

Outline

- Loose ends ...
- Algorithms, big data, and ethics
 - Unintended consequences
 - Inherent biases

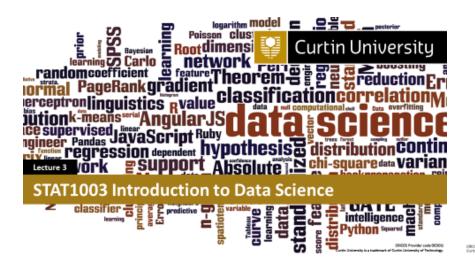


Recap - Elements of visualization (Nolan, 2017)

- Scale
- Conditioning
- Perception colour
- Perception length
- Transformations
- Context
- Smoothing and other large data considerations



...back to Lecture 3, slide 26



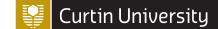
Perception - Length

- We are pretty good at judging length visually, by comparison to area, volumes, or angles
- Practical consequence
 - Bar charts are to be preferred to pie charts
- Practical considerations
 - Visually, the longer a bar, the greater the absolute value it represents
 - Can be vertical or horizontal
 - To judge magnitude, bars must represent the entire length, not just a portion

15/03/2018
06 Provider Code (ISSBE) on University of Technology

STAT1003 Lecture 3





Harvesting Facebook profiles



STAT1003 Lecture 4 Curtin University

Week 4/4

'Influencing' users' emotions

Facebook reveals news feed experiment to control emotions

Protests over secret study involving 689,000 users in which friends' postings were moved to influence moods

Poll: Facebook's secret mood experiment: have you lost trust in the social network?



▲ Activists and politicians called Facebook's experiment 'scandalous', 'spooky' and 'disturbing'. Photograph: Dado Ruvic/Reuters

In a study with academics from Cornell and the University of California, Facebook filtered users' news feeds – the flow of comments, videos, pictures and web links posted by other people in their social network. One test reduced users' exposure to their friends' "positive emotional content", resulting in fewer positive posts of their own. Another test reduced exposure to "negative emotional content" and the opposite happened.

The study concluded: "Emotions expressed by friends, via online social networks, influence our own moods, constituting, to our knowledge, the first experimental evidence for massive-scale emotional contagion via social networks."

Kramer *et al.* (2014) Experimental evidence of massive-scale emotional contagion through social networks. PNAS, https://doi.org/10.1073/pnas.1320040111

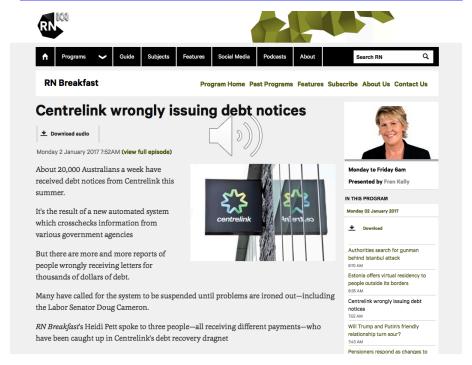
Week 4/4 STAT1003 Lecture 4



- Compliance system to automatically match data from multiple sources, including ATO, to detect when benefits were wrongly claimed
- Replacing manual checks by staff means that 'compliance interventions' increased from 20,000/year to 20,000/week
- If the algorithm identifies an individual as having incorrectly received benefits while earning income, a debt notice is issued and the onus falls on recipients to prove they were entitled to claim benefits
- But ... what happens when things go wrong?



http://www.abc.net.au/radionational/programs/breakfast/centrelink-wrongly-issuing-debt-notices/8157220



Week 4/4

STAT1003 Lecture 4



https://www.theguardian.com/commentisfree/2017/jan/09/fiona-the-unemployed-bettong-visits-centrelink-to-discuss-her-debt-notice



Week 4/4 STAT1003 Lecture 4



home > australia

https://www.theguardian.com/australia-news/2016/dec/30/centrelink-debt-notices-idiotic-big-data-assumptions-expert

nome / austrana	
Centrelink	Centrelink debt notices based on
	'idiotic' faith in big data, IT expert says

Lawyers, privacy advocates and data experts join calls for Centrelink's data-matching system to be suspended

'IT and data expert Justin Warren – who has worked for IBM, ANZ, Australia Post and Telstra, among others – said Centrelink's system appeared to rest on the "idiotic" assumption that "big data was magic".

"It's not. It's a messy, complex, statistical system that is wrong a lot," Warren said. "All models are wrong, but some are useful. It's the choice of how you deal with when the system is wrong that reveals how you view the world."



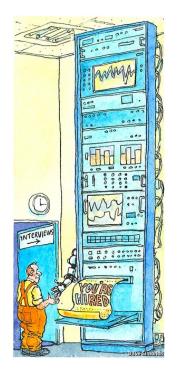
Centrelink debt recovery – what went wrong?

- Laudable objective to recover money that might have been wrongly paid out
- Algorithm was apparently neutral no explicit biases
- So what went wrong?
 - Little regard for what consequences of a 'false positive'
 - Demographic of people who are likely to receive Centrelink benefits
 - Fewer resources
 - Ability to contest
 - Record-keeping
 - Lack of transparency of algorithm



Algorithms and models: expanding use

- "Big data can avoid biases and spot things that may not be apparent to the naked eye"
 - Online job applications using browsers that were not installed by default
 - Assessing honesty by asking questions such as:
 - "How good at computers are you?
 - "What does control-V do on a word processing program
 - Detecting that customer-service workers who lived close to the company tended to stay longer, and hence basing hiring decisions (in part) on where a prospective employee lived





Algorithms - opportunities and challenges

Opportunities

- Efficiency
- Remove bias, e.g., in employment, sentencing, credit assessment

Challenges

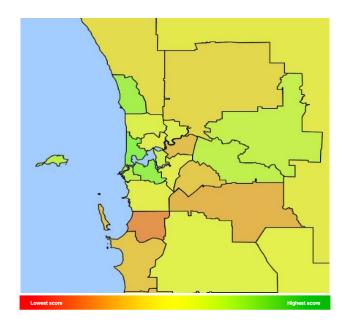
- Data used as inputs to an algorithm can induce bias
- Is the algorithm transparent can it be scrutinized?
- Processes for allowing people to challenge the results



Challenges - data

Poor/incomplete data as inputs

- Predicting recidivism: prior convictions may disadvantage certain groups
- Obtaining credit/insurance: little or no conventional credit history, demographics





Challenges - data

Selection bias and/or perpetuation of historical biases

- Companies hiring for 'culture fit' may perpetuate past hiring patterns in algorithms
- Inputs to algorithm may not be representative of the population at large

How to get ahead in Silicon Valley: hide being a woman, says male 'expert'

A venture capitalist's column for the Wall Street Journal has drawn outrage for suggesting women 'obscure their gender' online when applying for tech jobs



'A gender-neutral persona allows women to access opportunities that might otherwise be closed to them' wrote John Greathouse, a venture capitalist. Photograph: laflor/Getty Images

A Wall Street Journal article encouraging women in technology to "create an online presence that obscures their gender" has drawn expressions of outrage and shocked disbelief from the community it purports to advise.

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Challenges – algorithm design

- Poorly designed matching systems/recommendation engines
 - Narrow instead of expanding user options
- Decision-making systems that assume correlation necessarily implies causation
 - Income levels/ethnicity may go together but don't imply causal link
- Input data that disproportionately represents some groups over others
 - Predictions for under-represented groups will be poor
- Secrecy
 - Transparency not always possible because of competitive advantage or to prevent 'gaming'



Example – algorithms in criminal justice

- Risk assessments about whether someone should be granted bail, might reoffend upon release – are now routinely carried out by predictive models
- Such models use socioeconomic status, family background, employment status, prior conviction history to predict probability of, for example, recidivism
- Shouldn't such models be 'unbiased' because they are based on historical data?



Case Study - COMPAS

- COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) is widely used in the US to assess risk
- Early studies by the developer did not include assessment of predictive accuracy by ethnicity

COMPAS Scales and Risk Models Validity and Reliability

> A SUMMARY OF RESULTS FROM INTERNAL AND INDEPENDENT STUDIES

RESEARCH AND DEVELOPMENT DEPARTMENT

JULY 20, 2010



Independent evaluation of COMPAS

- Black defendants were often predicted to be at a higher risk of recidivism than they actually were
- White defendants were often predicted to be less risky than they were
- Even when controlling for prior crimes, future recidivism, age, and gender, black defendants were 45 percent more likely to be assigned higher risk scores than white defendants
- Black defendants were also twice as likely as white defendants to be misclassified as being a higher risk of violent recidivism. And white violent recidivists were 63 percent more likely to have been misclassified as a low risk of violent recidivism, compared with black violent recidivists
- The violent recidivism analysis also showed that even when controlling for prior crimes, future recidivism, age, and gender, black defendants were 77 percent more likely to be assigned higher risk scores than white defendants

How We Analyzed the COMPAS Recidivism Algorithm

by Jeff Larson, Surya Mattu, Lauren Kirchner and Julia Angwin May 23, 2016

← Read the story

Across the nation, judges, probation and parole officers are increasingly using algorithms to assess a criminal defendant's likelihood of becoming a recidivist – a term used to describe criminals who re-offend. There are dozens of these risk assessment algorithms in use. Many states have built their own assessments, and several academics have written tools. There are also two leading nationwide tools offered by commercial vendors.

We set out to assess one of the commercial tools made by Northpointe, Inc. to discover the underlying accuracy of their recidivism algorithm and to test whether the algorithm was biased against certain groups.



COMPAS - deficiencies

- Demographic, socioeconomic background, family characteristics serve as proxy for race
- Employment history disadvantages the poor regardless of race
- Prior convictions are also a proxy for race because of the higher incarceration rates of ethnic minorities for similar misdemeanors such as drug use





From the public to the individual

- Data science is a new field, so it draws its professional ethics from a number of different fields
- Baumer et al. (2017), after the contemporary Hippocratic oath:
 - "I will not be ashamed to say 'I know not,' nor will I fail to call in my colleagues when the skills of another are needed for a patient's recovery."
 - "I will respect the privacy of my patients, for their problems are not disclosed to me that the world may know."
 - "I will remember that I remain a member of society, with special obligations to all my fellow human beings, those sound of mind and body as well as the infirm."
- Still developing ...



Thou shalt not intentionally mislead

The only #climatechange chart you need to see. natl.re/wPKpro

(h/t @powerlineUS)

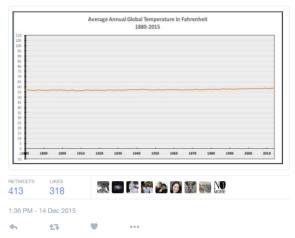


Figure 6.2: A tweet by $National\ Review$ on December 14, 2015 showing the change in global temperature over time.

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Thou shalt respect the privacy of individuals

- In May 2016, a open forum published a paper and corresponding dataset drawn from a dating website (OkCupid)
- Data included usernames, gender, and preferences
- Ostensible purpose was to provide an interesting dataset for researchers
- No consent was asked for from people whose data was scraped
- What are some of the ethical issues?



Thou shalt make thy analyses reproducible

- In 2010, a couple of Harvard economists argued that countries that pursued austerity measures did not necessarily suffer from slow economic growth
 - Influenced the thinking of public policymakers
- A reanalysis of the original Excel analysis showed that several errors that were hidden (unintentionally) in formulas embedded in the spreadsheet.
- Reproducible research and analyses!



Some ethical precepts for data scientists (Baumer *et al.* (2017))

- Do your work well by your own standards and by the standards of your profession.
- Recognize the parties to whom you have a special professional obligation.
- Report results and methods honestly and respect your responsibility to identify and report flaws and shortcomings in your work.



Example: SSAI Code of Conduct

- To act in the public interest
- Duty to employers and clients
- Duty to the profession
- Professional competence and integrity

The Statistical Society of Australia Inc.

(Incorporated in the Australian Capital Territory)

Code of Conduct

Introduction
Authority
Rules of professional conduct
The public interest
Duty to employers and clients
Duty to the profession
Professional competence and integrity
Disciplinary procedures

1. Introduction

The overall objective of the Statistical Society of Australia Incorporated (SSAI) and its branches is to further the study and application of statistical theory and methods in all branches of learning and enterprise. In general, the public has no ready means of judging the quality of professional service except from the reputation of the provider. Membership of an association of professionals service except from the taken by the public as an assurance of ability and integrity. It is therefore essential that the highest standards are maintained by all members of the SSAI whenever they are acting professionally and whatever their level of qualification. In common with professional bodies in other fields, the Society has formulated its own rules as a Code of Conduct to define the behaviour expected of Society members practising in everyday professional life. This code of conduct has been drawn up to reflect the standards of conduct and work expected of all practising statisticians. It is a guideline for all members of the SSAI and is mandatory for all accredited members.

2. Authority

The authority for the SSAI Code of Conduct derives from its formal adoption by the SSAI at the AGM of 7 July, 1998. The Society binds itself to observe the principles of the code.

3. Rules of Professional Conduct

As an aid to understanding, these rules have been grouped into the principal duties which all members should endeavour to discharge in pursuing their professional lives.

3.1 The Public Interest



Next week

- Computer lab: data wrangling and exploratory data analysis
- Workshop
- Lecture: EDA and introduction to statistical modelling

