

# An Introduction to Predictive Modeling in R

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# Build Something Useful!

- Predictive modeling: the process of combining data and algorithms in order to build *useful* models
- In contrast with explicitly programming rules, predictive modeling algorithms attempt to *learn patterns from the data itself*
- Predictive modeling has deep mathematical foundations, but in the end, it's extremely practical

# Predictive Modeling is Everywhere

- Is this email message spam?
- Will this person default on their loan?
- Which other products might this person also buy?
- Is that a cat?
- Which group of people should I target for my ad campaign
- Is this person sick or healthy?

# Lots of Contexts, Lots of Terms

- People have been predictively modeling for a long time, and in lots of different fields
- Therefore, lots of different terms used for similar things

## **The Subject**

Predictive modeling  
Predictive analytics  
Machine learning  
Data mining  
Statistics

## **The Data**

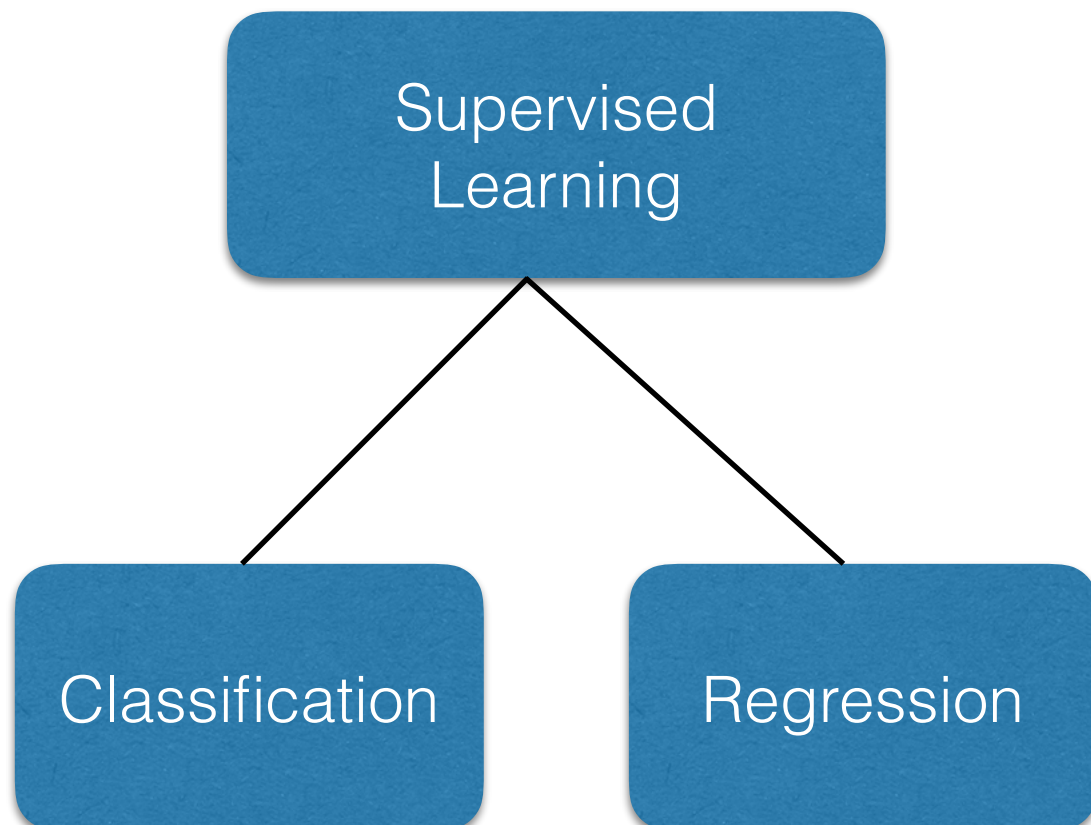
Features  
Predictors  
(Independent) Variables  
Measures  
Attributes

## **The Outcomes**

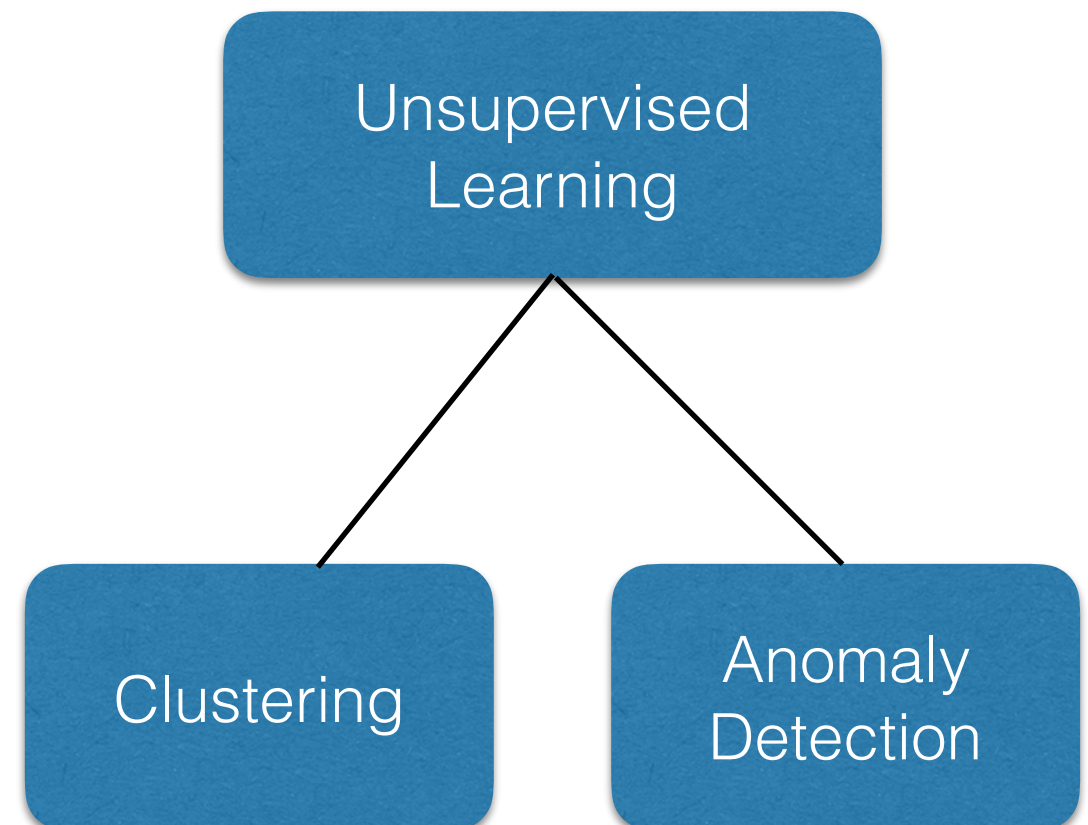
Classes  
Labels  
Dependent Variables  
Responses  
Targets

# Two Main Branches of Machine Learning

*If you have the answer for  
your training data*



*If you don't*



...

# Two Main Branches of Machine Learning

*If you have the answer for  
your training data*

Supervised  
Learning

most studied  
more mature  
most widely used

Classification

Regression

*If you don't*

Unsupervised  
Learning

Clustering

Anomaly  
Detection

...

# <sup>highly simplified</sup> The Model Building Process

Start with a question

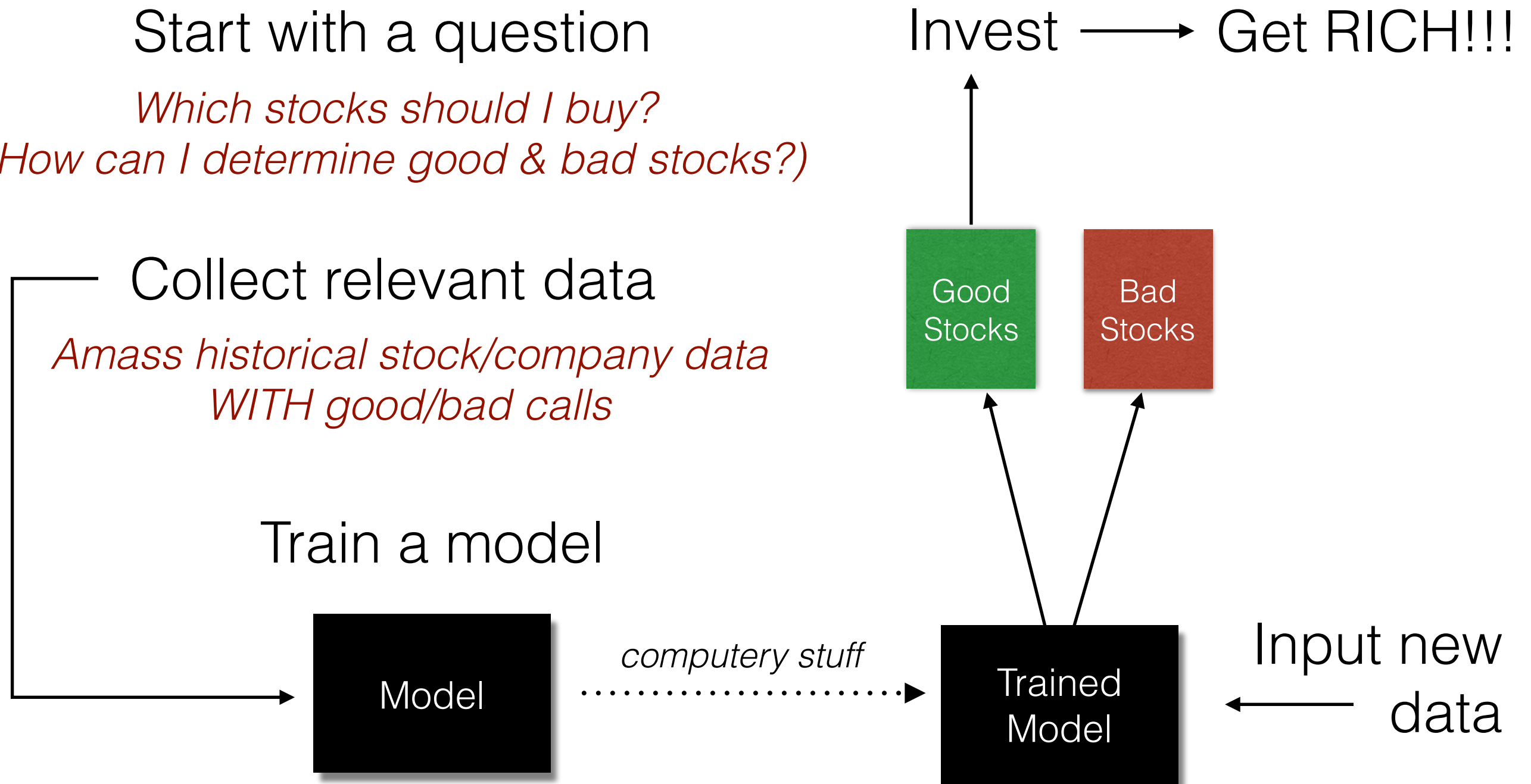
*Which stocks should I buy?*

*(How can I determine good & bad stocks?)*

Collect relevant data

*Amass historical stock/company data  
WITH good/bad calls*

Train a model



# Building Models with R and caret

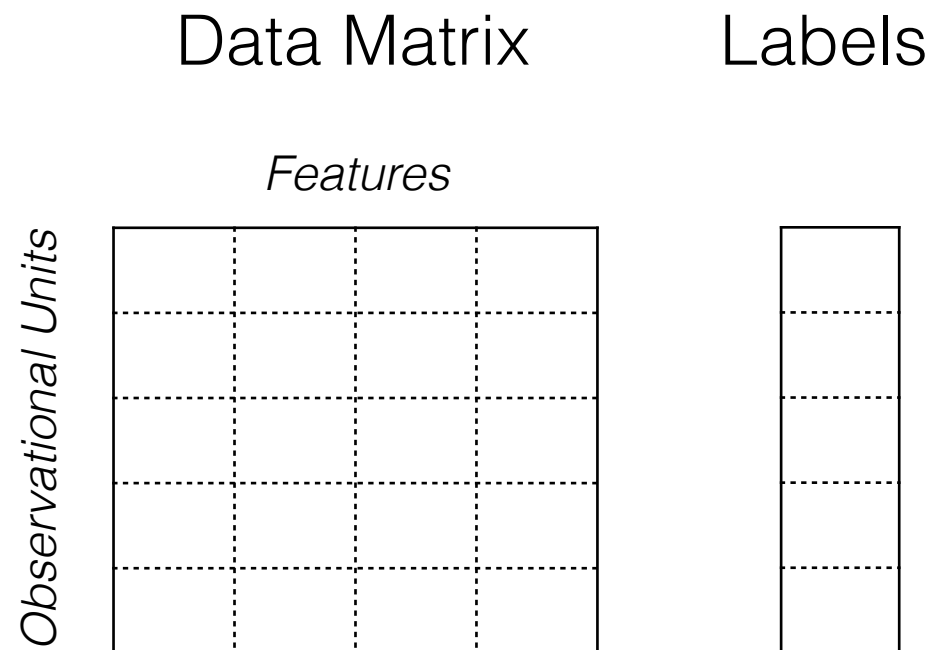


# Modeling in R

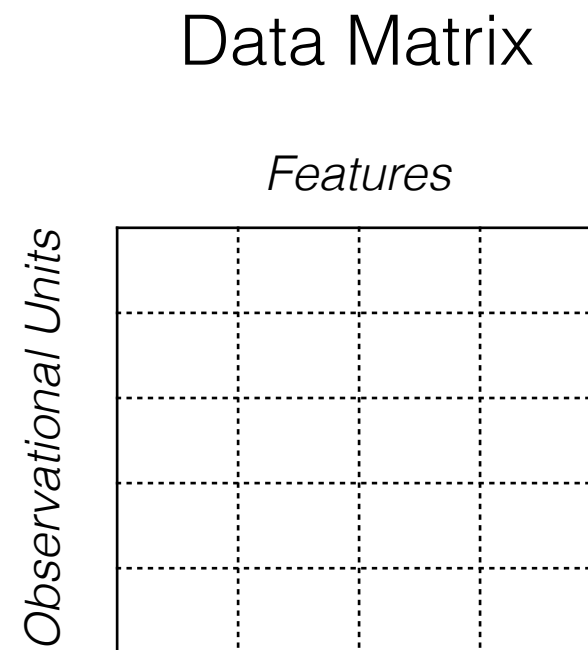
- R has 100's of modeling packages; if you know about it, there's probably an R package for it
- Lots (most?) modeling packages follow a somewhat standard way to work with models
  - train a model: `model_func(training_matrix, training_labels, ...)`
  - make predictions: `predict(model_obj, testing_matrix)`
- However, there are often subtle differences between packages so you have to be careful & read the documentation

# Building Models

## Training Data



## Testing Data



## Model Training

```
model_func(training_matrix, training_labels, ...)
```

## Model Predictions

```
predict(model_obj, testing_matrix)
```

# Some Examples

e1071

```
svm(train_mtrx, train_lbls, probability = TRUE, ...)  
predict(model_obj, test_mtrx, probability = TRUE)
```

randomForest

```
randomForest(train_mtrx, train_lbls, ...)  
predict(model_obj, test_mtrx, type = "prob")
```

stats

```
glm(formula, ...)  
predict(model_obj, test_mtrx, type = "response")
```

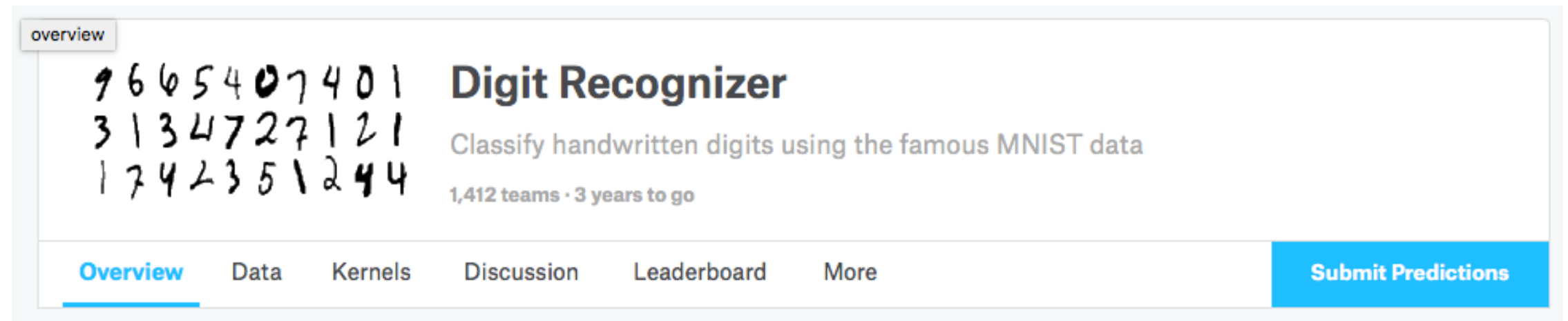
Can you spot the differences?

# Tips on Working with Models

- For a centralized listing of many of the models in R, check out the model listing on the caret repo  
<http://topepo.github.io/caret/available-models.html>
- Model training functions are typically named after the model (see previous slide)
- Use the documentation to remind yourself of the function arguments and what they mean
  - e.g. `?svm`, `?randomForest`, `?glm`
  - for most predict functions use:  
`?predict.svm`, `?predict.randomForest`, `?predict.glm`

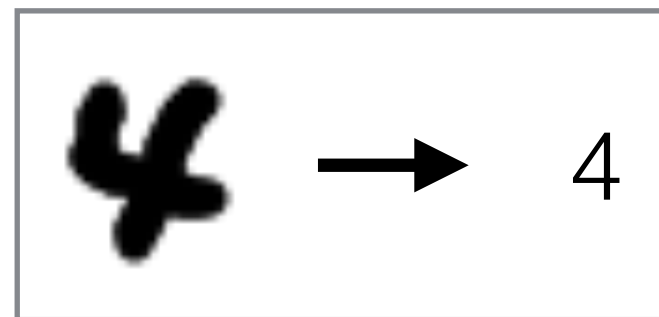
# A Real Example:

## Kaggle Digit Classification Competition



### Task

Given an image of a handwritten digit, determine which one it is



### Training Data

A vector of length 785 for each example (digit)

- first entry is the label (a digit 0 - 9)
- the remaining 784 entries are each numbers 0 - 255 representing a 28 x 28 gray-scale image of the digit

black white

e.g.: 3,0,0,0,27,59,82,171,201,163,74,30,0,0...0,0,0

### Testing Data

A vector of length 784 for each *new* example;  
NO LABELS

### Submission

```
ImageId,Label
1,3
2,7
3,8
(27997 more lines)
```

# A Real Example: Kaggle Digit Classification Competition

Code

This script has been released under the [Apache 2.0](#) open source license. [Download Code](#)

```
1 # Creates a simple random forest benchmark
2
3 library(randomForest)
4 library(readr)
5
6 set.seed(0)
7
8 numTrain <- 10000
9 numTrees <- 25
10
11 train <- read_csv("../input/train.csv")
12 test <- read_csv("../input/test.csv")
13
14 rows <- sample(1:nrow(train), numTrain)
15 labels <- as.factor(train[rows,1])
16 train <- train[rows,-1]
17
18 rf <- randomForest(train, labels, xtest=test, ntree=numTrees)
19 predictions <- data.frame(ImageId=1:nrow(test), Label=levels(labels)[rf$test$predicted])
20 head(predictions)
21
22 write_csv(predictions, "rf_benchmark.csv")
```

show less

Most of the code is  
about data prep!

One line to build the model, one line to  
make the predictions

This model is  
93.5%  
accurate

# The caret Package

- **C**lassification **A**nd **R**egression **T**raining
- Provides a uniform interface for working with most of R's modeling packages and a bunch of tools to streamline the modeling process
- *Pros*: takes care of the details for you, can help you avoid modeling mistakes
- *Cons*: can make modeling even more black-boxy, particularly for new users

# Training, Tuning & Evaluating Models

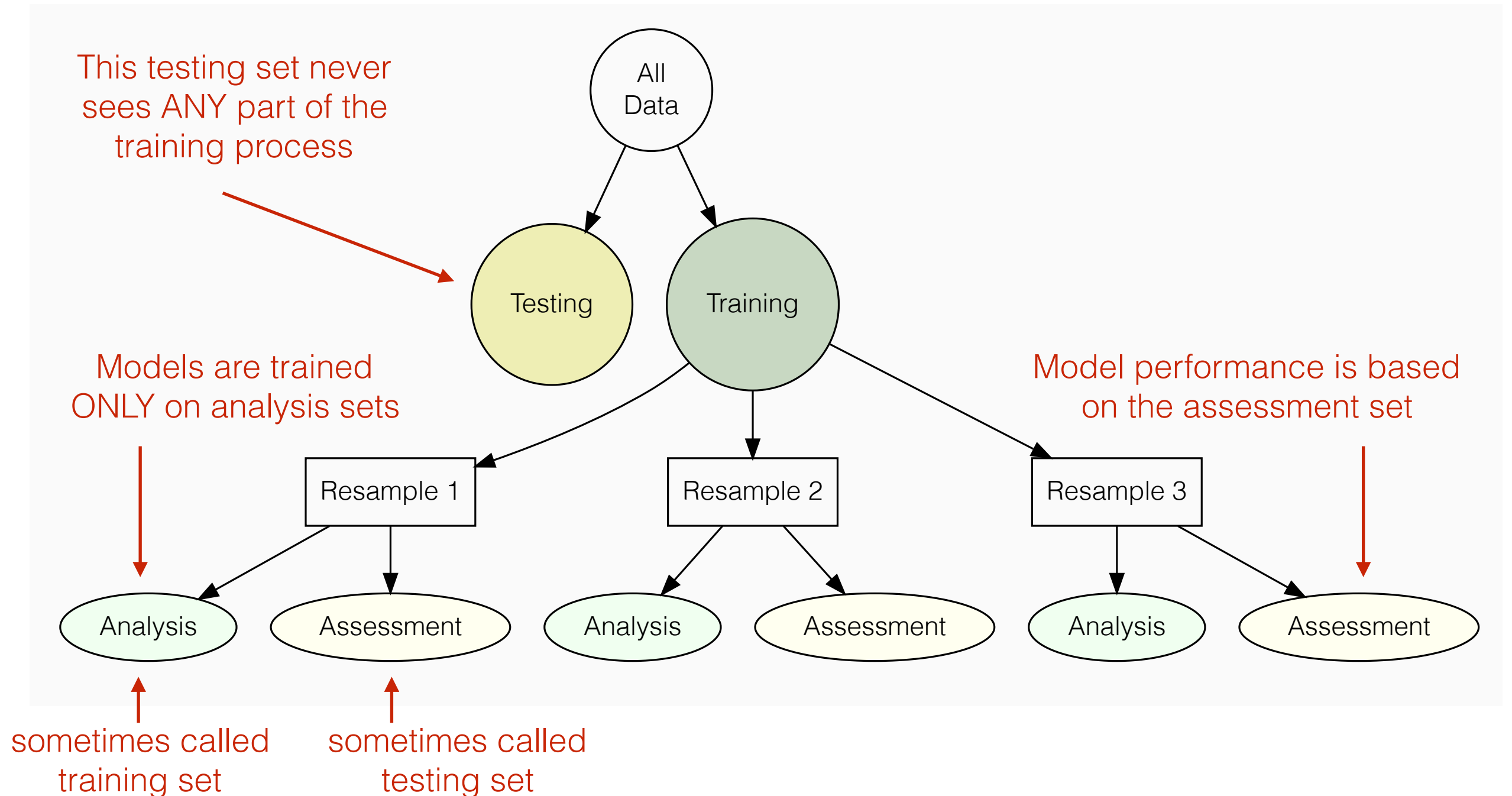
- Training: the process of fitting a model based on supplied data
- Model method: the underlying algorithm used in the training process
- Model parameters: adjustable parameters associated with a given modeling method that affect how the model is trained and the model output
- Model tuning: the process of adjusting the model parameters to find the ones that give the “best” performance
- Resampling: a process where you split your data into partitions, typically ones for training your model, and ones for evaluating it



# Resampling

- Lots of commonly used models have the flexibility to completely describe your training data
- Model performance on your training data is often over-optimistic, does not represent how well the model will generalize to new data
- Resampling can be used to help address this problem, e.g.
  - cross-validation
  - random splits


# Resampling



# A Model Training Workflow

Caret will take  
care of all of this

```
1 Define sets of model parameter values to evaluate
2 for each parameter set do
3   for each resampling iteration do
4     Hold-out specific samples
5     [Optional] Pre-process the data
6     Fit the model on the remainder
7     Predict the hold-out samples
8   end
9   Calculate the average performance across hold-out predictions
10 end
11 Determine the optimal parameter set
12 Fit the final model to all the training data using the optimal parameter set
```



# Building and Assessing Models with caret

- caret can automatically choose *parameter sets* and optimize them within a *resampling* approach
- Step 1: define a `trainControl` object
  - resampling method
  - how to evaluate performance
  - other model specific options
- Step 2: perform model training workflow with `train`
- Step 3: review performance and select “best” model

# Main Code

```
fitControl <- trainControl(method = "repeatedcv",  
                           number = 10,  
                           repeats = 10,  
                           ## Estimate class probabilities  
                           classProbs = TRUE,  
                           ## Evaluate performance using  
                           ## the following function  
                           summaryFunction = twoClassSummary)
```

```
model_fit <- train(Class ~ ., data = training,  
                  method = "gbm",  
                  trControl = fitControl,  
                  verbose = FALSE,  
                  tuneGrid = gbmGrid,  
                  ## Specify which metric to optimize  
                  metric = "ROC")
```

(live example)  
`caret_example.R`

# Some Thoughts About Building Predictive Models

- Ensuring your model is going to work on new, unseen data is really important
  - Is your training data representative of the new data?
  - Use resampling methods (e.g. cross validation) to estimate generalization performance
- Information “leakage” can ruin your model, is often subtle and not immediately evident; be careful
- Learning the mathematical/statistical details of various modeling algorithms and methods can be useful, though...
- It's usually advantageous to spend time understanding the problem domain, finding relevant data
- Predictive modeling is very practical, and you get good at it through lots of practice

# Resources

- THE Book by Kuhn & Johnson  
*Applied Predictive Modeling*  
<http://appliedpredictivemodeling.com>
- New Book by Kuhn & Johnson  
*Feature Engineering and Selection: A Practical Approach for Predictive Models*  
<http://www.feat.engineering>
- Other books
  - Elements of Statistical Learning (Hastie, et.al.)
  - Pattern Recognition and Machine Learning (Bishop)
  - Data Mining with R: Learning with Case Studies (Torgo)



# Resources

- R Packages
  - 100's of modeling packages are available (e.g. `e1071`, `randomForest`, `glmnet`)
  - **caret**: addresses the entire modeling workflow  
<http://topepo.github.io/caret/index.html>
  - `tidymodels`, `parsnip`, etc...
- Where to Practice
  - Kaggle ([www.kaggle.com](http://www.kaggle.com))
  - Flowing Data (<https://flowingdata.com/category/statistics/data-sources/>)
  - UCI Machine Learning Repository  
(<http://archive.ics.uci.edu/ml/index.php>)