Cornell Data Science

Meta-Learning

Logistics

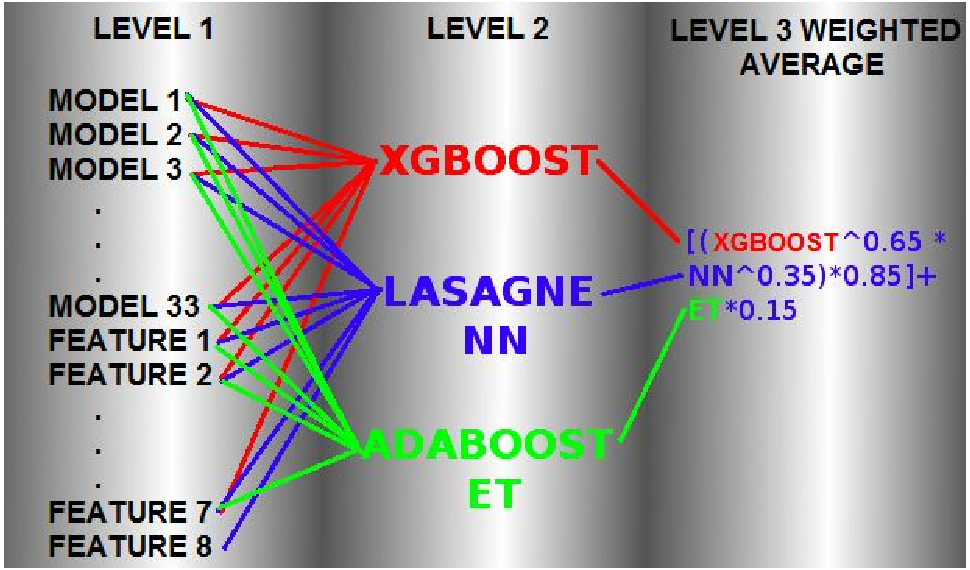
Project B grade will be released tonight

Project C due Sunday 11:59 PM

~~I want the school to be done~~

Layers of Learning

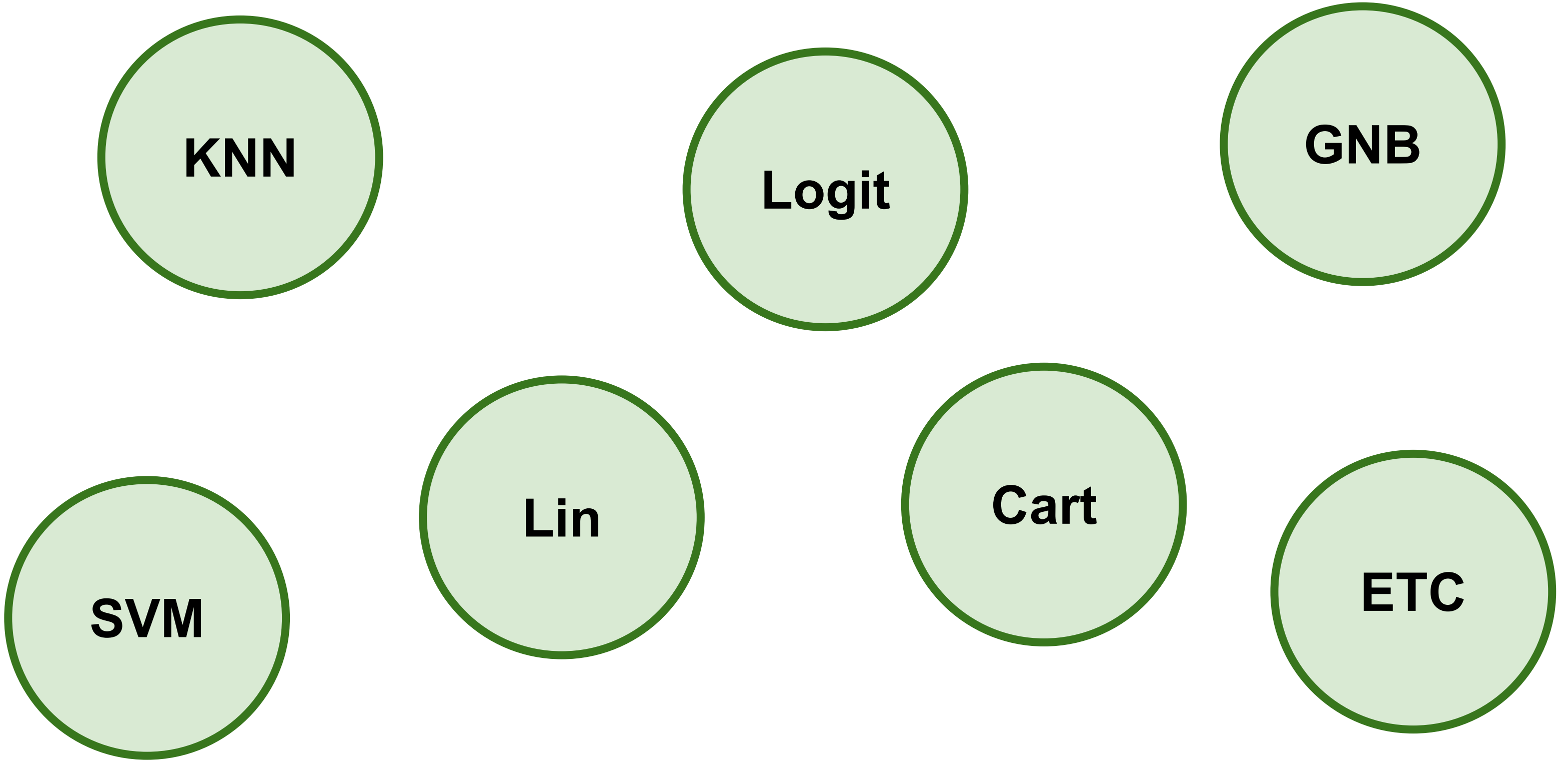
Gilberto Titericz Junior (top-ranked user on Kaggle.com) used this setup to win the $10,000 Otto Group Product Classification Challenge.



33 models???

3 levels???

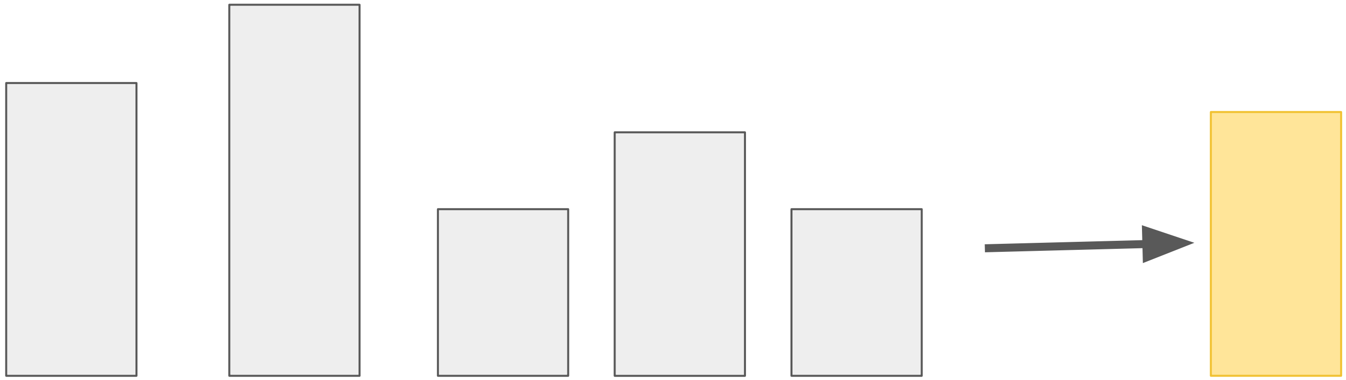
Lasagne NN??


KNN
Logit
GNB
Lin
Cart
SVM
ETC

Introduction: Ensemble Averaging

Basic ensemble composed of a **committee** of learning algorithms.

Results from each algorithm are averaged into a final result, reducing variance.



Binary Classification Example

Logit	SVM	KNN	Majority Voting	Actual
A	A	B		A
B	A	B		B
A	A	A		A
A	B	B		B
75%	75%	75%		

Binary Classification Example

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A	A	B	A	A
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A	A	A		A
A	B	B		B

Logit	SVM	KNN
75%	75%	75%

Binary Classification Example

Logit	SVM	KNN	Majority Voting	Actual
A	A	B	A	A
B	A	B	B	B
A	A	A	A	A
A	B	B		B
75%	75%	75%		

Binary Classification Example

Logit	SVM	KNN	Majority Voting	Actual
A	A	B	A	A
B	A	B	B	B
A	A	A	A	A
A	B	B	B	B
75%	75%	75%	100%	

Ensemble

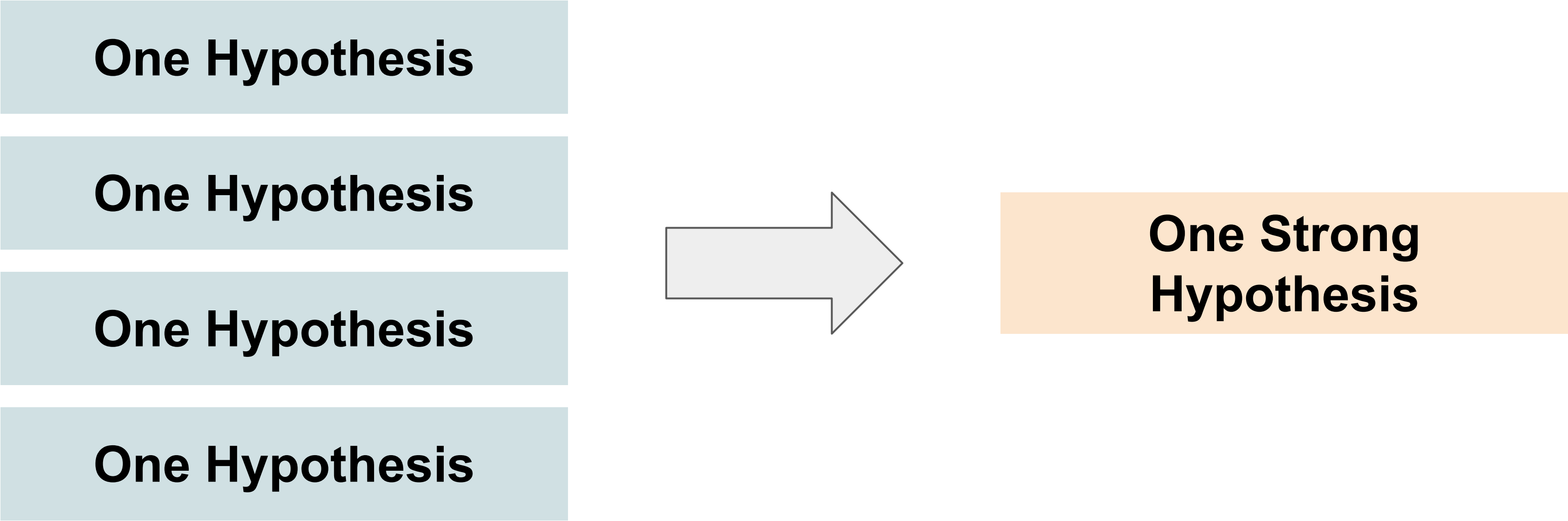
Meta-Learning

Ensembles and Hypotheses

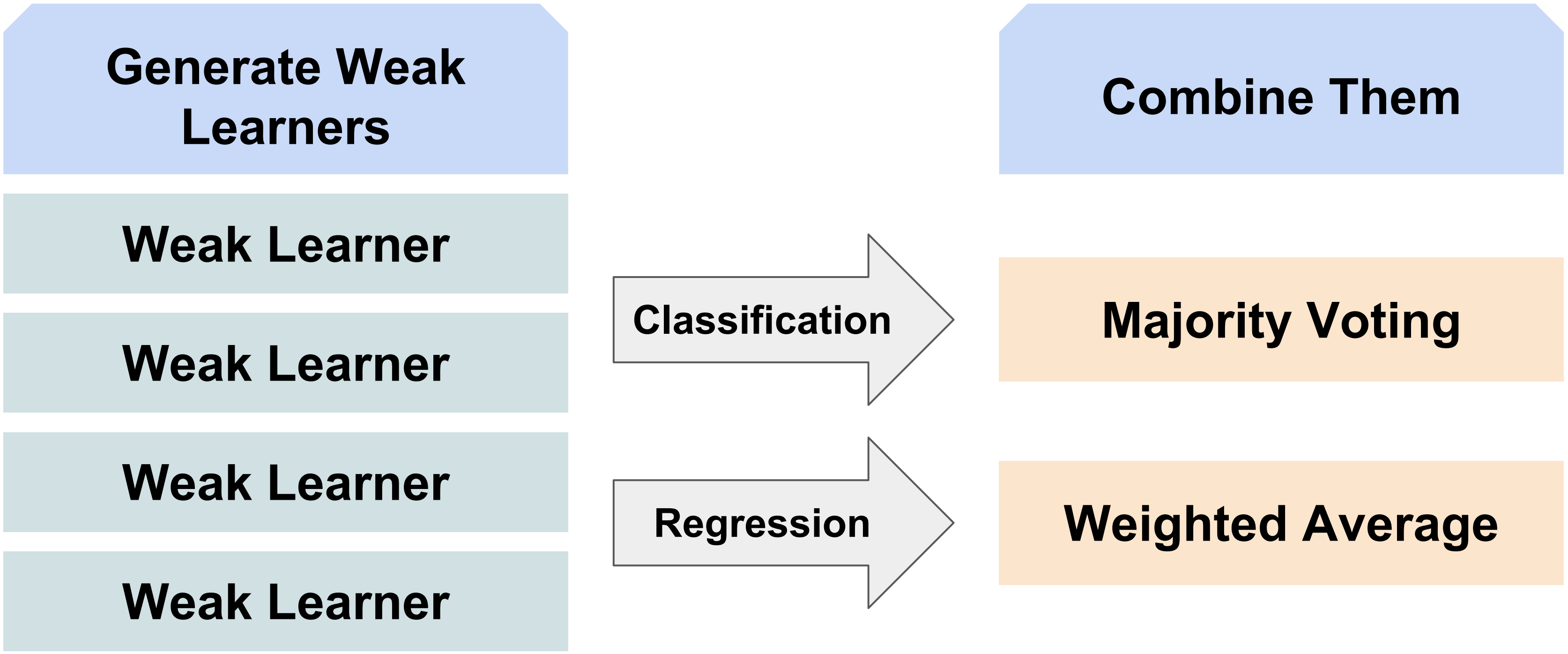
- Recall the definition of "hypothesis."
- Machine learning algorithms search the **hypothesis space** for hypotheses.
  - Set of mathematical functions on real numbers
  - Set of possible classification boundaries in feature space
- More searchers ⟶ more likely to find a "good" hypothesis

Source

General Definition



Paradigm



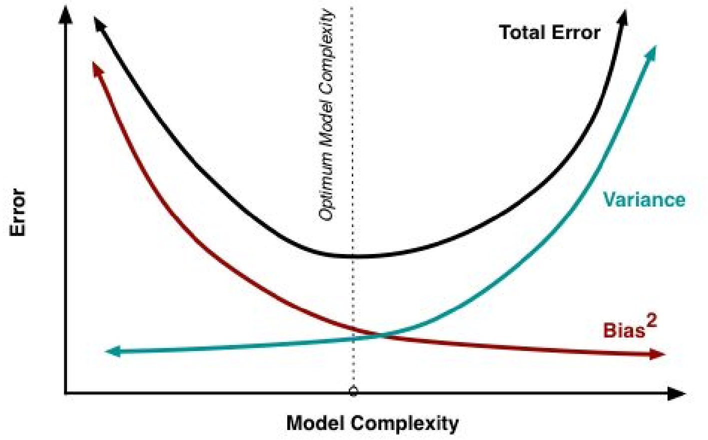
Generate Weak Learners
Weak Learner
Weak Learner
Weak Learner
Weak Learner
Classification
Regression
Combine Them
Majority Voting
Weighted Average

Why so many models?

A single model on its own is often prone to bias and/or variance.

- **Bias** - Systematic or “consistent” error. Associated with underfitting.
- **Variance** - Random or “deviating” error. Associated with overfitting.

A tradeoff exists. We want to minimize both as much as we can.



Source

Three Main Types

Bagging

Boosting

Stacking

Three Main Types

Bagging	Boosting	Stacking
Lower Variance	Lower Bias	Performance

Bagging

Short for **b**ootstrap **agg**regat**ing**.

A **parallel ensemble**. Models are applied without knowledge of each other.

- Apply each model on a random subset of data.
- Combine the output by averaging (for regression) or by majority vote (for classification)
- A more sophisticated version of ensemble averaging.

Bagging decreases **variance** and prevents **overfitting.**

Source

Random Forests

Designed to improve accuracy over CART.

Much more difficult to overfit

- Works by building a large number of CART trees
  - Each tree in the forest “votes” on outcome
  - Outcome with the most votes becomes our prediction

Source

Boosting

A **sequential ensemble**. Models are applied one-by-one based on how previous models have done.

- Apply a model on a subset of data.
- Check to see where the model has badly classified data.
- Apply another model on a new subset of data, giving preference to data badly classified by the model.

Boosting decreases **bias** and prevents **underfitting.**

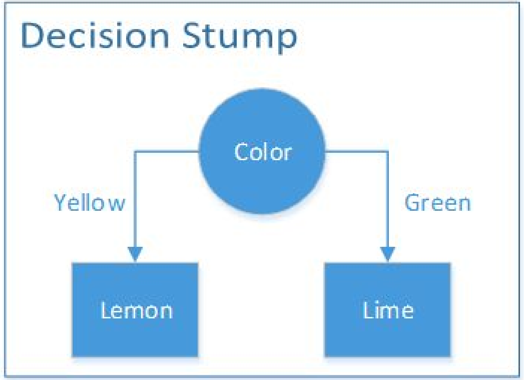
Source

Weak Learners

Important concept in boosting.

Weak learners do only slightly better than the baseline for a given dataset. In isolation, they are not very useful.

While boosting, we improve these learners sequentially to create hyper-powered models.



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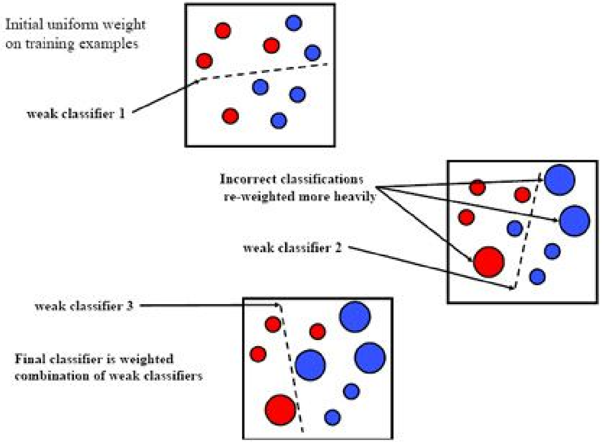
AdaBoost

Short for **ada**ptive **boost**ing. Sequentially generates weak learners, adjusting newer learners based on mistakes of older learners

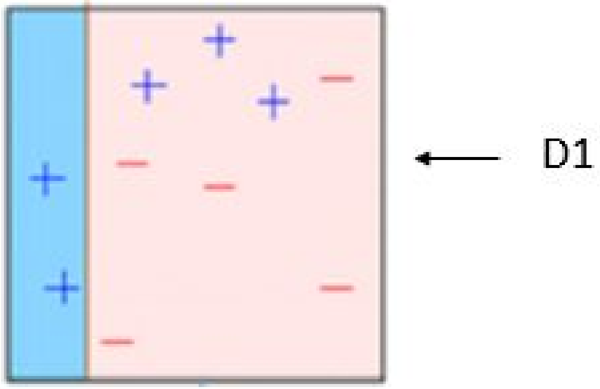
Combines output of all learners into weighted sum



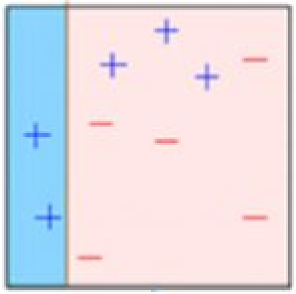
$$H(x) = sign(\alpha_1 h_1(x) + \alpha_2 h_2(x) + \alpha_3 h_3(x))$$

Source

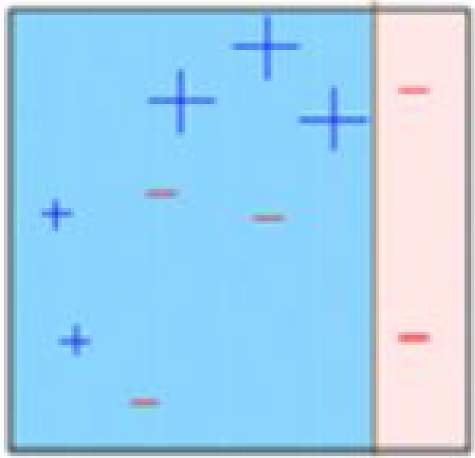
AdaBoost



AdaBoost

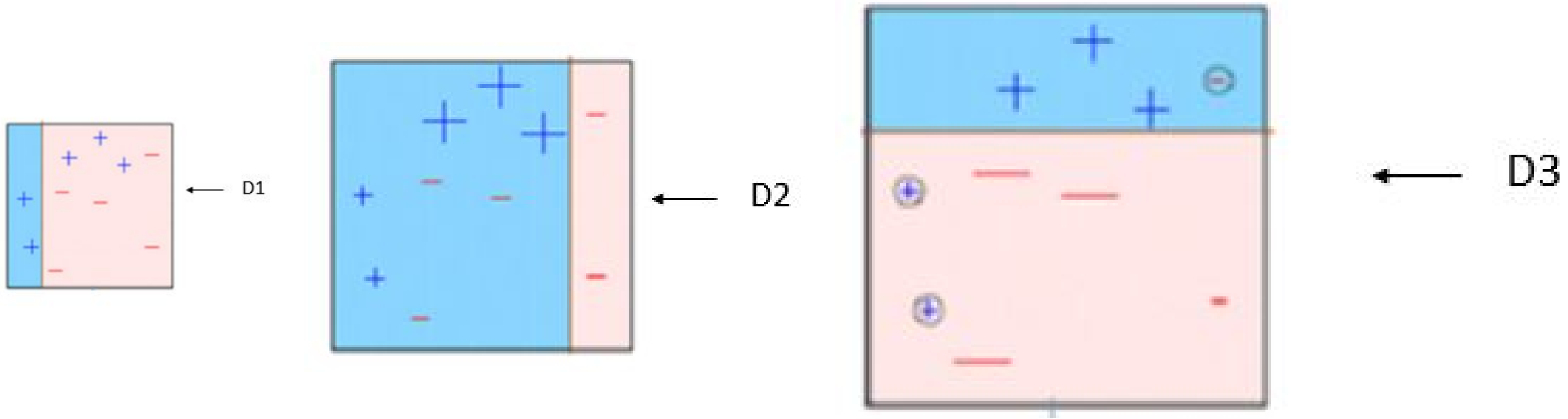


D1

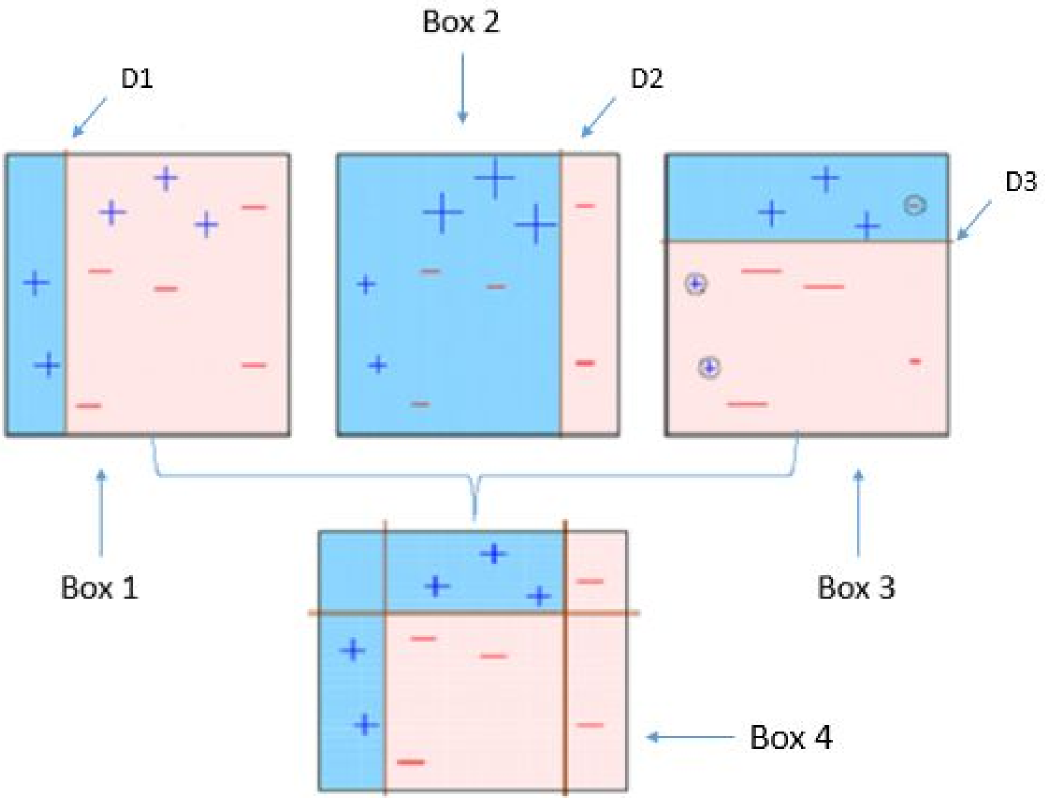


D2

AdaBoost



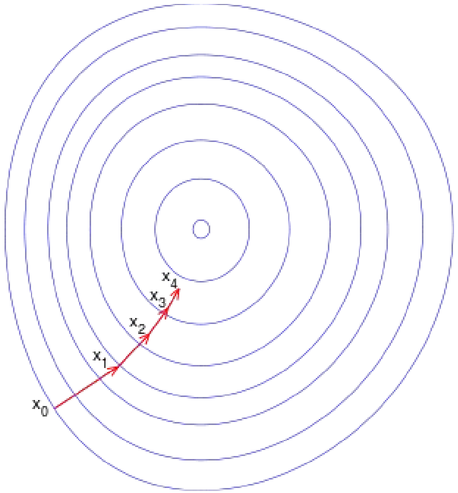
AdaBoost



XGBoost

Short for e**X**treme **G**radient **Boost**ing. Sequentially generates weak learners like AdaBoost

- Updates model by computing cost function
  - Computes gradient of cost function
  - Direction of greatest decrease = negative of gradient
  - Creates new learner with parameters adjusted in this direction

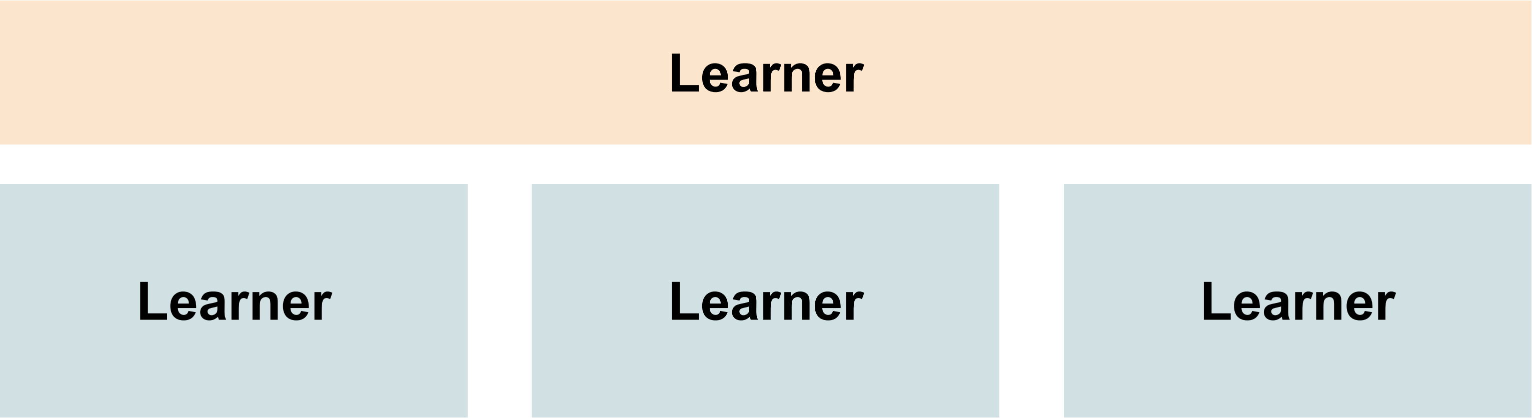


Source

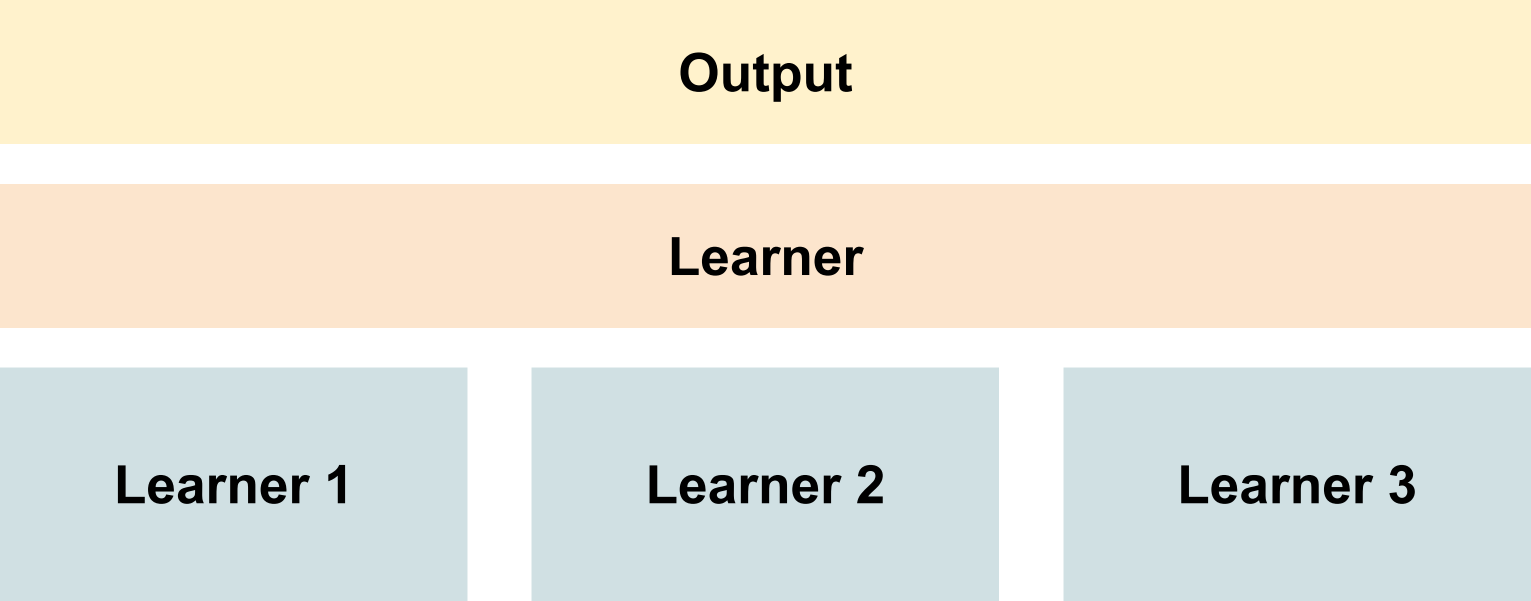
Stacking

Bagging	Boosting	Stacking

Stacking



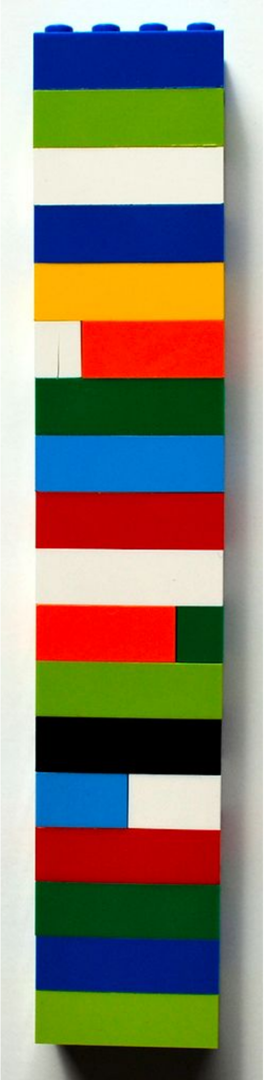
Stacking



Stacking pt. 1

Assumption: can improve performance by taking a **weighted average** of the predictions of models.

- Take a bunch of machine learning models.
- Apply these models on subsets of your data (how you choose them is up to you).
- Obtain predictions from each of the models.



Source

Stacking pt. 2

Once we have predictions from each individual model...

- Perform Top-Layer-ML on the predictions.
  - This gives you the coefficients of the weighted average.
- Result: a massive blend of potentially hundreds of models.

Source

CDS Core Team Example: Stacking

CDS Kaggle Team (2017 March Madness Kaggle competition)

- Each member of the Kaggle team made a logistic regression model based on different features
- Combined these using a stacked model

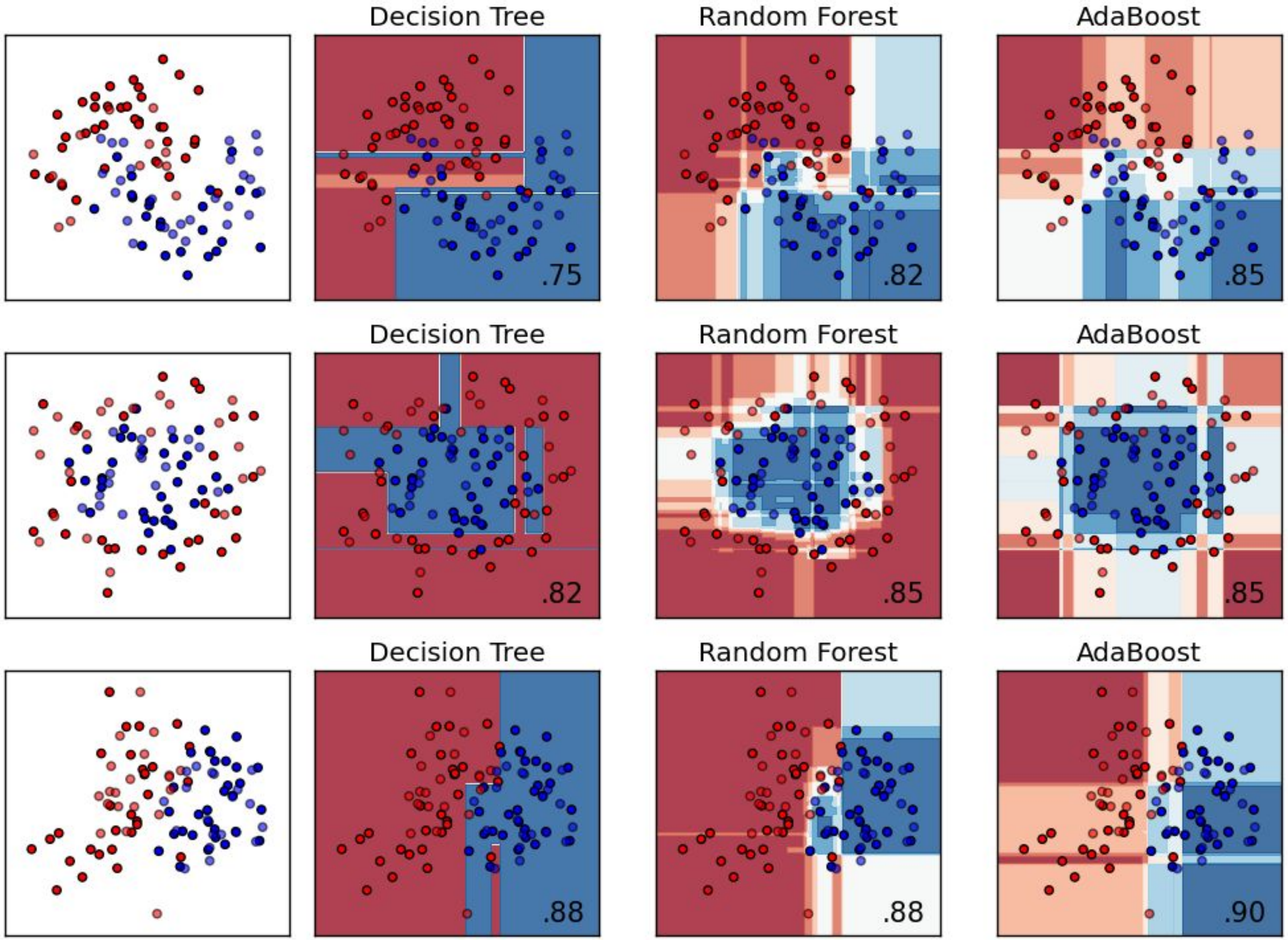
Source

Coming Up

Your problem set: Project Part C due this Sunday 11:59 PM

Next week: Bias-variance trade-off

See you then!


Decision Tree
Random Forest
AdaBoost
.75
.82
.85
Decision Tree
Random Forest
AdaBoost
.82
.85
.85
Decision Tree
Random Forest
AdaBoost
.88
.88
.90

Random Forest Parameters

- Minimum number of observations in a branch
  - `min_samples_split` parameter
  - Smaller the node size, more branches, longer the computation
- Number of trees
  - `n_estimators` parameter
  - Fewer trees means *less accurate* prediction
  - More trees means *longer computation* time
  - Diminishing returns after a couple hundred trees