GENERAL ASSEMBLY

PROGRESSING IN YOUR DATA SCIENCE CAREER

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!

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.

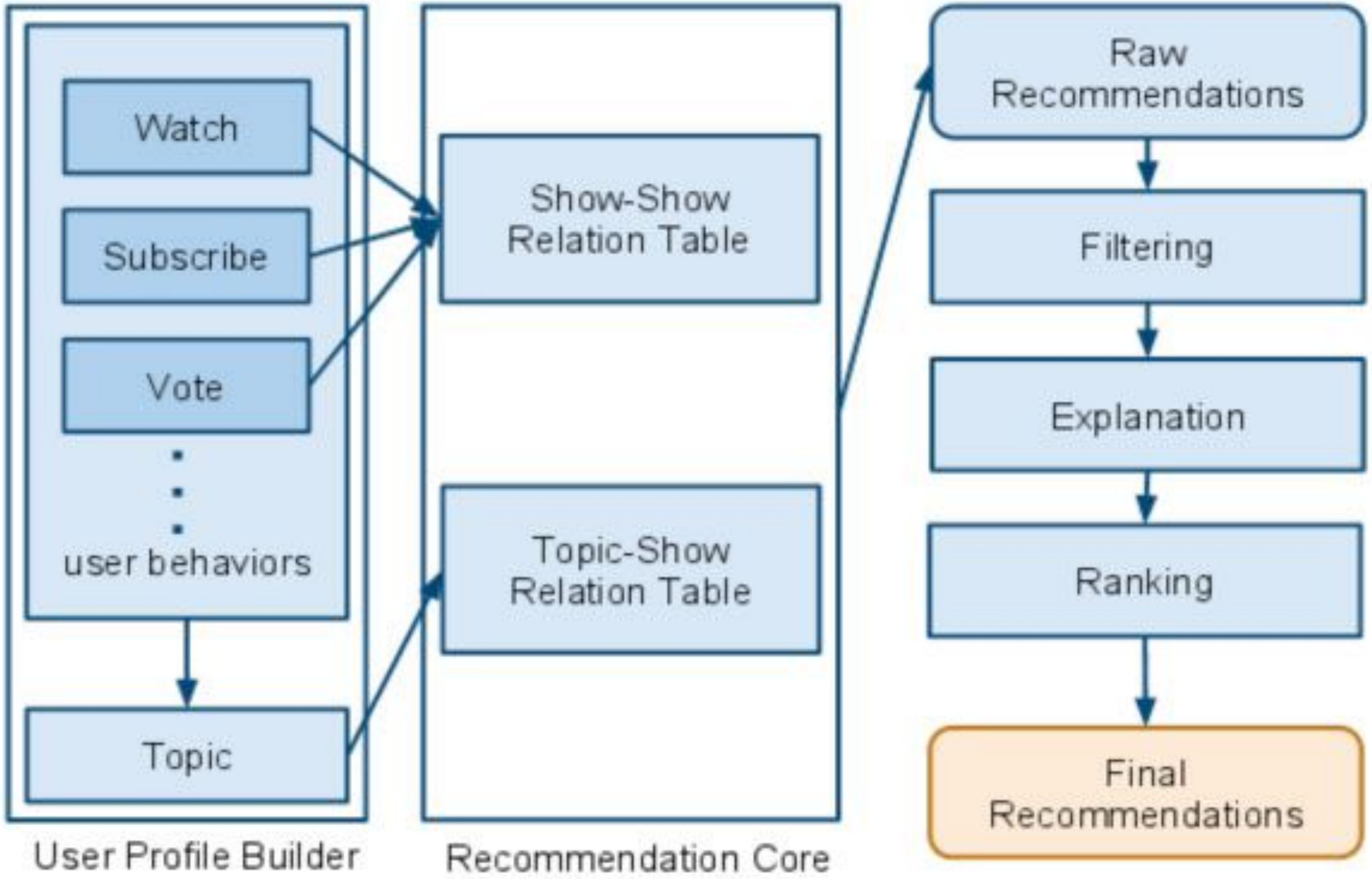
INTEGRATING A MODEL INTO A DATA PRODUCT

- 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.

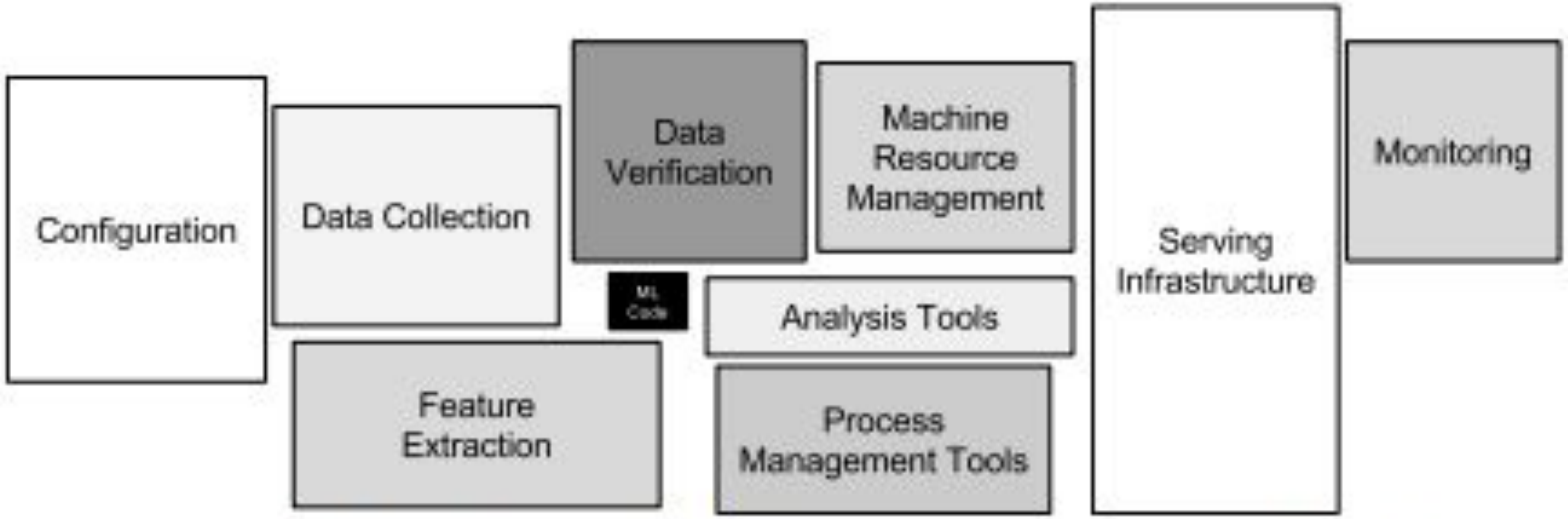


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

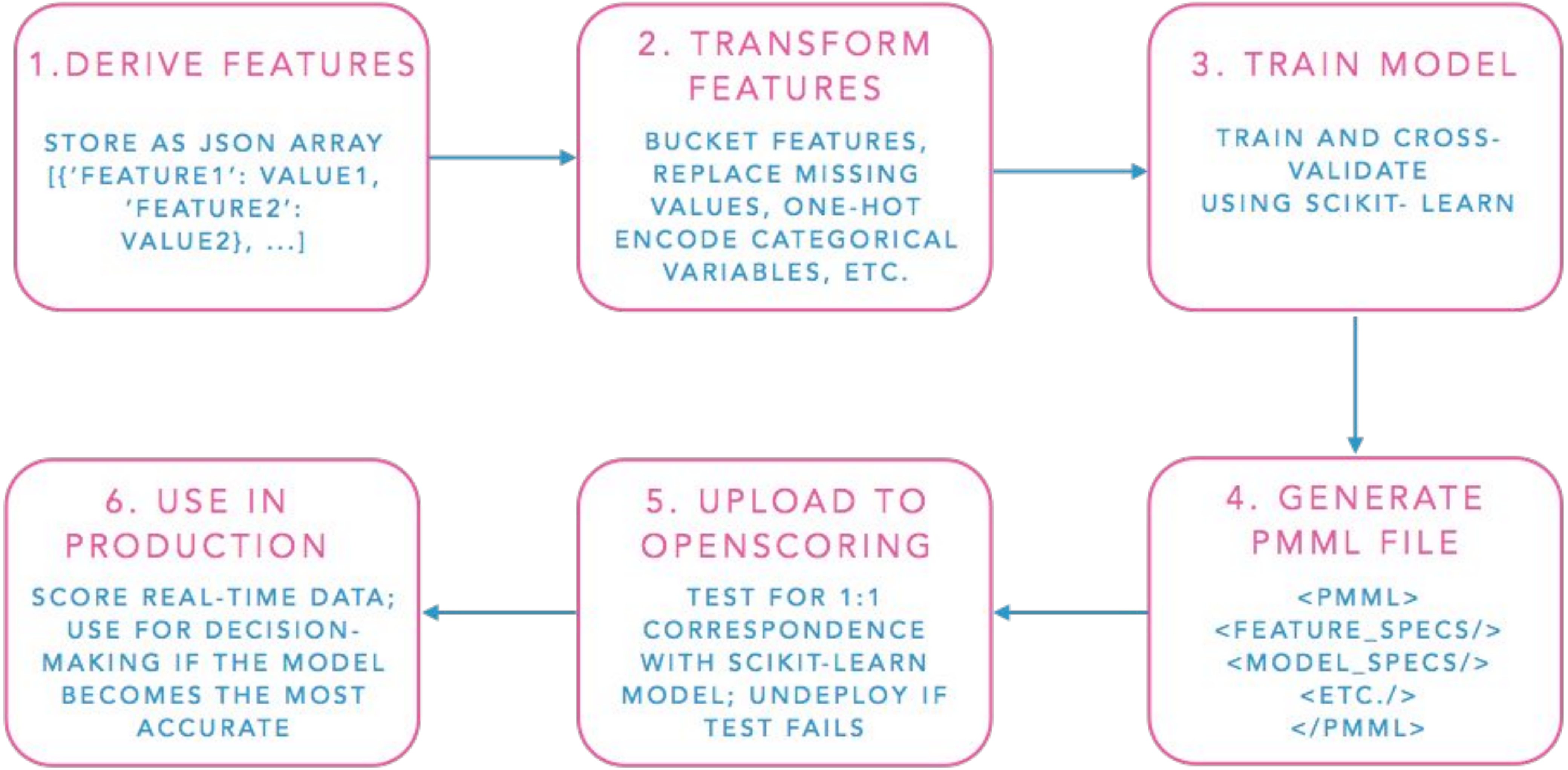
INTEGRATING A MODEL INTO A DATA PRODUCT

- 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?

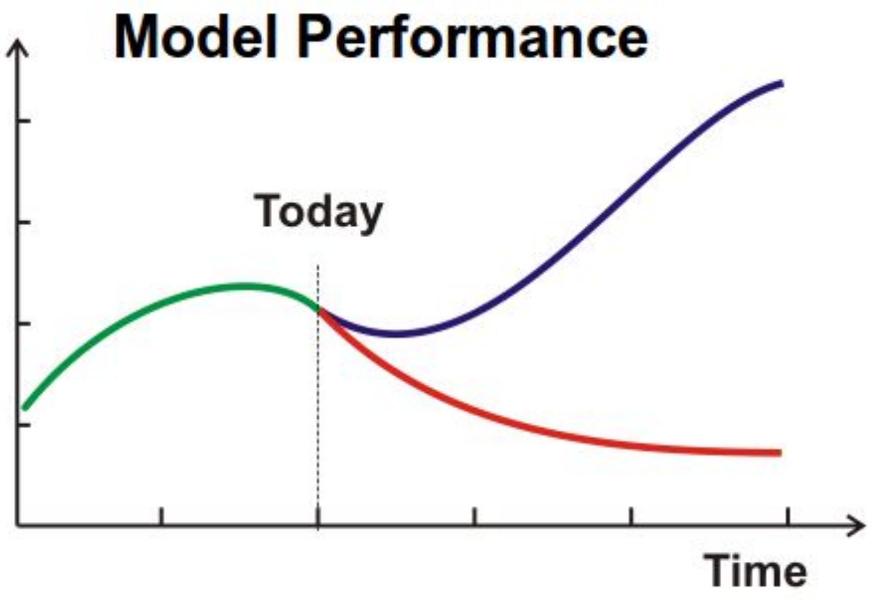
DELIVERABLE

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.

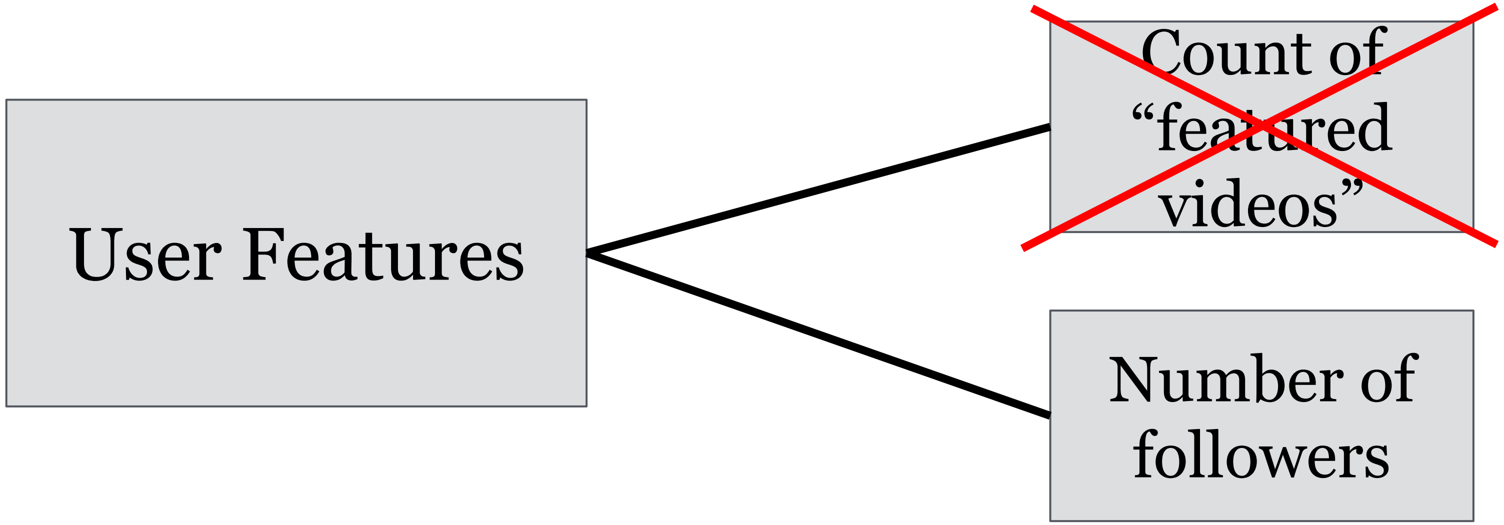
EVOLVING FEATURES

- 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”.



“Featured videos” removed in 2010

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. 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?
2. Describe possible interventions.
    a. Will this change the data collected in the future?
3. Describe ethical issues that may arise from these tasks.

DELIVERABLE

Specific plans descibed 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 `tranform` 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

```python
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

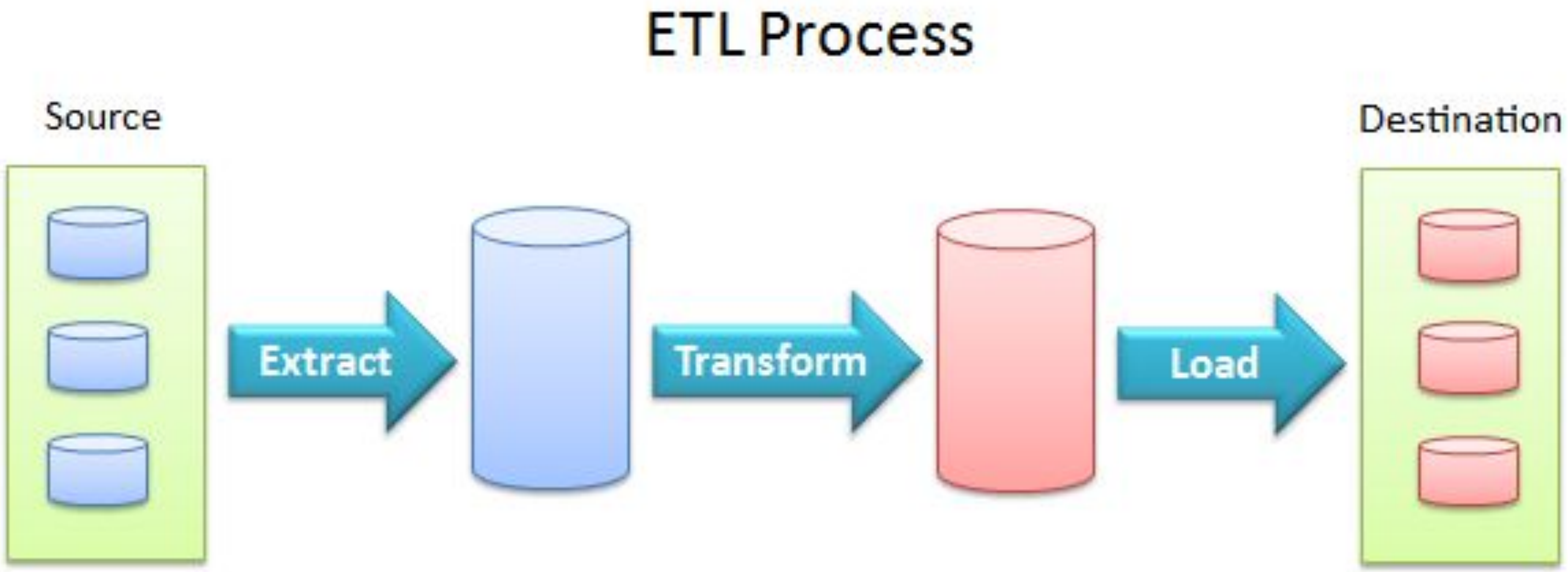
- Additionally, we may want to merge many different feature sets automatically. This can be done with `FeatureUnion`.

- While scikit-learn pipelines help manage raw data transformation, there may be many steps occuring 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.

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 and the ability to tie into other applications (web apps, etc).
- Python code is generally faster and more efficient.
- R has tried to replicate some of this extra functionality, but it is generally more native to Python.

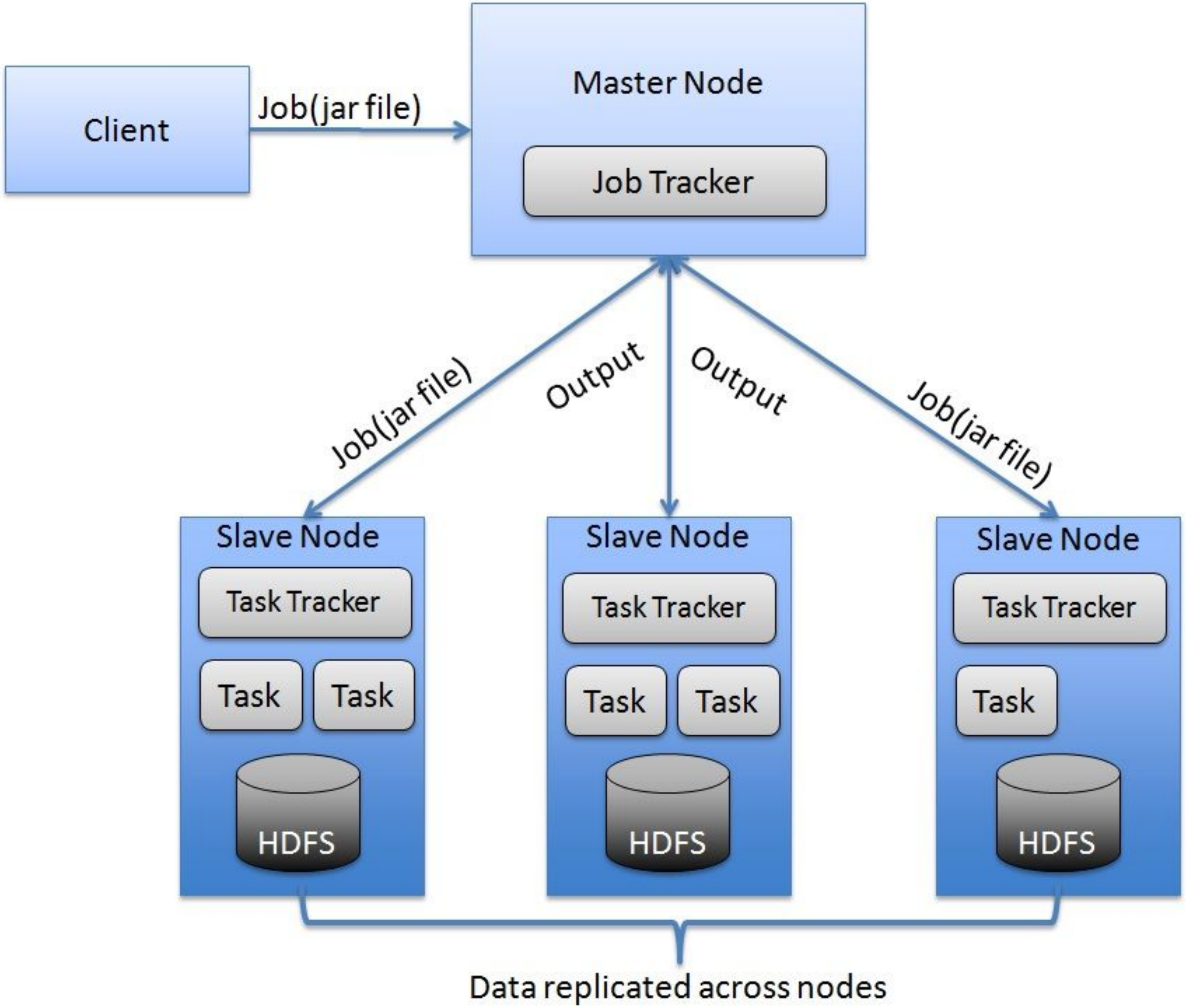
LANGUAGES

- 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

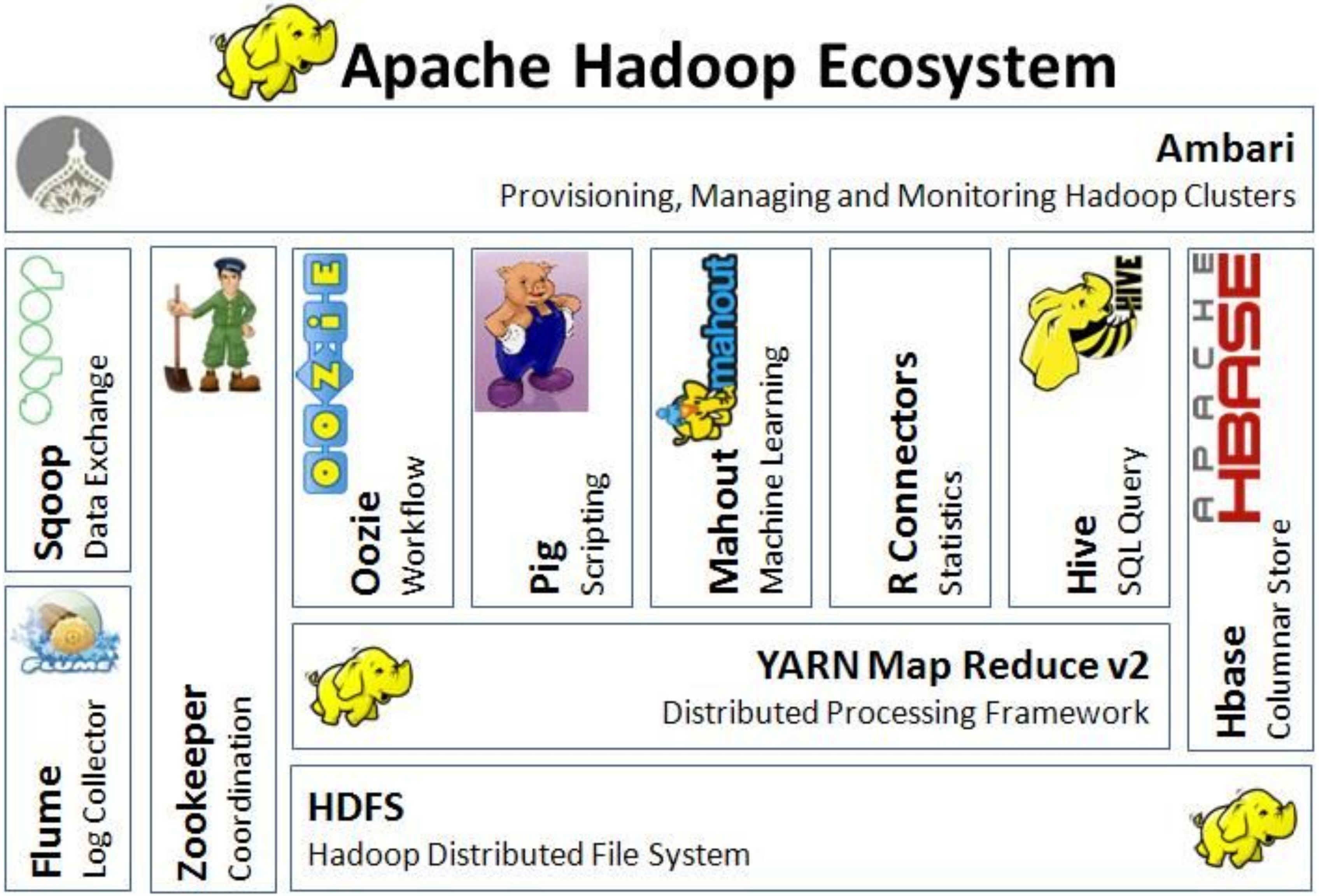
- What is Hadoop?

- 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.

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.

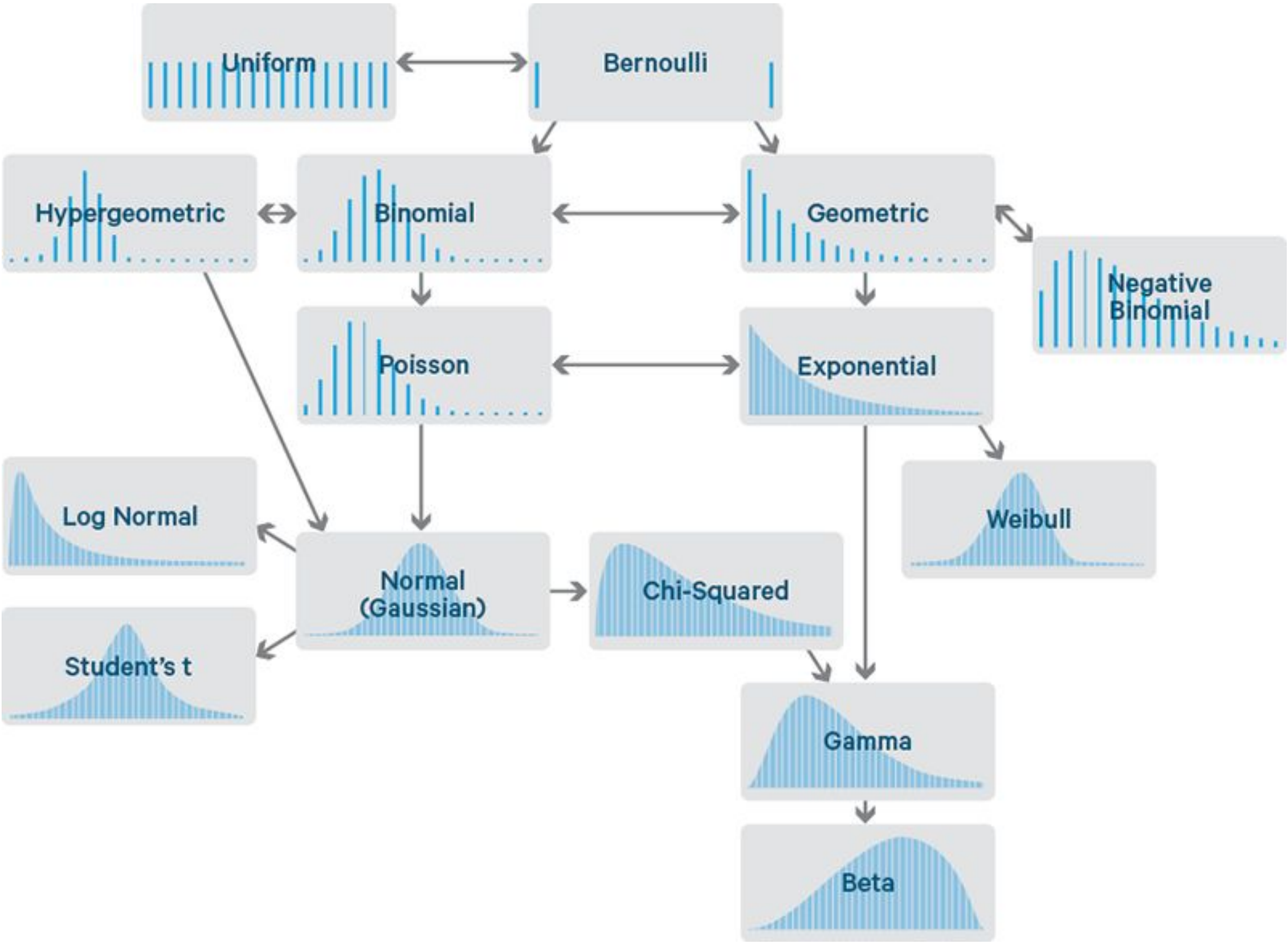
- Being able to view a histogram and summarize it by the distribution it resembles makes it much easier to discuss your data.

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



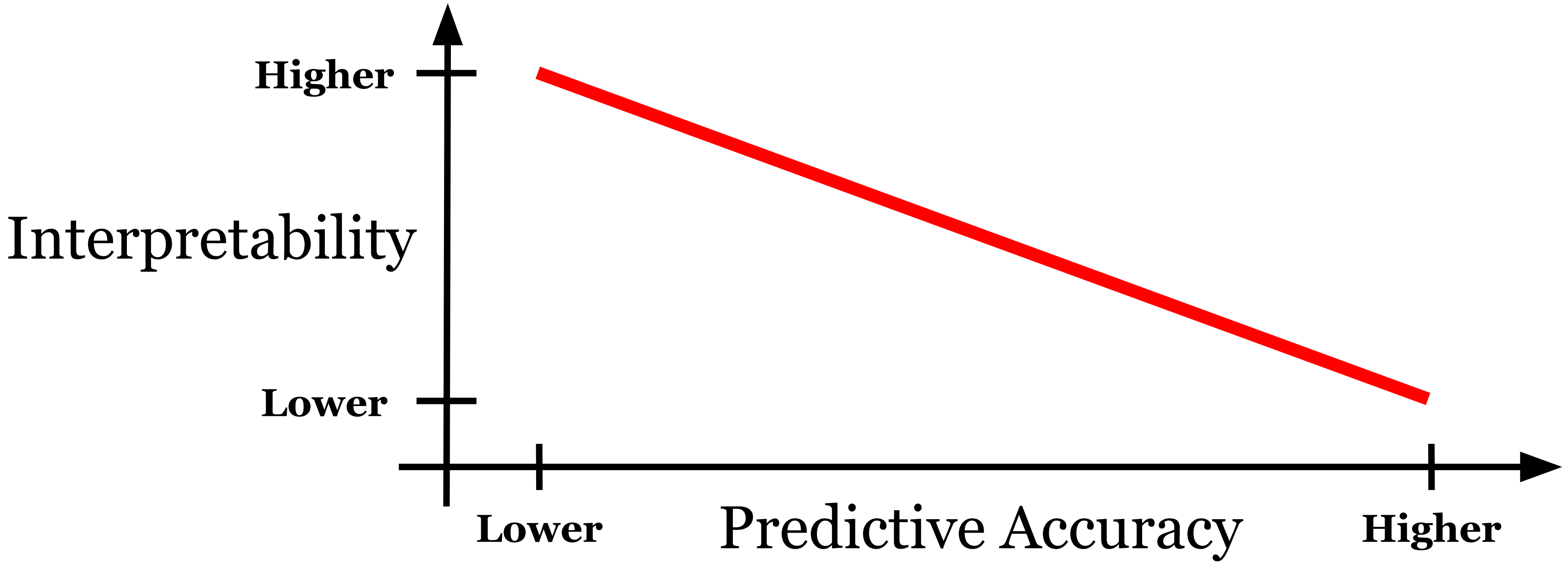
VISUALIZATION

- 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**.

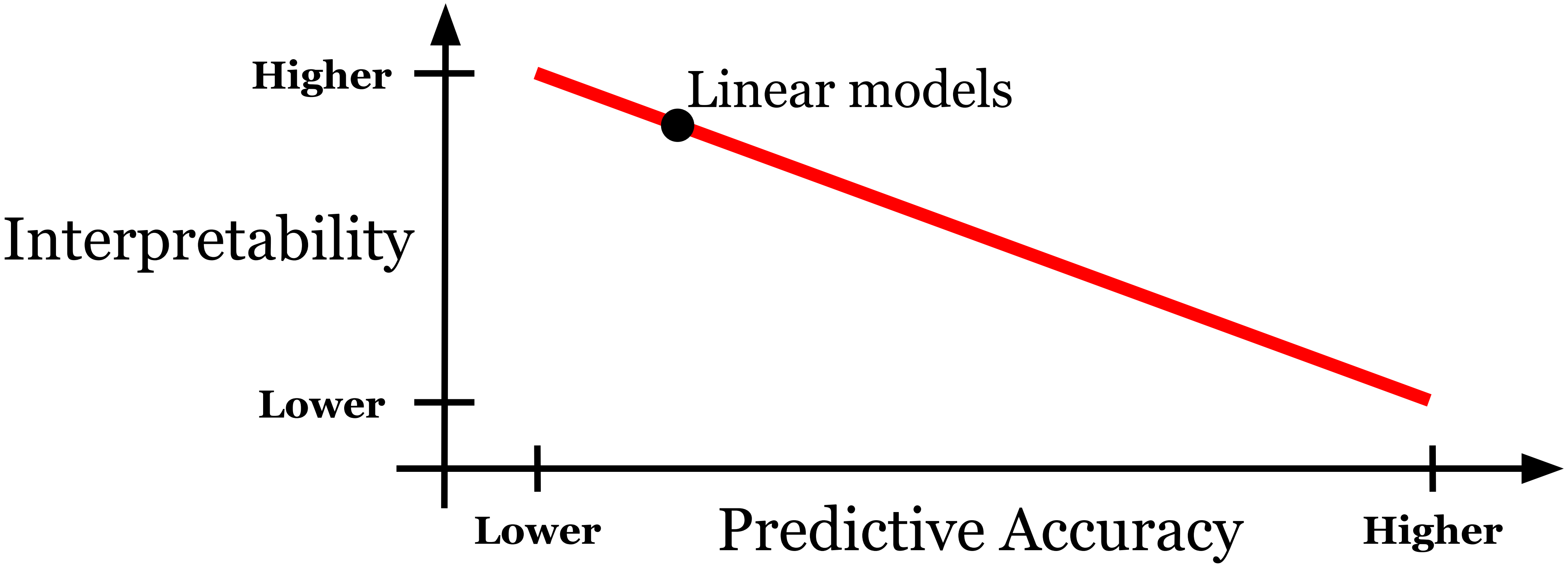
Predictive Accuracy vs Interpretability



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.

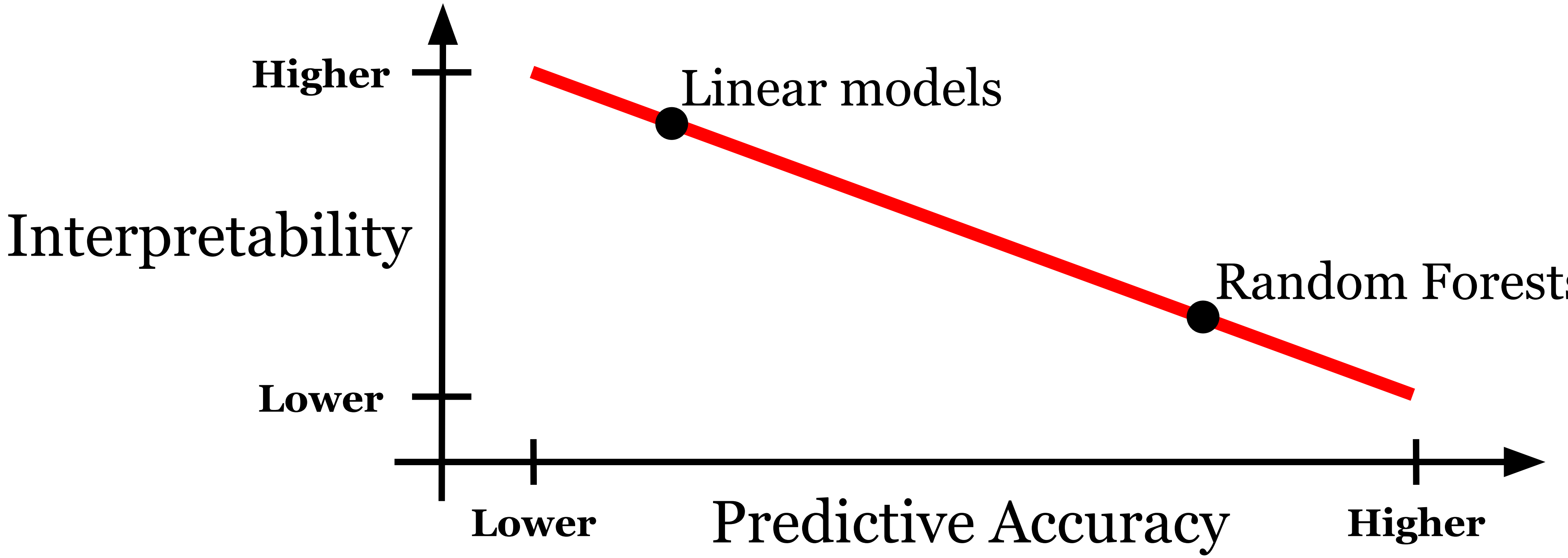
Predictive Accuracy vs Interpretability



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

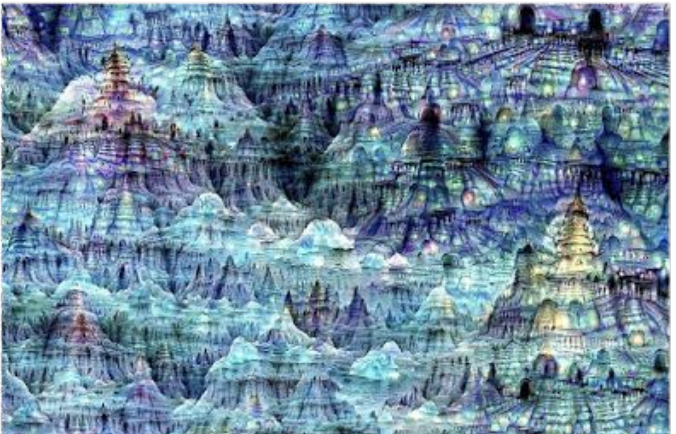
- On the other end of the spectrum, *deep learning models* are very powerful but offer little to no interpretable value.

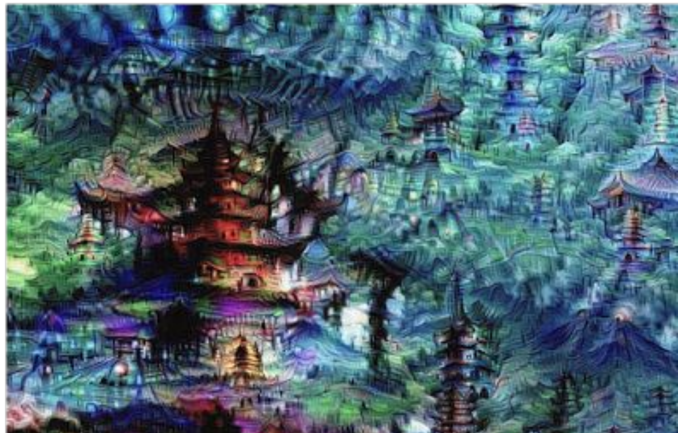
- Deep learning models like *neural networks* are highly accurate but complex to build and understand.

- 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

DUE DATE

- Project: Final Project, Part 5!!

LESSON

CREDITS

LESSON

Q & A

LESSON

EXIT TICKET

DON’T FORGET TO FILL OUT YOUR EXIT TICKET