Gradient Boosted Regression Trees



Material: https://github.com/pprett/pydata-gbrt-tutorial

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Motivation



















Motivation









1 Basics

- ② Gradient Boosting
- **3** Gradient Boosting in scikit-learn
- 4 Use Case: California Housing

About us

Peter

- @pprett
- \bullet Python & ML \sim 6 years
- sklearn dev since 2010

Gilles

- @glouppe
- PhD student (Liège, Belgium)
- sklearn dev since 2011 Chief tree hugger



Basics

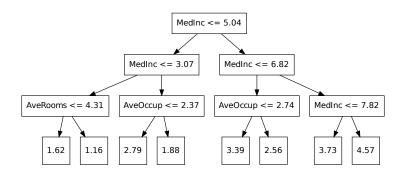
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Machine Learning 101

- Data comes as...
 - A set of examples $\{(\mathbf{x}_i, y_i)|0 \le i < \text{n_samples}\}$, with
 - Feature vector $\mathbf{x} \in \mathbb{R}^{n_features}$, and
 - Response $y \in \mathbb{R}$ (regression) or $y \in \{-1,1\}$ (classification)
- Goal is to...
 - Find a function $\hat{y} = f(\mathbf{x})$
 - Such that error $L(y, \hat{y})$ on new (unseen) **x** is minimal

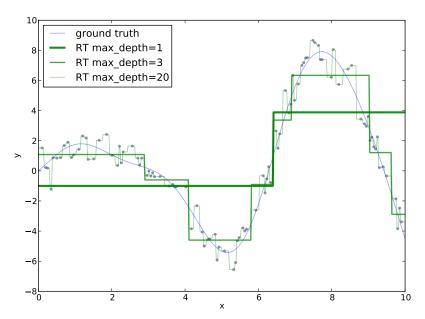


Classification and Regression Trees [Breiman et al, 1984]

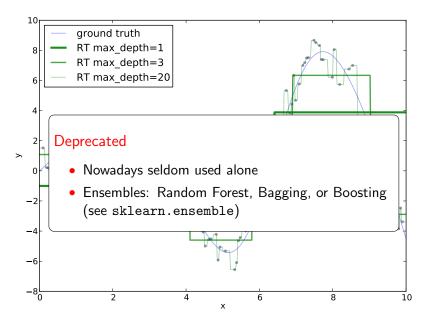




Function approximation with Regression Trees



Function approximation with Regression Trees



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Gradient Boosted Regression Trees

Advantages

- Heterogeneous data (features measured on different scale)
- Supports different loss functions (e.g. huber)
- Automatically detects (non-linear) feature interactions

Disadvantages

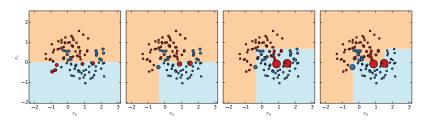
- Requires careful tuning
- Slow to train (but fast to predict)
- Cannot extrapolate



Boosting

AdaBoost [Y. Freund & R. Schapire, 1995]

- Ensemble: each member is an expert on the errors of its predecessor
- Iteratively re-weights training examples based on errors



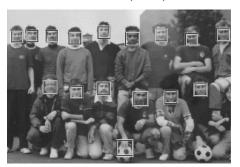


Boosting

Adal

Huge success

• Viola-Jones Face Detector (2001)



• Freund & Schapire won the Gödel prize 2003



sklearn.ensemble.AdaBoostClassifier|Regressor

Gradient Boosting [J. Friedman, 1999]

Statistical view on boosting

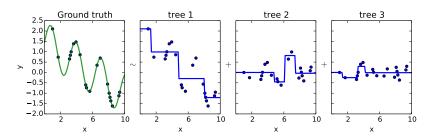
• ⇒ Generalization of boosting to arbitrary loss functions

Gradient Boosting [J. Friedman, 1999]

Statistical view on boosting

• ⇒ Generalization of boosting to arbitrary loss functions

Residual fitting





Functional Gradient Descent

Least Squares Regression

- Squared loss: $L(y_i, f(\mathbf{x}_i)) = (y_i f(\mathbf{x}_i))^2$
- The residual \sim the (negative) gradient $\frac{\partial L(y_i, f(\mathbf{x}_i))}{\partial f(\mathbf{x}_i)}$

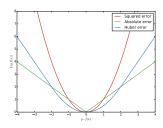
Functional Gradient Descent

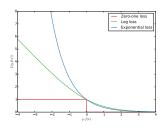
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Steepest Descent

- Regression trees approximate the (negative) gradient
- Each tree is a successive gradient descent step





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Notebook

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