

# Ensemble Method and Boosting

Son Nguyen

# Netflix Prize

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# Netflix Prize

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# Netflix Prize

- The winning team: BellKor's Pragmatic Chaos, used **ensemble models**
- The second-place team's name is "The Ensemble"

# Netflix Prize

- "During the nearly 3 years of the Netflix competition, there were two main factors which improved the overall accuracy:
  - The quality of the individual algorithms, and
  - the **ensemble idea**"



# Ensemble Success

"XGBoost (an ensemble algorithm) is an algorithm that has recently been dominating applied machine learning and Kaggle competitions for structured or tabular data." [Link](#)

- List of machine learning winning solutions with XGBoost :  
<https://github.com/dmlc/xgboost/tree/master/demo#machine-learning-challenge-winning-solutions>

# Ensemble Success

Adaboost (an ensemble algorithm) won 2003 **Godel Prize**: AdaBoost demonstrated novel possibilities in analysing data and is a permanent contribution to science even beyond computer science. [Link](#)

# Ensemble Success

AdaBoost (with decision trees as the weak learners) is often referred to as the best out-of-the-box classifier. [Link](#)

# Ensemble Success

Leo Brieman, who invented "Bagging" and "Random Forest" crowned AdaBoost the "best off-the-shelf classifier in the world (2000).

# Ensemble Machine Learning Approach

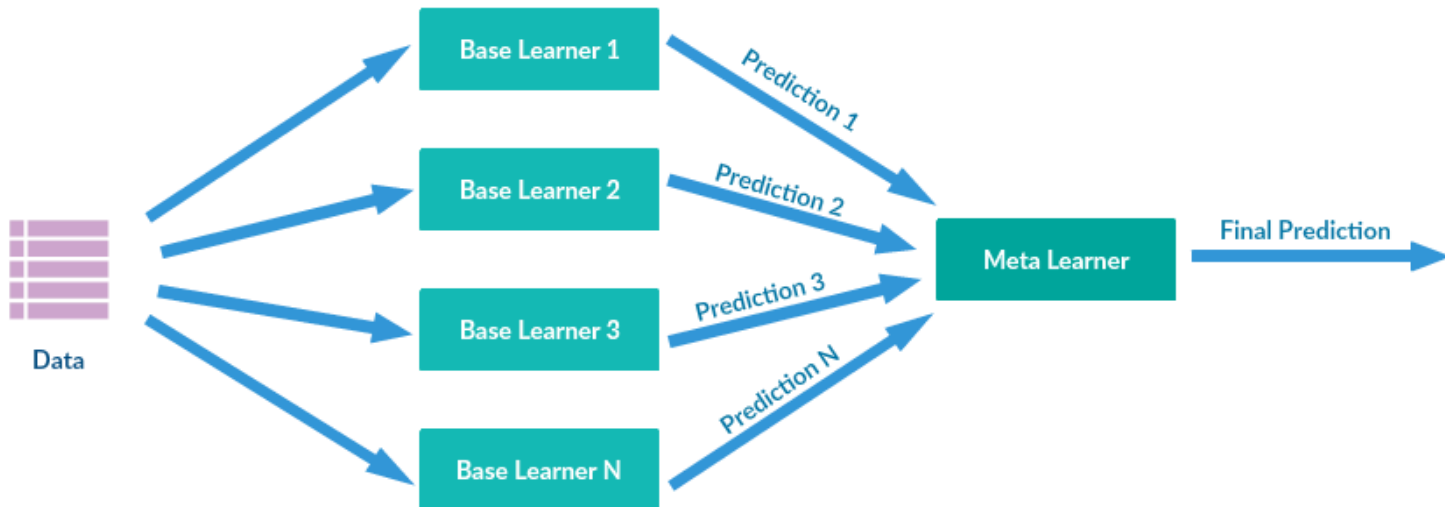
- An ensemble is a composite model, combining a series of low performing **classifiers**(classification models) or **learners** with the aim of creating an improved classifier.

# Ensemble Machine Learning Approach

- An ensemble is a composite model, combining a series of low performing **classifiers**(classification models) or **learners** with the aim of creating an improved classifier.
- Three common ensemble:
  - Stacking
  - Bagging
  - Boosting

# Stacking

- Stacking combines multiple base learners predictions into a new data set.
- This new data are treated as the **input data** for another learner (meta learner).



$x_1$	$x_2$	...	$x_k$	$y$	$M_1$	$M_2$	$M_3$

Stacking

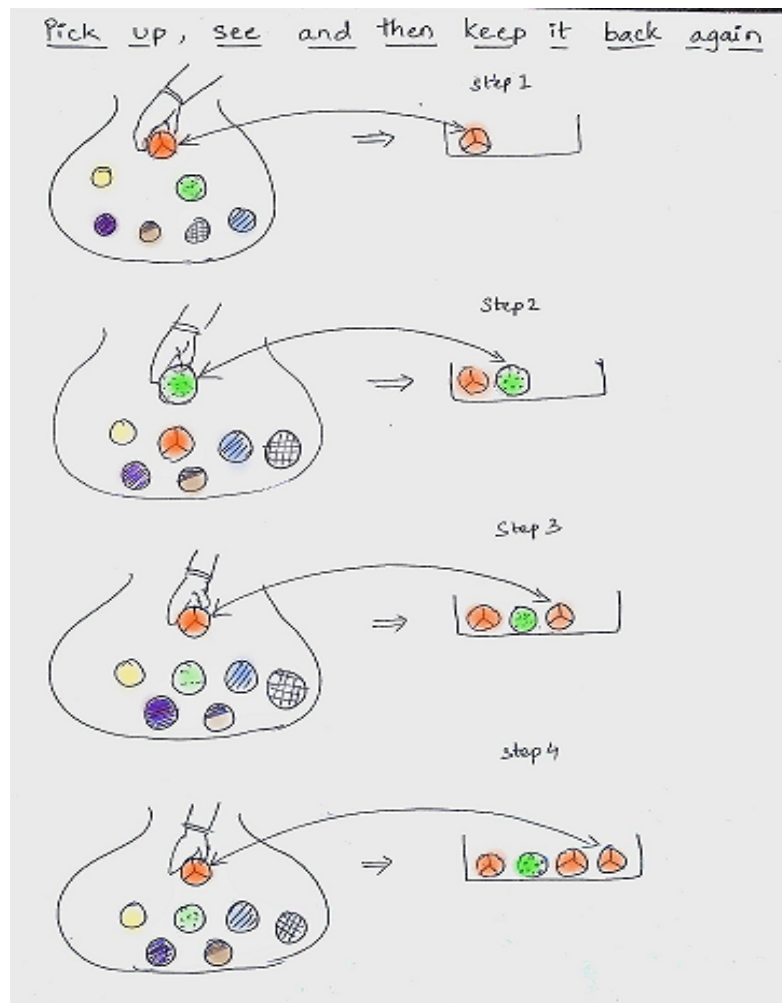
				$M_1$	$M_2$	$M_3$	$y$	meta model
$x_1$	$x_2$	...	$x_k$	$x_{k+1}$	$x_{k+2}$	$x_{k+3}$		

Data to train the "meta" model



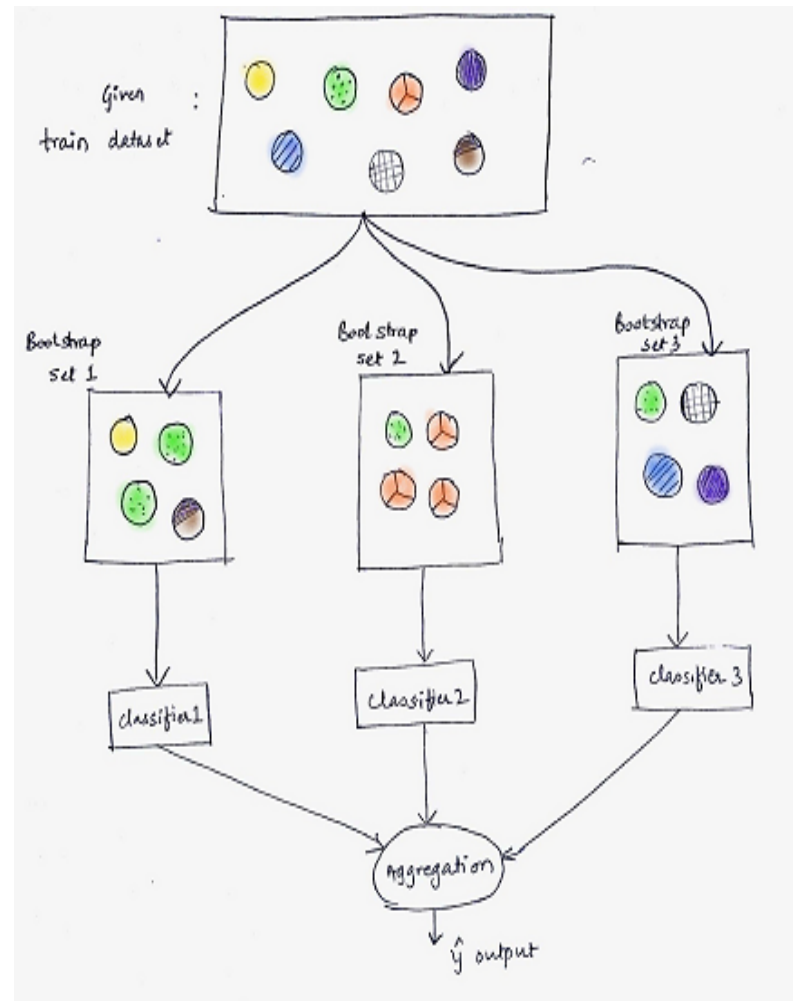
# Bagging = Bootstrap Aggregating

- Step 1: Bootstrapping



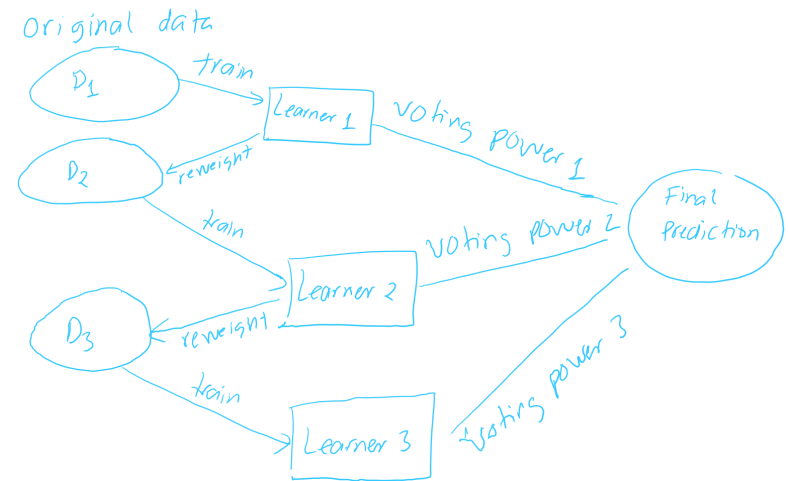
# Bagging = Bootstrap Aggregating

- Step 2: Aggregating



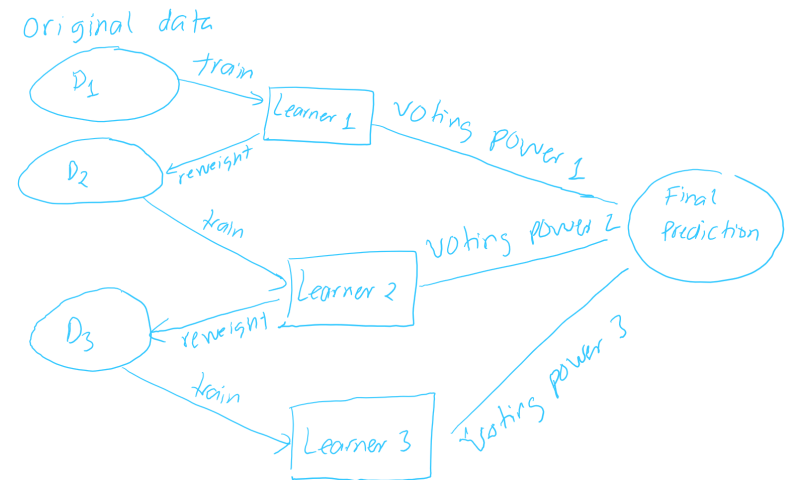
# Boosting

- Weak learners are sequentially converted into a strong learner.



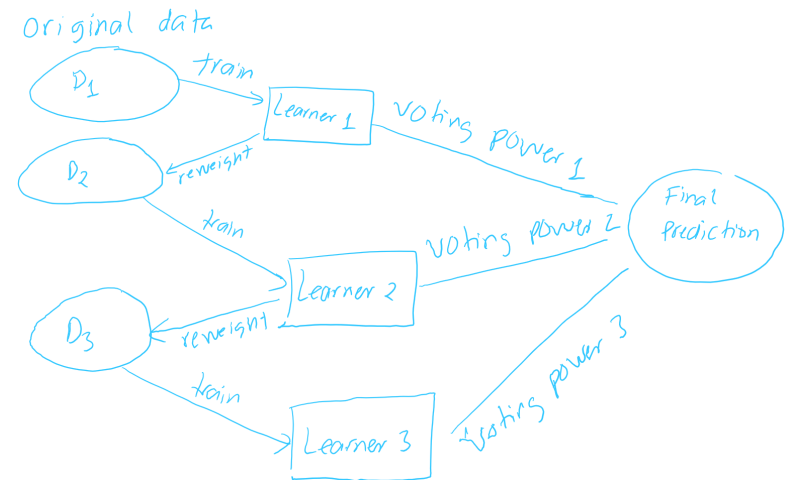
# Boosting

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- Each learner in the sequence tries to correct its predecessor.



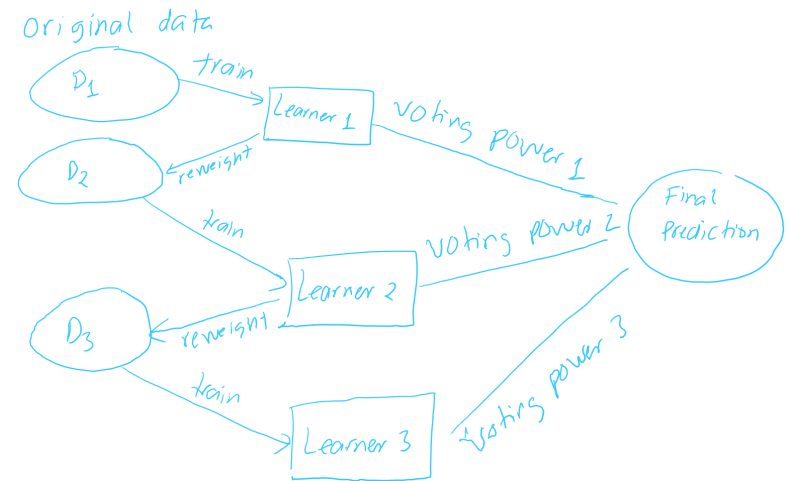
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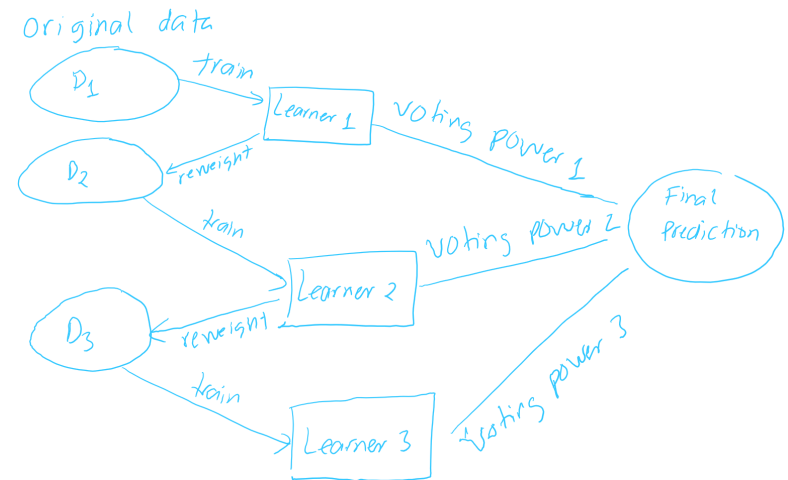
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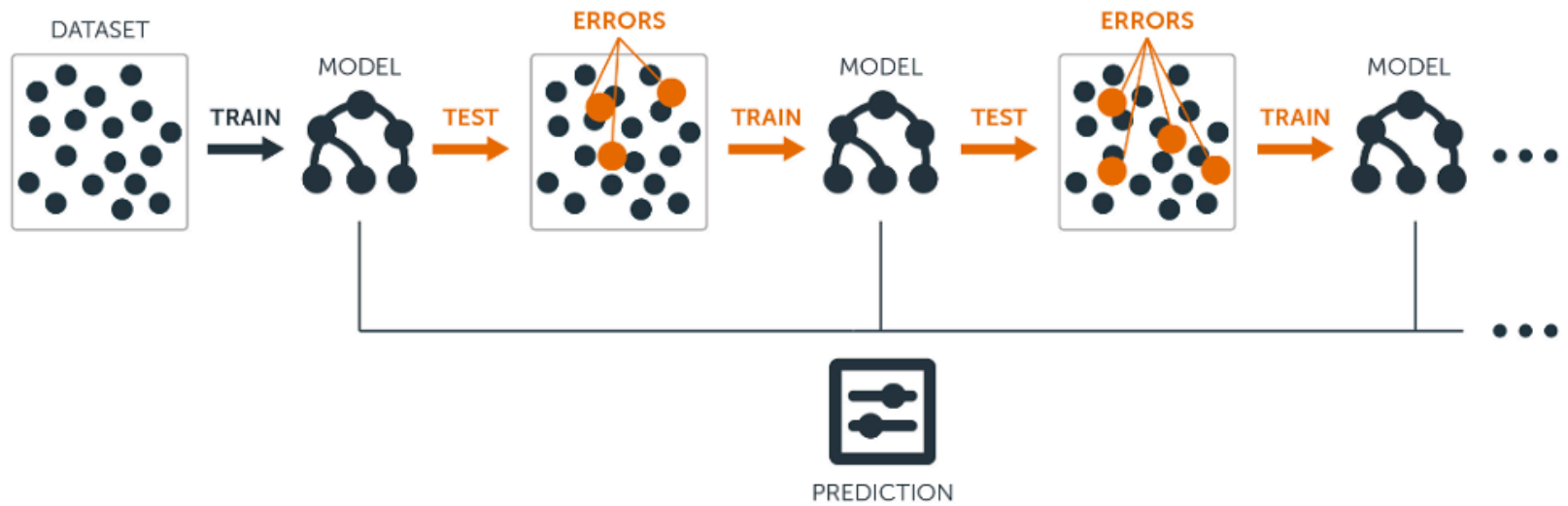


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- The learners are usually a tree with 2 leaves (**Stump**).
- In  $D_2$ , the wrong misclassified of Learner 1 gets higher weights.
- In  $D_3$ , the wrong misclassified of Learner 2 gets higher weights.

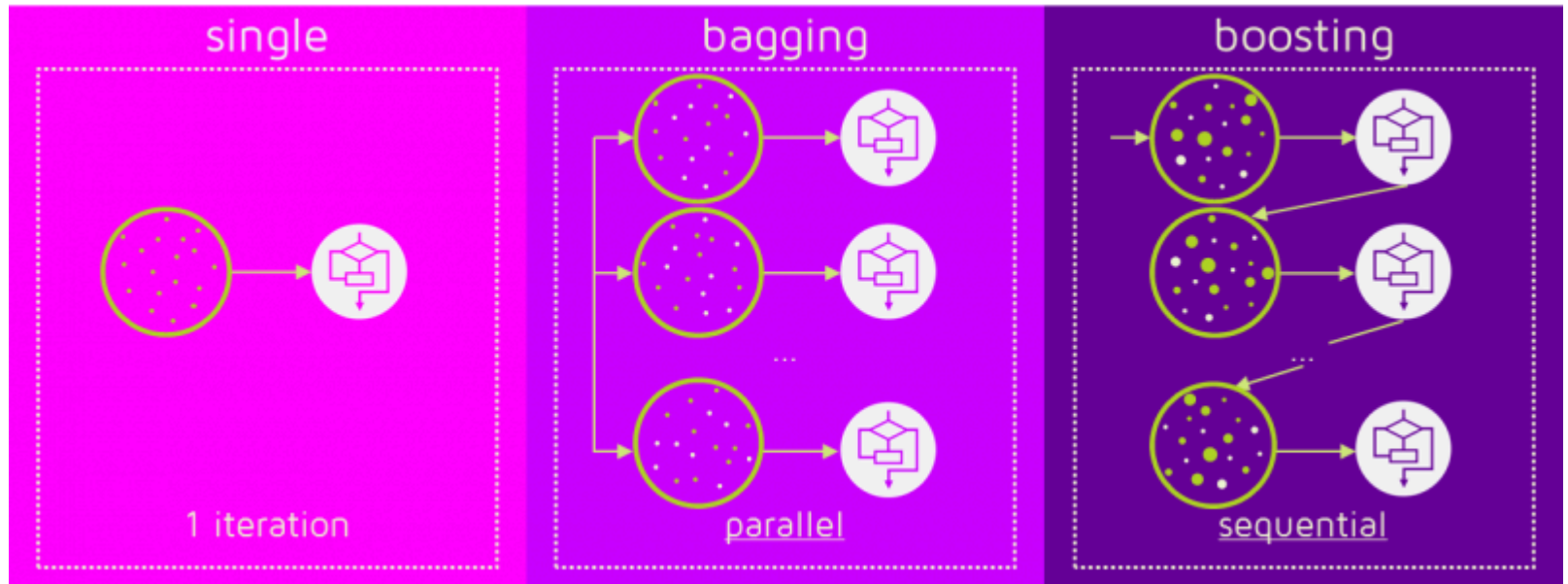


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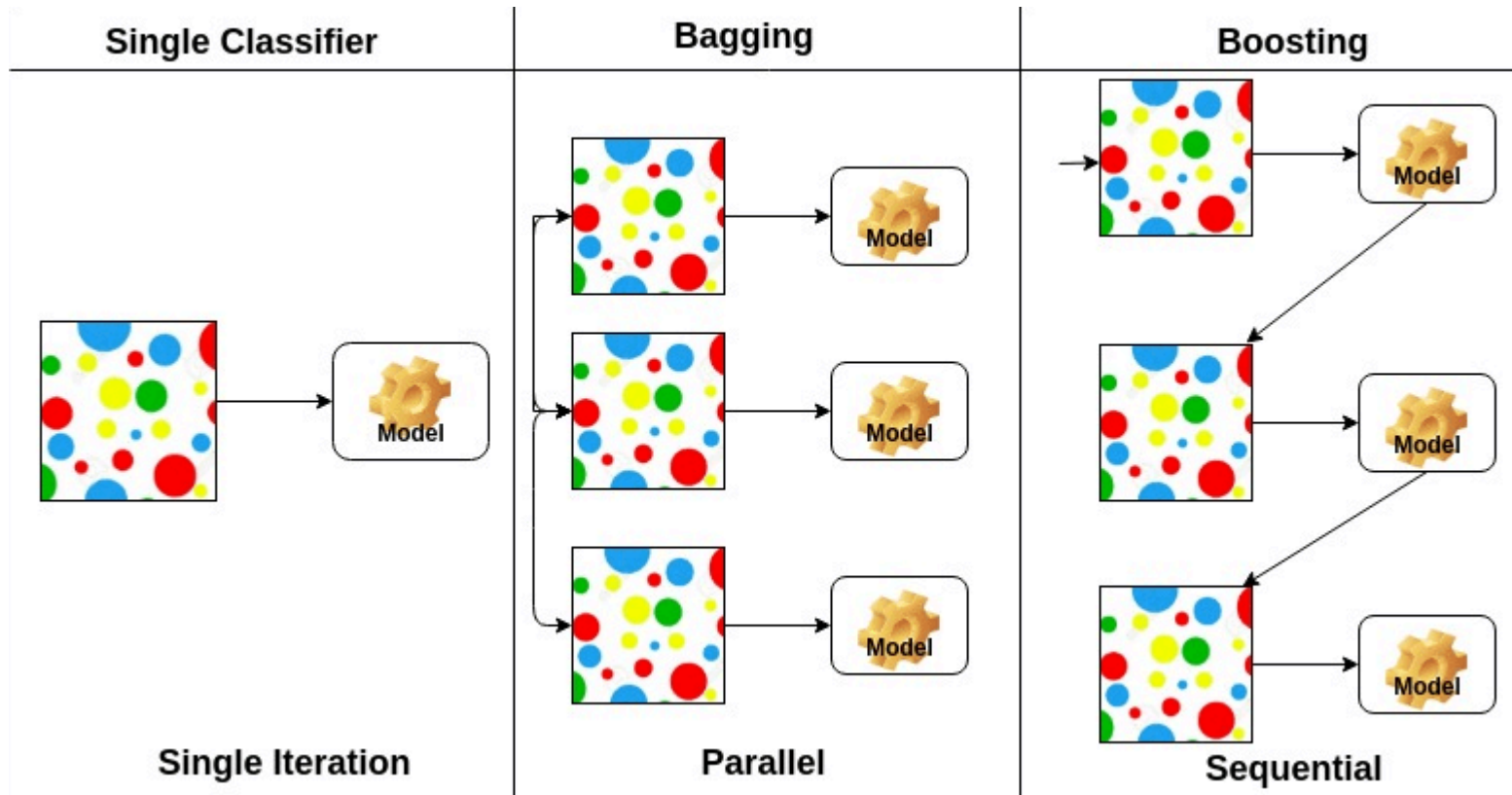




# Bagging vs. Boosting



# Bagging vs. Boosting



# Types of Boosting

- Adaboost
- Gradient Boosting

# Adaboost

## Idea Behind Ada Boost

- Examples of high weight are shown more often at later rounds
- Face/nonface classification problem:

### Round 1

best weak classifier:

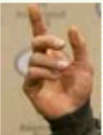
change weights:

						
1/7	1/7	1/7	1/7	1/7	1/7	1/7
✓	✗	✓	✓	✗	✓	✗
1/16	1/4	1/16	1/16	1/4	1/16	1/4

### Round 2

best weak classifier:

change weights:

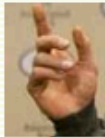
									
✓	✓	✓	✗	✗	✗	✓	✓	✓	✓
1/8	1/32	1/32	11/32		1/2		1/8	1/32	1/32

# Adaboost

## Idea Behind Ada Boost

Round 3



- out of all available weak classifiers, we choose the one that works best on the data we have at round 3
- we assume there is always a weak classifier better than random (better than 50% error)
-  image is half of the data given to the classifier
- chosen weak classifier **has to** classify this image correctly

# Adaboost, Clearly Explained

- Demonstration by StatQuest
- [Link](#)