Predictive Modeling in R

A Brief Introduction

NUIT Summer Data Science and Programming Workshop

July 25, 2019, 1 – 4 pm Chambers Hall

Andrew N Hall

Northwestern University

Our Agenda


Introduction
Regression-Based Methods
Single Decision Tree
Ensemble Methods: Random Forest, GBMs
Taking it Further: Neural Nets, NLP

Our Agenda

What is ML? Major Concepts

Application of classical statistics

Introduction to tree-based ML methods

The power of averaging weak learners

More complex methods (Touched upon briefly)

Introduction:
What is Machine Learning?


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS


Rules
Data
Classical Statistics
Answers


Rules
Data
Classical Statistics
Answers


Data
Answers
Machine Learning
Rules

Machine learning is…..

The “subfield of computer science that is concerned with building algorithms which, to be useful, rely on a collection of examples of some phenomenon. These examples can come from nature, be handcrafted by humans or generated by another algorithm.”

”Machine learning can also be defined as the process of solving a practical problem by 1) gathering a dataset, and 2) algorithmically building a statistical model based on that dataset. That statistical model is assumed to be used somehow to solve the practical problem.”

- Andriy Burkov

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Types of Machine Learning Algorithms

- **Supervised Learning**
  - Regression
    - e.g., Predict salary
  - Classification
    - e.g., Predict loan default
- **Unsupervised Learning**
  - PCA
    - e.g., Personality traits
  - K-Means
    - e.g., Clinical disorder clustering
- **Reinforcement Learning**
  - e.g., Teach computer how to play Mario

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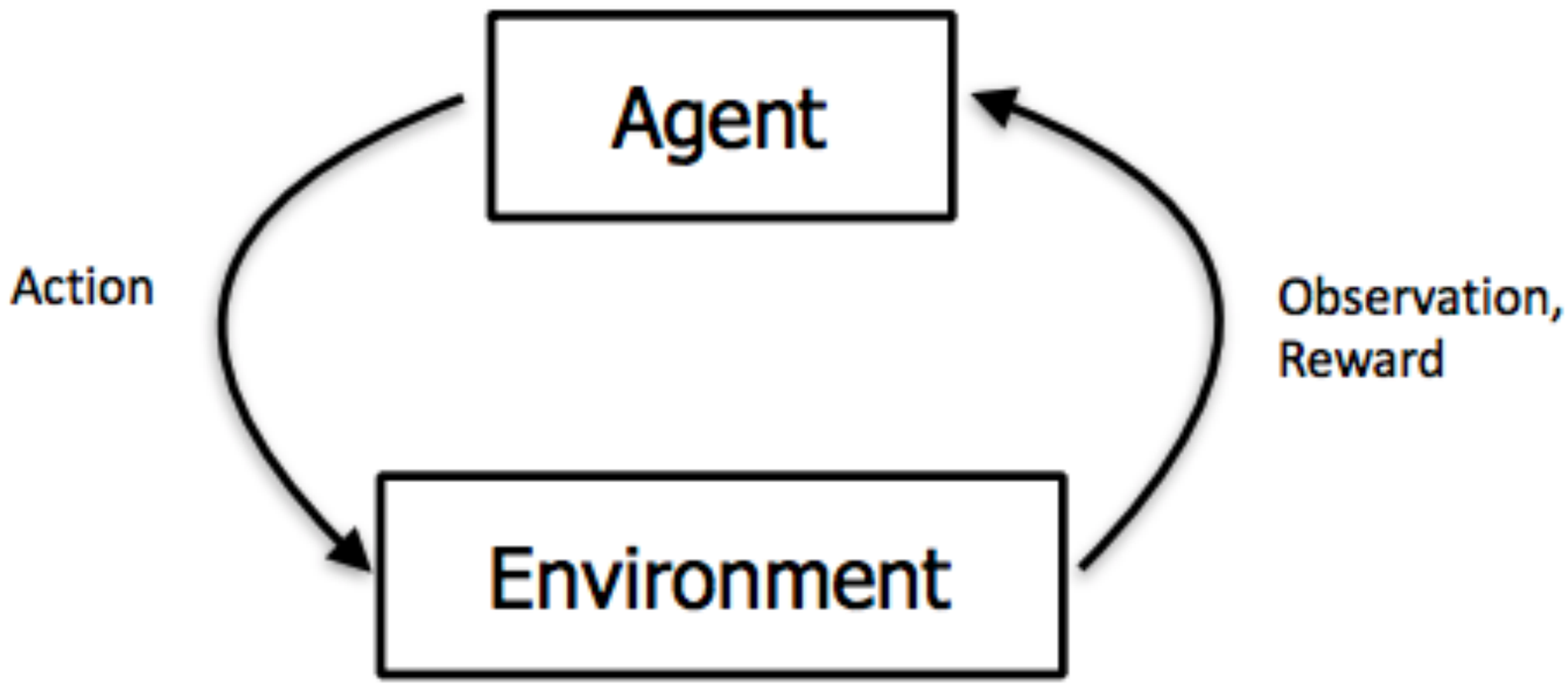
Reinforcement Learning

e.g., Teach computer how to play Mario

Reinforcement Learning (in *very* brief)



Machine placed in an environment where it executes actions, observes results, and responds to rewards to learn a policy of “behavior.”

Useful when: decision making sequential, goal is long term (e.g., game playing, logistics, robotics). Differs from one-shot predictions on data from past.

https://www.youtube.com/watch?v=qv6UVOQ0F44&t=2s

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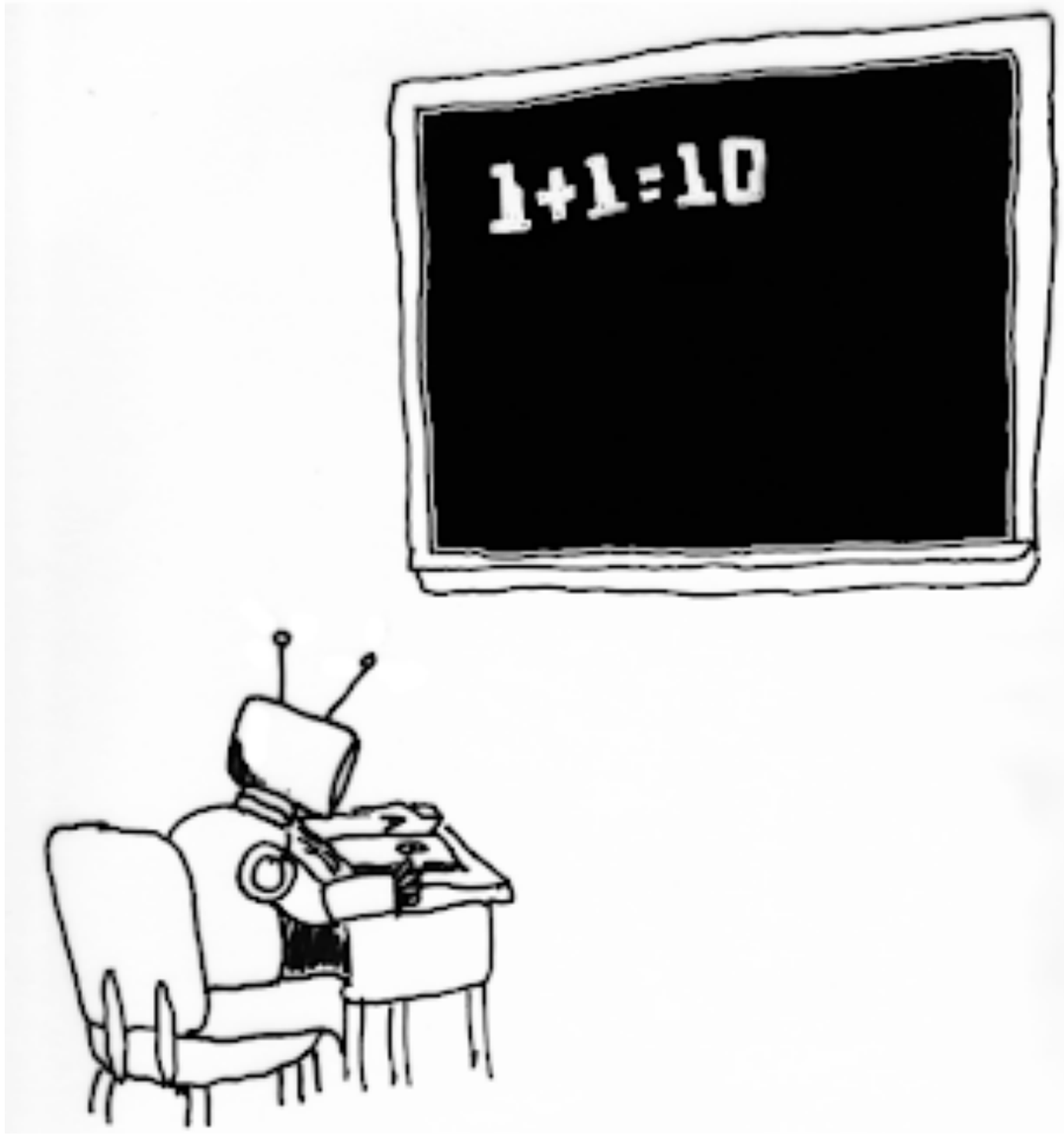
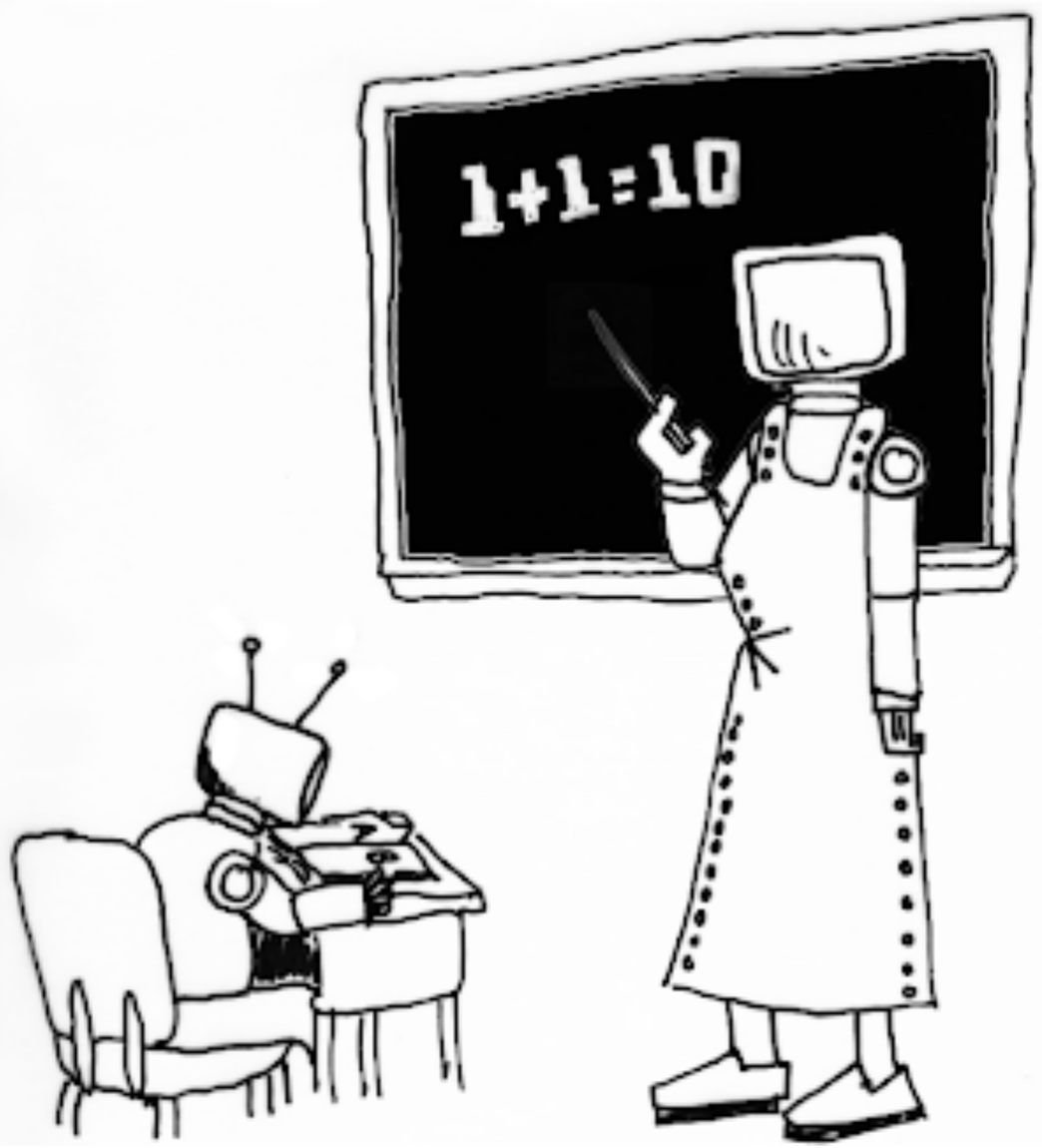
UNSUPERVISED MACHINE LEARNING

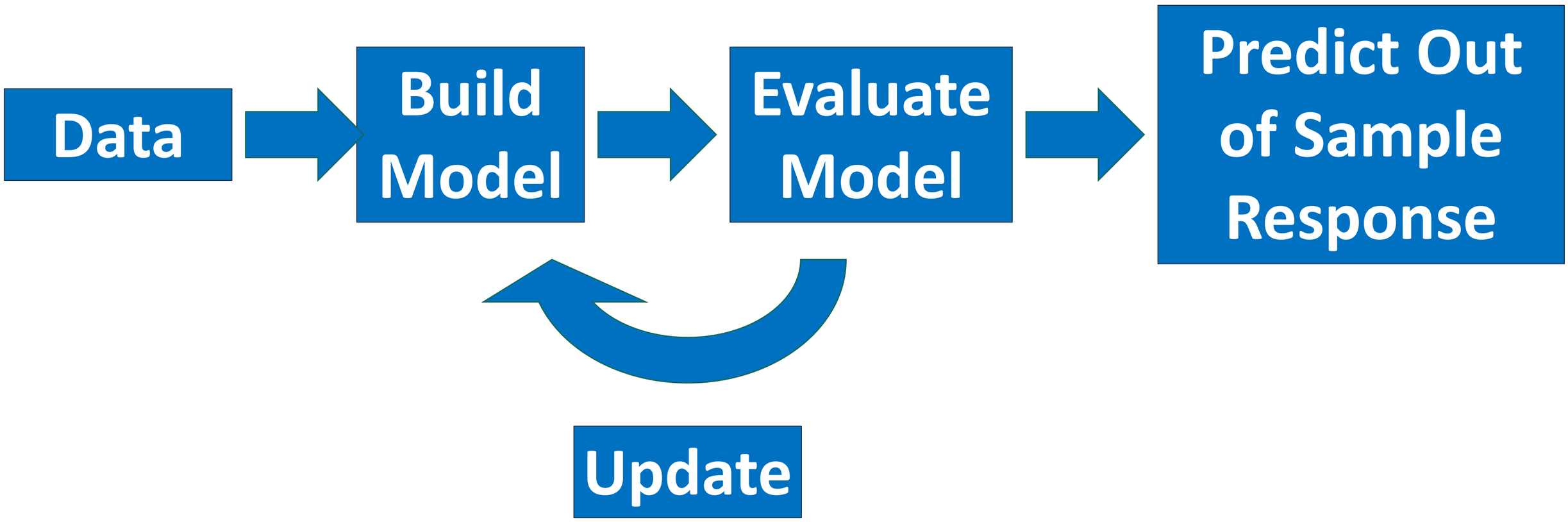


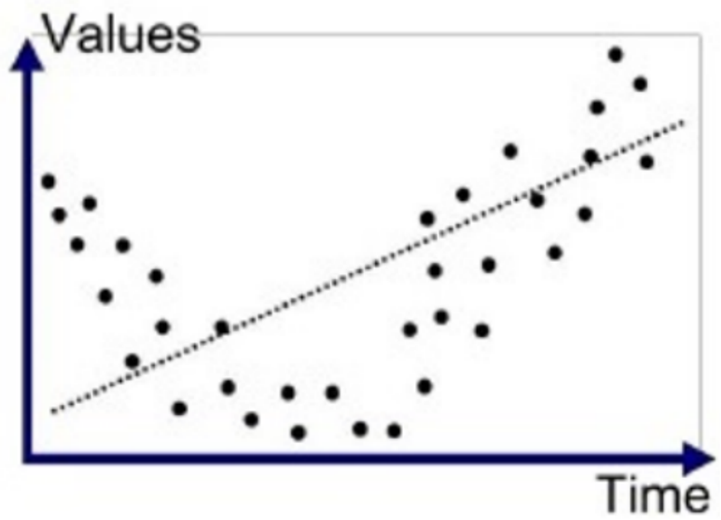
SUPERVISED MACHINE LEARNING



Key ML tenet #1: Emphasis on Prediction

- Out-of-sample generalizability is key
- Machine Learning “pipeline”





Underfit

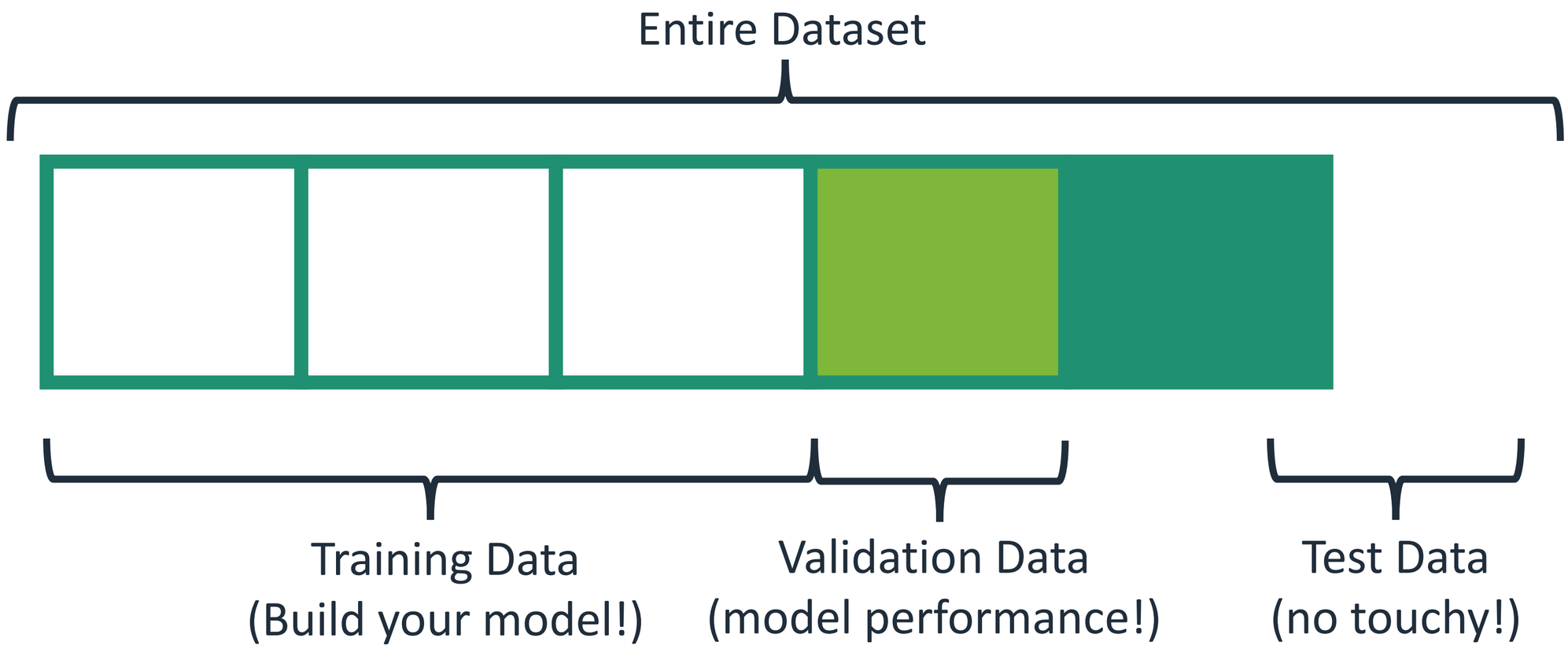
Key ML tenet #2: Bias-Variance Trade-off

Competing desires:

- Fit model to make accurate predictions for given data
- Vs. Fit model to predict future data

How do we solve this?

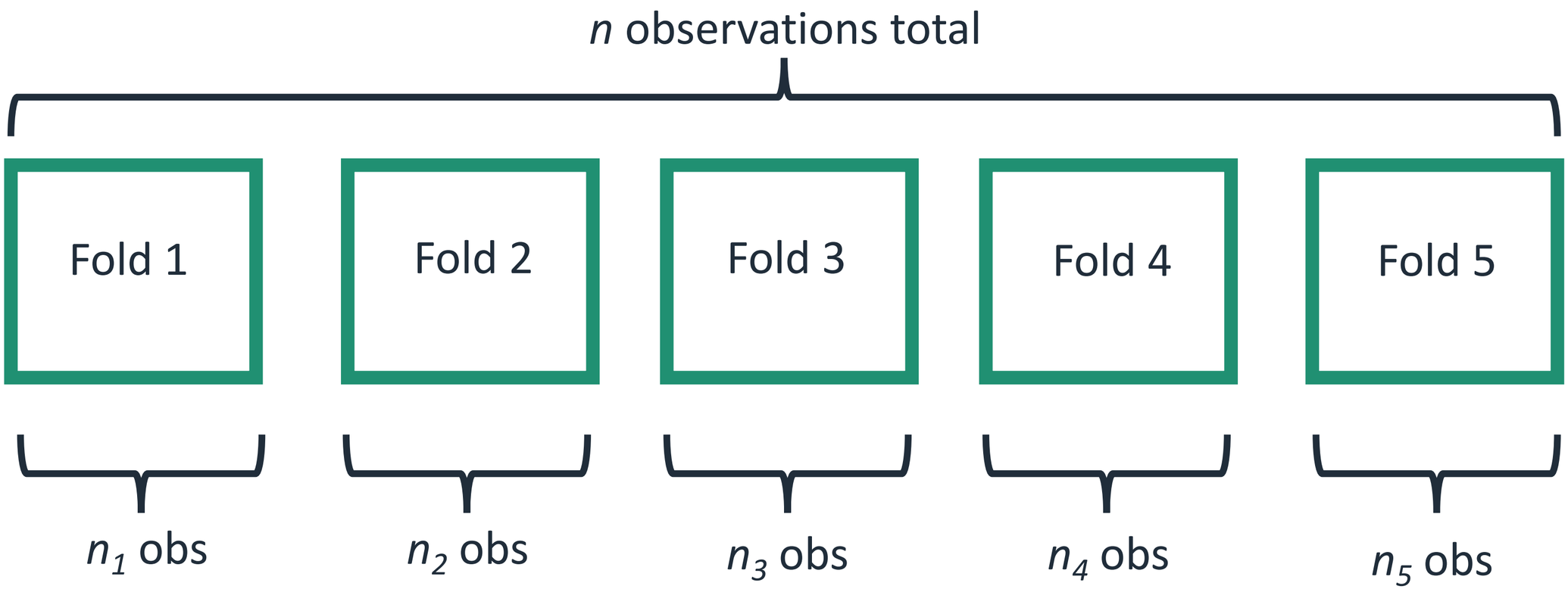
- Focus on *Test Se*t performance



Extension of test-set separation: Cross-Validation

- Separation of test set is great: completely unimplicated data, more confidence in generalizability of results.
- BUT!! You restrict data used in training.
  - If 100 observations, 40 as test set → only 60 for training
  - In general, want as many in training as possible while still leaving enough for test dataset.
- Solution? Cross-validation!

Cross-Validation (5-fold)



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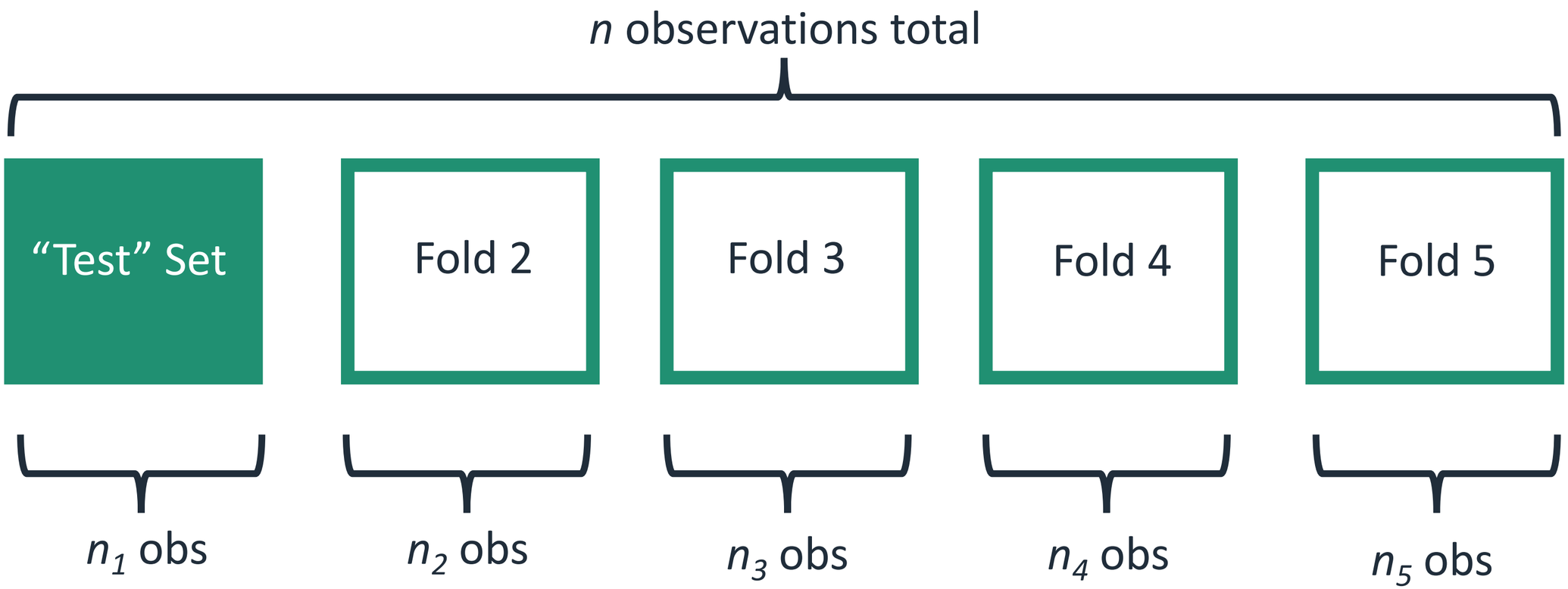

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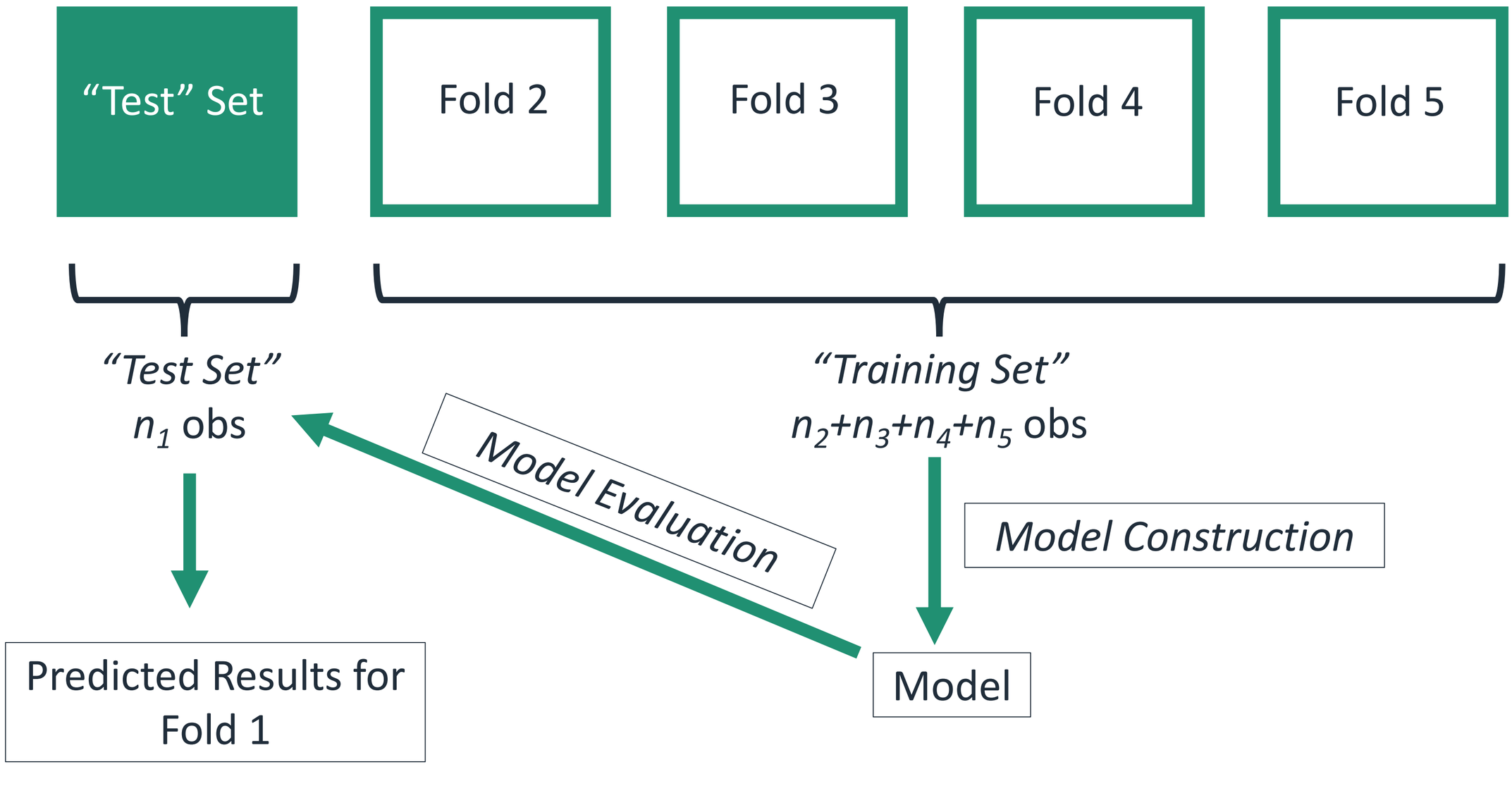

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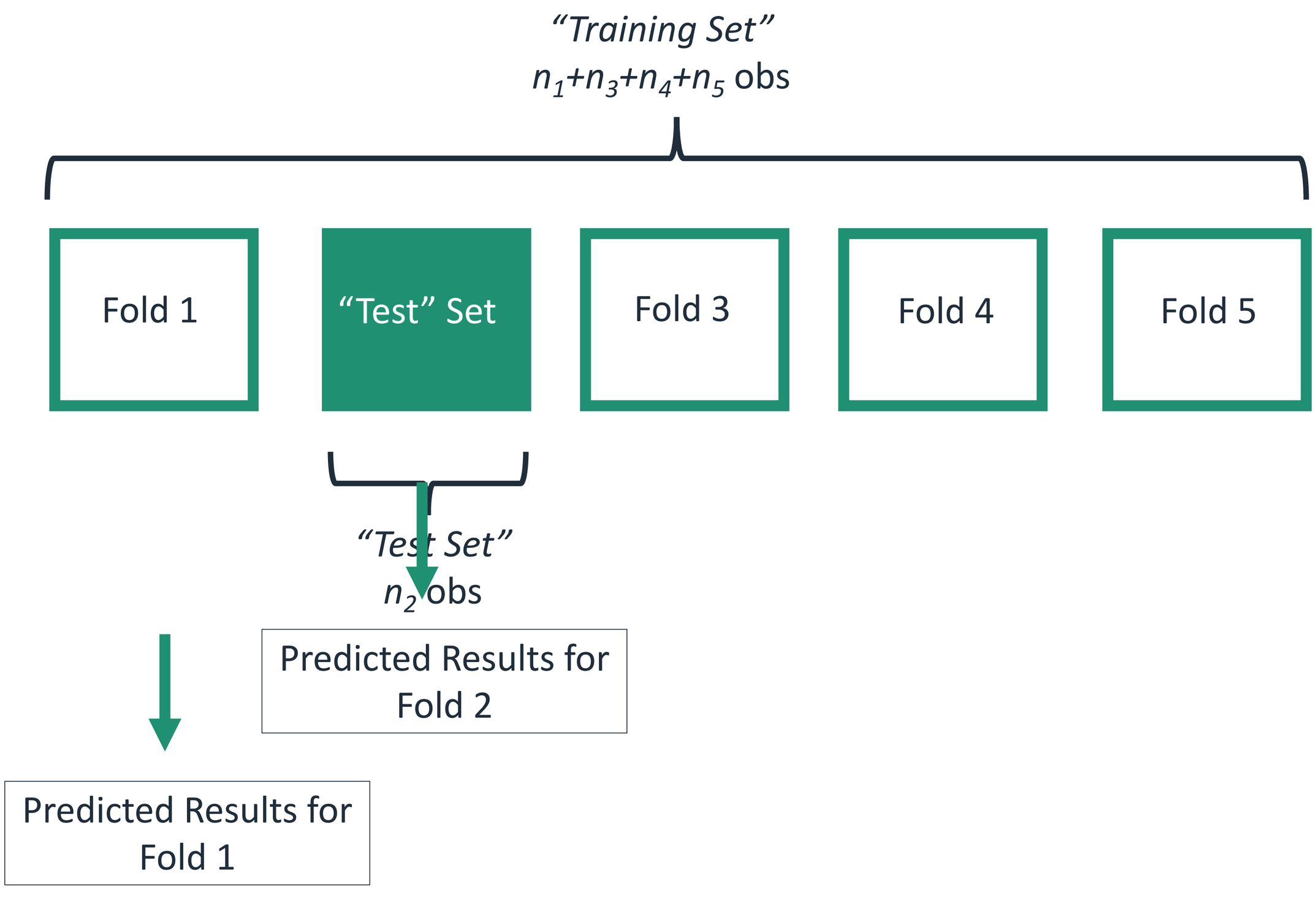

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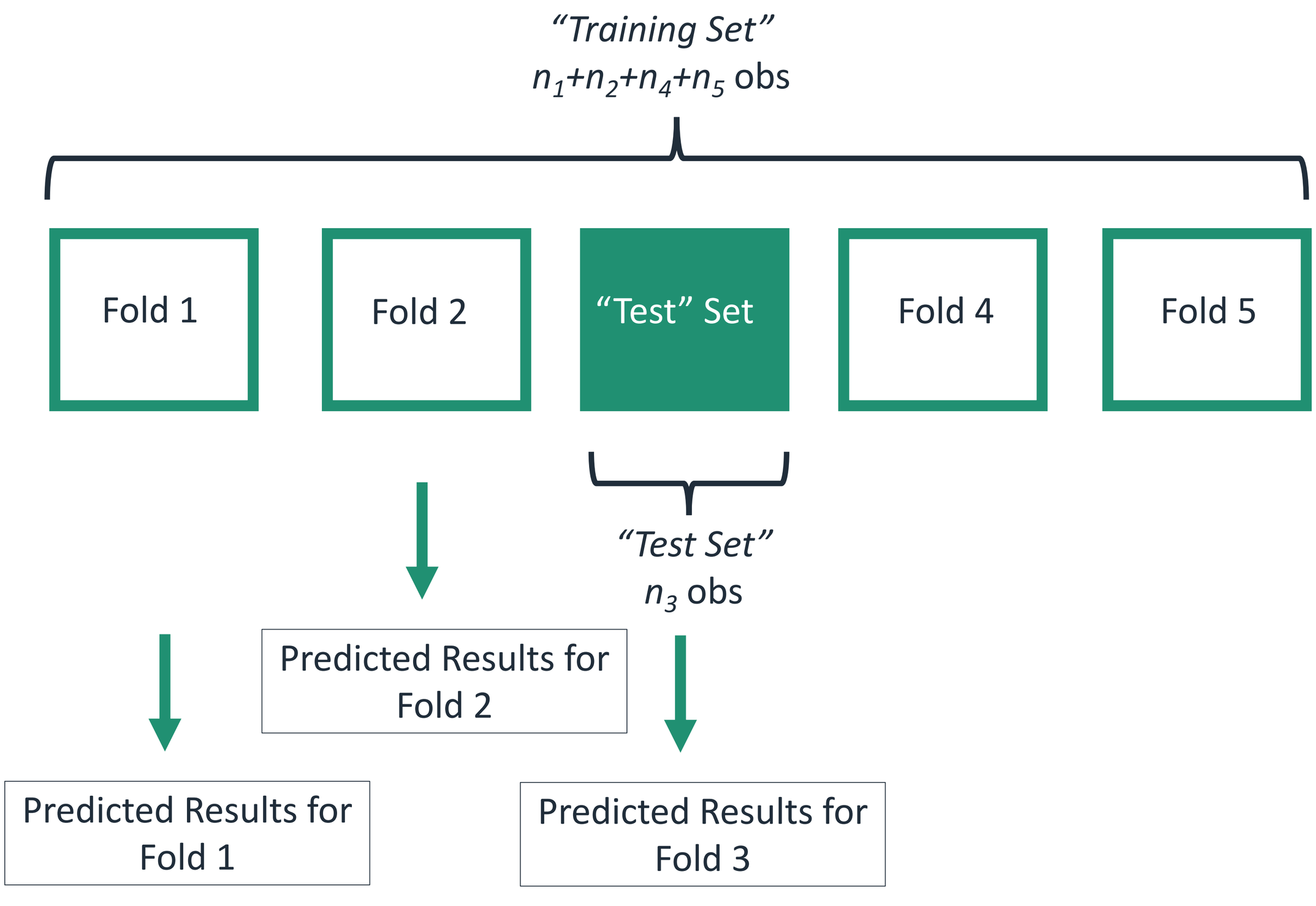

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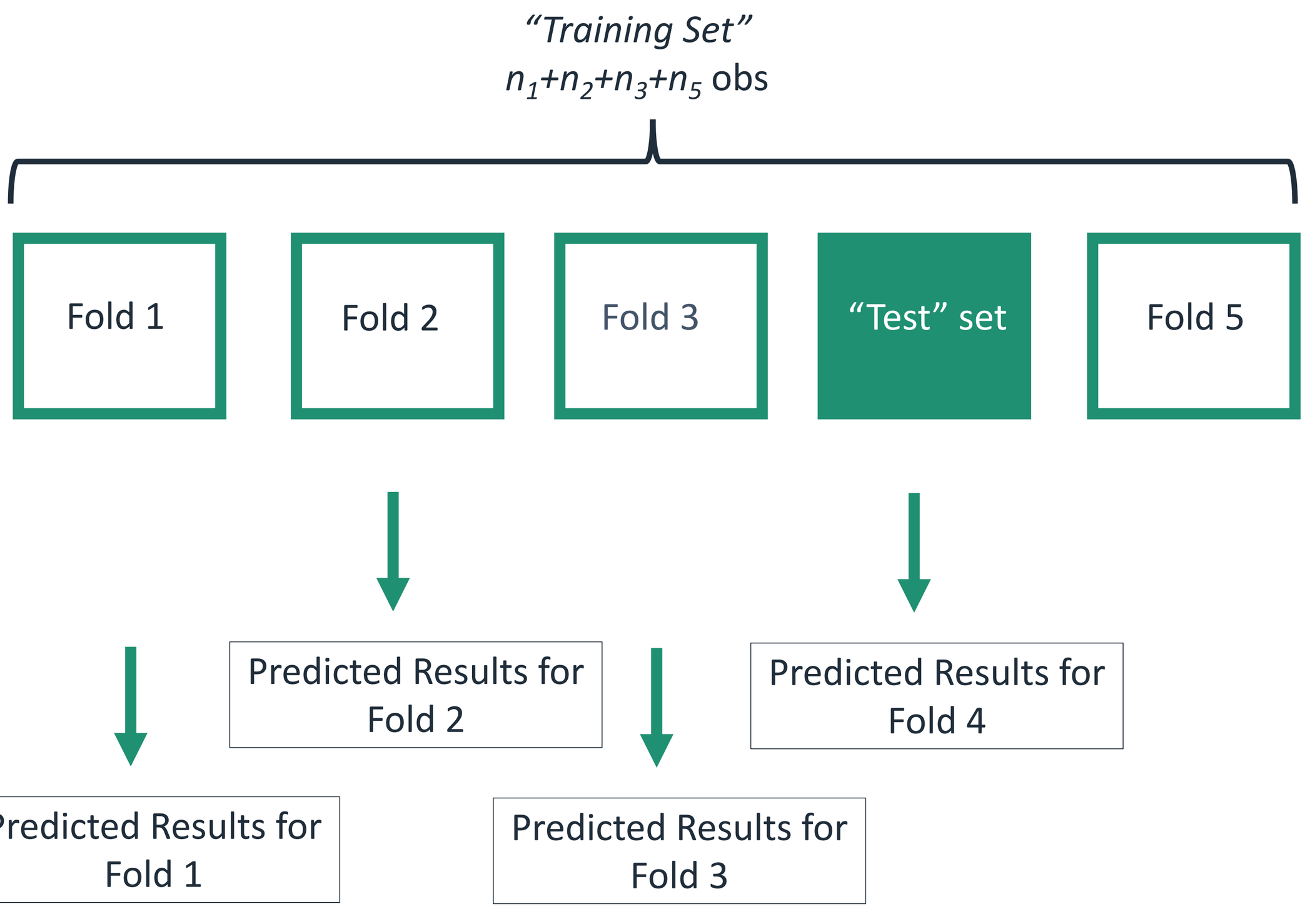


Cross-Validation (5-fold)

"Training Set"
$n_1+n_2+n_3+n_4$ obs

Fold 1 | Fold 2 | Fold 3 | Fold 4 | "Test" Set

Predicted Results for Fold 1

Predicted Results for Fold 2

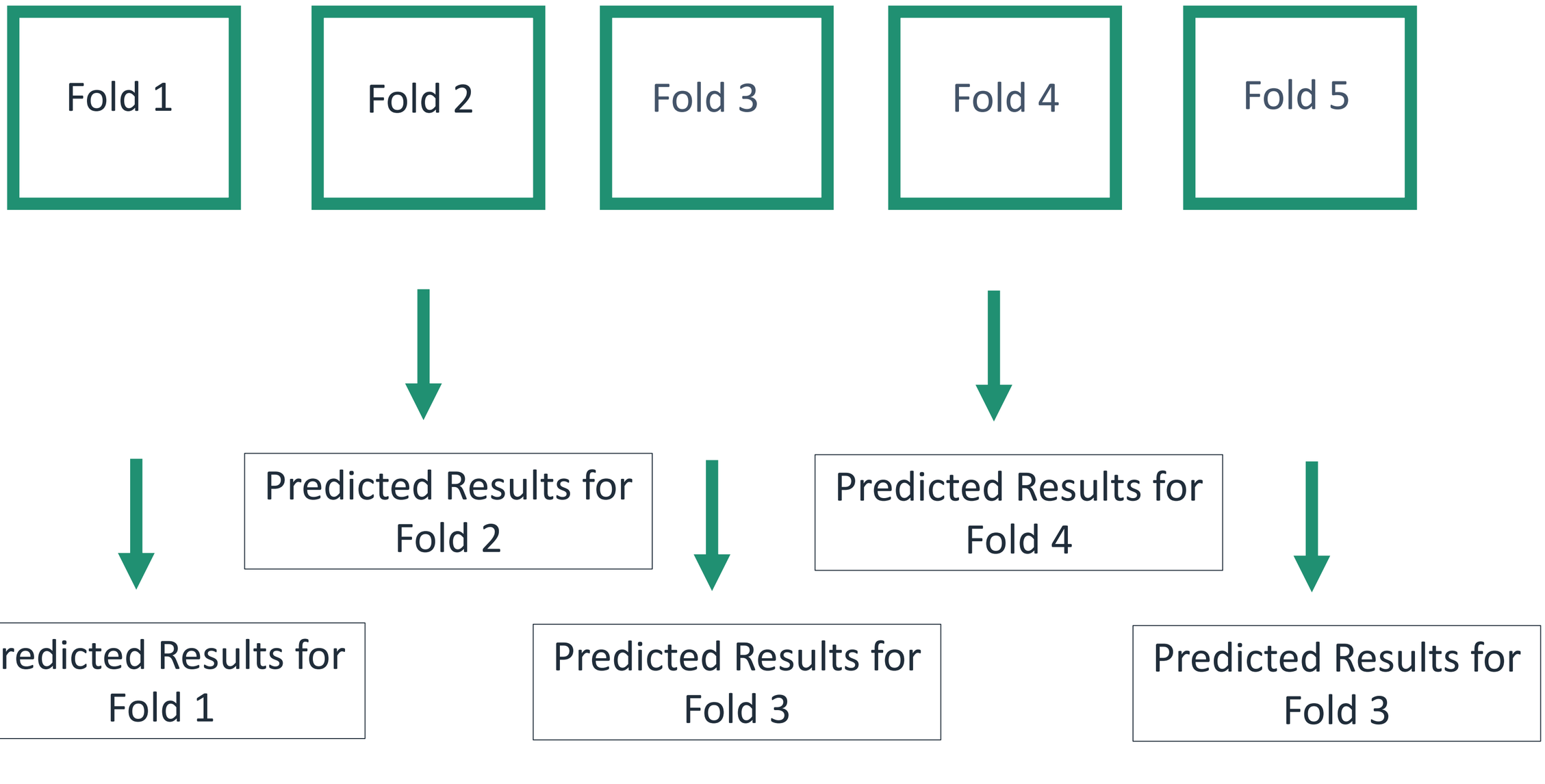
Predicted Results for Fold 3

Predicted Results for Fold 4

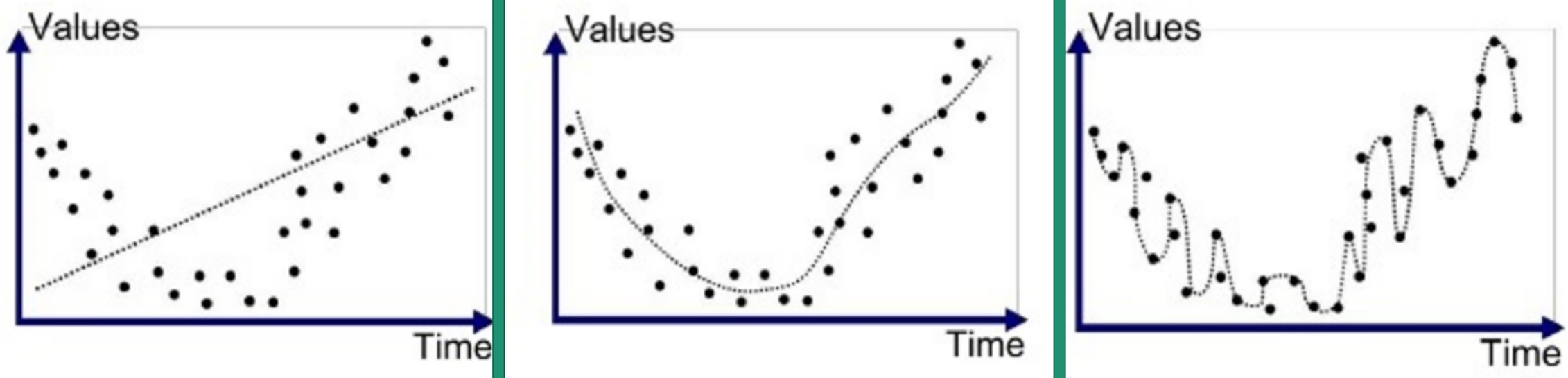
Predicted Results for Fold 5

Cross-Validation (5-fold)

We have predicted results for each fold based on the observations in all the other folds (e.g., fold 5 based on model trained on $n_1+n_2+n_3+n_4$ observations)



Cross-Validation helps avoid overfitting



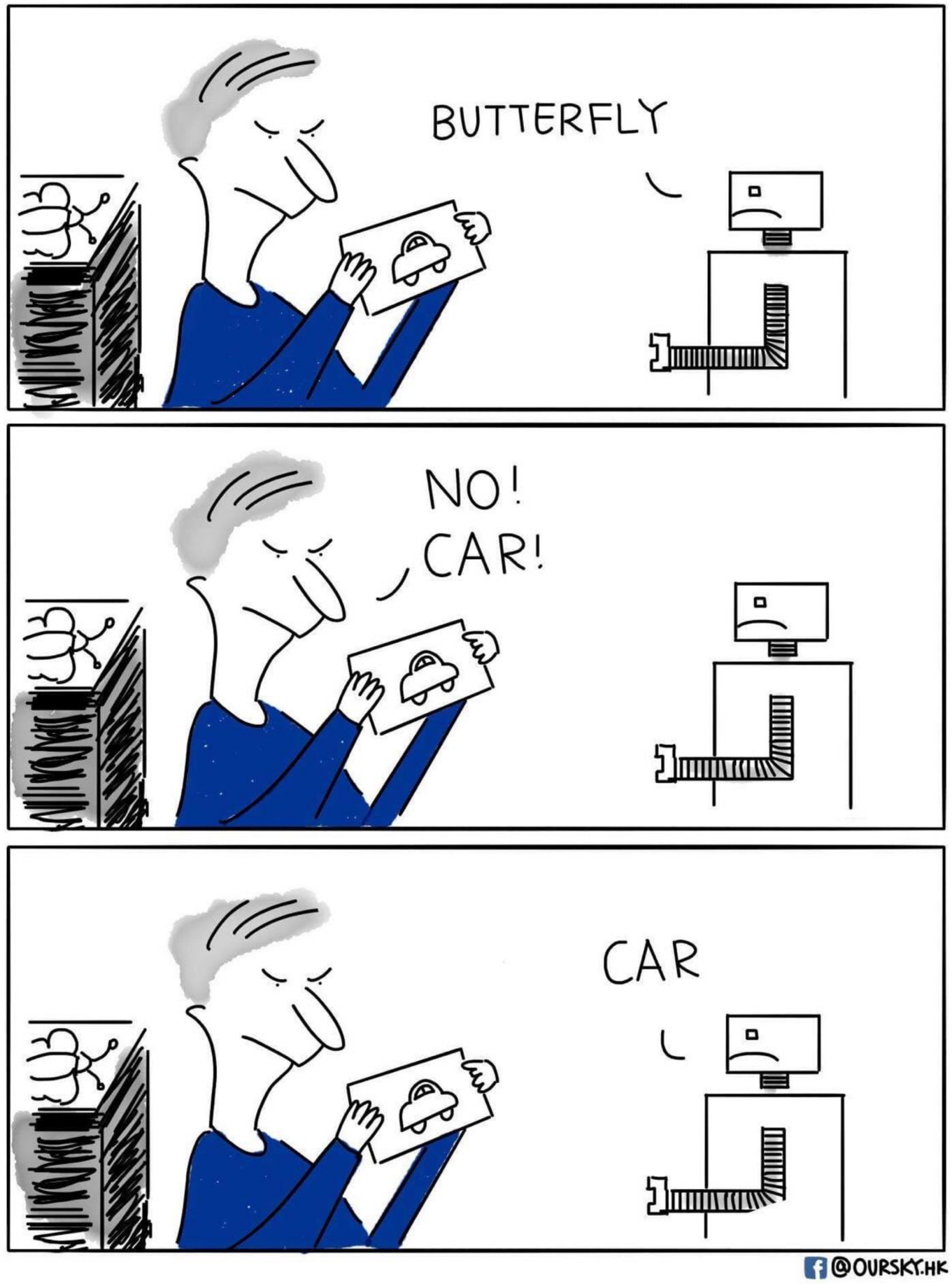
Underfit | **Good Fit/Robust** | **Overfit**

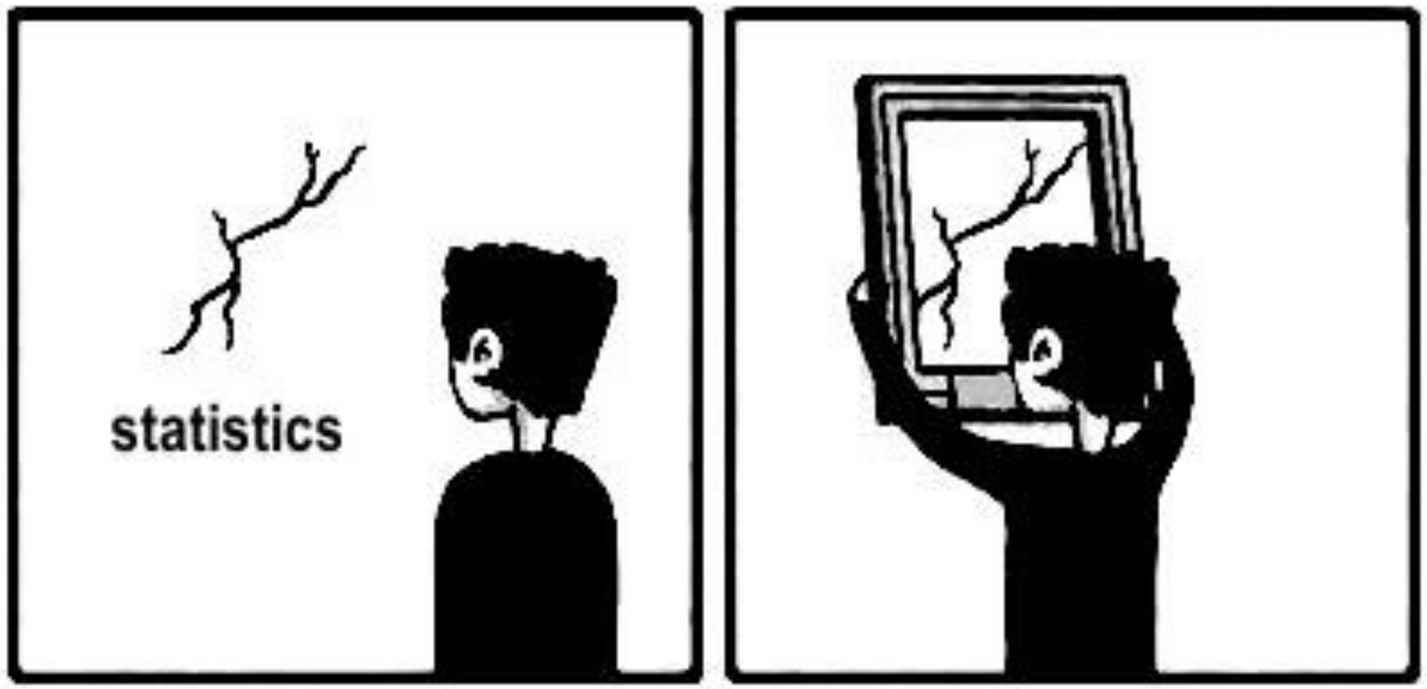
Thanks to machine-learning algorithms,
the robot apocalypse was short-lived.

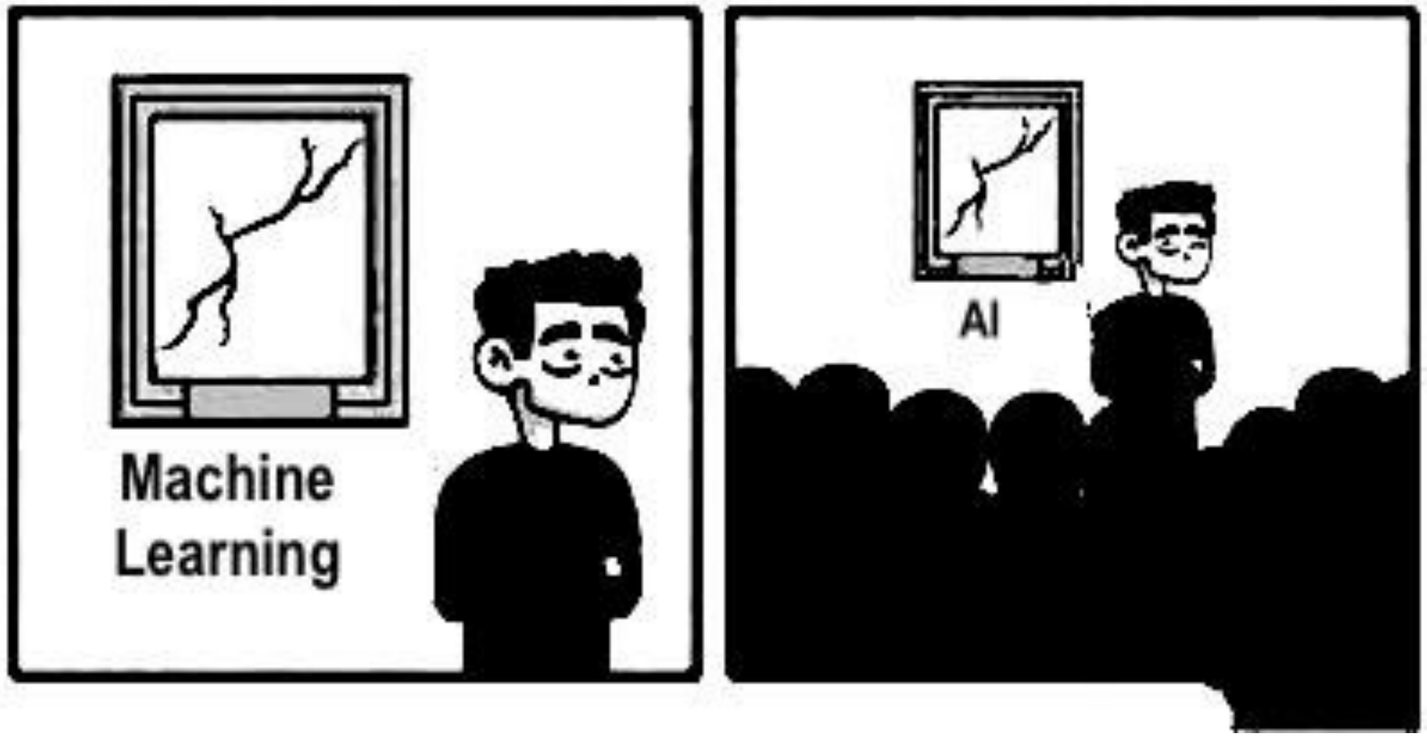
Regression-Based Methods

Classification vs. Regression

- Essentially: labelling outcomes vs. assigning outcomes a numeric value
- “Regression” not always used in the same way it’s used in statistics
  - Typically means “quantitative outcome”
- Fundamental “algorithm”:
  - Linear regression (typically least squares)
  - Logistic regression (typically log-odds, etc.)


BUTTERFLY
NO!
CAR!
CAR
@OURSKY.HK


statistics


Machine
Learning
AI


LinkedIn
foursquare
LIVEJOURNAL
vimeo
YouTube
Insta
facebook
Blogger
flickr
twitter
tumblr.
Like

1) Collect

2) Correlate

3) Predict

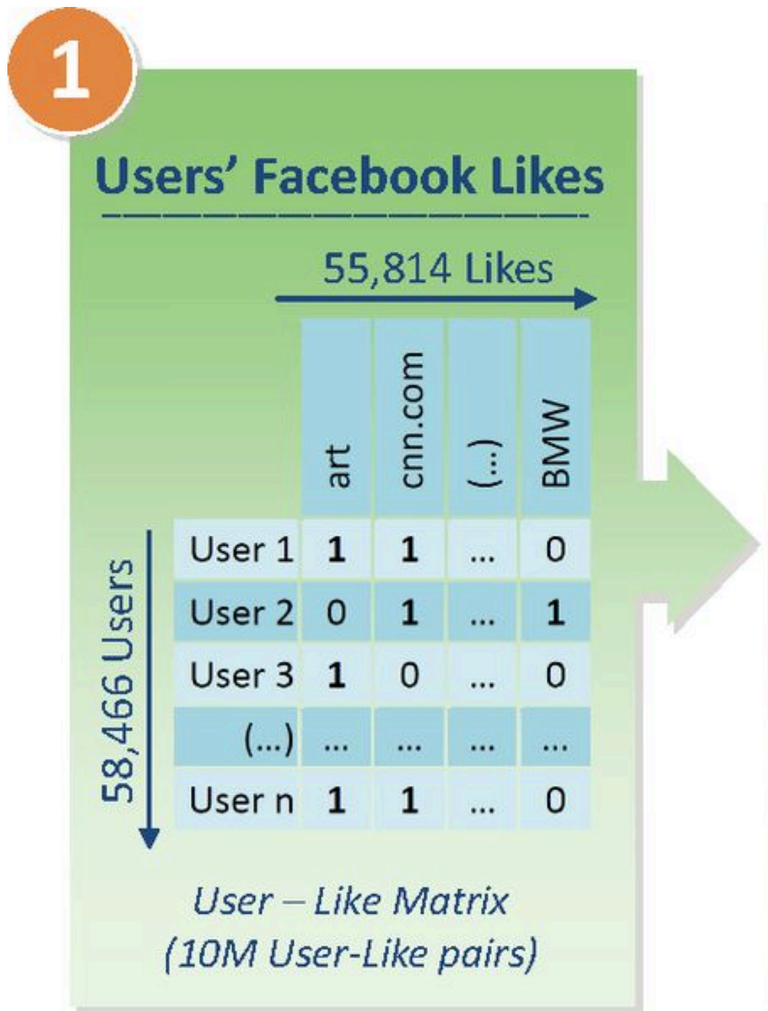
Conscientiousness

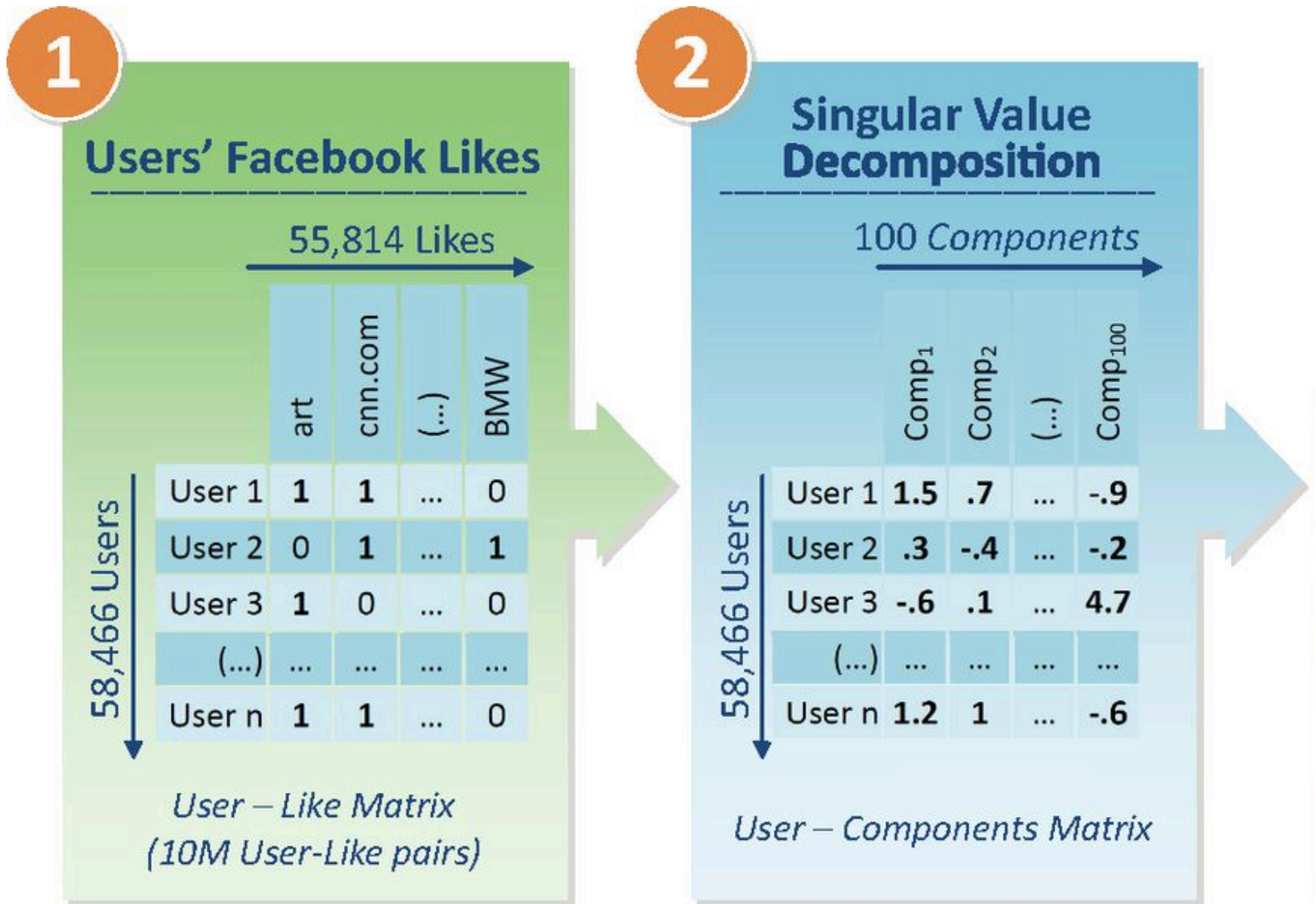
Agreeableness

Neuroticism

Extraversion

Openness


1
Users' Facebook Likes
55,814 Likes
art
cnn.com
(...)
BMW
58,466 Users
User 1 1 1 ... 0
User 2 0 1 ... 1
User 3 1 0 ... 0
(...) ... ...
User n 1 1 ... 0
User – Like Matrix
(10M User-Like pairs)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User 1 1 1 ... 0
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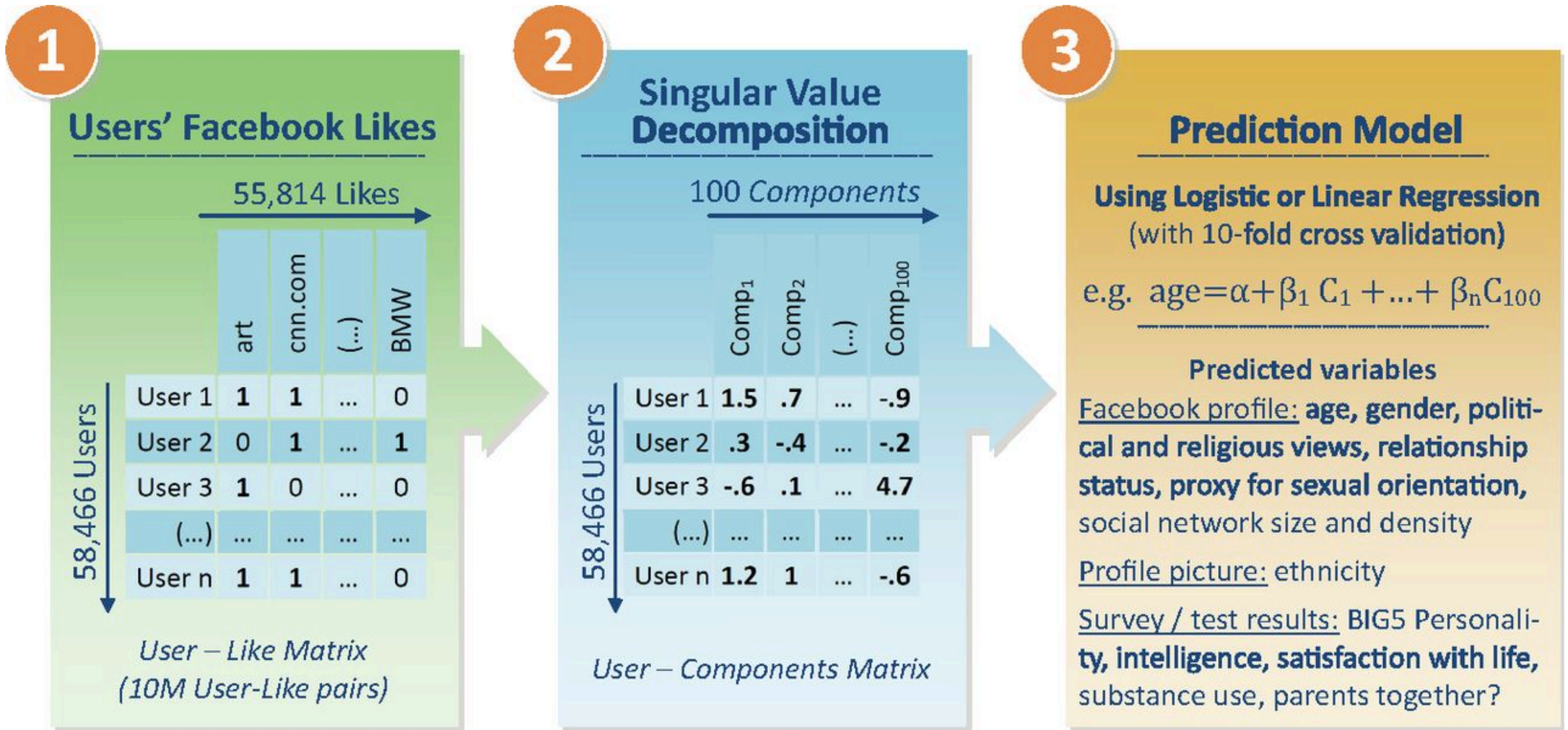
User – Like Matrix
(10M User-Like pairs)
2
Singular Value Decomposition
100 Components
Comp1
Comp2
(...)
Comp100
58,466 Users
User 1 1.5 .7 ... -.9
User 2 .3 -.4 ... -.2
User 3 -.6 .1 ... 4.7
(...) ... ...
User n 1.2 1 ... -.6
User – Components Matrix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(...) ... ...
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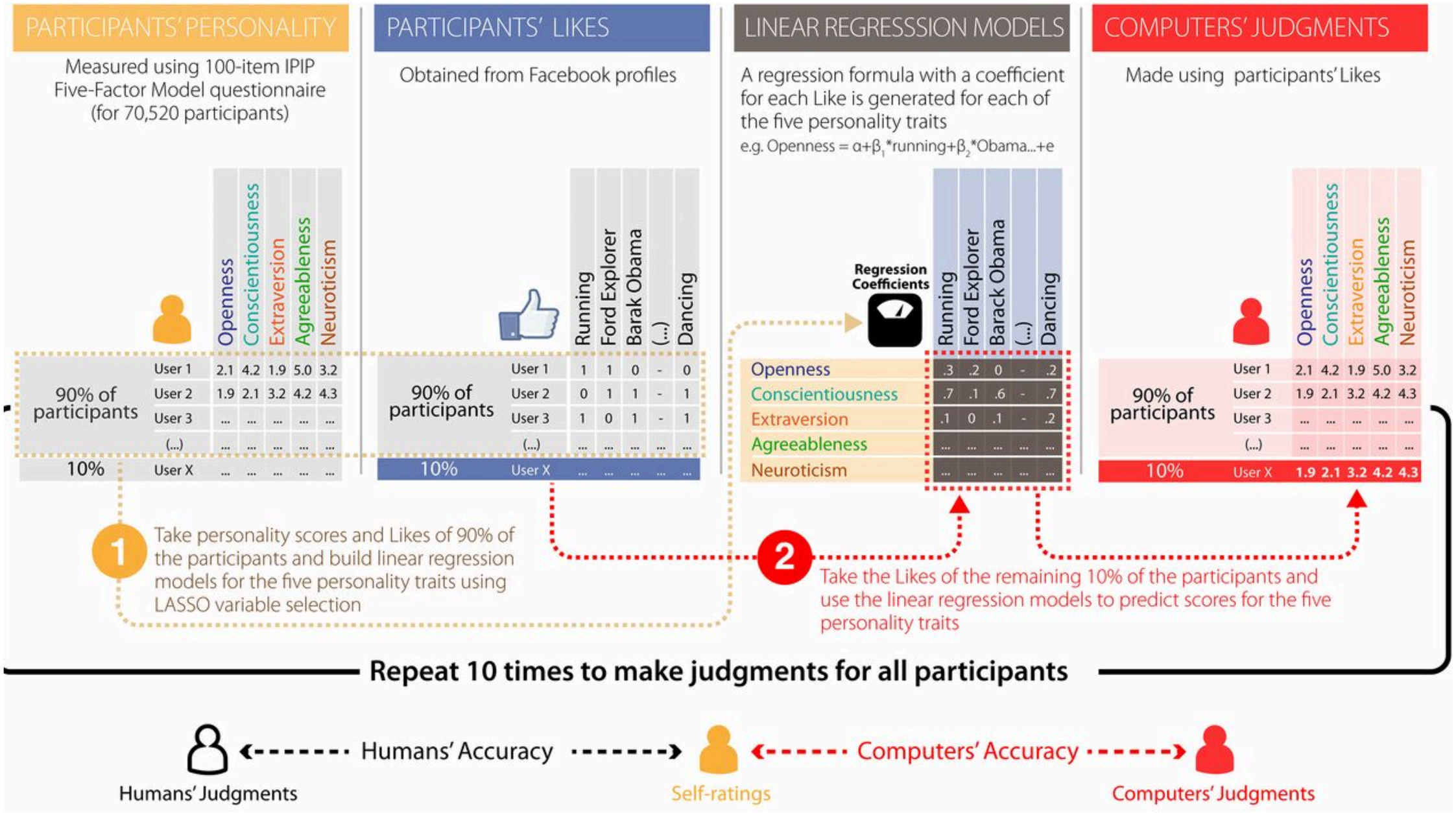
User – Components Matrix
3
Prediction Model
Using Logistic or Linear Regression
(with 10-fold cross validation)
e.g. age=α+β1 C1 +...+ βnC100
Predicted variables
Facebook profile: age, gender, political and religious views, relationship status, proxy for sexual orientation, social network size and density
Profile picture: ethnicity
Survey / test results: BIG5 Personality, intelligence, satisfaction with life, substance use, parents together?


PARTICIPANTS' PERSONALITY
Measured using 100-item IPIP Five-Factor Model questionnaire (for 70,520 participants)
Openness Conscientiousness Extraversion Agreeableness Neuroticism
90% of participants
User 1 2.1 4.2 1.9 5.0 3.2
User 2 1.9 2.1 3.2 4.2 4.3
User 3 ... ...
(...) ... ...
10% User X ... ...
PARTICIPANTS' LIKES
Obtained from Facebook profiles
Running Ford Explorer Barak Obama (...) Dancing
90% of participants
User 1 1 1 0 - 0
User 2 0 1 1 - 1
User 3 1 0 1 - 1
(...) ... ...
10% User X ... ...
LINEAR REGRESSSION MODELS
A regression formula with a coefficient for each Like is generated for each of the five personality traits
e.g. Openness = α+β1*running+β2*Obama...+e
Regression Coefficients
Running Ford Explorer Barack Obama (...) Dancing
Openness .3 .2 0 - .2
Conscientiousness .7 .1 .6 - .7
Extraversion .1 0 .1 - .2
Agreeableness ... ...
Neuroticism ... ...
COMPUTERS' JUDGMENTS
Made using participants' Likes
Openness Conscientiousness Extraversion Agreeableness Neuroticism
90% of participants
User 1 2.1 4.2 1.9 5.0 3.2
User 2 1.9 2.1 3.2 4.2 4.3
User 3 ... ...
(...) ... ...
10% User X 1.9 2.1 3.2 4.2 4.3
1 Take personality scores and Likes of 90% of the participants and build linear regression models for the five personality traits using LASSO variable selection
2 Take the Likes of the remaining 10% of the participants and use the linear regression models to predict scores for the five personality traits
Repeat 10 times to make judgments for all participants
Humans' Judgments
Humans' Accuracy
Self-ratings
Computers' Accuracy
Computers' Judgments

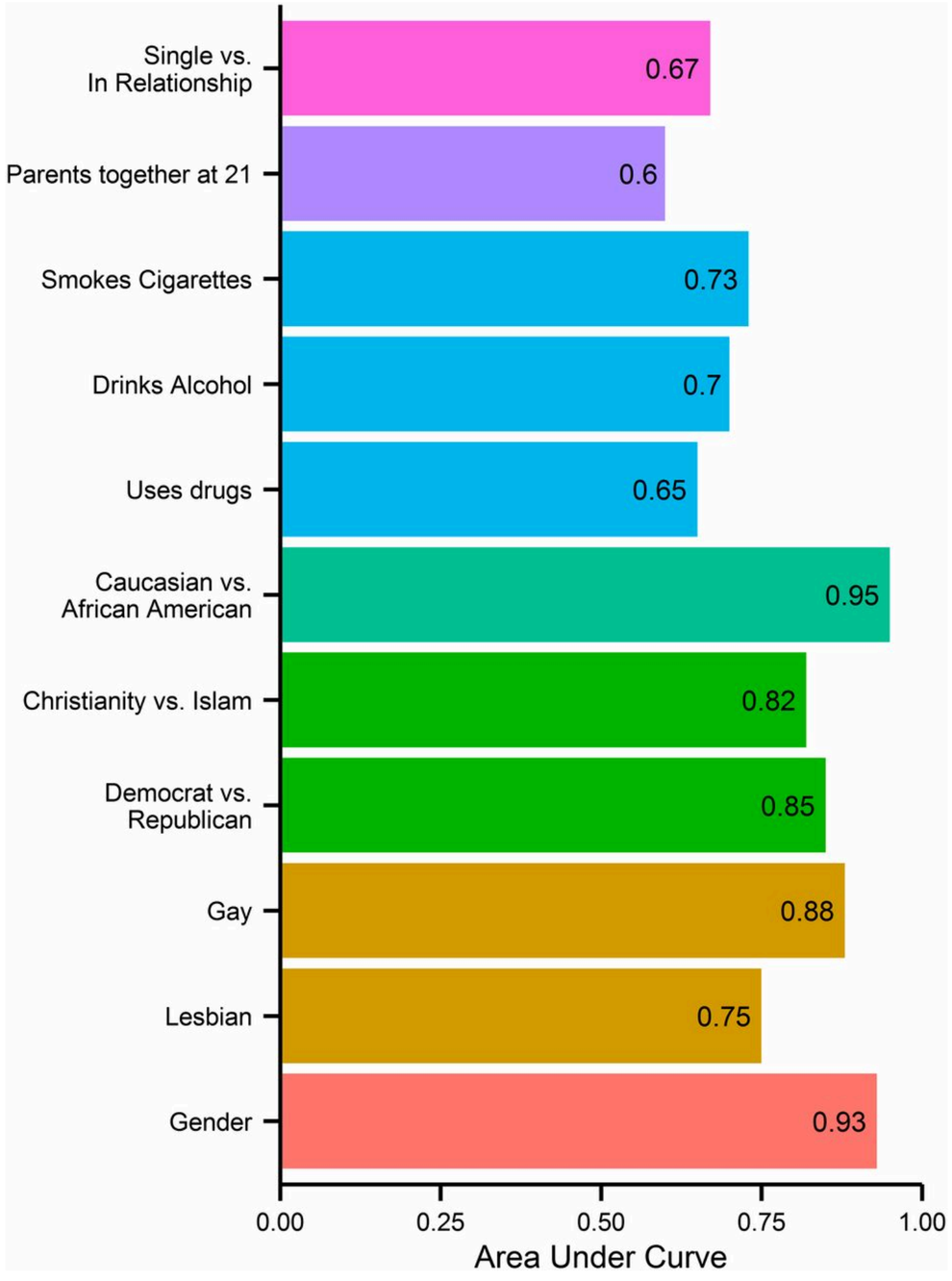
George W Bush	Joe Biden
John McCain	Speaker Nancy Pelosi
Conservative	Health Care Reform
Rush Limbaugh	The White House
Sean Hannity	Democrats
Bill Oreilly	Barbara Boxer
Positively Republican	Anthony Weiner
Sarah Palin	Being Liberal
Ronald Reagan	Left Action
Glenn Beck	Barack Obama2012
	Ted Kennedy

Politics	*Republican*			*Democrat*
	George W Bush		Joe Biden	
	John McCain		Speaker Nancy Pelosi	
	Conservative		Health Care Reform	
	Rush Limbaugh		The White House	
	Sean Hannity	**High Face Validity**	Democrats	
	Bill Oreilly		Barbara Boxer	
	Positively Republican		Anthony Weiner	
	Sarah Palin		Being Liberal	
	Ronald Reagan		Left Action	
	Glenn Beck		Barack Obama2012	
			Ted Kennedy	
	Mojo-Jojo		The Dark Knight	
	Biology		In'n'out Burger	
	Dollar General	**Low Face Validity**	Hard Rock	
	Hillary		Honey, Where Is My Supersuit	
	106 & Park		Hating ICP	
	Jennifer Lopez		Minecraft	
	Paid In Full		Iron Maiden	
	Yo Gotti		Walking With Your Friend & Randomly	
	The Dollar You Are Holding Could've		Pushing Them Into Someone/Something	

But doesn't matter (as much) if goal is prediction!

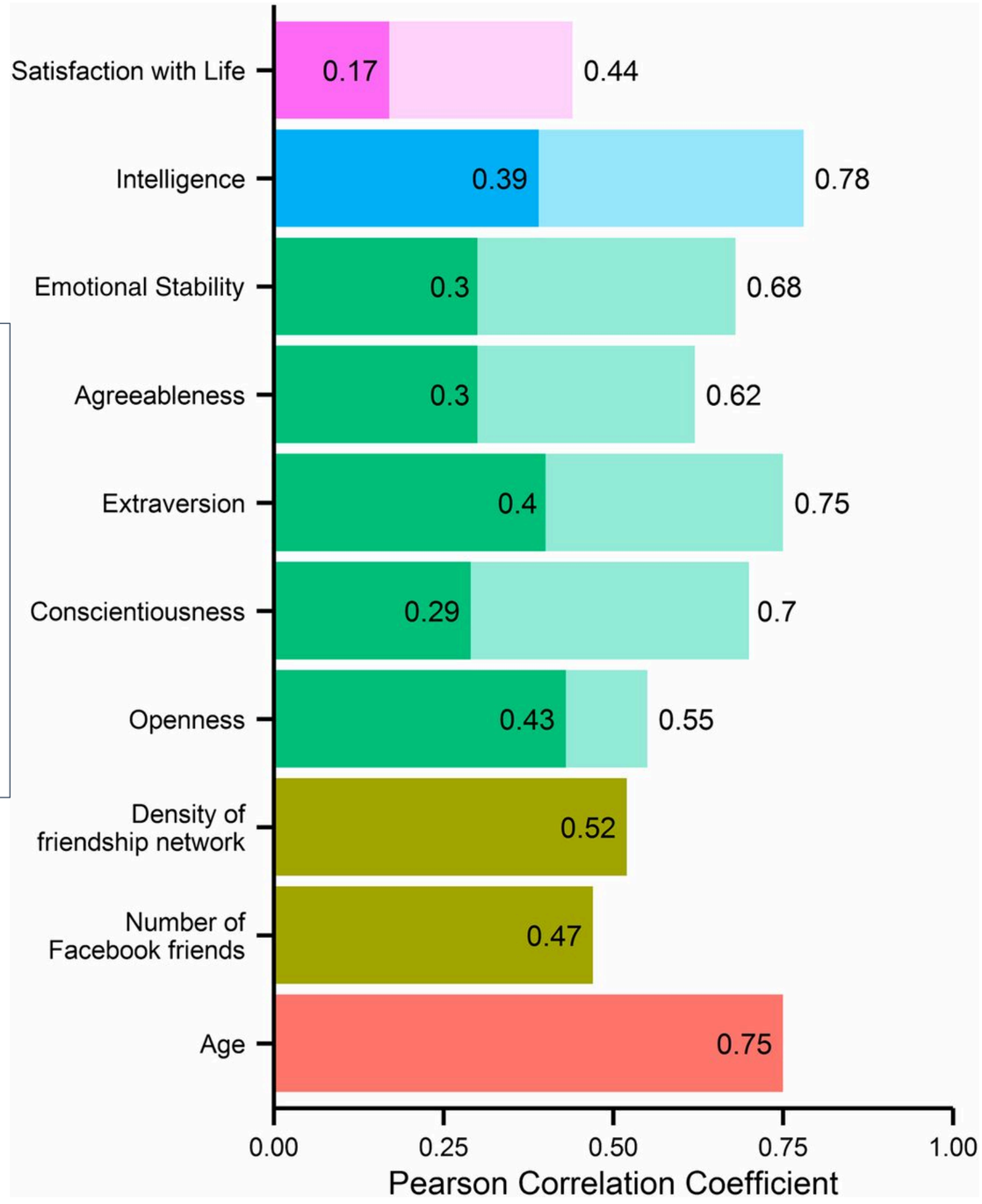
Compassion International	I Hate Everyone
Logan Utah	I Hate You
Jon Foreman	I Hate Police
Redeeming Love	Friedrich Nietzsche
Pornography Harms	Timmy South Park
The Book Of Mormon	Atheism / Satanism
Circles Of Prayer	Prada
Go To Church	Sun Tzu
Christianity	Julius Caesar
Marianne Williamson	Knives

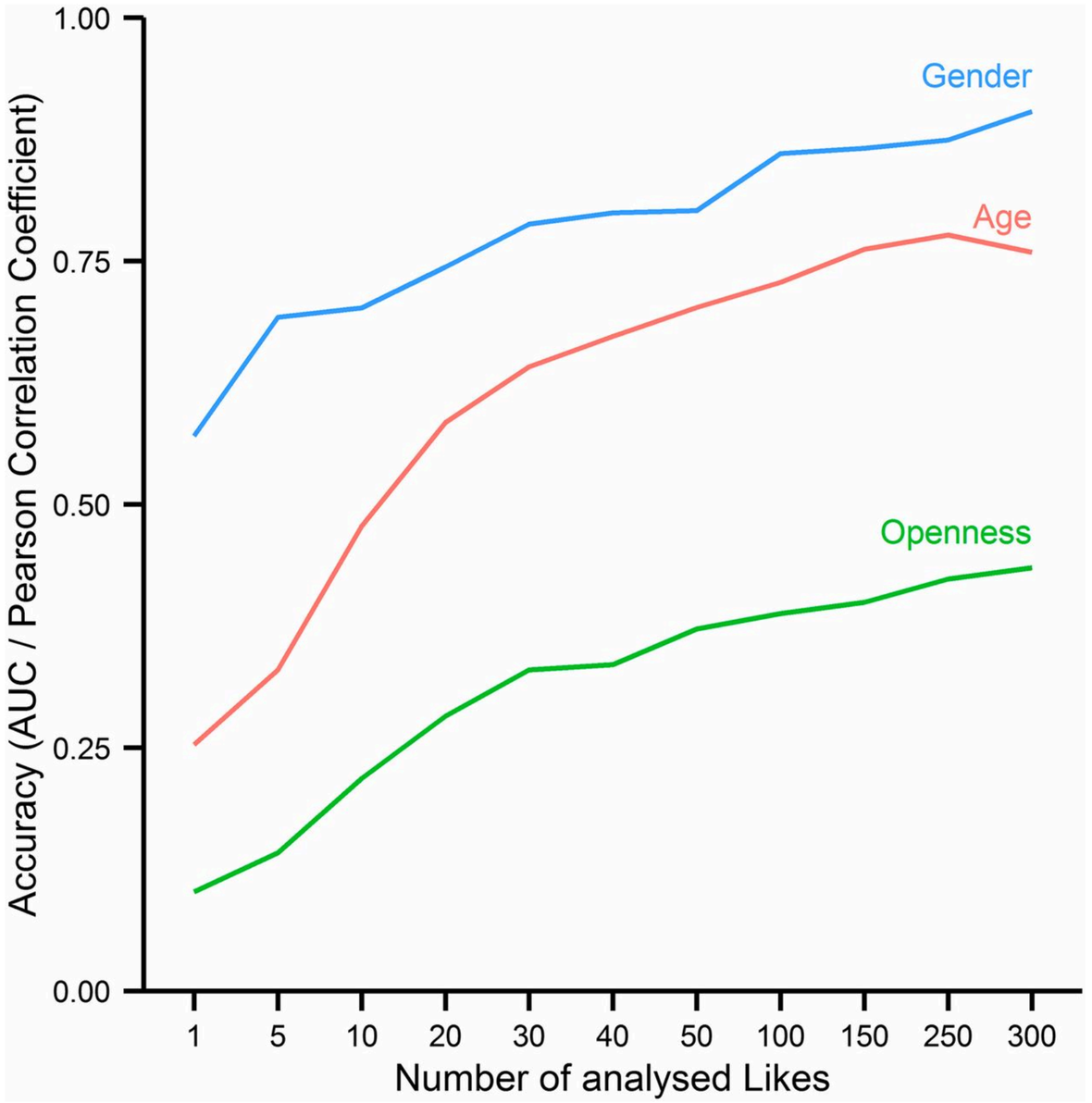
Agreeableness	***Cooperative***	***Competitive***
	Compassion International	I Hate Everyone
	Logan Utah	I Hate You
	Jon Foreman	I Hate Police
	Redeeming Love	Friedrich Nietzsche
	Pornography Harms	Timmy South Park
	The Book Of Mormon	Atheism / Satanism
	Circles Of Prayer	Prada
	Go To Church	Sun Tzu
	Christianity	Julius Caesar
	Marianne Williamson	Knives
	Oscar Wilde	NASCAR
	Charles Bukowski	Austin Collie
	Sylvia Plath	Monster-In-Law
	Leonardo Da Vinci	I don’t read
	Bauhaus	Justin Moore
	Dmt The Spirit Molecule	ESPN2
	American Gods	Farmlandia
	John Waters	The Bachelor
	Plato	Oklahoma State University
	Leonard Cohen	Teen Mom 2



- Prediction accuracy of dichotomous attributes from FB likes.
- Values represent AUC (area under the receiver operator characteristic curve)
- AUC: probability of correctly classifying two randomly-chosen individuals, one from each class.
  - Just know that it is a measure of accuracy with higher values denoting better classification accuracy.

- Personality trait prediction from FB likes alone.
- Values represent correlations between predicted and actual values.
- Transparent bars represent Cronbach's alpha (test-retest reliability or correlation of a test and itself).

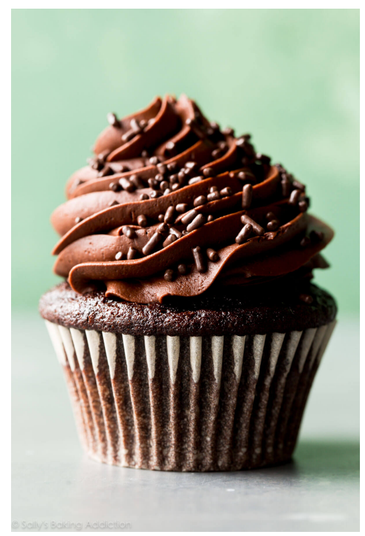



1.00
0.75
0.50
0.25
0.00
Accuracy (AUC / Pearson Correlation Coefficient)
Gender
Age
Openness
1
5
10
20
30
40
50
100
150
250
300
Number of analysed Likes

Key take-aways from Regression-Based Methods

- Same methods from classical statistics
  - But with an emphasis on prediction
  - You can use these methods with little change to your current research program!
- Can use numeric outcomes (”regression”) or binary/factor (“classification”)
- Parametric in nature
- Assume underlying linearity between predictors and outcome
- Utilize cross-validation to reduce likelihood of overfitting
- Dirty secret of machine learning….frequently these methods outperform the “more complicated” methods

Decision Trees



Non-Vegan

Vegan

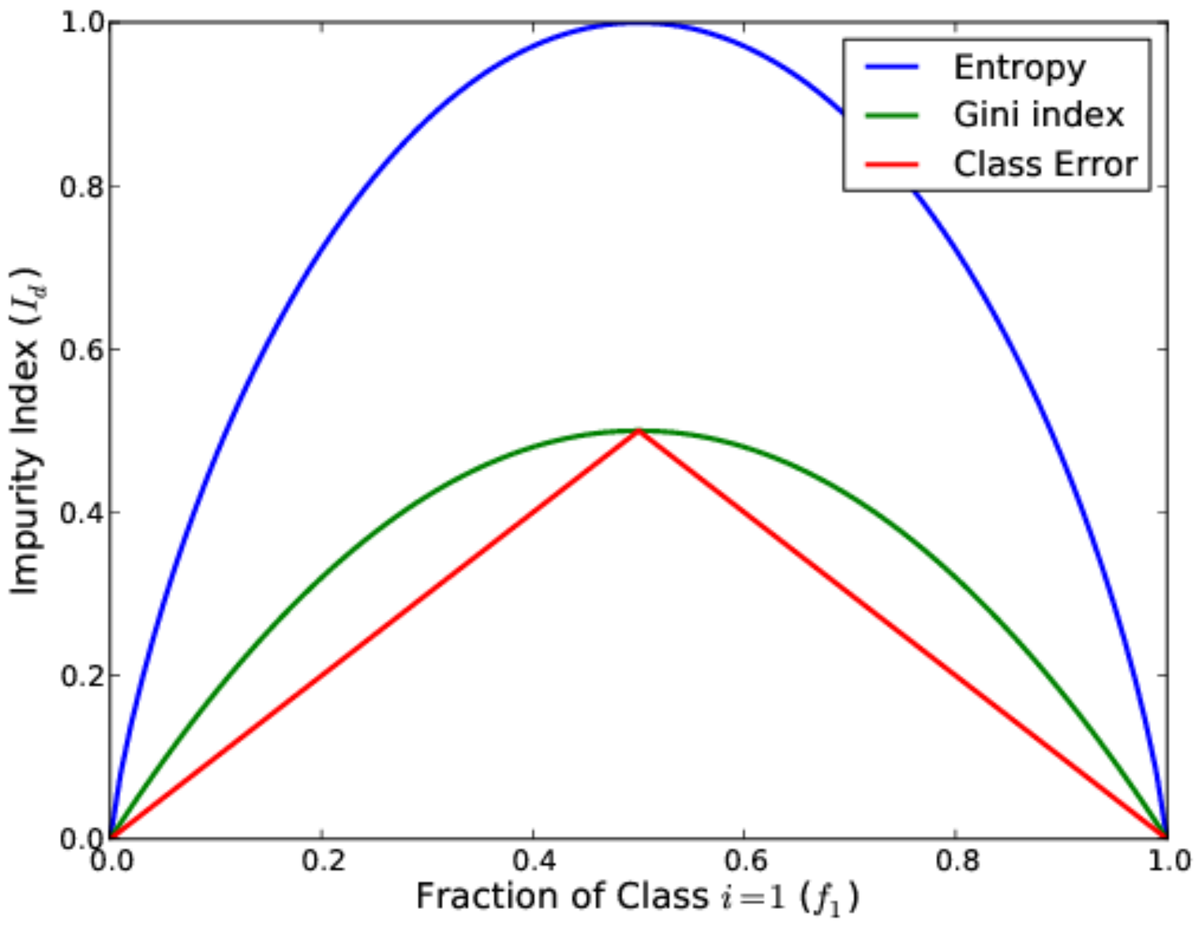
Non-Vegan

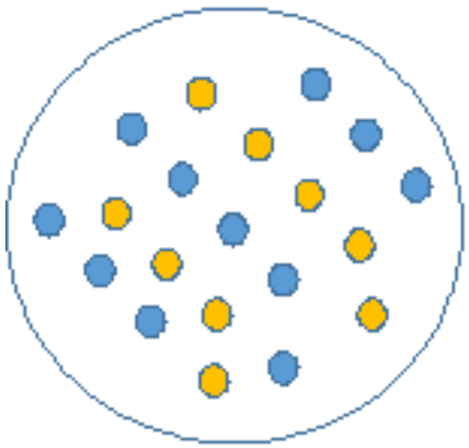
Vegan

How do we determine homogeneity of partitions?

- Many different methods possible (e.g., accuracy, information, entropy).
- Here, we use Gini impurity index:

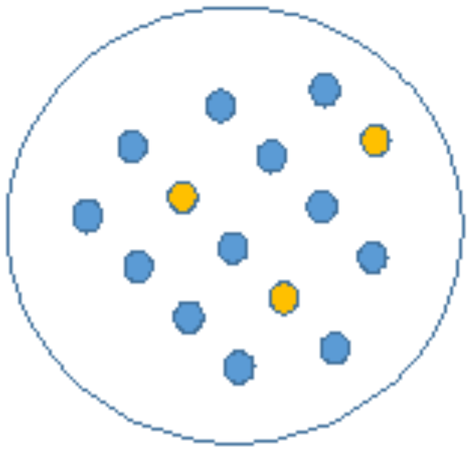
$$I(p,q) = 2pq = P(Y_1 \neq Y_2)$$





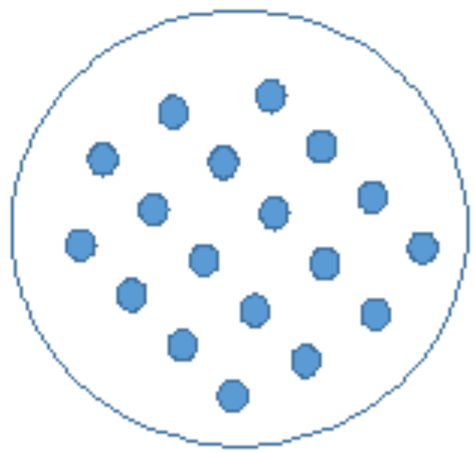
A

High Gini



B

Med Gini



C

Low Gini

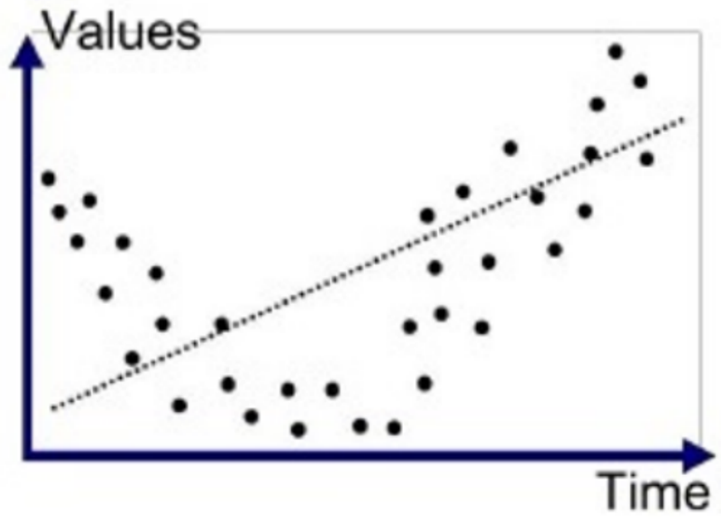
Recursive Partitioning Algorithm

- Suppose we have a response variable *Y* and a set of *P* predictor variables X_j for j = 1,…, P. For a partition *A* of records, recursive partitioning will find the best way to partition A into two subpartitions:
    1. For each predictor variable X_j:
        - For each value s_j of X_j:
            - Split the records in A with X_j values < s_j as one partition, and the remaining records where $X_j \geq s_j$ as another partition
            - Measure the homogeneity of class within each subpartition of A
            - Select the value of s_j that produces maximum within-partition homogeneity of class.
    2. Select the variable X_j and the split value s_j that produces maximum within-partition homogeneity of class across all variables.
- **Then comes the recursive part:**
    1. Initialize A with the entire data set
    2. Apply the partitioning algorithm to split A into two subparitions A_1 and A_2
    3. Repeat step 2 on subpartitions A_1 and A_2
    4. Algorithm terminates when no further partition can be made that sufficiently improves the homogeneity of the partitions

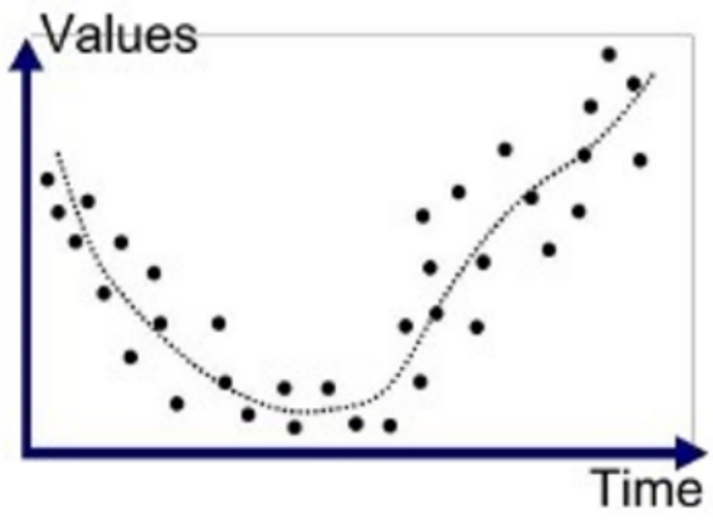
Bruce, P., & Bruce, A. (2017). *Practical statistics for data scientists.* Sebastopol, CA: O'Reilley Media, Inc.

Vegan

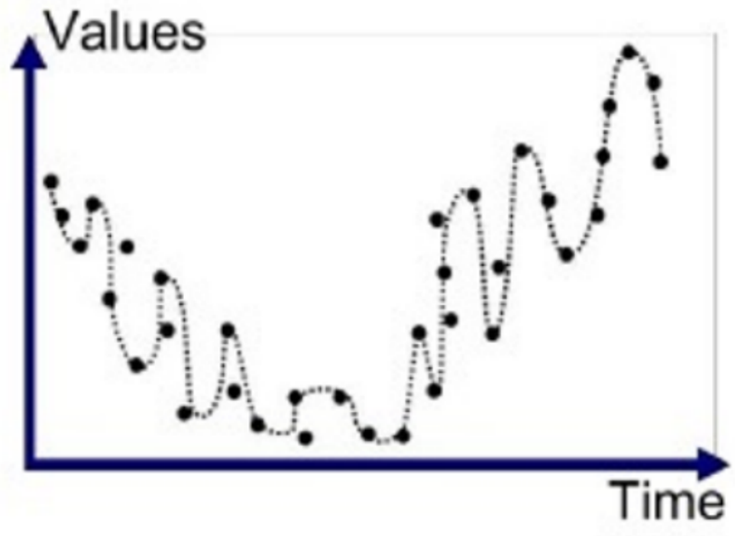
Non-Vegan



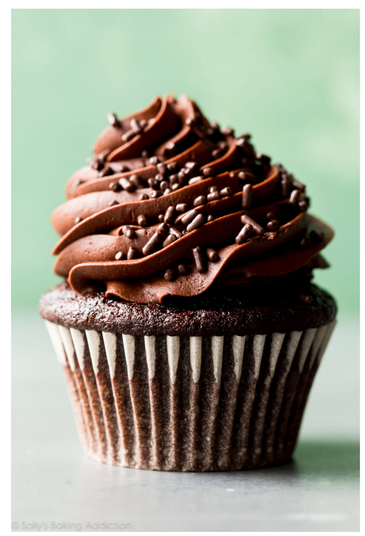
Underfit



Good Fit/Robust



Overfit



Non-Vegan

Vegan

Non-Vegan

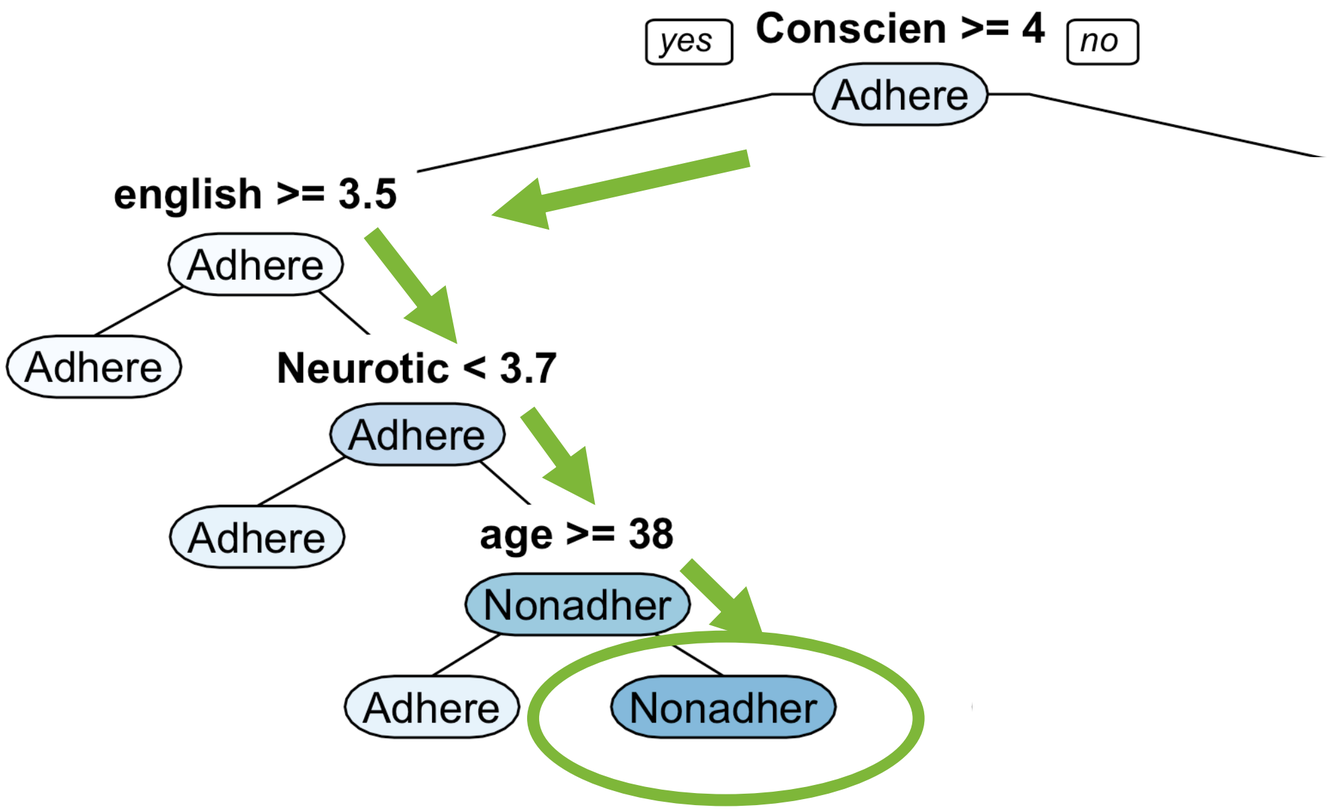
Vegan

Medication Adherence Decision Tree

Baker Bob

- Conscientiousness: 4.5
- English Proficiency: 3
- Neuroticism: 4
- Age: 35
- Prediction?

Medication Adherence Decision Tree



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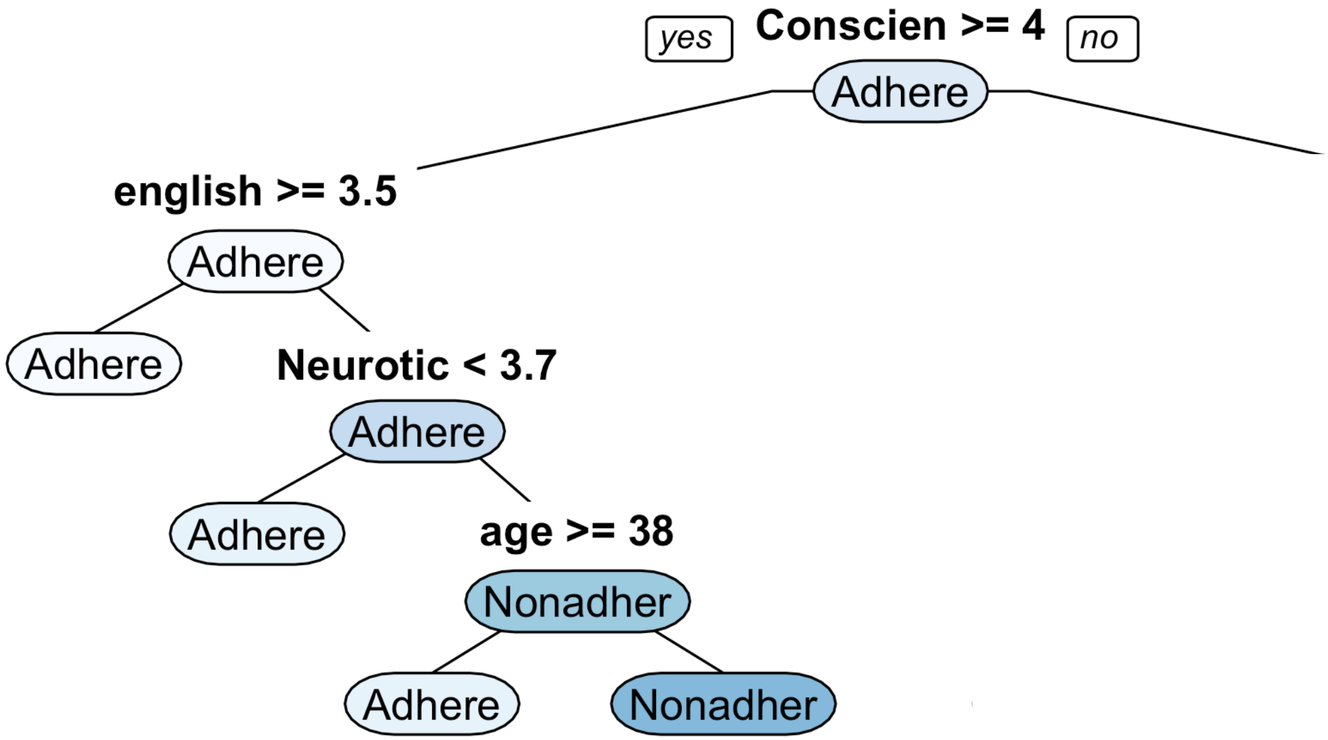
Medication Adherence Decision Tree



Key take-aways from tree-based methods

- Decision-focused, not trying to explain
- Pretty pictures!
- Intuitive, no stats background needed
- But…….
    - Pretty shitty when it comes to predicting anything. So like…..why use?

Ensemble Methods: Random Forest Gradient-Boosted Trees

cupcake
All your ~~base~~ are
belong to us!

Seeing the forest for the trees

- In general, follows recursive partition algorithm, but for a randomly selected subsample from the records.
- Algorithm:
    1. Take a bootstrap (with replacement) subsample from the records
    2. For the first split, sample p < P variables at random without replacement
    3. For each of the sample variables $X_{j(1)}$, $X_{j(2)}$,…,$X_{j(p)}$, apply the splitting algorithm:
        - For each value $s_{j(k)}$ of $X_{j(k)}$:
            - Split the records in A with $X_{j(k)}$ values < $s_{j(k)}$ as one partition, and the remaining records where $X_{j(k)} \geq s_{j(k)}$ as another partition
            - Measure the homogeneity of class within each subpartition of A
        - Select the value of $s_{j(k)}$ that produces maximum within-partition homogeneity of class.
    4. Select the variable $X_{j(k)}$ and the split value $s_{j(k)}$ that produces maximum within-partition homogeneity of class.
    5. Proceed to the next split and repeat the previous steps, starting with step 2.
    6. Continue with additional splits following the same procedure until the tree is grown
    7. Go back to step 1, take another bootstrap subsample and start the process over again
- How many at each step? Sqrt(P) is the rule of thumb for variabels, 2/3 of records.

Bruce, P., & Bruce, A. (2017). *Practical statistics for data scientists.* Sebastopol, CA: O'Reilley Media, Inc.

Taking advantage of the power of averages

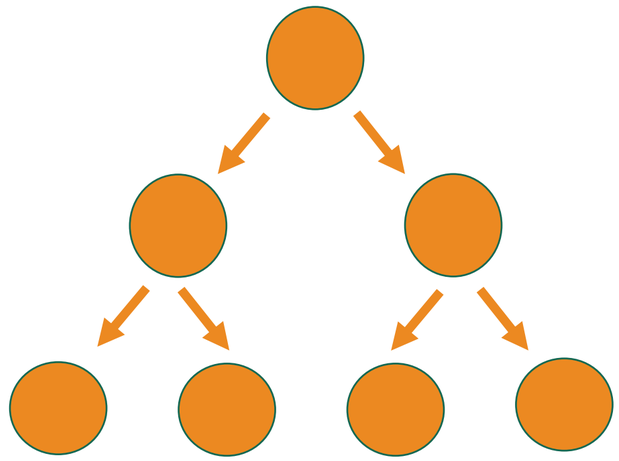
- Ensemble methods derive their utility from averages
- General ensemble algorithm:
  - Develop a predictive model and record the predictions for a given dataset
  - Repeat for multiple models, on the same data
  - For each record to be predicted, take and average (or a weighted average or a majority vote) of the predictions

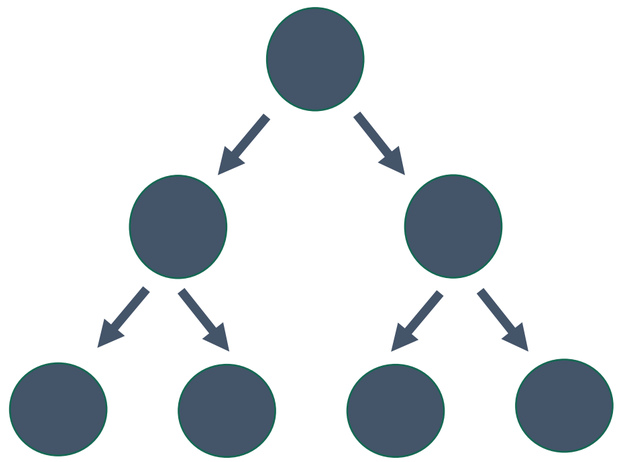
A	B	C	D	…	Z
a_1	b_1	c_1	d_1	…	z_1
a_2	b_2	c_2	d_2	…	z_2
a_3	b_3	c_3	d_3	…	z_3
:	:	:	:	:	:
a_{10}	b_{10}	c_{10}	d_{10}	…	z_{10}

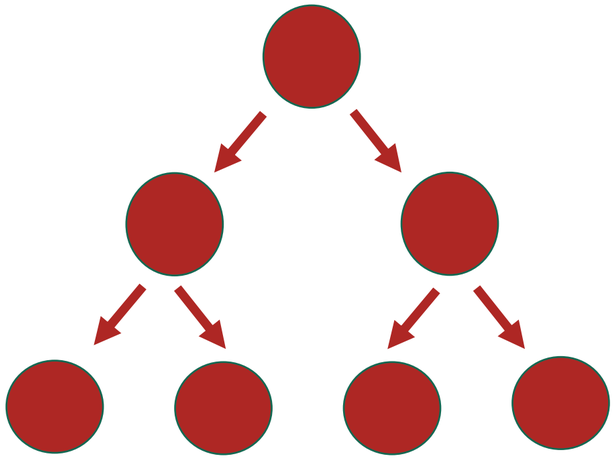
A	C	D	G
a_1	c_1	d_1	g_1
a_3	c_3	d_3	g_3
a_5	c_5	d_5	g_5
a_7	c_7	d_7	g_7

E	F	K	Z
e_1	f_1	k_1	z_1
e_2	f_2	k_2	z_2
e_3	f_3	k_3	z_3
e_{10}	f_{10}	k_{10}	z_{10}

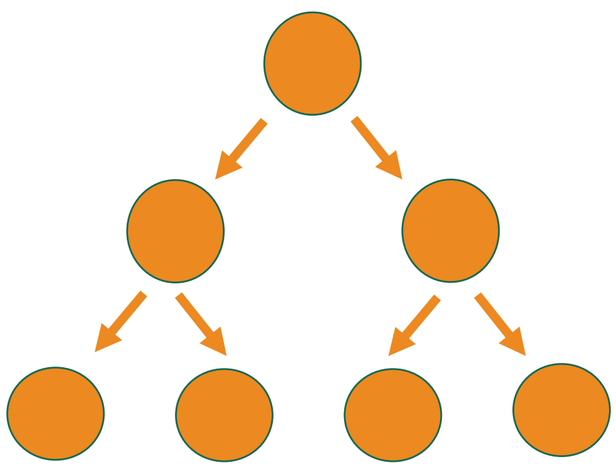
A	C	D	G
a_1	c_1	d_1	g_1
a_3	c_3	d_3	g_3
a_5	c_5	d_5	g_5
a_7	c_7	d_7	g_7

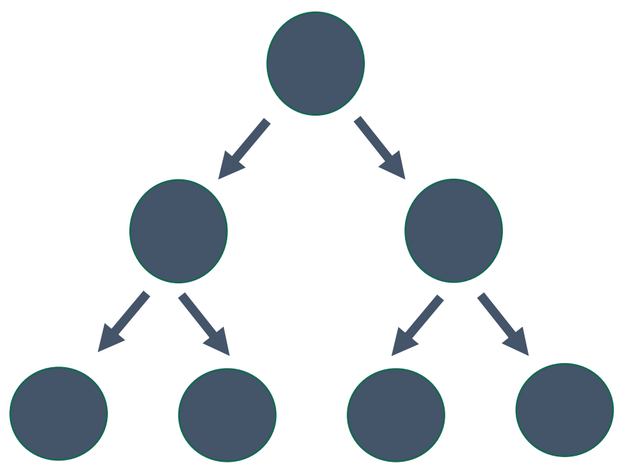


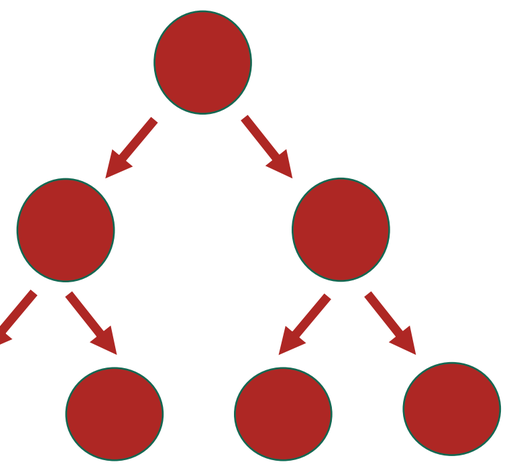




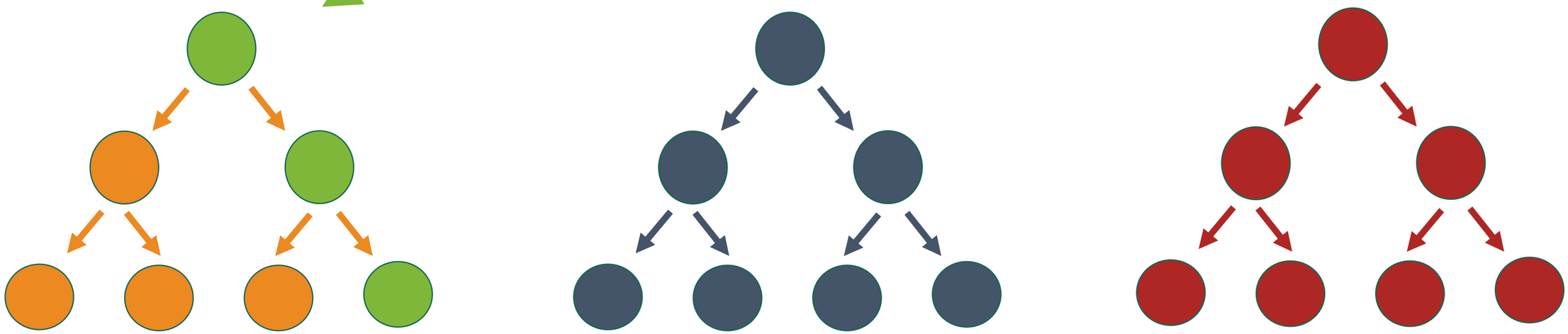
Obs 1







Obs 1



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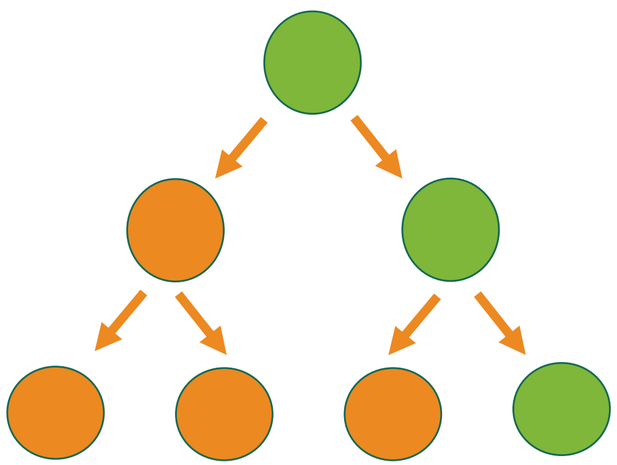
Obs 1



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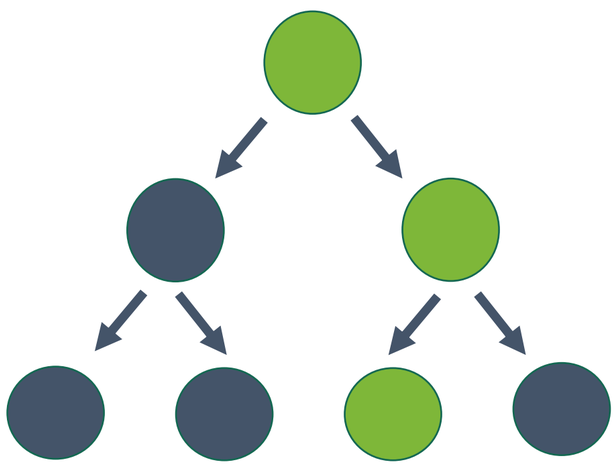

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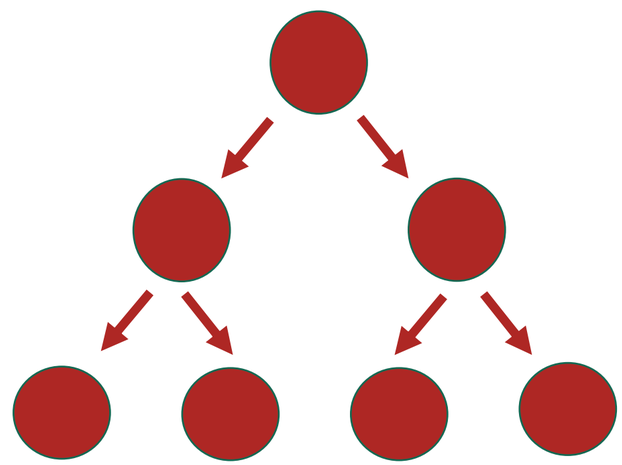

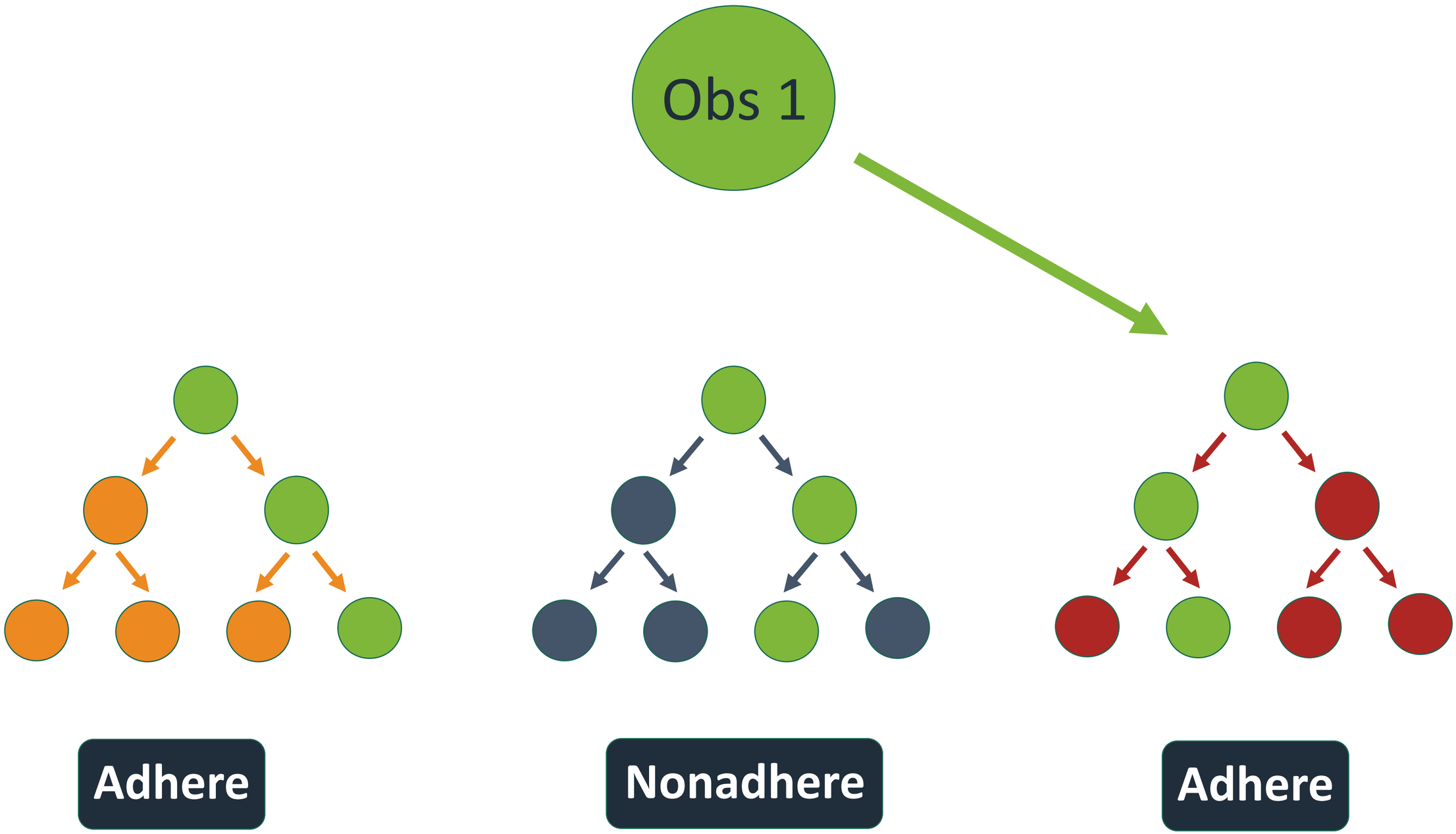
Obs 1
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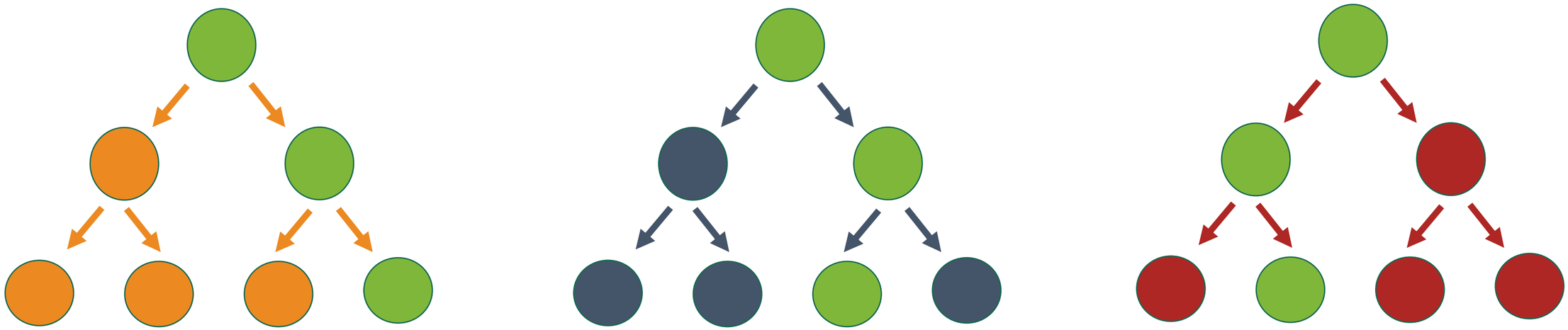
Obs 1



Adhere

Nonadhere

Adhere

Majority Vote

Adhere

Hyperparameters

Random Forest is “Black box”

- Can’t see inside
- But can control how the box functions!

Unable to estimate directly

- Use cross-validation

Hyperparameters for Random forest:

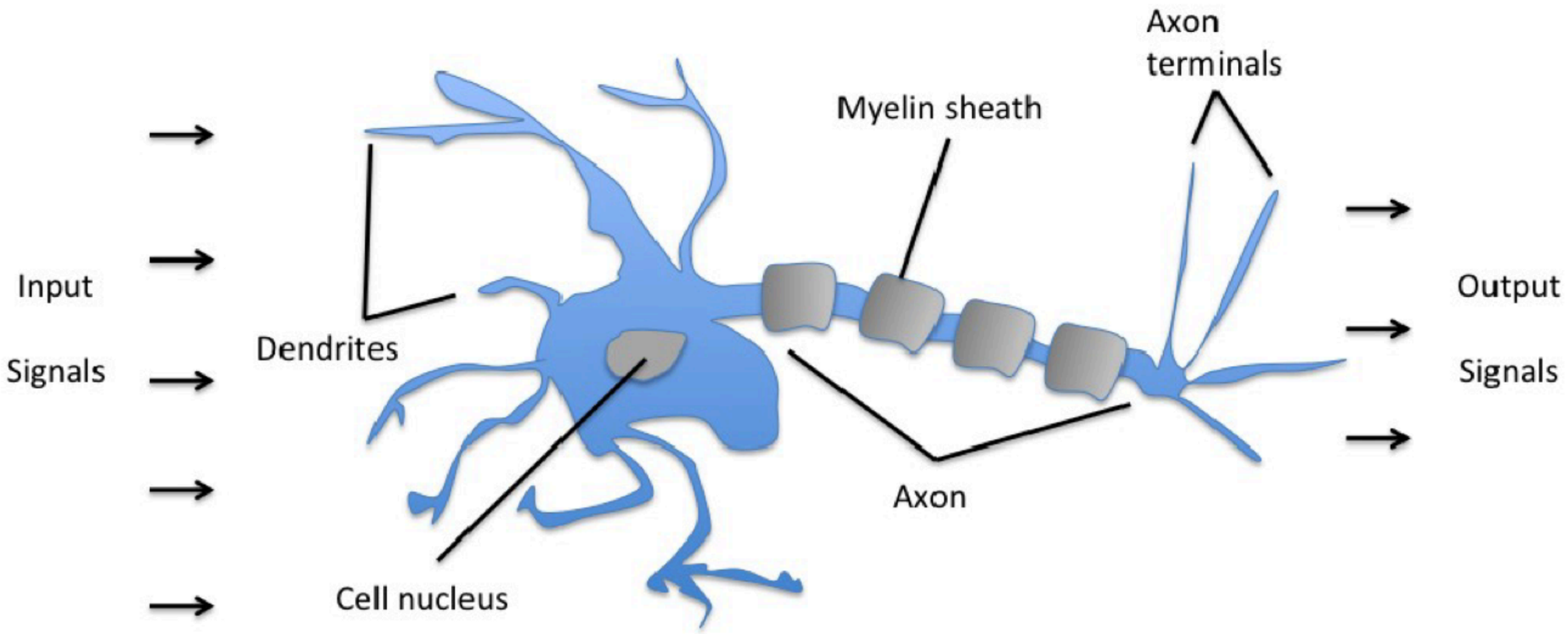
- Number of trees
- Number of variables selected at each node split

Key take-aways from ensemble methods

- Uses many different “weak learners” to create a strong learner
- GBMs and RFs provide top-tier accuracy in competitions
- BUT…..
    - Little interpretability (no visible trees)
    - Black box methods

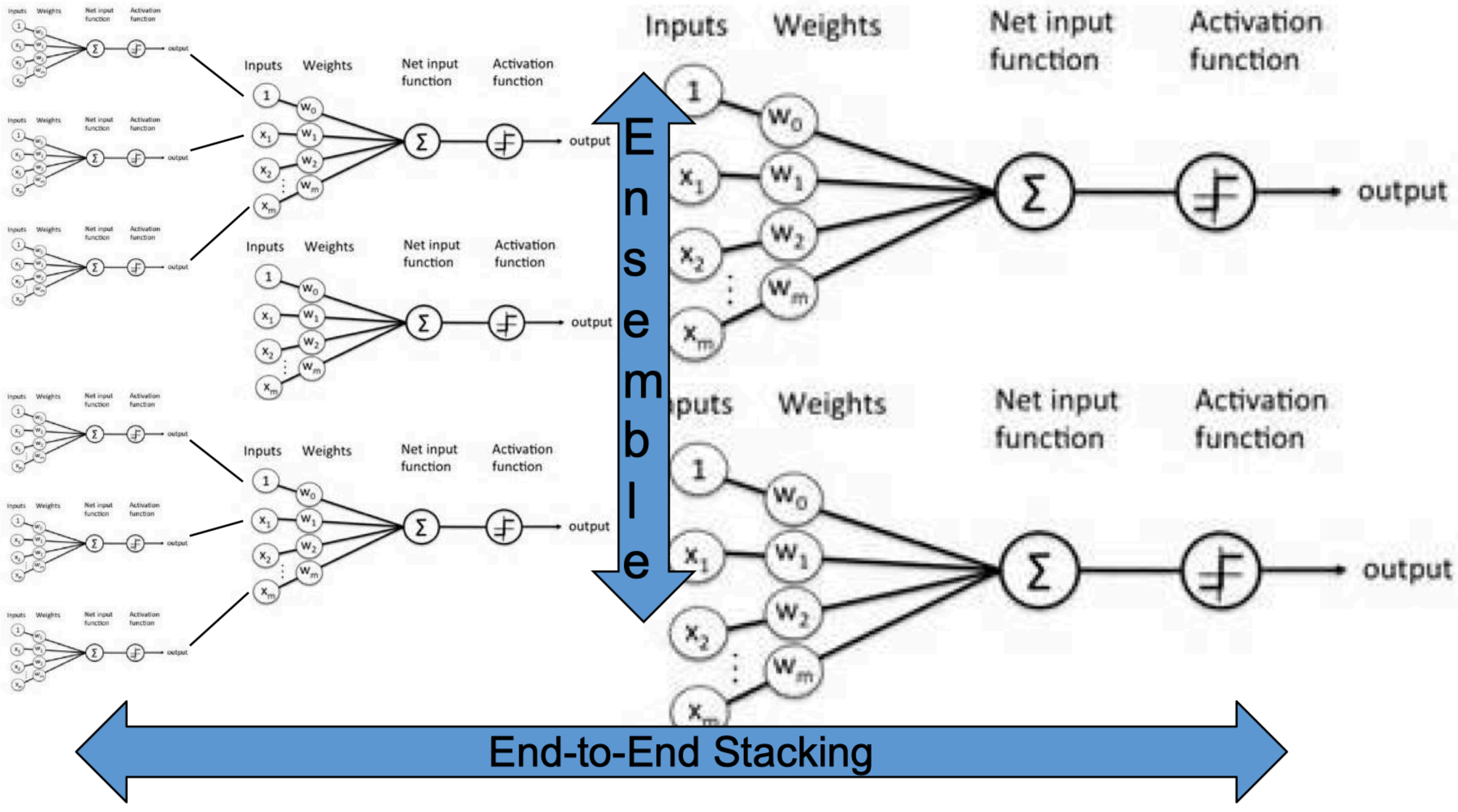
Advanced Methods: Neural Networks

It’s like a human neuron…..right?

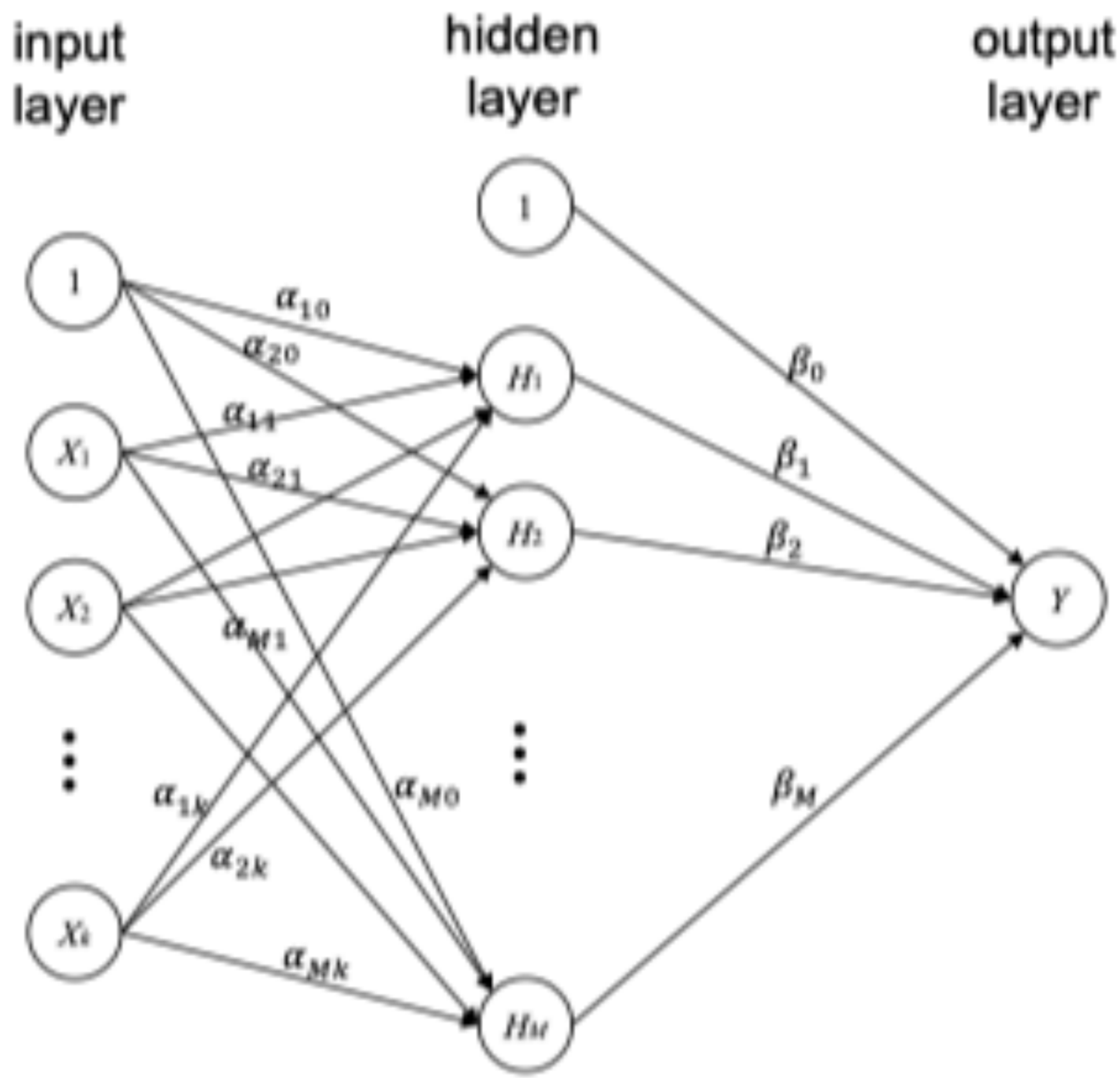


Schematic of a biological neuron.

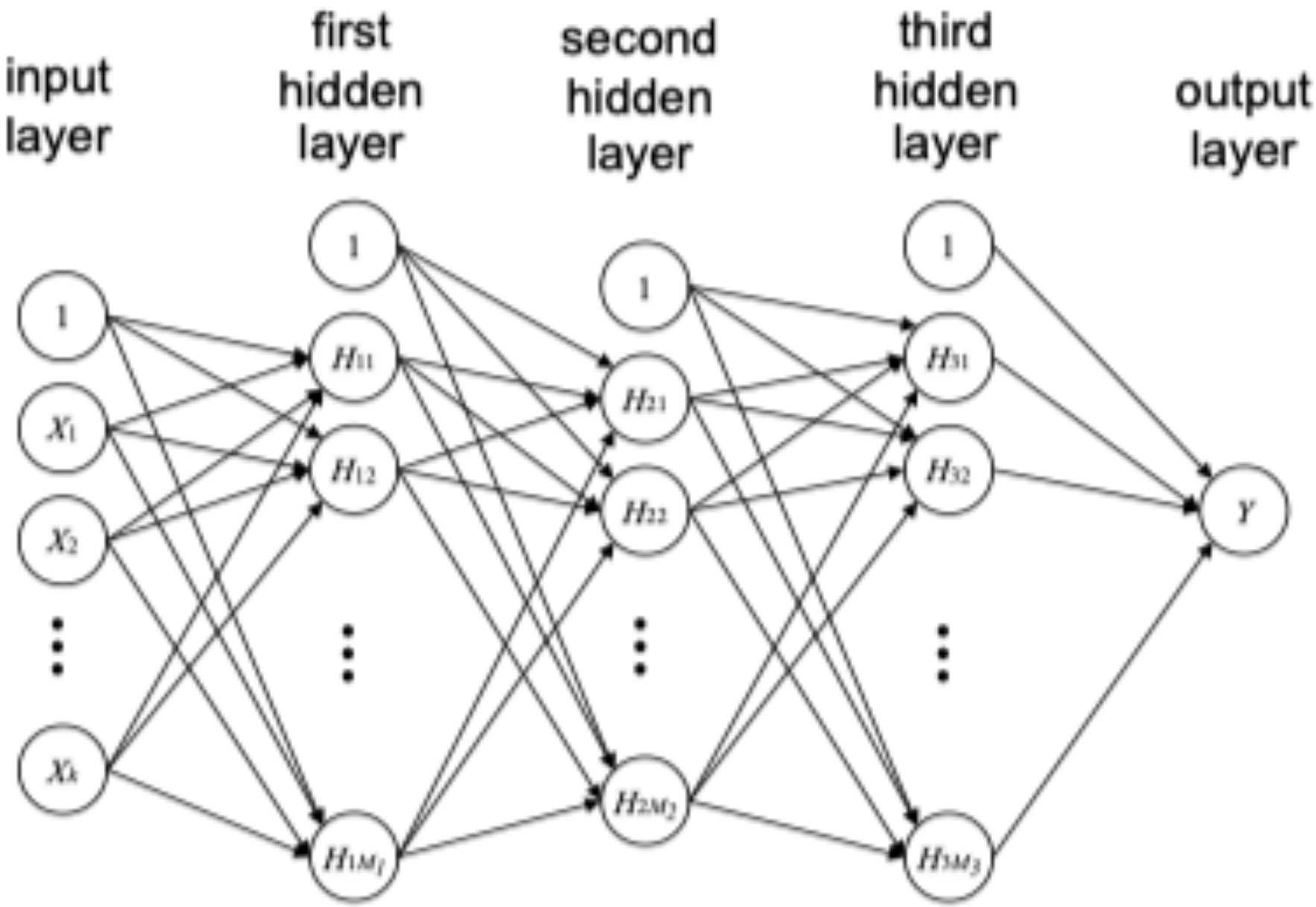
More accurate: Many logistic regressions



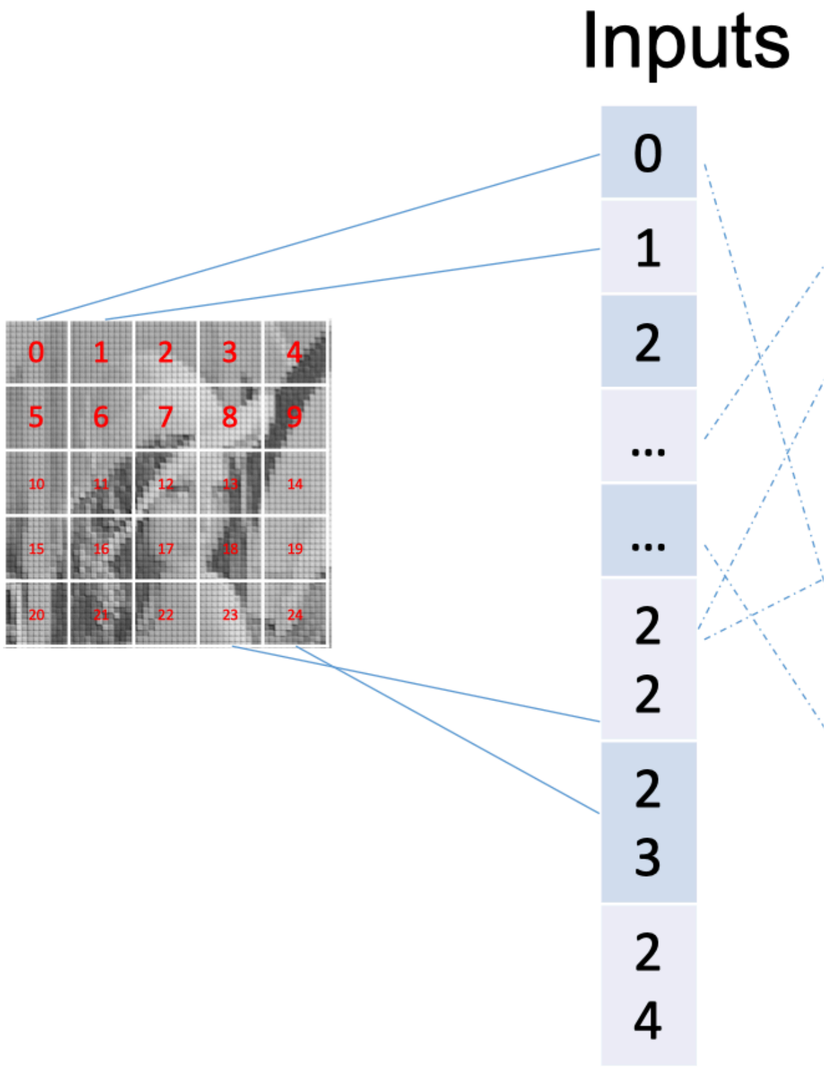
Neural Network with a single “hidden layer”



Neural Network with 3 Hidden Layers



How does a neural network “learn?”



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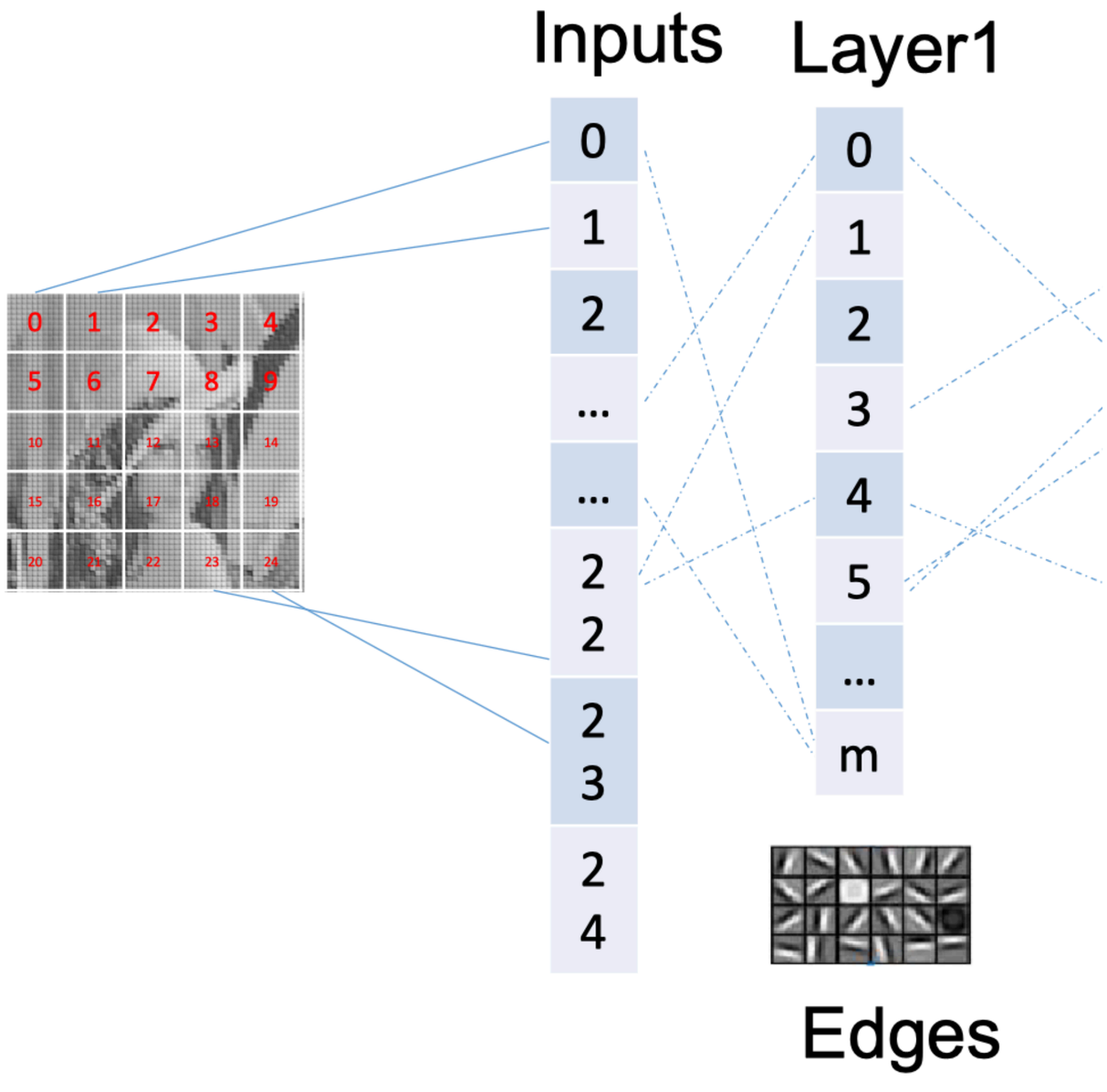
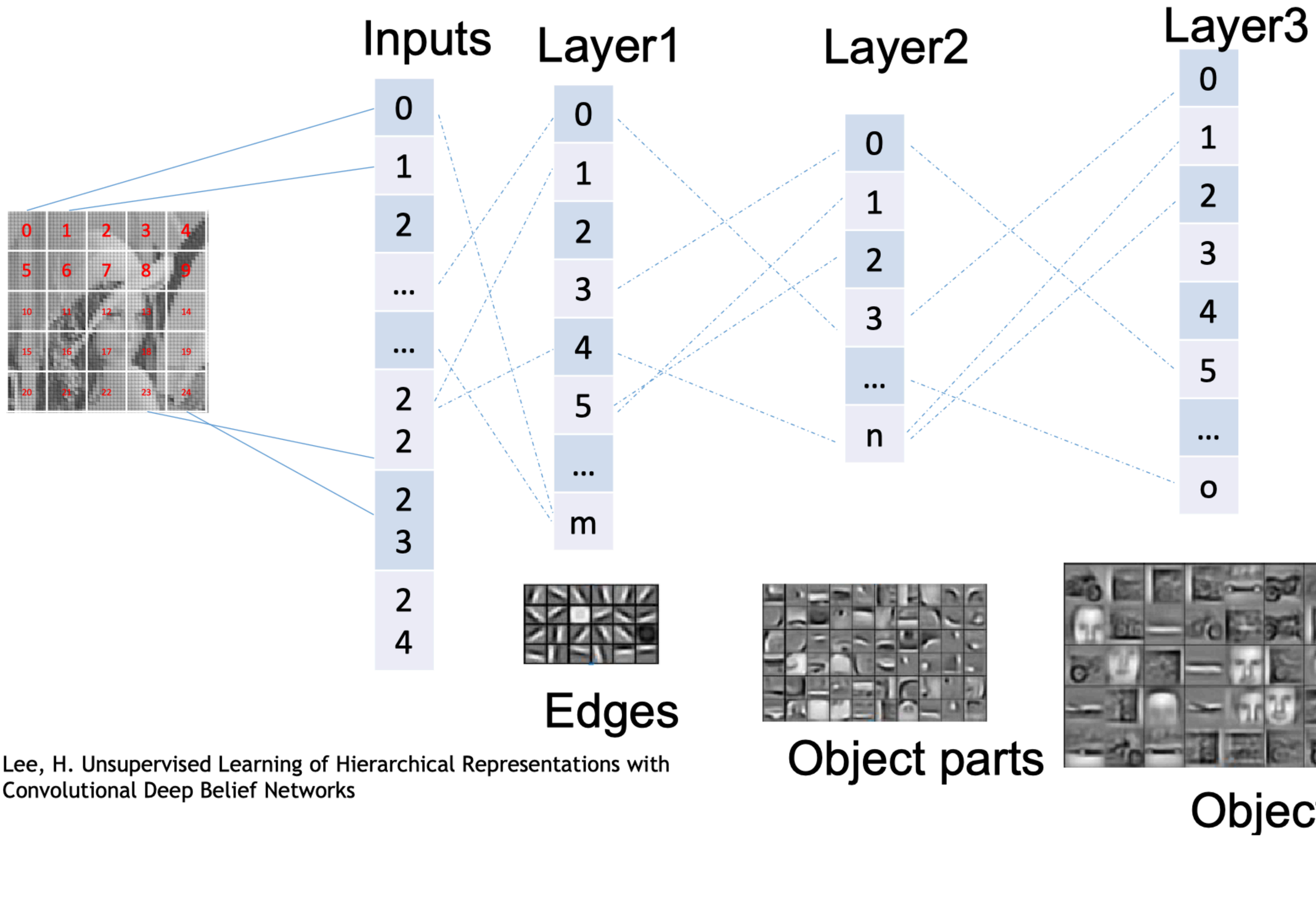


Lee, H. Unsupervised Learning of Hierarchical Representations with Convolutional Deep Belief Networks

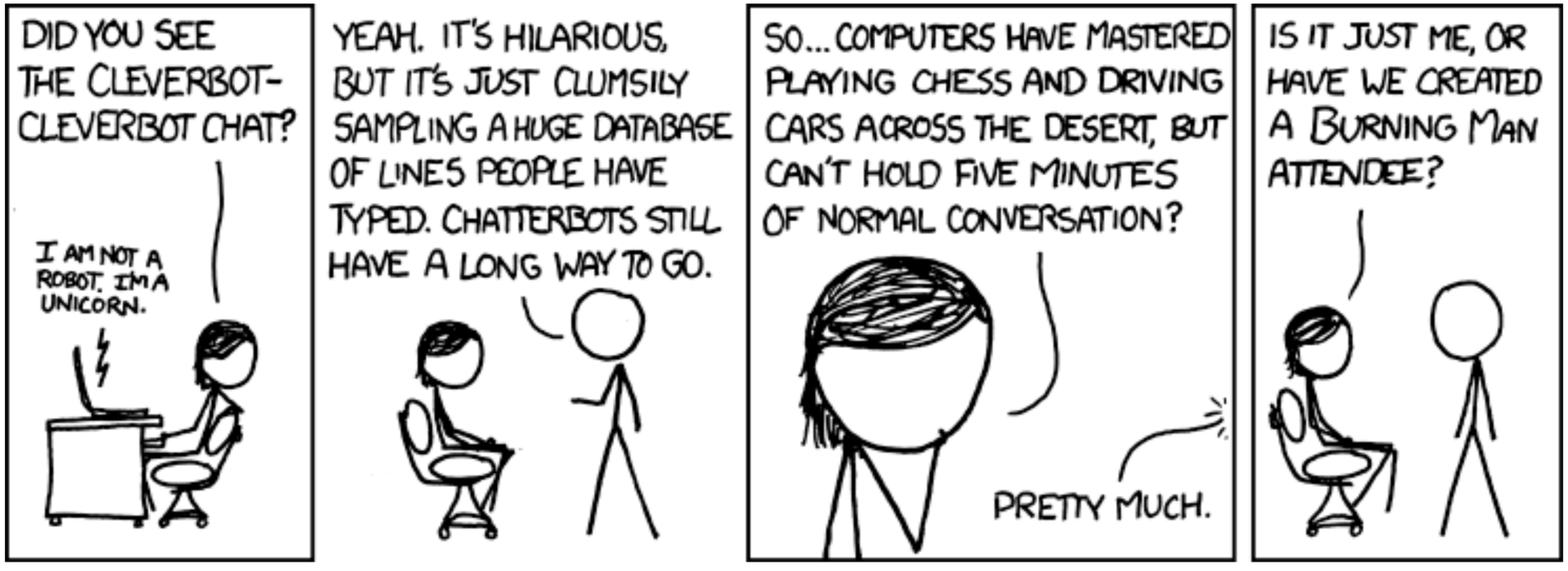
How does a neural network “learn?”



Lee, H. Unsupervised Learning of Hierarchical Representations with Convolutional Deep Belief Networks

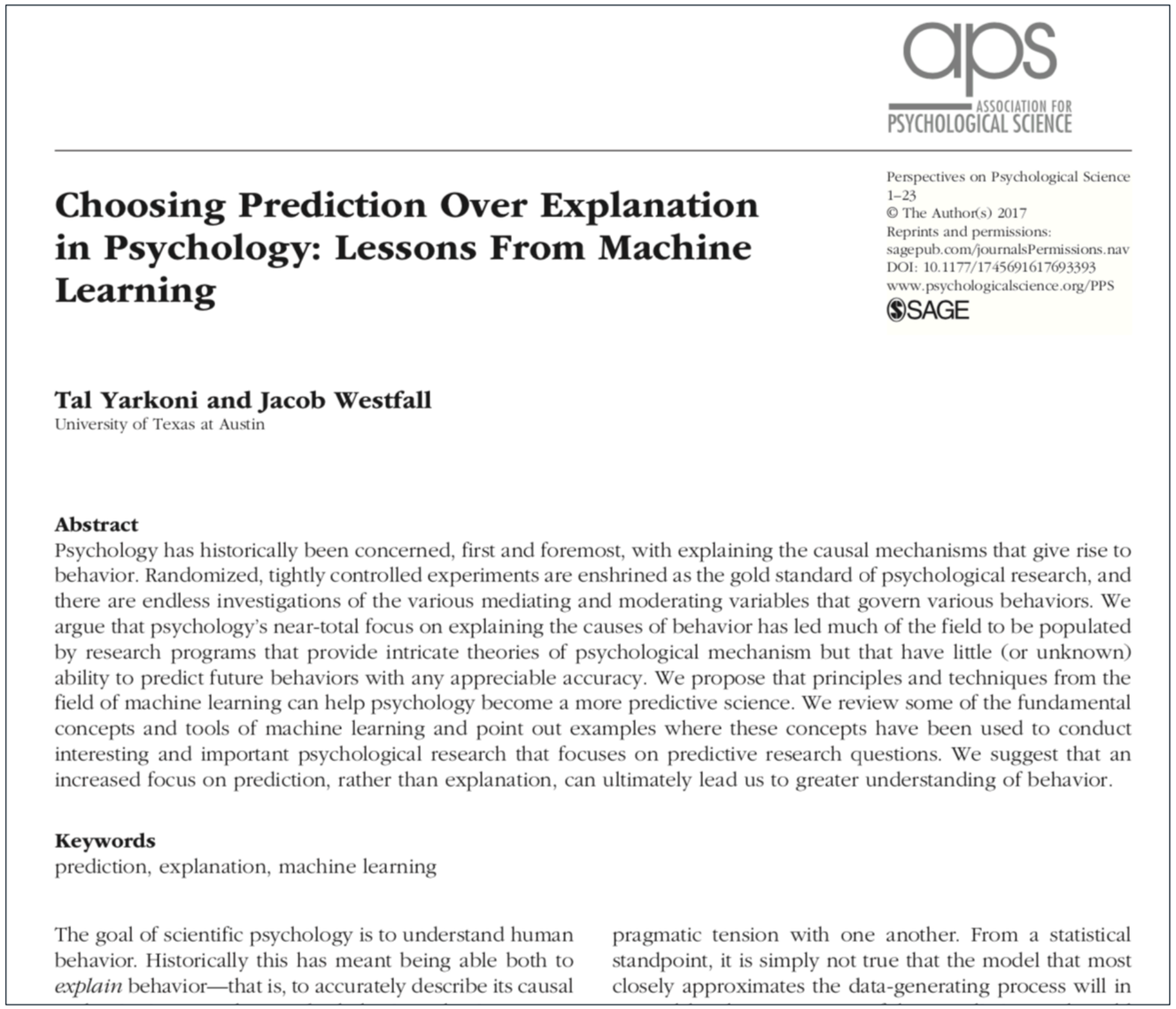
Future Directions

- Recurrent neural networks, convolutional neural networks
- Natural language processing
- Lots to learn!



Conclusions: Where to Learn More

Interested in Learning More?



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Perspectives on Psychological Science
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DOI: 10.1177/1745691617693393
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Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning

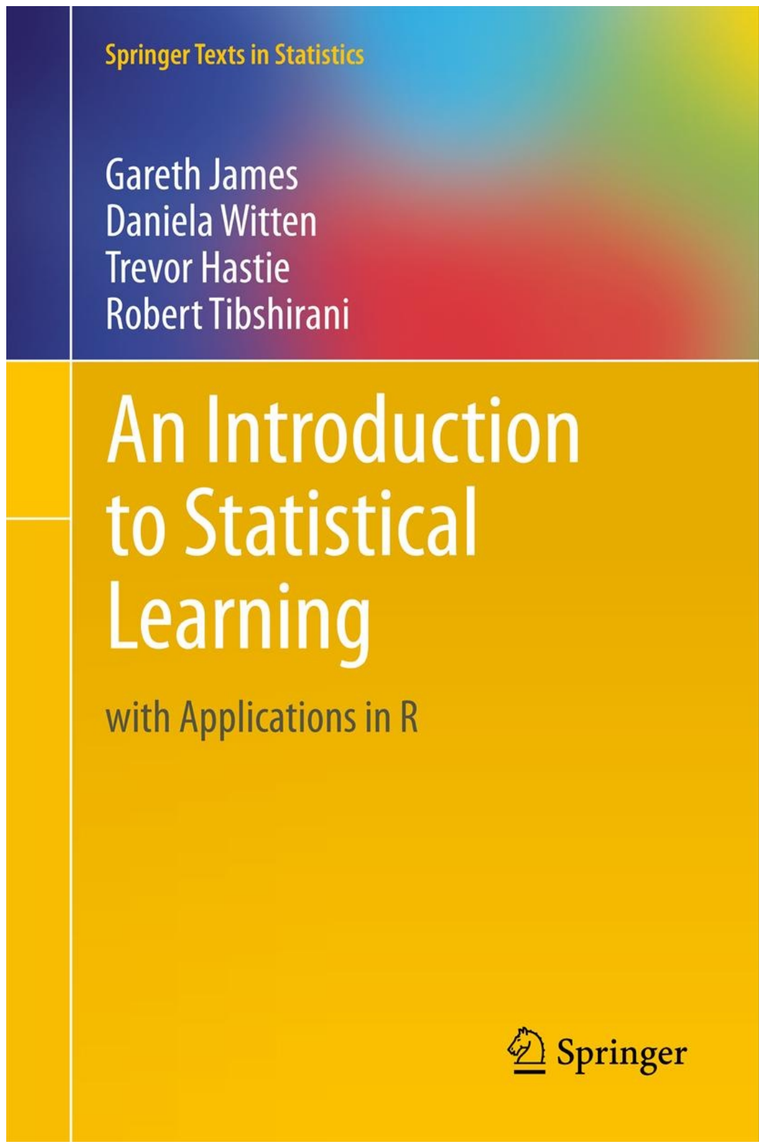
Tal Yarkoni and Jacob Westfall
University of Texas at Austin

Abstract
Psychology has historically been concerned, first and foremost, with explaining the causal mechanisms that give rise to behavior. Randomized, tightly controlled experiments are enshrined as the gold standard of psychological research, and there are endless investigations of the various mediating and moderating variables that govern various behaviors. We argue that psychology's near-total focus on explaining the causes of behavior has led much of the field to be populated by research programs that provide intricate theories of psychological mechanism but that have little (or unknown) ability to predict future behaviors with any appreciable accuracy. We propose that principles and techniques from the field of machine learning can help psychology become a more predictive science. We review some of the fundamental concepts and tools of machine learning and point out examples where these concepts have been used to conduct interesting and important psychological research that focuses on predictive research questions. We suggest that an increased focus on prediction, rather than explanation, can ultimately lead us to greater understanding of behavior.

Keywords
prediction, explanation, machine learning

The goal of scientific psychology is to understand human behavior. Historically this has meant being able both to *explain* behavior—that is, to accurately describe its causal

pragmatic tension with one another. From a statistical standpoint, it is simply not true that the model that most closely approximates the data-generating process will in



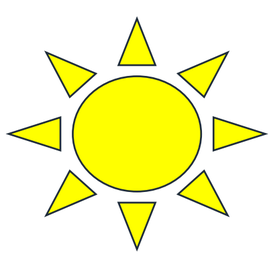
Springer Texts in Statistics

Gareth James
Daniela Witten
Trevor Hastie
Robert Tibshirani

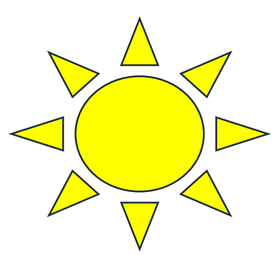
An Introduction to Statistical Learning

with Applications in R

Springer



I will be leading a workshop on these and other methods through NUIT:
July 25 1-4 pm, Location TBD



The end

THANK YOU!

Full Citations from Slides

Bruce, P., & Bruce, A. (2017). *Practical statistics for data scientists.* Sebastopol, CA: O'Reilley Media, Inc.

Hastie, T., Tibshirani, R., & Friedman, J. (2001). *The Elements of Statistical Learning: Data mining, inference, and prediction 2nd Edition*. New York, NY: Springer.

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McCarthy, R. (1998). The price you pay for the drug not taken. *Business Health, 16,* 27-28.

[1]Neiheisel, M. B., Wheeler, K. J., & Roberts, M. E. (2013). Medication adherence part one: Understanding and assessing the problem. *Journal of the American Association of Nurse Practitioners, 26,* 49-55.

[2]Osterberg, L. & Blaschke, T. (2005). Adherence to medication. *New England Journal of Medicine, 353,* 487-497.

[3]Bosworth, H. B., Granger, B. B., Mendys, P., Brindis, R., Burkholder, R., Czajkowski, M., Grander, C. B, (2011). Medication adherence: A call for action. *American Heart Journal, 162,* 412-424.

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[6] Hill, P. L., & Roberts, B. W. (2011). The role of adherence in the relationship between conscientiousness and perceived health. *Health Psychology, 30,* 797-804.

[7] Molloy, G. J., O'Carroll, R. E., Ferguson, E. (2014). Conscientiousness and medication adherence: A meta-analysis. *Annals of Behavioral Medicine, 47,* 92-101.

Code time!

```
#########################
## R Script accompanying "Recursive Binary Partitioning and the Random Forest: An Introduction to
Tree-Based Machine Learning Methods in R"
## In-text Walkthrough
## Authors: Andrew N Hall, David M Condon, Daniel K Mroczek
#########################

# Install and load required packages
packages = c("psych", "rpart", "randomForest", "dplyr", "ggplot2") #packages needed for
walkthrough
packages.notinstalled <- packages[!(packages %in% installed.packages()[,"Package"])] #check for
packages installed
if(length(packages.notinstalled)) install.packages(packages.notnstalled)
library(psych); library(rpart); library(randomForest); library(dplyr); library(ggplot2) #load
relevant packages

# Load dataset from psych package
data(spi) #load spi data
dat = spi #assign spi data to the variable `data`

# Split data into training and test datasets
set.seed(44) #set seed for reproducible results
dat_train = sample_frac(dat, size = 7/10) #take 70% of observations for training data
dat_test = setdiff(dat, dat_train) #leave remaining 30% for test data
```

Code time!

```
####
# Decision Tree - Regression Using Recursive Binary Partitioning
###
dtree = rpart(health ~ ., method = "anova", parms = list(split= "gini"), data = dat_train) #apply
rpart to data to create decision tree

plot(dtree, uniform = T, main = "Regression Decision Tree Predicting Health") #create plot for
decision tree
text(dtree, pretty = 0, use.n = TRUE, cex = .9) #add text to decision tree

## Decision Tree -- Pruning
printcp(dtree) #cost complexity tuning parameters

plotcp(dtree, upper = c("none"), main = "Cross Validated Cost Complexity Results") #plot cross-
validated cost complexity results

dtree_pruned <- prune(dtree, cp=0.022) #prune tree using the relevant cp value

plot(dtree_pruned, uniform = T, main = "Pruned Regression Decision Tree Predicting Health") #plot
pruned decision tree
text(dtree_pruned, pretty = 0, use.n = TRUE) #add text to pruned decision tree

## Decision Tree -- Prediction
pred_dtree <- predict(dtree_pruned, newdata = dat_test) #predict outcome value for test set using
the pruned decision tree
dtree_RMSE <- sqrt(mean((pred_dtree-dat_test$health)^2, na.rm=T)) #calculate RMSE values from
test set predictions
print(dtree_RMSE) #print RMSE value
```

Code time!

```
####
# Random Forest
###
# Create a complete dataset
set.seed(44)
dat_complete <- dat[complete.cases(dat),] #takes only complete cases from the dataset
dat_complete_train <- dat_complete %>%
  sample_frac(size = 7/10) #sample 7/10 of the observations for the training dataset
dat_complete_test <- dat_complete %>%
  setdiff(dat_complete_train) #take the rest for the test dataset

# Random Forest

rf <- randomForest(health ~ ., data = dat_complete_train, ntree = 500, importance = TRUE)
#function to create a random forest using default values for ntree and mtry
sqrt(mean(rf$mse)) #OOB RMSE value

## Tuning RF
set.seed(44)
tuneRF(dat_complete_train[,-3], dat_complete_train[,3], ntreeTry=1000, stepFactor=1.5,
improve=0.05,
       trace=TRUE, plot=TRUE, doBest=FALSE) #tries different values of mtry and looks at impact
on performance.

## Final RF model
set.seed(44)
rf_final <- randomForest(health ~ ., mtry = 48, ntree = 500, importance = TRUE, data =
dat_complete_train) #final model using the mtry=48 value from above.

## Variable importance
varImpPlot(rf_final, type = 1, main = "Variable Importance for Random Forest Regression")
#creates importance plot

# Evaluate RF performance
pred_rf = predict(rf_final, newdata = dat_complete_test) #predict outcome value for test set
using the random forest
rf_RMSE = sqrt(mean((pred_rf-dat_complete_test$health)^2)) #calculate RMSE values from test set
predictions
print(rf_RMSE)
```

Code time!

```
## Multiple Regression
multreg = lm(health ~ ., data = dat_train) #create a multiple regression model predicting health
pred_multreg = predict(multreg, newdata = dat_test, type = "response") #predcit outcome value for
test set using multiple regression
multreg_RMSE = sqrt(mean((pred_multreg -dat_test$health)^2, na.rm = T)) #calculate RMSE values
from test set predictions
print(multreg_RMSE)
```

Code time! Classification

```
#########################
## R Script accompanying "Recursive Binary Partitioning and the Random Forest: An Introduction to
Tree-Based Machine Learning Methods in R"
## Code for supplemental classification example
## Authors: Andrew N Hall, David M Condon, Daniel K Mroczek
#########################

## Load packages
packages = c("psych", "rpart", "randomForest", "dplyr", "ggplot2")
#install.packages(packages)
library(psych); library(rpart); library(randomForest); library(dplyr); library(ggplot2)

## Extract data from psych package
dat <- spi # using same dataset as regression but will manipulate one variable to create binary.
dat <-  dat[complete.cases(dat),] #take only complete cases for this example
dat <- dat %>%
  mutate(ER = if_else(ER == 1, 0, 1)) %>% #create binary variable for binary classification. In
original data, 1 = Never been to ER, 2-4 represented increasing number of visits. We create a
binary variable such that 0 = Never been to ER, 1 = Been to ER at least once.
  mutate(ER = as.factor(ER))

## Recursive Binary Partitioning (Decision Tree) for Classification
## Separate training and test datasets
set.seed(44)
dat_train <- dat %>%
  sample_frac(size = 7/10) #sample 7/10 of the observations for the training dataset
dat_test <- dat %>%
  setdiff(dat_train) #take the rest for the test dataset

## Build decision tree
dtree <- rpart(ER~., method = "class", parms = list(split= "gini"), data = dat_train) #construct
classification decision tree

plot(dtree, uniform = T, main = "Decision Tree for Classification of ER Visits") #create decision
tree plot
text(dtree, pretty = 0) #add text to decision tree plot

pred_dtree <- predict(dtree, newdata = dat_test, type = "class") #make predictions on test set
cm_dtree <- table(pred_dtree, dat_test$ER) #create a confusion matrix of accurate vs. inaccurate
predictions. We see the model is doing a poor job of classifying people who did visit ER!
(cm_dtree[1] + cm_dtree[4])/nrow(dat_test) #calculate
```

Code time! Classification

```
## Random Forest Classification

set.seed(44)
tuneRF(dat_train[,-57], dat_train[,57], mtryStart = 8, ntreeTry=100, stepFactor=2, improve=0.05,
       trace=TRUE, plot=TRUE, doBest=FALSE) #run tuning plot of mtry vs. OOB error. Tells us to
use mtry = 32.

set.seed(44)
rf <- randomForest(ER ~ ., data = dat_train, ntree = 500, importance = TRUE, mtry = 32) #run
random forest model using mtry = 32

varImpPlot(rf, type = 1) #variable importance plot. type = 1 tells it to only select the plot
based on accuracy.

pred_rf <- predict(rf, newdata = dat_test, type = "class") #construct predictions on the test
dataset
cm_rf <- table(pred_rf, dat_test$ER) #construct the confustion matrix. We see RF model is
predicting everyone to be a value of 0! Thus, accuracy may be high, but it will just be the
proportion of people who reported 0. Illustrates a danger in only reporting overall
classification accuracy.
(cm_rf[1] + cm_rf[4])/nrow(dat_test) #overall accuracy of RF
```

Code time! Classification

```
## Comparison to logistic regression
logreg <- glm(ER ~ ., family = "binomial", data = dat_train) #construct logistic regression model
with ER as binary outcome

pred_logreg <- predict(logreg, newdata = dat_test, type = "response") #make predictions on test
dataset making "response" outcomes of probability of inclusion in a class.
pred_logreg <- if_else(pred_logreg > 0.5, 1, 0) #cutoff for probability of inclusion. Here we use
0.5, which is arbitrary. Would likely want a different cutoff due to unbalanced groupings in a
real scenario.
pred_logreg <- as.factor(pred_logreg) #make predictions a factor
cm_log <- table(pred_logreg, dat_test$ER) #construct confusion matrix of predictions by actual
values.
(cm_log[1] + cm_log[4])/nrow(dat_test) #calculates overall accuracy rates
```

Code time! Classification

```
#########################
## R Script accompanying "Recursive Binary Partitioning and the Random Forest: An Introduction to
Tree-Based Machine Learning Methods in R"
## Code for examples in paper pre walkthrough section using iris dataset
## Authors: Andrew N Hall, David M Condon, Daniel K Mroczek
#########################

# In-text example code using iris (pre-tutorial section)
library(datasets) #load datasets library
library(tidyverse) #load tidyverse for data manipulation
library(rpart) #load rpart for construction of decision tree
data(iris)

# Split data into training and test datasets
set.seed(44)
iris_train = sample_frac(iris, size = 1/2) #sample 1/2 of observations for training set
iris_test = setdiff(iris, iris_train) #take remaining 1/2 for test set

# Decision tree Iris
dtree_iris <- rpart(Species~., data = iris_train) #create basic decision tree based on iris data

plot(dtree_iris, uniform = T, main = "Example Decision Tree Using Iris Dataset") #plot decision
tree
text(dtree_iris, pretty = 0, use.n = T, cex = .9) #add text to decision tree
```