Summary

Machine Learning – Tools and applications for policy – Lecture 10

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DNB Data Science Hub

Summary

1. Discuss some things that can go wrong
   - survivorship bias, input errors and deceit
   - fairness and discrimination
2. What is the reaction of authorities?

Outline

Summary
- What can go wrong?
- Why is this sensitive?
- Should we intervene?
- Evaluation

Knowledge clips

- No clips for this lecture

What could possibly go wrong?

- We have discussed overfitting to you training data
  - Solutions: more data, regularization
- We generally assume that the Data Generating Process (DGP) is the same between training and production
  - In practice this might not always be true:
    - The training set was put together with bespoke (==expensive) information and only some features were retained. The real data is from a different population
  - We might have missed crucial feature information
  - The world changes ...

Let's see some examples ...

0. Training data
1. Model maintenance
2. Survivorship bias: WWII airplanes
3. Crucial input error: Skin cancer (Esteva et al. (2017))
4. Derailing a DNN
5. Neutrality of the methods
6. Discrimination: assessing recidivism (Wu and Zhang (2016) and Wu and Zhang (2017))

0. Challenges of Real Data Collection

- Collection of real data can be challenging because:
  - High cost and resource requirements
  - Limited availability of data sources
  - Ethical or privacy concerns
- Alternative could be to generate synthetic data
- Benefits of Synthetic Data
  - Prototyping: Useful for prototyping and proof of concept.
  - Resource Savings: Cost-effective alternative to real data collection.
  - Privacy: Can be generated without sensitive information.
  - Model Development: development and testing in the absence of real data.

Limitations and Considerations of Synthetic data

- May not perfectly represent the real-world distribution.
- Model performance on synthetic data may not directly translate to real data.
- Quality of synthetic data depends on generative model and source data.
- Careful validation, rigorous testing, and ethical considerations are essential.

1. Model maintenance —Complex Models Erode Boundaries

- Dependale software enfoces strict abstraction boundaries. Data is data. Model is model. etc
- Unfortunately, it is difficult to enforce strict abstraction boundaries for machine learning systems by prescribing specific intended behavior (Sculley et al. (2015)).

- Resulting problems:
  - Entanglement: Machine learning systems mix signals together, entangling them and making isolation of improvements impossible.
    - CACE principle: Changing Anything Changes Everything
    - Mitigation strategies: isolate models and serve ensembles or detecting changes in prediction behavior as they occur.
  - Correction Cascades: There are often situations in which models for problem A exists, but a solution for a slightly different problem A' is required.
  - Undeclared Consumers: Without access controls, some consumers of results may silently use the output of a given model as an input to another system.

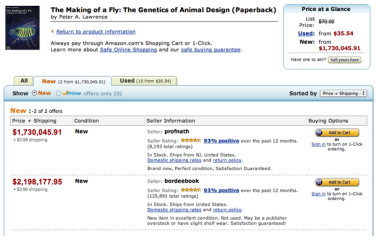
Data Dependencies Cost More than Code Dependencies

- Unstable Data Dependencies
- Underutilized Data Dependencies: Similar to packages that are mostly unneeded, underutilized data dependencies are input signals that provide little incremental modeling benefit.
  - Legacy features
  - Bundled Features
  - ϵ-Features
  - Correlated features

Feedback Loops

- Direct
  - What if the model leads to the selection of a particular trading strategy, this influences prices, influencing the trading strategy
  - Is this bad? Maybe points to retraining or modelling the feedback loop explicitly
- Hidden
  - What if Firm A has an algorithm setting price as the average price at $t-1$ and Firm B has the rule $p^A_{t-1}+1$ ...

Price starts at 1.7 million ...



... and jumps to 18 million

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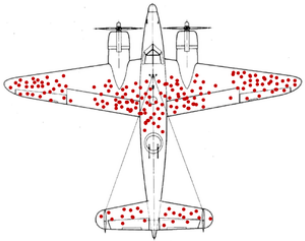
Bad patterns in ML-Systems (aka Anti-Patterns)

- Glue Code: code to get to standard packages can be more work than writing things yourself. On the other hand we have the ”Iwannadoitmyself” bug
  - Solution: wrap black-box packages into common API’s
- Pipeline Jungles
- Dead Experimental Codepaths
  - Knight Capital’s system losing $ 465 million in 45 minutes, apparently because of unexpected behavior from obsolete experimental codepaths
- Abstraction Debt. The above issues highlight the fact that there is a distinct lack of strong abstractions to support ML systems (check out MLFlow)
- Smells
  - Plain-Old-Data Type Smell
  - Multiple-Language Smell.
  - Prototype Smell.

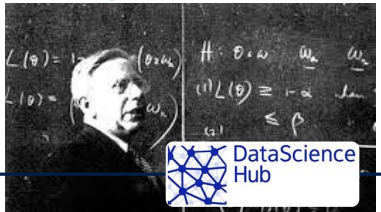
2. Survivorship bias

- In WWII the Royal Airforce wanted to find out how to increase aircraft resilience
- Red dots indicate damage of returning bombers
- Where would you add armor?



Source: Wikipedia

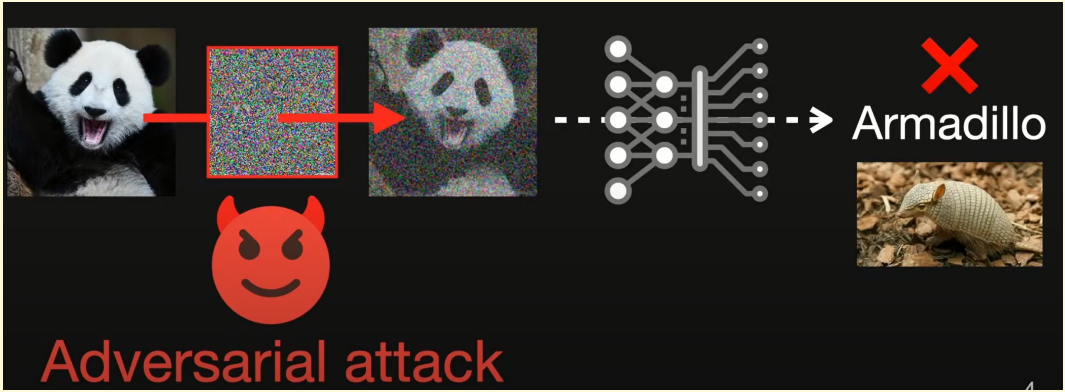
- The army wanted to add armor where they observed damage
- Luckily statistician Abraham Wald noted that the sample suffered from survivorship bias: sample was only the surviving airplanes
  - planes hit in engines or cockpit do not return



3. Skin cancer

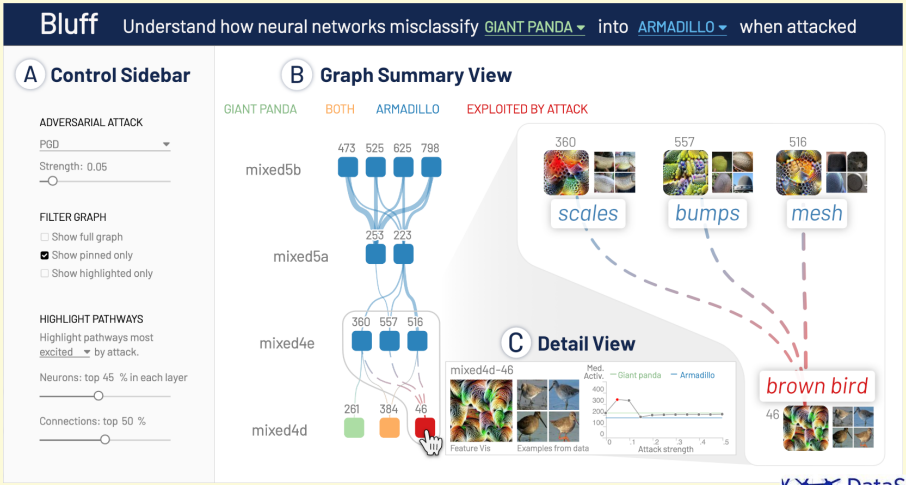
- Skin cancer, the most common human malignancy, is primarily diagnosed visually, beginning with an initial clinical screening and followed potentially by more (invasive) tests
- Esteva et al. (2017, Nature) train a CNN using a dataset of 129,450 clinical images consisting of 2,032 different diseases. We test its performance against 21 board-certified dermatologists on biopsy-proven clinical images
- It would be great if this method could be rolled out to your smartphone ...
- ... but turns out that a ruler is bad for you

4. Derailing a Deep Neural Network



Source: Das *et al*, 2020, Github repo

An attack can derail a Deep Neural Network



Source: github.com/poloclub/bluff

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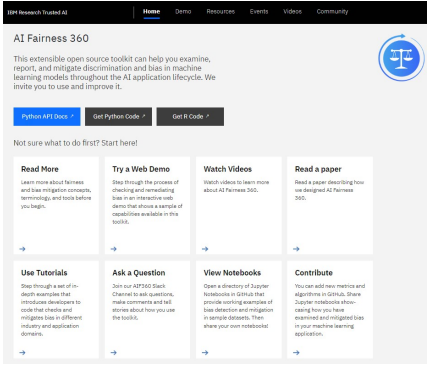
5. ML is not neutral

- We've discussed many ways in which ML models can be flawed
- One more way is that ML models allow for non-linearity (and dislike (relatively) high variance)
- Fuster et al. (2022): guidance to identify the specific groups most likely to win or lose from the change in technology.
  - Consider the decision of a lender who uses a single exogenous variable (e.g., a borrower characteristic such as income) to predict default
  - Who wins or loses with new technology depends on 1) the functional form of the new technology, and 2) differences in the distribution of income across groups
  - Primitive prediction technology which simply uses the mean level of a single characteristic to predict default $\rightarrow$ the predicted default rate = same for all borrowers
  - More sophisticated linear model with default linearly decreasing $\rightarrow$ groups with lower income than the mean will lose
  - Convex quadratic function: penalize groups with higher variance of the characteristic
  - etc. etc.

What is a fair definitions of fair?



Source: IBM AIF 360. Also see Godata driven blog.

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Why is this relevant for finance?

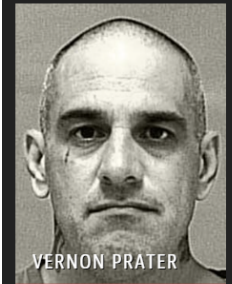
- Regardless of what you think of positive discrimination, these concepts can be useful in finance
  - What will be the performance of my portfolio if I can't trade in particular sin stocks or sanctioned regions
  - How similar are two vectors or matrices
  - etc etc

6. Do we discriminate in who to send to jail?

- Similar to the (Ludwig and Mullainathan 2023), the Compass system is a commercial product to help judges make decisions about incarceration.
- Pro Publica article discusses how this how this system seems biased
-

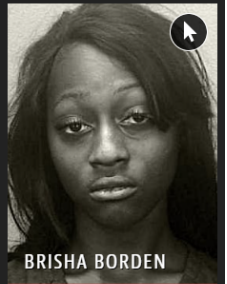
How Compass scores get it wrong

Two Petty Theft Arrests



VERNON PRATER

LOW RISK 3



BRISHA BORDEN

HIGH RISK 8

Borden was rated high risk for future crime after she and a friend took a kid's bike and scooter that were sitting outside. She did not reoffend.

Two Petty Theft Arrests

VERNON PRATER

Prior Offenses
2 armed robberies, 1 attempted armed robbery

Subsequent Offenses
1 grand theft

LOW RISK 3

BRISHA BORDEN

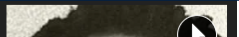
Prior Offenses
4 juvenile misdemeanors

Subsequent Offenses
None

HIGH RISK 8

Borden was rated high risk for future crime after she and a friend took a kid's bike and scooter that were sitting outside. She did not reoffend.

Two Drug Possession Arrests



Two Drug Possession Arrest

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Finding the criminal

- Wu and Zhang (2016) used ML to classify 'criminal' faces. They compare criminal ID photo's with website scraped ones
- This led to a storm of protest – what issues can you think of?
- Critics point to:
  - sample size was too small
  - non-criminals are smiling (according to westerners) and have a white collar
  - claim of causality
- In Wu and Zhang (2017) the authors discuss (refute?) each of these point

(a) Three samples in criminal ID photo set S_c.

(b) Three samples in non-criminal ID photo set S_n

Outline

Summary
- What can go wrong?
- Why is this sensitive?
- Should we intervene?
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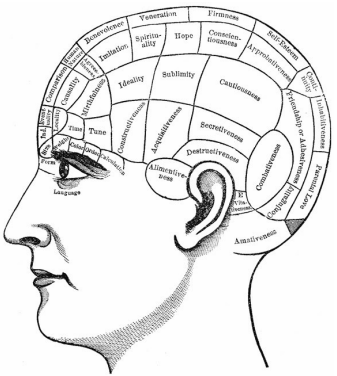
Why is this an important and touchy subject?

- In 19th century many believed in phrenology – the shape of the skull determines behaviour
- This is now widely discredited

- But how does a police officer decide to check a suspect?

- How are loans and mortgages granted?
- Who is responsible for a market crash caused by algorithmic trading?
- What if ML is used for Anti Money Laundering? And what if crooks use an adverserial neural network to counter this (cf Triepels (2019))



Source: Wikipedia

Supervisors warning: no “illegal distinction”

- The insurer must have systems and processes in place that prevent the implementation of AI applications that lead to discriminatory outcomes
- When setting up such systems and processes for AI applications, questions are:
  - How to organise the process to challenge possible discriminatory bias in input variables?
  - How can results be tested for discriminatory bias? Possibilities are adversarial modeling, as well as two identical test groups, where only one discriminatory (proxy) variable differs between groups. If the model differs significantly, this may indicate potential discriminatory bias in the model. Hypothetical cases can also be used
  - How can testing for discriminatory bias become more refined and robust? For example, specific testing of biases in the false positive outcomes (instead of just testing the overall model outcomes)
- If for an AI model it cannot be sufficiently established that it does not contain unauthorized discriminatory biases, should you use it in processes that directly affect customers (for example pricing and acceptance, fraud detection)?

Source: AFM and DNB (2019). My translation

Outline

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- What can go wrong?
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Opinion **Artificial intelligence**

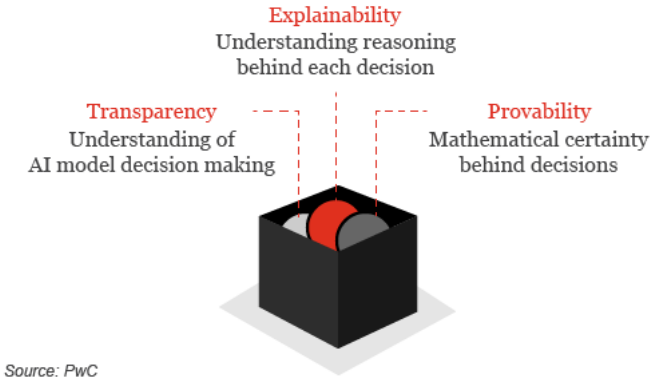
Why Google thinks we need to regulate AI

Companies cannot just build new technology and let market forces decide how it will be used

SUNDAR PICHAI + Add to myFT

Further words of caution

- Explainability
- Environmental impact
- Market power (cf Farboodi et al. (2022))



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Regulatory reaction

- Surveys: Broeders et al. (2018), Bundy (2017), Chakraborty and Joseph (2017), Frost (2020), Petralia et al. (2019), and World Economic Forum (2018)
- Regulator sandboxes
  - Bank regulation can be over the top for fintech startups
  - Several supervisors provide 'bank light'-regimes
  - iForum
- Fintech hubs
  - BIS, Singapore, Lithuania
- Guidelines (van der Burgt (2019))
  - SAFEST: Soundness, Accountability, Fairness, Ethics, Skills, Transparency
- Proposed EU regulation

New European AI regulation will have a big impact

EUROPEAN COMMISSION

Brussels, 21.4.2021

COM(2021) 206 final

2021/0106(COD)

Proposal for a

REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL

LAYING DOWN HARMONISED RULES ON ARTIFICIAL INTELLIGENCE (ARTIFICIAL INTELLIGENCE ACT) AND AMENDING CERTAIN UNION LEGISLATIVE ACTS

{SEC(2021) 167 final} - {SWD(2021) 84 final} - {SWD(2021) 85 final}

EXPLANATORY MEMORANDUM

1. CONTEXT OF THE PROPOSAL

1.1. Reasons for and objectives of the proposal

This explanatory memorandum accompanies the proposal for a Regulation laying down harmonised rules on artificial

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New European AI regulation will have a big impact

- On 21 April 2021, the European Commission published its Proposal for a Regulation laying down harmonised rules on artificial intelligence (Artificial Intelligence Regulation (AIR))
- AI defined as "a software that is developed with one or more of approaches and technique and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with"
- Aim: The regulatory proposal aims to provide AI developers, deployers and users with clear requirements and obligations regarding specific uses of AI.
- Scope: This regulation applies to a natural or legal person, public authority, agency or other body that:
  - developed (or commissioned) an AI system to bring to market (directly or indirectly) (AI systems providers)
  - is using an AI system under its authority (AI systems users)
  - is established in a third county if the system output is used in the Union

The regulation follows a risk-based approach

- Unacceptable risk: All AI systems considered as a clear threat to the safety, livelihoods and rights of people will be banned (e.g. social scoring by governments, toys using voice assistance that encourages dangerous behaviour.)
- High risk: All high-risk AI systems will be subject to "strict obligations" before they can be put on the market. As one of the high risk applications include systems that determine individuals' credit scores.[1]
- Limited risk: Limited risk AI systems, such as chatbots, will be subject to transparency obligations, with users clearly told that they are interacting with intelligent software rather than a human, and voluntary codes of conduct.
- Minimal risk: free use of applications such as AI-enabled video games or spam filters. The vast majority of AI systems currently used in the EU fall into this category

[1] see Annex III, Article 5 (b) of the Proposal

Obligations for credit scoring at banks: Providers

- AI system to comply with requirements on i) data and data governance, ii) technical documentation, iii) record-keeping, iv) human oversight and v) accuracy, robustness and cybersecurity Art. 8 to 15
- Put a quality management system in place Art. 17(3) → Art. 74 CRD
- Establish risk management procedure Art. 9(9) → Art. 74 of CRD
- Technical documentation is part of internal governance framework
  Art. 18(2) → Art. 74 of CRD
- Maintain automatic logs of high-risk AI systems Art. 20 (2) → Art. 74 CRD
- Carry out conformity assessment Art. 19 and 43 which shall be carried out as part of SREP
  Art. 43(2) → Art. 97 to 101 of CRD)
- Establish and document a post-market monitoring system Art. 61(1) + (4)
- Obtain EU declaration of conformity and CE marking Art. 48(1) + 49

Obligations for credit scoring at banks: Users

- Ensure human oversight measures Art.29 (2)
- Ensure that input data is relevant in view of the intended purpose of AI system Art. 29 (3)
- Monitor the AI system Art. 29(4) → Art. 74 of CRD
- Maintain automatic logs of high-risk AI systems Art. 29(5) → Art. 74 of CRD

Outline

Evalueer via **app.evalytics.nl**

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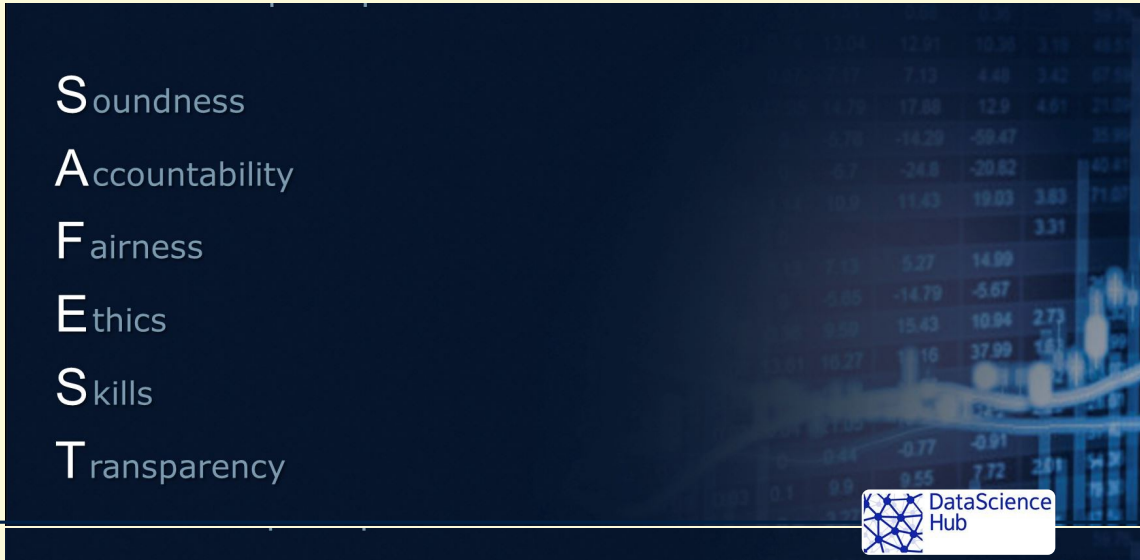
Summary

In this lecture we covered:

1. discussed aspects that can invalidate ML results – survivorship bias, input errors and sensitive results
2. introduced the regulatory response


Soundness
Accountability
Fairness
Ethics
Skills
Transparency
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