

# Machine Learning Infrastructure - The "hidden figure" of applied Al

Jack Song / Feb 15th, 2023 / CMU Applied Al Class

# Hello!

### I am Jack Song

- → Engineering Director of Machine Learning Infrastructure , Airbnb
- Previous VP of Data Engineering and ML platform, Mastercard

#### Tips for the talk

- → Github project for useful resource links is here <a href="https://github.com/jack1981/evoluation\_machine\_learning\_infra/blob/main/READ\_ME.md">https://github.com/jack1981/evoluation\_machine\_learning\_infra/blob/main/READ\_ME.md</a>
- → Learn the tips maybe help you
- → Have fun with fun of fact :)



Helpful tips for study and career



Do you know something?

# The story of 'Hidden Figures'



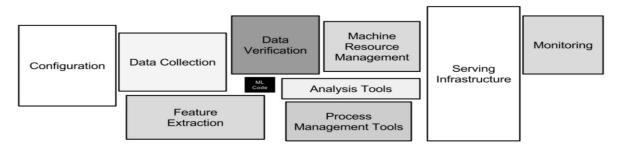
"Hidden Figures" (2016 movie) is a title that's rich with meaning. It refers group of women, who were doing work for many years and people didn't see them; There were parts of this whole endeavor of the space program that were very high-profile like the astronauts, test pilots, and Mission Control; but we didn't really understand how much work went on behind-the-scenes to make that successful. These women were very much part of that. Their numbers were the bedrock of so much of the work that was done in American aeronautics in the 19th century

### The truth behind 'Applied AI'

Hidden Technical Debt

#### **Hidden Technical Debt in Machine Learning Systems**

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips {dsculley, gholt, dgg, edavydov, toddphillips}@google.com Google, Inc.





Learning happens mainly at the workplace: 80% compared to 20% in school.

# 1

## Machine Learning Infrastructure

The "Hidden Figure" of Applied Al

#### The rise of Machine learning Infrastructure

- → Venturebeat published infrastructure 3.0 for Al revolution.
- → Michelangelo: Uber's Machine Learning Platform
- → Bighead: Airbnb's End-to-End Machine Learning Infrastructure



- Data Acquisition, Preparation, Validation
- Feature Engineering
- Training
- Model Evaluation and Tuning
- Deployment
- Inference and Monitoring



Do you know why Uber named it "Michelangelo"?

#### **Glance of Industry ML Infra**

Research from ML Platform/Infra Meetup Club (M13)

Y: Home grown mostly N: Buy or OSS mostly

Steering Co	ommittee N	Member	
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Airbnb Uber

Cruise Netflix

Databricks Twitter

Dropbox Pinterest

Meta Lyft

Google

Intuit

ML Infra

**Engineers Size** 

Linkedin ML Infra Internal Users Size

25000 +

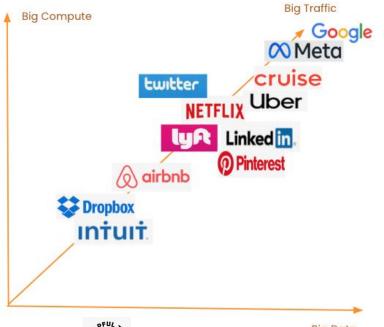
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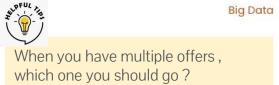
	Company	ML lifecycle Tooling /Platform	ML Framework	Distributed Computing	Cluster Management	Build Cloud/ Premise Infra	AI Hardware
	Google	Υ	Υ	Υ	Υ	Υ	Υ
	Meta	Υ	Υ	Υ	Υ	Υ	Ν
	Databricks	Υ	Υ	Υ	Υ	Ν	N
	Uber, Twitter, Cruise	Υ	N	N	Υ	Υ	N
-	<b>Airbnb</b> , Lyft, Netflix, Pinterest	Υ	N	N	Υ	N	N
+	Linkedin, Dropbox	Υ	N	N	N	N	N
	Intuit	N	Ν	N	Ν	Ν	Ν

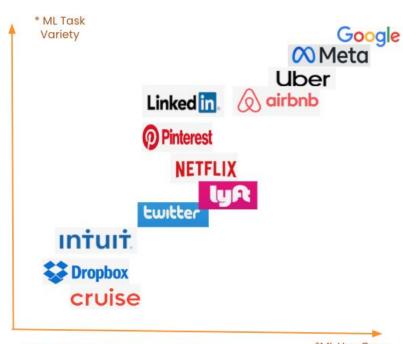


#### **Quadrant of ML Infra**

Research from ML Platform/Infra Meetup Club (M13)







\*ML Task Variety : Tabular , non structure, classical ML , deep learning ...

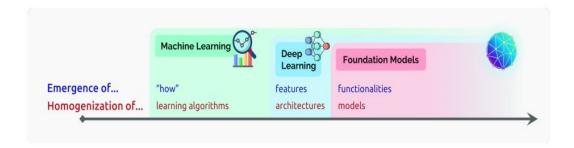
\*ML Use Case Diversity : ChatBot , Relevance , Personalization , Dynamic Pricing, Fraud detection , Risk assessment , Recommendation ... \*ML Use Case Diversity

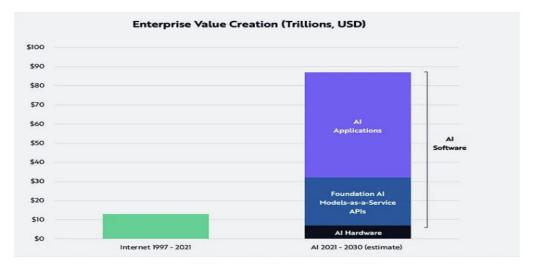
# 2

# The evolution of Machine Learning Infrastructure

- Foundation Models as a service
- Data Centric Al
- Open MLOps

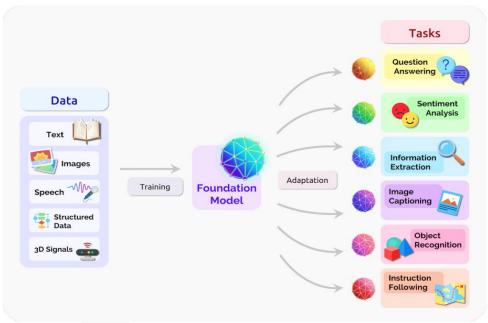
#### Foundation Models as a service







#### **Rise of Foundation Models**



A foundation model can centralize the information from all the data from various modalities. This one model can then be adapted to a wide range of downstream tasks.

~7%
Foundation Models
2022

~40% Foundation Models 2025



Applied AI will been impacted significantly due to rise and development of Foundation Models, lots of existing modeling approaches (including Deep Learning) will be replaced

#### Foundation Models – Large Language Model

**GPT** series

Unsupervised learning served as pre-training objective for supervised fine-tuned models, hence the name Generative Pre-training.

GPT 1 GPT 2 GPT 3 Instruct GPT ChatGPT

- 2018
- 117 million parameters
- Showed the power of generative pre-training
- NLP

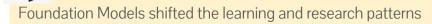
- 2019
- 1.5 billion parameters
- Unsupervised learning only
- showed better performance due to larger dataset and more parameters
- NLP+AIGC

- 2020
- 175 billion parameters
  - Incontext learning + few-shot learning
- NLP + AIGC+

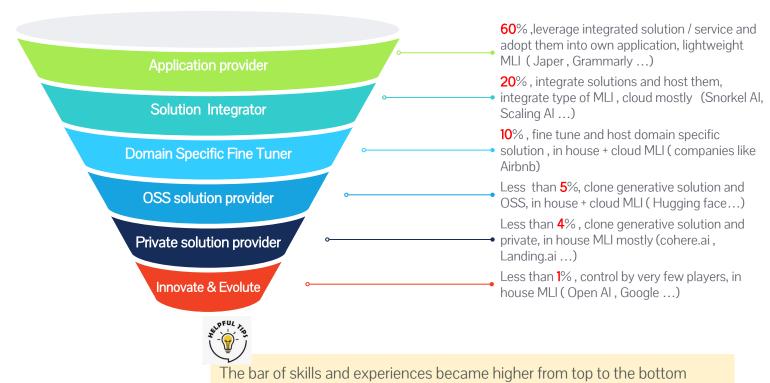
- 2022.01
- 175 billion+1.3 billion fine tune parameters
- Instruction Tune
  GPT 3 with
  zero-shot
  learning,\*RLHF
  and \*COT
- More truthful and less toxic
- NLP + AIGC+ (Code + Chat)

- 2022.12
- 175 billion + parameters
- Instruction tune
  Instruct GPT with
  human-generated
  prompts and
  example
  responses
- More Safety
- NLP + AIGC+ (Chat)

RLHF:reinforcement learning from human feedback COT:chain-of-thought



#### **Adoption patterns of Foundation Models**



#### **Data Centric AI**

Data is food for Al

Andrew Ng, pioneer of the data-centric Al philosophy

# More data beats clever algorithms, but better data beats more data

Peter Norvig, Distinguished Education Fellow at the Stanford Institute for Human-Centered Al



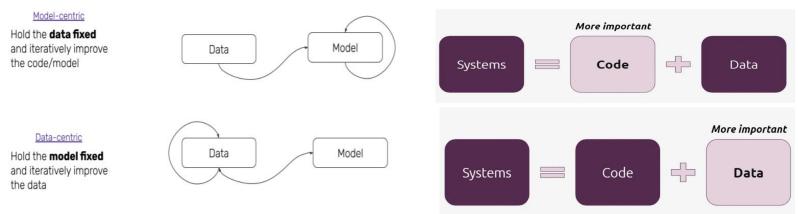
#### What is Data Centric Al?

A data-centric Al approach provides a systematic method for improving data, reaching a consensus on the data, and cleaning up inconsistent data.



#### Andrew NG's story:

The founder of the Google Brain research lab, co-founder of Coursera, and former chief scientist at Baidu, also the founder and CEO of Landing Al.



#### Call to action 1: Bring human in the loop

#### Training language models to follow instructions with human feedback

## Mentally scarred: Kenyan workers taught ChatGPT to recognize offensive text

Spare a thought for the workers who read the worst content scraped from the internet to keep you safe

A <u>Kahyanna Quach</u>

Pri 20 Jan 2023 14:15 UTC

OpenAI reportedly hired workers in Kenya – screening tens of thousands of text samples for sexist, racist, violent and pornographic content – to help make its ChatGPT model less toxic.

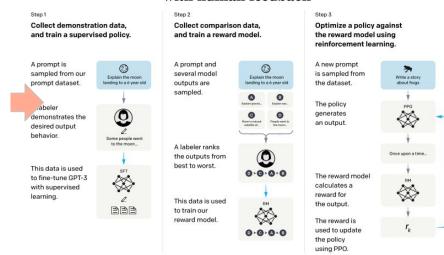
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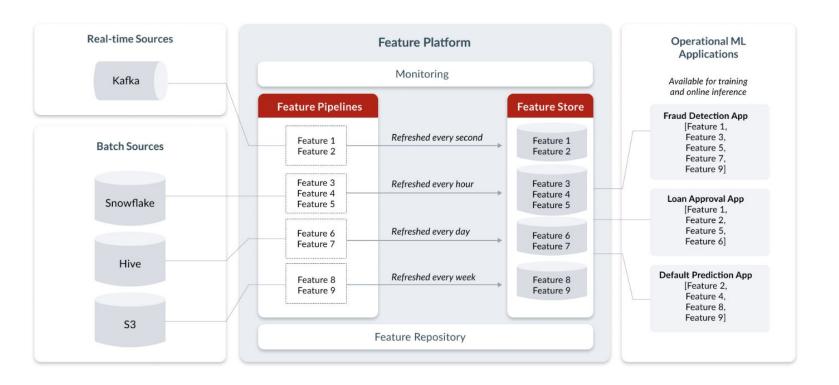


Labelers significantly prefer InstructGPT outputs over outputs from GPT-3. On our test set, outputs from the 1.3B parameter InstructGPT model are preferred to outputs from the 175B GPT-3, despite having over 100x fewer parameters. These models have the same architecture, and differ only by the fact that InstructGPT is fine-tuned on our human data. This result holds true even when we add a few-shot prompt to GPT-3 to make it better at following instructions. Outputs from our 175B InstructGPT are preferred to 175B GPT-3 outputs  $85 \pm 3\%$  of the time, and preferred  $71 \pm 4\%$  of the time to few-shot 175B GPT-3. InstructGPT models also generate more appropriate outputs according to our labelers, and more reliably follow explicit constraints in the instruction.

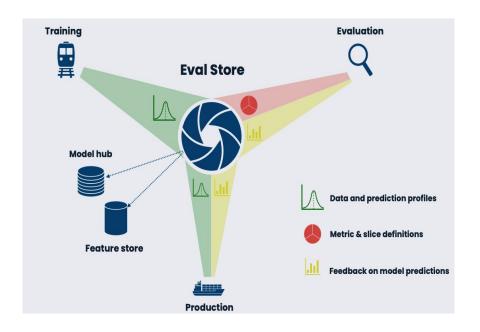


**RLHF** 

#### Call to action 2: Feature platform



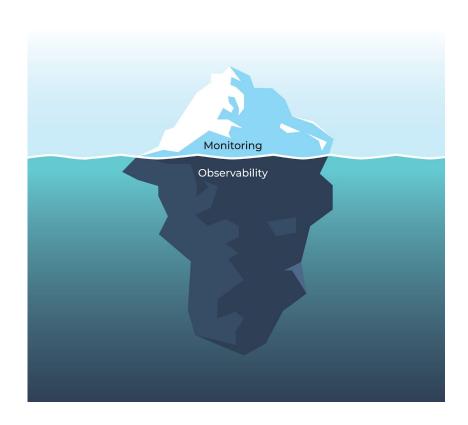
#### Call to action 3: Evaluation Store



A central place to store and query online and offline ground truth and approximate model quality metrics

- Reduce organization friction: Get stakeholders (ML Eng,DS, PM, etc) on the same page about metric and slice definitions
- Deploy models more confidently: Evaluate metrics and slices consistently in testing and prod. Make the metrics visible to stakeholders
- Catch production bugs faster: Catch degradations across any slice, and drill down to the data that caused the degradation
- Reduce data-related costs: Collect and label production data more intelligently
- Make your model better: Decide when to retrain. Pick the right data to retrain on.

#### Call to action 4: ML Observability



#### 4 Pillars of ML Observability

- Drift: Data Distribution Changes over lifetime of model
- **Performance Analysis:** Surfacing worst performing slices
- **Data Quality**: Ensure high quality inputs & outputs
- **Explainability**: Attribute why a certain outcome was made

#### **Open MLOps**

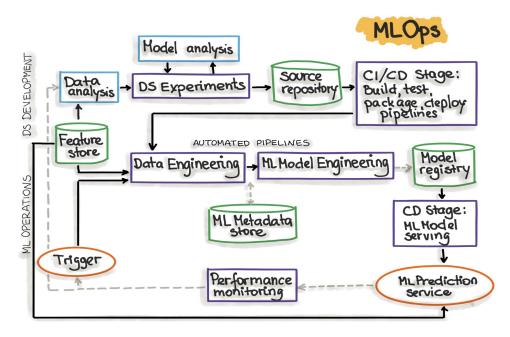
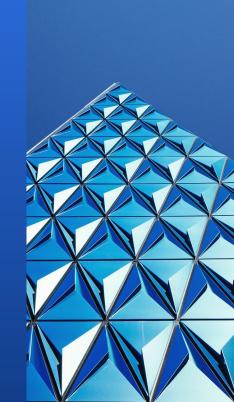
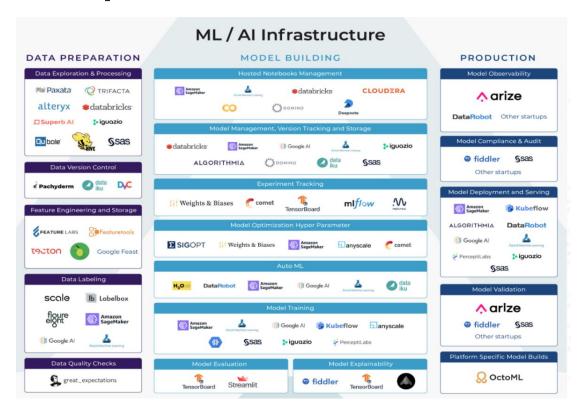


Figure adopted from "MLOps: Continuous delivery and automation pipelines in machine learning"



#### MLOps Infrastructure eco is very chaotic

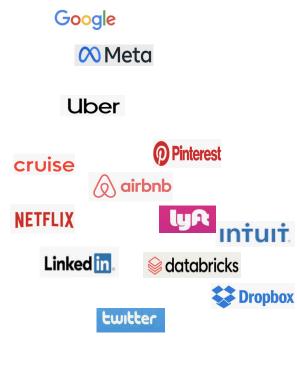


The MLOps Infrastructure space is crowded, confusing, and complex. There are a number of platforms and tools spanning a variety of functions across the model building workflow.

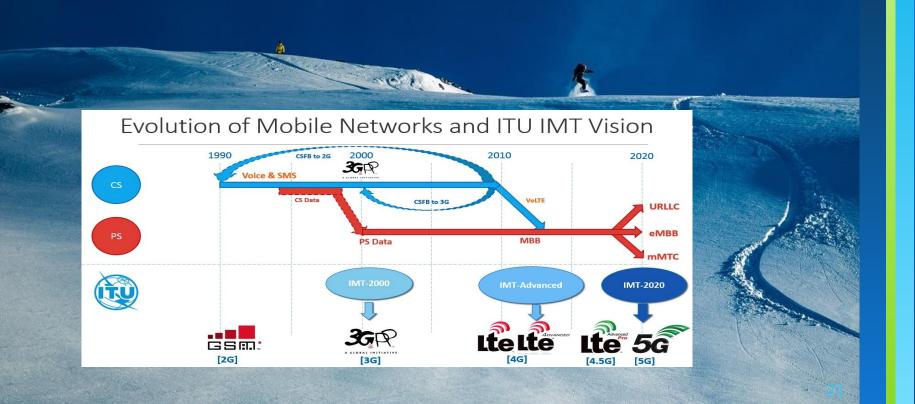
#### Tech companies are reinventing the wheel

"Ice and Fire"





# Openness and Standardization are catalysts of Evolution Example: 2G ~ 5G Mobile Networks



#### Academic institutions advocates the evolution

#### Example: Machine Learning Systems Design Course from Stanford



Mon Jan 3	Understanding machine learning production	Lecture note	Lecture
		Lecture slides	
		Lessons learned from 150 ML models at Booking.com	
Wed Jan 5	ML and Data Systems Fundamentals	Lecture note	Lecture
		Lecture slides	
		Case study: Predict Value of Homes On Airbnb	
		Breakout exercise: Designing Twitter's Trending Hashtags	
Mon Jan 10	Training Data	Lecture note	Lecture
		Lecture slides	
Wed Jan 12	Feature engineering	Lecture note	Lecture
		Lecture slides	
		W 2 1 2 10 1 5	
Mon Jan 17	No class	Martin Luther King, Jr. Day	
Wed Jan 19	Model selection, development, and training	Lecture note	Lecture
		Lecture slides	
Mon Jan 24	Offline evaluation	Lecture note	Lecture
		Lecture slides	
Wed Jan 26	Model evaluation	Goku's ML tutorial	Tutorial

#### Why machine learning systems design?

Machine learning systems design is the process of defining the software architecture, infrastructure, algorithms, and data for a machine learning system to satisfy specified requirements.

The tutorial approach has been tremendously successful in getting models off the ground. However, the resulting systems tend to go outdated quickly because (1) the tooling space is being innovated, (2) business requirements change, and (3) data distributions constantly shift. Without an intentional design to hold all the components together, a system will become technical liability, prone to errors and quick to fall apart.

#### Rise of Open MLOps

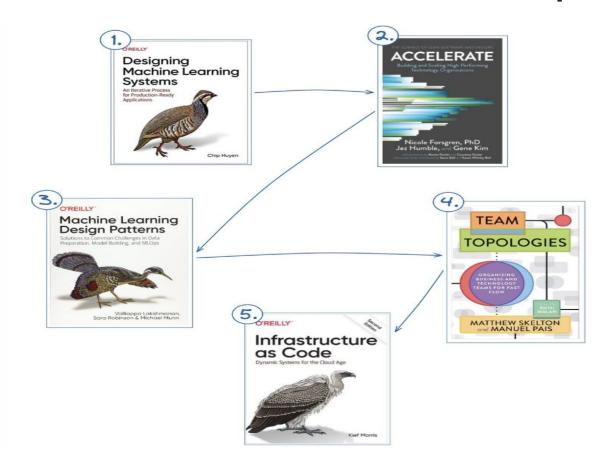
#### "2023 Dream Team"



- Jupyter, still the most popular notebook platform open-source product, Label Studio from HearTex, made significant improvements since 2021, including active learning enhancements.
- **Michelangelo**, the famous ML lifecycle solution from Uber since 2017, is proceeding private beta approach before fully open source.
- **Chronon(Zipline)**, the competitive feature store solution from Airbnb since 2017, are running a couple of private beta trials before fully open source
- Metaflow from Netflix, already open source, has been proved to be a strong candidate for the ML flow engine.
- ML Flow from Databricks, the leading solution for ML experiments, is fully open source.
- Looper is a new evaluation store solution from Meta published in 2021.

  The team had a plan to open source it at 2023
- Ray, from Anyscale, fully open source, had more and more adoptions and showed the leading position of training & turning.
- **Kubeflow** is one of the popular open-source deployment and serving engines to connect ML and Cloud infra closer and better.
- **Alibi** from Seldon, for ML interpretability, has the most active open-source community in this area.
- MLP observability, Lyft spent years enhancing it, and they claimed it is a better solution than most of the commercial vendors in the market; the team had a plan to open source it at 2023

#### **Book recommendation for MLI and MLOps**



# Thanks!

## Any questions?

You can find me at

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