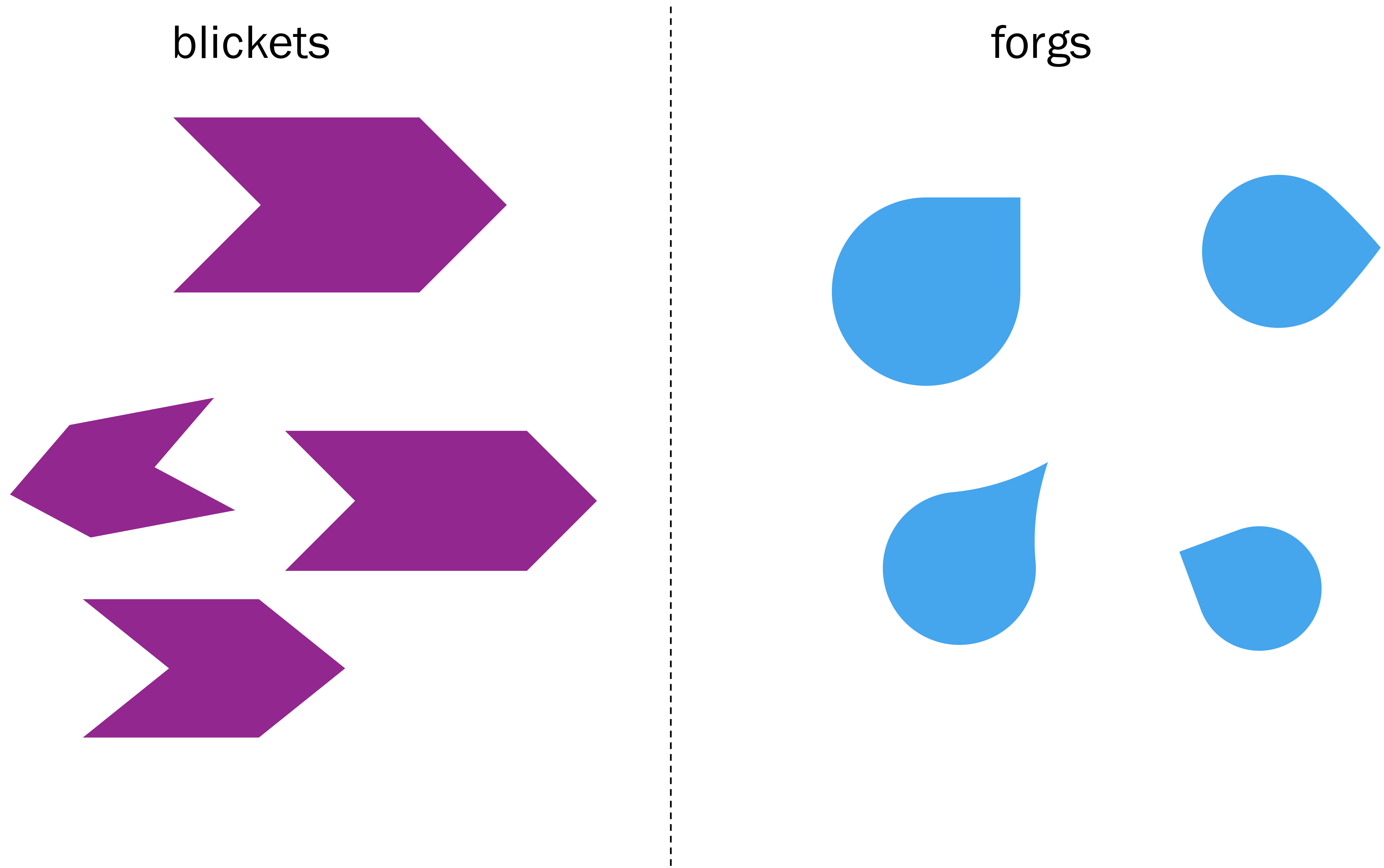
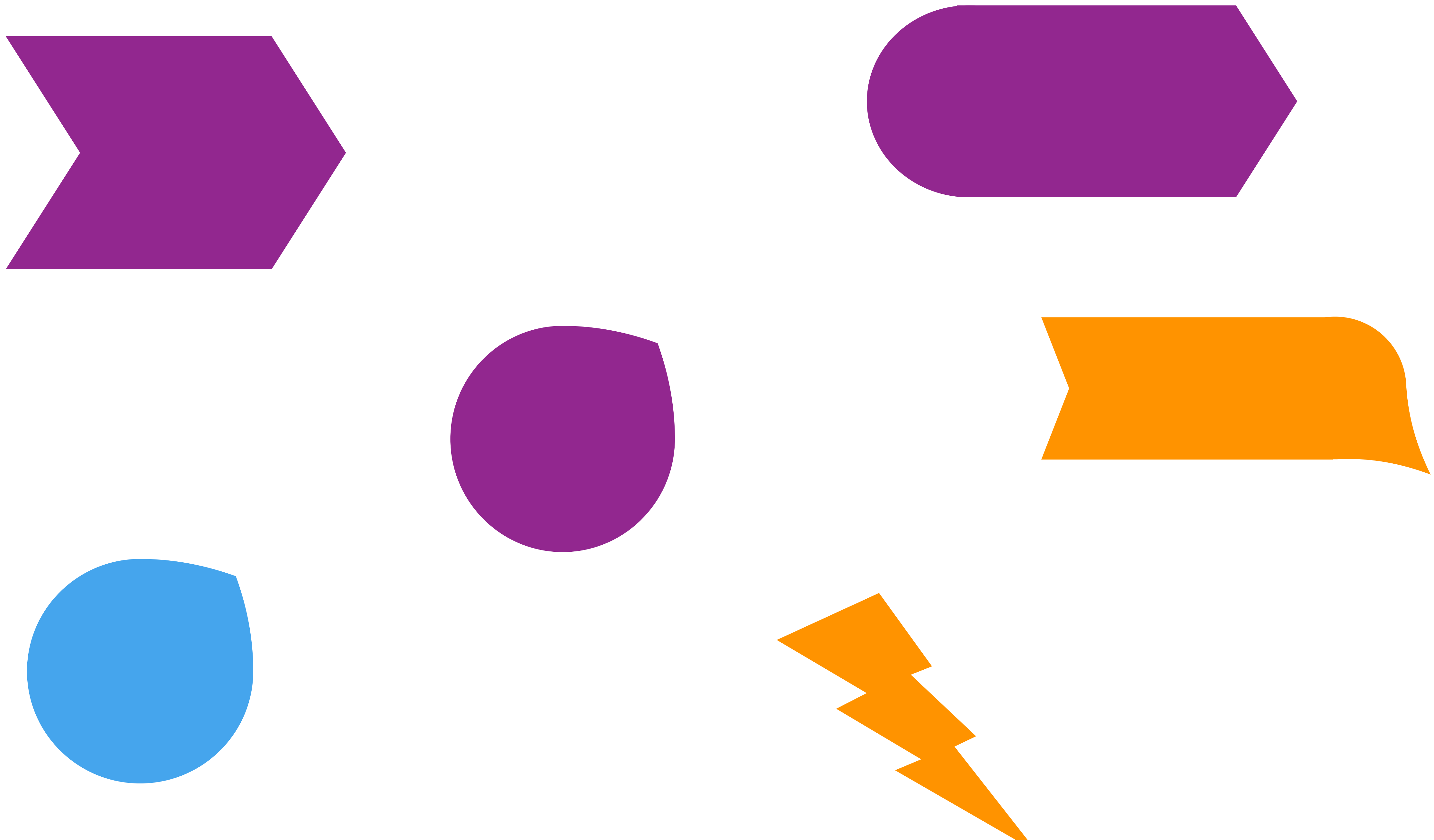
Machine Learning, Bias, and Hype

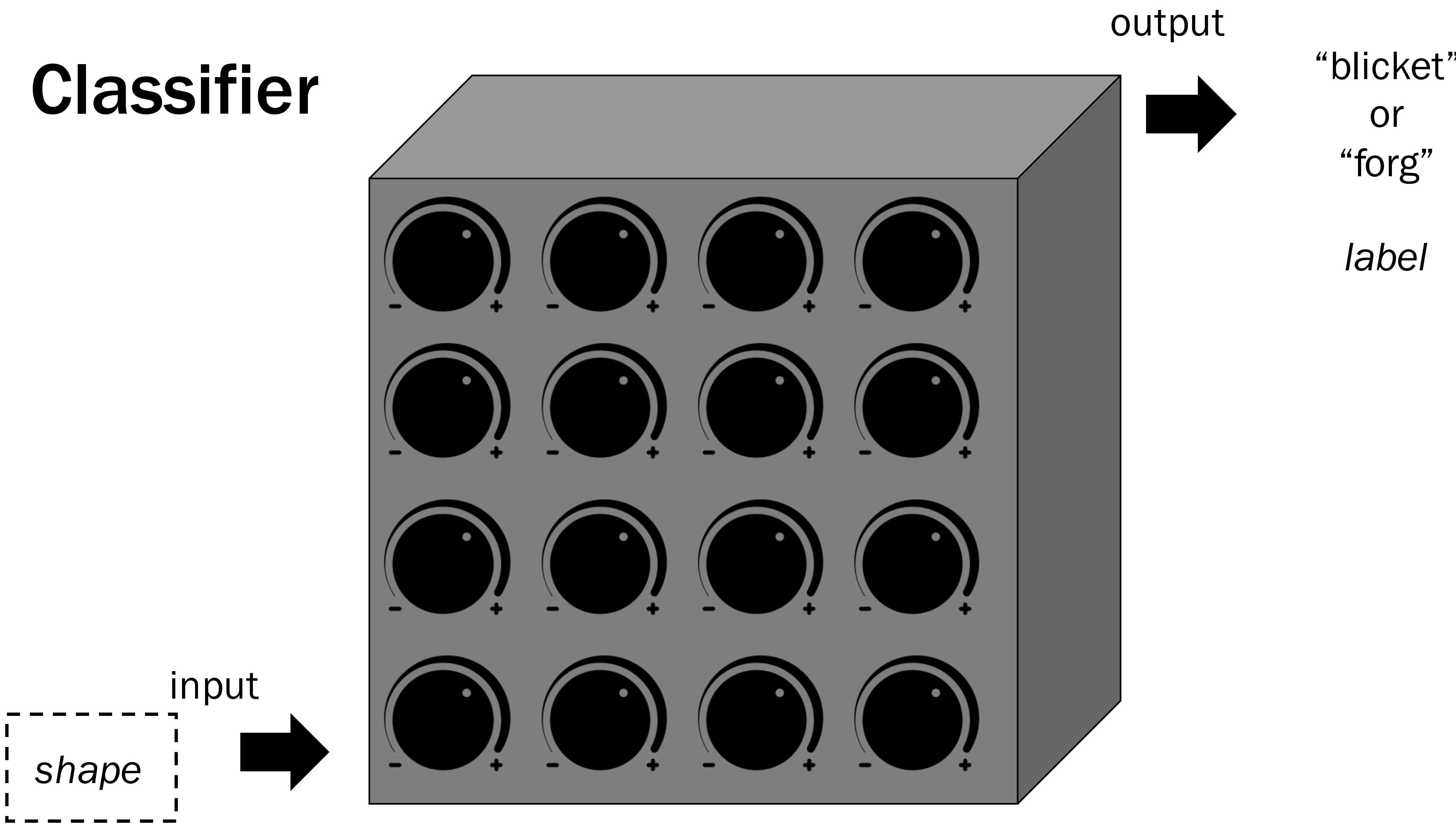
Noah Smith
Professor of Computer Science & Engineering , University of Washington
& Senior Research Manager, Allen Institute for Artificial Intelligence
nasmith@cs.washington.edu noah@allenai.org @nlpnoah

Outline

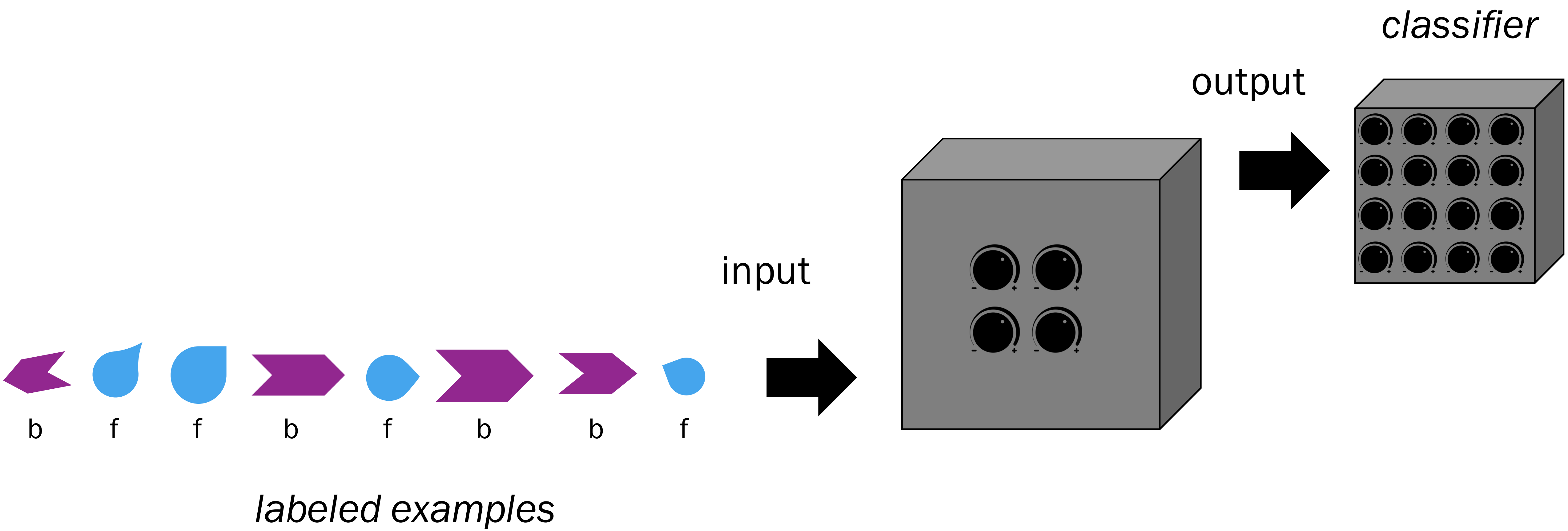
1. Basic introduction to machine learning
2. Bias in machine learning
3. Inoculation against AI hype


blickets
forgs




Classifier
output
"blicket"
or
"forg"
label
input
shape

Supervised Learner



Some Secrets about Supervised Learning

- The data matter **a lot**
- How we represent the data as an “input” matters **a lot**
- Sources of error in generalizing to new (non-training) examples:
  - Flaws in our representation of the problem (“irreducible”)
  - Assumptions made by a learning algorithm (“bias”)
  - Randomness/noise in the data (“variance”)
- There is a **tradeoff** between bias and variance!

On Bias

- Bias is prejudice or preference held prior to exposure to evidence (held by a human or a program)

- Learners cannot generalize without (inductive) bias!

- Put another way: if you eliminate all bias, your model will be extremely *flexible* and will tend to be extremely sensitive to the particular training instances.
  - Result: higher variance, unless there's "enough" data

Examples of Bias

Input	Output	Result
image of tank	American or Russian?	clear/blurry
tweet	abusive?	AAVE
speech stream	sequence of words	only worked for men
details about person convicted of a crime	sentence length	longer sentences for minorities
two English sentences	semantic relationship (entailment, contradiction, …)	"cat" ⟶ contradiction
product reviews	sentiment of author	fails on political speech

Where does bias come from?

1. The real-world process that produced the labels, or the data sample, might be biased.
   Just because something comes from data, that doesn't mean it's "fair" or "unbiased"!
2. The design/definition of the task might encode bias.
3. The design of the program itself might encode bias.
4. Deployed systems that affect their own future inputs can create feedback loops and exacerbate their own biases.

Disparate Impact

- US law (hiring and housing): 80% rule

  Informally: your rate of hiring women (for instance) must be at least 80% of your rate of hiring men.

- Can we just hide the sex attribute from the learner?

No!

- There are many alternative definitions of fairness.
- Open question: can we guarantee high accuracy and still be unbiased?

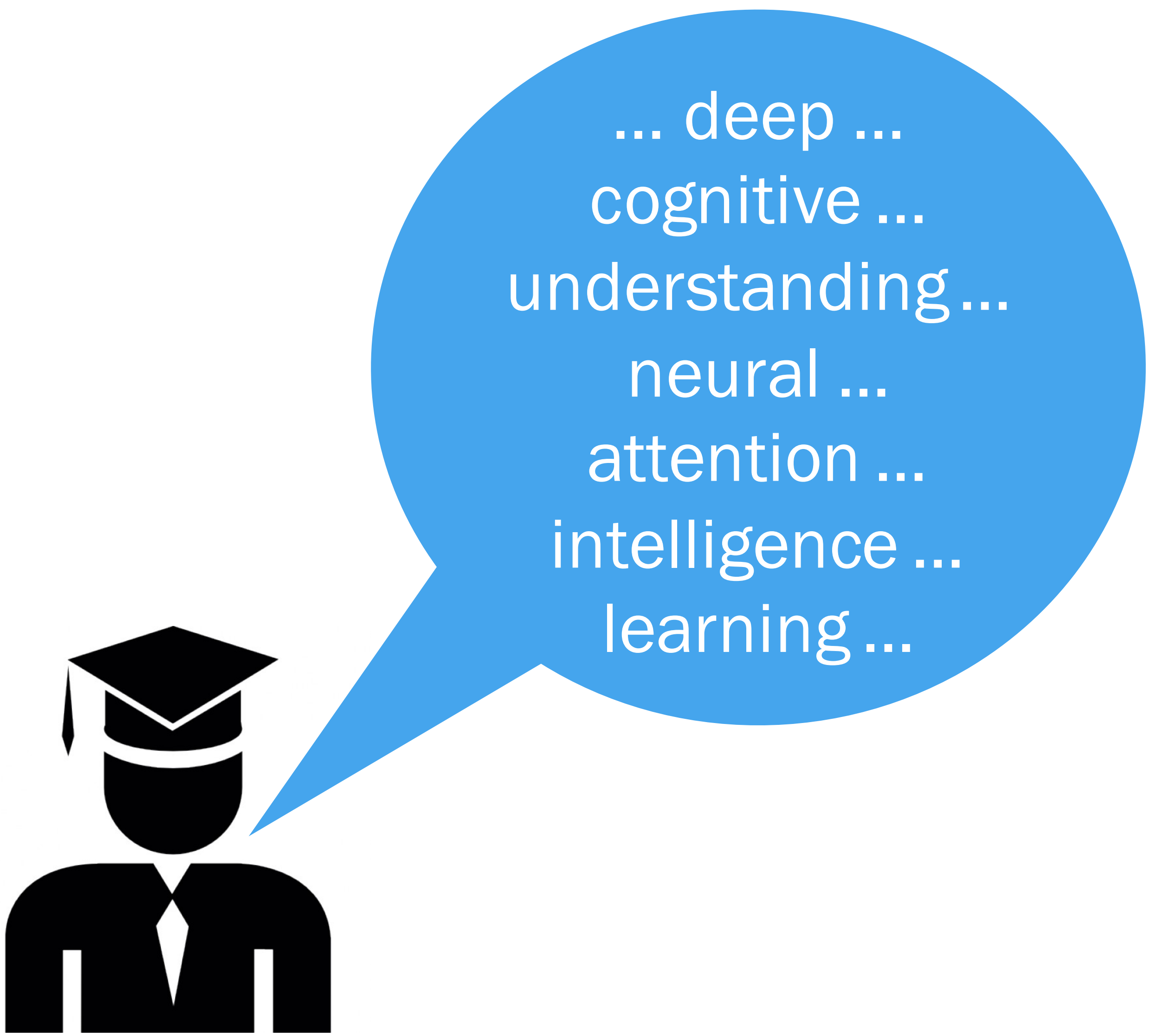
We aren't aware of all the biases!

- Typically we measure the **accuracy** of learned programs: what proportion of inputs do they correctly label, in a held out test set?
  - Sometimes we look at accuracy for particular subcategories.

- We don't always know which biases to look for!

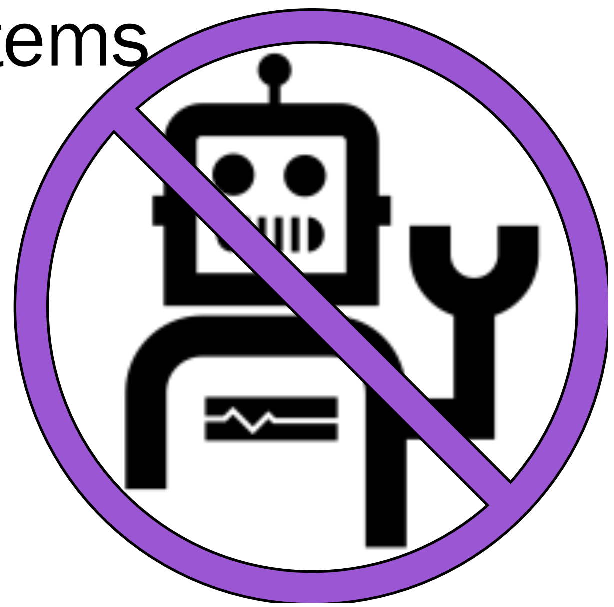
Inoculation against Hype

A translation problem



Tips

- ✓ "Human level performance" has a *very narrow* meaning
- ✓ "95% accuracy" was measured only on a *specific* type of input
- ✓ Ask about the data and computation requirements (i.e., cost)
- ✓ Researchers' benchmarks are *not* real-world systems
- ✓ Do not trust anthropomorphic descriptions of systems



Learn More

- *A Course in Machine Learning*, by Hal Daumé III. http://ciml.info
- CSE 416 or 446