

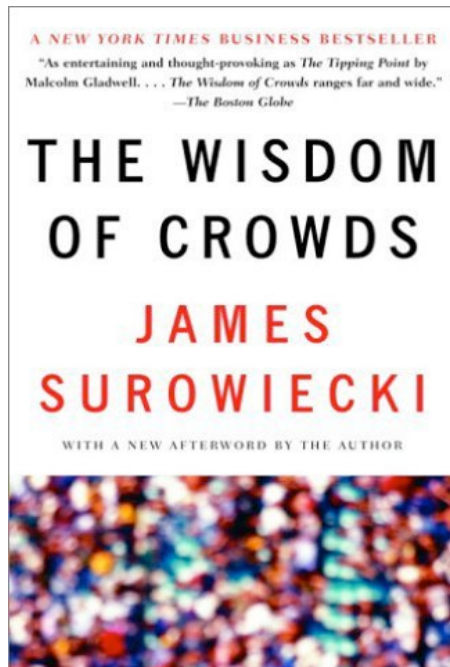
# Introduction to Data Science

**INTRO TO ENSEMBLES AND STACKING**  
**BRIAN D'ALESSANDRO**

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# WISDOM OF CROWDS

This concept can be applied to Machine Learning.  
This is called Ensemble Learning



## *Conditions for This to Work*

### **Diversity**

Each person should have private information

### **Independence**

Peoples opinions aren't determined by opinions of others

### **Aggregation**

Some mechanism exists for turning individual opinions into a collective decision.

# TYPES OF ENSEMBLE METHODS

## Stacking

Taking a weighted combination of the predictions of a total of  $S$  different classifiers.

## Bagging

Generating multiple classifiers from the same data by resampling, and aggregating the multiple classifications into a single prediction

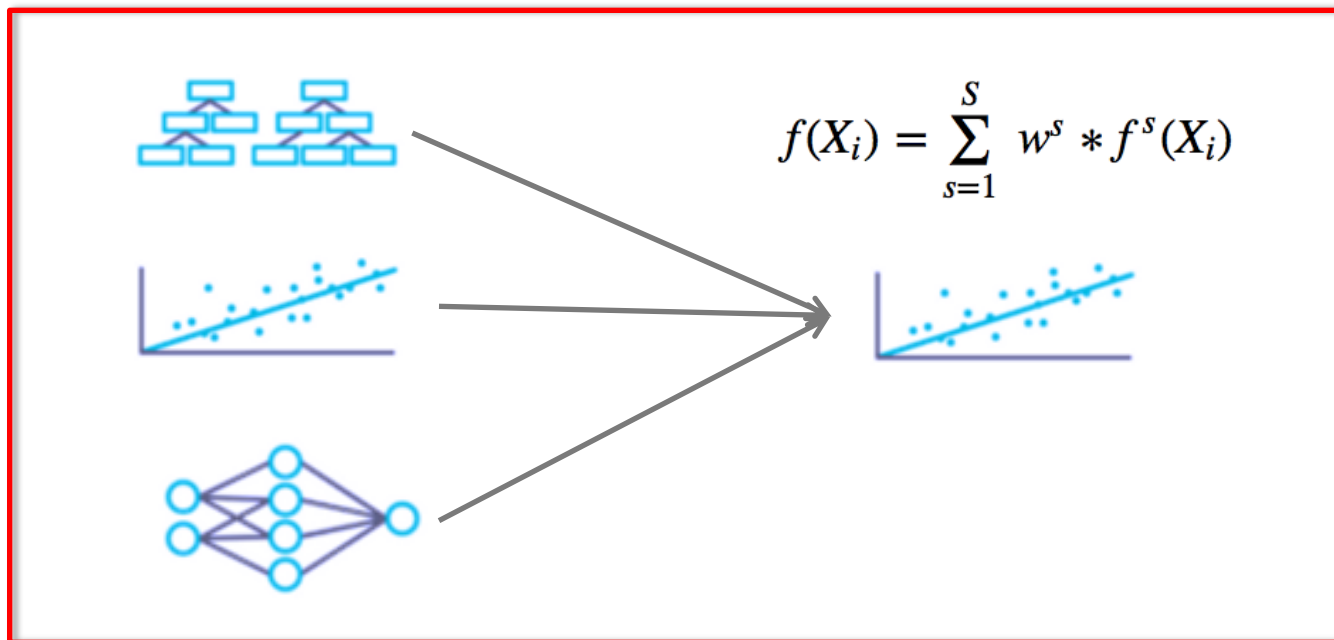
## Boosting

Building new classifiers iteratively, using cumulative errors to inform or weight additional classifiers. Aggregating the set of classifiers into a single prediction.

# A SIMPLE ENSEMBLE METHOD

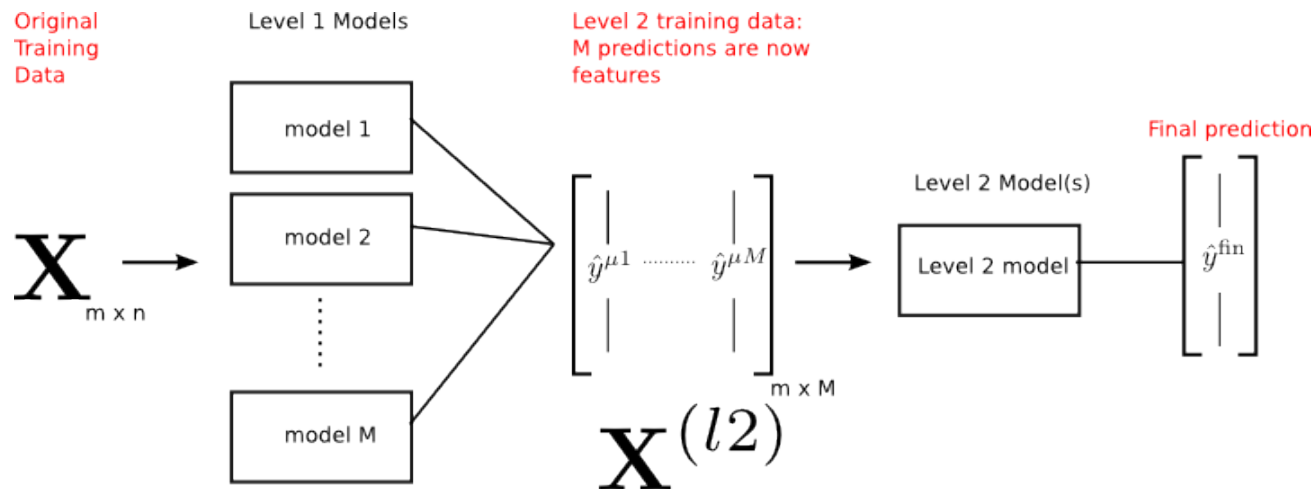
**Stacking** – Let  $f^s(X_i)$  be some prediction on a sample using some arbitrary classifier  $s$ . Stacking is the process of taking a weighted combination of the predictions of a total of  $S$  different classifiers.

The weights can be a simple average, or learned via a secondary classification/regression process.



# BUILDING A STACKED ENSEMBLE

When we wish to learn the weights (using ML), we build the ensemble in two stages.



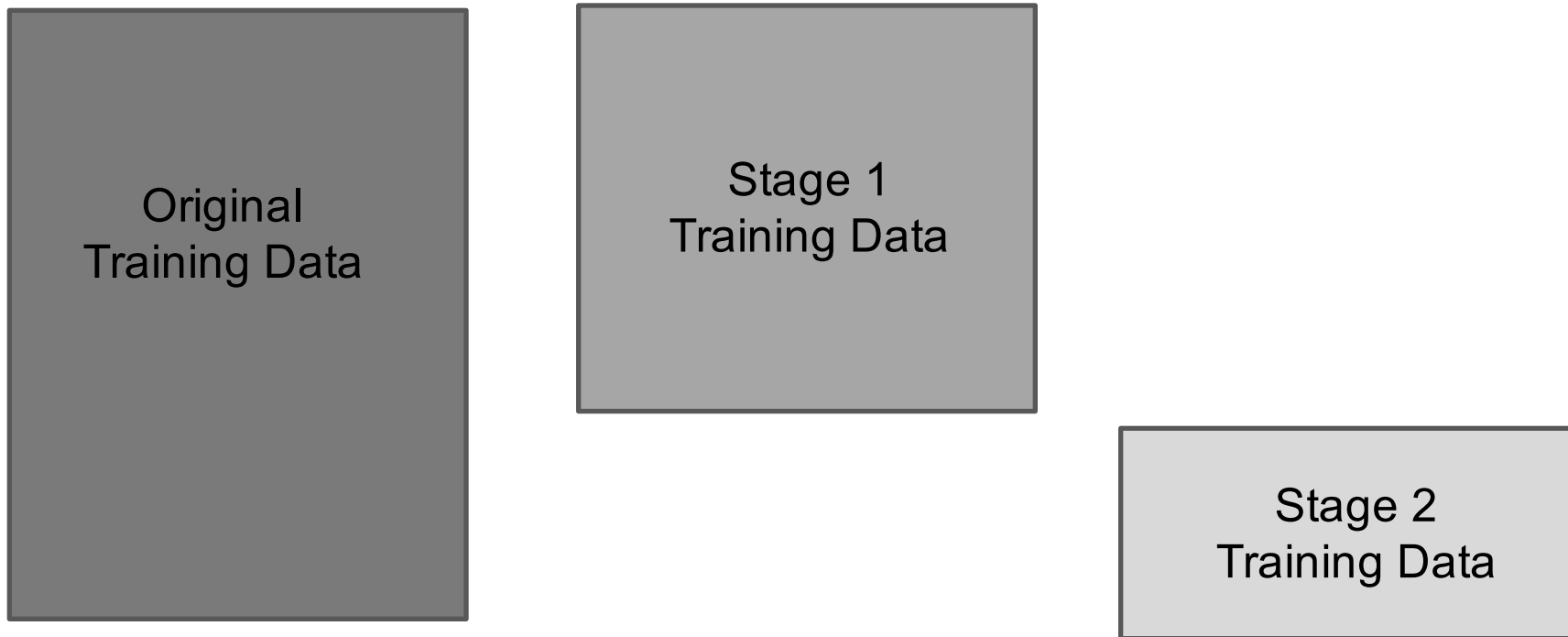
**Stage 1:** Build M different (and diverse) classifiers on the original training data.

**Stage 2:** Score each of the M classifiers from stage 1 on stage 2 training data. Use the output of M stage 1 classifiers as features for stage 2 model

Image source: <https://www.kdnuggets.com/2017/02/stacking-models-improved-predictions.html>

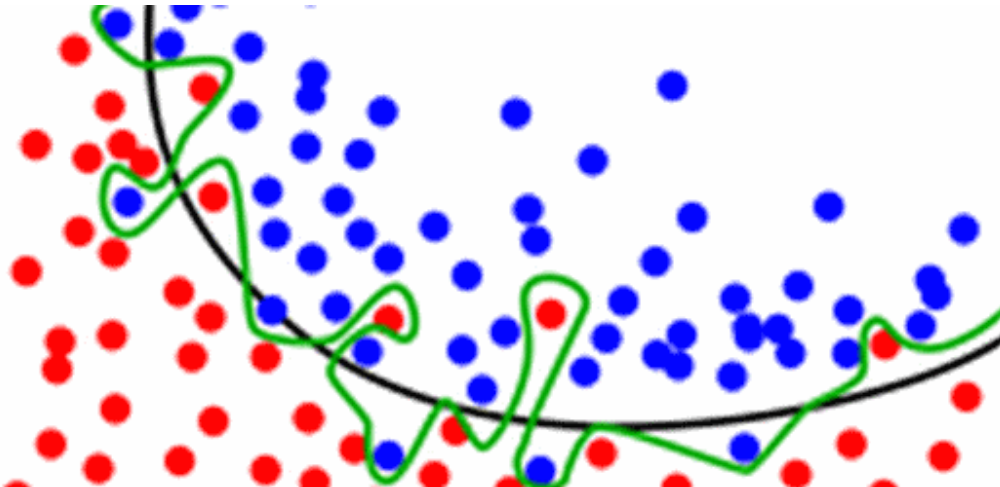
# BEING CAREFUL ABOUT GENERALIZATION

In order for learned stacking to generalize appropriately, the stage 2 model needs to be built from data that is separate from the stage 1 models. Otherwise the system risks overfitting. Note that this is best accomplished when sample sizes are large.



Further reading: <https://bradleyboehmke.github.io/HOML/stacking.html>

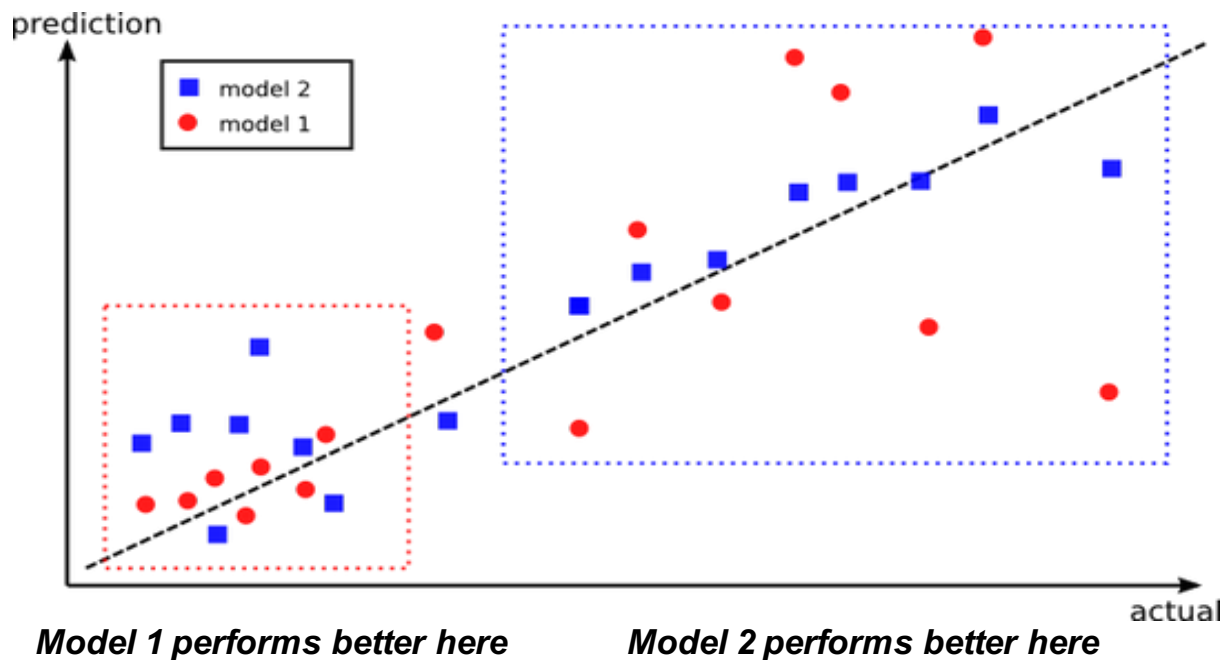
# WHY DOES STACKING WORK?



**Case 1:** In the case of simple averaging (or learned simple models), the weighted average model de-noises individual models that are potentially overfit around the decision boundaries

Image source: <https://mlwave.com/kaggle-ensembling-guide/>

# WHY DOES STACKING WORK?



**Case 2:** Different models perform better on different parts of the input space  $X$ . I.e., more complex models will do better on regions of  $X$  with higher support. More biased models may then be better where there is lower support. Stacking learns the best of both worlds.

Image source: <https://www.kdnuggets.com/2017/02/stacking-models-improved-predictions.html>