Boosting

Gradient Boosting

@cambridgespark

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Boosting

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Boosting - Intuition

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Start with an ensemble **H** of a single base classifier $\mathbf{h}_1$

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3. Repeat

We fit classifiers that increasingly and actively focus on "hard points"

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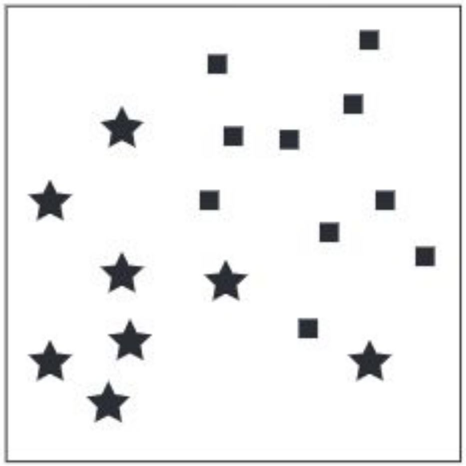
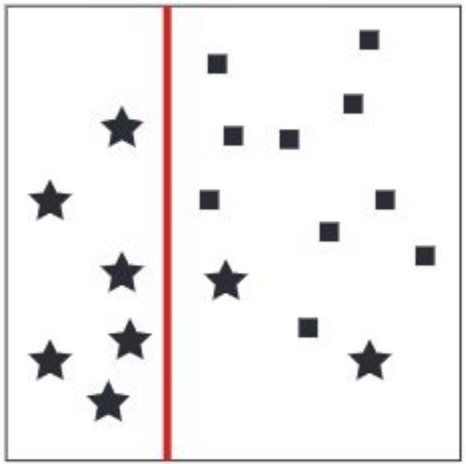
Visually



Visually



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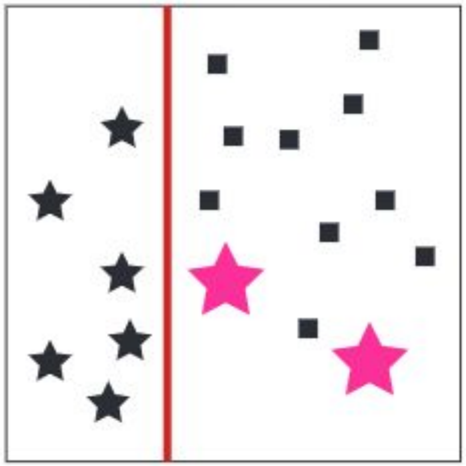

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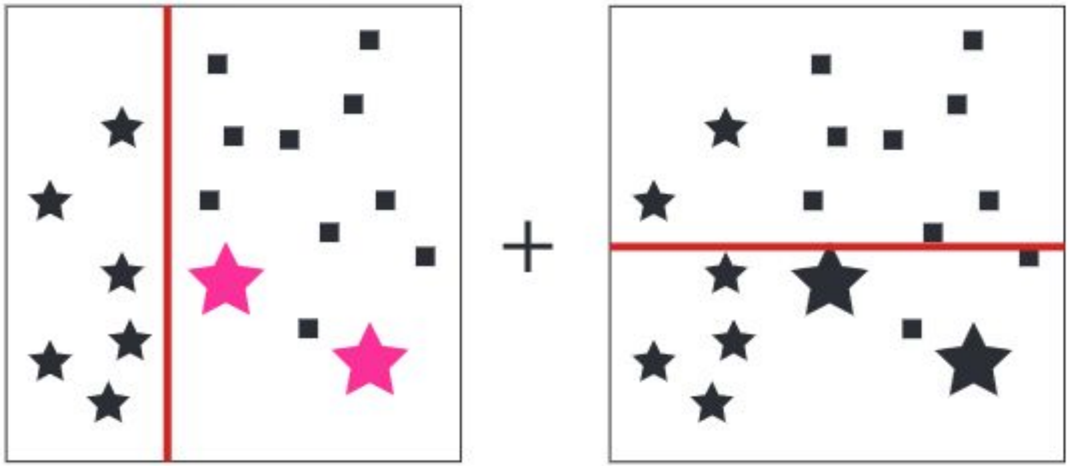

Comments on boosting

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  - weight of $\mathbf{h}_{\mathbf{k}}$ > weight of $\mathbf{h}_{\mathbf{k+1}}$

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- Sequential algorithm
- Later classifiers have decreasing weight in the aggregation
  - weight of $\mathbf{h}_{\mathbf{k}}$ > weight of $\mathbf{h}_{\mathbf{k+1}}$
- The same principles work for regression

Boosting methods

- What "weights" to use for misclassified points?

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Many different approaches based on answers.

AdaBoost ('96), LogitBoost ('98), BrownBoost ('01), . . .

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Many different approaches based on answers.

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Boosting methods can be interpreted as a **gradient descent** which leads to a more generic framework (" AnyBoost ") and to extremely popular libraries:

XGBoost ('14), LightGBM ('16), CatBoost ('17)

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Gradient Boosting

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5. Repeat

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Boosting - Gradient Boosting

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- Getting the number of stages right is **extremely** important

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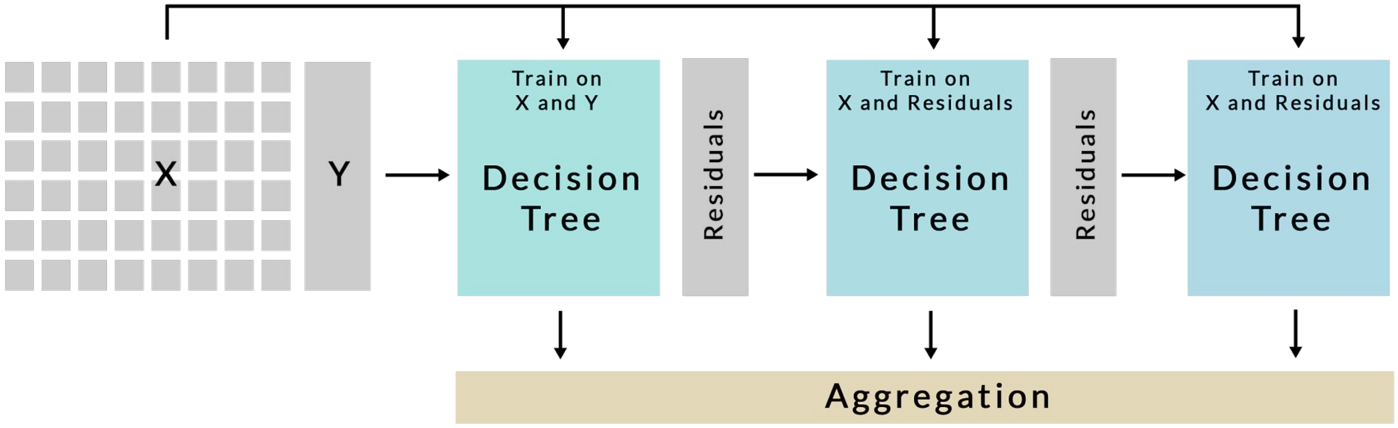
- Getting the number of stages right is **extremely** important
- We need to build **small**, **constrained** trees

Boosting - Gradient Boosting



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Some pros and cons

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+ Decision Trees = we can get **feature importance**
− Hard to run in **parallel**
− Hard to **interpret**
− Can easily **overfit**

Gradient Boosting

In Practice

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Gradient Boosting in practice

A lot of things depend on the family of base models and can be optimised a lot.

XGBoost and **LightGBM** essentially consider decision trees of fixed depth . Then a lot of tricks are applied:

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A lot of things depend on the family of base models and can be optimised a lot.

XGBoost and **LightGBM** essentially consider decision trees of fixed depth . Then a lot of tricks are applied:

- (approximate) computation of residuals (fast)
- Sophisticated computations of γ_k (“step size” or “learning rate”)
- Shrinkage methods to avoid "bad" trees (regularisation)
- Lots of software optimisation. . . (and open source!)

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Boosting in Python

With Scikit-Learn:

- *AdaBoostClassifier*, *AdaBoostRegressor*
- *GradientBoostingClassifier*, *GradientBoostingRegressor*
  - not as optimised as XGB or LGBM but work with any estimator, not just trees

Other gradient boosting libraries include:

- *XGBoost*
- *LightGBM*
- *CatBoost*

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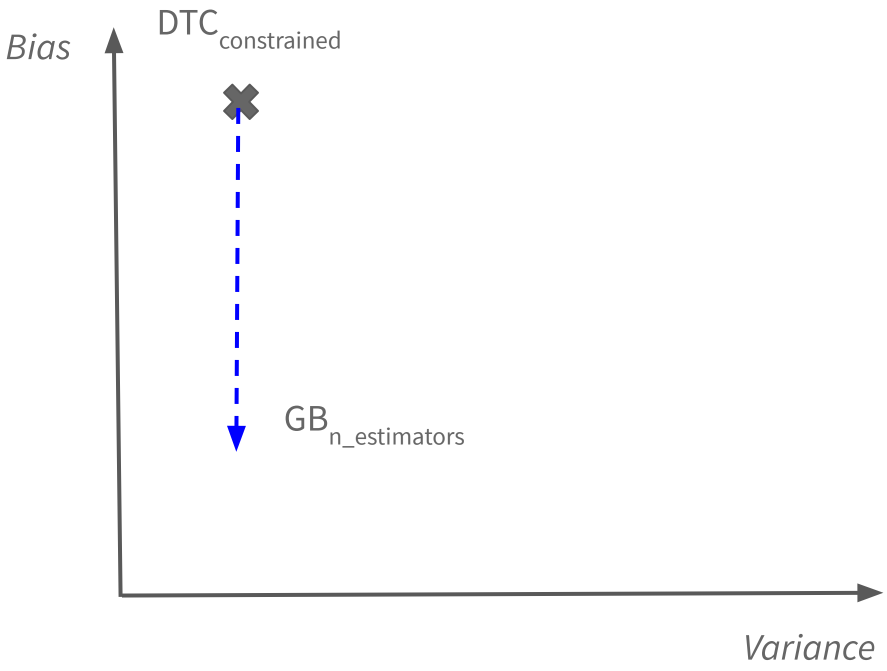
Bias vs Variance



- Gradient Boosting allows to reduce bias of shallow trees
- What happens if we keep adding trees?

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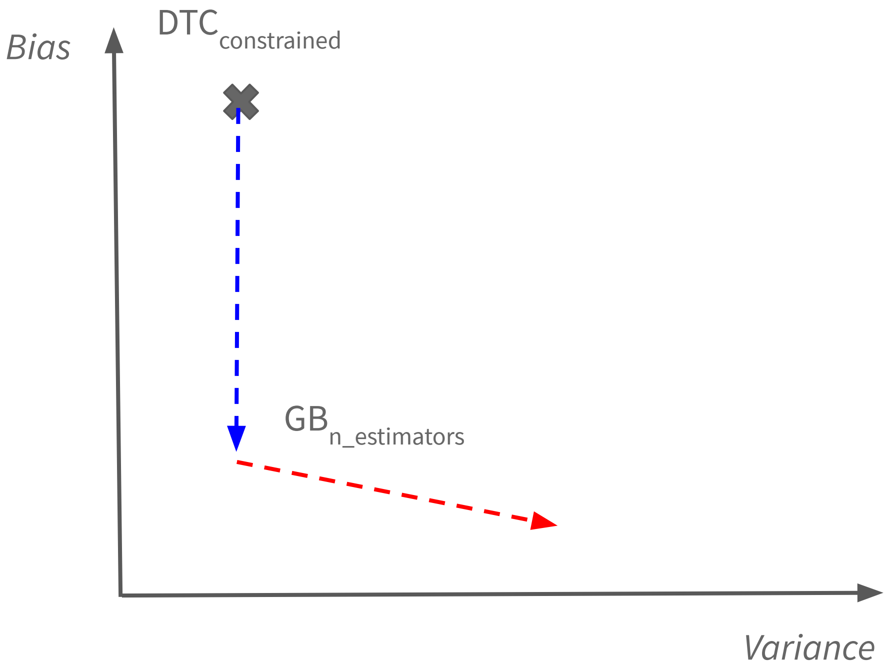

- Gradient Boosting allows to reduce bias of shallow trees
- What happens if we keep adding trees?
    - We'll start overfitting

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Hands-on session

01-boosting.ipynb

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