#ODSC

Ensemble Models Demystified

@KevinLemagnen

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Ensembles: Why do we care?

- Good performance
- General purpose
- Usually easier to train than other fancy techniques
- Really popular in industry and ML competitions

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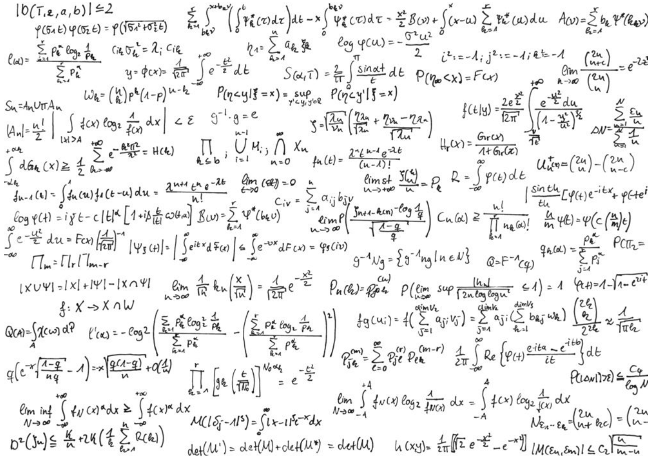
Why this talk?

Theory



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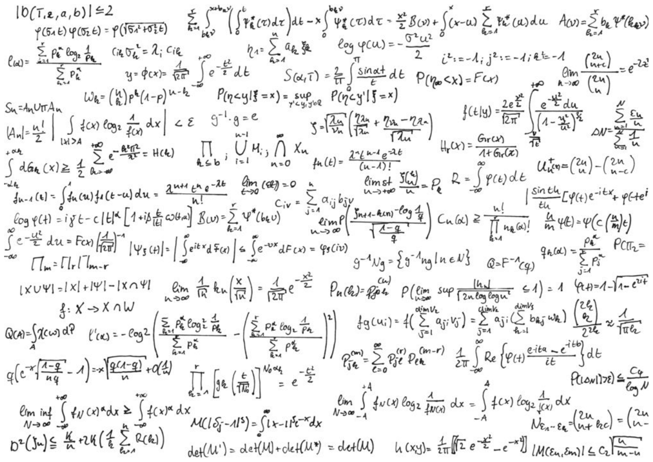
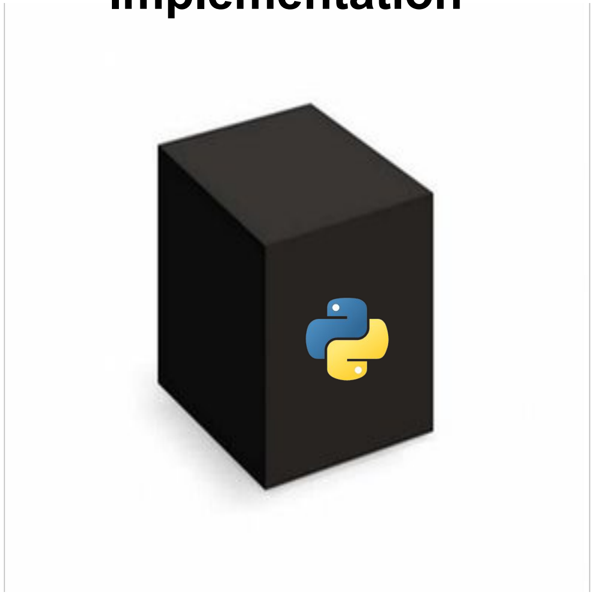


Implementation



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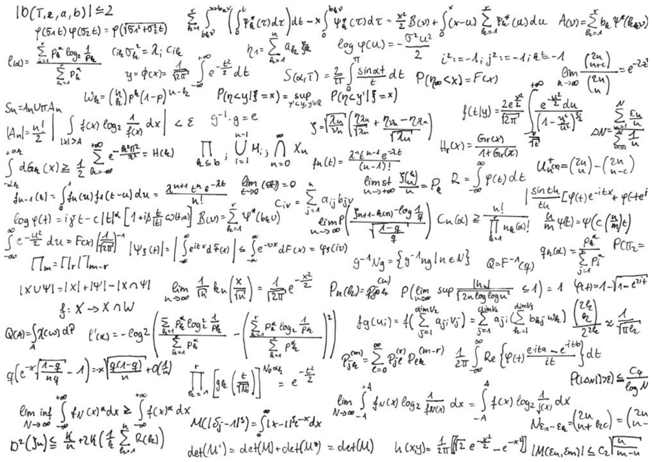

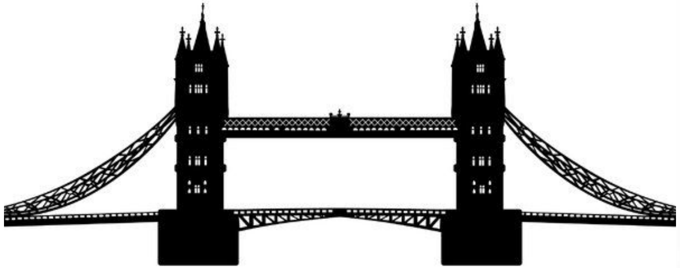

Implementation

Agenda

1. Intuition
2. Weak learner (Decision Tree)
3. Bagging (Random Forest)
4. Boosting (Gradient Boosting)
5. Other boosting libraries

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1. Intuition

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What are ensemble models?

- Combining multiple simple models (weak learners) into a larger one (ensemble)
- Two popular techniques:
    - Bagging
    - Boosting
    - Usually with decision trees as weak learner

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Intuition

Accuracy = 60%

Accuracy = 75%

Both say you have **X**… what's the likelihood that you really have **X**?

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Two big assumptions

- **Weak Learner:** “Experts” need to be more right than wrong on average

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- **Weak Learner:** “Experts” need to be more right than wrong on average
- **Diversity**: “Experts” need to make different errors

2. Weak Learners

Decision Trees

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Why are they good?

- Can capture complex relationships in the data
  - We’ll often be able to get our > 50% accuracy!
- Overfits easily
  - We can use that to create diverse models!

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How do we control them?

No constraints = one leaf per sample = **massive overfitting**

Some good constraints:

- Pick a **maximum depth**
- Pick a **minimum number of samples** needed in a new node/leaf

3. Bagging

Random Forest

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- Good performance per tree (no underfitting)

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Don't overdo it… We still need:

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- Able to generalise (no overfitting)

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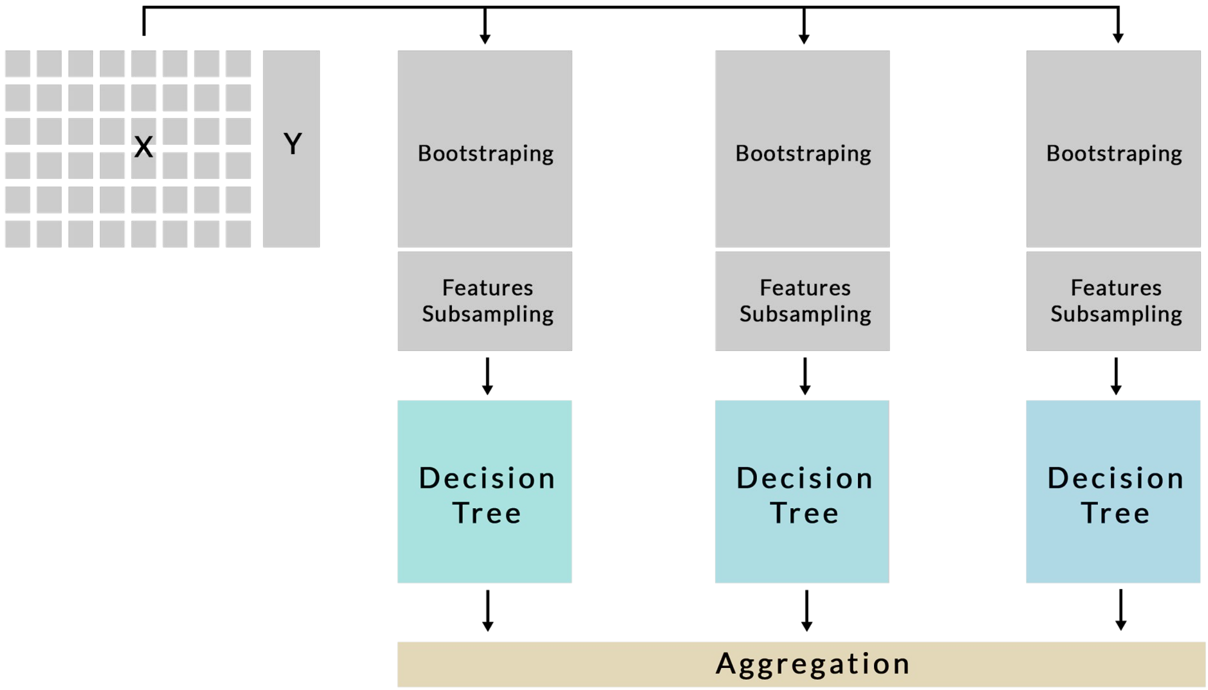
Bagging - Random Forest



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Some pros and cons

+ Easy to run in **parallel**

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? **Outliers** likely to be ignored by most weak learners

4. Boosting

Gradient Boosting

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Boosting - Intuition

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2. Compute residuals — $r = 100 - 95 = 5$
3. Train DT2 on **(X, 5)** — $DT2(X) = 4$

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4. Aggregate DT1 and DT2 — $DT1(X) + DT2(X) = 95 + 4 = 99$

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Weak learners increasingly focus on "hard points"

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Boosting - Gradient Boosting

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- Getting the number of stages right is **extremely** important
- We need to build **small**, **constrained** trees

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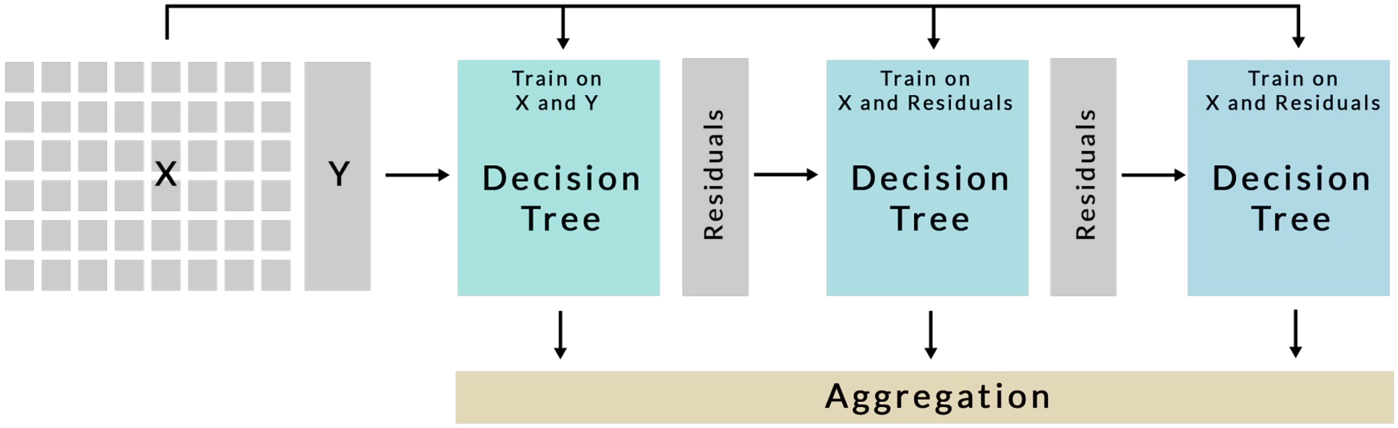
Boosting - Gradient Boosting



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- − Hard to run in **parallel**
- − Hard to **interpret**
- − Can easily **overfit**

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Any questions?

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