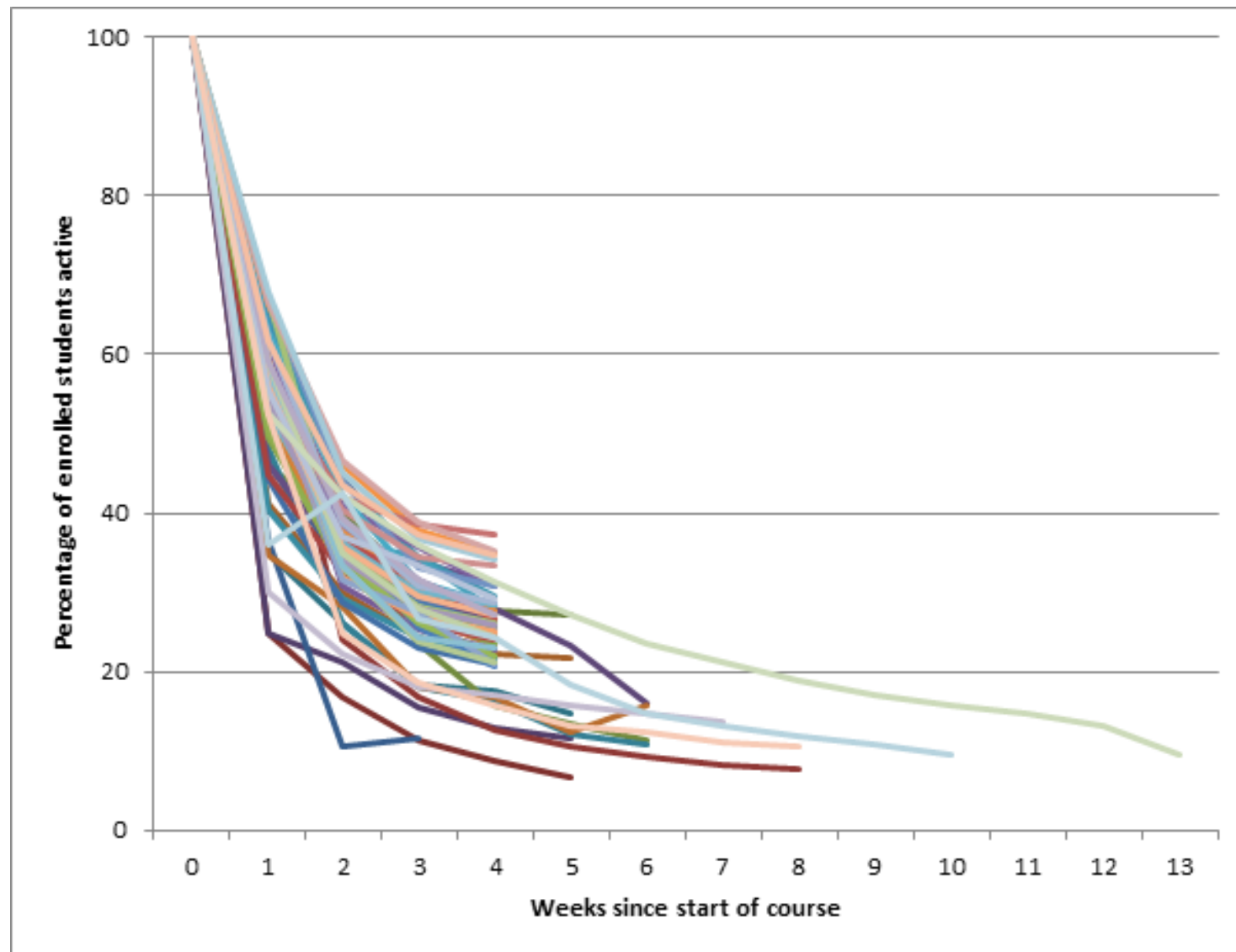


# Prediction

- There are times when we want to automate a process in education
- Want to be able to predict what a student might do in the future: next question, next move in a game, drop out



# Prediction



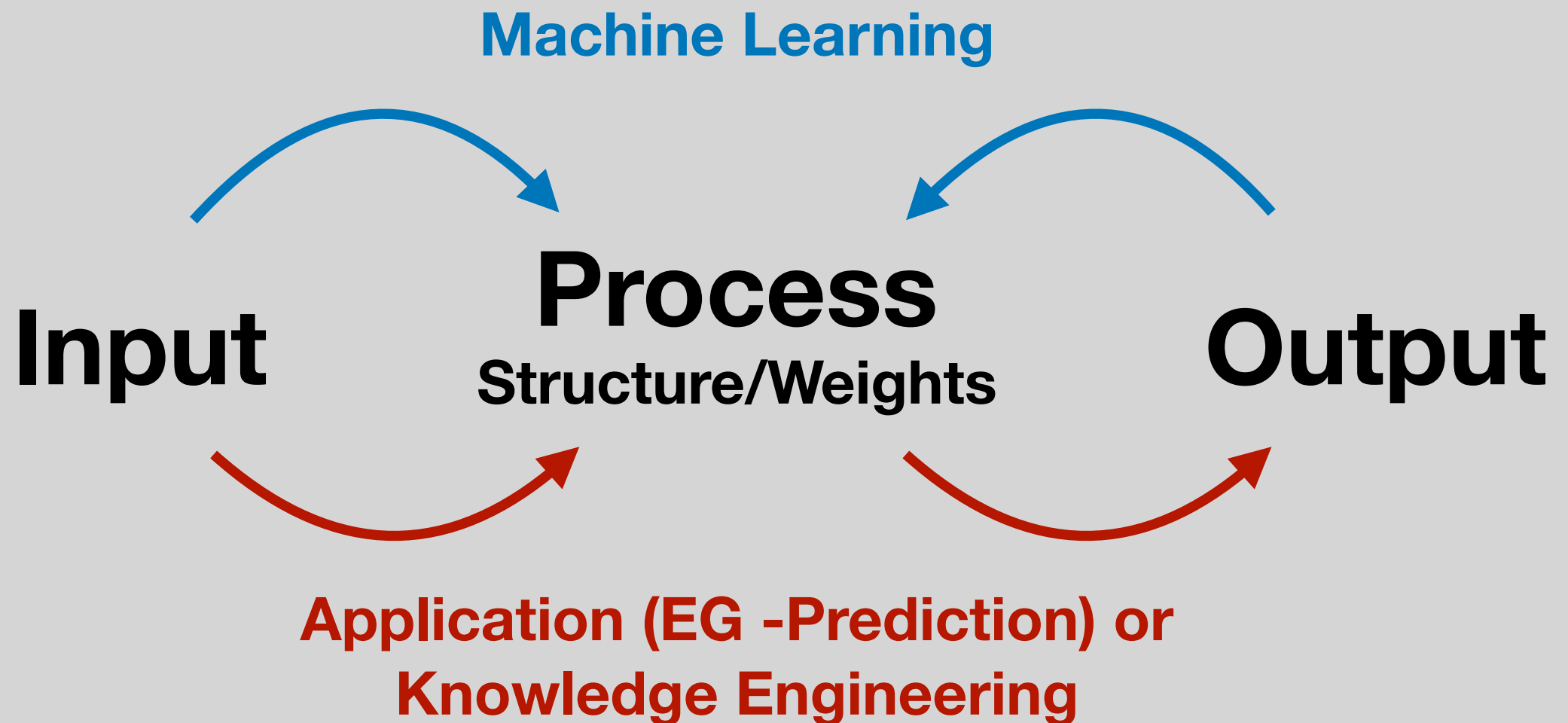
K Jordan, Open University, 2013



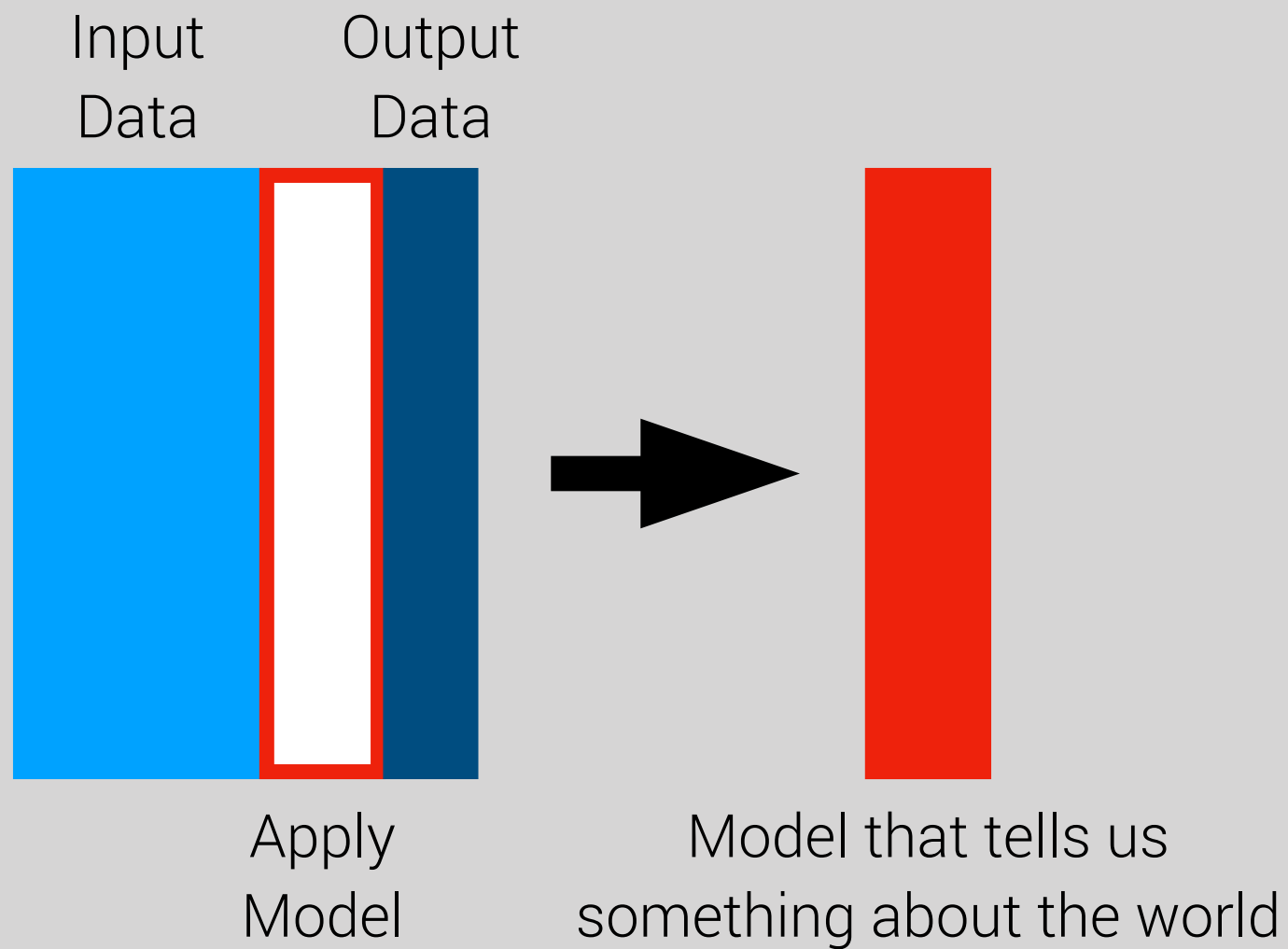
**CARNEGIE**  
**LEARNING**



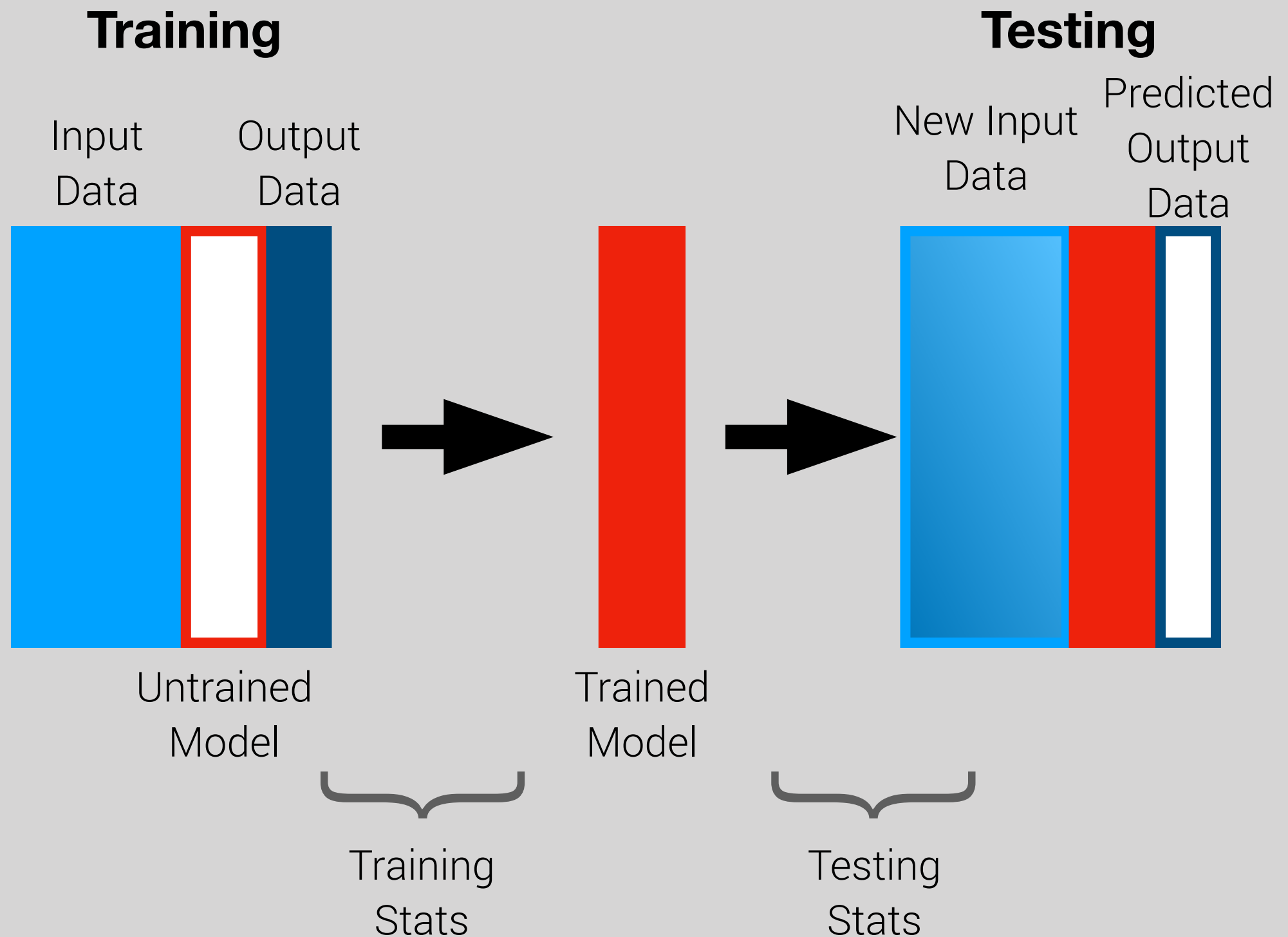
# Machine Learning



# Educational Statistics



# Machine Learning



# Classification Confusion Matrix

		Actual Class (Observations)	
		P	N
Predicted Class (Predictions)	P	TP	FP
	N	FN	TN

# Classification Confusion Matrix

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{Sensitivity/Recall/TPR} = \frac{TP}{TP + FN}$$

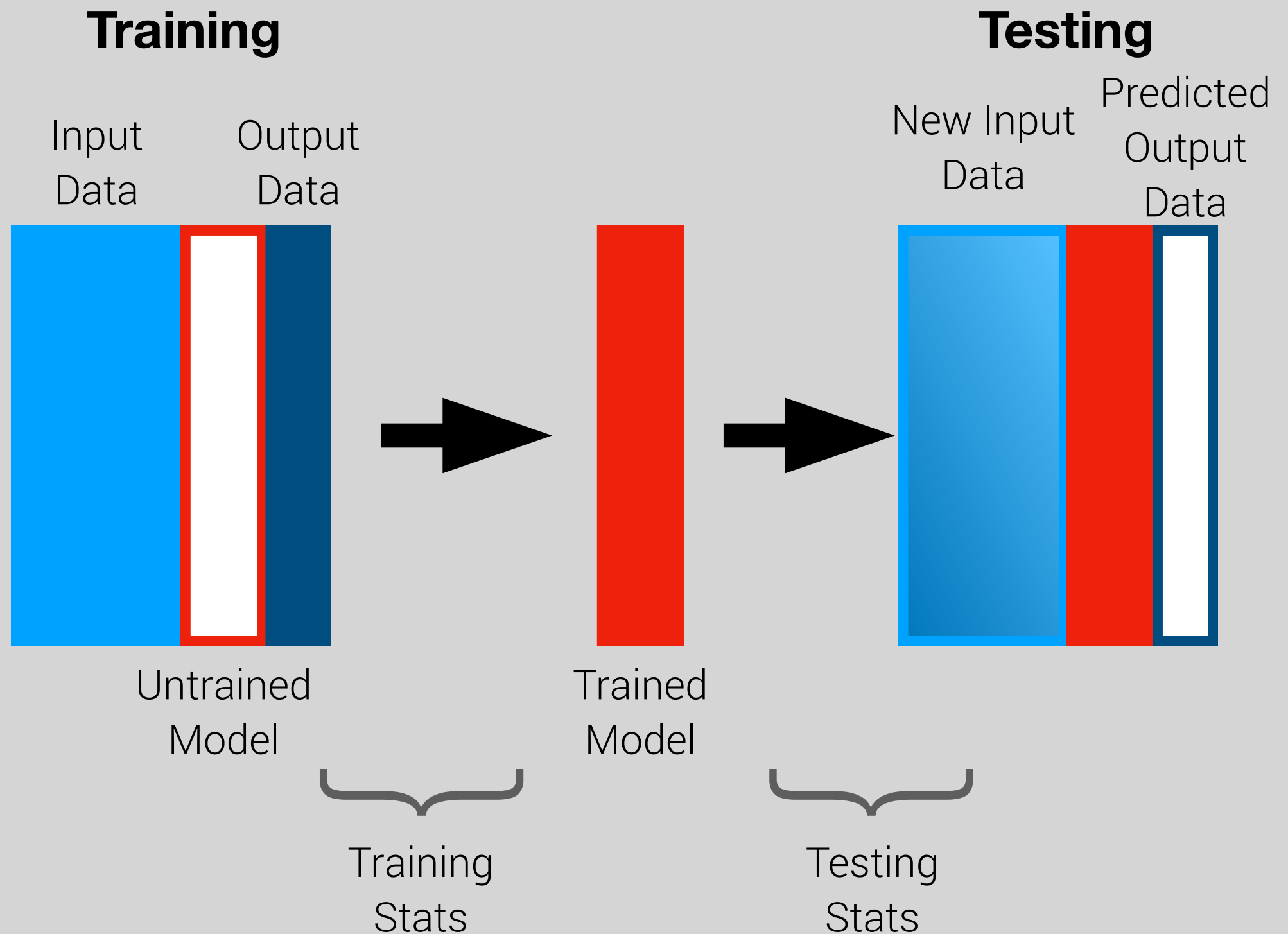
$$\text{Specificity/Selectivity/TNR} = \frac{TN}{TN + FP}$$

$$\text{Precision/Positive Predictive Value (PPV)} = \frac{TP}{TP + FP}$$

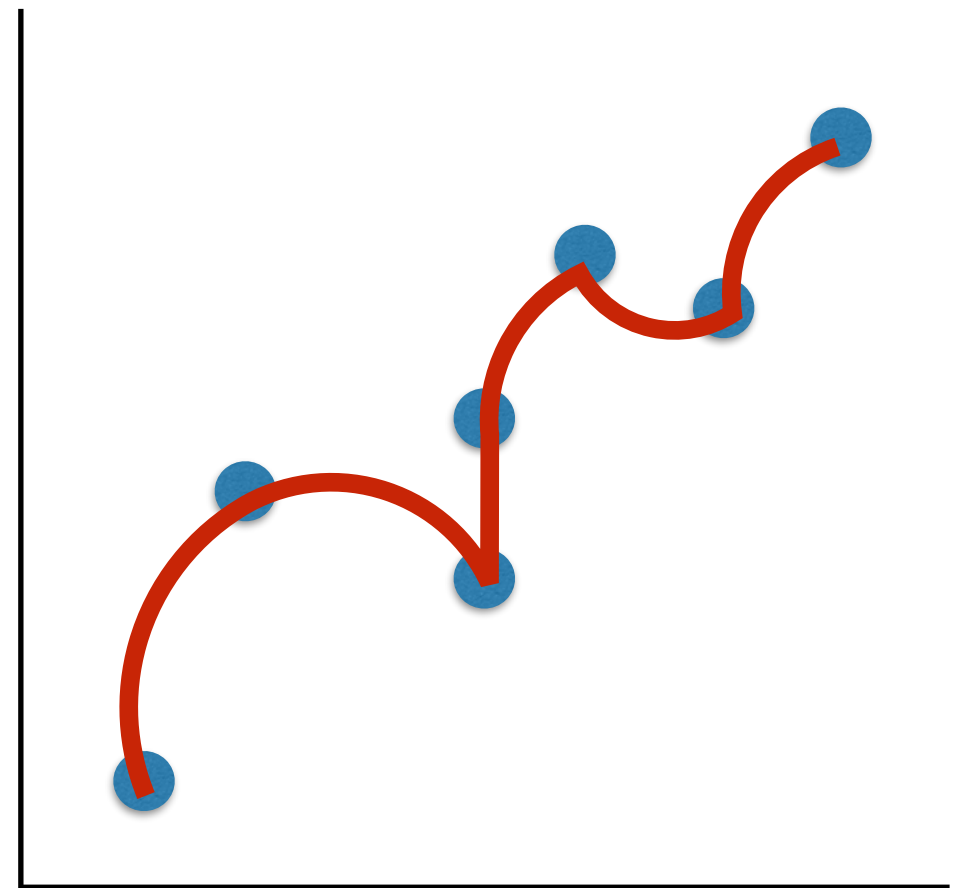
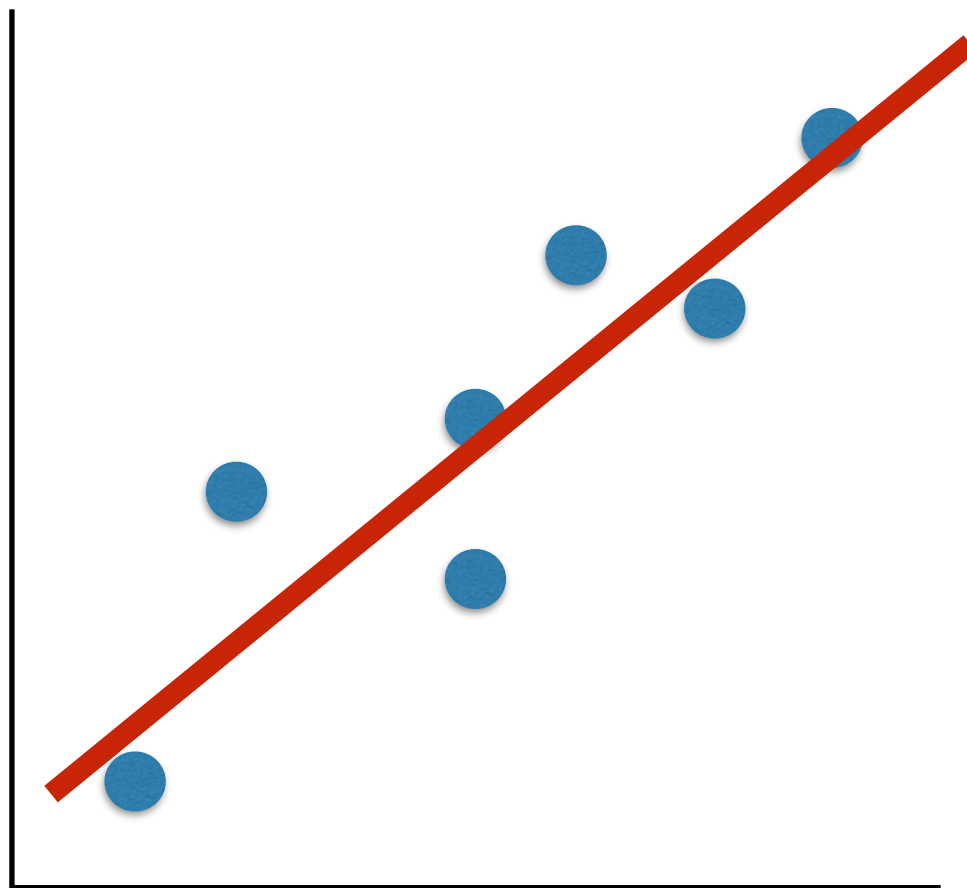
$$F1 = \frac{2TP}{2TP + FP + FN}$$

		Actual Class	
		P	N
Predicted Class	P	TP	FP
	N	FN	TN

# Machine Learning







Which is more “accurate”?

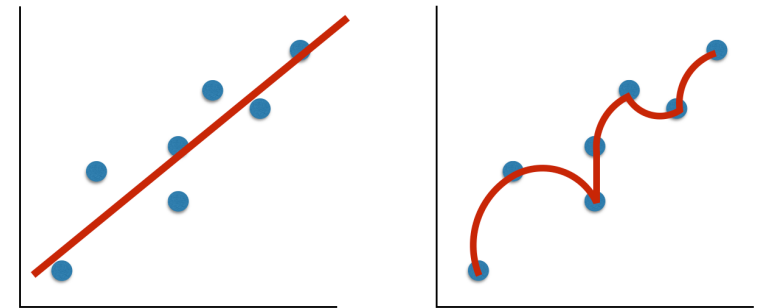
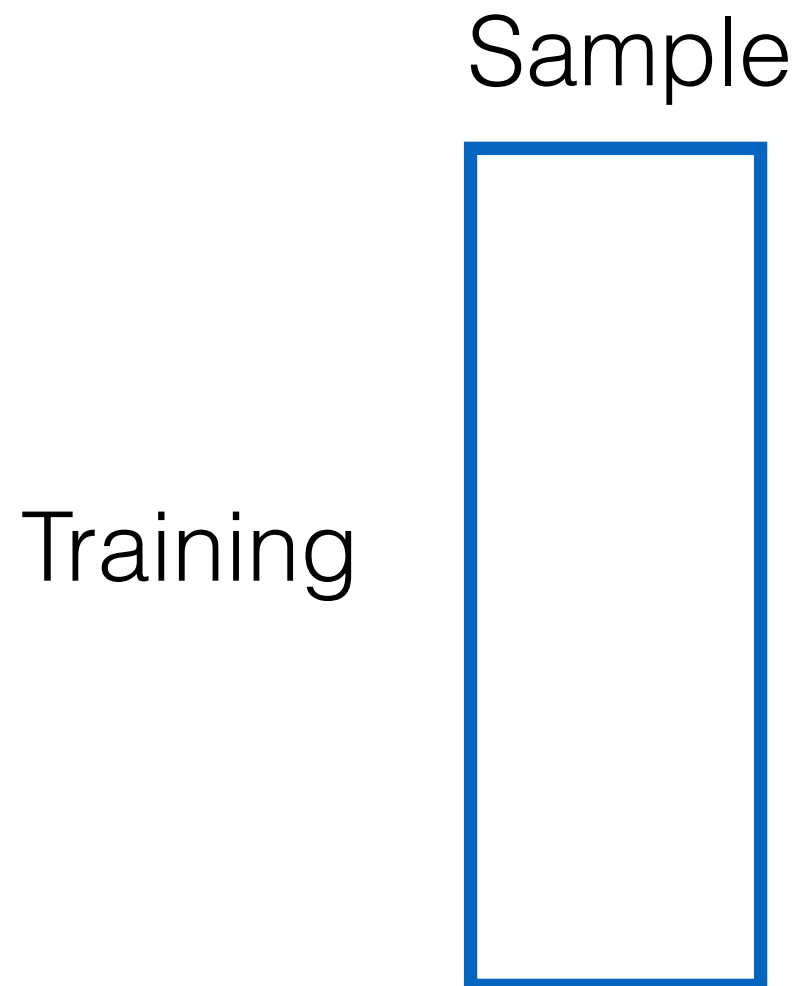
Which is more “useful”?

How can we tell?

# Cross Validation

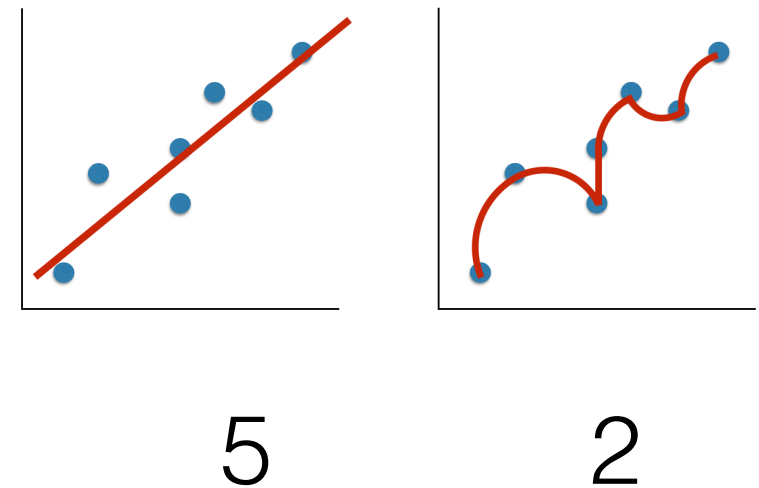
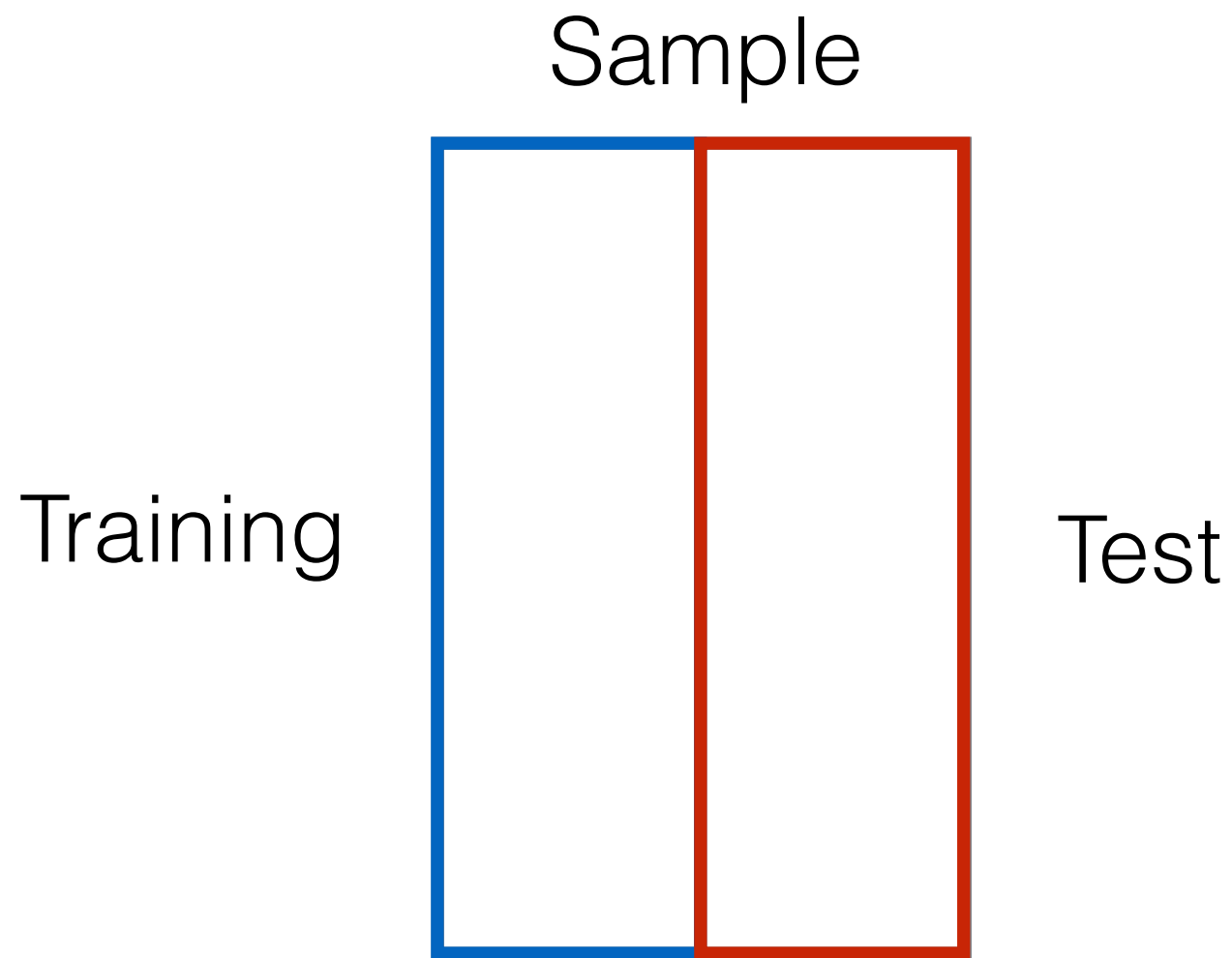
- Estimate how accurately a predictive model will perform in practice
- Give an insight on how the model will generalize to an independent dataset

# No Validation



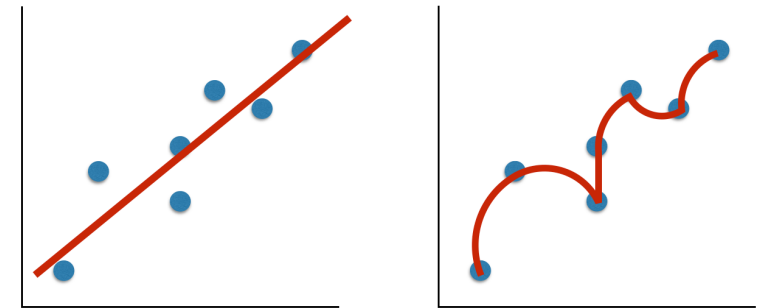
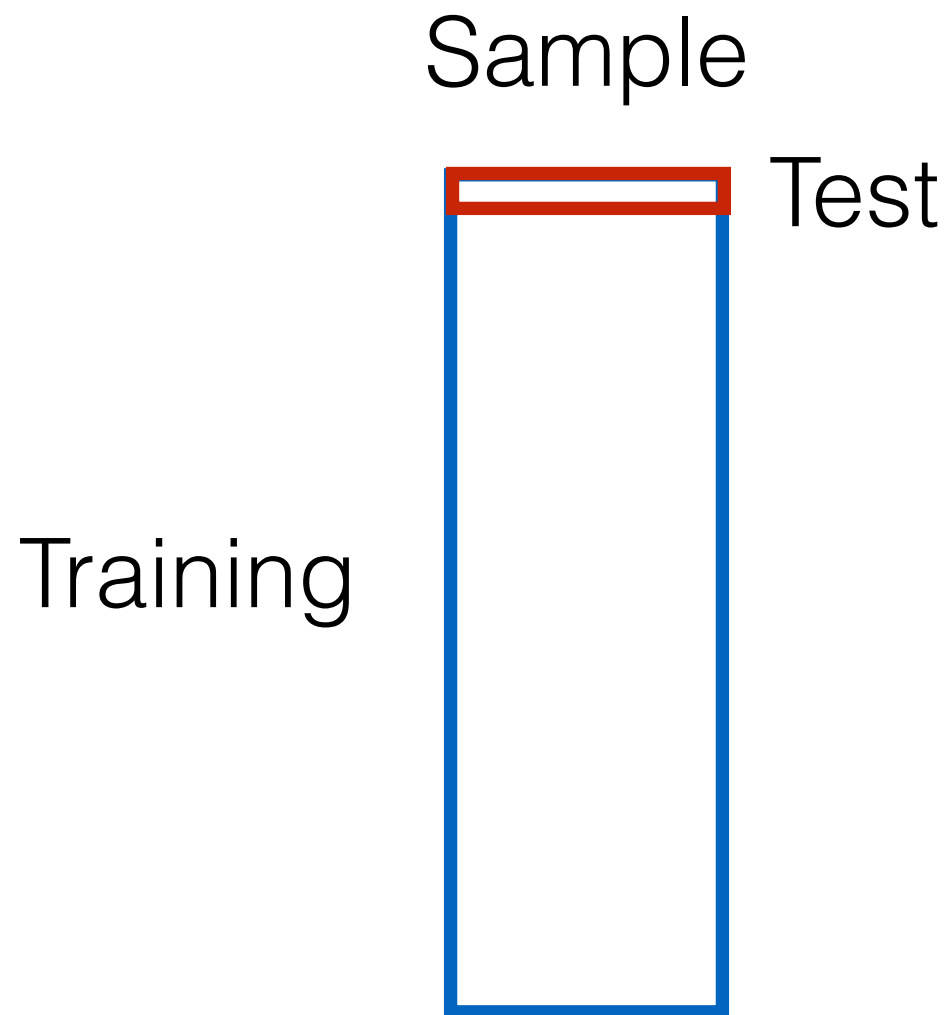
**Problem:** Can't compare generalizability of models

# Hold-out Validation



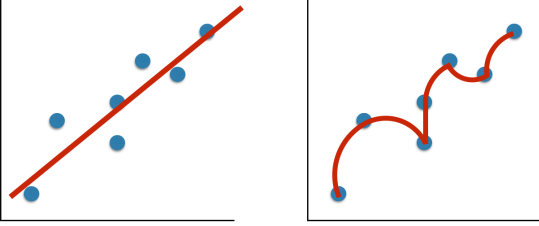
**Problem:** very dependent on which data are in each group

# Hold One-out Validation

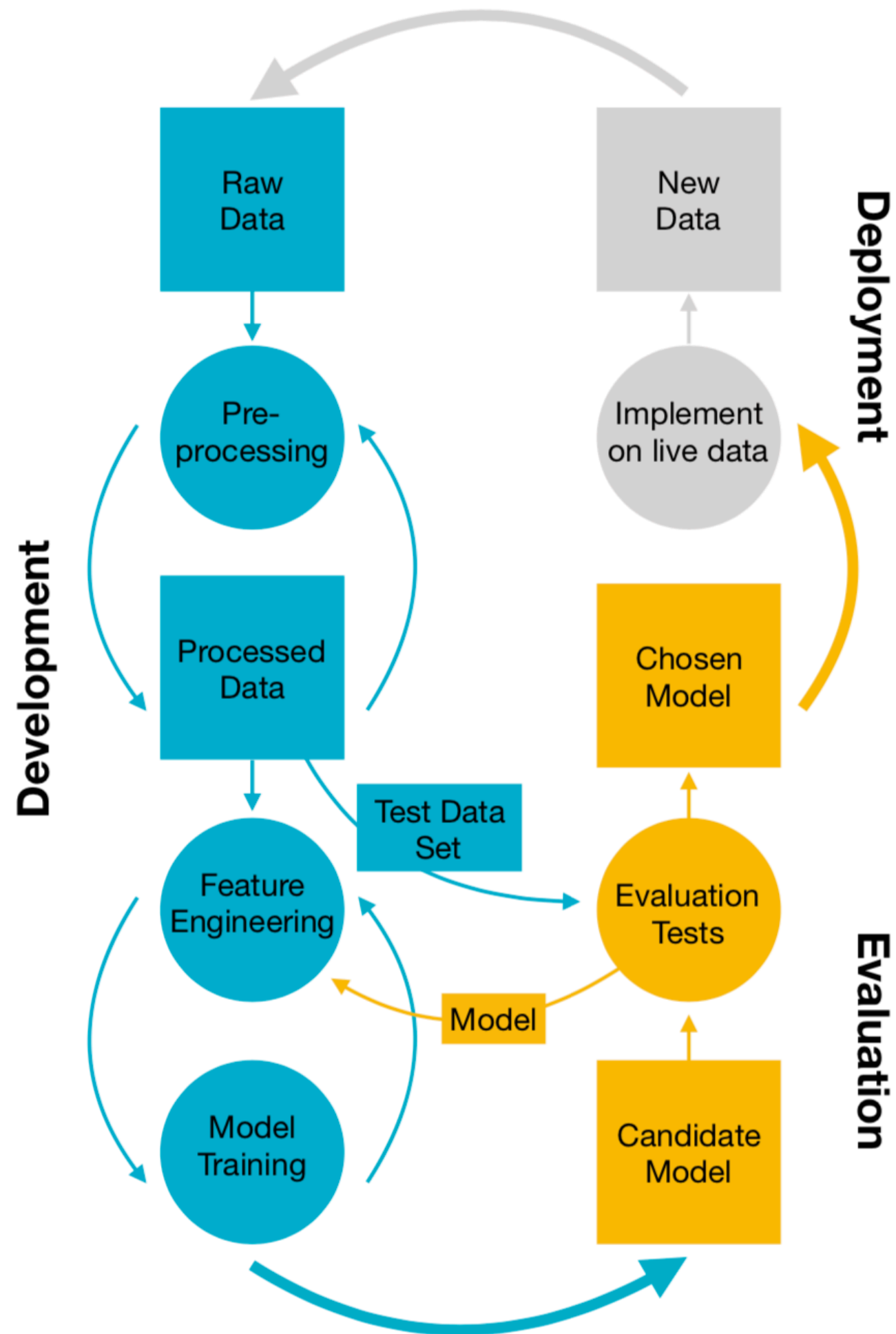


**Problem:** very computationally expensive

# K-Fold Cross Validation

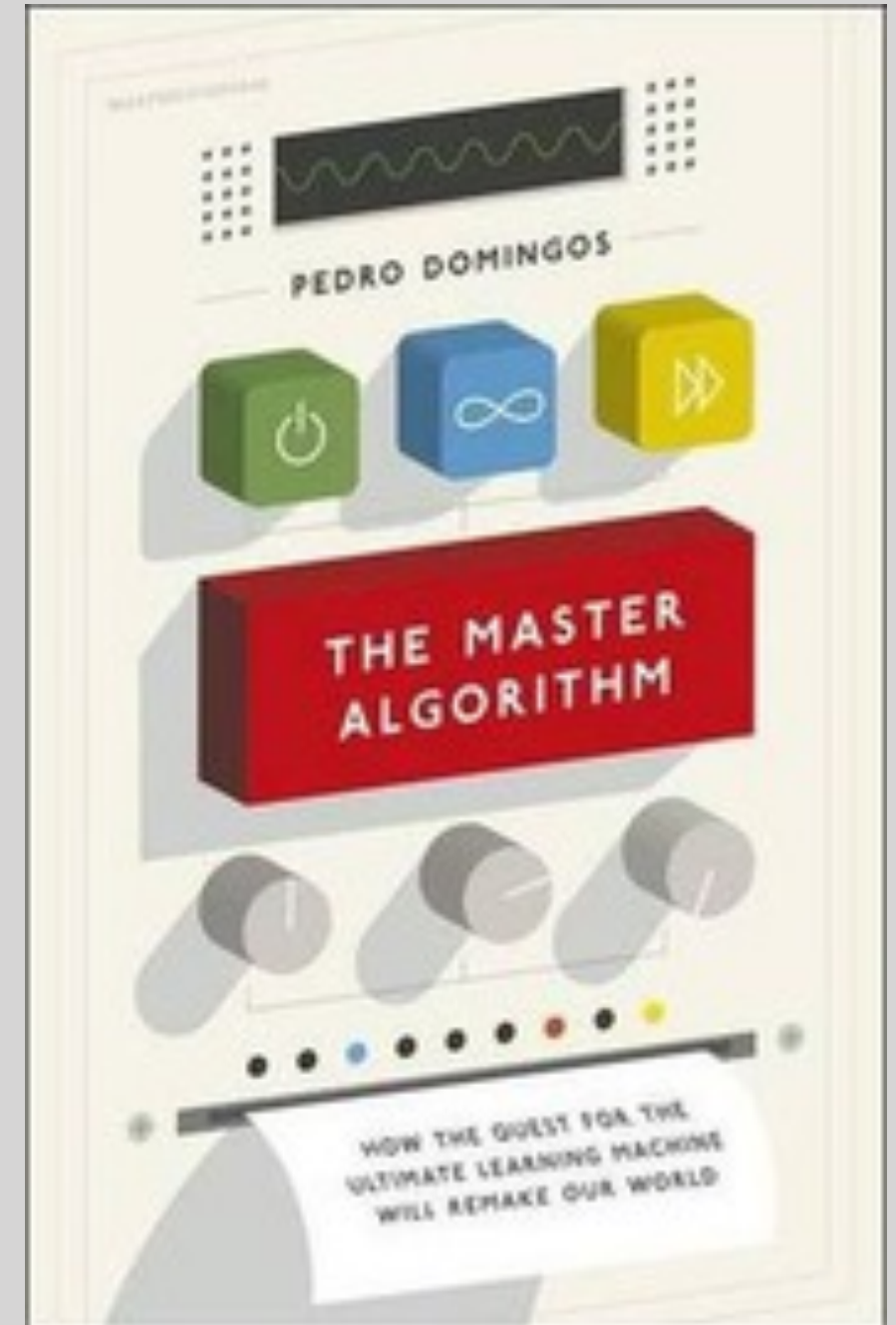
Sample			
Test 1	Training 1	5	2
Test 2	Training 2	4	2
Test 3	Training 3	3	1
Test 4	Training 4	5	4
Test 5	Training 5	4	2
		<hr/>	<hr/>
		4.2	2.2

Calculate how accurate we are in each “fold”  
and average the answer



# Five Tribes

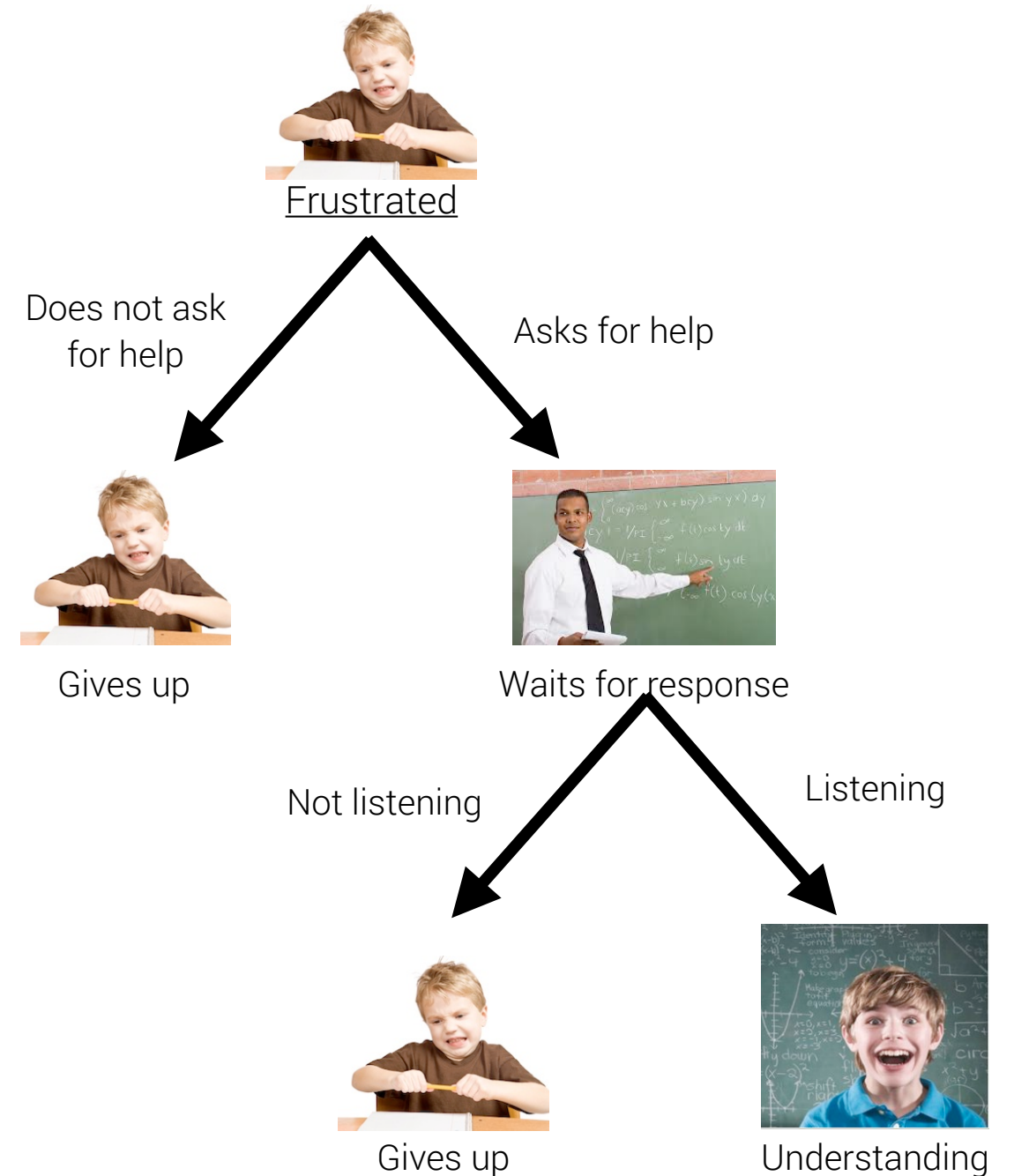
- Symbolists
- Connectionists
- Evolutionaries
- Bayesians
- Analogizers





# Classification Tree

- Decision tree
- Map observations (branches) onto classes (leaves)
- Tree describes the data but can be used as classification
- EG: student states = leaves, student actions = branches



Machine Learning

Input

Process  
Structure/Weights

Output

Does not ask  
for help

Asks for help

Not listening

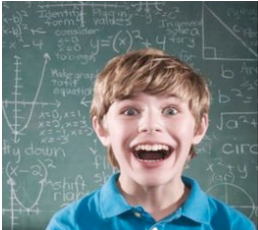
Listening



Frustrated



Gives up



Understanding

Does not ask  
for help

Asks for help



Gives up



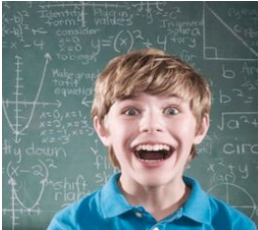
Waits for response

Not listening

Listening



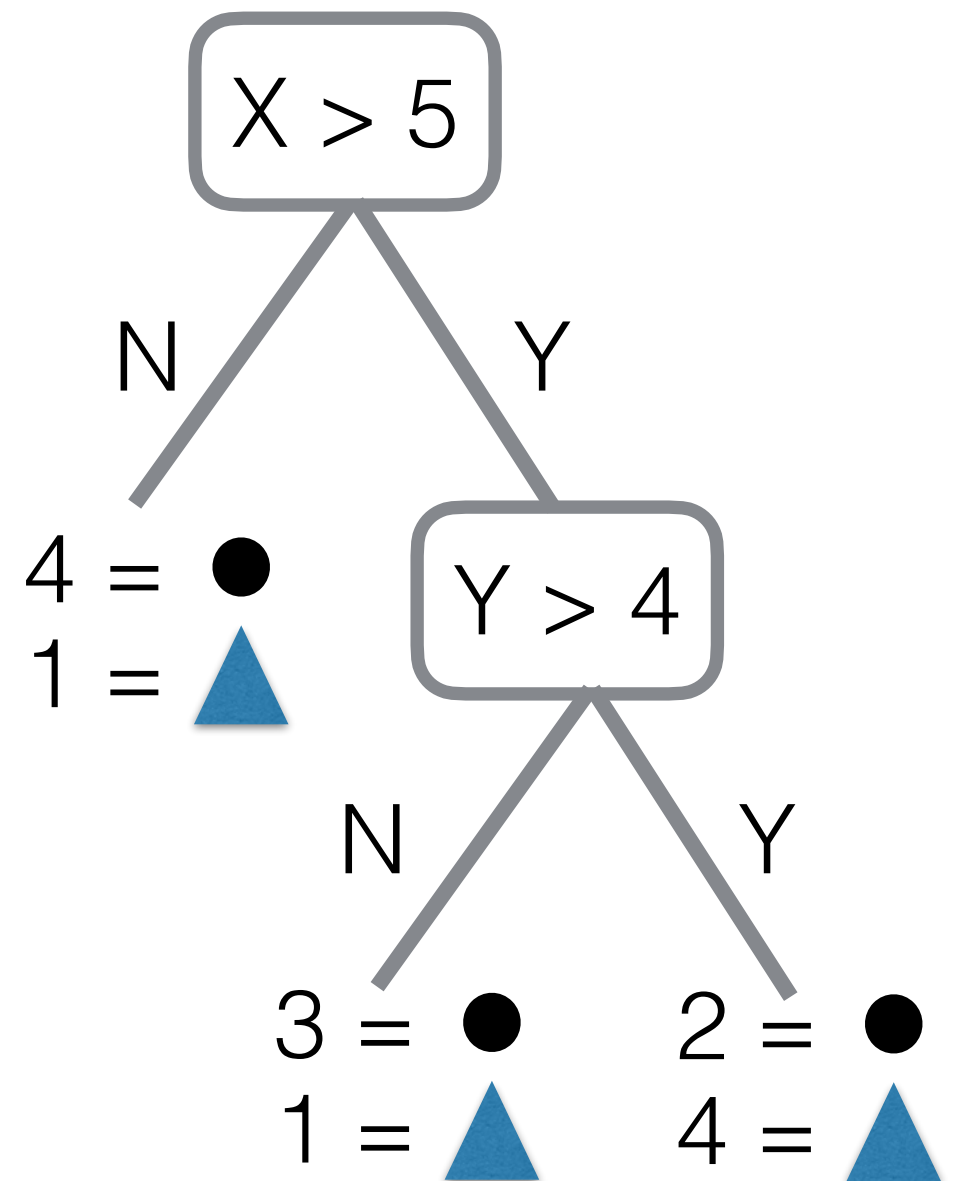
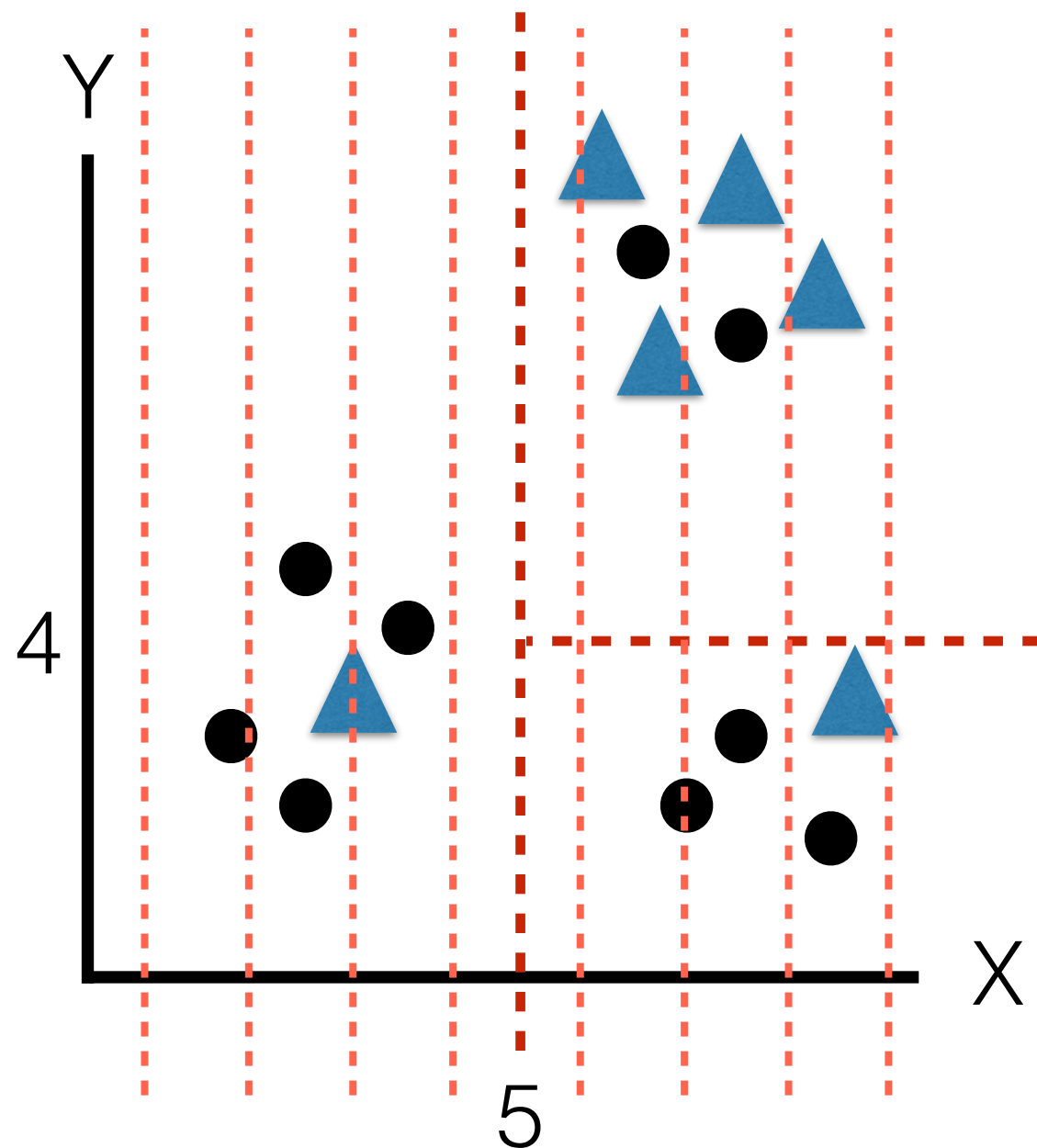
Gives up



Understanding

# Binary Classification Tree

\* Minimize the error



# caret

- Standard syntax for comparing many models
- Generate training and testing data sets
- Run several model types
- Run resampling algorithms and alter parameters to generate the best model
- Compare using the same diagnostic metrics
- <https://topepo.github.io/caret/>

# caret

## Generate Training/Test Data Sets

```
trainData <- createDataPartition(  
  y = data$thing, ## the outcome data are needed  
  p = .75, ## The percentage of data in the  
training set  
  list = FALSE)  
  
#Generates a list of index numbers for the sample  
  
training <- DATA[ trainData,]  
testing  <-DATA[-trainData,]
```

# caret

## K-Fold Cross Validation

```
ctrl <- trainControl(method = "cv", repeats = 3)
```

# caret

## Train Model

```
fit1 <- train(  
  thing ~ .,  
  data = training,  
  method = "model",  
  preProc = c("center", "scale")## Center and scale  
the predictors for the training set and all future  
samples.  
  trControl = ctrl #add cross validation specs  
  metric = "cp"  
)
```

# caret

## Test Model

```
pred1 <- predict(fit1, newdata = testing)
confusionMatrix(data = pred1, DATA$thing)
```



# Project

Train and test three tree-based models (CART, Conditional Inference Trees and C50) using data from the University of Michigan Open Data Set.