PS132B
Machine Learning for Social Scientists

Introduction

Kirk Bansak

January 17, 2023

Why Machine Learning for Social Science or Public Policy?

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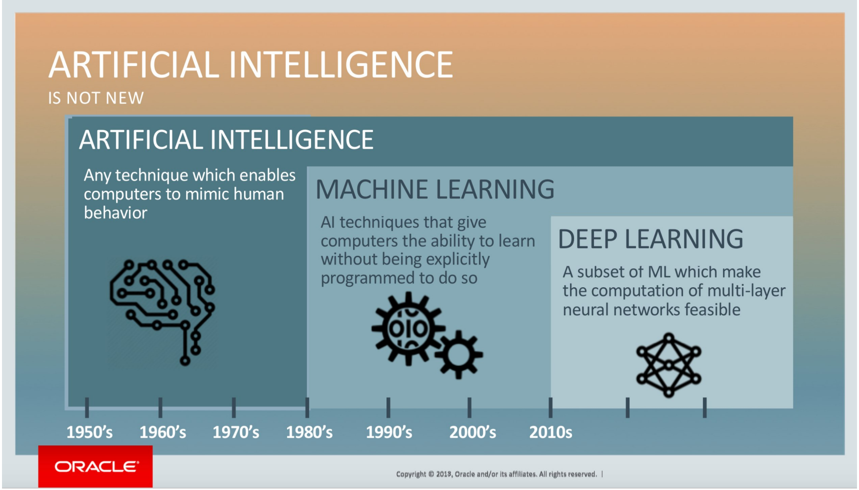
- Classify online posts as either "fake news" or "real news" based on the words in the title and/or in the body of the article.
- Identify substantive topics or themes in a collection of documents.

Machine learning refers to a vast set of tools that can learn, encode insights, and/or make predictions from data.

Supervised learning: Predict or estimate an output, usually quantitative (e.g. wage) or categorical (e.g. Republican/Democrat), based on a set of inputs.

Unsupervised learning: We observe only the inputs, but no measure for the outputs. Our task is to learn relationships and structures hidden in the data.


ARTIFICIAL INTELLIGENCE
IS NOT NEW
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Any technique which enables computers to mimic human behavior
MACHINE LEARNING
AI techniques that give computers the ability to learn without being explicitly programmed to do so
DEEP LEARNING
A subset of ML which make the computation of multi-layer neural networks feasible
1950's
1960's
1970's
1980's
1990's
2000's
2010s
ORACLE
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From AI to Machine Learning

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  - Have computer run algorithms to learn from the data
  - Automatically uncover a wider landscape of subtle patterns
  - Systematize those into insights (models)
  - Apply those insights (models) to new instances (new data) to make assessments or decisions

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  - In essence, will evaluate all of the features (subject line, sender, text, metadata, etc.) of a new email and systematically compare them to the patterns of past (spam vs. non-spam) emails to make determination.

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Math & Algorithms + Computation + Data

(Navigation + Engine + Fuel)

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$=$

Unique value across a diversity of domains

Machine Learning Applications

Industry: Increasing Revenue

- Measuring consumer opinion and behavior
- Delivering engaging content to users

Public Sector: Optimizing Public Policy Decision-making

- Predict health and safety risks
- Assist pre-trial release and parole decisions

Campaigns: Winning the Vote

- Classify voters based on likely voting, using consumer information
- Identify ideological patterns based on social media behavior

Social Science: Understanding our Social and Political World

- Polarization in political institutions: Clinton, Jackman, and Rivers (2004)
- Extent/strategy of Chinese censorship: King, Pan, and Roberts (2014, 2017)
- Public support for economic austerity: Bansak, Bechtel, and Margalit (2021)

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Automated machine learning model building and assessment methods can help with small, medium, and big data problems!

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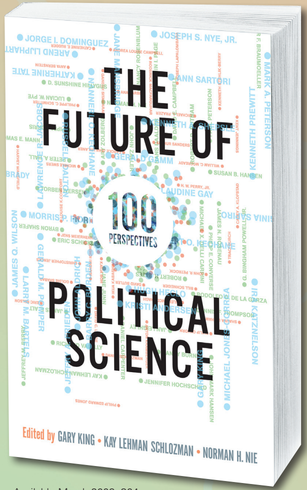

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—Lawrence C. Dodd, Manning J. Dauer Eminent Scholar in Political Science, University of Florida

Routledge

Evaluators' Rate Machine Choices Better Than Their Own (Grimmer and King)

Generate pairs of similar documents: Humans vs Machines

- Scale: (1) unrelated, (2) loosely related, or (3) closely related
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P.S. The hand-coders were themselves the evaluators!

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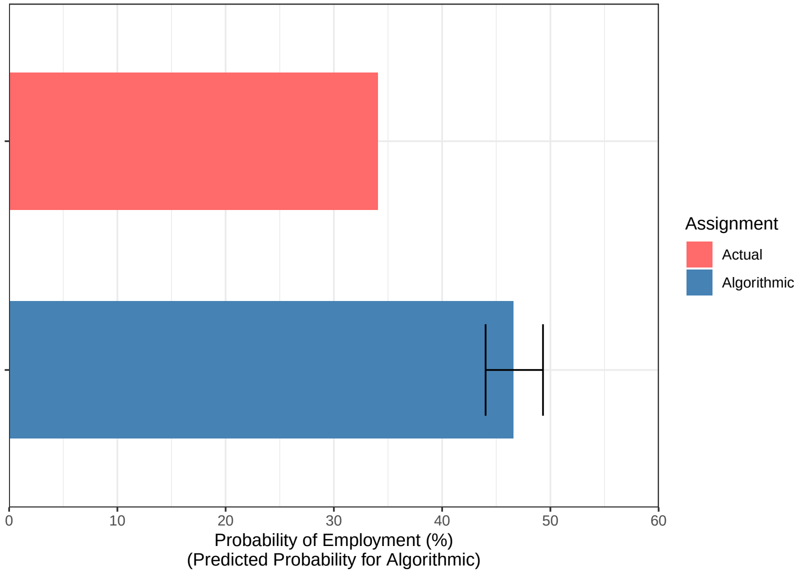
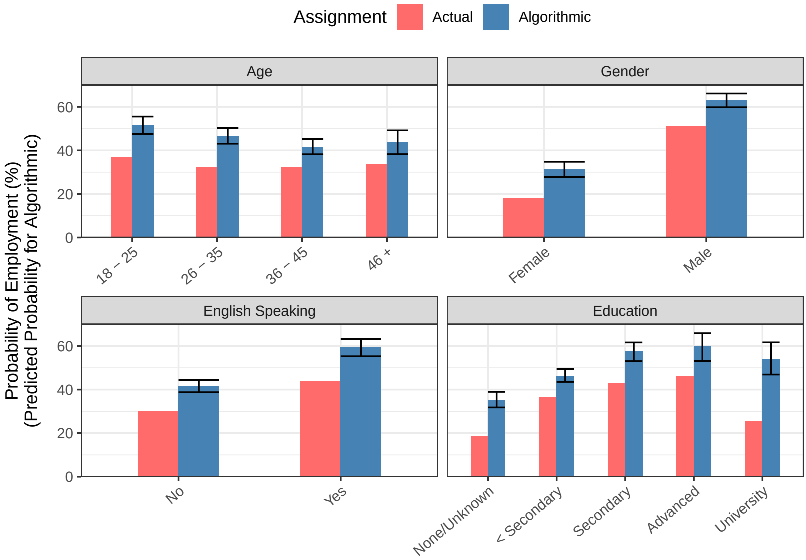
- Two-stage algorithm
  1. Modeling: machine learning models to predict refugees' employment outcomes at their different possible geographic destinations
  2. Matching: assignment of refugees to optimal locations, subject to capacity and other constraints
- Backtests using data in United States and Switzerland show that algorithmic assignment can lead to 40-70% gains in employment relative to status quo assignment procedure.


0
10
20
30
40
50
60
Probability of Employment (%)
(Predicted Probability for Algorithmic)
Assignment
Actual
Algorithmic


Assignment
Actual
Algorithmic
Age
Gender
English Speaking
Education
Probability of Employment (%)
(Predicted Probability for Algorithmic)
0
20
40
60
18 – 25
26 – 35
36 – 45
46 +
Female
Male
No
Yes
None/Unknown
< Secondary
Secondary
Advanced
University

Presumptions for this Course

1. Machine learning is relevant and useful in a wide range of academic and non-academic fields.
2. We will be able to broadly understand the models, intuitions, and strengths and weaknesses of the various approaches.
3. While it is important to know what general job is performed by each cog, it is not necessary to have the skills to completely construct the underlying algorithms.
4. Applying machine learning methods to "real-world problems" requires not only quantitative skills but also conceptual reasoning and subject matter understanding.

Core Objectives

Ultimate Goal: introduce students to modern machine learning techniques and provide the skills necessary to apply the methods widely.

Two Broad Categories of Machine Learning Covered:

- Supervised Learning
- Unsupervised Learning

Proximate Goals:

1) Learn a variety of machine learning techniques and how to effectively choose between them and use them with real-world data.
2) Learn about core concepts in machine learning and statistics, developing skills that are transferable to other types of data and inference problems.
3) Develop programming abilities in R.
4) Introduce substantive problems in lectures, homework, and sections.

Core Objectives

This class is not a course on:

1) Classical statistical inference or causal inference
2) Full technical details behind machine learning methods, such as optimization algorithms and theoretical properties
3) The full universe of machine learning
4) How to become a professional programmer

Prerequisites

PS 3 or Data 8 (or equivalent coursework). This includes:

- A mechanical understanding of regression
- A brief introduction to statistical inference
- Experience with `R` or `Python`

⋆ We will exclusively use `R`, but previous knowledge of `Python` will enable getting up to speed on `R`

As our primary reference, we will use the book listed below:

Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani. *An Introduction to Statistical Learning with Applications in R*, **Second Edition**, 2021.

Logistics

Teaching Staff

Sections

Evaluation

- Problem Sets: Six assignments, 40% of final grade
  - Should be submitted in R markdown
  - Can think through and discuss problem in small groups (of 2-3), but (a) you must write your own answers and code, and (b) you must specify whom you worked with
- Challenges: Two group challenges, 25% of final grade
  - Challenge 1: Predicting recidivism
  - Challenge 2: Analyzing political text
- Midterm exam (in-class): 15%
- Final exam (official exam schedule): 20%

Ed Discussion

Course Plan

- Introductory Week

1. R
2. Supervised Learning
3. Unsupervised Learning

- Concluding Week

Introduction	Week 1	01/17	Introduction
	Week 1	01/19	A Machine Learning Focus on Regression *Read: ISLR pp. 15 - 39*
Unit 1: **R**	Week 2	01/24	Data and Datasets *Read: Kelleher and Tierney (2018); Kaplan (2009)*
	Week 2	01/26	(Re)Introduction to `R` *Do: Install/Update `R` and `RStudio` on your computer*
	Week 3	01/31	Introduction to `R Markdown` *Do: Install the `tidyverse` and `knitr` packages* **PSet 1 assigned**
	Week 3	02/02	Diving Deeper into `R`: Core Functionality *Read: Venables et al. (2022), Chapters 2, 3, and 6*
	Week 4	02/07	Diving Deeper into `R`: Data Visualization and Exploration *Read: Wickham and Grolemund (2017), Chapter 3* **PSet 1 due, PSet 2 assigned**
	Week 4	02/09	Diving Deeper into `R`: Functions and Iteration

For Next Class

Read: ISLR pp. 15 - 39