AI Ethics and Insurance
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Neil Raden
Ethical Use of Artificial intelligence for Actuaries

Material for this presentation partially derived from the report issued by the SOA in 2019 and written by Neil Raden
AI is an accelerator, but not without risks

“The invention of the ship was also the invention of the shipwreck...Every technology carries its own negativity, which is invented at the same time as technical progress.”
— Paul Virilio

But where would we be without ships?
The most important thing to think about

AI can do wonderful things for insurance companies
- It can attack costs, (partially) automate claims
- Backstop new products, insure more people

But the effort will be wasted

If customers don’t trust the technology you deploy
Which is why ethics are so important
Agenda

• Forms of analytics: Let's get the taxonomy right
• AI and actuaries
• Bias and ethical issues
• Data
• The five pillars of ethical AI
• Thing's to watch out for
• Concluding thoughts
First of All, What is AI?

- Everything from predictive analytics, to data science, to machine learning, to deep learning, Natural Language Processing, Facial recognition
- Cognitive Computing
- Artificial General Intelligence (doesn’t yet exist)
- For commercial operations - first three – things that are roughly predictive.
- I use the term AI for everything that is predictive: Data Science, Viz, etc.
What does a ML Model do?

- Finds patterns, regressions in labeled data, a million times faster than you
- Attempts to converge on the objective function using gradient descent/scent
- **What happens if it doesn’t converge?**
- It has no context; can tell you nothing about Flaubert’s Madame Bovary

Next: AI and Actuaries
What Does a Data Scientist do?

• Acquire, process and clean data. Integrate and manage storage of data.
• Initial data investigation and exploratory data analysis.
• Choose one or more potential models and algorithms.
• Apply data science methods and techniques, such as, statistical modeling.
• Measure and improve results.
• Present final results to stakeholders.
• Make adjustments based on feedback.
• Wash and repeat.
What Does an AI Engineer do?

• Coordinate between Data Scientists and Business Analysts
• Automate infrastructure DevOps, AIOps
• Convert machine learning models into APIs (or containers.) so that other applications can access them
• Write code, test (rinse and repeat) and deploy models
• Develop minimum viable machine learning products; optimize resources, IOW, computer science
• Automate processes by utilizing machine learning
• Use AI to empower the company with novel capabilities
What Does an Actuary Do?

• Ascertain cash reserves and premium rates. Shareholders, company executives, government officials and others expect an actuary to explain complex technical matters and help determine company policies.

• Review, design and maintain insurance instruments.

• Analyze statistical information and other data. Explain probabilistic results; give testimony to public agencies on proposed legislation.

• Aware of economics, legal codes, government regulations

• Remain technically current with pertinent job information and apply any new knowledge to his or her work.
In your work you will be in two types

1. “Departmental” models you develop and deploy
   - Statistical Models for your own research
     - Excel, SAS, Viz (Tableau, Qlik, Spotﬁre, PowerBI)
   - Data Science
     - R, Python, Open Source
   - Data Wrangling
     - Informatica, Trifacta, Alteryx

2. Production AI Models
   - You are part of a team
The AI Team: Diverse, Cross-Functional

- Domain Experts (that’s you)
- Data Scientists
- Data Engineers
- Product Designers
- AI Ethicists
- Lawyers
- Executives and Strategists
- Operations
My Dismal Recommendation?

- Actuaries should play a pivotal role in any AI project
- Coding and AI Engineering are a different career
- Data scientists don’t know how to do: solvency, valuation, lapse, pricing reserving
- Any strategic AI project should be produced by a team
- Because it it too easy to make a mistake with AI

Your most important role?
Be the moral compass
Example 1 – Programming Error/Bias?

• Attempt to have program identify skin cancer
• There were too many false positives

• Why?
• Dermatologists always use a standard ruler to measure the size of the lesion. If it is greater than 3 cm, they choose to do a biopsy.
• Neural Network assumed every picture with a ruler was malignant
Example 2 – Programming Error/Bias?

• Two competing Neural Networks were tested for speed and accuracy in identifying a horse in pictures
• One operated on the features in the photos and took 11 hours (76% accurate)
• The other took 36 seconds with 100% accuracy
• Why?
• Second method picked up the word “horse” embedded in the picture metadata (can’t be seen by eye)
• This isn’t for amateurs
Then Why Am I Presenting AI Ethics to You?

• Everyone in the organization has their role
• Your role is enterprise risk
• It takes **reflective, creative and holistic thinking** to make responsible decisions with an informed moral compass
• I’m here to inform you about ethical risk with AI
Where We Start with AI Ethics: The Fundamental Concept of Social Context

Autonomous Underground Drilling Machine

No Social Context

The social context means people. If the social context is involved, ethical questions are required

Insurance Clients

Social Context
Learning: We Had Blinders On

We thought of, and modeled everything that could happen in 10,000 years, FEPS: Features, Events, Processes and Scenarios Physically
But our hubris kept us from considering the human factor

BOOM!

"Los Alamos Labs did not consider the chemical reactions that unique combinations of radionuclides, acids, salts, liquids and organics might create."
Repeatable Algorithms Can Work Against People

- Misconception: Algorithms are accurate, make no mistakes.
- People comfortable accepting the algorithm’s output
- Algorithms “fire” at high cadence and repeat bias at scale.

Solution: Augmented Intelligence, Less biased decision-making tools by combining the capabilities of humans and AI

Closing the GAP: Group-Aware Parallelization for Online Selection of Candidates with Biased Evaluation
Can we create better algorithms for screening candidates - and reduce hiring bias?
There Is No One Size Fits All

Different regions have different cultural models of what constitutes sociability and thus, ethics.

If a team developing an AI system is made up of similar types of people who rely on similar first principles, the resulting output is likely to reflect that

https://www.verywellmind.com/conformity-experiment-2795661

How to Test Conformity with your own psychology experiment.
What are the obvious ethical issues?

- Discrimination
  - Age, race, gender, religion
- Privacy
  - Confidential information/data protected/retained
- Bias
  - Assumptions, data, code, algorithms, results
- Unrepresentative Data
  - Does not represent the population you are modeling
What Are the Not So Obvious Issues

1. Should a mega-tech company be writing legislation about a controversial AI application? MSFT Facial Recognition/Washington
2. AI engineers, data scientists and predictive modelers crave new data.
3. People building AI are not sophisticated enough in domain expertise.
4. Good intentions are that AI will augment workers not replace them.
5. Understand the limits of what the AI can tell you (Conway’s Law)
6. Using AI ethically ought to reflect diversity
Some Examples of ML Bias

- Bias in design ("Homeless people are mentally ill or addicts")
- FICO has a *causal* relationship with risk
- Bias in how data is collected encoded and published for AI can be biased, either explicitly (people in that state are poorly educated) or implicitly when it over or under-represents segments of the population.
- Bias in selection (feature engineering)
- PII de-anonymization: age, gender, race, religion.
- The model does not converge: Poorly constructed model leaves the algorithm too loose to use "latent values," that relate exactly to those protected classes
- "The algorithm finds a way"
What parts of AI you need to think about

What you need to know w.r.t AI Ethics:

• Algorithms designed to repeat in high volume
• Products you use with embedded AI
• Data sourced from outside of your organization and/or the complexity of blending multiple data sources
• Primarily, you need to think about the “social context,” what you are potentially doing to people beyond your primary reasoning
• Fairness: Ex FICO score, zip code, incomplete harvested data $R_x$ e.g.
The #1 Ethical Issue of AI

• A biased AI can quickly create a multitude of unfortunate effects
• There can be thousands or millions of victims
• It can propagate quickly; costs nothing to fire a million times
• The harmed are the first to notice something is wrong
• And they are in the weakest position to act

“Debiasing humans is harder than debiasing AI systems.”
OLGA RUSSAKOVSKY, PRINCETON
(Some) Sources of Ethical Risk in AI
There are more in the report

AI in actuarial practice has potential for many ethical dilemmas

• Amateurish development: come prepared

• Discrimination

• Tone deaf to Diversity and Inclusion

• Disruption of Privacy

• Indiscriminate use of “new” data
Beyond Bias: Fairness

- Fairness in a process or decision requires difficult measurement
- How to measure whether the decision was fair and non-discriminatory?
- Building confidence in AI delegated or algorithm-based decisions require three elements:
  - Transparency in design and implementation
  - Explaining how a decision was reached
  - Accountability for its effects
- Performing and documenting a fairness analysis and the actions taken to solve the findings can be of great use.
Fairness

• XAI of a learning model emphasizes the bias prevalent in the data used for training.
• Predictions made by the learning model must be fair
• Research publications concerned with fairness in the XAI field aim for use of AI for social good.

This is equivalent to our formulation of the social context
THESE MAY SEEM LIKE THE CULPRITS

BUT THEY’RE NOT. THEY ARE ALL DERIVATIVE FROM ONE THING

Let me tell you a story about the Chief Actuary of New México

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<thead>
<tr>
<th>Bias</th>
<th>PRIVACY</th>
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Difference between ethics and compliance

Compliance
• Following the law
• Something that government or other legal entity requires you to do

Ethics
• Doing what is right
• Something you choose to consider when taking action
Data Doesn’t Speak for Itself

Context of data: Why and how it was collected, how it was transformed

It is the result of human decisions about what to measure, when and where and by what methods

Bias of the designers are burned into the data

Data does not represent the population it appears to be

There is no context-free data
The largest part of AI work is data

• You cannot fit ML models on raw data directly. It requires data to be numeric
• Algorithms impose specific requirements
• Raw data contains errors
• Columns may be redundant or irrelevant
• That’s why you must spend a great deal of time on
  ...Data Cleaning to delete duplicate rows are redundant columns
  ...Outlier Detection and removal
  ...Missing Value identification and imputation
  ...Feature Selection with statistics and models
  ...Feature Importance with models
  ...Data Transforms to change data scales, types, and distributions
  ...Dimensionality Reduction to create low-dimensional projections
First Principals: The Five Pillars of Ethical AI

- Creating **Responsibility** for what a developer creates and uses
- Using **Transparency** to ensure the logic of an AI is viewable
- Ensuring **Predictability** and produces consistent results
- Guaranteeing **Auditability** of the outcomes
- Ensuring AI systems have **Incorruptibility**; protected from manipulation.
Responsibility

• When AI is developed by an ensemble team and creates havoc, who is to blame?
• Should there be laws?
• Laws ALWAYS look for the perpetrator
• In this case, there could be many victims, but no identifiable perpetrator...except the firm!
• There are better solutions than laws
Transparency and Explainability

Can an action be explained?

- AI difficult to explain, especially GANs, etc.
- Transparent and explainable not the same thing
- Developers concerned that there is a tradeoff between explainability and performance
- Hot debate in AI that XAI will degrade performance
- Causality is creeping up, but not widely accepted yet
- Trustworthy and Responsible (Ethical AI) is aspirational, but currently, XAI focused on developers and owners of the systems

Transparent – I can see what you’re doing
Explainable – I can understand it
Explainability

• EXPLAIN TO JUSTIFY for a particular outcome rather than a description of the inner workings of the logic of reasoning behind the decision-making process, particularly when unexpected decisions are made.

• EXPLAIN TO CONTROL prevent things from going wrong. Understanding system behavior gives visibility over unknown vulnerabilities and can correct errors in low criticality situations.

• EXPLAIN TO IMPROVE digital code needs continuous improvement. knowing why system produced specific outputs, you will learn how to make it smarter.

• EXPLAIN TO DISCOVER If machine can explain its learned strategy (knowledge) It can verify predictions, improve models, gain new insights into the problem These are all intrusive. An out-of-the-black-box approach is counterpactuals
Interpretability

The amount of consistent prediction a model’s result without knowing the reasons behind the scene. The higher the interpretability of the model, the easier to know the reason behind certain decisions or predictions.

These are currently research topics. Commercial products have not released yet.

- **Application Level Evaluation**: Putting the explanation into the product and the end user will do all the tests.

- **Human Level Evaluation**: Experiments are carried out by laypersons by making the experiments cheaper and testers can be found easily.

- **Function level evaluation**: An anonymous person already evaluates the class of model. This approach is also known as a proxy task.
One Approach To Explainability

Daniel Schreiber, CEO & Co-Founder at Lemonade Inc., an Insurtech startup, wrote a blog recently: *AI Can Vanquish Bias: Algorithms We Can’t Understand Make Insurance Fairer.*

Posterior Explainability
- Using Differential loss ratios
- If you can evaluate risk so precisely to charge each a differential premium you can examine differential loss ratios
- Any grouping should have uniform loss ratios.
- ML creates groups of people in novel ways, and if the loss ratios are not the same for any arrangement of grouped policies, then you’ve made a mistake.

Phase 1: All people treated the same
Phase 2: Divided into risk groups
Phase 3: AI produces complex multivariate risk scores, groupings relentlessly shrunk, until – ultimately – each person is a ‘group of one.’

QUESTION 1: Is it feasible yet to evaluate risk at this level?
QUESTION 2: Is a posterior Explanation acceptable?
Auditability

• Have independent reviewer
• Have a process
  • If results are reasonable, does that mean they are correct?
  • Are results based on a random pattern?
  • Are there potentially any unintended consequences/users?
Auditability

- **CREATE A QUALITY ASSURANCE COMMITTEE**
- Put together an independent quality assurance committee to review the test data, monitor the training / process and audit the outcomes
Incorruptibility

- **PROTECT AGAINST MALICIOUS ACTORS AND PREDATORS**
  - As AI becomes more prevalent, the more it becomes the target of “poisoning.” Bad actors inject false information into the stream of data, algorithm behaves differently. Sophisticated criminals use Trojan horse attacks, which are more vicious and harder to detect.

- **STATISTICAL TESTING AND AI MODELS TO SEE POTENTIAL ISSUES**
  - AI solution should include a separate, “policing” AI algorithm continuously running in the background to identify any issues.

- **TRAIN YOUR STAFF**
  - The more people who are aware of potential bias issues, the better chance of preventing it—or at least shutting it down before it reaches critical mass.

This isn’t kid stuff
AI Ethics Guidelines

• At last count, there are over 100 of them
• Governments, regulators, vendors, academics
• They all say about 80% of the same thing
• They are useful background material
• Some ethical principles as we’ve described are useful
• But, they rarely cover how to address the complexity of putting these principles into practice into an existing organization
• Beyond ethics, you need people with virtues. Not everyone, but in every team. Prudence, Forebearance, Temperence and Justice
Internal Ethical Review Board

Enron had a code of ethics practices 64 pages long

It may be useful, but don’t just jump into it
Some Concluding Thoughts

• It’s really easy to mess up on bias
• Find diversity in your team to match your target.
• Don’t underestimate how difficult this is
• You will need infrastructure and data architects
• Start with what you know that has up-stream potential
• The big wins will come
• DIY tools are great learning tools, but not for production
• The data work is terribly hard, but AI-driven tools and catalogs are helping
NEIL RADEN is an author, consultant, former actuary, and industry analyst, skilled in big data management, analytics, AI and Ethics and decision management.

With an academic background in Algebraic Topology, Neil began his work as a P&C actuary with AIG in New York before forming Hired Brains to deliver statistical and predictive analytics services, software engineering, systems integration, and data architecture in industries ranging from Nuclear Waste Management/Nuclear Weapons Stockpile Stewardship (DOE/Sandia) to Cosmetics and many in between. He is consistently rated in "Top X" surveys in AI, Analytics, Big Data, etc.

Clients appreciate Neil’s frank and direct assessments, his independence from vendors and popular methodologies. In client engagements, he sticks to the business at hand. He was the author of the SOA report “Ethical Use of Artificial Intelligence for Actuaries,” and has been conducting training and consulting in AI specifically for the insurance industry for three years. Details at [www.hiredrains.com/insurance](http://www.hiredrains.com/insurance). You can find his articles (about four/month) at [https://www.diginomica.com/author/neil-raden](https://www.diginomica.com/author/neil-raden) or directly at nraden@hiredbrains.com
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# Actuarial Innovation and Technology

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The purpose of this circular letter is to advise insurers authorized to write life insurance in New York of their statutory obligations regarding the use of external consumer data and information sources in underwriting for life insurance.

- Insurance Law § 4224;
- Insurance Law Articles 24 and 26;
- General Business Law Article 25 (Fair Credit Reporting Act);
- Executive Law Article 15 (Human Rights Law); and the
- Federal Civil Rights Act of 1964

Anything new here?

Two key concerns addressed:

1. Responsibility of the insurer to establish that the does not use and is not based in any way on protected classes
2. The insurer must be able to provide details as to how the decision was reached including specific sources of information

Specific reference to accelerate underwriting

How did we react?

Social Context, and Three Pillars from Neil’s list:

- Responsibility
- Transparency
- Auditability
External Data

MIB, MVR and Criminal History Search – not included in scope of NY Circular

Rx
Credit scores
Retail activity
Social media
Internet activity
Geographic location tracking
Facial analysis

Social Context, and
Five Pillars of Ethical AI:
1. Responsibility
2. Transparency
3. Predictability
4. Auditability
5. Incorruptibility
CEJ Letter

Insurers need to take responsibility

Potential for algorithmic bias and proxy discrimination has grown dramatically

Perpetuation of historic discrimination

Disparate impact analysis offered as a solution
The TransUnion Criminal History Score is just one example – egregious and obvious – of algorithms that reflect and perpetuate historic discrimination against protected classes in insurance – algorithms that reinforce inherent bias and systemic discrimination. Others include:

• Employment categories and education levels for marketing, underwriting and pricing
• Price Optimization and Customer Lifetime Value Algorithms used for marketing, underwriting, pricing and claims settlement
• Facial analytics used in life insurance underwriting
• Household composition used for underwriting and pricing
• Credit scores for marketing, underwriting, pricing, claims settlement and anti-fraud efforts
• Fraud detection models based on biased learning data
Disparate impact analysis discussed in the letter

general model: $b_0 + b_1X_1 + b_2X_2 + b_3X_3 + e = y$

elementary approach: $b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4R_1 + e = y$

Is this sufficient?
How do you train an underwriting model?

Previous decisions
- easily validated with recent data
- bake in past bias

Wait for experience
- standards change over time, etc.

Operational Systems → Anonymized → Protected class data → Analysis staging tables

Validate performance of underwriters before the model is built

Sentinel effect
How do you train an underwriting model?

Previous decisions
• easily validated with recent data
• bake in past bias

Wait for experience
• standards change over time, etc

Both suffer from survival bias

RAF Bomber Command 1940
The Story of Abraham Wald and RAF Bomber Analysis

https://people.ucsc.edu/~msmangel/Wald.pdf
Concluding Thoughts

Be familiar with, and open to, concerns from regulators, agencies and the public

Use the Five Pillars as a check list

Remember your role as an actuary
Thank you

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