Machine Learning, Automated Algorithms, and Risk

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The Machine Learning for Good Lab @ NYU

- Public health and disease surveillance
- Violence, conflict, unrest, human rights
- Event Detection and Situational Awareness
- Crime prediction and prevention
- Novel ML Theory and Methods for Pattern Detection and Prediction
- Optimizing, Deploying, and Evaluating Targeted Interventions for Good
- Causal Inference and Learning
- Opioid and overdose surveillance
- Healthcare best practices
- Environmental health and prevention
- Allocating city services
- Fairness and Equity in Algorithmic Decision-Making
- Criminal justice

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The use of **automated algorithms** for decision making has become increasingly ubiquitous across a wide variety of fields...

Online marketing  
Lending  
Hiring  

Health care  
diagnosis & treatment  

Policing & criminal justice  
Allocation of city services

Across all of these domains, the use of such algorithms, often based on machine learning and “big data”, has **great potential** to identify, quantify, and reduce risks…

But their use can also create **new types of risk** (e.g., algorithmic bias and discrimination)
Machine Learning in a nutshell

**Machine Learning (ML)** is the study of systems that improve their performance with experience (typically by **learning** from data).

ML algorithms have many advantages compared to classical methods: **flexible** and **interpretable** models, **robustness** to “messy” data, and the ability to **scale** to massive, complex datasets.

**Supervised Learning**

Data/input | Labels/output
---|---
\(x_1\) | \(y_1\)
\(x_2\) | \(y_2\)
... | ...
\(x_N\) | \(y_N\)

Learn dependence:

\[ y = f(x) \]

Discrete y = classification
Continuous y = regression

**Example of supervised learning:**
Predicting risk of, and expected loss resulting from, a severe weather event.

This is most of what you learn in an intro ML class, but only a small fraction of today’s talk!
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**Supervised Learning**

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>$x_1$</td>
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<tr>
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Learn dependence:

$y = f(x)$

Discrete $y =$ classification
Continuous $y =$ regression

In unsupervised learning problems, we have a set of data records with no labels.

Unsupervised ML tasks include clustering data into groups, and detecting anomalies or outliers.

What I do is mostly unsupervised learning, specifically, detection of emerging events and patterns in massive and complex data.
What are some potential benefits of ML to the (re-)insurance industry?

More accurate advance prediction of risks could improve **underwriting**: pricing, risk selection, new insurance products for emerging risks…

Early detection can provide detailed **situational awareness** prior to first notice of loss (reserving, claims management, fraud detection…)

Can target specific geographic or subpopulation-level **interventions** to reduce risks and mitigate losses.

Can identify and fix underlying problems (e.g., hazardous conditions, or systematic bias and discrimination) which can result in legal **liability**.

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**Case studies: what types of risk does our work address?**

- **Crime** prediction and prevention (theft, assault, …) → property, health, life
- Catastrophic **events** (natural disaster, disease pandemic, …) → property, health, life
- Emerging patterns of **behavioral** risks (opioid overdoses, …) → health, workforce
- **Occupational** risks (safety, training, external hazards, …) → workers comp, liability
- Suboptimal **healthcare** practices (procedures, meds, …) → health, malpractice/liability
- **Environmental** risks (poor housing, air/water quality, …) → health, liability
- Systematic **bias** and discrimination (human and algorithmic) → liability
Better predictive models can lead to improved organizational decisions, allocation of public resources, and quantification of risks.

Which geographic areas within a city are likely to become crime hot spots?

**Short time horizon:**
Targeted police patrols in these areas reduce crime.

**Longer time horizon:**
Quantify risk of loss from theft, assault. Also informs city planning and policy.
Early Warning for Critical Events

Early detection can reduce costs to society by enabling a targeted and effective response.

Advance prediction can both quantify and reduce risk.

Disease pandemic
Natural disaster
Terrorist attack
Civil unrest

Twitter Event Surveillance

Accurately predicts civil unrest, ~1 week in advance

Enables earlier detection of emerging disease outbreaks

Can identify emerging human rights issues

(Chen and Neill, KDD 2014)
Opioid and overdose surveillance

Identifying emerging patterns of **behavioral risk factors** and health outcomes can help to assess risks and target behavioral health interventions.

**Example:** opioid misuse $\Rightarrow$ fatal drug overdoses.

**Loss mitigation by:** prevention, treatment, rescue, recovery

(Where to target? Who to target? With which interventions?)

**Individual level:** using data from state prescription drug monitoring programs, we track individuals’ total opioid prescription (milligrams morphine equivalent) over time, and correlate with overdoses and “red flag” risk behaviors.

**Subpopulation level:** we identify emerging clusters of overdoses among subpopulations defined by any combination of geography, demographics, and behaviors.

“elderly African-American males living downtown”

“individuals combining methadone with the prescription drug Xanax”
Health surveillance for emerging events

Typical health surveillance systems group cases into known categories (e.g., flu-like illness) and identify clusters of disease in space and time.

But what about newly emerging patterns (e.g., a novel outbreak with an unusual combination of symptoms) that they were not already looking for?

Our **pre-syndromic surveillance** system monitors free-text chief complaints from clinics and hospital EDs, combining text analysis and cluster detection to find novel outbreaks and other emerging trends of interest to public health.

Monitoring data from NYC Emergency Departments:
Novel outbreaks (e.g., “nosebleed and stomach pain”)
Disaster prep (acute injuries → mental health → chronic)
Unusual health events (e.g., “glass in coffee”)

Occupational health (NYC Dept. of Sanitation):
Exposure to illness, external hazards (e.g., needle sticks)
Lapses in safety and training (e.g., lower back injuries)
→ Implications for worker’s comp, sick leave mgmt., liability
Identifying **causal** effects of treatments and exposures

1. Healthcare treatments

   We are using health insurance claims data from ~125K individuals to identify anomalous patterns of patient care that impact health outcomes.

   * Correct suboptimal care *
   * Identify new best practices *

   **Key idea**: treatment effects may be **heterogeneous**; look for most positively and negatively affected subpopulations.

   “**Glucocorticoids** significantly increase hospitalizations following treatment in the subpopulation of hypertensive, overweight males with endocrine disorders.”

2. Environmental health

   We are using Medicaid data linked to detailed building characteristics in order to identify impacts of poor-quality housing on chronic health.

   “Which housing conditions impact which health conditions, for which subpopulations, to what extent?”

   Must adjust for known confounders, selection into treatment/exposure.

   “**Crowded housing** is associated with increased respiratory conditions & injuries among Asians living in Manhattan.”

Implications for health, liability/malpractice, …
Subset scanning for pattern detection

One key methodological idea of our work is **subset scanning**:

- We frame the pattern detection problem as a search over subsets of the data (e.g., spatial areas or subpopulations), maximizing some measure of the “interestingness” or “anomalousness” of a subset.

- This allows us to find **subtle patterns** which typical anomaly detection methods would miss (“needle in the haystack + connect the dots”)

- Once we have found the highest scoring subset, we perform a statistical test to see whether it is unlikely to have occurred by chance.

**Search over subsets would be computationally infeasible but...**

- Our **fast subset scan** algorithm can efficiently identify the most interesting subsets of data records **without** exhaustive search.

This enables us to solve detection problems in **milliseconds** that would previously have required **millions of years**!
Northpointe’s COMPAS software has been used for criminal justice in many jurisdictions to predict individuals’ re-offending risk.

ProPublica compared COMPAS predictions to observed re-arrests and concluded that COMPAS is **racially biased**.

**Huge potential impacts:** civil and criminal liability, loss of reputation, loss of future business, erosion of public trust in civil institutions…
Auditing algorithms for fairness

- Is the COMPAS algorithm for predicting re-offending risk **fair**, or is it **biased** against some subpopulation defined by observed characteristics?
  - **Black box** algorithm. All we observe is predictions vs. gold standard (re-offending) for a sample of individuals (ProPublica data from Broward County, FL).
  - Many possible biases: race, gender, age, past offenses…
  - Combinations of factors, e.g., “elderly white females”

- This led us to develop a new and general approach ("**bias scan**") to audit black box algorithms for fairness and to correct systematic biases.
  - Uses fast subset scan to efficiently identify subpopulations for whom a classifier over- or under-estimates risk.
Results of bias scan on COMPAS

Start with maximum likelihood risk estimates for each COMPAS decile score.

**Detection result 1:** COMPAS underestimates the importance of prior offenses, overestimating risk for 0 priors, and underestimating risk for 5 or more priors.

**Detection result 2:** Even controlling for prior offenses, COMPAS still underestimates risk for males under 25, and overestimates risk for females who committed misdemeanors.
After controlling for number of prior offenses and for membership in the two detected subgroups, there are no significant systematic biases in prediction.
Results of bias scan on COMPAS

After controlling for number of prior offenses and for membership in the two detected subgroups, there are no significant systematic biases in prediction. The resulting probabilistic classifier has greater interpretability (though still based partially on a black box) and is less biased than the original COMPAS predictions… but does this mean it is “fair”? 

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Discussion: predictive fairness in context

• The method does not account for **target variable bias**: we predict re-offending risk but the gold standard is based on re-arrests not re-offenses.
  – Big problem with drug possession, weapon possession charges. Leads to feedback loops.

• How to avoid **disparate impacts** when making decisions based on even unbiased predictions?

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Conclusions

Automated machine learning algorithms have great, mostly untapped potential to benefit the insurance and reinsurance fields:

**Underwriting** – advance prediction of crisis events, risk estimation

**Risk mapping/surveillance** – early detection of events, trends, patterns

**Loss mitigation** – reducing impact through early and targeted response

They inform many types of risk (e.g., events, behavioral, environmental, occupational), with relevance to property, health, liability, workers comp...

But they also create **new risks** of systematic failures and unforeseen consequences, including potential for algorithmic bias and discrimination.

These new risks should be carefully considered and mitigated, ideally through a combination of human oversight and algorithmic auditing. Auditing approaches also have great potential to assess and mitigate biases in humans’ risk-assessment decisions!
Thanks for listening!

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