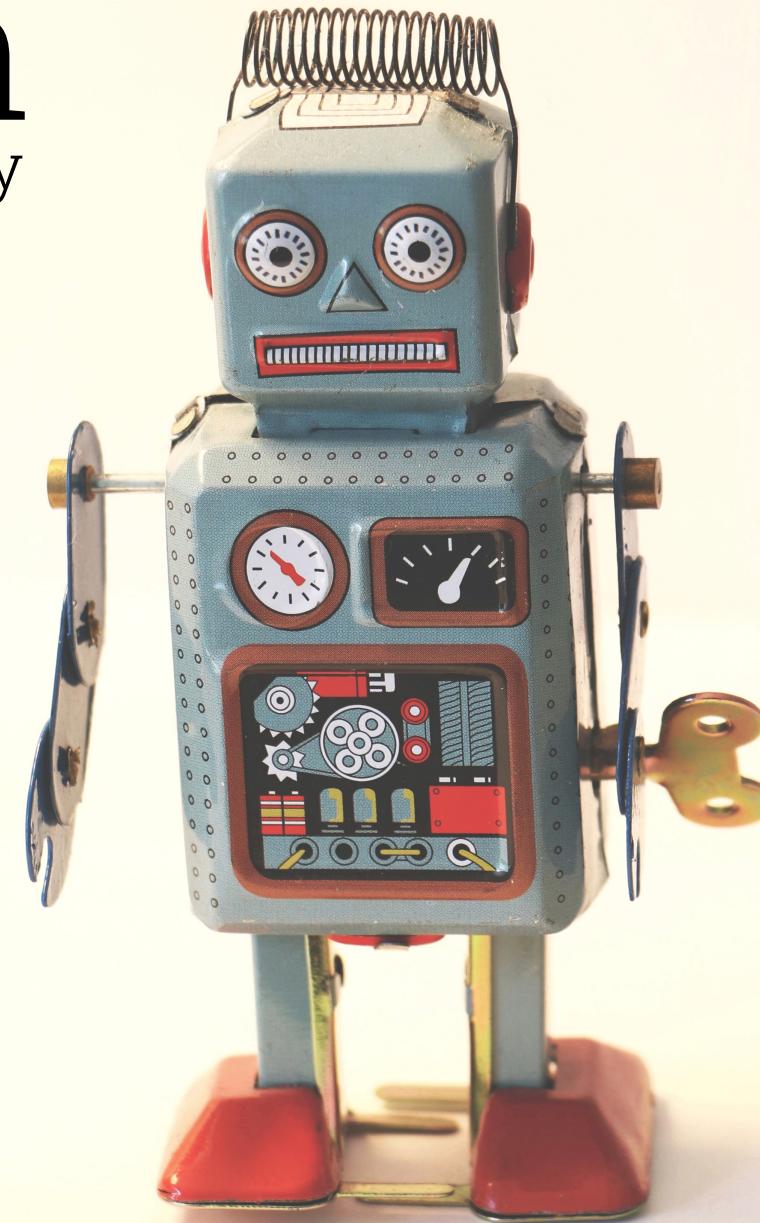
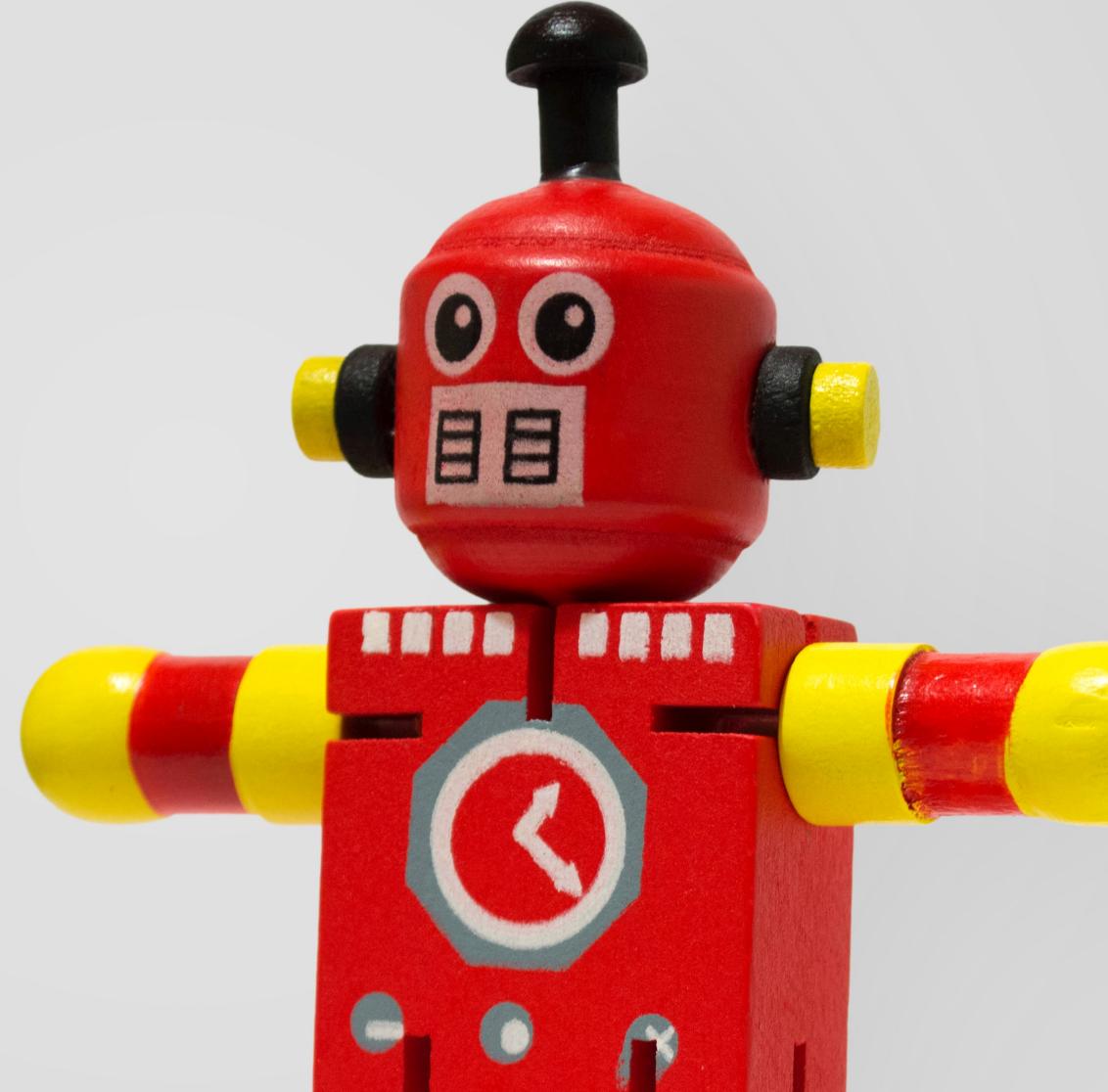


# AI Is Broken

Sophie Searcy



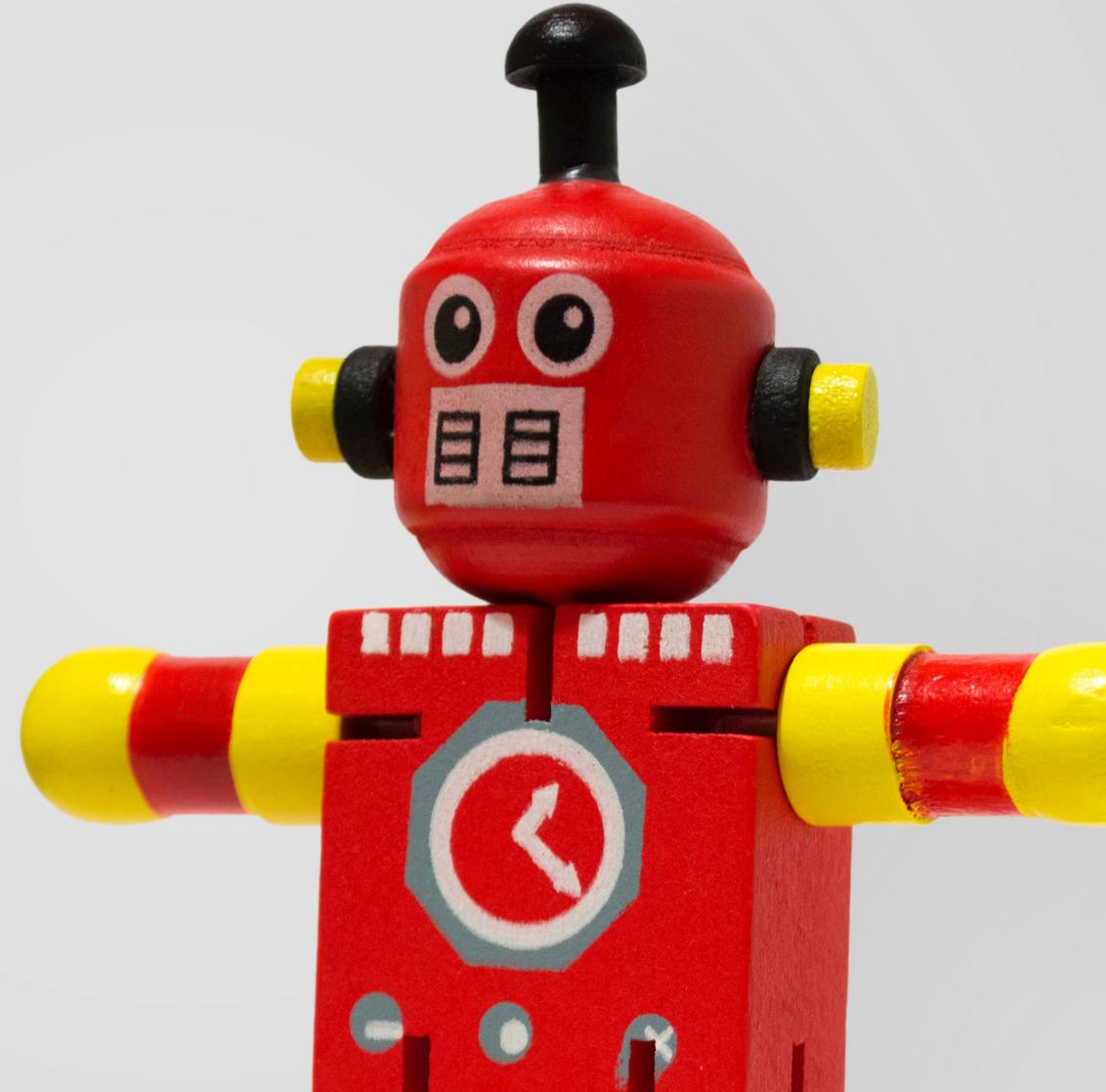
# What is AI?



# Caveats

- AI
  - lumping together Data Science, Artificial Intelligence, Machine Learning, Data Mining, etc.
- Audience
  - Conversant in AI topics. Not necessarily experts or practitioners.

# What is AI?



# Learn

verb

\'lern\

to process past experience and update a model  
such that the the model is more useful for future  
experience

# Learn

verb

\'lern\'

to process past experience

and update a model  
such that the model is useful for future  
experience

# Learn

verb

\'lern\'

to process past experience and **update a model**  
such that the the model is useful for future  
experience

# Learn

verb

\'lern\'

to process past experience and update a model

such that the the model is useful for future  
experience

# Model: a learning algorithm

- A model is a small thing that captures a larger thing.
- A good model omits unimportant details while retaining what's important.



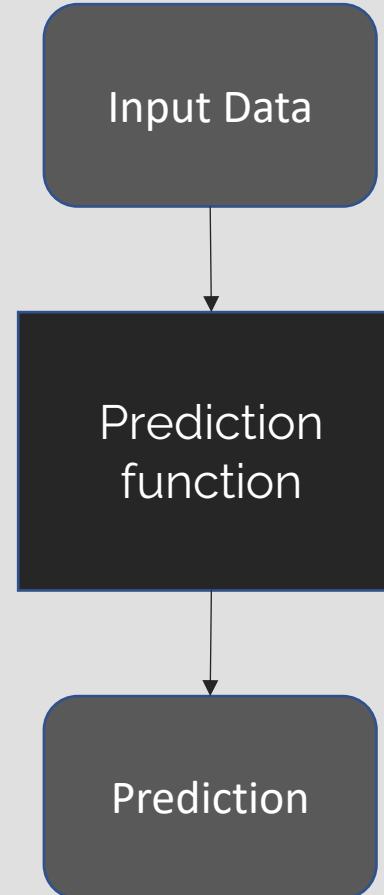
# Model: a learning algorithm

- Industry sometimes uses “algorithm” and “model” interchangeably.
  - Words are complicated (ask anyone who works in NLP)



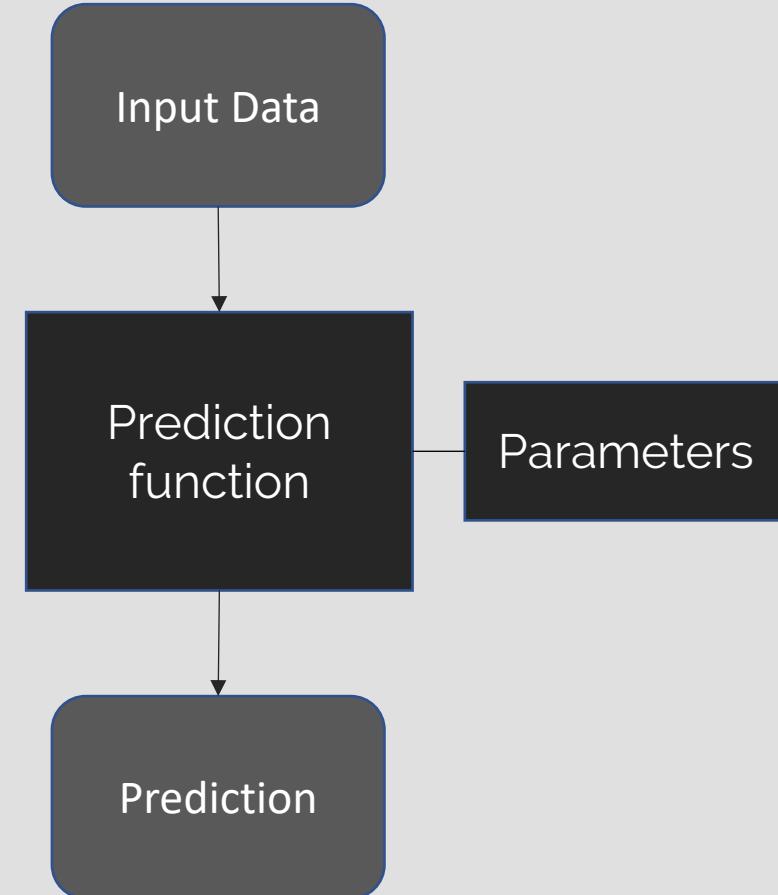
# Model: a learning algorithm

- All models contain a prediction function



# Model: a learning algorithm

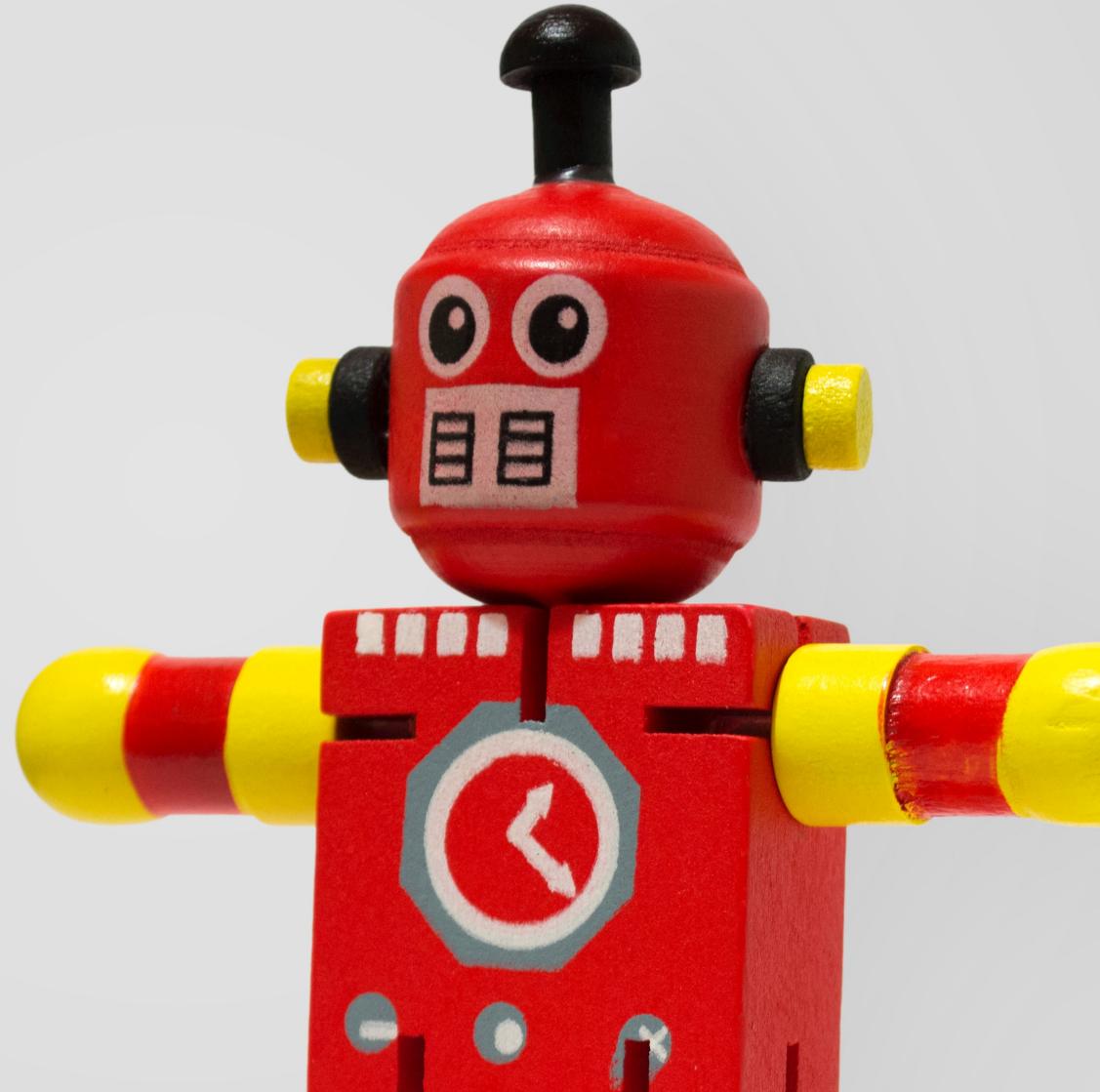
- Parameters
  - Determine model output
  - Learned from data



# Model: a learning algorithm



# Models are data hungry



# Models are data hungry

## Models

- Learn from a limited set of training data
- Apply what was learned to *production*
  - “Production” is data science lingo for the entire world

# Models are data hungry

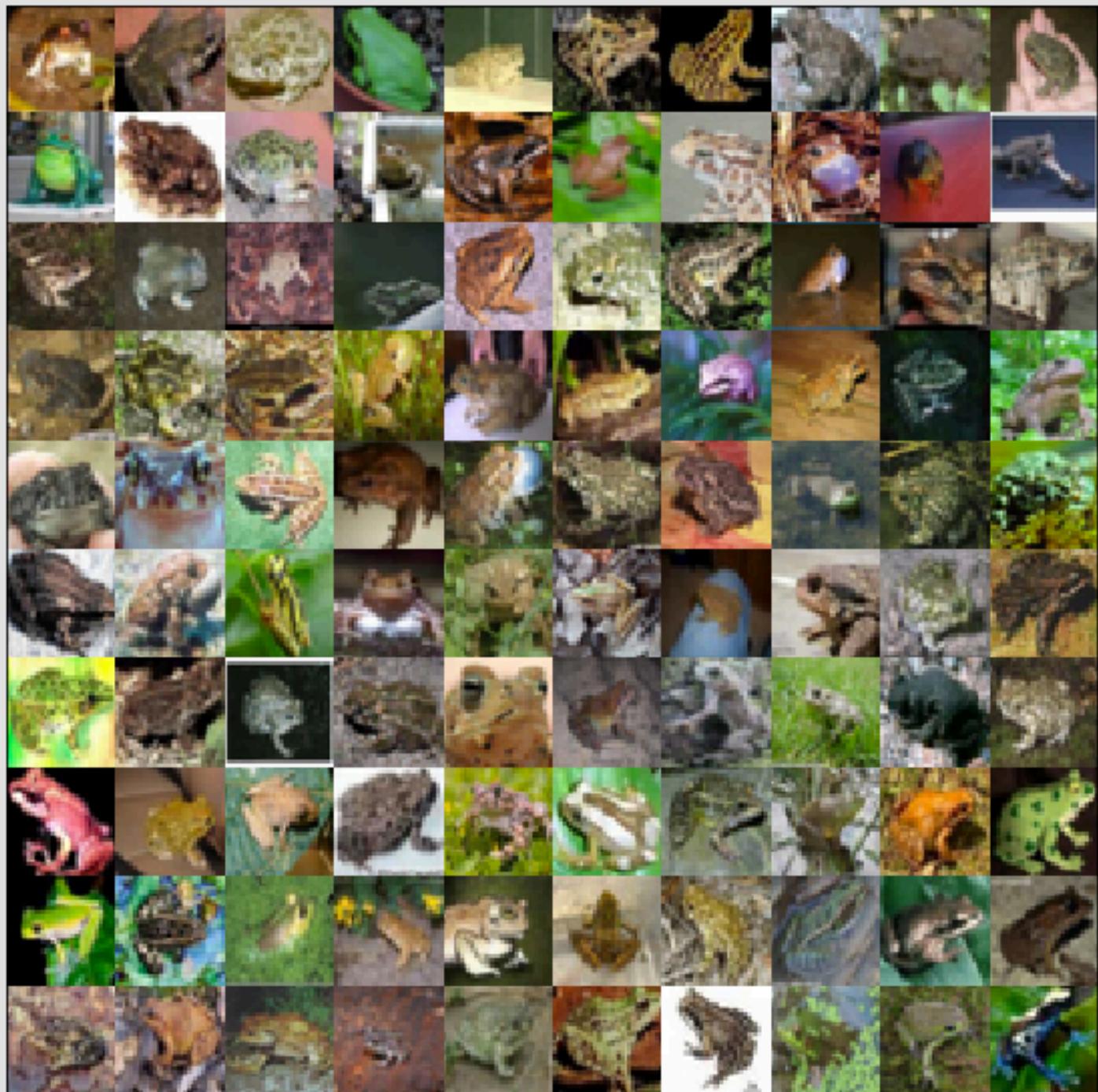
## Models

- Learn from a limited set of training data
- Apply what was learned to *production*
  - “Production” is data science lingo for the entire world

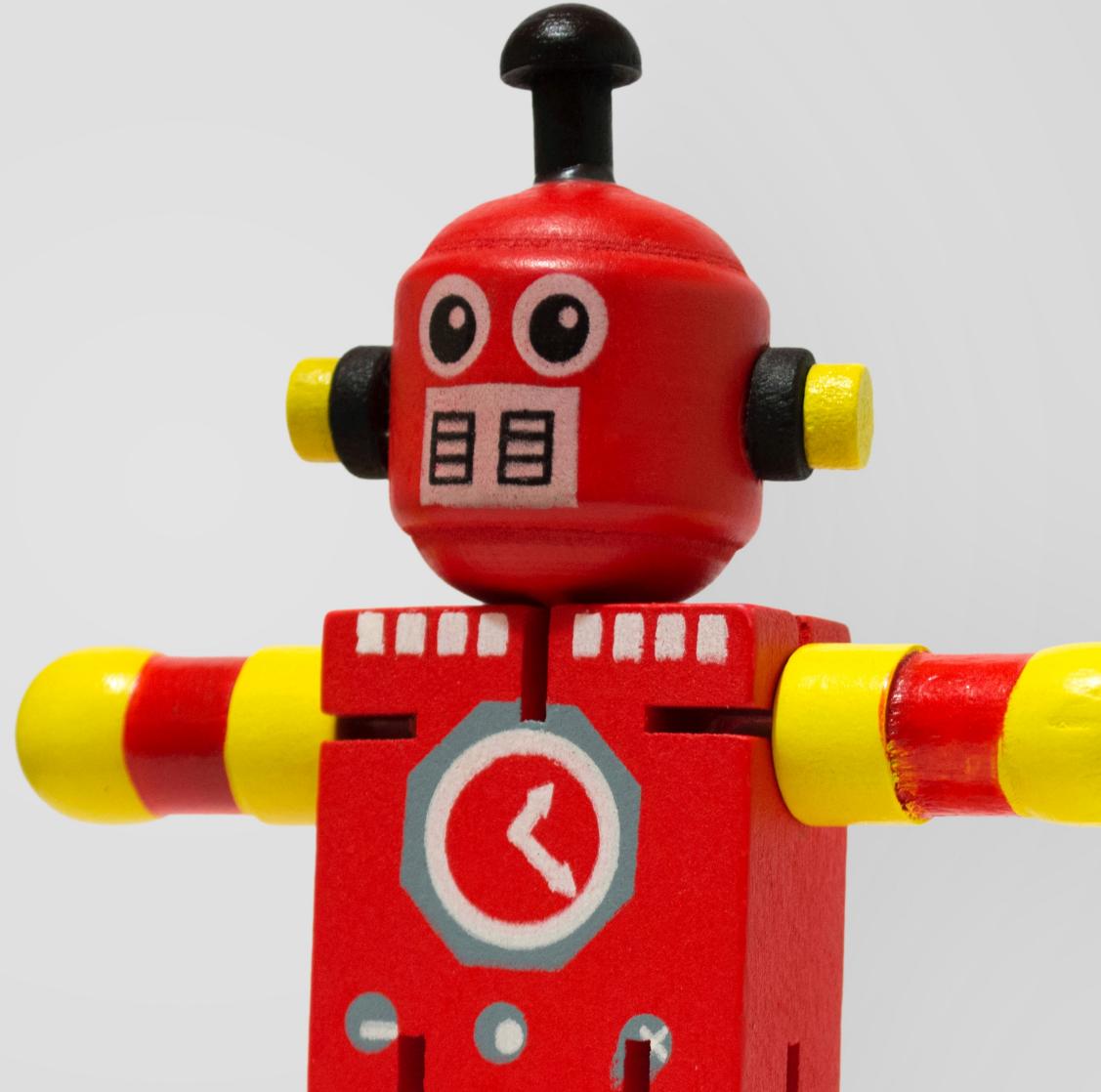
One of the most difficult tasks in AI:

- use training data (data you have) to judge how a model will perform in production (data you don't have) .





# Speed limits for data



# Speed limits for data

“Traditional” models (Support Vector Machines, Linear Models, Random Forests, K Nearest Neighbors)

- Batch data: look at the entire dataset at once.
- Training time increases with dataset size.

# Speed limits for data

| Data Set Size   | Time to train |
|---|---------------|
|  |               |
|  |               |
|  |               |

# Speed limits for data

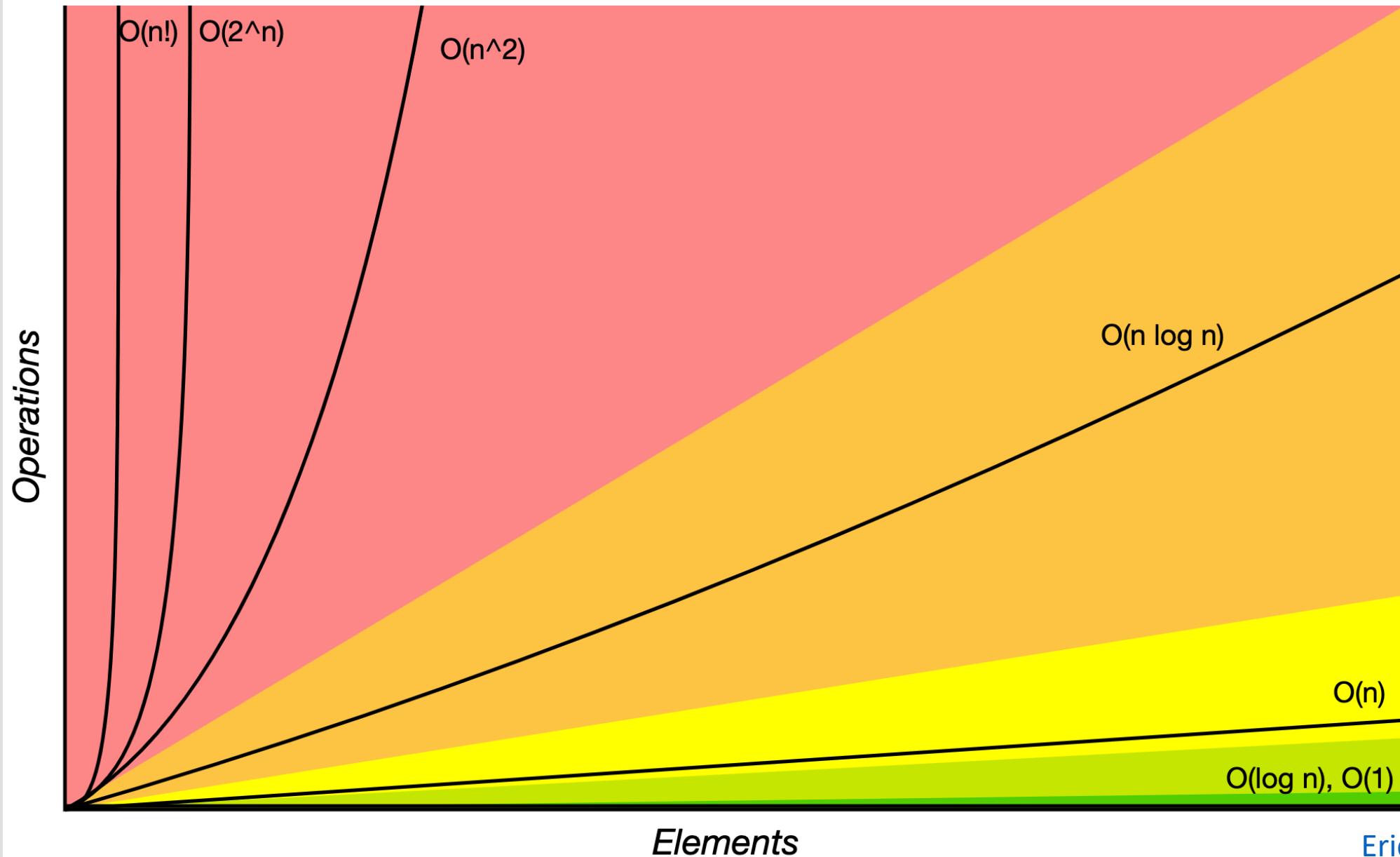
| Data Set Size   | Time to train |
|---|---------------|
|  |               |
|  |               |
|  |               |

# Speed limits for data

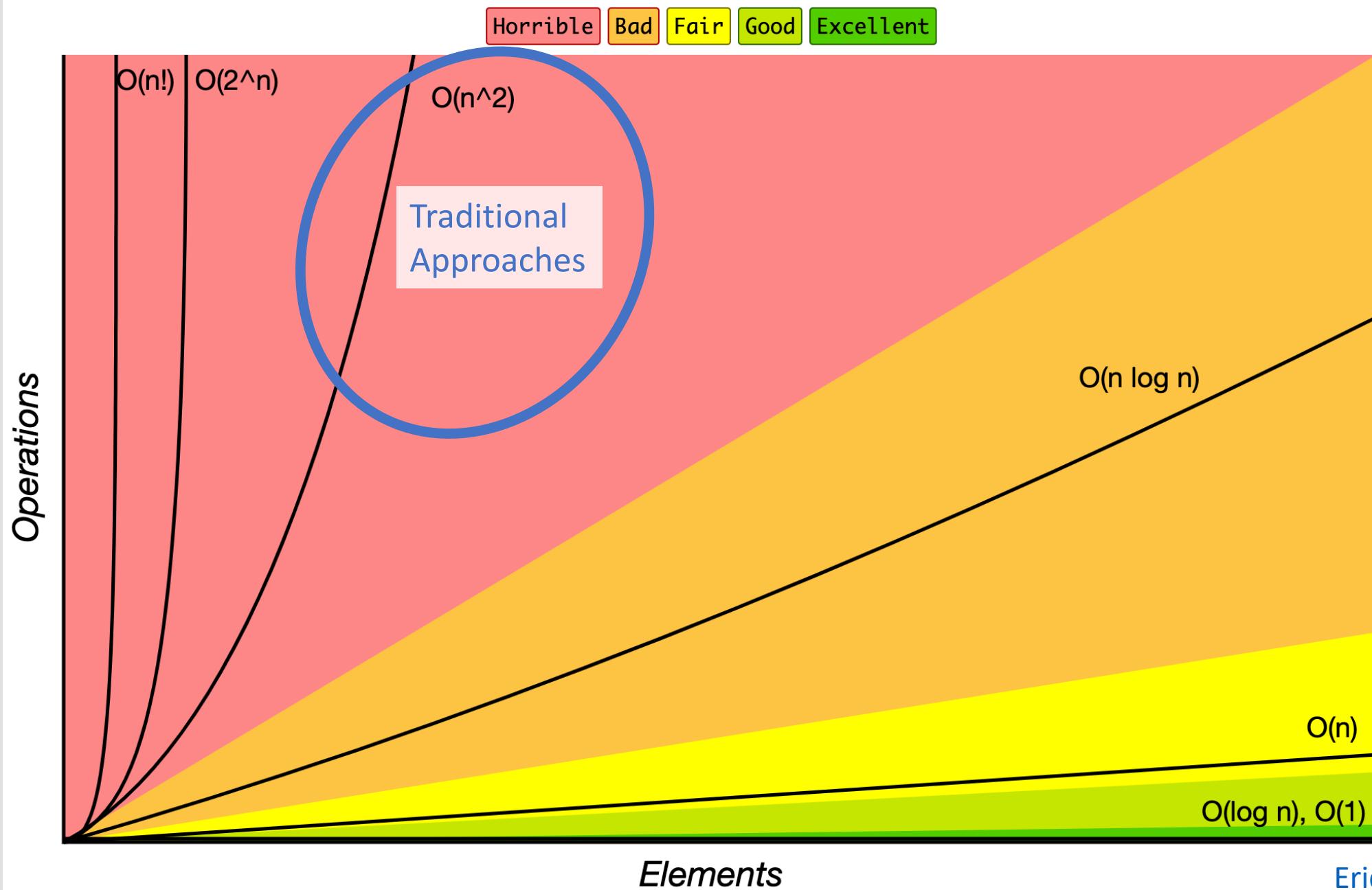
| Data Set Size   | Time to train |
|---|---------------|
|  |               |
|  |               |
|  |               |

# Big-O Complexity Chart

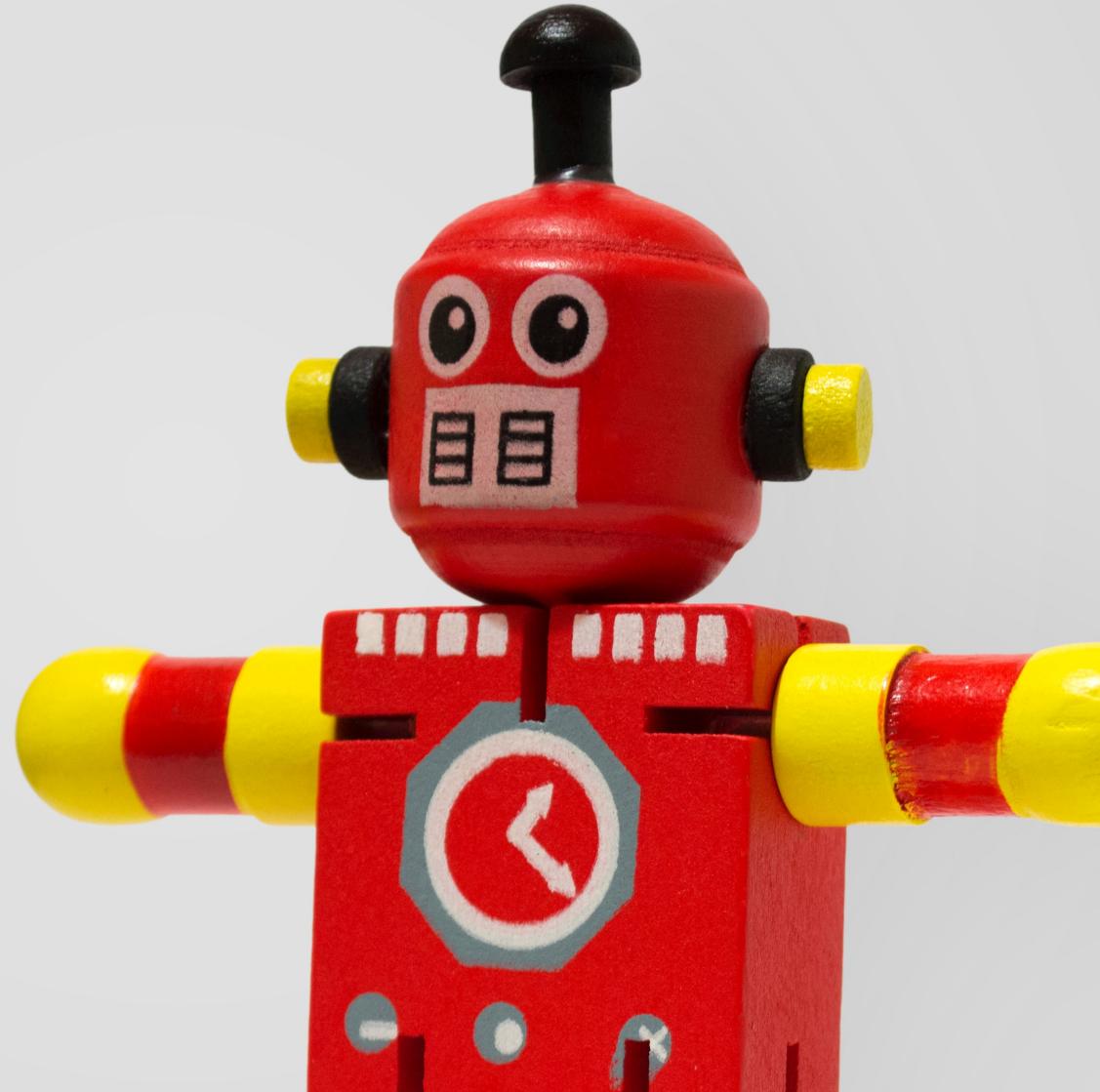
Horrible   Bad   Fair   Good   Excellent



# Big-O Complexity Chart



# Modern AI removes the speed limit



# Enter Stochastic Gradient Descent

- In the last two decades, AI has shifted to approaches that strongly incentivize large datasets
- SGD powers Deep Learning models
- Traditional AI models have been modified to take advantage of SGD

# How does SGD work?

**Gradient descent** (*not stochastic*)

1. Put a number on your model's performance. (Loss function)
2. Determine which direction decreases the loss function.  
(Find the Gradient).
3. Turn the knob in that direction. (Backpropagation)

(Wash, rinse, repeat for every parameter)

# How does SGD work?

**Stochastic** Gradient Descent:

- Use a small subset of your dataset to estimate the loss for the entire dataset (Minibatch)

# The Tradeoffs of Large Scale Learning

---

**Léon Bottou**

NEC laboratories of America  
Princeton, NJ 08540, USA  
[leon@bottou.org](mailto:leon@bottou.org)

**Olivier Bousquet**

Google Zürich  
8002 Zurich, Switzerland  
[olivier.bousquet@m4x.org](mailto:olivier.bousquet@m4x.org)

- For SGD-based models, the amount of time it takes to fit a model **does not depend on the size of the dataset.**

# Stochastic Gradient Descent

| Data Set Size   | Time to train |
|---|---------------|
|  |               |
|  |               |
|  |               |

# Stochastic Gradient Descent

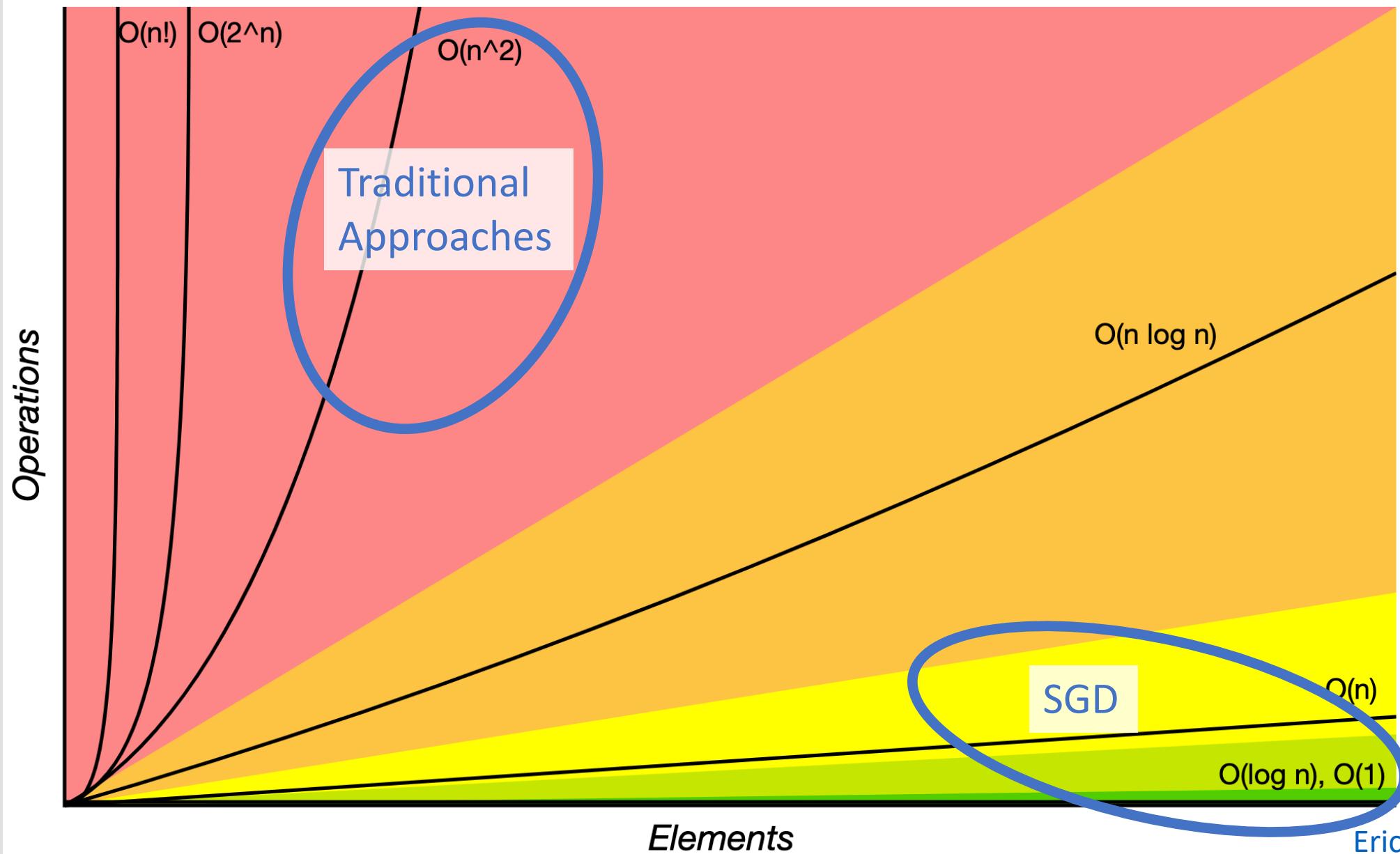
| Data Set Size   | Time to train |
|---|---------------|
|  |               |
|  |               |
|  |               |

# Stochastic Gradient Descent

| Data Set Size   | Time to train |
|---|---------------|
|  |               |
|  |               |
|  |               |

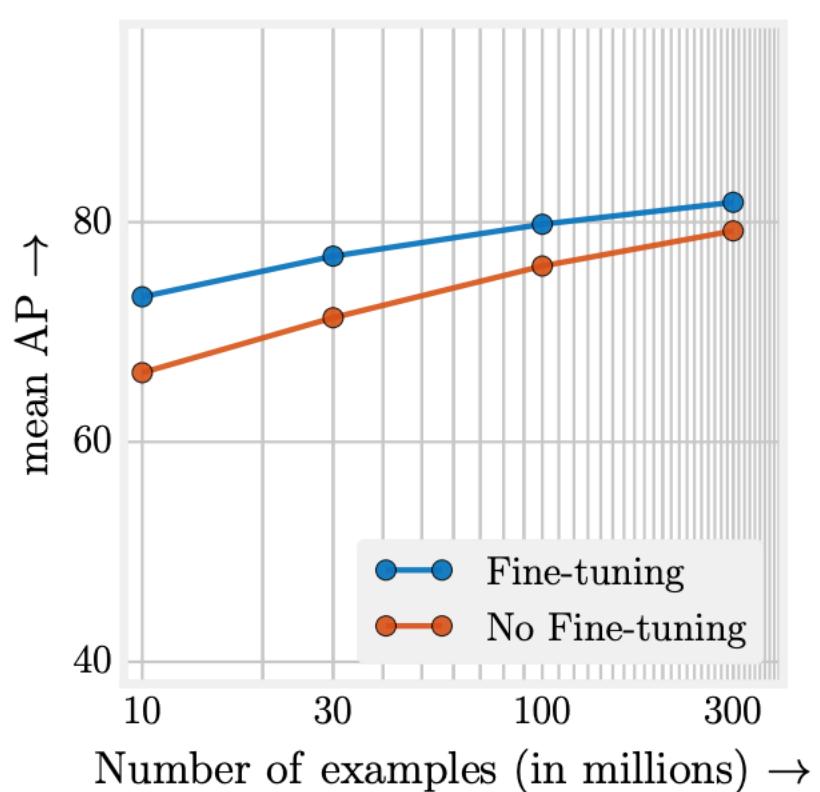
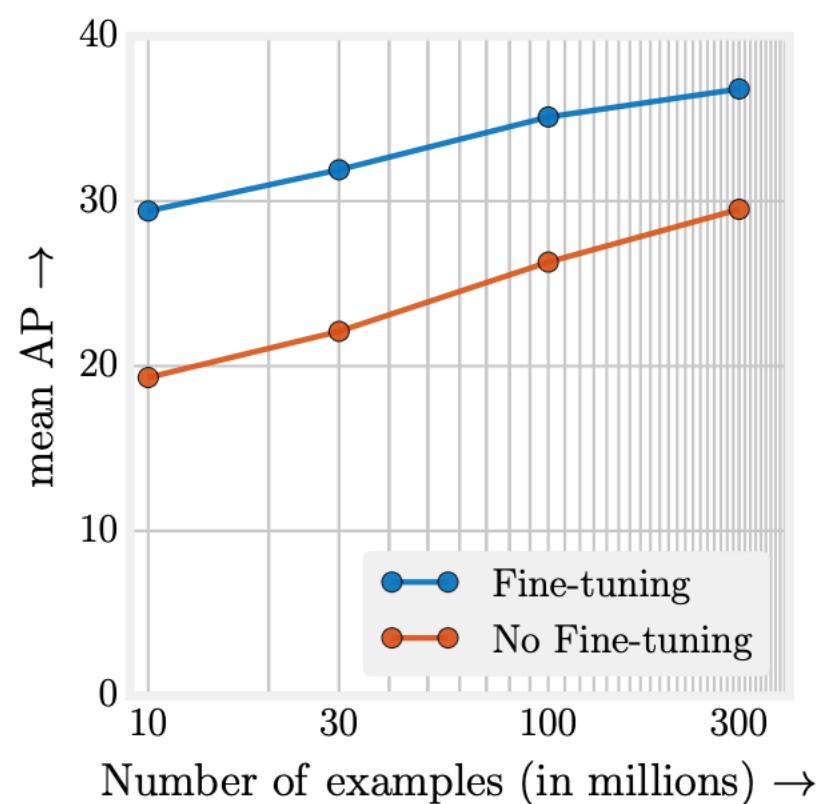
# Big-O Complexity Chart

Horrible Bad Fair Good Excellent



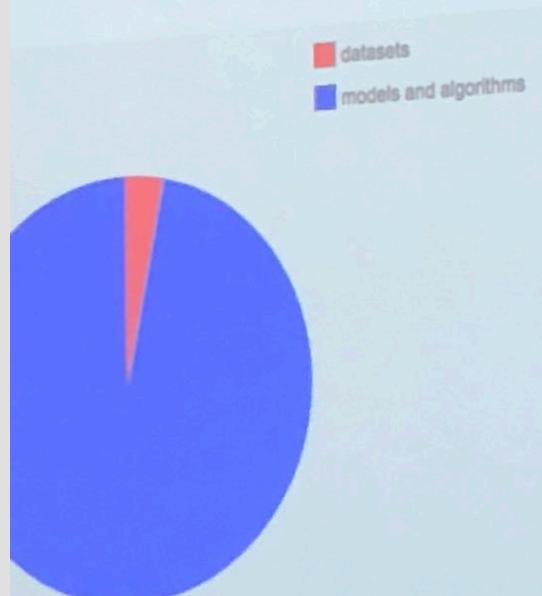
# Revisiting Unreasonable Effectiveness of Data in Deep Learning Era

Chen Sun<sup>1</sup>, Abhinav Shrivastava<sup>1,2</sup>, Saurabh Singh<sup>1</sup>, and Abhinav Gupta<sup>1,2</sup>



## Amount of lost sleep over...

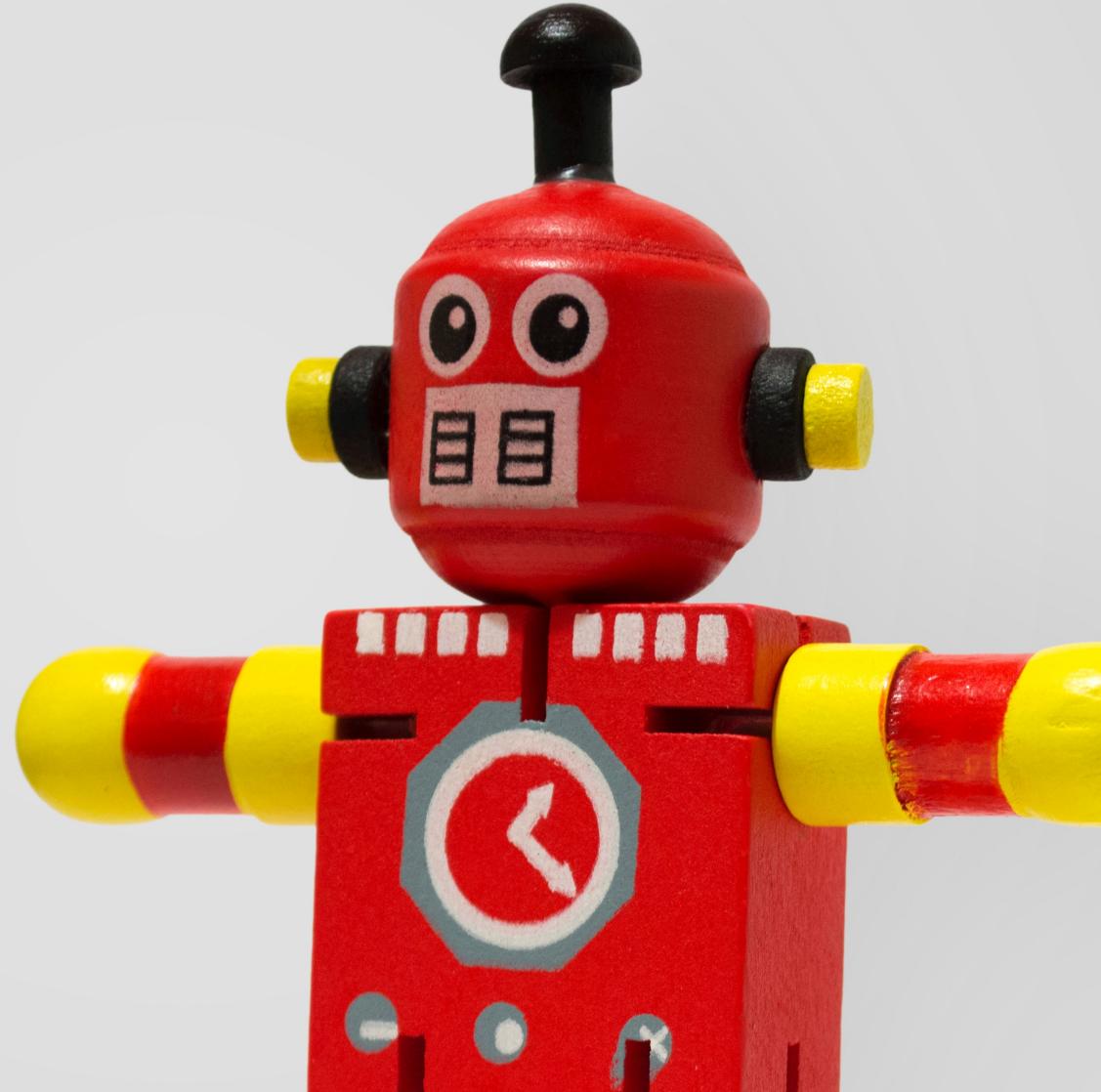
PhD



Tesla



# Scale is bad



# Scale is bad

AI models either

- Replace labor humans would do
- Make new forms of labor possible

Both of these are most profitable at scale!

# Scale is bad

- Cathy O'Neil: “the three elements of a WMD: Opacity, **Scale**, and Damage”

# Scale is bad

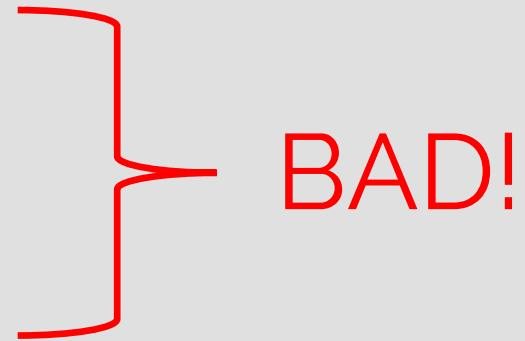
For AI companies bigger means

- Better performing models
- Monopolies on data/content
- Monopsonies on AI developers
- Leverage over regulators

# Scale is bad

For AI companies bigger means

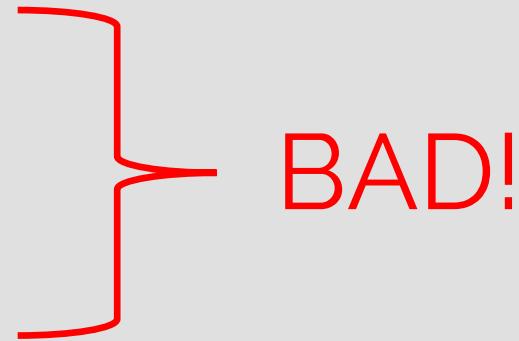
- Better performing models
- Monopolies on data/content
- Monopsonies on AI developers
- Leverage over regulators



# Scale is bad

For AI companies bigger means

- Better performing models
- Monopolies on data/content
- Monopsonies on AI developers
- Leverage over regulators



These incentives have always been present. But now there's no speed limit!

# What now?

There is a fundamental incentive for AI to scale

This will not be fixed by:

- Technical advances
- A more diverse industry
- Quantifying or removing bias in models/datasets

# What now?

AI as an industry **must** be treated as one with inherent risk.

- Regulation with teeth.
- Professional accountability.
- Default presumption of harm.

Examples

- Medicine
- Weapons

# AI Is Broken

Sophie Searcy

web: [soph.info](http://soph.info)

github: [@artificialsoph](https://github.com/artificialsoph)

twitter: [@artificialsoph](https://twitter.com/artificialsoph)

