

# PROGRESSING IN YOUR DATA SCIENCE CAREER

*Nauman Nayyar*

# LEARNING OBJECTIVES

- ▶ Specify common models used within different industries
- ▶ Identify the use cases for common models
- ▶ Discuss next steps and additional resources for data science learning

---

**COURSE**

---

# PRE-WORK

---

## **PRE-WORK REVIEW**

---

- ▶ Define the data science workflow
- ▶ Apply course information to your own professional interests

**OPENING**

---

# **PROGRESSING IN YOUR DATA SCIENCE CAREER**

---

## OPENING

---

- ▶ Let's discuss how to adapt this course to some real-world problems.
- ▶ We'll talk about how to maintain and improve your analyses.
- ▶ We'll also talk about what steps can be taken to make your work “production” ready.
- ▶ Lastly, we'll focus on a few other tools and topics in the data science ecosystem that you should explore in the future!

## INTRODUCTION

---

# REAL WORLD MACHINE LEARNING SYSTEMS

---

## INTEGRATING A MODEL INTO A DATA PRODUCT

---

- ▶ As you move into real world projects, it's important to remember that models and analysis are only *one part* of a larger goal or business objective.
- ▶ Typically, the model may only answer one of *many* questions that need to be addressed.
- ▶ Even within modeling itself, there are many differences between how a model runs during testing vs production.



---

## INTEGRATING A MODEL INTO A DATA PRODUCT

---

- ▶ For example, in a system that will present recommendations, we may have many modeling components that come together.
- ▶ Different aspects may categorize content, extract text features, analyze popularity, etc.
- ▶ These will all tie back into the final data product.

---

## INTEGRATING A MODEL INTO A DATA PRODUCT

---

- ▶ For example, in Hulu's recommendation system, they:
  - ▶ Pull data from multiple sources
  - ▶ Build user profiles and summaries
  - ▶ Then apply a recommendation model

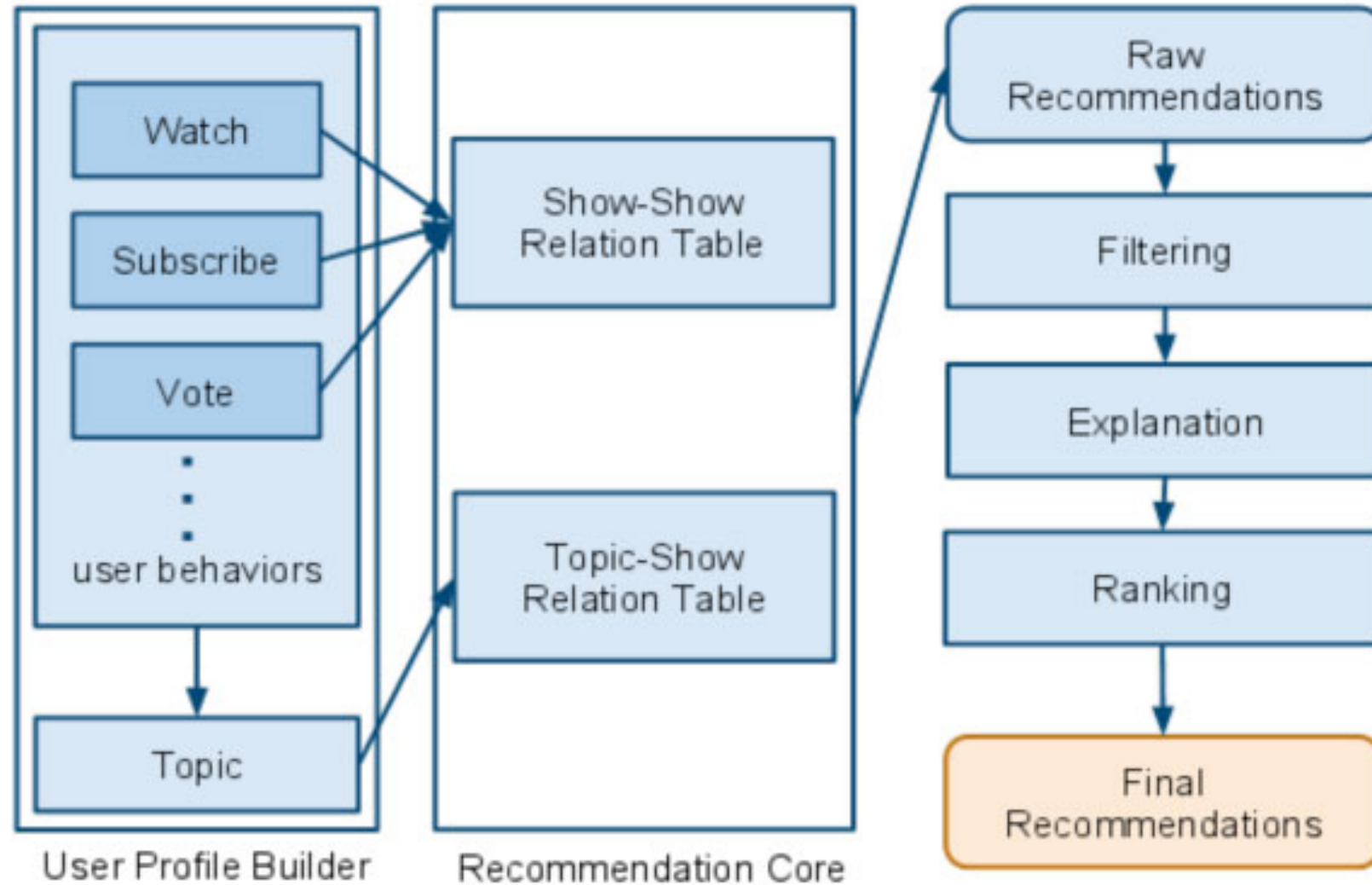
---

## INTEGRATING A MODEL INTO A DATA PRODUCT

---

- ▶ However, this isn't the final step! Additional filters are placed to refine the model in order to ensure the predictions are novel and don't overlap with previous content.

# INTEGRATING A MODEL INTO A DATA PRODUCT



## INTEGRATING A MODEL INTO A DATA PRODUCT

- Organizing and managing the systems and data dependencies can become an important part of the job.

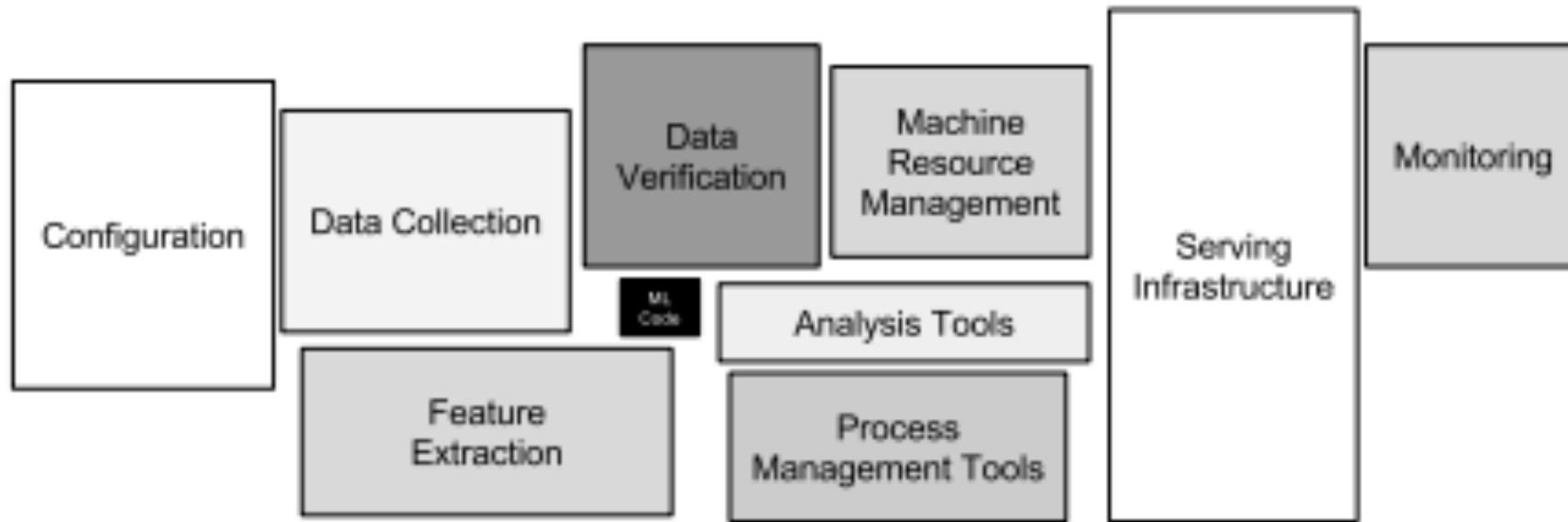


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

---

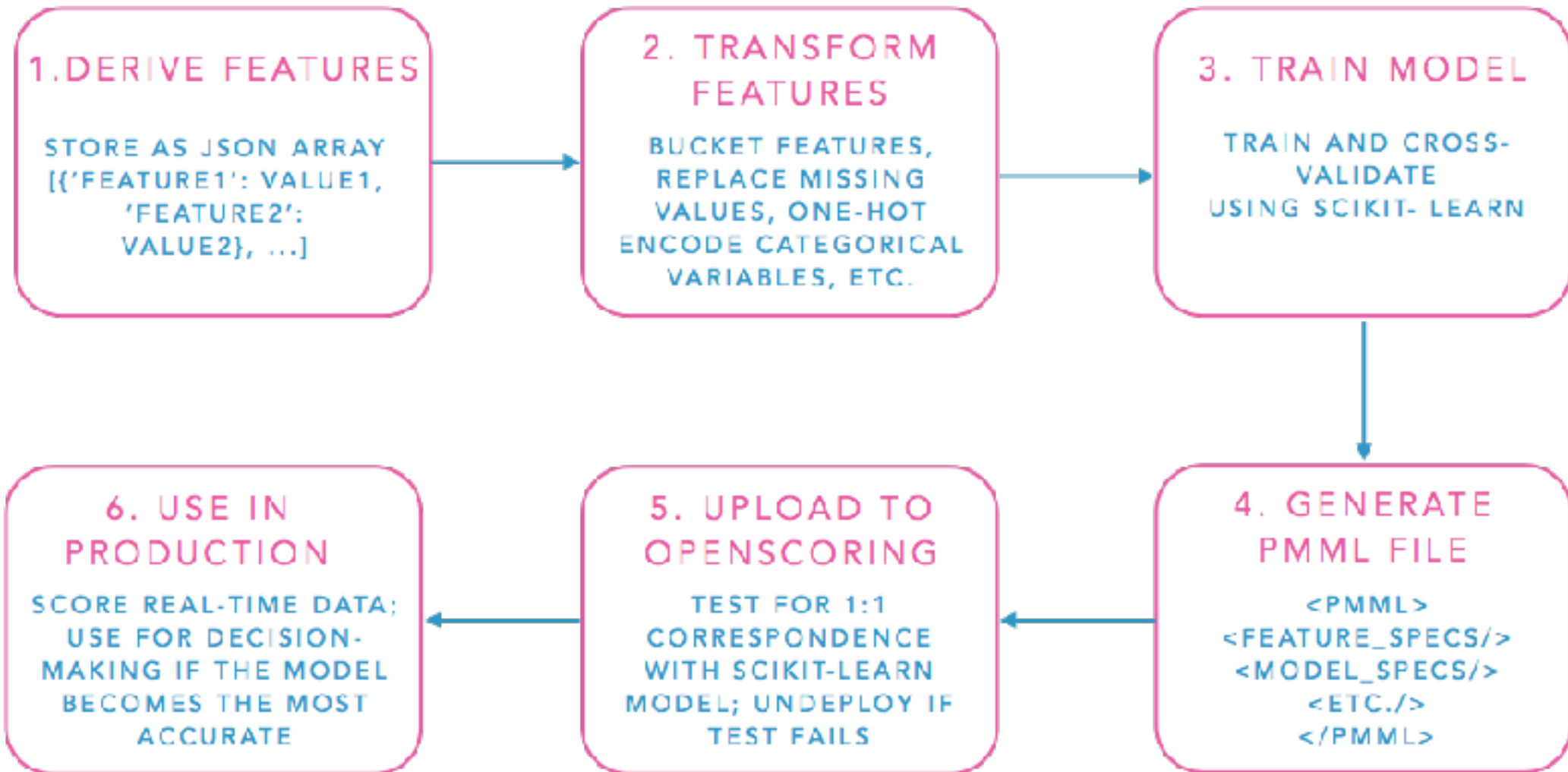
## INTEGRATING A MODEL INTO A DATA PRODUCT

---

- ▶ Many organizations rely on data engineering teams to code these common task into pipelines.
- ▶ **Data pipelines** are a series of automated data transformations that ensure the validity of your work for routine data maintenance tasks.

# INTEGRATING A MODEL INTO A DATA PRODUCT

► Below is a description of the AirBnB model building pipeline.



---

## MODEL MAINTENANCE

---

- ▶ Our class has mostly focused on building an initial model and analysis
- ▶ However, once a final model is trained (and we're happy with performance), the model also needs to be **maintained**!
- ▶ Plus, as new data is gathered, the model will likely need to be **retrained**.
- ▶ Over time, previously predictive features may begin to lose their value, requiring you to investigate once more.



---

# MODEL MAINTENANCE

---

- ▶ Google addresses this phenomenon, describing the “Technical Debt” of machine learning systems in a paper called:  
["Machine Learning: The High Interest Credit Card of Technical Debt"](#)
- ▶ They focus on a few core issues that affect model maintenance:
  - ▶ Code complexity
  - ▶ Evolving features
  - ▶ Monitoring and testing

---

# CODE COMPLEXITY

---

- ▶ Most of the code for our class has been written in notebooks.
- ▶ However, as your analysis and models develop, you are likely to revise and reuse parts of this code.
- ▶ Improving the quality of your code can simplify this process!
- ▶ This isn't always the responsibility of data scientists, but keep in mind - *more clarity in your code will lead to more clarity in your analysis.*
- ▶ This is especially true for long term or open source projects where your code has to make sense to other people (or yourself) in the future!

---

## CODE COMPLEXITY

---

- One way to write better code is to create (and follow!) a *styleguide*.
- A *styleguide* is a clear set of rules for organizing your code.
- Columbia recently developed [a special styleguide just for data scientists](#).
- Some rules are pretty straightforward:
  - Give variables, methods, and attributes descriptive names.
  - Write functions that take well-defined inputs and produce well-defined outputs.

---

## CODE COMPLEXITY

---

- ▶ Another common practice is *unit testing*.
- ▶ Unit testing involves writing short statements that *test* if a piece of code or function is working correctly.
- ▶ Typically, these tests provide a few sample inputs and outputs and then check that your code can produce the same outputs.
- ▶ According to Google, “ensuring that code has been tested is vital to ensuring that your analysis results are correct.”

---

## CODE COMPLEXITY

---

- Suppose we have the following function that calculates the area of a circle.

```
def calculate_area_of_circle(radius):  
    # Use value of pi  
    pi = 3.14  
    area = pi * radius ** 2  
    return area
```

---

## CODE COMPLEXITY

---

► A unit test for this may look like the following.

```
def test_calculate_area_of_circle():  
    # Various test cases  
    assert calculate_area_of_circle(2) == 12.56  
    assert calculate_area_of_circle(4) == 50.24  
    assert calculate_area_of_circle(0) == 0.0
```

---

## CODE COMPLEXITY

---

- ▶ On long term or big data projects, the code supporting a machine learning model can get complex.
- ▶ This “glue code” holds the model together, but it can get weighed down with bloat and feature creep over time.
- ▶ Thus, this code often needs to be *refactored* in order to trim the fat.

---

## CODE COMPLEXITY

---

► Google describes the need to review your code, stating that:

“Only a tiny fraction of the code in many machine learning systems is actually doing "machine learning"”

“Without care, the resulting system for preparing data in an ML-friendly format may become a jungle of scrapes, joins, and sampling steps, often with intermediate files output.”

“Managing these pipelines, detecting errors, and recovering from failures are all difficult and costly.”



---

## CODE COMPLEXITY

---

- ▶ Creating and following a clear **styleguide** as well as **testing** and **refactoring** your code will help maintain your machine learning algorithm over time.
- ▶ Plus, reducing *technical debt* saves time and money in the long term!
- ▶ Even Google is not immune:  
  
"In a recent cleanup effort of an important machine learning system at Google, it was possible to rip out tens of thousands of lines of unused experimental code-paths!"

# ACTIVITY: KNOWLEDGE CHECK



## EXERCISE

### ANSWER THE FOLLOWING QUESTIONS

1. Take a look at the following code which parses an apartment description for the apartment's square footage. What corner cases would it fail?

```
def extract_sqft(apt_description):  
    # Split the text on spaces  
    words = apt_description.split(' ')  
    for (i, word) in enumerate(words):  
        # Look for "sqft"  
        if word == 'sqft':  
            # Select the word before sqft  
            return int(words[i-1])  
        else:  
            return np.nan
```

### DELIVERABLE

Answers to the above questions

---

## ACTIVITY: KNOWLEDGE CHECK

---



### EXERCISE

#### ANSWER THE FOLLOWING QUESTIONS

1. Think back to your earlier projects; are there any places where your code could be cleaned up and optimized?

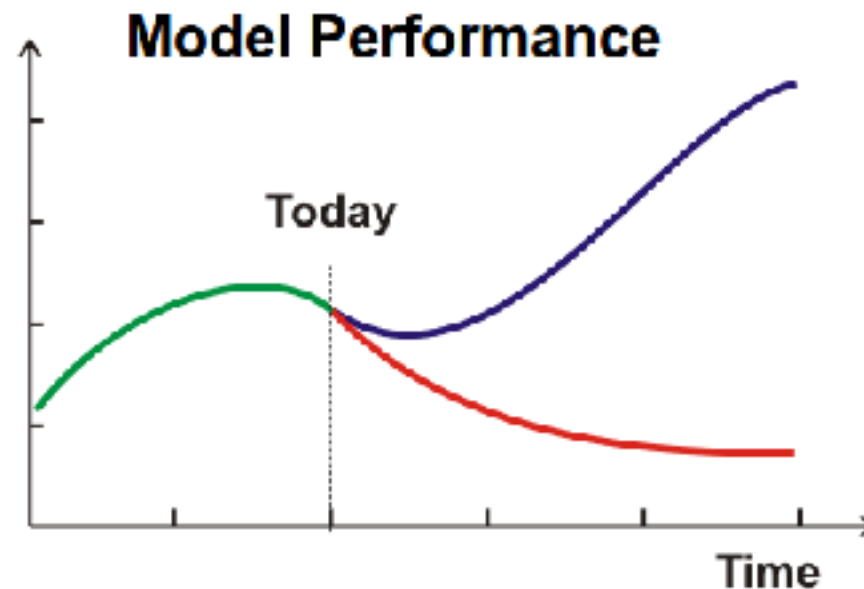
#### DELIVERABLE

Answers to the above questions

## EVOLVING FEATURES

---

- ▶ Once your model is trained, it's important to track its performance over time.
- ▶ Many of the correlations found or features predicted may not remain true in a few months or years into the future.



---

## EVOLVING FEATURES

---

- ▶ For example, our “evergreen” article prediction example looks for food mention to predict the popularity of certain recipes.
- ▶ However, it doesn’t know how to gauge trends in popular foods. Over time, it will return a smaller and smaller sample unless we readjust the model’s parameters.
- ▶ As one trend takes off, the model trained on old trends may not be able to pick that up.

---

## EVOLVING FEATURES

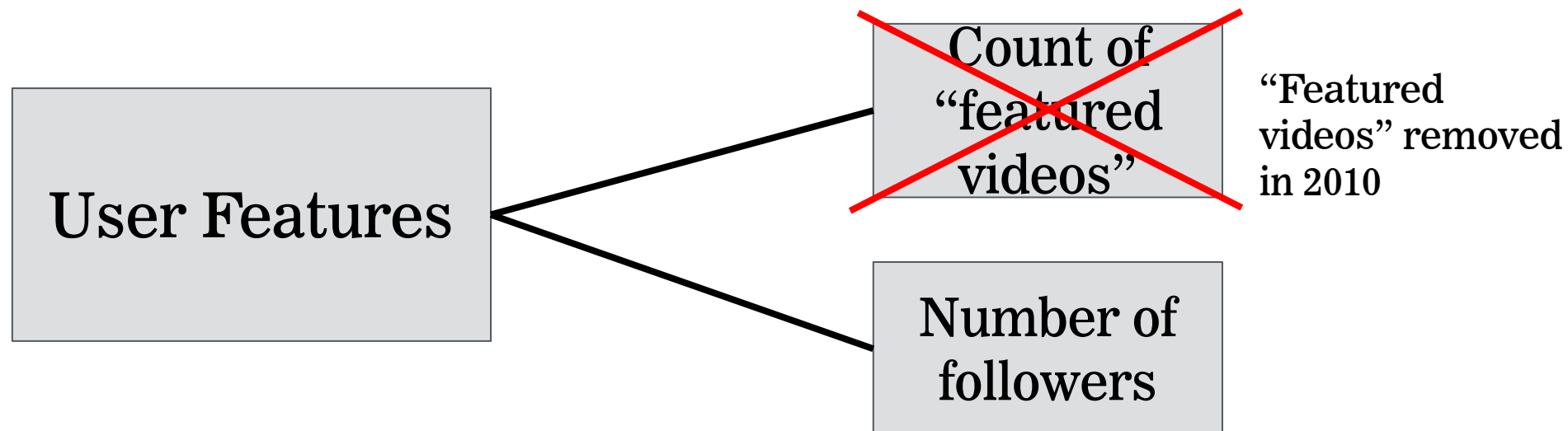
---

- ▶ Google's technical debt paper groups troublesome features into two groups: *legacy features* and *bundled features*.
  - ▶ **Legacy features:** When a feature “F” is included in a model early on, but later other features are added that make F redundant.
  - ▶ **Bundled features:** When a group of features are all bundled together, it can be hard to differentiate the features that aren't performing well from the ones that are.

## EVOLVING FEATURES

---

- ▶ Features can also be “bundled” with commonly occurring variables, but those variable occurrences may change over time, making the features obsolete.
- ▶ For instance, we may have features a Youtube user that are no longer tracked or relevant. These may be bundled with other “user features”.



---

## EVOLVING FEATURES

---

► From Google's paper:

"Machine learning systems often have a difficult time distinguishing the impact of correlated features.

This may not seem like a major problem: if two features are always correlated, but only one is truly causal, it may still seem okay to ascribe credit to both and rely on their observed co-occurrence.

However, if the world suddenly stops making these features co-occur, prediction behavior may change significantly."



---

## EVOLVING FEATURES

---

- ▶ Changing variables is especially important for *black box models*.
- ▶ Such models rely on correlations from a wide range of features. However, in doing so, we can typically ignore one of two variables that are highly correlated.
- ▶ If these variables are no longer correlated, we may need to update this.

---

## EVOLVING FEATURES

---

- ▶ Another common way for features to evolve is through *feedback loops*.
- ▶ Once you've performed an analysis and built your model, it's likely you will make decisions and take actions based on your findings.
- ▶ It's important to think about how these actions may change the data you are using for future analysis.
- ▶ Are you introducing bias to your data and model?

---

## EVOLVING FEATURES

---

- ▶ For example, imagine we are investigating ways to reduce the spread of infections in hospitals:
  - ▶ We may find that whenever a doctor sees more than 5 patients in an hour, those patients have a greater risk for infection.
  - ▶ Based upon this, we implement a policy that doctors cannot see more than 5 patients in one hour.
  - ▶ If we perform our same analysis a year after this policy is enacted, the feature “saw >5 patients in an hour” won’t exist!

---

# ACTIVITY: KNOWLEDGE CHECK

---



## EXERCISE

### ANSWER THE FOLLOWING QUESTIONS

1. Brainstorm two correlated features from our prior work in this class that may not be correlated in the future.

### DELIVERABLE

Answers to the above questions

---

## MONITORING MODELS

---

- ▶ Once a model is deployed and making predictions, it's important to track its performance.
- ▶ From the Google again!

"Unit testing of individual components and end-to-end tests of running systems are valuable, but in the face of a changing world such tests are not sufficient to provide evidence that a system is working as intended.

Live monitoring of system behavior in real time is critical."

---

## MONITORING MODELS

---

- ▶ One common monitoring technique is to compare your model's performance to a baseline.
- ▶ The baseline can be something simple, like a naive model that only predicts the average or most frequently occurring value.
- ▶ When monitoring a model, you can update your baseline as information becomes available.
- ▶ Your “better” model should always outperform the baseline!

---

## ETHICAL CONSIDERATIONS

---

- ▶ Another (often overlooked) aspect of managing real world data science projects are *ethical considerations*.
- ▶ It's important to understand the biases of your data and how this influenced our analysis and models.
- ▶ Two common examples are criminal justice and financial loans applications.

---

## ETHICAL CONSIDERATIONS

---

- ▶ When analyzing crime, we often want to consider what drives criminal activity and what actions might reduce it.
- ▶ However, it's important to consider how our data is collected. For example, current data is based off the current criminal justice system.
- ▶ It can be difficult to separate the biases of the current system from the correlations/predictions that you are trying to make in your model.
- ▶ If data from the current justice system overweighs specific concerns or attributes, your model will too.



---

## ETHICAL CONSIDERATIONS

---

- ▶ Similarly, data from financial lenders may be biased, as their goal is to find borrowers who are most likely to pay back in a timely fashion.
- ▶ These analyses need to be strongly regulated so that protected factors (e.g. race, gender, etc) are not considered. However, they can still leak in through proxy features.
- ▶ Proxy features are not protected per se, and are strongly correlated with specific protected features.
- ▶ For example, neighborhood zip code can be used as a proxy for race.

---

# ACTIVITY: KNOWLEDGE CHECK

---



## EXERCISE

### ANSWER THE FOLLOWING QUESTIONS

1. In small groups, discuss other areas of possible ethical issues in Data Science.
  - a. How might this occur when examining health data?
  - b. What about when examining educational records?

### DELIVERABLE

Answers to the above questions

---

## **GUIDED PRACTICE**

---

# **DATA SCIENCE IN AN ORGANIZATION**

---

# ACTIVITY: TITLE OF ACTIVITY

---



## EXERCISE

### **DIRECTIONS (20 minutes)**

Break into groups of 4-5 students. Each group will get a company and 1-2 data products that company is building.

1. What data do you need to build the model? How might you build this model?
2. Brainstorm maintenance that might be performed.
  - a. When should you redo the study?
  - b. What features may change or become difficult to collect in the future?
3. Describe possible interventions.
  - a. Will this change the data collected in the future?
4. Describe ethical issues that may arise from these tasks.

### **DELIVERABLE**

Specific plans described above

**DEMO**

---

# PIPELINES IN SCIKIT-LEARN

---

## PIPELINES IN SCIKIT-LEARN

---

- ▶ One way to improve coding and model management is to use pipelines in scikit-learn
- ▶ Pipelines tie together all the steps you may need to prepare your dataset and make your predictions.
- ▶ Because you will need to perform all of the same transformations on your test data, encoding the *exact same steps* is important.

```
from sklearn.pipeline import Pipeline
```

---

## PIPELINES IN SCIKIT-LEARN

---

► Previously we built a text classification model using CountVectorizer

```
import pandas as pd
import json

data = pd.read_csv("../assets/dataset/stumbleupon.tsv", sep='\t')
data['title'] = data.boilerplate.map(lambda x: json.loads(x).get('title',
''))
data['body'] = data.boilerplate.map(lambda x: json.loads(x).get('body', ''))

titles = data['title'].fillna('')
```

---

# PIPELINES IN SCIKIT-LEARN

---

► We can fit the vectorizer and transform our data.

```
from sklearn.feature_extraction.text import CountVectorizer
```

```
vectorizer = CountVectorizer(max_features = 1000,  
                             ngram_range=(1, 2),  
                             stop_words='english',  
                             binary=True)
```

```
# Use `fit` to learn the vocabulary of the titles  
vectorizer.fit(titles)
```

```
# Use `transform` to generate the sample X word matrix - one column per feature (word or n-grams)  
X = vectorizer.transform(titles)
```



---

# PIPELINES IN SCIKIT-LEARN

---

- ▶ We used this input X, matrix of all common n-grams in the dataset, as the input to a classifier.
- ▶ We wanted to classify how evergreen a story was.

```
from sklearn.linear_model import LogisticRegression
```

```
model = LogisticRegression(penalty = 'l1')  
y = data['label']
```

```
from sklearn.cross_validation import cross_val_score
```

```
scores = cross_val_score(model, X, y, scoring='roc_auc')  
print('CV AUC {}, Average AUC {}'.format(scores, scores.mean()))
```

---

## PIPELINES IN SCIKIT-LEARN

---

- ▶ Often, we will want to combine these steps to evaluate on some future dataset.
- ▶ Therefore, we need to make sure we perform the *exact same* transformations on the data.
- ▶ Pipelines combine both **preprocessing** and **model building** into a single object, tying all the steps together.

---

# PIPELINES IN SCIKIT-LEARN

---

- ▶ Similar to models and vectorizers in scikit-learn, pipelines have `fit` and `predict` or `predict_proba` methods.
- ▶ However, they also make sure the proper data transformations occur.

```
# Split the data into a training set
training_data = data[:6000]
X_train = training_data['title'].fillna('')
y_train = training_data['label']
```

```
# These rows are rows obtained in the future, unavailable at training time
X_new = data[6000:]['title'].fillna('')
```

---

# PIPELINES IN SCIKIT-LEARN

---

```
from sklearn.pipeline import Pipeline
```

```
pipeline = Pipeline([  
    ('features', vectorizer),  
    ('model', model)  
])
```

```
# Fit the full pipeline. This means we perform the steps laid out above
```

```
# First we fit the vectorizer,
```

```
# and then feed the output of that into the fit function of the model
```

```
pipeline.fit(X_train, y_train)
```

```
# Here again we apply the full pipeline for predictions
```

```
# The text is transformed automatically to match the features from the pipeline
```

```
pipeline.predict_proba(X_new)
```

---

## ACTIVITY: KNOWLEDGE CHECK

---



### EXERCISE

#### ANSWER THE FOLLOWING QUESTIONS

1. Add a `MaxAbsScaler` scaling step to the pipeline. This should occur after vectorization.

#### DELIVERABLE

Answers to the above questions

---

## PIPELINES IN SCIKIT-LEARN

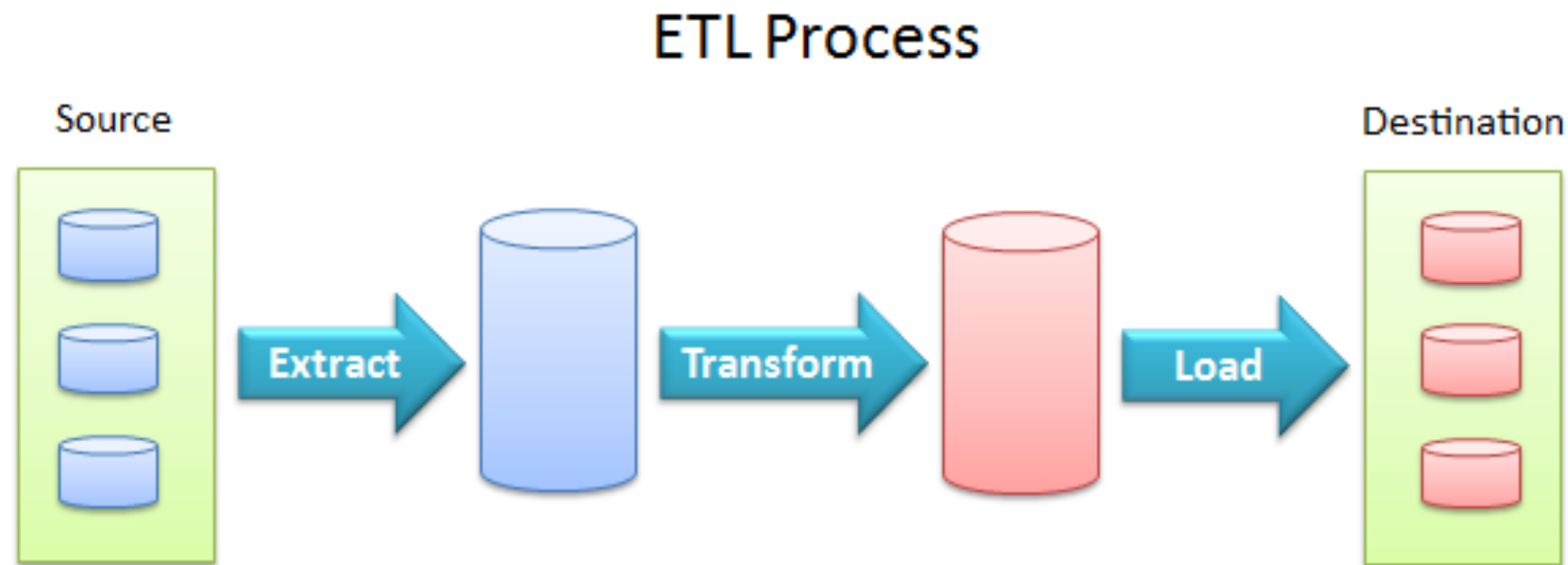
---

- ▶ Additionally, we may want to merge many different feature sets automatically. This can be done with `FeatureUnion`.
- ▶ While scikit-learn pipelines help manage raw data transformation, there may be many steps occurring before this takes place in your pipeline.
- ▶ Such pipelines are often referred to as *ETL pipelines* for “Extract, Transform, Load”.

## PIPELINES IN SCIKIT-LEARN

---

- In an *ETL pipeline*, the data is pulled or extracted from some source (like a database), transformed or manipulated, and then “loaded” into whatever system or analysis requires them.



---

## PIPELINES IN SCIKIT-LEARN

---

- ▶ This combines many steps from the data science workflow into one repeatable process.
  - ▶ Acquire - Extract the data from the source
  - ▶ Parse - Verify the quality of the data
  - ▶ Mine - Format, clean, slice, derive columns
  - ▶ Refine (possibly) - Transform the data



---

## PIPELINES IN SCIKIT-LEARN

---

- ▶ Many data science teams rely on software tools to manage these ETL pipelines.
- ▶ These tools can alert you to failures and schedule jobs to run periodically, maybe daily or weekly.
  - ▶ One of the most popular Python tools for this is [Luigi](#), developed by Spotify.
  - ▶ Another alternative is [Airflow](#) by AirBnB.

---

## INTRODUCTION

---

# ALTERNATIVE TOOLS

---

# LANGUAGES

---

- ▶ While we've mostly talked about Python in this class, there are many other languages and tools that Data Scientists might use.
- ▶ These tools have their various advantages and disadvantages.
- ▶ For example, other common programming languages for data science include:
  - ▶ R
  - ▶ Java/Scala

---

# LANGUAGES

---

- ▶ “R” is often used in data science and is the basis for many features found in Python data analysis.
- ▶ Pandas dataframes actually replicate the functionality of the R dataframe!
- ▶ R often contains many more specialized algorithms than Python.
- ▶ Between `statsmodels` and `scikit-learn`, Python has access to the most popular statistical algorithms. But if your problem becomes more specialized, you may require the niche algorithms available in R.

---

## LANGUAGES

---

- ▶ Python's advantages over R are speed (not really anymore!) and the ability to tie into other applications (web apps, etc).
- ▶ Python code is generally faster (again, not really anymore!) and more efficient.
- ▶ R has tried to replicate some of this extra functionality, but it is generally more native to Python.

---

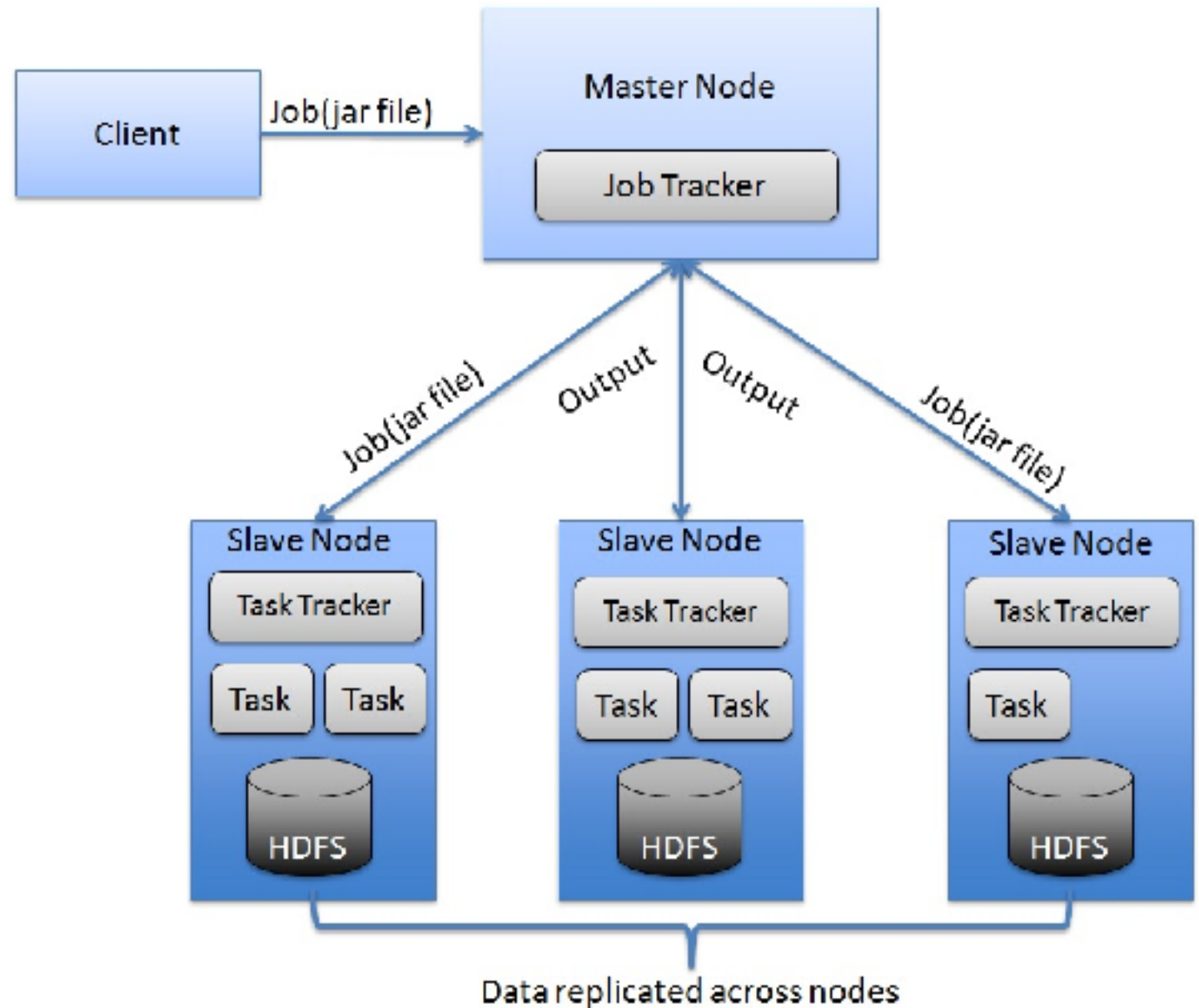
## LANGUAGES

---

- ▶ Meanwhile, Java/Scala are popular for their link to the Hadoop ecosystem.
- ▶ Many larger organizations store their data in a Hadoop system and most connectors to access data are built in Java and Scala.

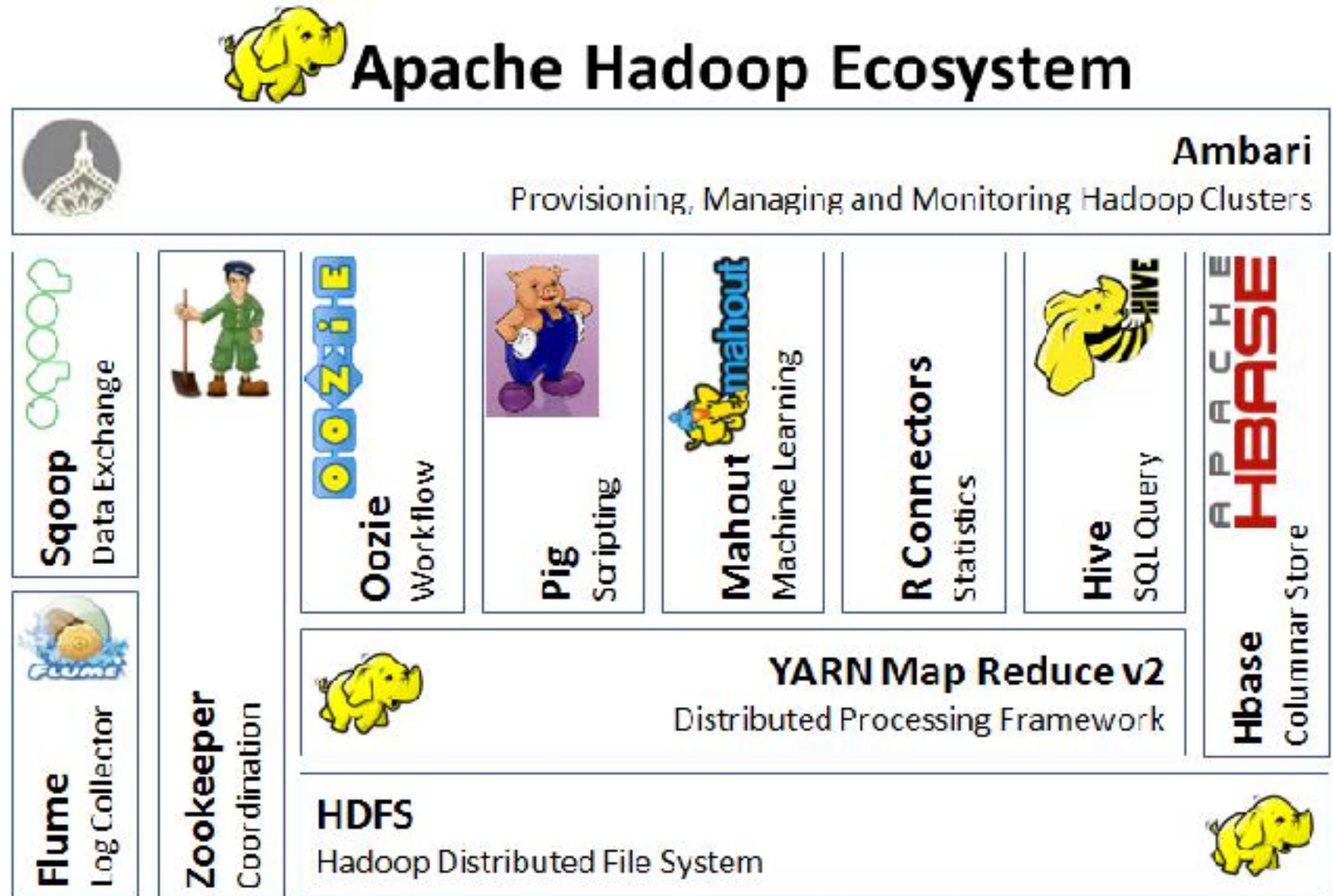
# LANGUAGES

- ▶ What is Hadoop?
- ▶ A distributed computing system/environment.



# LANGUAGES

- Here is a sample of the Hadoop ecosystem.





---

## LANGUAGES

---

- ▶ It can be easier to interact with Hadoop systems using these languages.
- ▶ However, in general they lack the interactivity and ease of use that R and Python have.

---

## MODELING FRAMEWORKS

---

- ▶ While `scikit-learn` is the most popular machine learning framework in Python, there are alternatives for specialized use cases.
- ▶ For example, most models in `scikit-learn` require datasets to be small enough to fit into memory.

---

## MODELING FRAMEWORKS

---

- ▶ Other frameworks can work around this limitation.
- ▶ One example is `xgboost`, which provides efficient Random Forest implementations that train much faster than `scikit-learn` models.
- ▶ Similarly, the `Vowpal Wabbit` library is often used to train very large linear models, using computational tricks to operate on tens of millions of datapoints.

---

## INTRODUCTION

---

# NEXT STEPS

---

## NEXT STEPS

---

- ▶ Most of this class has focused on statistical knowledge while practicing various methods of supervised and unsupervised learning.
- ▶ Of course, for each of these topics there are **many** alternative methods to learn! :)

---

## STATISTICAL TESTING

---

- ▶ While you don't need to know all of them, being aware of some common statistical tests and their assumptions is useful.
- ▶ Additionally, having a clear sense of distributions (and what they look like) is important when communicating your findings.
- ▶ Being able to view a histogram and summarize it by the distribution it resembles makes it much easier to discuss your data.

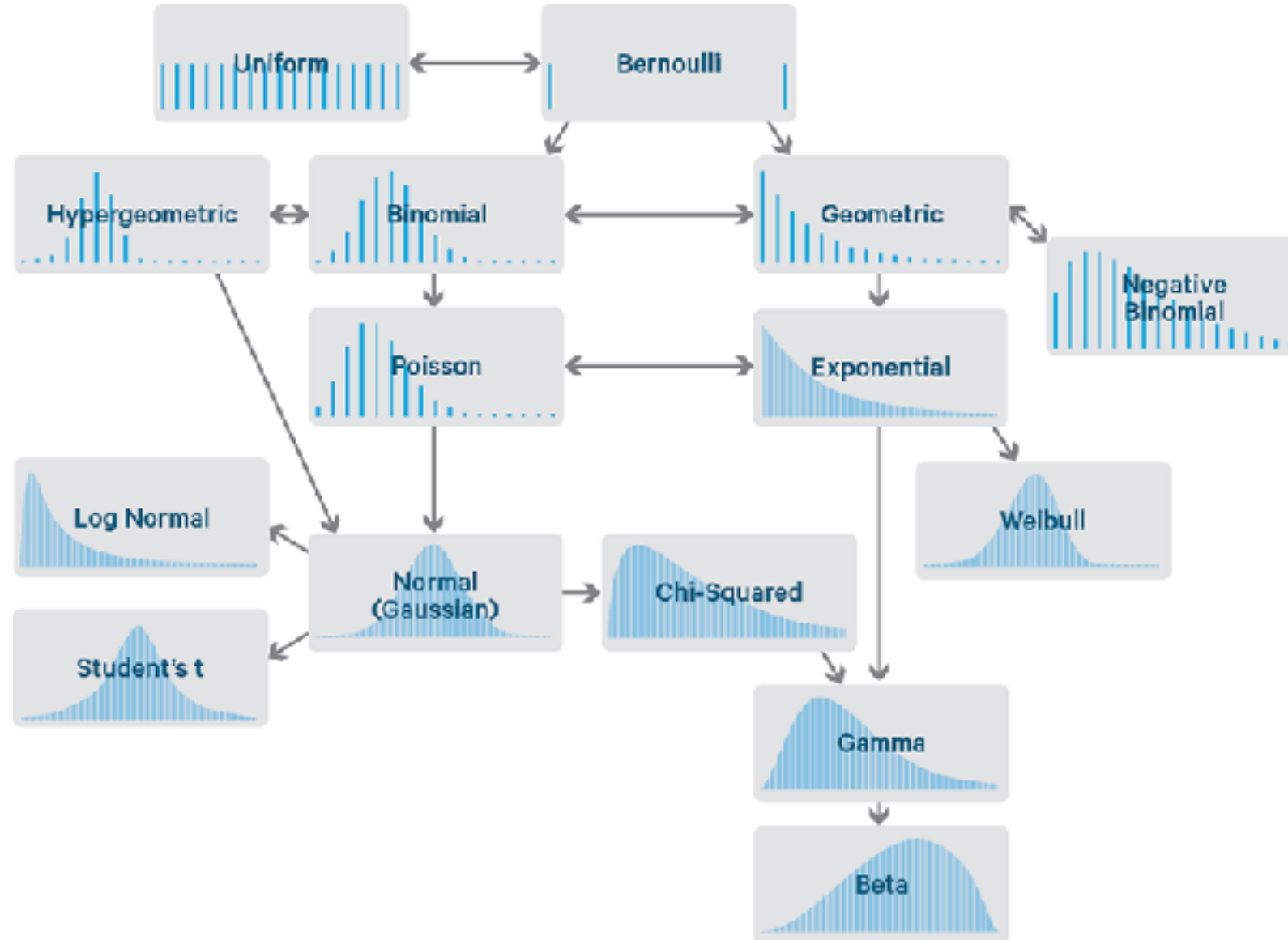
---

## STATISTICAL TESTING

---

- ▶ There are many different types of distributions you may encounter in your work.
- ▶ The following is an example of a few and their interactions.

# STATISTICAL TESTING





---

# VISUALIZATION

---

- ▶ Visualizing data in business presentations is typically a much better way to transfer information to your audience.
- ▶ Most of the plotting for our class was done in Python, but keep in mind that these plots are often not the most visually appealing...
- ▶ Luckily, many other tools exist to build prettier plots!
- ▶ For example, you can play around with tools like plot.ly or [D3.js](#) (a javascript framework) to make your plots interactive.

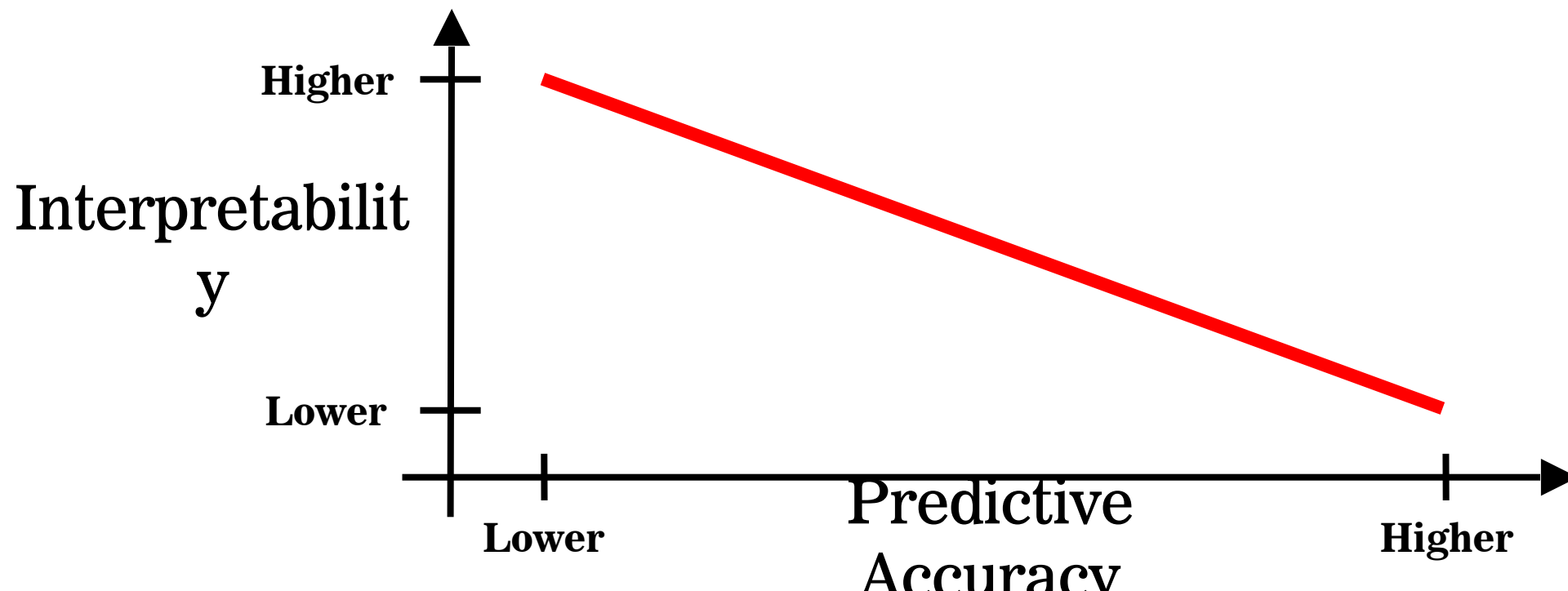
---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ Another important point to review is that data modeling is a constant trade-off between **predictive accuracy** and **interpretability**.

### Predictive Accuracy vs Interpretability



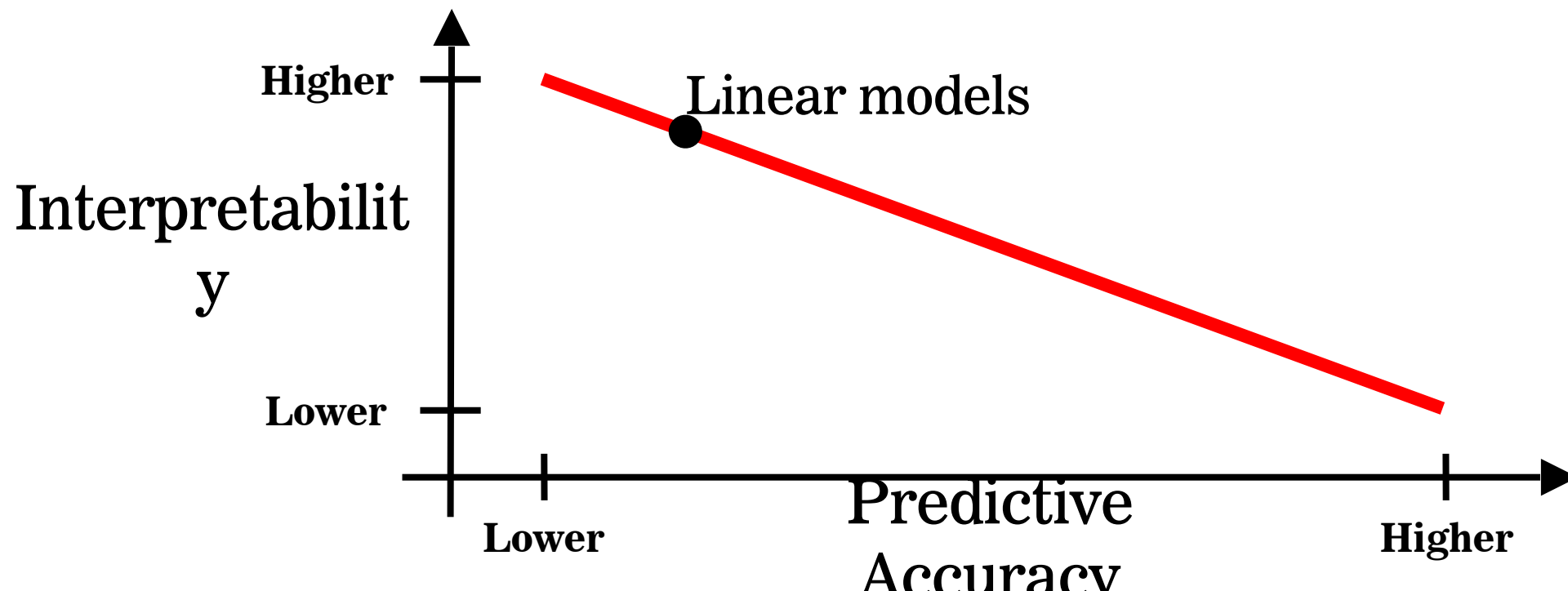
---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ Linear models are simple, perform well, and offer a concise summary of the impact of various features through coefficients. Thus, they have a high degree of *interpretability*, but typically less predictive accuracy.

### Predictive Accuracy vs Interpretability



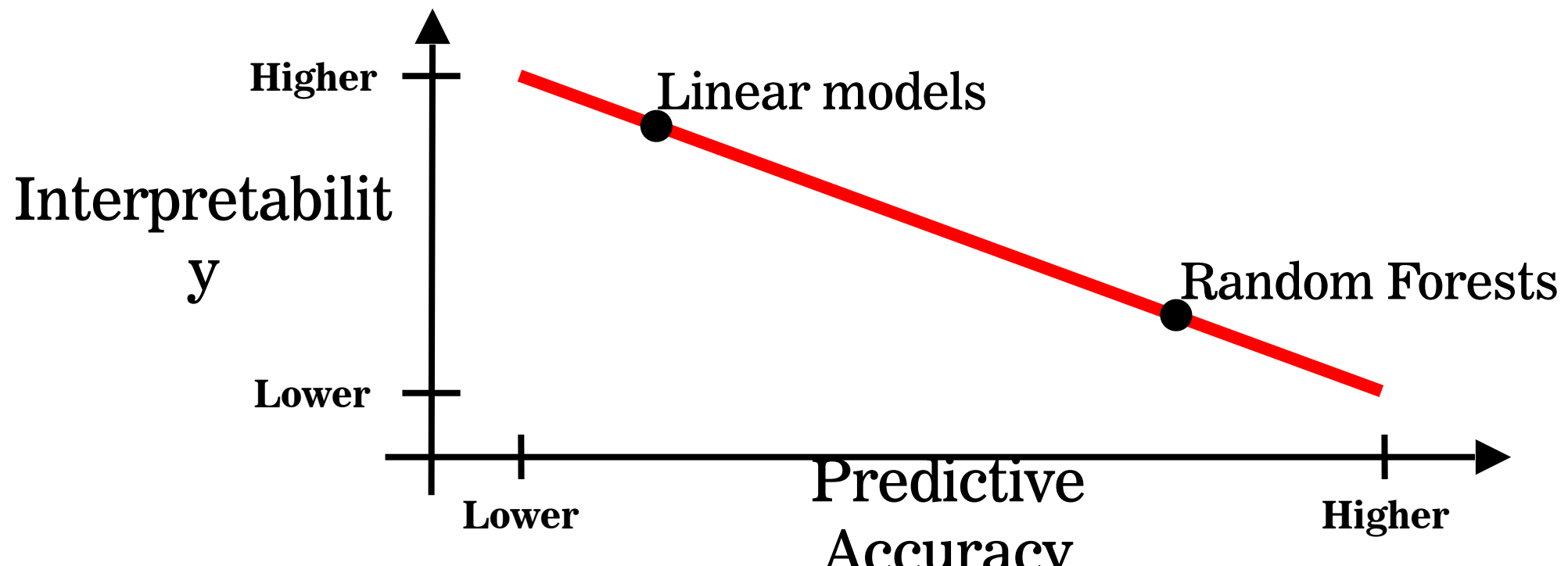
---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ Black box models, such as Random Forests, may outperform linear models, but without as much transparency. They have a high degree of predictive accuracy, but less interpretability.

### Predictive Accuracy vs Interpretability



---

# MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ You should always consider whether you care more about interpretability or accuracy, and communicate your findings accordingly.
- ▶ The division between these two outcomes is very common in data science.
- ▶ Two advanced models (that you should experiment with in the future!) perfectly capture this divide. They are:
  - ▶ Bayesian data analysis
  - ▶ Deep learning algorithms

---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ *Bayesian data analysis* is a method of analysis that requires you to capture your expectations about the interactions of your data, then attempt to learn how strong these interactions are.
- ▶ This assumes you have some idea of how things work before you build a model and you allow this to affect your model build.

---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ For example, suppose you are analyzing the roll-out of a new educational policy and want to measure the impact of this policy on test scores.
- ▶ You'll need to know what else will impact those test scores and build a model that can measure the impact of this policy.
- ▶ However, you'll also want to enforce additional constraints. For example, this policy may have a related but different effect on outcomes depending on location and region.

---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ We may also think of other reasons that this new policy will affect subgroups differently (e.g. local resources, demographics, budgets, etc).
- ▶ We should explicitly state how these aspects further constrain our model.
- ▶ Bayesian models are typically small and their main strengths are interpretability and capturing uncertainty in the data.
- ▶ Rather than stating that X will change Y by some amount, they give a *distribution* or *range of possible amounts* and attempt to tell what will happen in all cases.



---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ This makes Bayesian models very useful when interpretability and defining interactions are the most important goals.; they give us a clear definition of how right or wrong we are.
- ▶ For example, we may want to predict that candidate X is likely to win the election while also quantifying the degree of uncertainty.
- ▶ One tool you can use to build these models in Python is [pymc](#).
- ▶ [Bayesian Methods for Hackers](#) is a good reference for this.

---

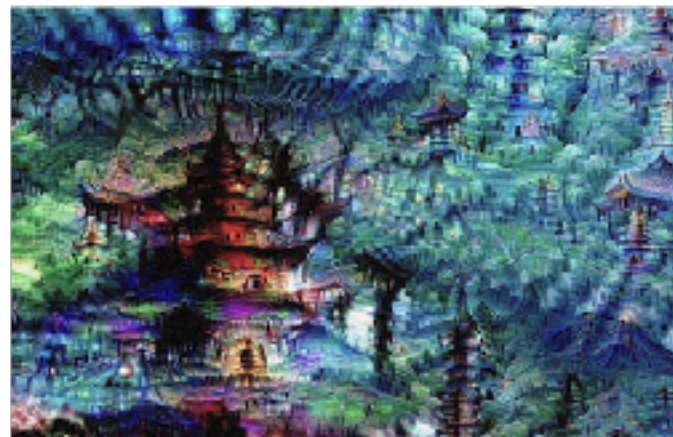
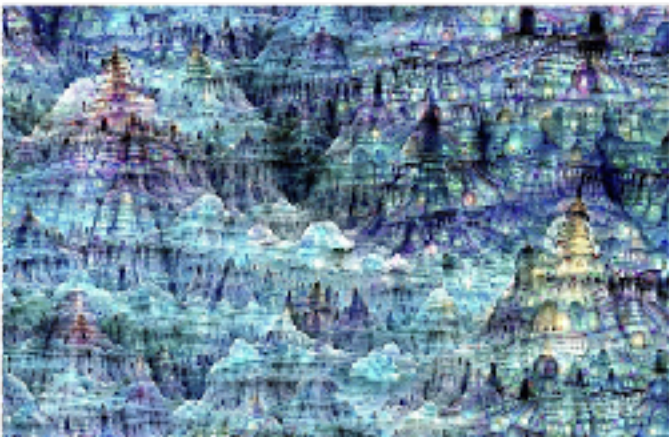
## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ On the other end of the spectrum, *deep learning models* are very powerful but offer little to no interpretable value.
- ▶ Deep learning models like *neural networks* are highly accurate but complex to build and understand.
- ▶ Google's has produced some interesting “art” using neural networks trained to identify certain objects.



# MODEL INTERPRETABILITY VS ACCURACY





---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ Deep learning models operate in a stage fashion.
  - ▶ First, they perform a dimensionality reduction to extract patterns or representations of the input data.
  - ▶ These representations are then used for the predictive task.
- ▶ Deep learning models tie these two steps together, attempting to learn the best representation for the task.

---

## MODEL INTERPRETABILITY VS ACCURACY

---

- ▶ Deep learning methods include many non-linear operations to capture complex relationships in the data.
- ▶ These models are particularly well suited for image or audio analysis.
- ▶ Some Python deep learning libraries include [Keras](#), [lasagne](#), and [Tensorflow](#).

---

**CONCLUSION**

---

# TOPIC REVIEW

---

## CONCLUSION

---

- ▶ Data science results are often incorporated into a larger final product
- ▶ These final products - including pipelines and models - need to be maintained and changes over time need to be addressed.
- ▶ Maintaining complex models includes considering multiple logistical and ethical considerations

---

## CONCLUSION

---

- ▶ Alternative languages used in data science include R or Java/Scala (although Python has many advantages)
- ▶ Visualization skills are vital to communicate and improve your models!
- ▶ Advanced machine learning methods you should explore include Bayesian methods and deep learning



**COURSE**

---

**BEFORE NEXT CLASS**

---

## **BEFORE NEXT CLASS**

---

# **DUE DATE**

► Project: Final Project, Part 5!!

---

**LESSON**

---

# EXIT TICKET

**DON'T FORGET TO FILL OUT YOUR EXIT TICKET**