GOALS AND SUCCESS MEASURES FOR AI-ENABLED SYSTEMS

Eunsuk Kang

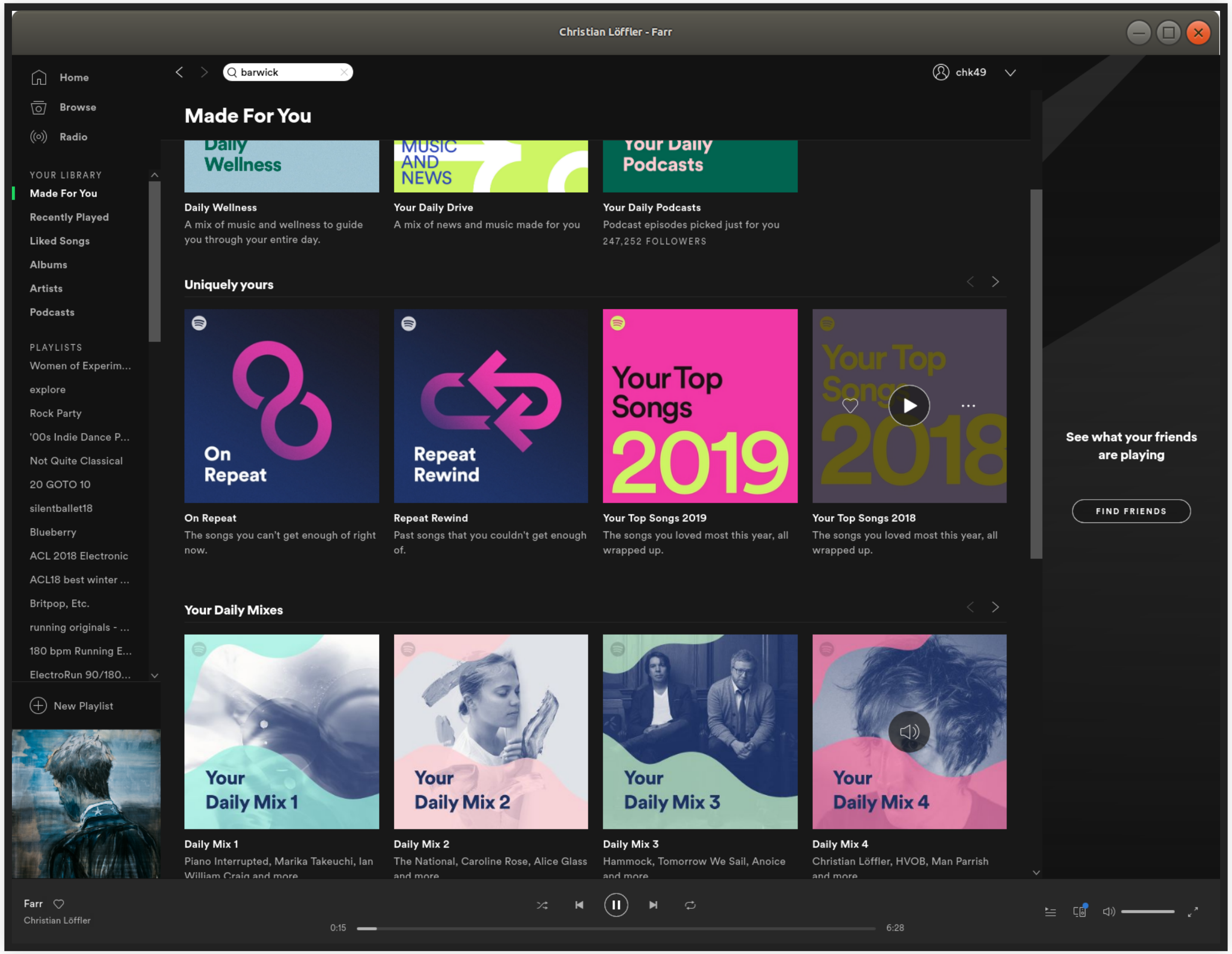
Required Readings: Hulten, Geoff. "Building Intelligent Systems: A Guide to Machine Learning Engineering" (2018), Chapters 2 (Knowing when to use IS) and 4 (Defining the IS's Goals)

Suggested complementary reading: Ajay Agrawal, Joshua Gans, Avi Goldfarb. "Prediction Machines: The Simple Economics of Artificial Intelligence" 2018

LEARNING GOALS

- Judge when to apply ML for a problem in a system
- Define system goals and map them to goals for ML components
- Understand the key concepts and risks of measurement

TODAY'S CASE STUDY: SPOTIFY PERSONALIZED PLAYLISTS



WHEN TO USE MACHINE LEARNING?

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WHEN NOT TO USE MACHINE LEARNING?

- Clear specifications are available
- Simple heuristics are *good enough*
- Cost of building and maintaining the ML system outweighs its benefits (see the technical debt paper)
- Correctness is of utmost importance
- ML is used only for the hype (e.g., to attract funding)

Examples of these?

Speaker notes

Heuristics: Filtering out profanity in languages

Tasks that are done infrequently or once in a while

Accounting systems, inventory tracking, physics simulations, safety railguards, fly-by-wire

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- Consider simple heuristics -- how far can you get?
- Consider semi-manual approaches -- cost and benefit?
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- Examples:
  - Recommending products on Amazon
  - Filtering comments with profanity on public forums
  - Credit card fraud detection
  - Controlling a washing machine

WHEN TO USE MACHINE LEARNING

- Big problems: Many inputs, massive scale
- Open-ended problems: No single "final" solution; incremental improvements and growth over time
- Time-changing problems: Adapting to constant changes, learning with users
- Intrinsically hard problems: Unclear rules, heuristics perform poorly

Examples?

see Hulten, Chapter 2

ADDITIONAL CONSIDERATIONS FOR ML

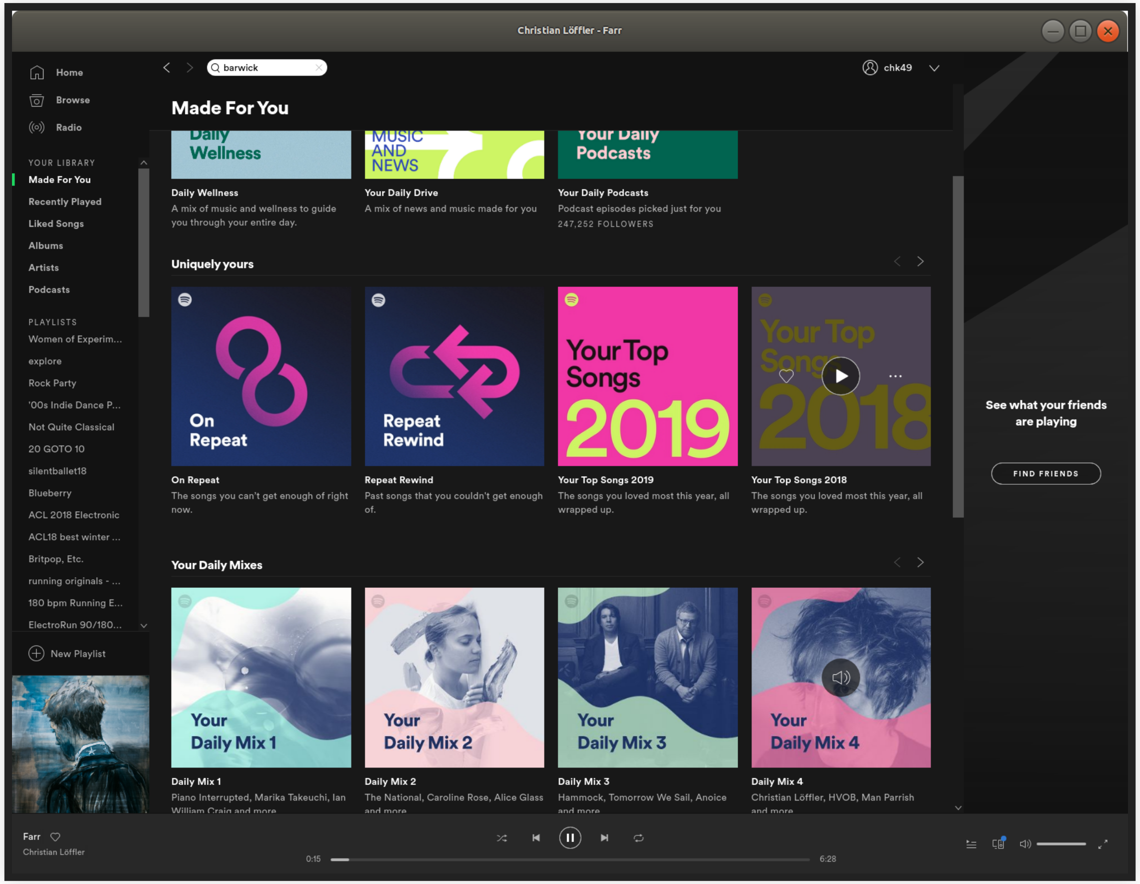
- Partial solution is acceptable: Mistakes are acceptable or mitigable
- Data for continuous improvement is available
- Predictions can have an influence on system objectives: Does it actually contribute to organizational objectives?
- Cost effective: Cheaper than other approaches, or benefits clearly outweigh costs

Examples?

see Hulten, Chapter 2

SPOTIFY: USE OF ML?

Big problem? Open ended? Time changing? Hard? Partial solution acceptable? Data continuously available? Influence objectives? Cost effective?



RECIDIVISM: USE OF ML?

Big problem? Open ended? Time changing? Hard? Partial solution acceptable? Data continuously available? Influence objectives? Cost effective?

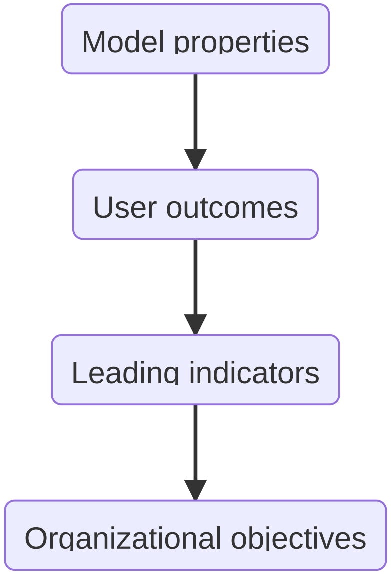
Photo art by Jay Stanley using images by jurvetson & Trevor Yannayon via Flickr

SYSTEM GOALS

LAYERS OF SUCCESS MEASURES

- Organizational objectives: Innate/overall goals of the organization
- Leading indicators: Measures correlating with future success, from the business perspective
- User outcomes: How well the system is serving its users, from the user's perspective
- Model properties: Quality of the model used in a system, from the model's perspective

Ideally, these goals should be aligned with each other



ORGANIZATIONAL OBJECTIVES

Innate/overall goals of the organization

- Business
    - Current revenue, profit
    - Future revenue, profit
    - Reduce business risks
- Non-Profits
    - Lives saved, animal welfare increased
    - CO_2 reduced, fires averted
    - Social justice improved, well-being elevated, fairness improved
- Often not directly measurable from system output; slow indicators

Implication: Accurate ML models themselves are not the ultimate goal!

ML may only indirectly influence such organizational objectives; influence is often hard to quantify; lagging measures

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Measures correlating with future success, from the business perspective

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- Customer engagement: How often do they use the product?
  - Regular use, time spent on site, messages posted
  - Growing user numbers, recommendations
- Caveats
  - Often indirect, proxy measures
  - Can be misleading (e.g., more daily active users => higher profits?)

USER OUTCOMES

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- Examples:
  - Users choosing recommended items and enjoying them
  - Users making better decisions
  - Users saving time thanks to the system
  - Users achieving their goals

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  - Users saving time thanks to the system
  - Users achieving their goals
- Easier and more granular to measure, but only indirect relation to organization objectives

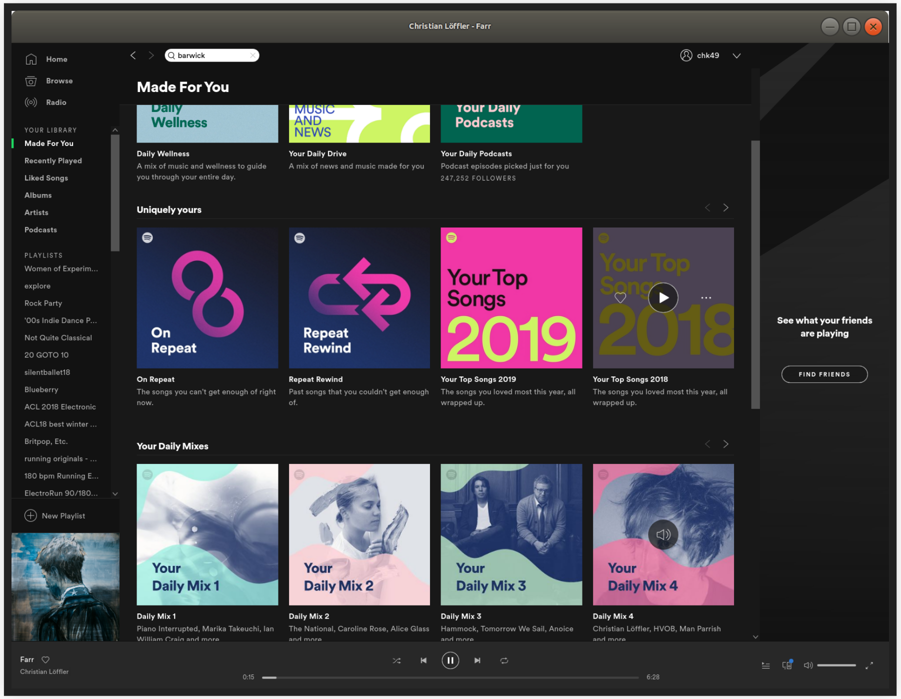
MODEL PROPERTIES

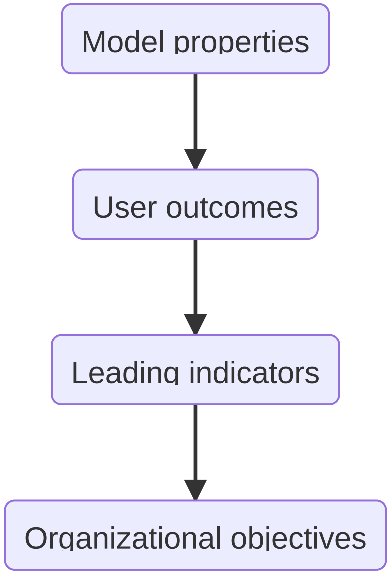
Quality of the model used in a system, from the model's perspective

- Model accuracy
- Rate and kinds of mistakes
- Successful user interactions
- Inference time
- Training cost

Often not directly linked to organizational goals

SUCCESS MEASURES IN THE SPOTIFY SCENARIO?





Organizational objectives? Leading indicators? User outcomes? Model properties?

Speaker notes

Accuracy of song predictions does not necessarily lead to increased user engagement (e.g., if the UI is terrible)

BREAKOUT: AUTOMATING ADMISSION DECISIONS TO MASTER'S PROGRAM

What are different types of goals behind automating admissions decisions?

Post answer to `#lecture` in Slack using template:

Organizational objective: ...
Leading indicators: ...
User outcomes: ...
Model properties: ...
AndrewIDs: ...

MEASUREMENT

WHAT IS MEASUREMENT?

- *Measurement is the empirical, objective assignment of numbers, according to a rule derived from a model or theory, to attributes of objects or events with the intent of describing them.* – Craner, Bond, “Software Engineering Metrics: What Do They Measure and How Do We Know?"
- *A quantitatively expressed reduction of uncertainty based on one or more observations.* – Hubbard, “How to Measure Anything …"

EVERYTHING IS MEASURABLE

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- If X is something we care about, then X, by definition, must be detectable.
    - How could we care about things like “quality,” “risk,” “security,” or “public image” if these things were totally undetectable, directly or indirectly?
    - If we have reason to care about some unknown quantity, it is because we think it corresponds to desirable or undesirable results in some way.

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But: Not every measure is precise, not every measure is cost effective

ON TERMINOLOGY

- *Quantification* is turning observations into numbers
- *Metric* and *measure* refer a method or standard format for measuring something (e.g., number of mistakes per hour)
    - Metric and measure synonymous for our purposes (some distinguish metrics as derived from multiple measures, or metrics to be standardizes measures)
- *Operationalization* is identifying and implementing a method to measure some factor (e.g., identifying mistakes from telemetry log file)

MEASUREMENT IN SOFTWARE ENGINEERING

- Which project to fund?
- Need more system testing?
- Need more training?
- Fast enough? Secure enough?
- Code quality sufficient?
- Which features to focus on?
- Developer bonus?
- Time and cost estimation? Predictions reliable?

MEASUREMENT IN DATA SCIENCE

- Which model is more accurate?
- Does my model generalize or overfit?
- How noisy is my training data?
- Is my model fair?
- Is my model robust?

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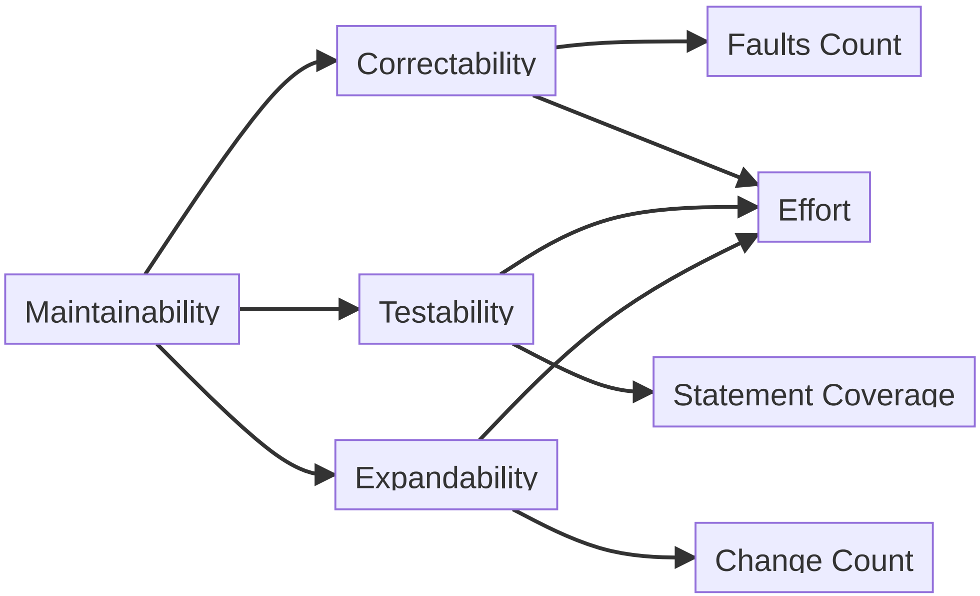
    - e.g., mass, length, temperature (Kelvin)
- Understand scales of features and use an appropriate encoding for learning algorithms!
    - e.g., One-hot encoding for nominal features

DECOMPOSITION OF MEASURES

Often higher-level measures are composed from lower level measures

Clear trace from specific low-level measurements to high-level metric



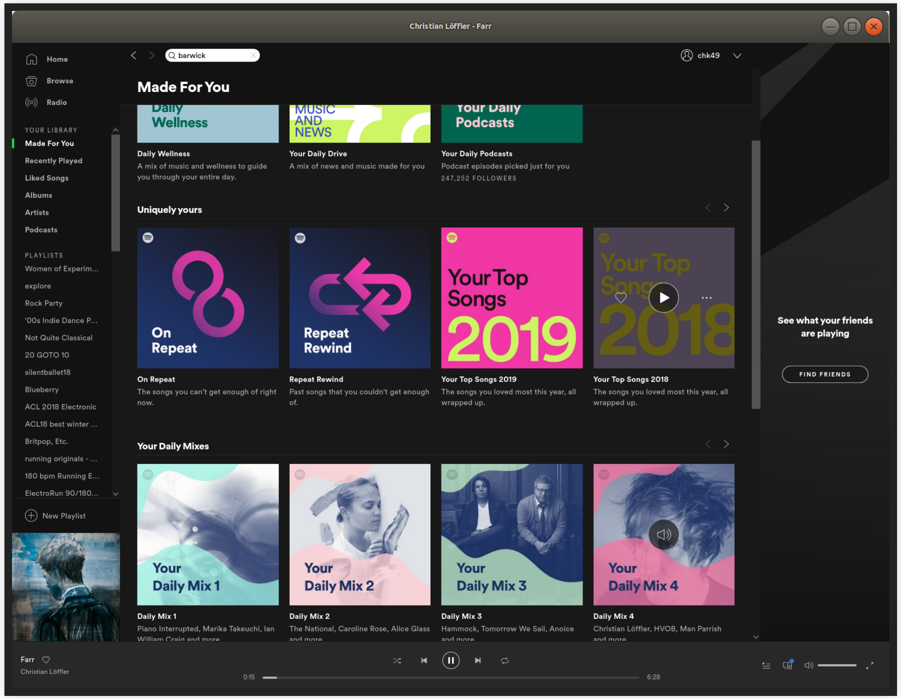
For design strategy, see Goal-Question-Metric approach

SPECIFYING METRICS

- Always be precise about metrics
    - "measure accuracy" -> "evaluate accuracy with MAPE"
    - "evaluate test quality" -> "measure branch coverage with Jacoco"
    - "measure execution time" -> "average and 90%-quantile response time for REST-API x under normal load"
    - "assess developer skills" -> "measure average lines of code produced per day and number of bugs reported on code produced by that developer"
    - "measure customer happiness" -> "report response rate and average customer rating on survey shown to 2% of all customers (randomly selected)"
- Ideally: An independent party should be able to independently set up infrastructure to measure outcomes

EXAMPLE: SPECIFIC METRICS FOR SPOTIFY GOALS?

- Organization objectives?
- Leading indicators?
- User outcomes?
- Model properties?
- What are their scales?



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- Bad decisions: The incorrect use of measurement data, leading to unintended side effects.
- Bad incentives: Disregard for the human factors, or how the cultural change of taking measurements will affect people.

MEASUREMENT VALIDITY

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- Construct: Are we measuring what we intended to measure?
    - Does the abstract concept match the specific scale/measurement used?
    - e.g., IQ: What is it actually measuring?
    - Other examples: Pain, language proficiency, personality...

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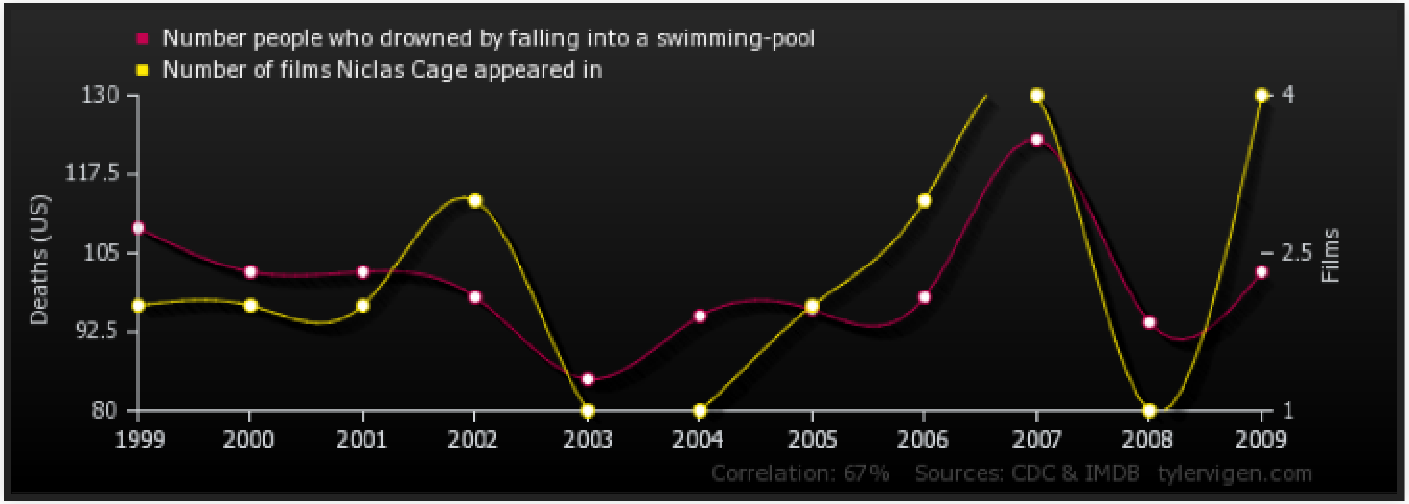
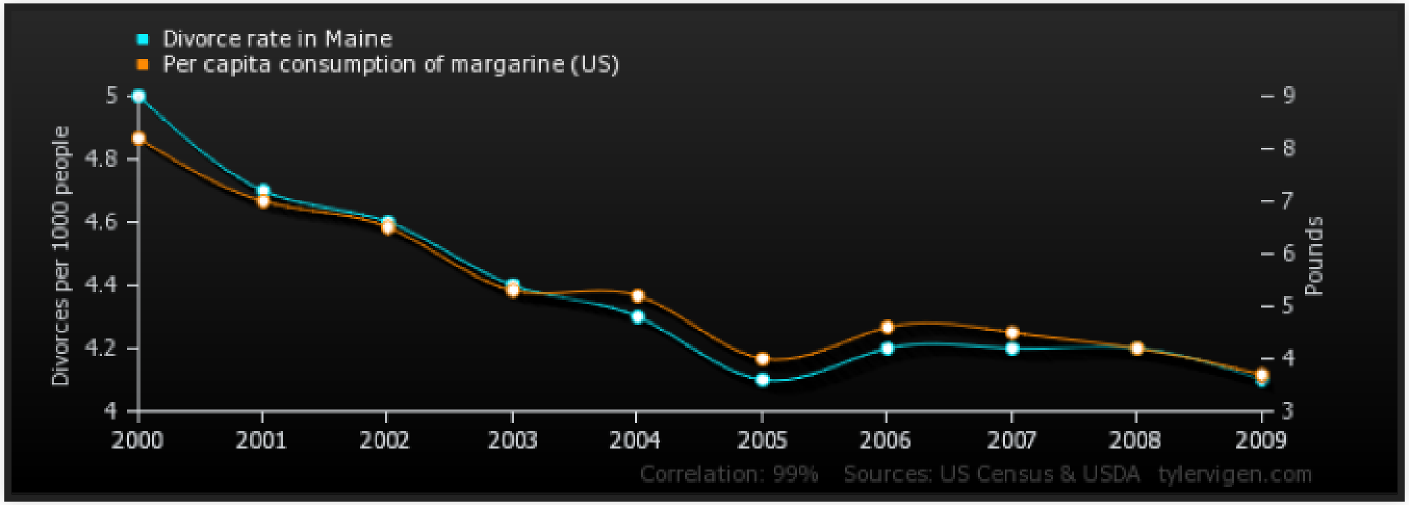
  - e.g., Higher SAT scores => higher academic excellence?
- External validity: Concerns the generalization of the findings to contexts and environments, other than the one studied
  - e.g., Drug effectiveness on a test group: Does it hold over the general public?

CORRELATION VS CAUSATION

https://www.tylervigen.com/spurious-correlations



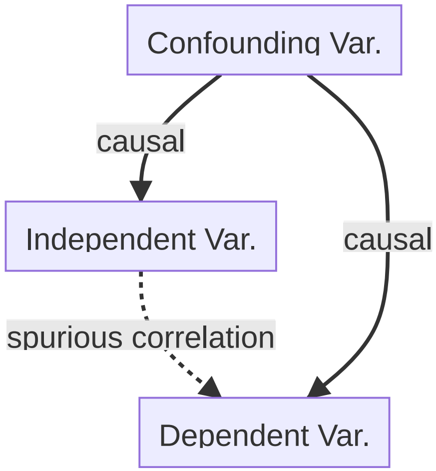


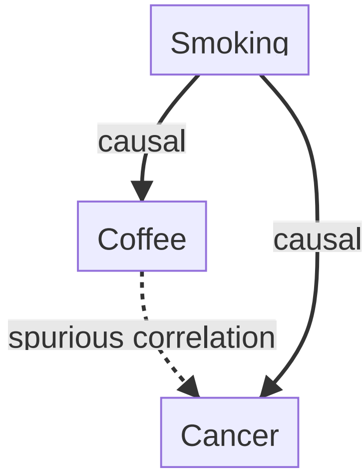
Divorce rate in Maine
Per capita consumption of margarine (US)
Divorces per 1000 people
Pounds
5
4.8
4.6
4.4
4.2
4
9
8
7
6
5
4
3
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
Correlation: 99%
Sources: US Census & USDA
tylervigen.com

CORRELATION VS CAUSATION

- In general, ML learns correlation, not causation
  - (exception: Bayesian networks, certain symbolic AI methods)
  - For more details: See causal inference
- Be careful about interpretation & intervention based on correlations
  - e.g., positive correlation between exercise and skin cancer
  - Exercise less => reduce chance of skin cancer?
- To establish causality:
  - Develop a theory ("X causes Y") based on domain knowledge & independent data
  - Identify relevant variables
  - Design a controlled experiment & show correlation
  - Demonstrate ability to predict new cases

CONFOUNDING VARIABLES





CONFOUNDING VARIABLES

- To identify spurious correlations between X and Y:
  - Identify potential confounding variables
  - Control for those variables during measurement
    - Randomize, fix, or measure + account for during analysis
    - e.g., control for ''smoke'', check whether ''drink coffee" => "pancreatic cancer"
- Other examples
  - Degree from top-ranked schools => higher salary
  - Age => credit card default rate
  - Exercise => skin cancer
  - and many more...

STREETLIGHT EFFECT

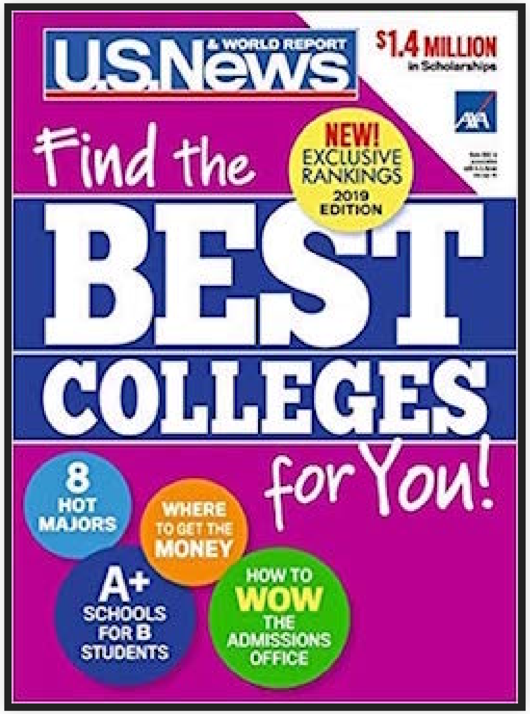
- A type of *observational bias*
- People tend to look for something where it's easiest to do so
  - Use cheap proxy metrics that only poorly correlate with goal
  - e.g., number of daily active users as a measure of projected revenue

RISKS OF METRICS AS INCENTIVES

- Metrics-driven incentives can:
  - Extinguish intrinsic motivation
  - Diminish performance
  - Encourage cheating, shortcuts, and unethical behavior
  - Become addictive
  - Foster short-term thinking
- Often, different stakeholders have different incentives

Make sure data scientists and software engineers share goals and success measures

EXAMPLE: UNIVERSITY RANKINGS



- Originally: Opinion-based polls, but complaints by schools on subjectivity
- Data-driven model: Rank colleges in terms of "educational excellence"
- Input: SAT scores, student-teacher ratios, acceptance rates, retention rates, campus facilities, alumni donations, etc.,

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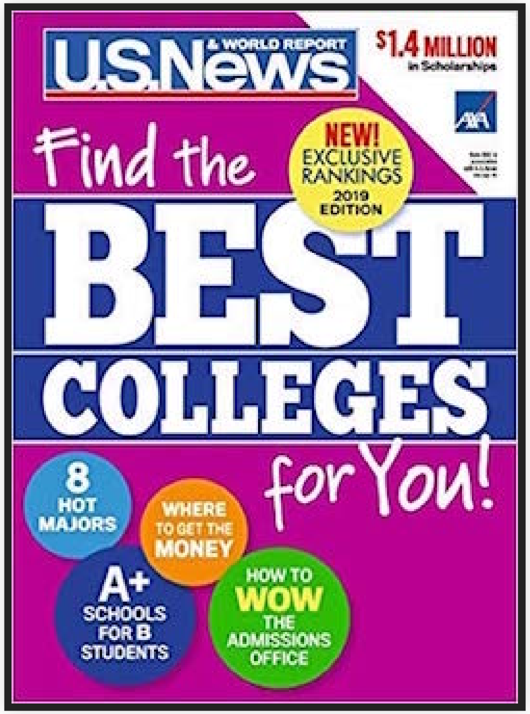

- Can the ranking-based metric be misused or cause unintended side effects?

For more, see Weapons of Math Destruction by Cathy O'Neil

Speaker notes

- Example 1
    - Schools optimize metrics for higher ranking (add new classrooms, nicer facilities)
    - Tuition increases, but is not part of the model!
    - Higher ranked schools become more expensive
    - Advantage to students from wealthy families
- Example 2
    - A university founded in early 2010's
    - Math department ranked by US News as top 10 worldwide
    - Top international faculty paid $$ as a visitor; asked to add affiliation
    - Increase in publication citations => skyrocket ranking!

SUCCESSFUL MEASUREMENT PROGRAM

- Set solid measurement objectives and plans
- Make measurement part of the process
- Gain a thorough understanding of measurement
- Focus on cultural issues
- Create a safe environment to collect and report true data
- Cultivate a predisposition to change
- Develop a complementary suite of measures

SUMMARY

- Ask yourself: Do you really need ML?
    - Establish a non-ML solution as a baseline & consider cost vs benefit
- Align your system goals
    - Better ML models does not always lead to better business goals!
- Consider risks of measurement
    - Are you really measuring what you want? Can your metric incentivize bad behaviors?