Machine Learning and Risk Analysis

COMPSS 224B: Quantitative Political Risk

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11 April 2025

Recap

Where We've Been:

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- Politics matters, but unclear how, when, why...
- Existing approaches typically qualitative
- Explosion of big data creates new opportunities...and challenges

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New Terminology:

- Event versus structural risks
- Enterprise risk management
- Scenario analysis

Overview: ML for Political Risk Analysis

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- Monitoring and validation tools:
- Interpretable ML and Analytics:
  - Understanding your results
  - Communicating your results

Agenda

1. Motivation
2. Types of ML for Political Risk
3. Prediction vs Inference
4. MLOps and Data Science Pipelines

Motivation

Machine Learning (ML) and AI are hot buzzwords in political risk...

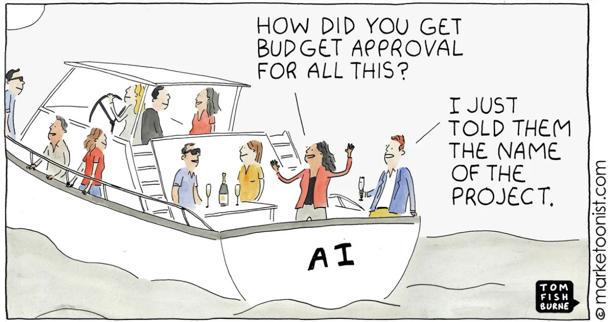


Figure 1: AI Washing, Credit: Marketoonist

...but still misunderstood...

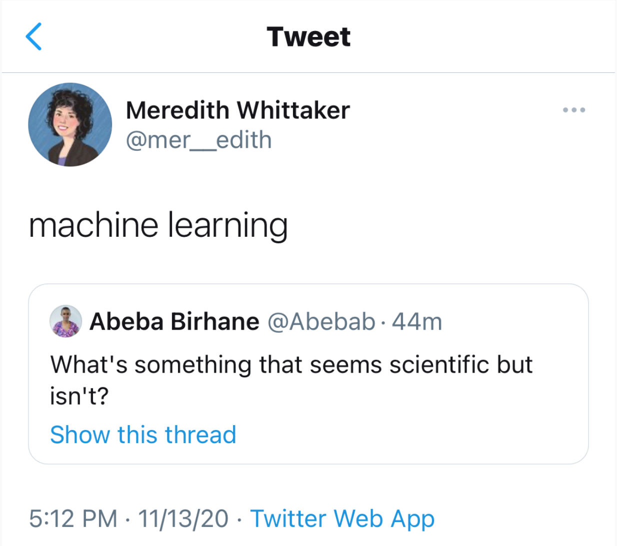
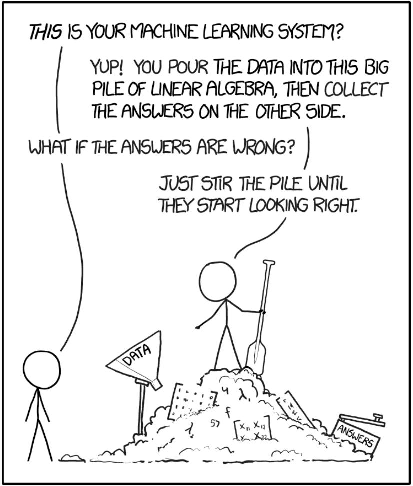


Figure 2: Faculty Director AI Now Institute, Research Prof NYU. Ex-Google.

...and prone to abuse.



Types of ML for Political Risk

Main Intuition Behind ML

Main Idea: ML is a form of artificial intelligence increasingly used in political risk analysis to solve complex prediction problems.

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- Estimate a country's credit risk based on likelihood of default
- Anticipate government expropriation of commercial goods
- Forecast the risk of terrorism and insurgency using a country's socio-economic data

ML Political Risk Applications

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- Academia
  - Measure polarization in political institutions (Clinton, Jackman, and Rivers 2004)
  - Infer extent and strategy of Chinese censorship (King, Pan, and Roberts 2014)
  - Assess risk of conflict onset and escalation (Malone 2022)

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- **Non-Technical Take:** ML involves a set of computer algorithms which ‘learn’ patterns in existing data to assist in prediction and inference.
- **Technical Take:** We want to build a model f that optimizes a given cost function in order to maximize model performance

2 Types of Machine Learning

1. Unsupervised Learning
2. Supervised Learning

Supervised vs Unsupervised Learning

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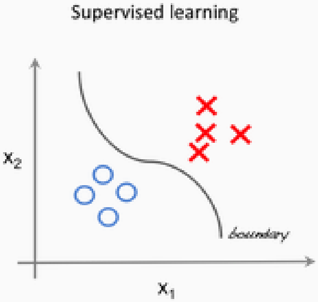
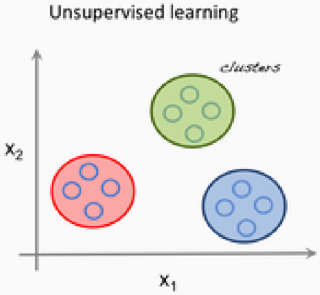




Supervised vs Unsupervised Learning

Supervised Learning:

- Predicts a given outcome
- Data includes x and y
- Evaluate accuracy

Unsupervised Learning:

- Descriptive data analysis
- Data includes x
- No standard evaluation

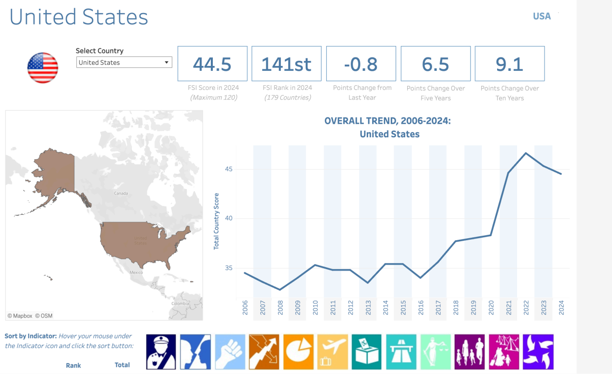
Unsupervised Learning

- Main Idea: Descriptive Data Analysis
- Common Objectives:
  - Identify meaningful groupings of the data $\rightarrow$ **clustering**
  - Simplify high-dimensional data to explain variation in as few dimensions as possible $\rightarrow$ **principal component analysis**
  - Analyze unstructured text data $\rightarrow$ **sentiment analysis**

Unsupervised Learning

Real-World Applications:

- Stock market anomaly detection (insider trading)
- Define 'Nationalism' or 'State Capacity'
- Measure state fragility
- Automated content analysis of the news



Types of Unsupervised Learning

- Principal Component Analysis (PCA)
- Clustering
  - K-Means Clustering
  - Hierarchical Clustering
  - DBSCAN
- Text Analysis
  - Sentiment
  - Topic
  - Context (Embeddings)
  - LLMs

Supervised Learning

- Main Idea: Learn patterns in existing data and extrapolate good predictions based on this information.

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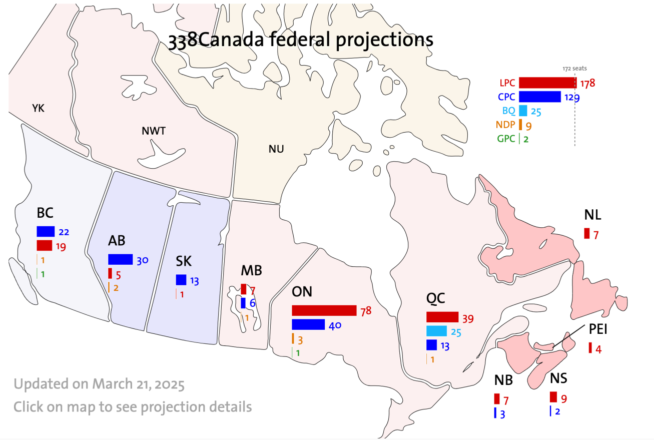
- Real-World Applications: Predict terrorist attacks, predict election results, predict market movements



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Supervised Learning

- Common Objective: Learn relationship between outcome variable (Y) and input variables ($X = (X_1, X_2, \ldots, X_i)$) by estimating f
- Assume relationship between Y and X_i such that...

$$y = f(X) + \epsilon \tag{1}$$

  - f is fixed, but unknown function.
  - f captures information (systematic patterns) about how X affects Y
  - ϵ is “noise” in the model (error term)

Prediction vs Inference

Why Learn the Relationship Between X and Y?

1. Inference

2. Prediction

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    1.3 Better model $\rightarrow$ more explanatory
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2. Prediction
   2.1 Inputs are readily available, but Y is not
   2.2 Want to predict $\hat{Y} = \hat{f}(X)$
   2.3 Better model $\rightarrow$ more accurate predictions ($\hat{Y} \approx Y$)

An Analogy

- Inference: Why is the car running?
- Prediction: Where is the car going?

A Real-World Example

- **Inference:** What *explains* Russia invasion of Ukraine?
- **Prediction:** What *predicted* Russia invasion of Ukraine?

Map of arms build-up prior to invasion.
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Warning!

Inference and prediction results can overlap, but...

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Inference and prediction results can overlap, but...

A statistically significant indicator is not necessarily a good predictor. Why?

- Small Effect Size
- Spurious Correlations
- Omitted Variable Bias
- External Validity

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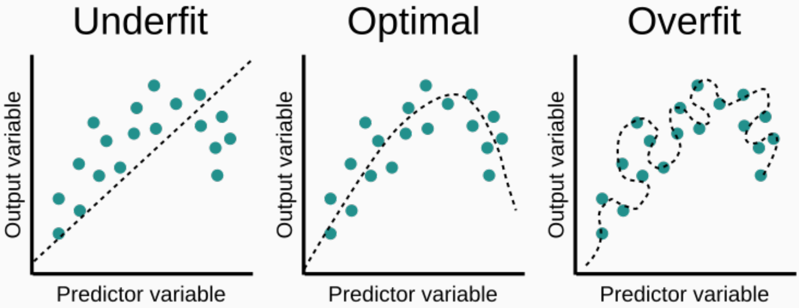
- **Problem:** Easier said than done.

Bias-Variance Trade-Off

- Bias-Variance Trade-Off: Models tend to result in either (1) low variance and high bias (under-fitting) or (2) high variance and low bias (over-fitting).



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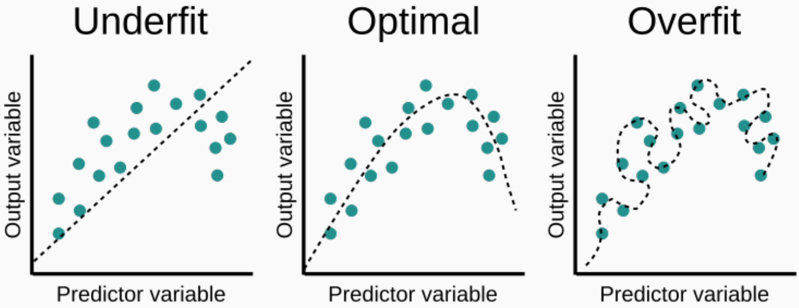

- A central ML challenge is finding a method that minimizes *both* variance and bias.
- Rule of Thumb: More flexible methods will result in higher variance, but lower bias <u>and</u> less interpretability.

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Supervised learning algorithms fall into 2 classes:

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2. Non-Parametric

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    1.2 Assumes f has fixed form with fixed number of parameters $(\beta_1, \ldots \beta_p)$
    1.3 Estimating f $\rightarrow$ estimating parameters
    1.4 Ex. Linear Regression Model

$$\hat{f}(X) = X_1\beta_1 + \cdots + X_p\beta_p \tag{3}$$

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2. Non-Parametric
   2.1 More flexible $\rightarrow$ low bias
   2.2 No fixed f to describe data
   2.3 $\hat{f}$ is "black box"

MLOps and Data Science Pipelines

Lingering Questions

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  Provide data, analytics, and communication around it

Solving for Political Risk

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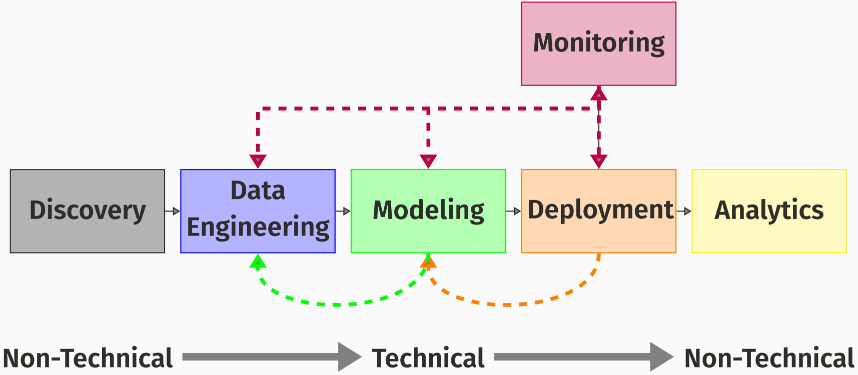
1. **Conceptual:**
    - What do we mean by political risk?
    - What is a risk solution? Mitigate? Monitor? Management?
    - This is a story about...
2. **Practical:**
    - Costs
    - Transparency and regulatory requirements
    - Data Availability
    - Performance Metrics

ML Operations: Project Life Cycle



Discovery

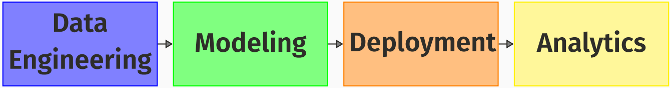
Business Understanding

- What is the problem? How do you define risk?
- What's the current approach to the problem?
- What's the limit to this approach?
- Who is affected by this?

Scoping

- Translate non-technical needs into technical action items
- Research Design and Mapping
- Hypotheses
- Requirements
- Minimum Viable Product

Data Science Pipeline: Post-Discovery



Data Engineering

Not So Fun Part

- Data Wrangling
- Data Cleaning
- Data Preparation

Fun Part

- Exploratory Data Analysis
- Signals Analysis
- Data Mining
- Index Creation

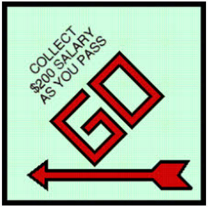


Figure 3: Go directly to deployment!

Fun Part

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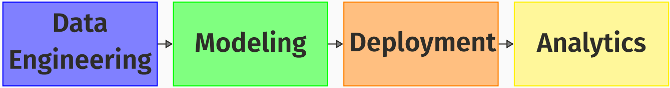
Data Science Pipeline: Modeling



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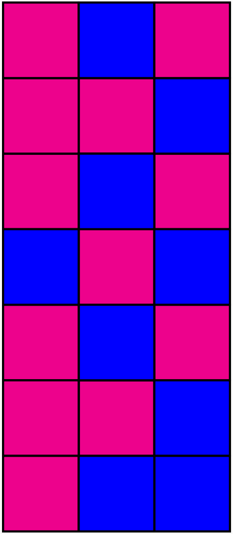
   2.3 Evaluate whether $\hat{f}$ good model by comparing predicted response $\hat{f}(x)$ (aka $\hat{Y}$) with true response Y

Data Set

Data: $(x_1, y_1), (x_2, y_2), \ldots (x_n, y_n)$

Test and Training Set



Partition Data into Test and Training Set

Figure 4: Training Set

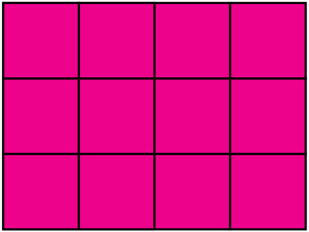
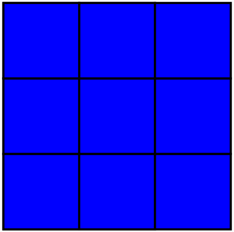
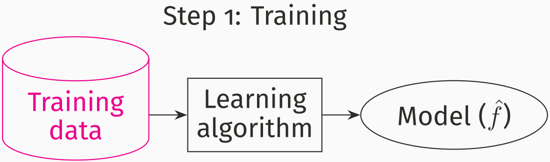


Figure 5: Test Set



Python Rec: Use `sklearn.train_test_split`

Train Model $\hat{f}$ then Test Accuracy of Predictions



Python Rec: instantiate model $\longrightarrow$

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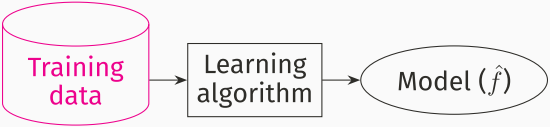
Step 1: Training



Python Rec: instantiate model $\longrightarrow$ model.fit(X_train, y_train) $\longrightarrow$

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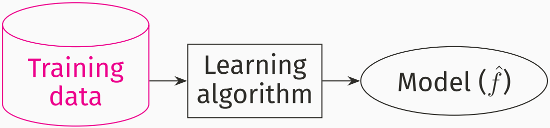

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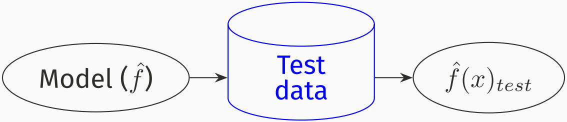

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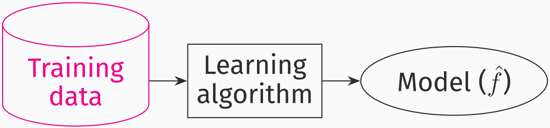

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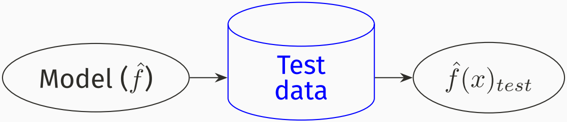


Step 3: Evaluate Test Predictions

$$\boxed{\hat{f}(x)_{test} \approx Y_{test}\text{?}}$$

Python Rec: instantiate model $\longrightarrow$ model.fit(X_train, y_train) $\longrightarrow$ model.predict(X_test) or model.predict_proba() $\longrightarrow$ accuracy_score(y_test, yhat)

Modeling

Common Supervised Models

- OLS (bread and butter)
- Lasso and ridge
- CART, esp. GBM and RF
- NN, esp. LSTM RNN and increasingly transformers
- Markov models

For good overview of examples, see Rod, Gasste, and Hegre (2024).

Deployment

- Work with broader dev team
- Refactor code to be efficient
- Scale up process to larger and dynamic datasets
- Deploy to production
- Create automated pipelines for output and monitoring

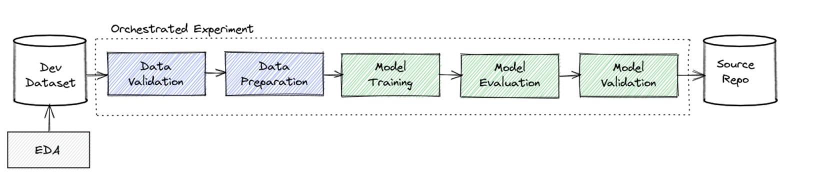
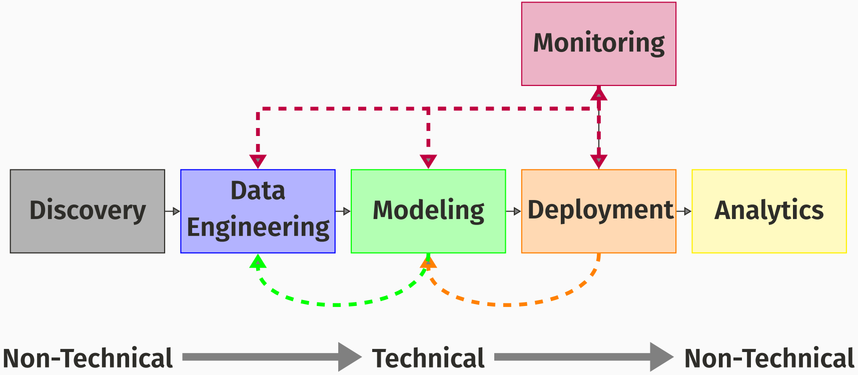


Figure 6: Source: Yashaswi Nayak

Monitoring is a constant and iterative process



Analytics

- Translate technical results back to non-technical terms.
- Provide end users actionable insights to better monitor, understand, and better manage risks.
- **Narratives from numbers:** data storytelling, written work, and other risk communications.

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Unsupervised ML Products

Supervised ML Products

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- Risk Monitoring
- Text Data $\rightarrow$ Structured Data
- Index Creation
- Clusters
- Scorecards and Dashboards

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Supervised ML Products

- Risk Management
- (Trading) Algorithms
- Politically Oriented Risk Signals
- Forecasts
- LLM Tools

Conclusion

- Real-world is interested in prediction more than inference
- ML for political risk aims to learn patterns and make good predictions about out-of-sample (test) data
- Picking best model means optimizing bias-variance trade-off
- ML Ops is an iterative process, requiring cross-functional skills (this is your **super power:** non-technical and technical, computational and social scientific)