

# GOALS AND SUCCESS MEASURES FOR AI- ENABLED SYSTEMS

Eunsuk Kang

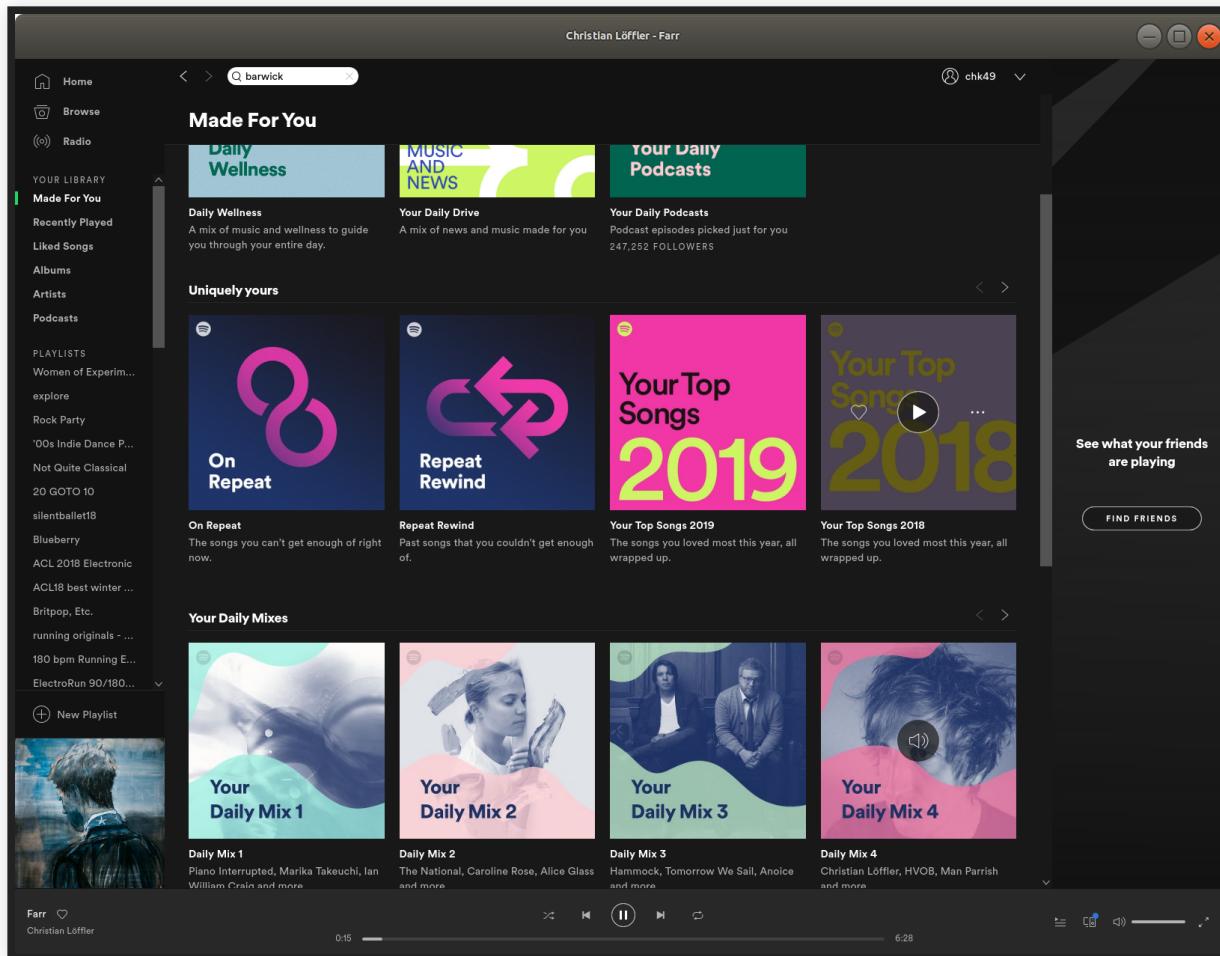
Required Readings: Hulten, Geoff. "[Building Intelligent Systems: A Guide to Machine Learning Engineering](#)" (2018),  
Chapters 2 (Knowing when to use IS) and 4 (Defining the IS's Goals)

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 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

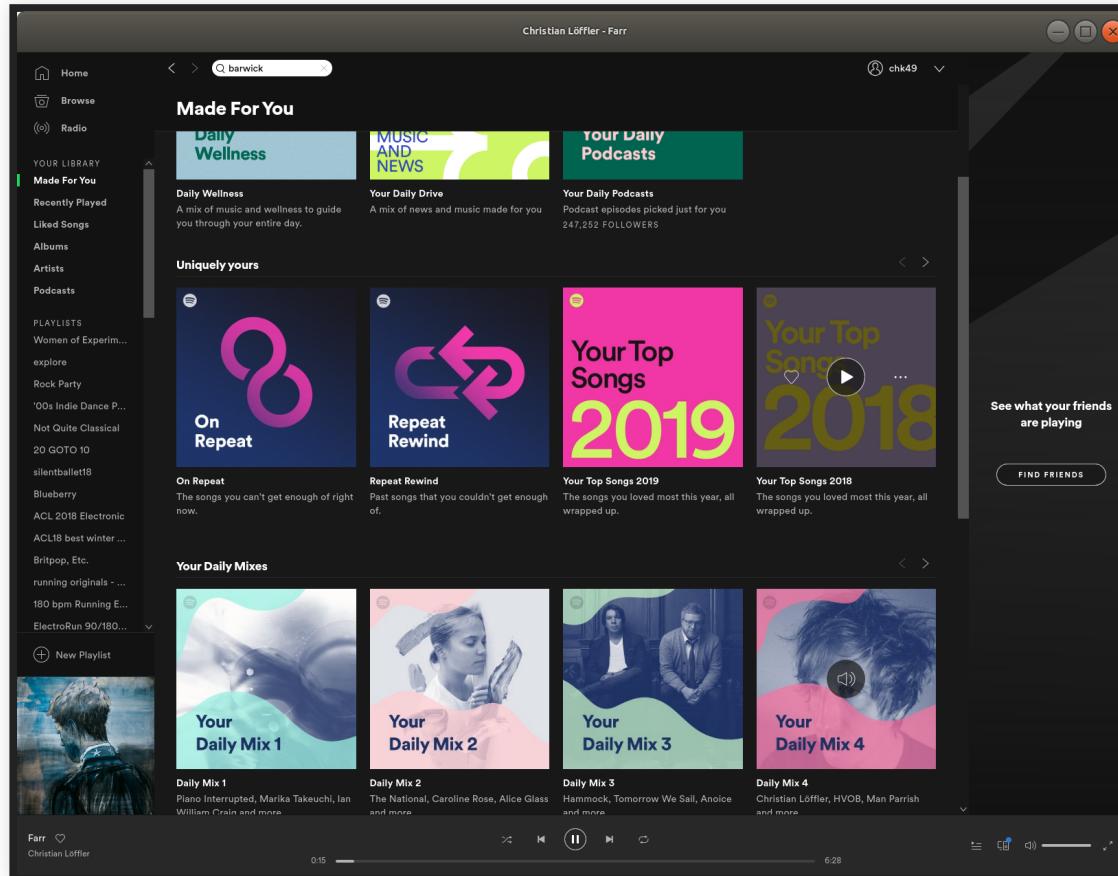
- Partial solution is acceptable: Mistakes are acceptable or mitigable
- Data for continuous improvement is available
- Predictions can have an influence on system objectives: Does it actually contribute to organizational objectives?
- Cost effective: Cheaper than other approaches, or benefits clearly 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
  - CO2 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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- Caveats
  - Often indirect, proxy measures
  - Can be misleading (e.g., more daily active users => higher profits?)

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  - 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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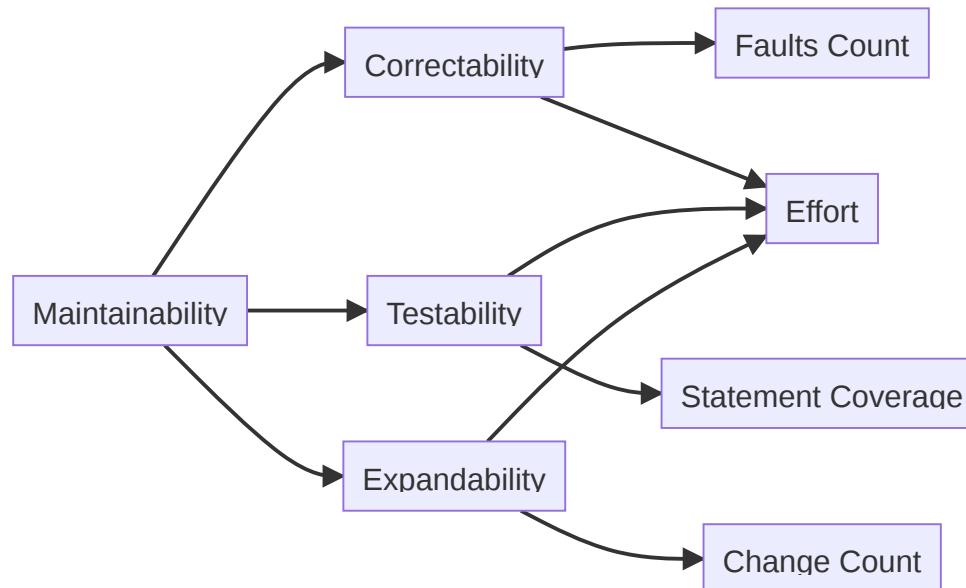
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- Understand scales of features and use an appropriate encoding for learning algorithms!
  - e.g., One-hot encoding for nominal features

# DECOMPOSITION OF MEASURES

Often higher-level measures are composed from lower level measures

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



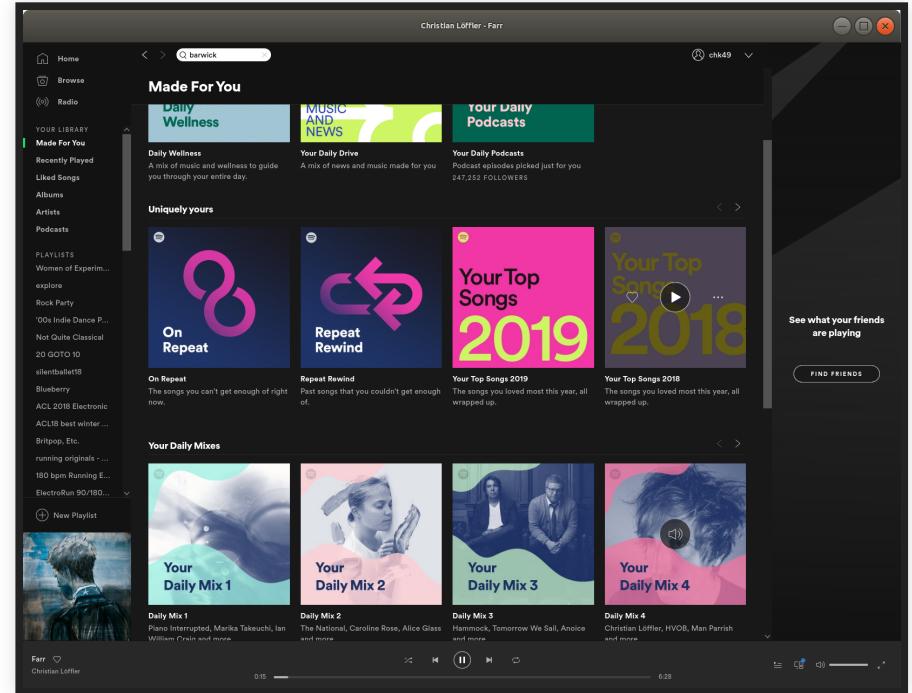
For design strategy, see [Goal-Question-Metric approach](#)

# 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.

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- Construct: Are we measuring what we intended to measure?
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  - e.g., IQ: What is it actually measuring?
  - Other examples: Pain, language proficiency, personality...

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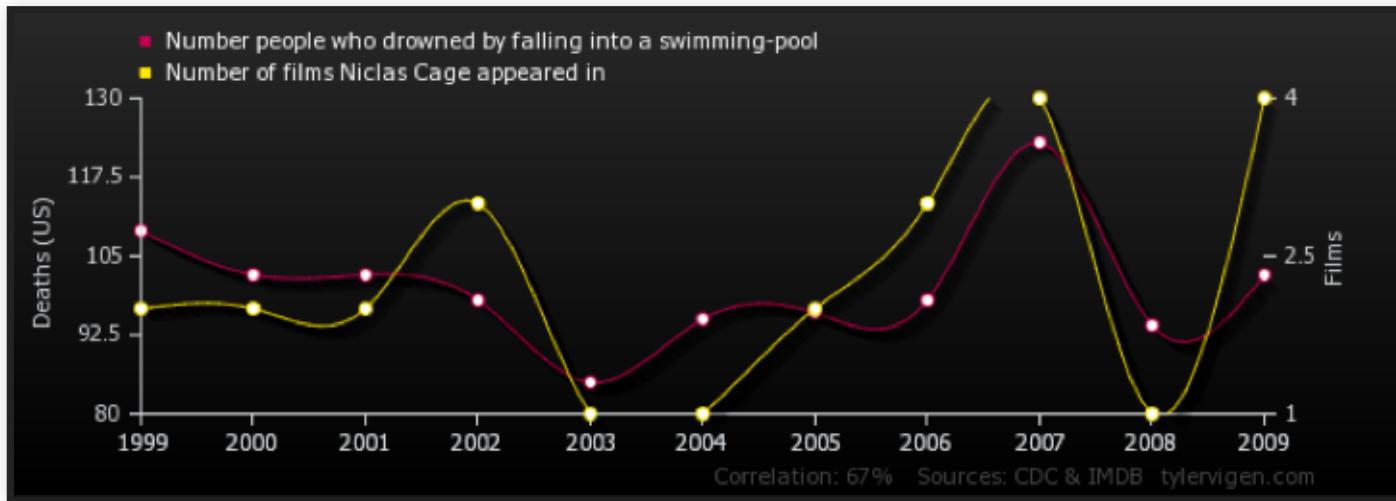
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- External validity: Concerns the generalization of the findings to contexts and environments, other than the one studied
  - e.g., Drug effectiveness on a test group: Does it hold over the general public?

# CORRELATION VS CAUSATION

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





# 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



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- 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.,

# EXAMPLE: UNIVERSITY RANKINGS



- 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?