
# CSCE 585: Machine Learning Systems

## Lecture 5: Machine Learning Systems in Production

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# Okay, let's step back and see where we are!

CSCE 585

LECTURES PROJECTS RESOURCES POLICIES PIAZZA

## Lectures

Lecture recordings are available on YouTube.

Tutorials are available on GitHub.

**Lecture 1: Reconciling Accuracy, Cost, and Latency of Inference Serving Systems**

**tl;dr:** This lecture reviews three related works out of AISys lab to set the context for the course and will be served as an example of MLSys research.

**Lecture 2: Machine Learning Systems: Course Overview**

**tl;dr:** This lecture reviews a brief overview of the course, its requirements, learning goals, policies, and expectations.

**Lecture 3: How to Read an MLSys Paper?**

**tl;dr:** In this lecture, we discuss a systematic approach for understanding, both high-level ideas and technical details in MLSys papers.

**Lecture 4: Designing and Motivating (ML) Systems Experiments**

**tl;dr:** This lecture offers students both theoretical understanding and practical guidance by using InferLine as a concrete example, while giving them a clear roadmap for how to motivate their own projects experimentally.

# ML in research vs. production

This part of lecture is mainly adopted from CS 329S: Machine Learning Systems Design at Stanford

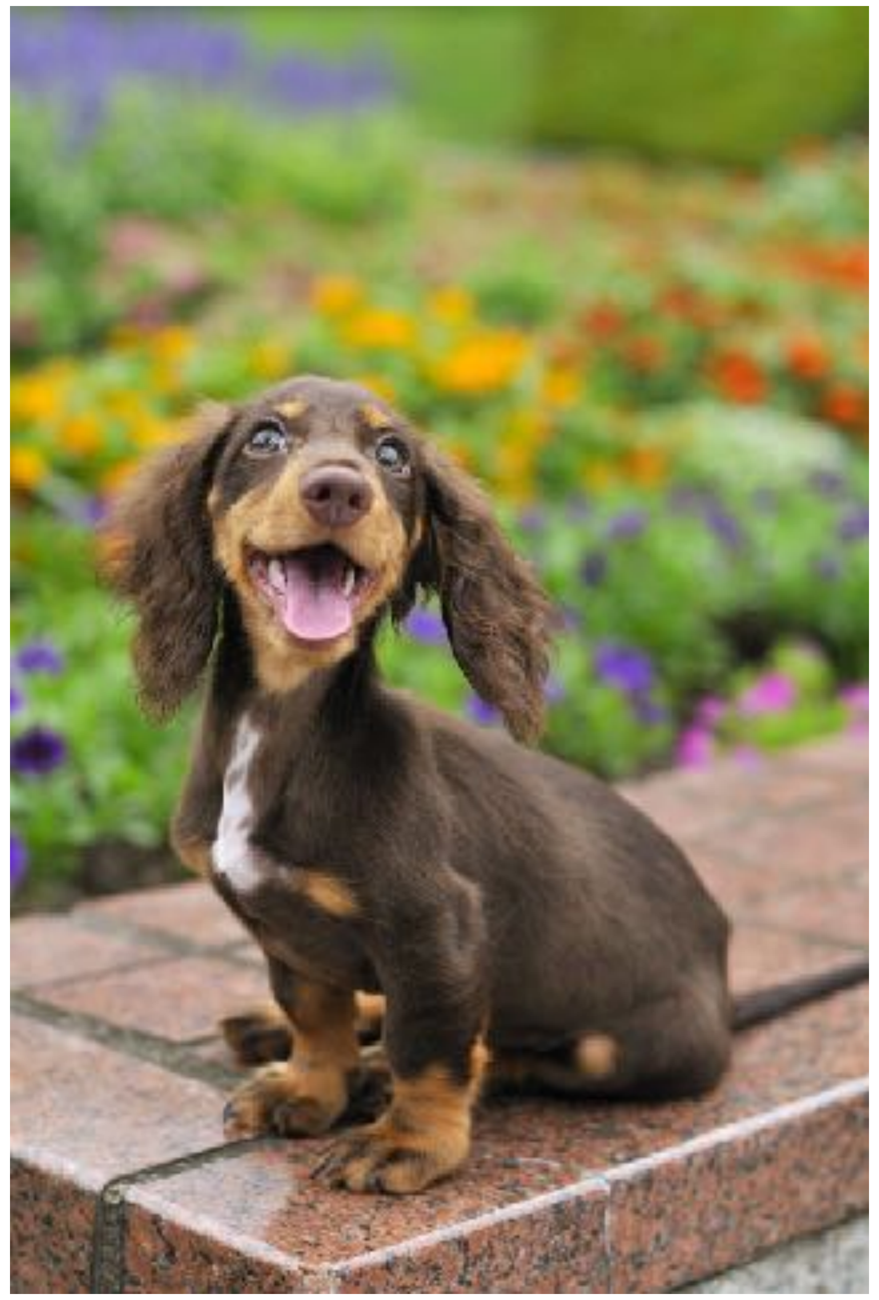
# ML in research vs. in production

| | Research | Production |
|---|---|---|
| Objectives | Model performance* | Different stakeholders have different objectives |

“*” It’s actively being worked. See Utility is in the Eye of the User: A Critique of NLP Leaderboards (Ethayarajh and Jurafsky, EMNLP 2020)

# Stakeholder objectives

**ML team**
highest accuracy



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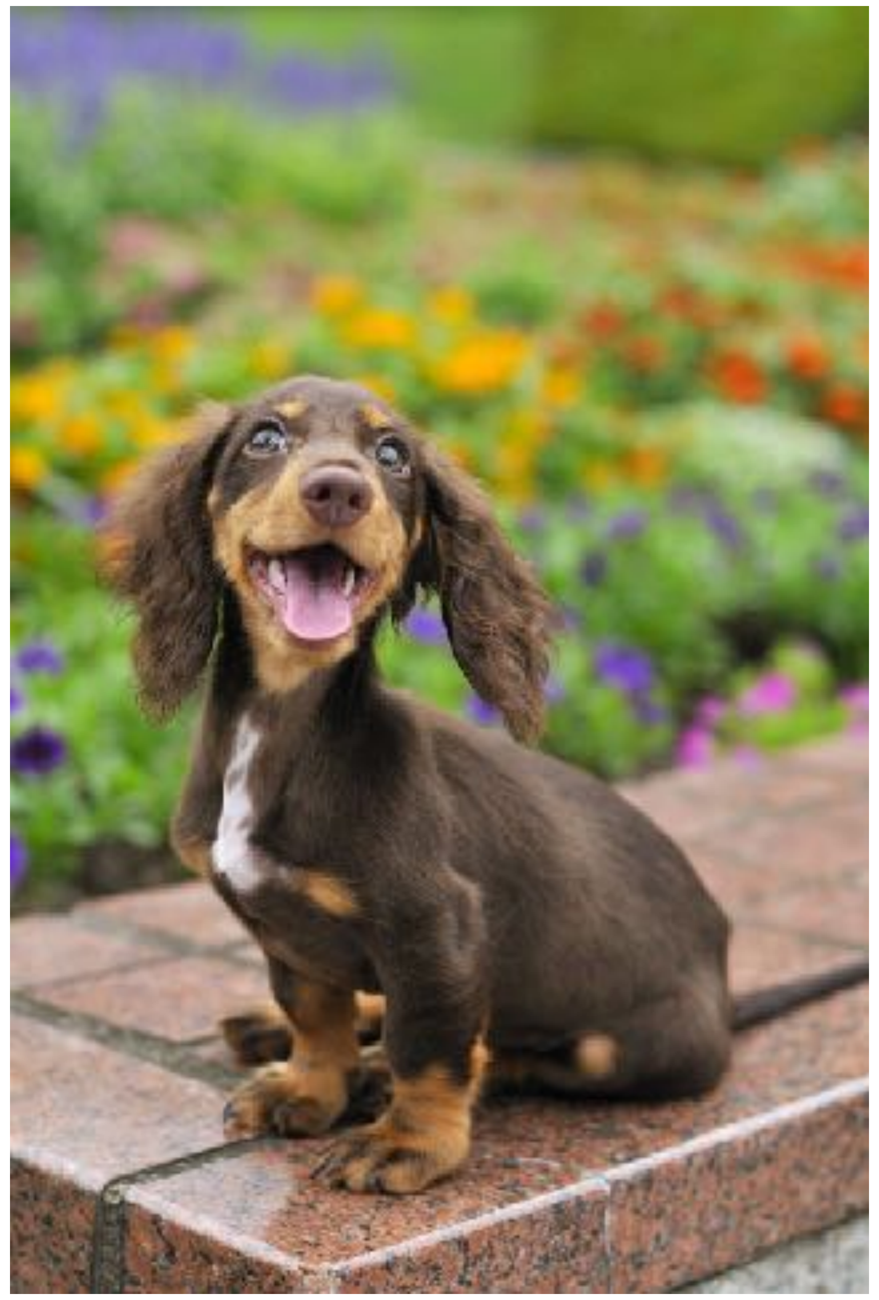

**Sales**
sells more ads

# Stakeholder objectives

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**Sales**
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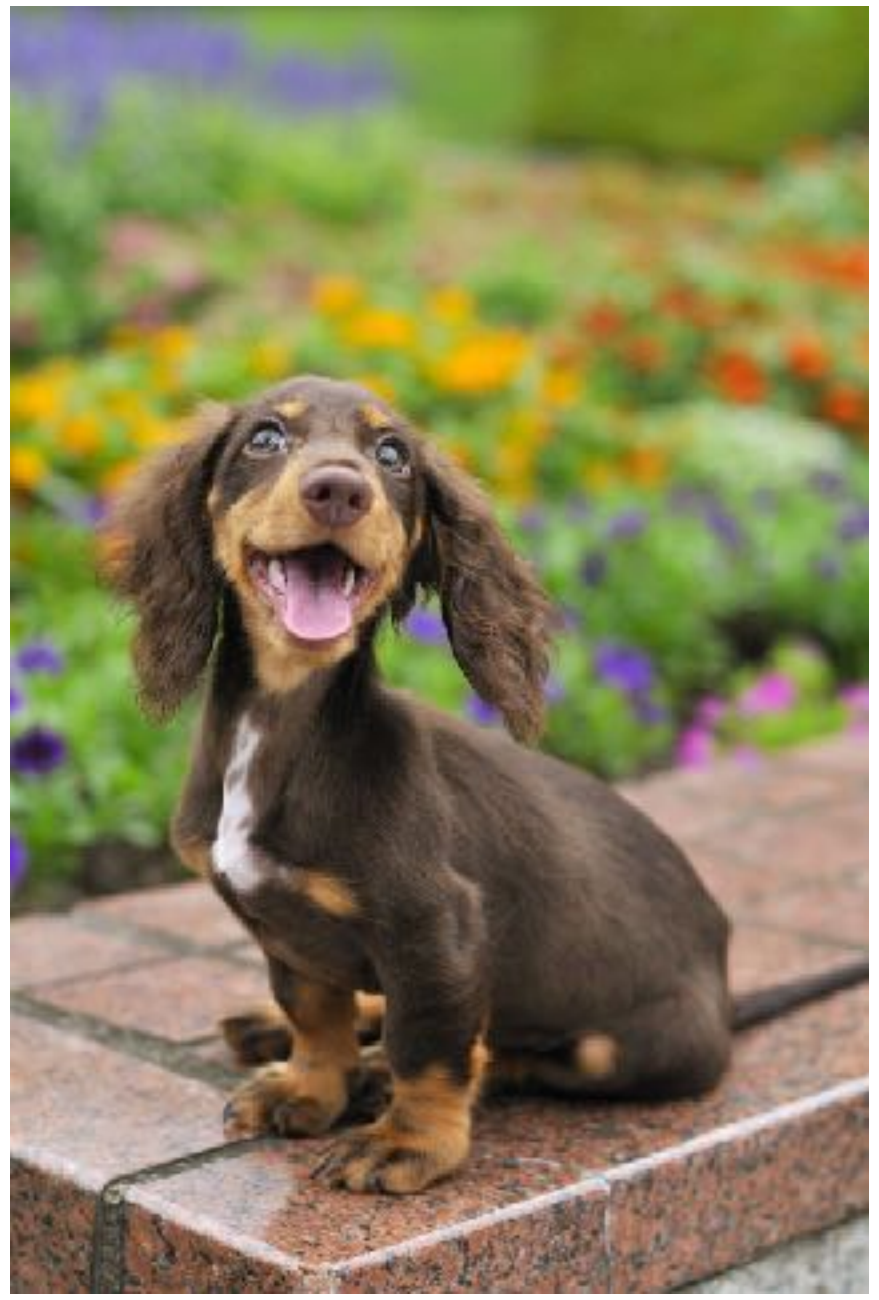
**Product**
fastest inference



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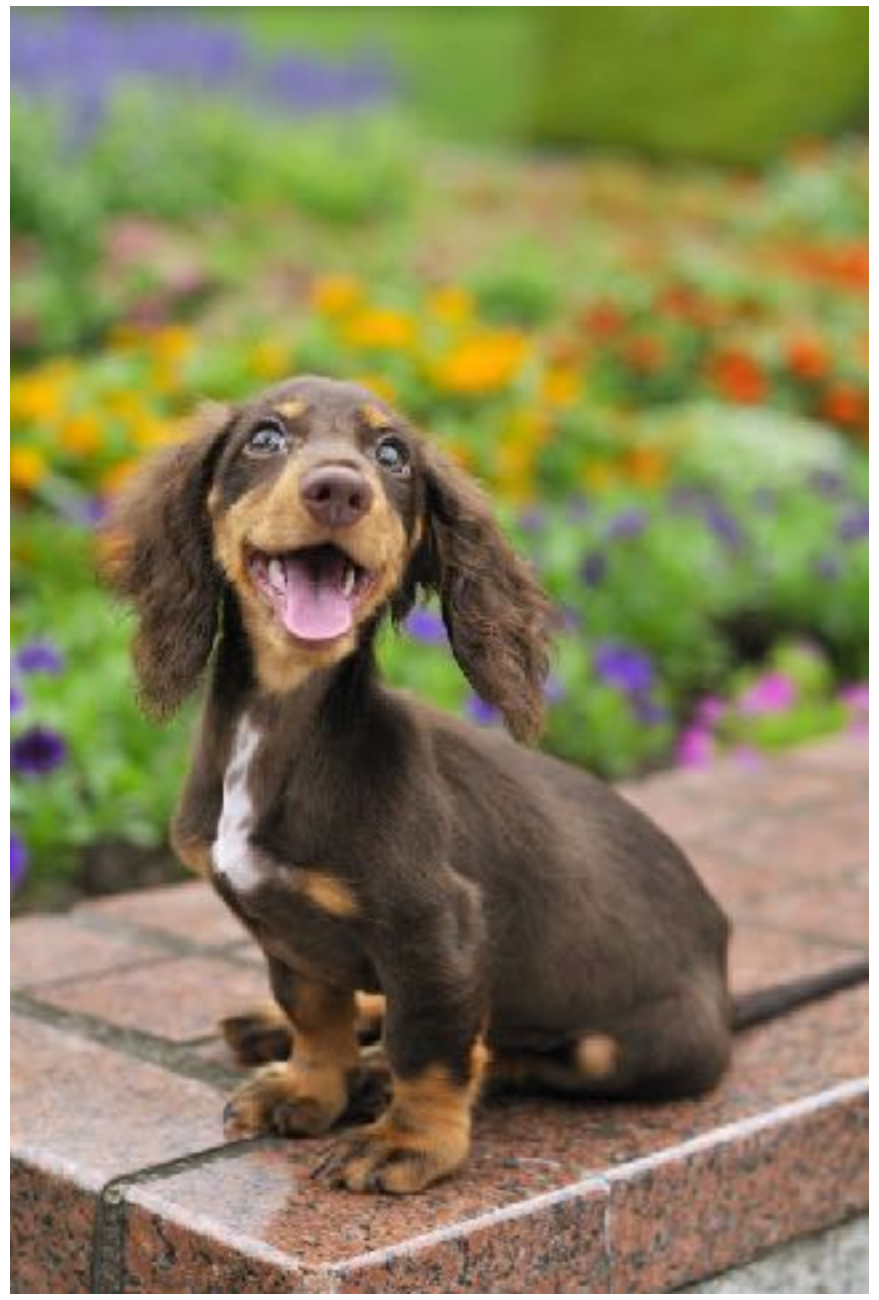
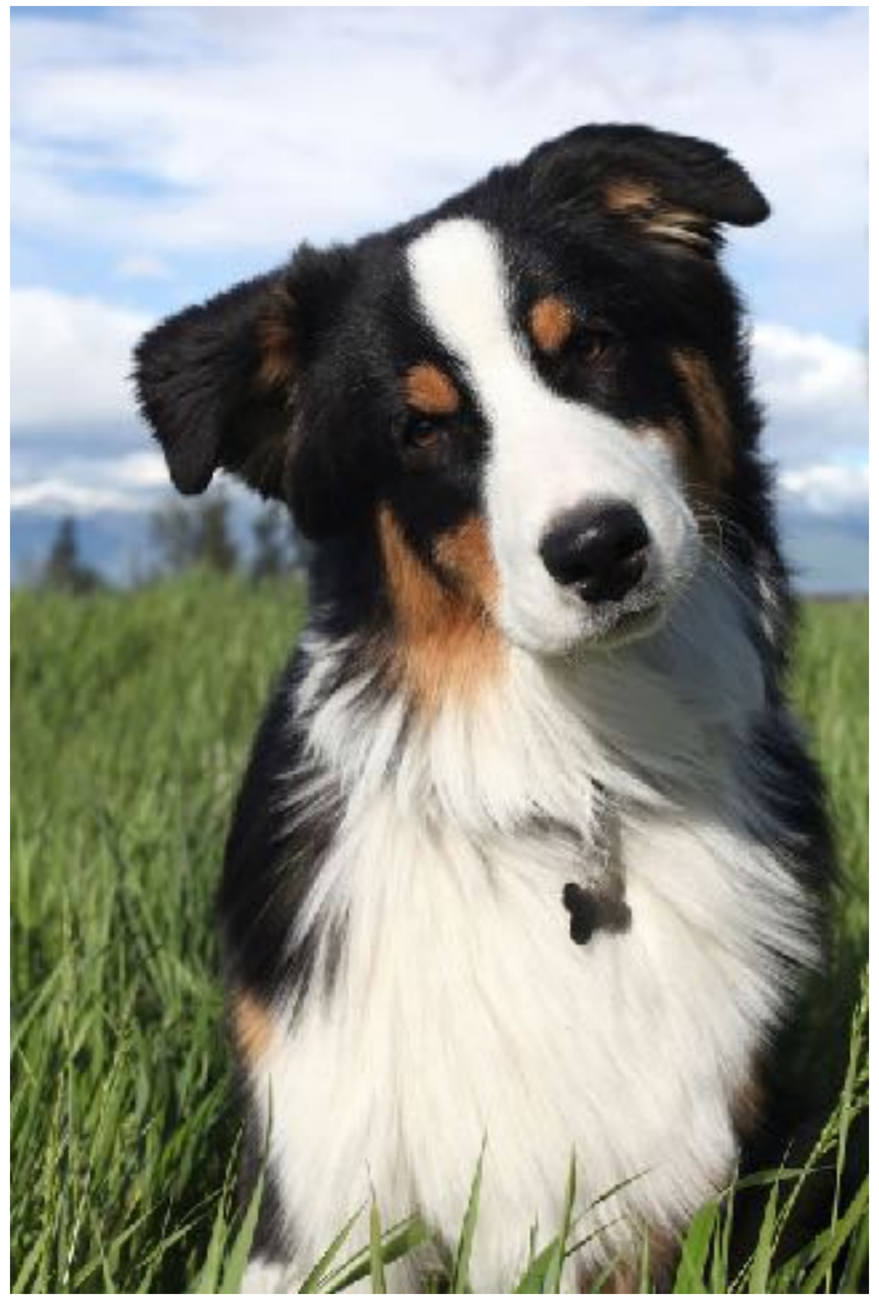


**Sales**
sells more ads

**Product**
fastest inference

**Manager**
maximizes profit
= laying off ML teams



# Computational priority

| | **Research** | **Production** |
|---|---|---|
| Objectives | Model performance | Different stakeholders have different objectives |
| Computational priority | Fast training, high throughput | Fast inference, low latency |

generating predictions

# Latency matters

Latency 100 -> 400 ms reduces searches 0.2% - 0.6% (2009)

30% increase in latency costs 0.5% conversion rate (2019)

- **Latency: time to move a leaf**
- **Throughput: how many leaves in 1 sec**

- Real-time: low latency = high throughput
- Batched: high latency, high throughput

# ML in research vs. in production

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| Data | Static | Constantly shifting |

# Data

| Research | Production |
| --- | --- |
| ● Clean<br>● Static<br>● Mostly historical data | ● Messy<br>● Constantly shifting<br>● Historical + streaming data<br>● Biased, and you don’t know how biased<br>● Privacy + regulatory concerns |

THE COGNITIVE CODER

By Armand Ruiz, Contributor, InfoWorld | SEP 26, 2017 7:22 AM PDT

# The 80/20 data science dilemma

Most data scientists spend only 20 percent of their time on actual data analysis and 80 percent of their time finding, cleaning, and reorganizing huge amounts of data, which is an inefficient data strategy

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| Fairness | Good to have (sadly) | Important |

# Fairness



The Berkeley study found that both face-to-face and online lenders rejected a total of 1.3 million creditworthy black and Latino applicants between 2008 and 2015. Researchers said they believe the applicants "would have been accepted had the applicant not been in these minority groups." That's because when they used the income and credit scores of the rejected applications but deleted the race identifiers, the mortgage application was accepted.

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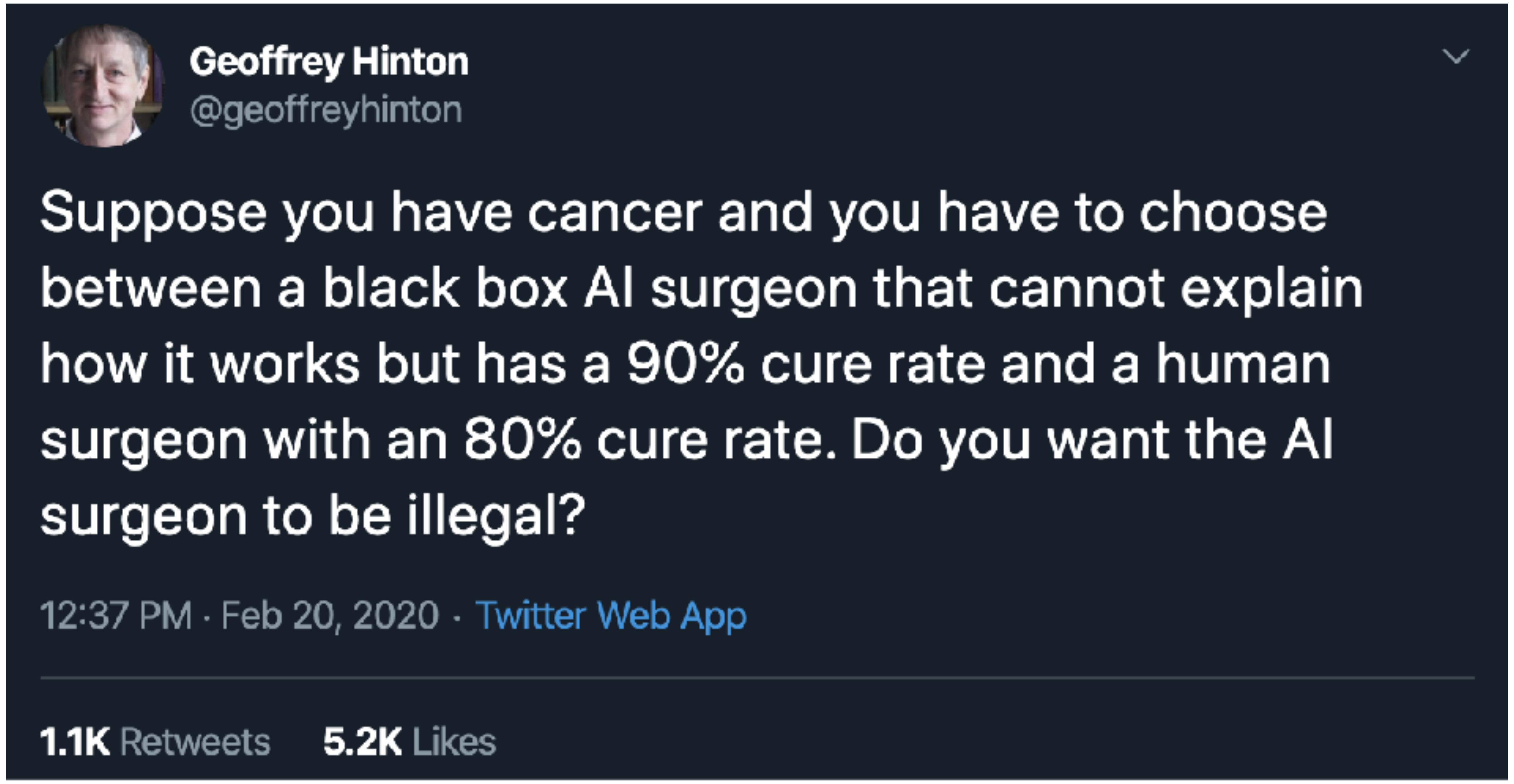
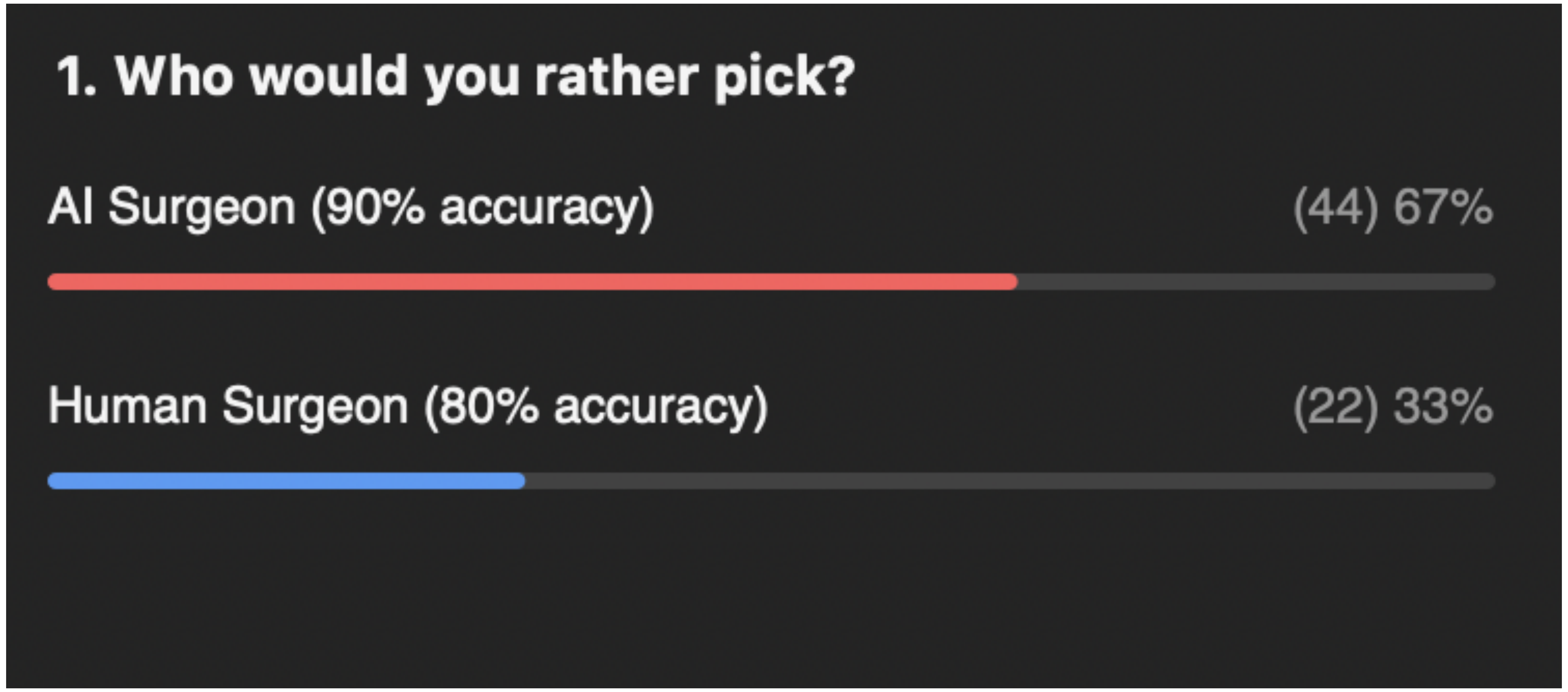
| Interpretability* | Good to have | Important |

# Interpretability




Result from the Zoom poll



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# ML systems vs. traditional software

Software 1.0 vs Software 2.0

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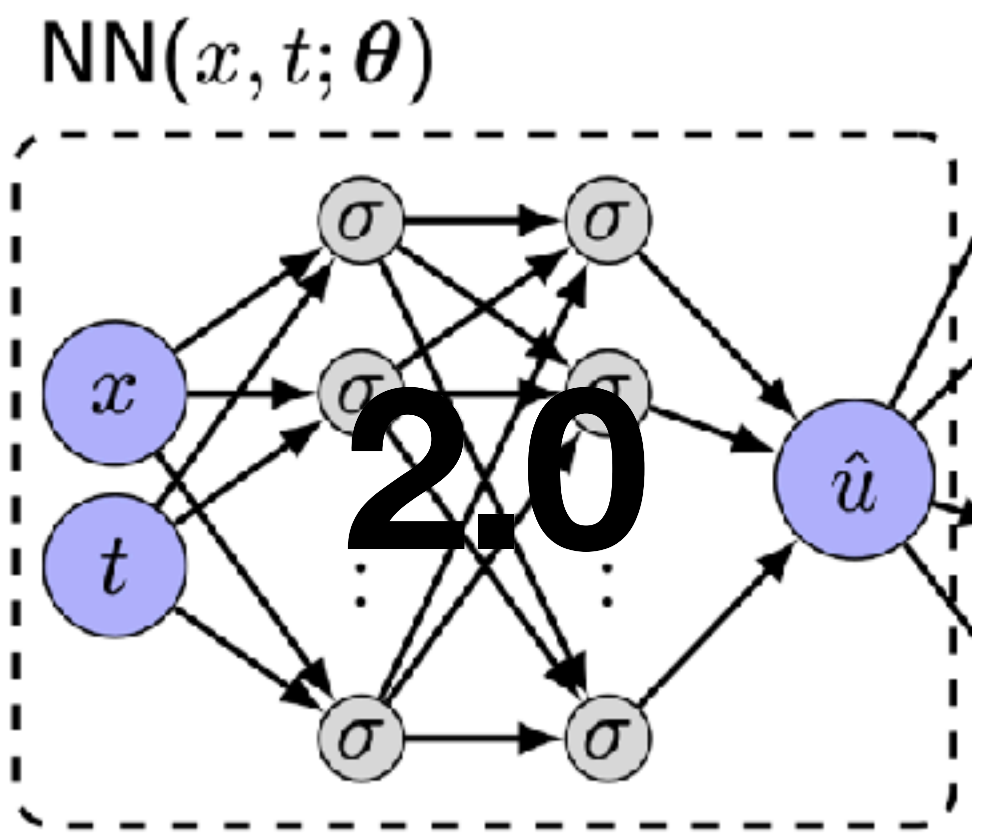
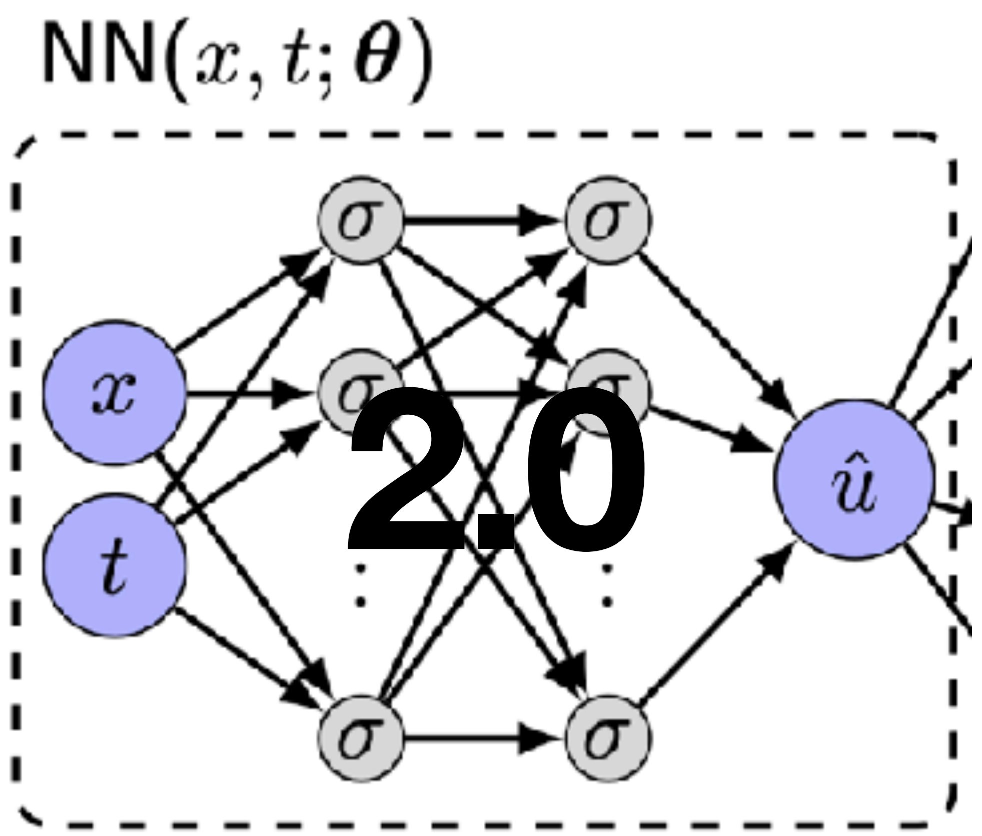



- Written in code (C++, ...)
- Requires domain expertise
  1. Decompose the problem
  2. Design algorithms
  3. Compose into a system

- Written in terms of a neural network model with
  - A model architecture
  - Weights that are determined using optimization

https://medium.com/@karpathy/software-2-0-a64152b37c35

# Software 1.0 vs Software 2.0

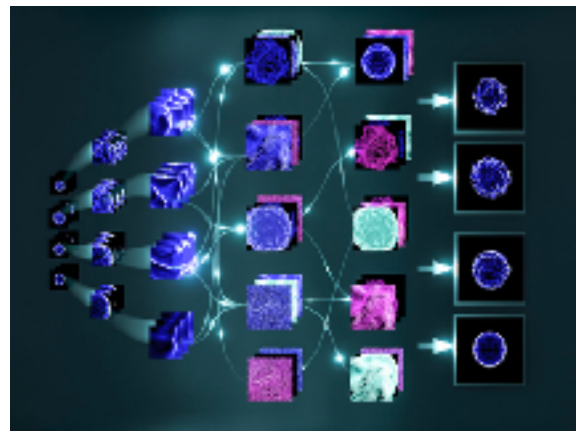
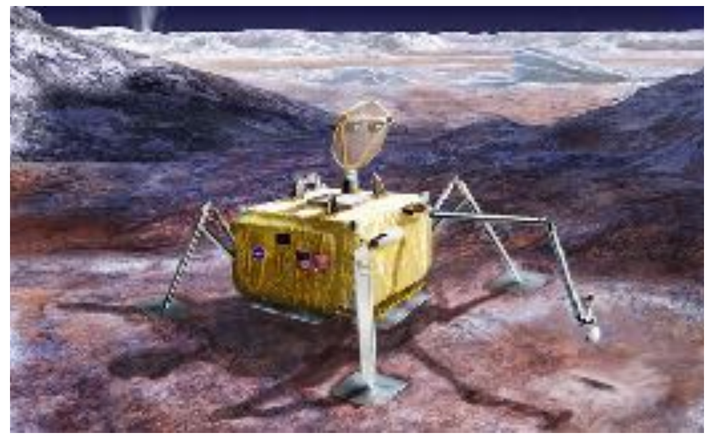

- **Input**: Algorithms in code
- **Compiled to**: Machine instructions


- **Input**: Training data
- **Compiled to**: Learned parameters

https://medium.com/@karpathy/software-2-0-a64152b37c35

# Software 1.0 vs Software 2.0




AI for Social Good

- **Easier to build and deploy**
  - Build products faster
  - Predictable runtimes and memory use: easier qualification

- A **wide range of applications** from self-driving cars, to game, healthcare, robotics, space, and social good.
- **1000x Productivity**: Google shrinks language translation code from 500k LoC to 500

https://jack-clark.net/2017/10/09/import-ai-63-google-shrinks-language-translation-code-from-500000-to-500-lines-with-ai-only-25-of-surveyed-people-believe-automationbetter-jobs/

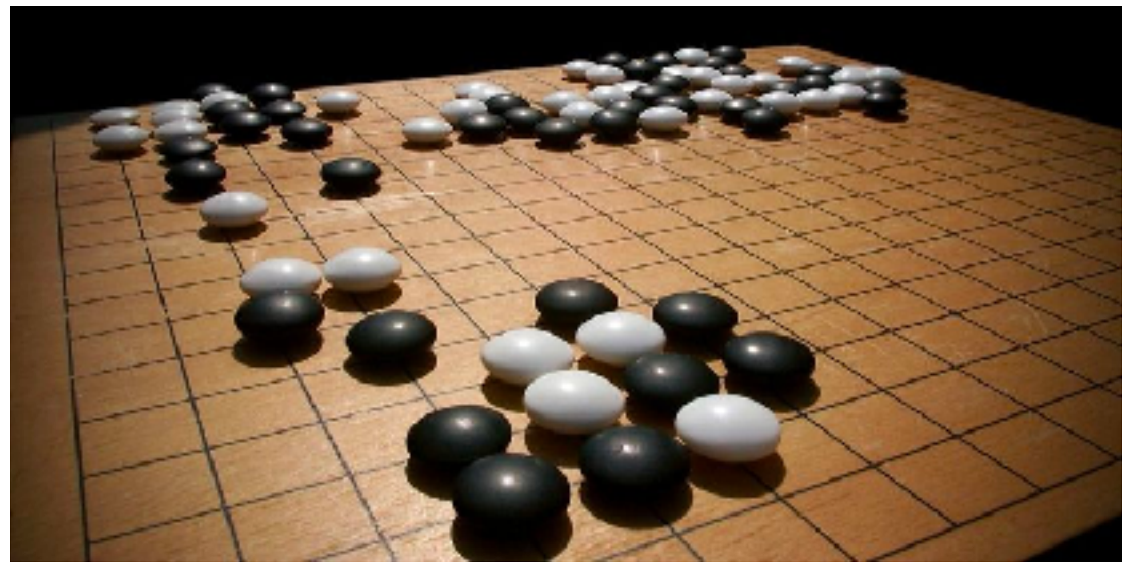
https://ai.google/social-good/

# What is going on in this mad era of AI/ML!

## It’s incredible, isn’t it?

Incredible advances in:

1. Image Recognition (ImageNet + Deep Learning)
2. Reinforcement Learning (DeepMind AlphaGo Zero)
3. Natural Language Processing (GPT-3)



# Traditional software

**Separation of Concerns** is a design principle for separating a computer program into distinct components such that each component addresses a separate concern

- Code and data are separate
    - Inputs into the system shouldn't change the underlying code

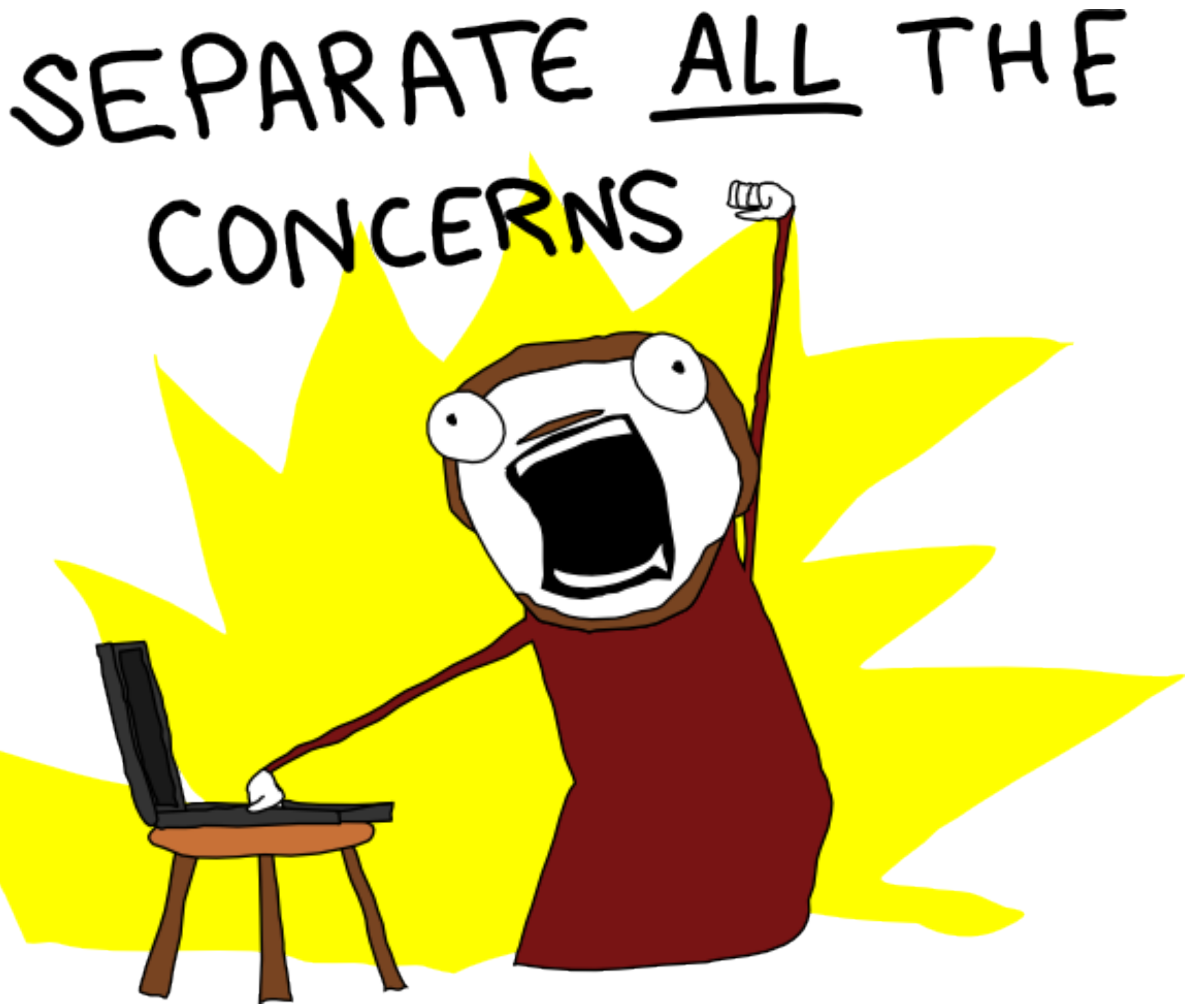



Image by [Arda Cetinkaya](#)

# ML systems

- Code and data are tightly coupled
    - ML systems are part code, part data
- Not only test and version code, need to $\underbrace{\text{test and version data}}_{\text{the hard part}}$ too

# ML System: version data

- Line-by-line diffs like Git doesn't work with datasets
- Can't naively create multiple copies of large datasets
- How to merge changes?

# ML System: test data

- How to test data correctness/usefulness?
- How to know if data meets model assumptions?
- How to know when the underlying data distribution has changed? How to measure the changes?
- How to know if a data sample is good or bad for your systems?
    - Not all data points are equal (e.g. images of road surfaces with cyclists are more important for autonomous vehicles)
    - Bad data might harm your model and/or make it susceptible to attacks like data poisoning attacks

# Engineering challenges with large ML models

- Too big to fit on-device
- Consume too much energy to work on-device
- Too slow to be useful
  - Autocompletion is useless if it takes longer to make a prediction than to type
- How to run CI/CD tests if a test takes hours/days?

# ML production myths

# Myth #1: Deploying is hard

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Deploying is easy. Deploying reliably is hard

# Myth #2: You only deploy one or two ML models at a time

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Booking.com: 150+ models, Uber: thousands

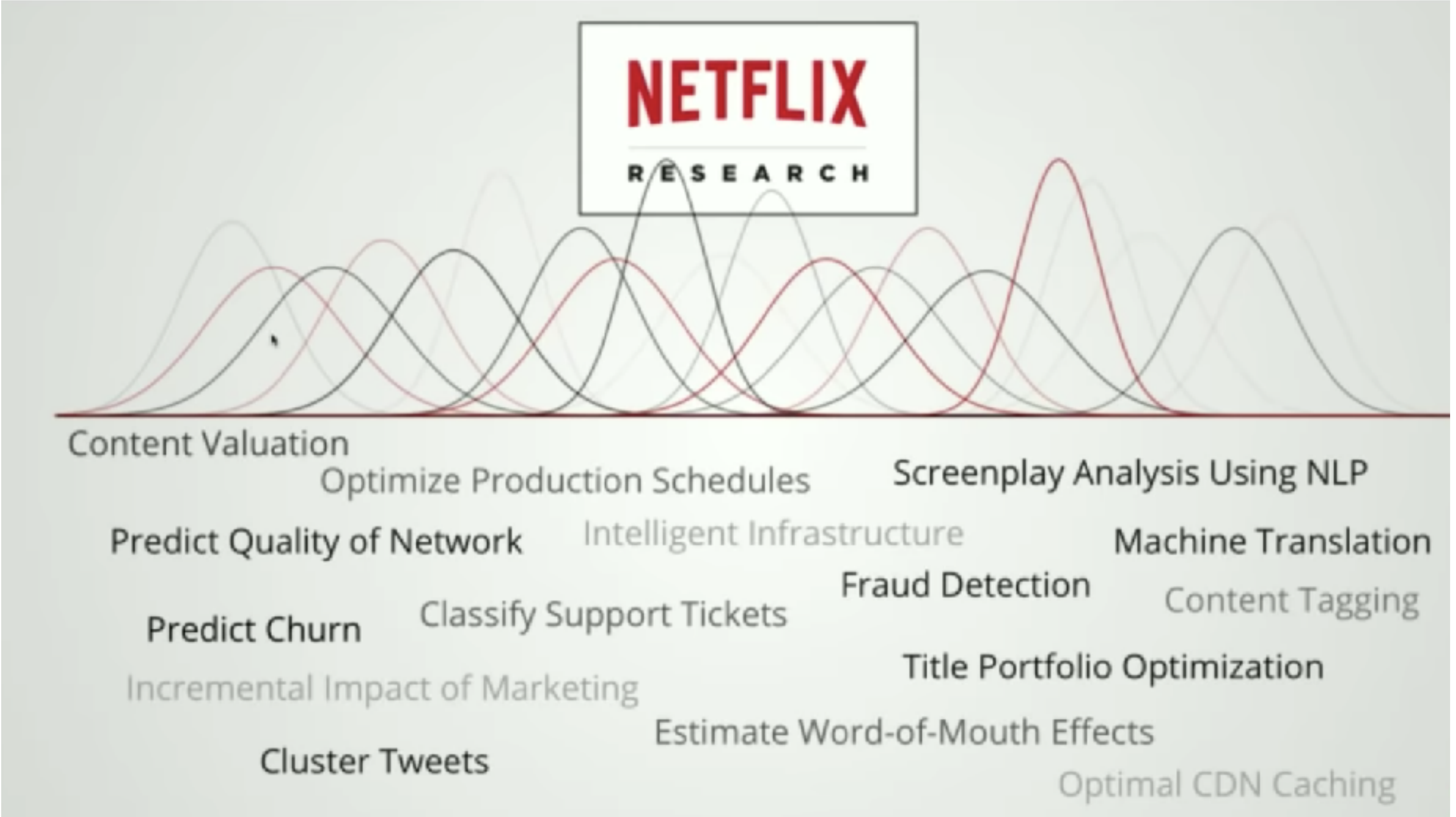





Image from Ville Tuulos (Netflix, Outerbounds)

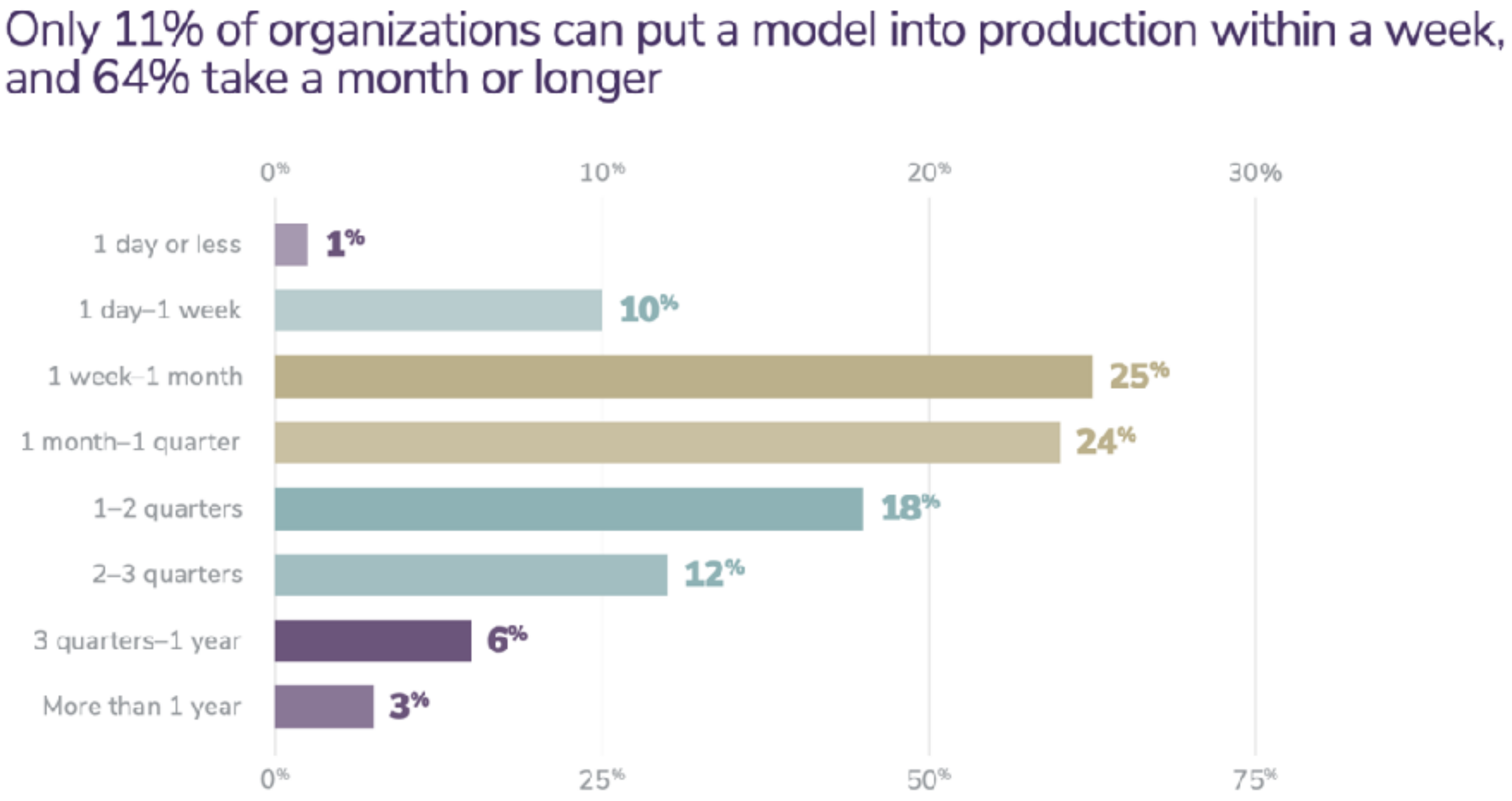
# Myth #3: You won’t need to update your models as much

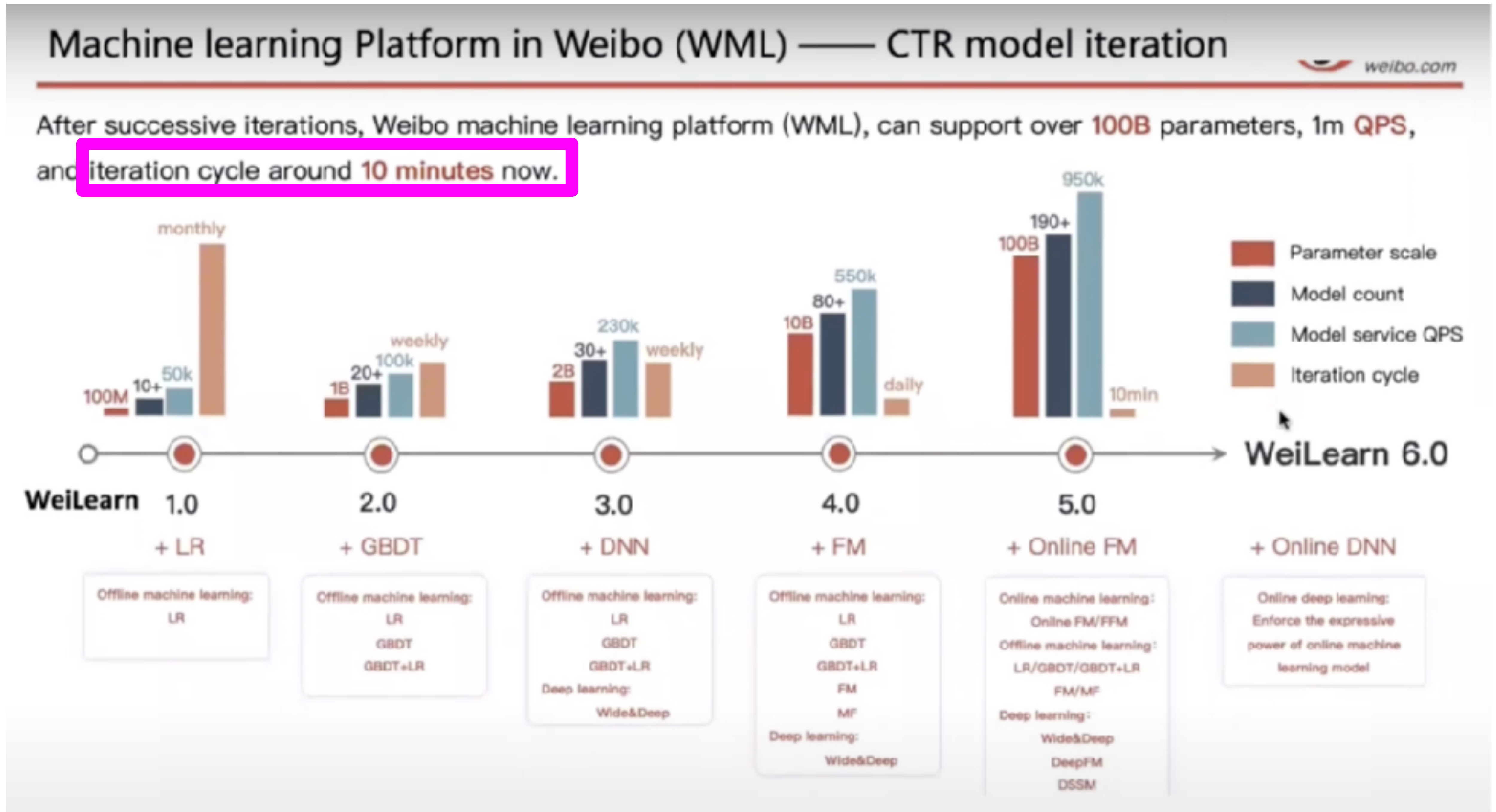
# DevOps: Pace of software delivery is accelerating

- Elite performers deploy **973x** more frequently with **6570x** faster lead time to deploy (Google DevOps Report, 2021)
- DevOps standard (2015)
  - Etsy deployed 50 times/day
  - Netflix 1000s times/day
  - AWS every 11.7 seconds

# DevOps to MLOps: Slow vs. Fast

We'll learn how to do minute-iteration cycle!






Left image from Algorithmia | Right image: [Machine learning with Flink in Weibo]() (Qian Yu, QCon 2019)

# Accelerating ML Delivery

# ML + DevOps = 🚀

# Myth #4: ML can magically transform your business overnight

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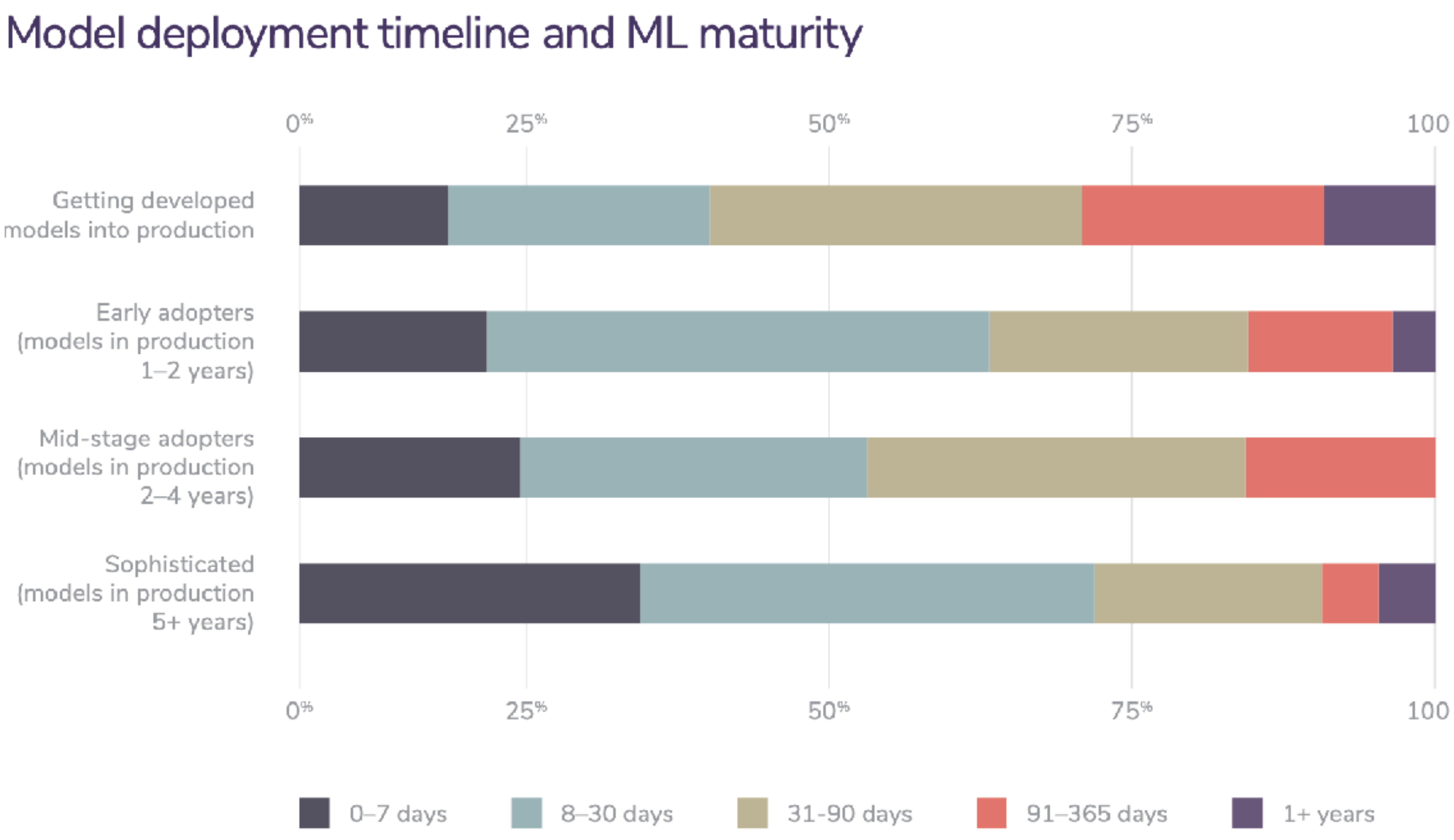
Magically: possible
Overnight: no

# Efficiency improves with maturity




2020 state of enterprise machine learning (Algorithmia, 2020)

# ML engineering is more engineering than ML

MLEs might spend most of their time:

- wrangling data
- understanding data
- setting up infrastructure
- deploying models

instead of training ML models

# Myth #5: Most ML engineers don’t need to worry about scale

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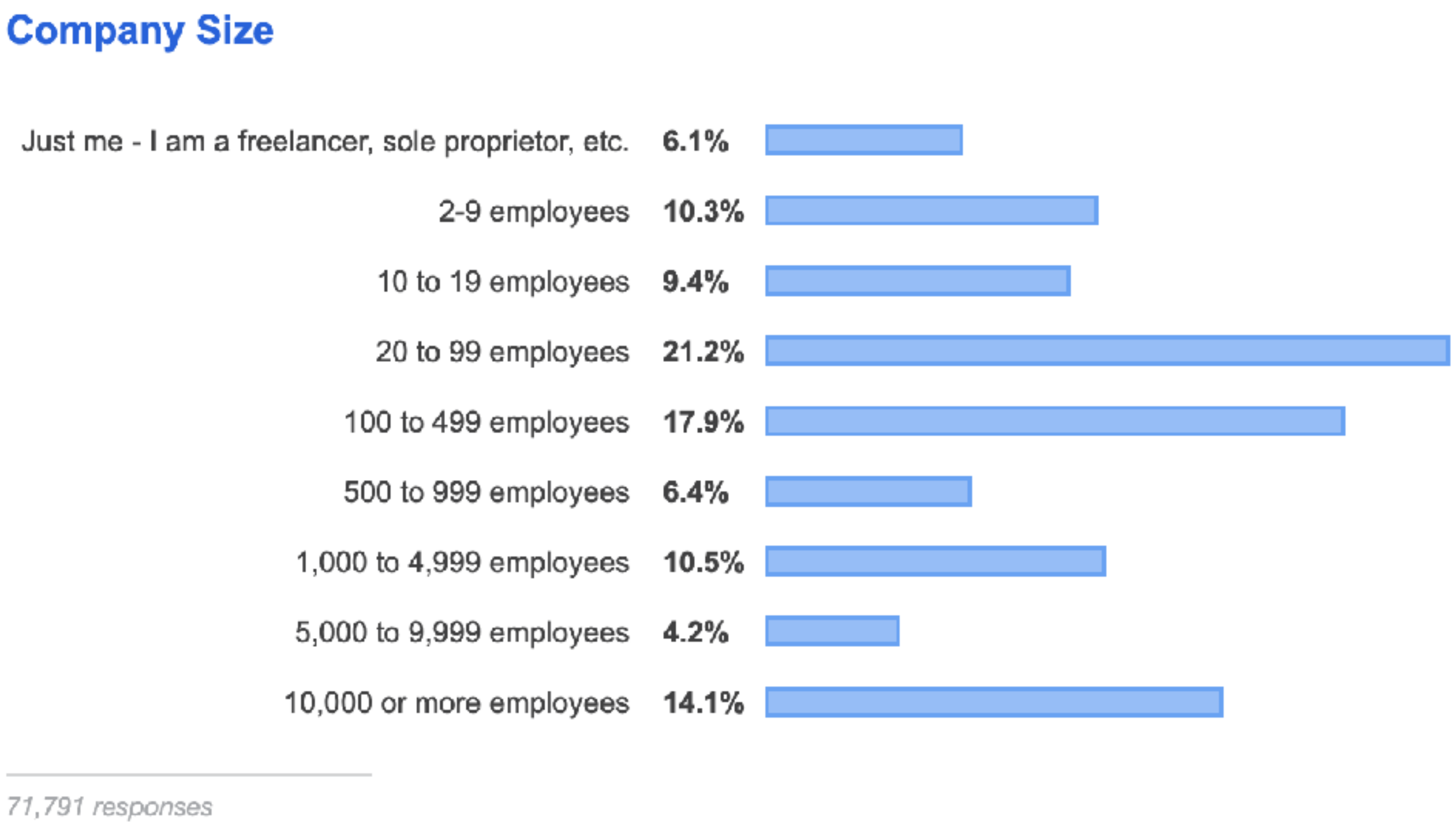


[StackOverflow Developer Survey 2019]