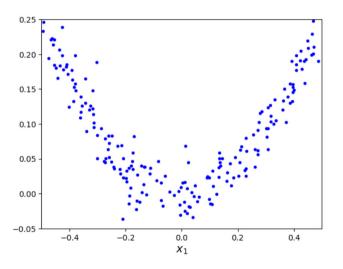
Lecture 9: 7 February, 2023

Madhavan Mukund

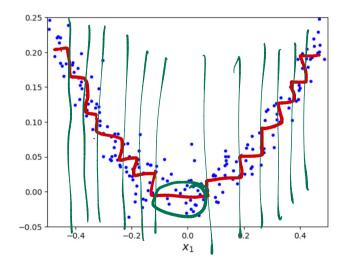
https://www.cmi.ac.in/~madhavan

Data Mining and Machine Learning January–April 2023

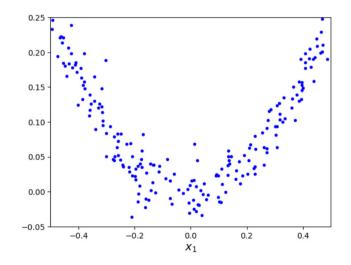
How do we use decision trees for regression?



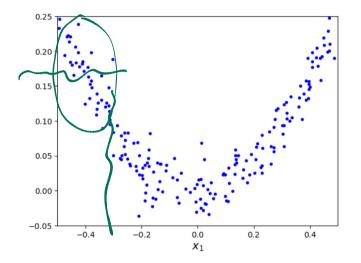
- How do we use decision trees for regression?
- Partition the input into intervals



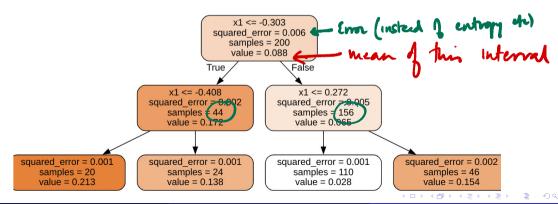
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- How do we use decision trees for regression?
- Partition the input into intervals
- For each interval, predict mean value of output, instead of majority class
- Regression tree

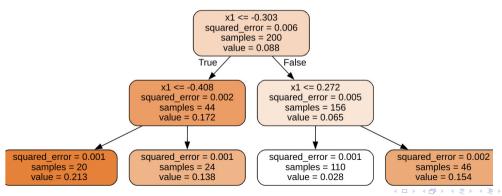


■ Regression tree for noisy quadratic

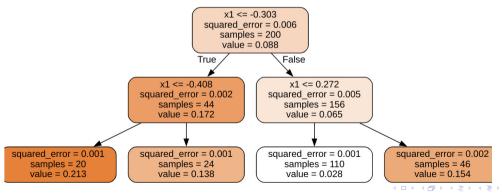


Madhavan Mukund Lecture 9: 7 February, 2023 DMML Jan-Apr 2023

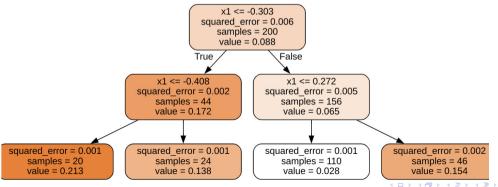
- Regression tree for noisy quadratic
- For each node, the output is the mean y value for the current set of points

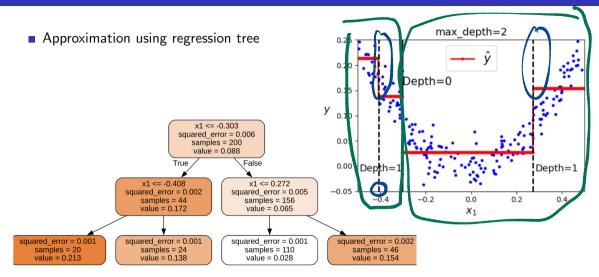


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- Instead of impurity, use mean squared error (MSE) as cost function

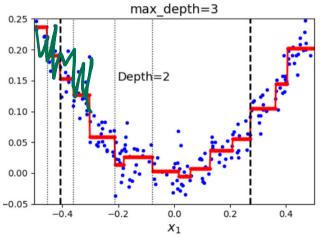


- Regression tree for noisy quadratic
- For each node, the output is the mean y value for the current set of points
- Instead of impurity, use mean squared error (MSE) as cost function
- Choose a split that minimizes MSE

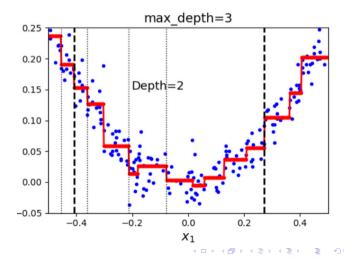




 Extend the regression tree one more level to get a finer approximation

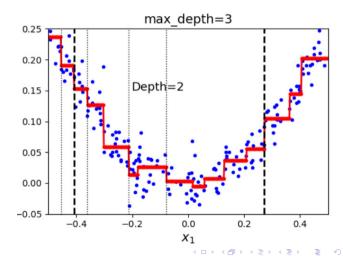


- Extend the regression tree one more level to get a finer approximation
- Set a threshold on MSE to decide when to stop

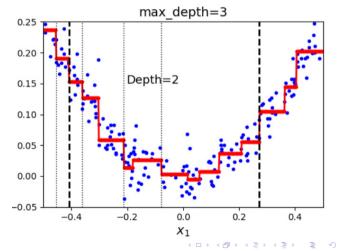


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- Classification and Regression Trees (CART)

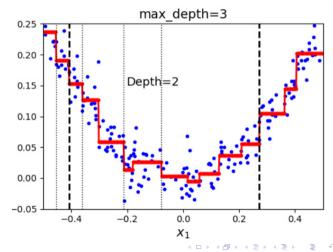
Les Breiman



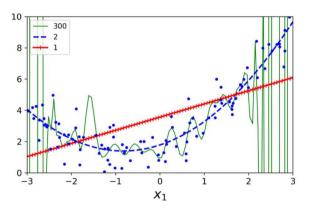
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- Set a threshold on MSE to decide when to stop
- Classification and Regression Trees (CART)
 - Combined algorithm for both use cases
- Programming libraries typically provide CART implementation



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

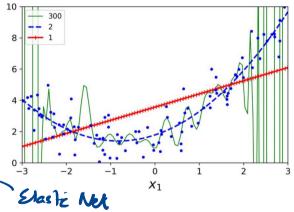


 Overfitting: model too specific to training data, does not generalize well

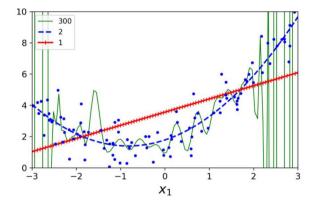
 Regression — use regularization to penalize model complexity

MSE + w. REG

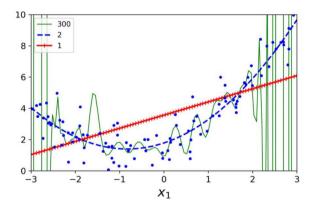
hac lasso Elastic



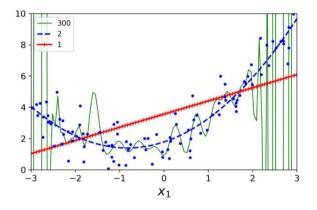
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- Deep, complex trees ask too many questions



- 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



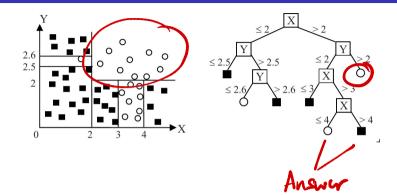
■ Remove leaves to improve generalization

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

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 - How to decide the depth in advance?
 - Fix a threshold to split a leaf do not split a leaf with fewer than k items
 - How to set the threshold?
- Bottom-up pruning
 - Build the full tree
 - Remove a leaf if the reduced tree generalizes better
 - How do we measure this?

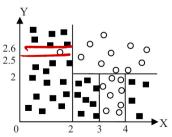
Overfitted tree

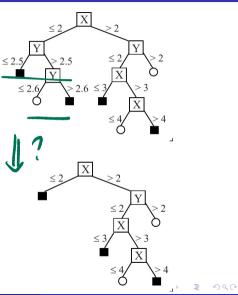


Overfitted tree

2.6 2.5 2 0 2 3 4 X

Pruned tree





Madhavan Mukund

- Build the full tree, remove leaf if the reduced tree generalizes better
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- Pruning leaves creates a larger impure sample one level above
- 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 = v: democrat (9)
        education spending = u: republican (1)
physician fee freeze = y:
    synfuels corporation cutback = n: republican (97/3
    synfuels corporation cutback = u: republican
    synfuels corporation cutback == v:
        duty free exports = v: 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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