Machine Learning Engineering

A few key concepts & some learnings

fcfm Ingeniería Química, Biotecnología y Materiales 2002-2005

dcc CIENCIAS DE LA COMPUTACIÓN UNIVERSIDAD DE CHILE 2005-2008

INGENIERIA INDUSTRIAL UNIVERSIDAD DE CHILE 2008-2009

glhuilli.github.io

DOCODE CMM Centro de Modelamiento Matemático 2009~2010

+

Zappedy 2010-2011

GROUPON 2011-2015

2015-2020

indeed 2020-...

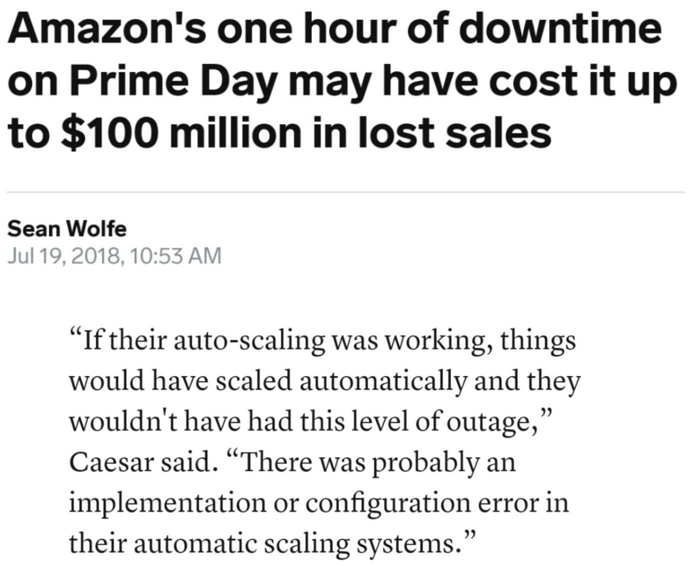
Disclaimer

1. Full of personal comments (own perspective and biases).
2. I don’t know everything/remember well (I’ll be wrong in some details).
3. I’ll skip important nuances as we have 40min, but please ask!

ML Engineering

Use software engineering principles
to build **robust** and **reliable** machine learning systems.

ML Engineering - Horror Stories



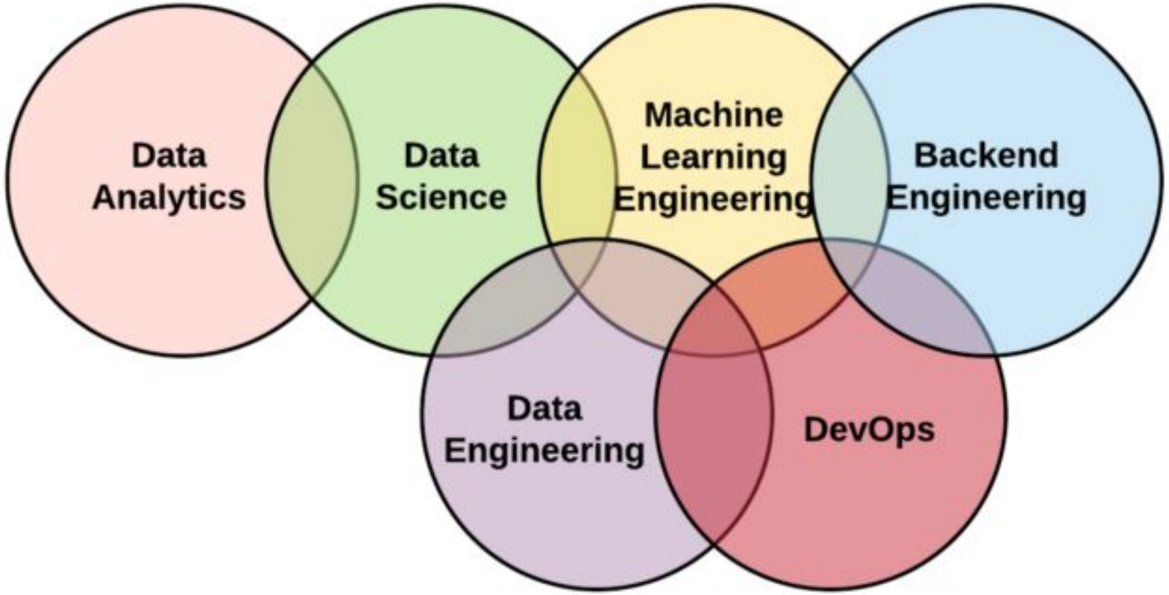
Amazon's one hour of downtime on Prime Day may have cost it up to $100 million in lost sales

Sean Wolfe
Jul 19, 2018, 10:53 AM

"If their auto-scaling was working, things would have scaled automatically and they wouldn't have had this level of outage," Caesar said. "There was probably an implementation or configuration error in their automatic scaling systems."

CNBC news

Roles Landscape



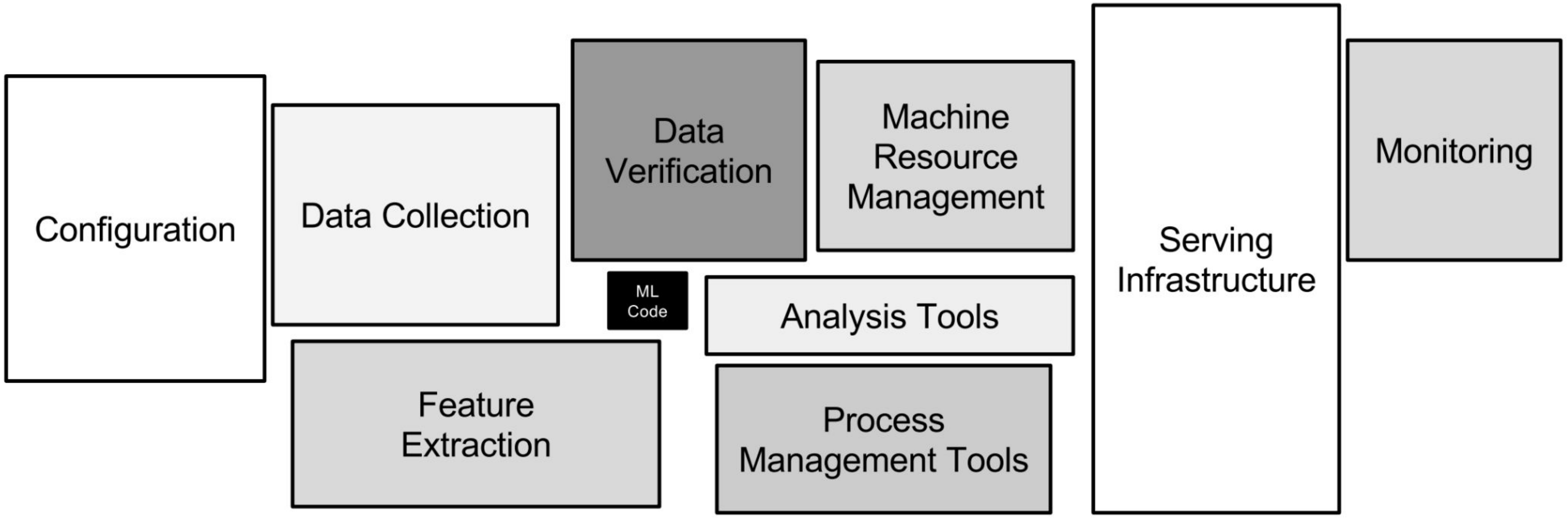
Source: [Medium post]

ML Engineering vs ML Research

	Research	**Production**
Objectives	Model performance	Different stakeholders have different objectives
Computational priority	Fast training, high throughput	Fast inference, low latency
Data	Static	Constantly shifting
Fairness	Good to have (sadly)	Important
Interpretability	Good to have	Important

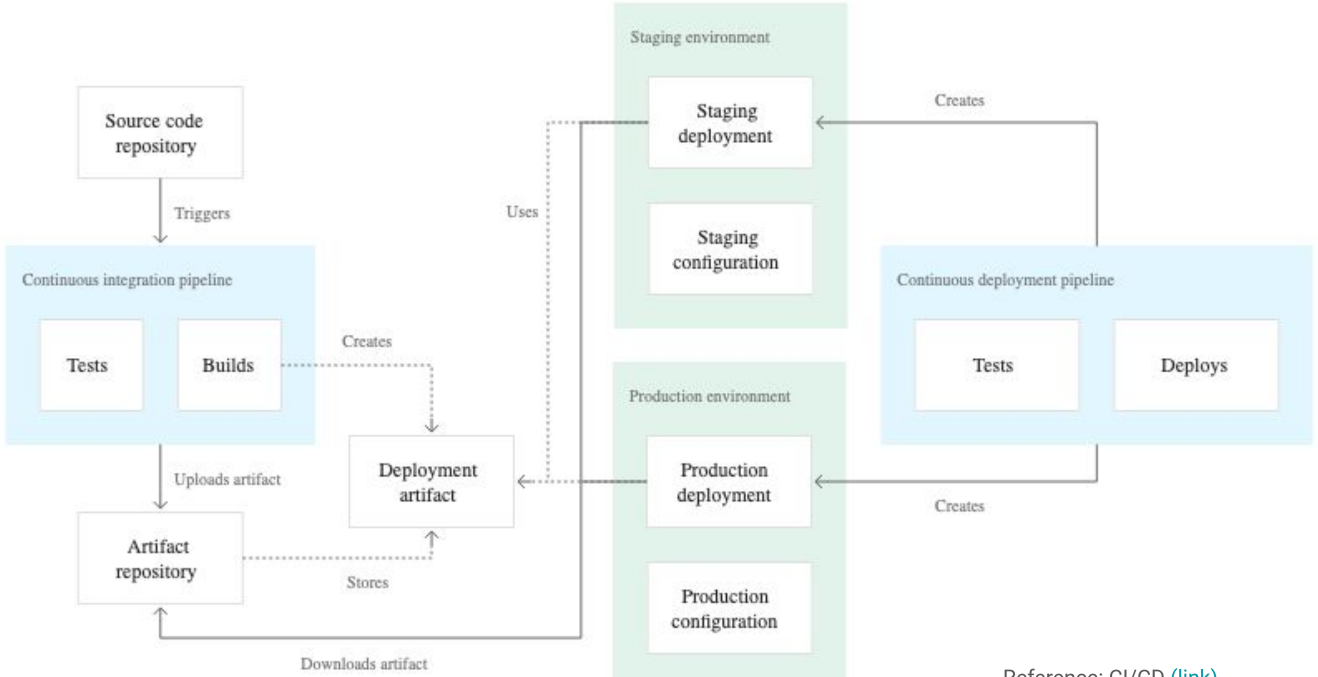
Source: Chip Huyen's ML Eng course (course, link for content above)

ML Engineering is much more than just ML



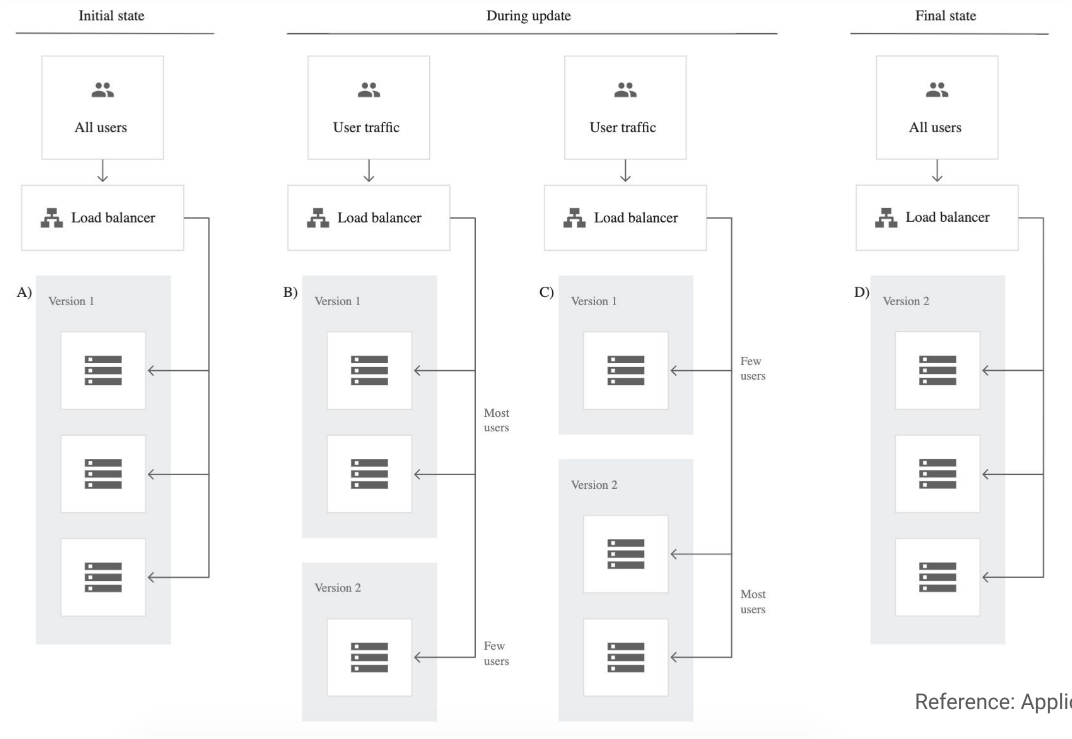
Scully et al., NeurIPS (2004) (paper)

Production Systems Concepts (CI/CD)



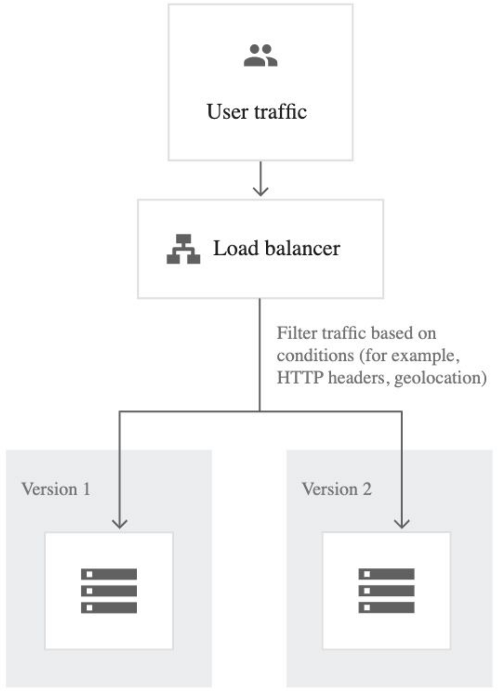
Reference: CI/CD (link)

Production Systems Concepts (Canary Testing)



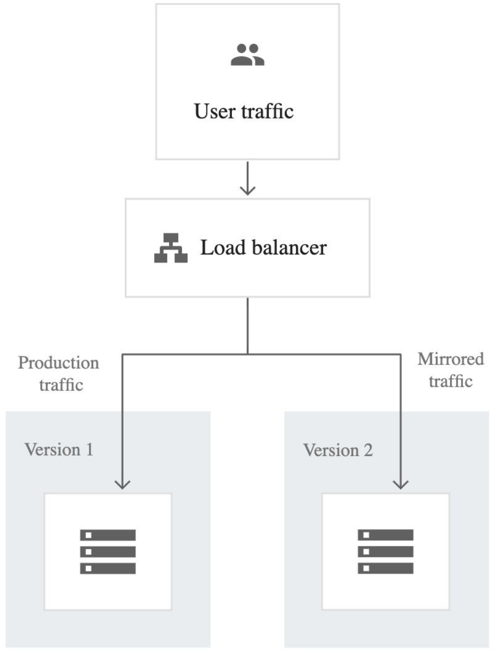
Reference: Applications deployment (link)

Production Systems Concepts (A/B Testing)


User traffic
Load balancer
Filter traffic based on conditions (for example, HTTP headers, geolocation)
Version 1
Version 2

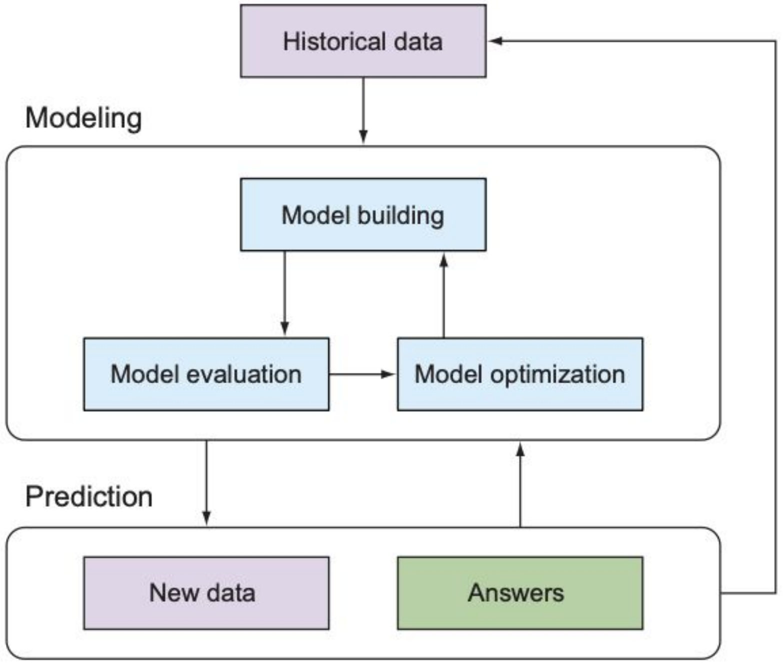
Reference: Applications deployment [(link)]()

Production Systems Concepts (Shadow Testing)



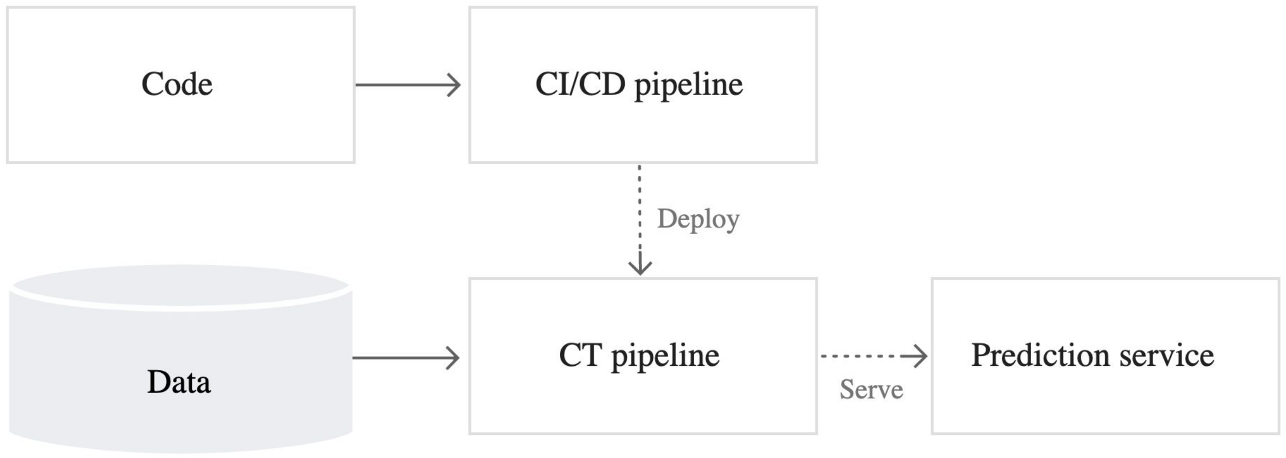
Reference: Applications deployment [(link)]()

Simplest ML System



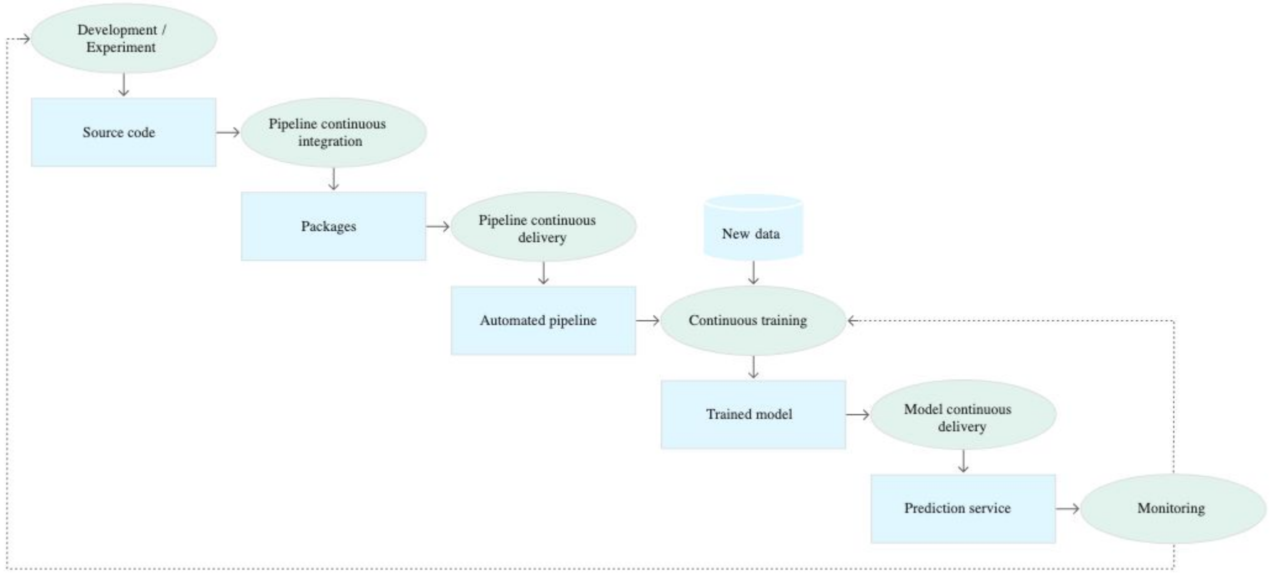
Real-world Machine Learning (link)

CI/CD + Continuous Training (CT)



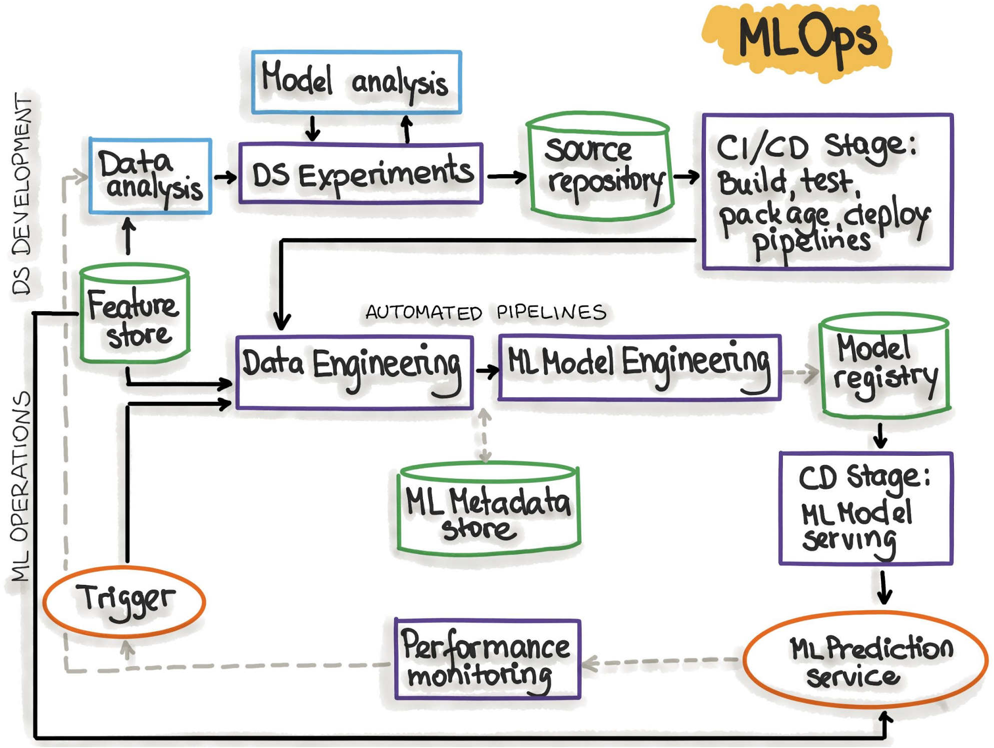
Reference: CI/CD/CT (link)

CI/CD/CT **+** Model Continuous Delivery (mCD)



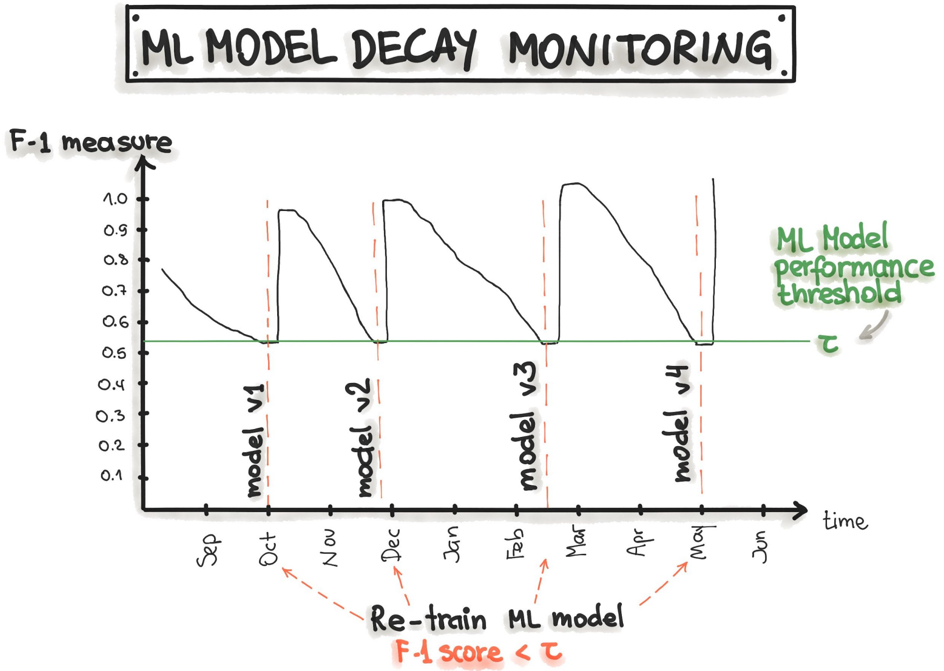
Reference: CI/CD/CT [(link)]

ML Ops



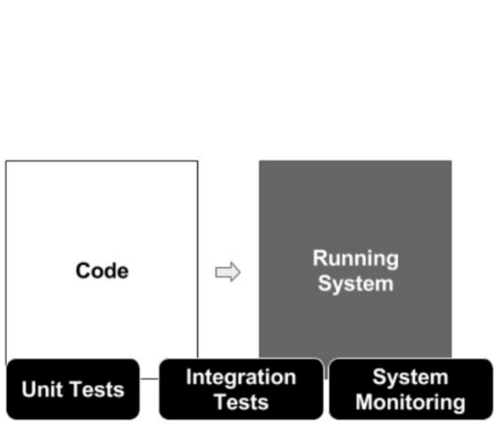
ML Ops principles (link)

ML Ops

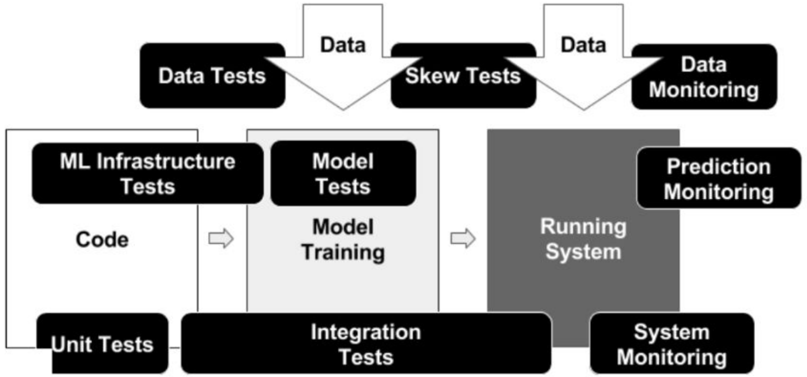


ML Ops principles (link)

ML Ops



Traditional System Testing and Monitoring



ML-Based System Testing and Monitoring

ML Test Score, Breck, et al. (2017) (link)

ML System Inference Paradigms

- Offline Inference
  - All possible predictions in batch
  - Feed predictions to cache/lookup table
  - Pros:
    - Cost/speed of inference not very important.
    - Post-verification on predictions on data before pushing
  - Cons:
    - Only predict what it's known
    - Update latency takes time

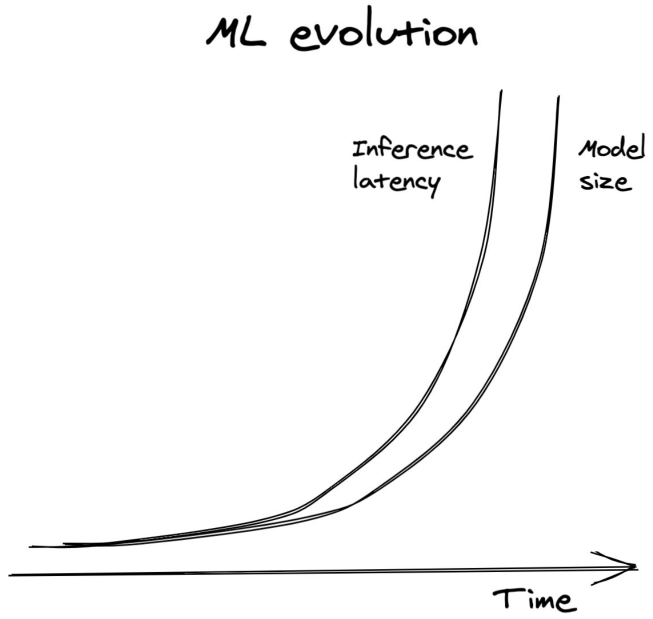
Reference: Google ML crash course link

ML System Inference Paradigms

- Online Inference
    - Predict on demand.
    - Feed predictions to cache/lookup table
    - Pros:
        - Predicts any item that comes in.
    - Cons:
        - Computational intensive, latency sensitive
            - Limits model complexity
        - Monitoring more intensive

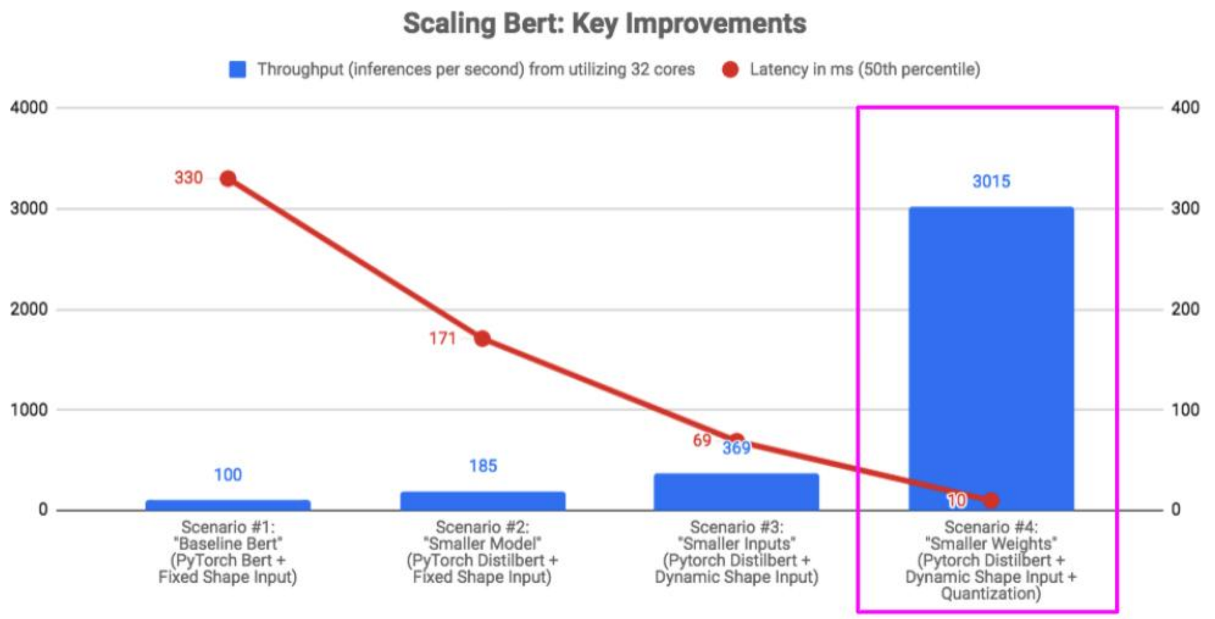
Reference: Google ML crash course link

Size/Complexity has an effect on latency



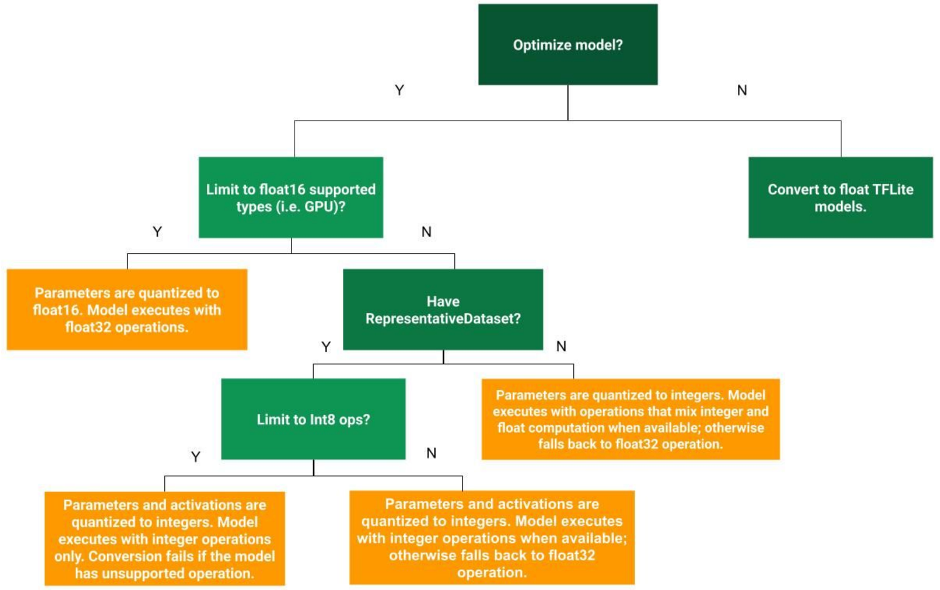
Source: Chip Huyen's ML Eng course (course)

Scaling ML Systems



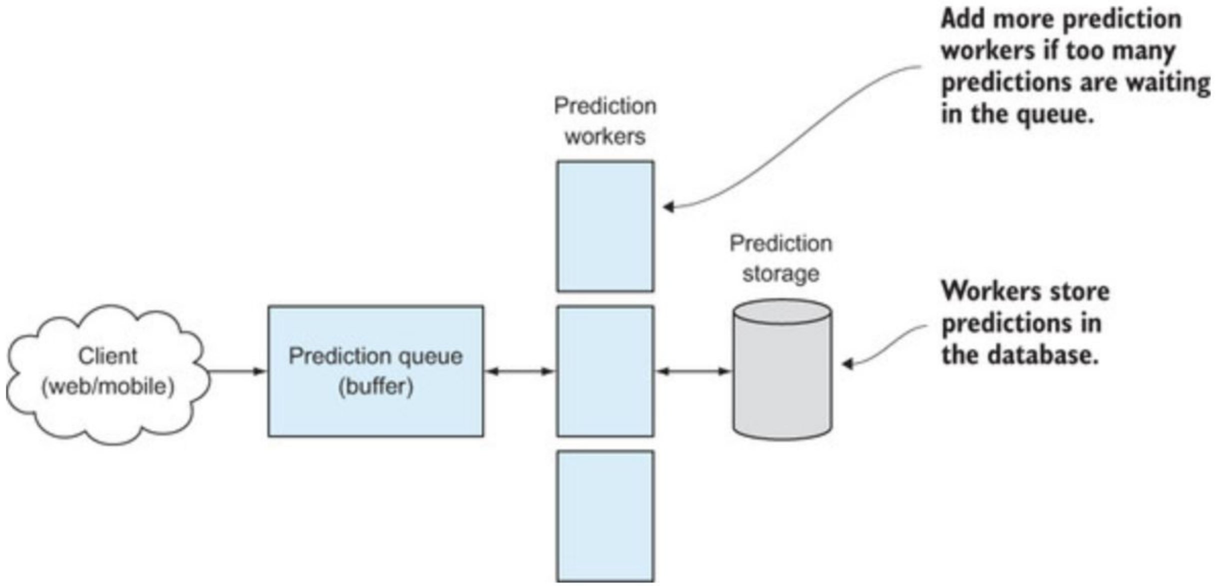
Reference: How We Scaled Bert To Serve 1+ Billion Daily Requests on CPUs (Roblox, 2020)

Scaling ML Systems


Optimize model?
Y
N
Limit to float16 supported types (i.e. GPU)?
Convert to float TFLite models.
Y
N
Parameters are quantized to float16. Model executes with float32 operations.
Have RepresentativeDataset?
Y
N
Limit to Int8 ops?
Parameters are quantized to integers. Model executes with operations that mix integer and float computation when available; otherwise falls back to float32 operation.
Y
N
Parameters and activations are quantized to integers. Model executes with integer operations only. Conversion fails if the model has unsupported operation.
Parameters and activations are quantized to integers. Model executes with integer operations when available; otherwise falls back to float32 operation.

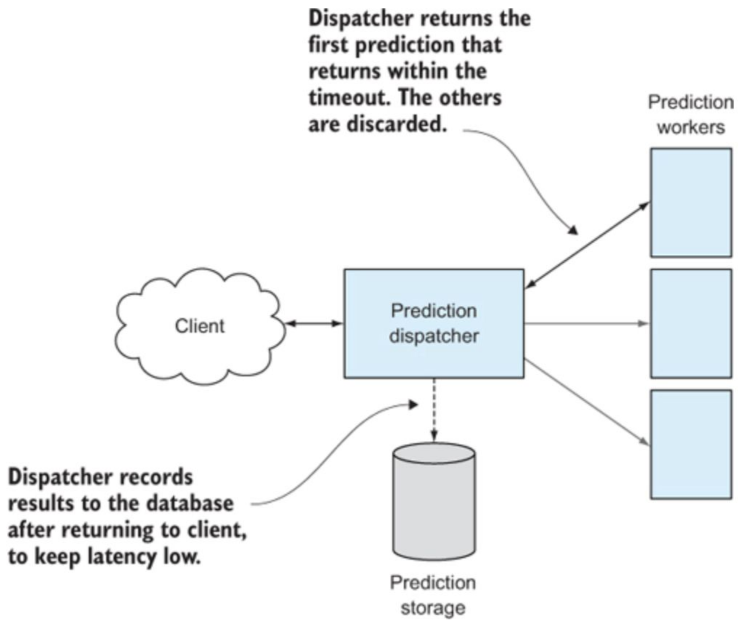
Reference: [Tensorflow Quantization]

Scaling ML Systems


Add more prediction workers if too many predictions are waiting in the queue.
Prediction workers
Prediction storage
Workers store predictions in the database.
Client (web/mobile)
Prediction queue (buffer)

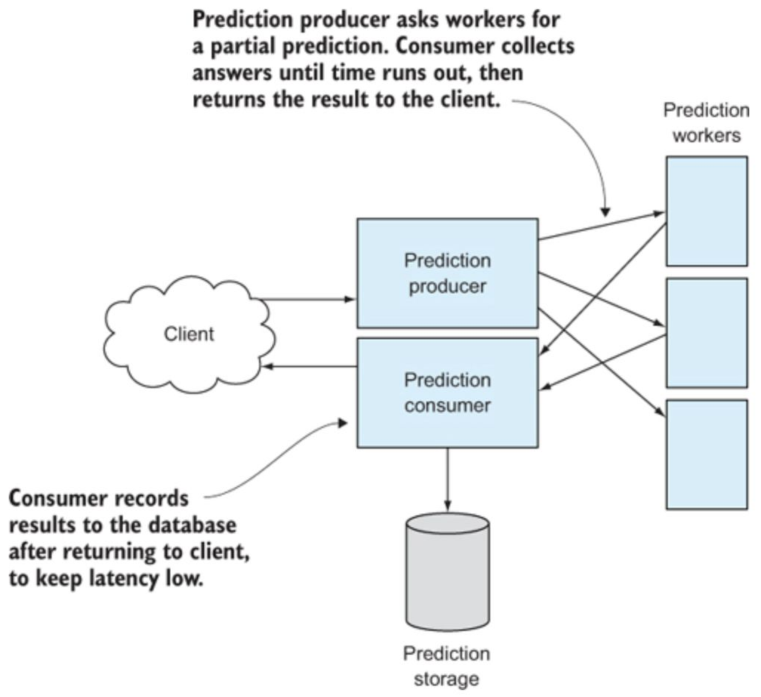
Real-world Machine Learning (link)

Scaling ML Systems


Dispatcher returns the first prediction that returns within the timeout. The others are discarded.
Prediction workers
Client
Prediction dispatcher
Dispatcher records results to the database after returning to client, to keep latency low.
Prediction storage

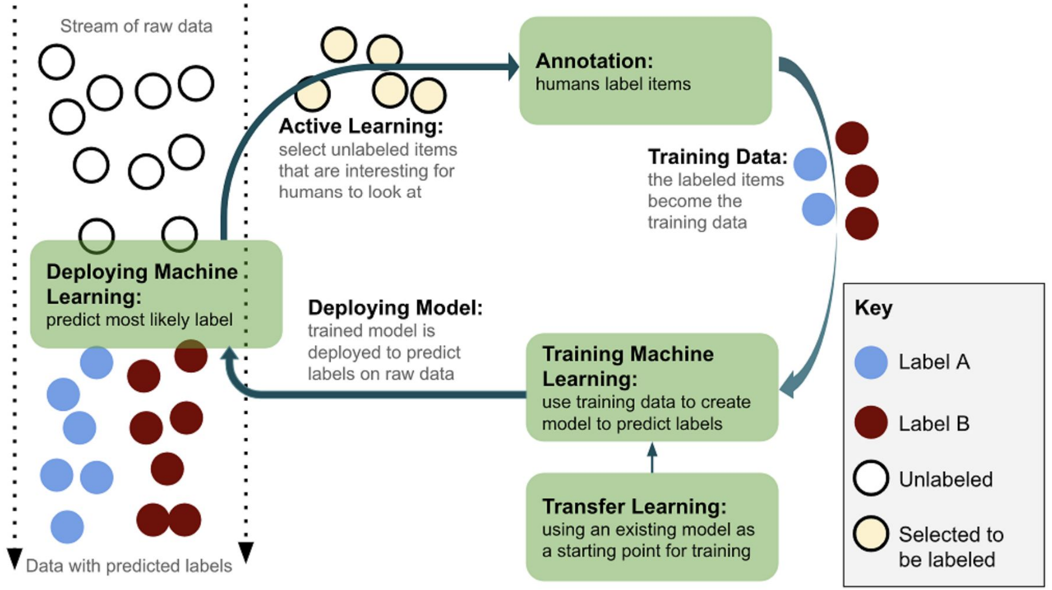
Real-world Machine Learning (link)

Scaling ML Systems


Prediction producer asks workers for a partial prediction. Consumer collects answers until time runs out, then returns the result to the client.
Prediction workers
Prediction producer
Client
Prediction consumer
Consumer records results to the database after returning to client, to keep latency low.
Prediction storage

Real-world Machine Learning (link)

Human-in-the-Loop ML

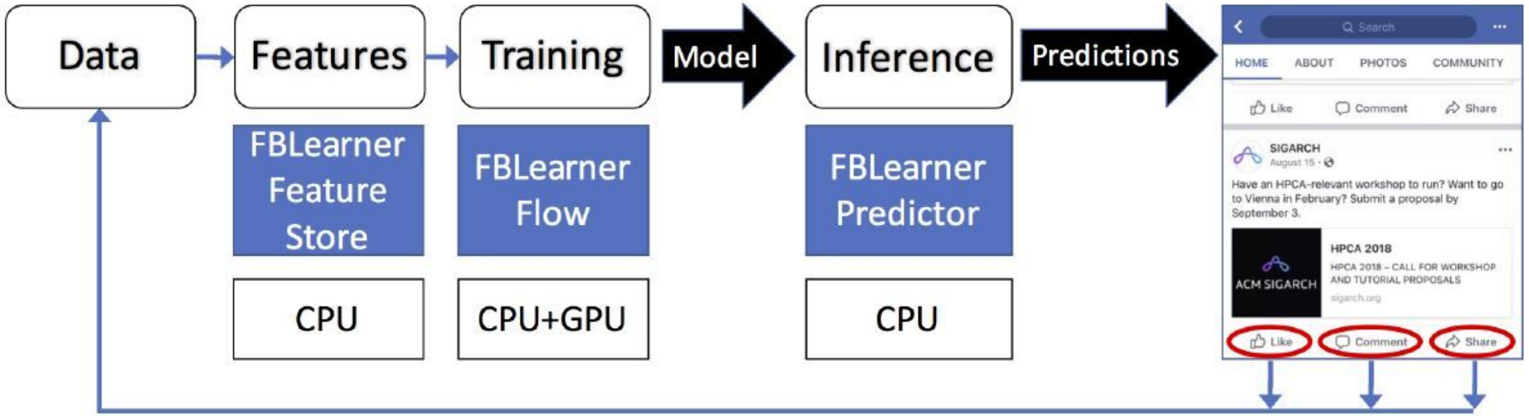

Stream of raw data
Active Learning: select unlabeled items that are interesting for humans to look at
Annotation: humans label items
Training Data: the labeled items become the training data
Deploying Machine Learning: predict most likely label
Deploying Model: trained model is deployed to predict labels on raw data
Training Machine Learning: use training data to create model to predict labels
Transfer Learning: using an existing model as a starting point for training
Data with predicted labels
Key
Label A
Label B
Unlabeled
Selected to be labeled

Human in the loop ML (link)

ML Infra

- Different teams with different standards building ML systems into prod.
    - Tensorflow vs PyTorch vs Sklearn vs XGBoost, etc…
    - Deployment process, tracking tools, monitoring, versioning, config, etc… it’s a nightmare.
- When big enough, some companies build ML infrastructure to standardize ML best practices
    - Monitoring, deployment, versioning, Feature stores, Concept drift tracking, AB testing & experimentation frameworks, etc.. all following the same standards within a company.

ML Infra (e.g. @ Facebook - FBLearner)

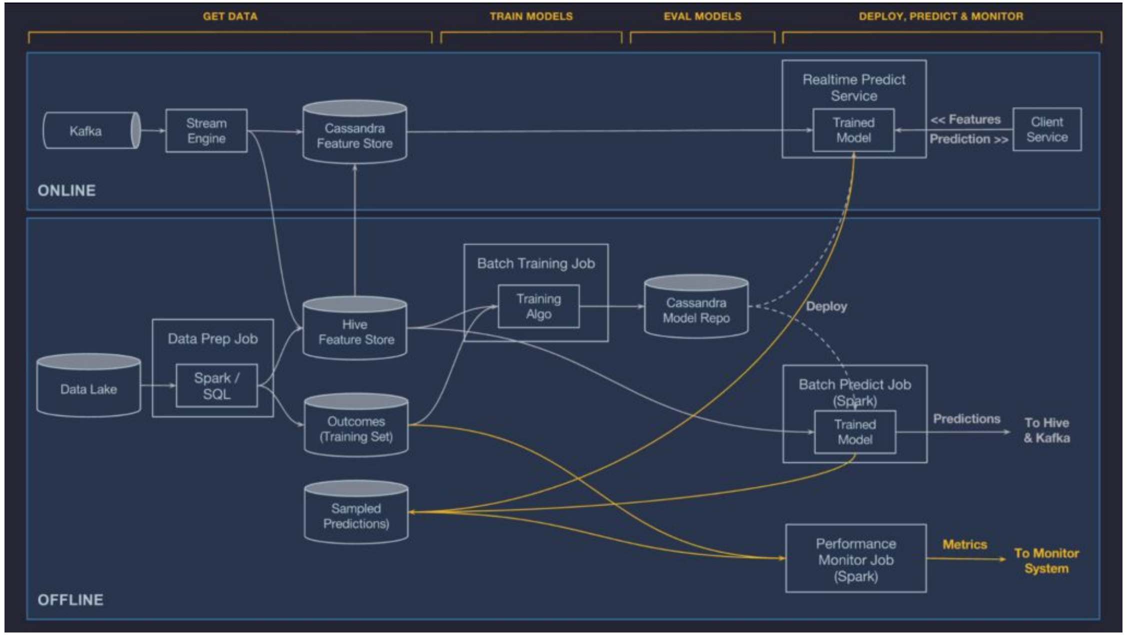


Have an HPCA-relevant workshop to run? Want to go to Vienna in February? Submit a proposal by September 3.

HPCA 2018 – CALL FOR WORKSHOP AND TUTORIAL PROPOSALS

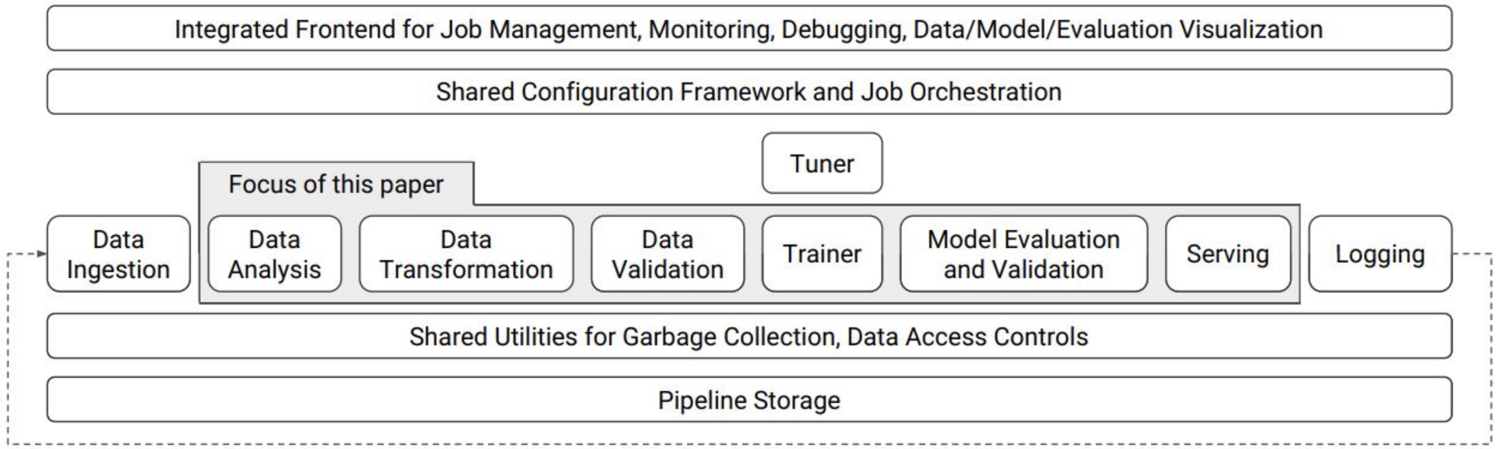
Reference: FBLearner - AI Infra at Facebook link

ML Infra (e.g. @ Uber - Michaelangelo)



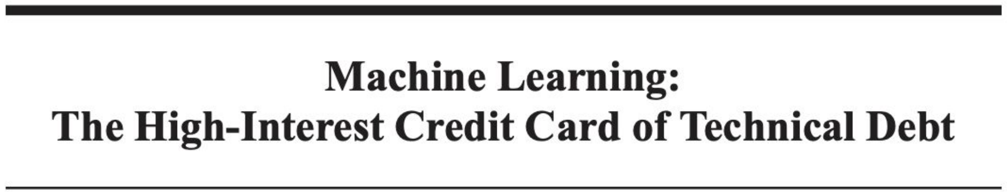
Reference: Michaelangelo link

ML Infra (e.g. @ Google - TFX)


Integrated Frontend for Job Management, Monitoring, Debugging, Data/Model/Evaluation Visualization
Shared Configuration Framework and Job Orchestration
Tuner
Focus of this paper
Data Ingestion
Data Analysis
Data Transformation
Data Validation
Trainer
Model Evaluation and Validation
Serving
Logging
Shared Utilities for Garbage Collection, Data Access Controls
Pipeline Storage

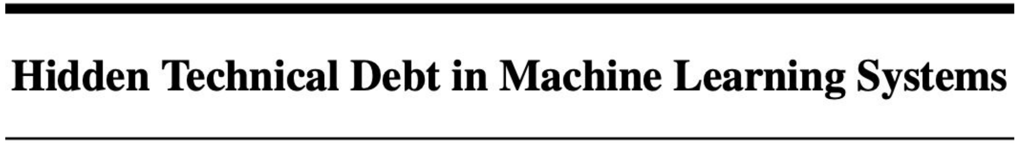
Reference: TensorFlow Extended link

Recommended trilogy



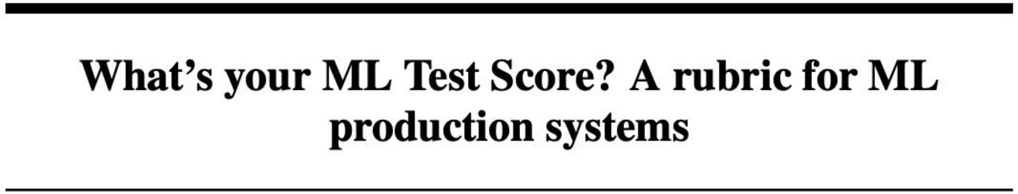
Machine Learning:
The High-Interest Credit Card of Technical Debt

Sculley, et al., SE4ML (2014) (link)



Hidden Technical Debt in Machine Learning Systems

Sculley, et al., NeurIPS (2015) (link)



What's your ML Test Score? A rubric for ML production systems

Breck, et al., NeurIPS (2016) (link)

ML Eng Projects & Learnings

- Extract Aspects+Sentiment from customer reviews
  - It can take a week to get a prototype but +6 months to get production working.
    - Very obvious: Proving value early on is fundamental.
  - Prototypes are great to minimize the project risk and understand the scope.
    - Classic: 80% of the problem can be solved with a 20% effort.
  - Sometimes scaling horizontally >> scale vertically.
    - You should thrive for this when problems are trivial to parallelize.
- Dynamic pricing
  - Small teams can have massive impact.
    - They need to work on the right problems though...
  - Running MVP online tests can take a big toll to the DS teams...
    - Imagine to collect data + fit a model + run prediction + update production on a daily basis. Far from sustainable.

ML Eng Projects & Learnings

- Search @ www.groupon.com
    - I broke production for the very first time -- countless learnings.
        - Integration testing for ML-based models is particularly hard.
    - A/B testing IS FUNDAMENTAL but can get pretty complex very quickly.
        - Many moving pieces can make the stats analysis very time consuming.

- Improve freshness of rec-sys
    - Online experiments more expensive than offline experiments but more trustworthy.
        - Expensive in every sense (wait time, engineering investment, resource intensive, etc.)
    - Counterfactuals in offline experiments that involves user behavior are **hard**.
        - Creating a gold standard for offline rec sys experiments == death.

ML Eng Projects & Learnings

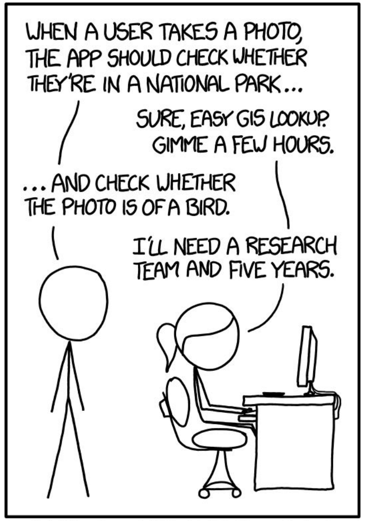
- Chatbot for Sales
    - The more complex your ML system the harder is to maintain and the more $ you pay to AWS.
        - Keep things simple at all costs.
    - Deploying DL-based models (or at least vector size-wise) is **hard** (of course).
        - Particularly pressing if you need a fast iteration environment.

- Graph-based RecSys for Sales
    - Node predictions based on graph embeddings can be a pretty bad idea.
        - If the graph evolves constantly, keeping up retraining the embeddings is painful.
    - ML using user behavior data can be very effective.
        - Not necessarily good and can be very creepy.

ML Eng Projects & Learnings

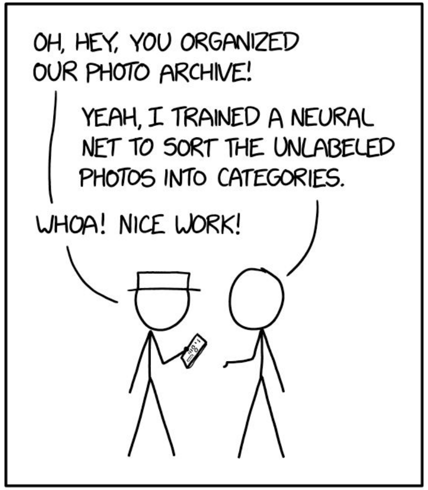
- Very common anti-patterns
  - **“If I just become the most amazing computer scientist, I’ll get very far!”**
    - There’s much more than just coding/modeling/designing. Soft skills are a core skill.
    - Extremely important skill: Communicate your ideas effectively and efficiently.
  - **“I worked SOooo hard on this feature, but no one appreciates my work!”**
    - If you see no value in that feature, say something. Make your own luck.
    - Very easy to fall in love with a problem that could drive Zero value.
  - **“Nah, it was trivial” (..*after working silently the whole weekend on a problem*..)**
    - This will create unrealistic expectations and will most likely burn you out.
    - Working hard is great and really appreciated.
  - **“I’m a 10x Engineer. I can ship everything by myself in 2 weeks.”**
    - “Journey before destination” if you want to be able to maintain a complex architecture.
    - Hero journeys are likely to end poorly. “Bus factor” is life or death for some companies.

ML Engineering - more learnings...


WHEN A USER TAKES A PHOTO, THE APP SHOULD CHECK WHETHER THEY'RE IN A NATIONAL PARK...
SURE, EASY GIS LOOKUP. GIMME A FEW HOURS.
...AND CHECK WHETHER THE PHOTO IS OF A BIRD.
I'LL NEED A RESEARCH TEAM AND FIVE YEARS.

IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

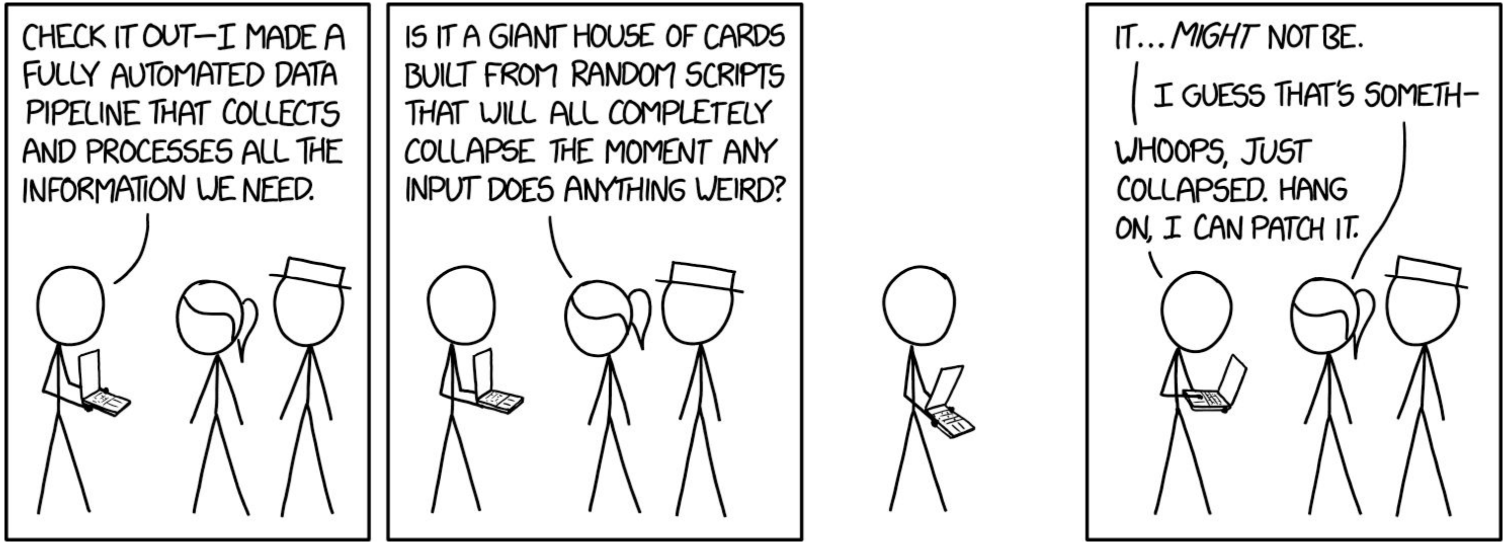
https://xkcd.com/1425/


OH, HEY, YOU ORGANIZED OUR PHOTO ARCHIVE!
YEAH, I TRAINED A NEURAL NET TO SORT THE UNLABELED PHOTOS INTO CATEGORIES.
WHOA! NICE WORK!

ENGINEERING TIP:
WHEN YOU DO A TASK BY HAND, YOU CAN TECHNICALLY SAY YOU TRAINED A NEURAL NET TO DO IT.

https://xkcd.com/2173/

ML Engineering - more learnings...


CHECK IT OUT—I MADE A FULLY AUTOMATED DATA PIPELINE THAT COLLECTS AND PROCESSES ALL THE INFORMATION WE NEED.
IS IT A GIANT HOUSE OF CARDS BUILT FROM RANDOM SCRIPTS THAT WILL ALL COMPLETELY COLLAPSE THE MOMENT ANY INPUT DOES ANYTHING WEIRD?
IT... MIGHT NOT BE.
I GUESS THAT'S SOMETH–
WHOOPS, JUST COLLAPSED. HANG ON, I CAN PATCH IT.

https://xkcd.com/1425/

ML Engineering - more learnings...

THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

https://xkcd.com/1838/

References

- Machine Learning System Design (link)
  - Good collection of case studies (link)
- ML Engineering Best Practices (link)
- Check the slides!
  - Full of references through the presentation.

Thanks!