Universidad Popular del Cesar

Machine Learning Systems Design

Lecture 8: Deployment - Prediction Service

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Logistics

- Proposal graded. Feedback in the comments.
- Teams are encouraged to out to your grader/mentor for 1:1 discussion!

Project proposal feedback

- MVP not MVP enough
  - Underestimation of how much work it'll take to build the MVP
  - START NOW!
- Unclear features/outputs of your system
  - What data is available when generating predictions?
  - How are users going to interact with predictions?
- Get training data now!
- Use cases not compelling enough
  - Imagine you were a user for your application.
  - What problem you want it to solve for you?
  - What information you'd need to enter?
- Literature review
  - Is anyone else solving similar problems? How do they do it? What challenges they encountered?
- Model component

Agenda

1. Why stream processing?
2. Batch prediction vs. online prediction
3. Cloud computing vs. edge computing
4. Break out exercise
5. Model compression
6. Compiling & optimizing models for edge devices

Why stream processing?

How to pass data between processes?

Ride management

Need driver availability & price to show riders

Driver management

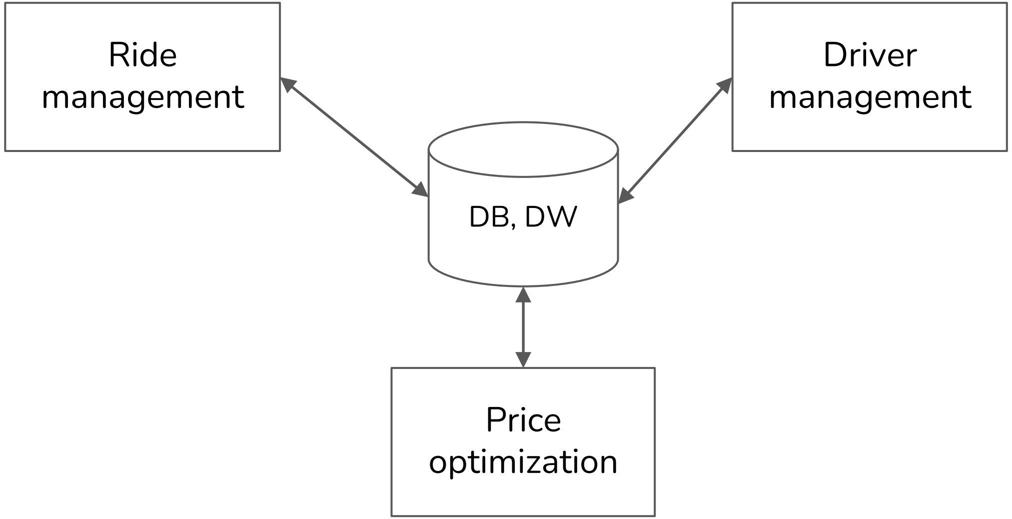
Need ride demand & price to incentivize drivers

Price optimization

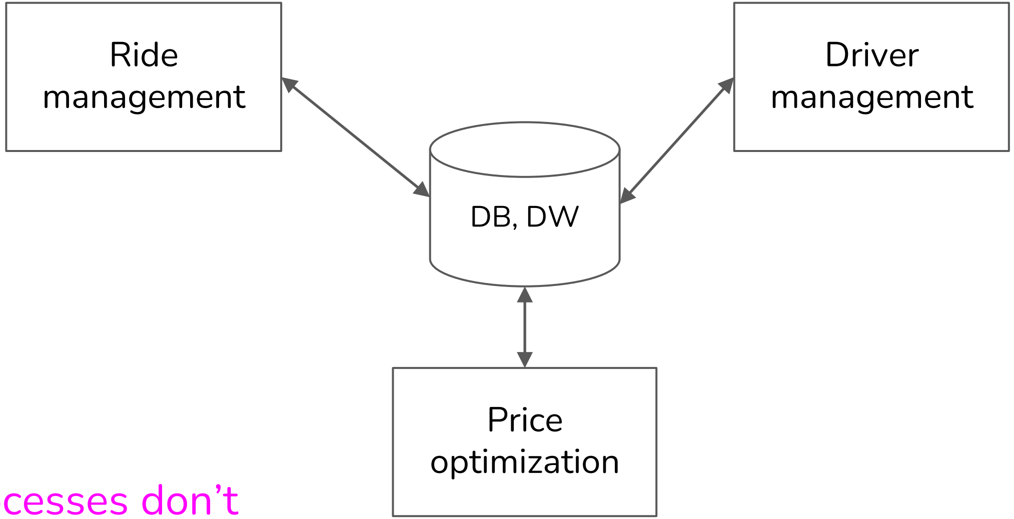
Need ride demand & driver availability to set price

A simple ride-sharing microservice

Data passing through databases

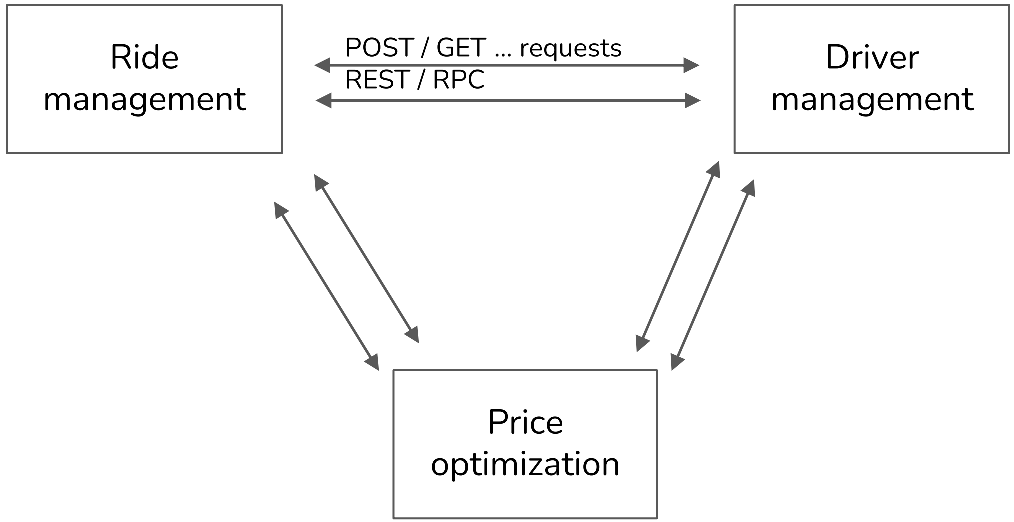


Data passing through databases

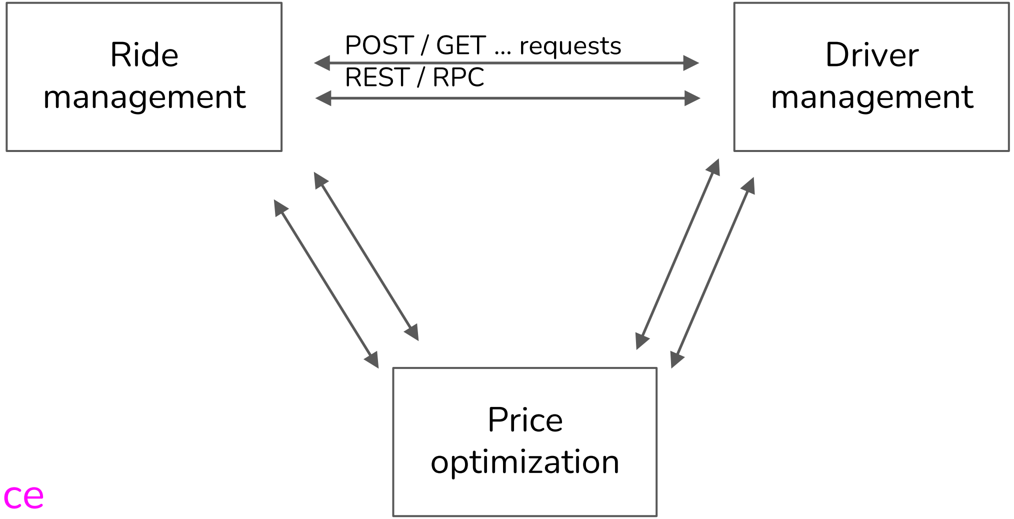


1. What if processes don't share database access?
2. Read & write from databases can be slow

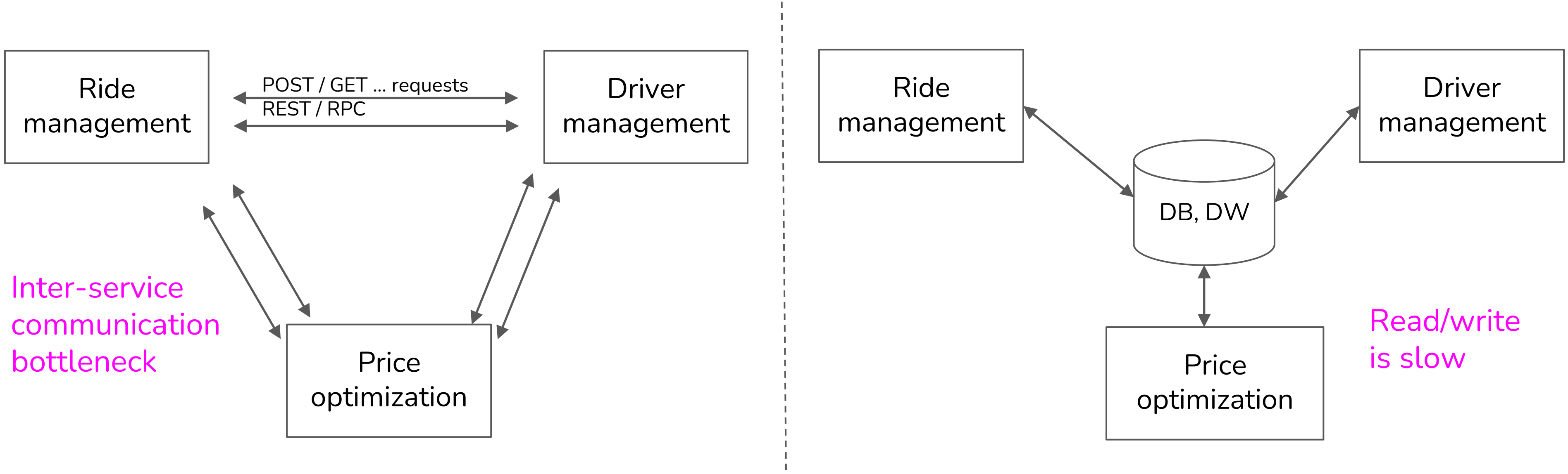
Data passing through services

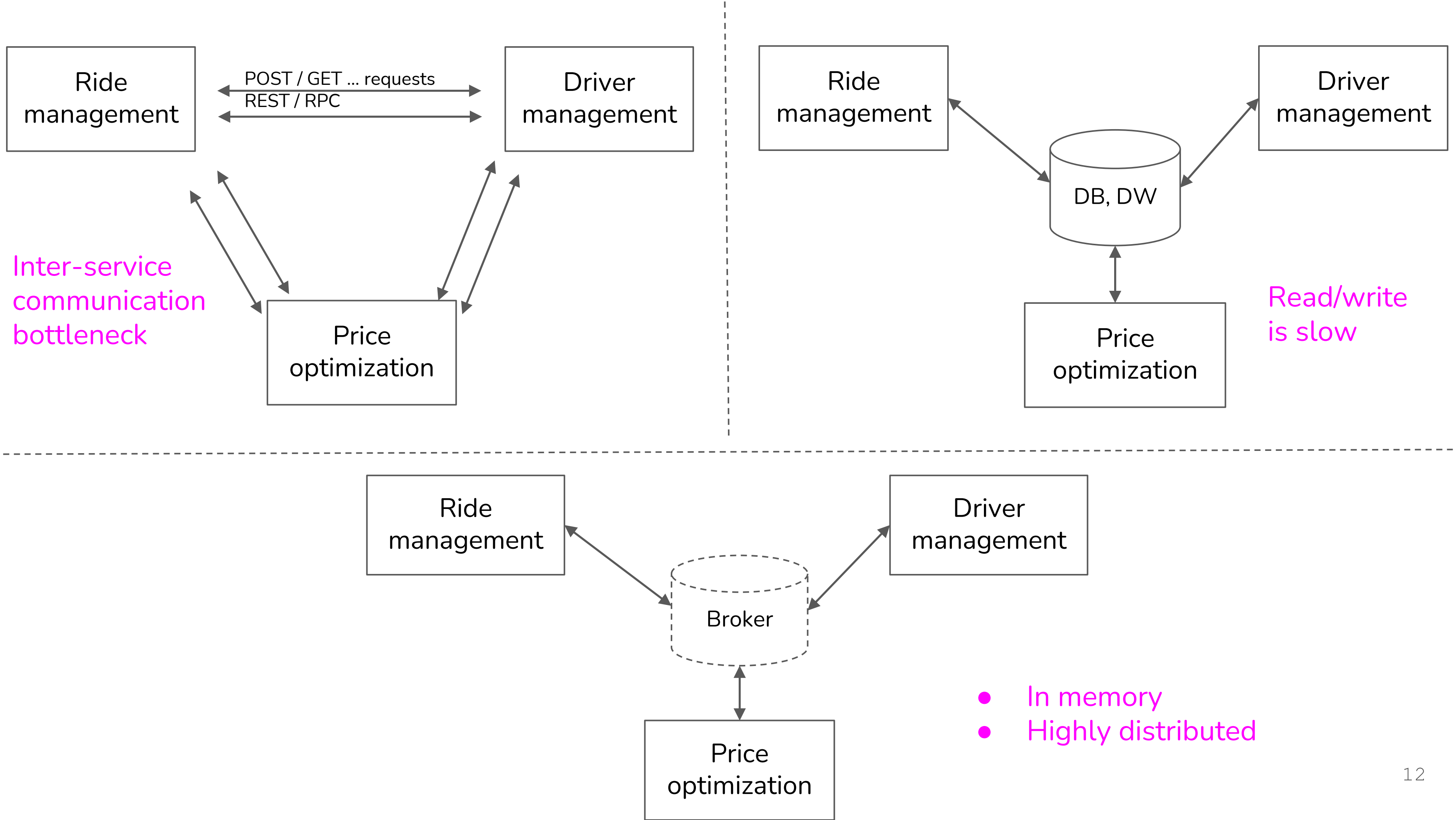


Data passing through services

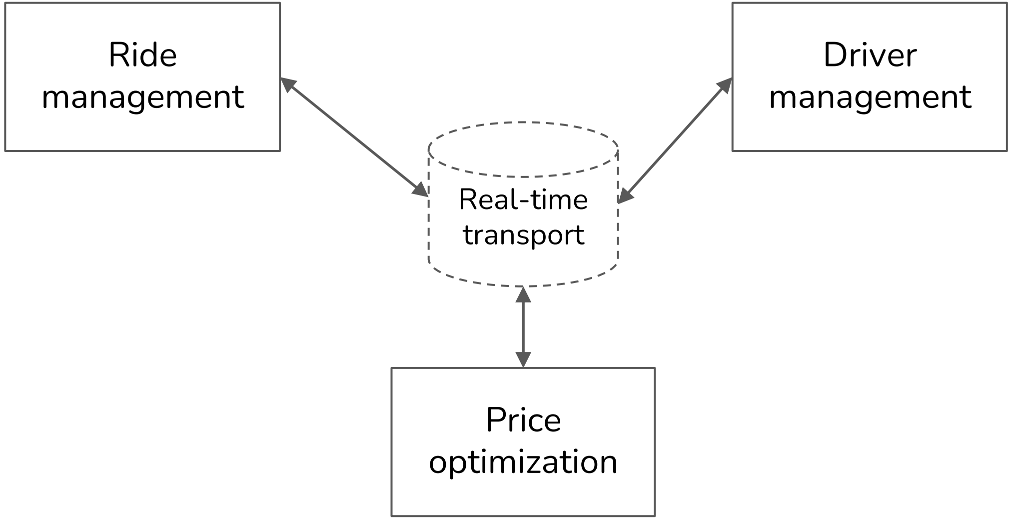


Inter-service communication can blow up


Ride management
POST / GET ... requests
REST / RPC
Driver management
Inter-service communication bottleneck
Price optimization
Ride management
Driver management
DB, DW
Price optimization
Read/write is slow


Ride management
POST / GET ... requests
REST / RPC
Driver management
Inter-service communication bottleneck
Price optimization
Ride management
DB, DW
Driver management
Price optimization
Read/write is slow
Ride management
Driver management
Broker
Price optimization
In memory
Highly distributed

Data passing through brokers



Need for speed: ride-sharing example

To detect whether a transaction is fraud, need features from:

- this transaction
- user's recent transactions (e.g. 7 days)
- credit card's recent transactions
- recent in-app frauds
- etc.

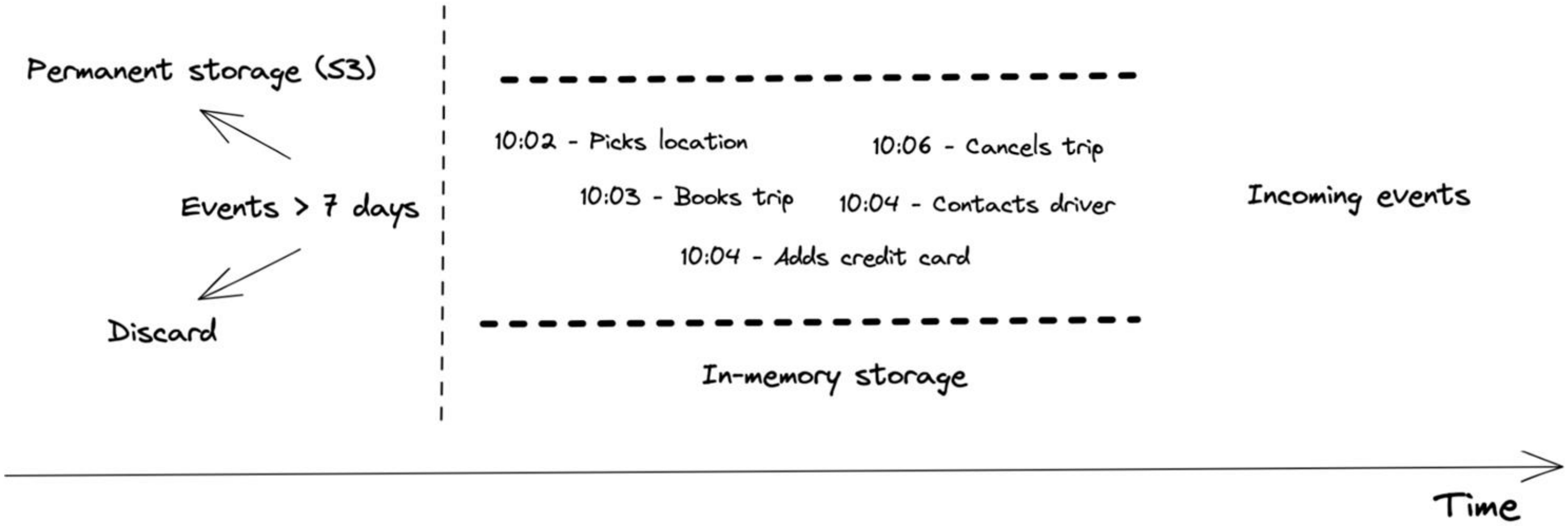
Need for speed: ride-sharing example

To detect whether a transaction is fraud, need features from:

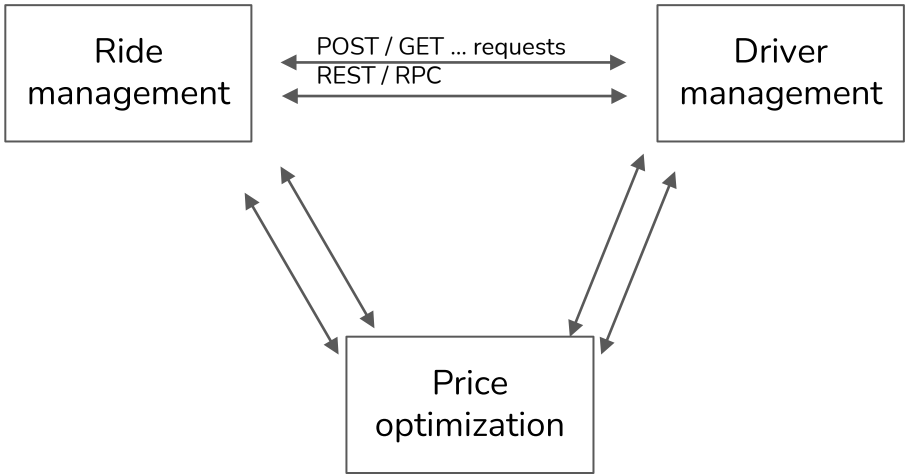
- this transaction
- user's recent transactions (e.g. 7 days)
- credit card's recent transactions
- recent in-app frauds
- etc.

How to quickly access these features?

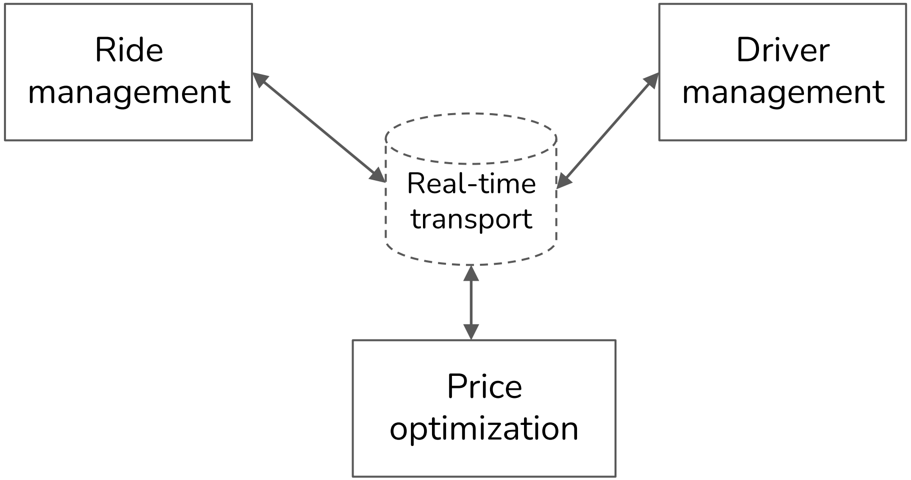
Real-time transport



Request-driven



Event-driven



Real-time transport: pubsub

- Any service can publish to a stream [producer]
- Any service can subscribe to a stream to get info they need [consumer]

```
from confluent_kafka import Consumer, SerializingProducer

producer = SerializingProducer(producer_config)
producer.produce(
            topic=”prediction”,
            key=example_id,
            value=prediction,
         )

pred_consumer = Consumer(consumer_config)
pred_consumer.subscribe([”prediction”])
```

Real-time transport: pubsub, message queue, etc.

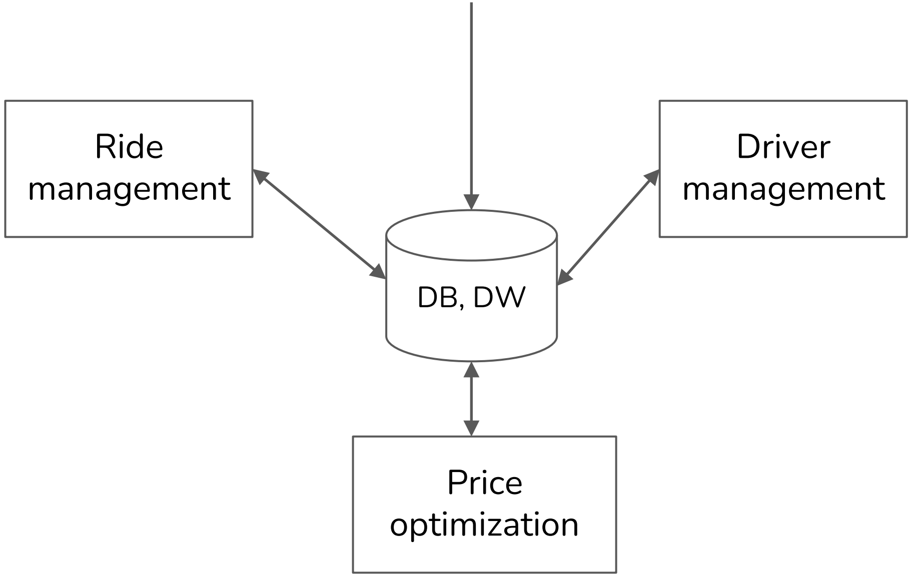
1240 companies reportedly use **Kafka** in their tech stacks, including **Uber**, **Shopify**, and **Spotify**.

Uber Shopify Spotify Udemy Robinhood Slack LaunchDarkly Nubank The New York Times

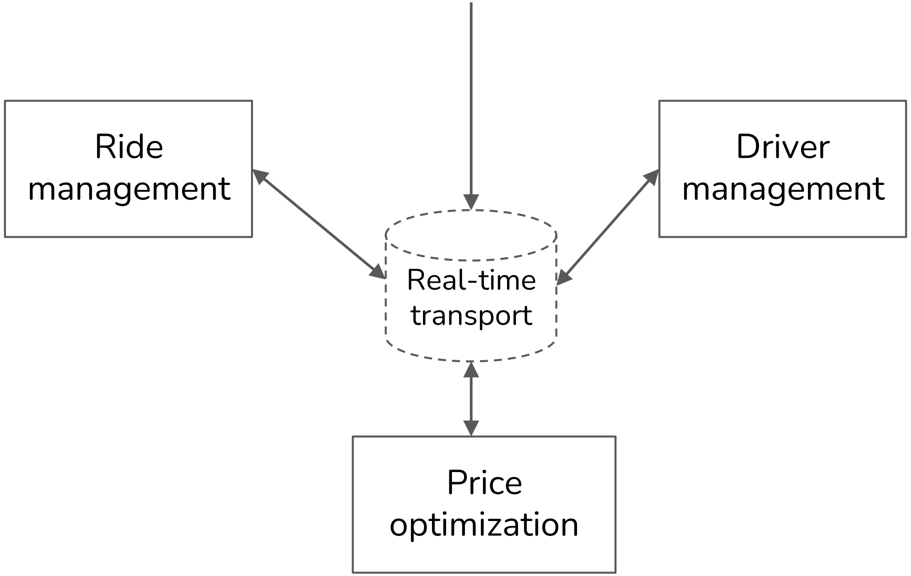
1811 companies reportedly use **RabbitMQ** in their tech stacks, including **Robinhood**, **reddit**, and **Stack**.

Robinhood reddit Stack Accenture Hepsiburada CircleCI Alibaba Travels trivago ViaVarejo

Batch processing



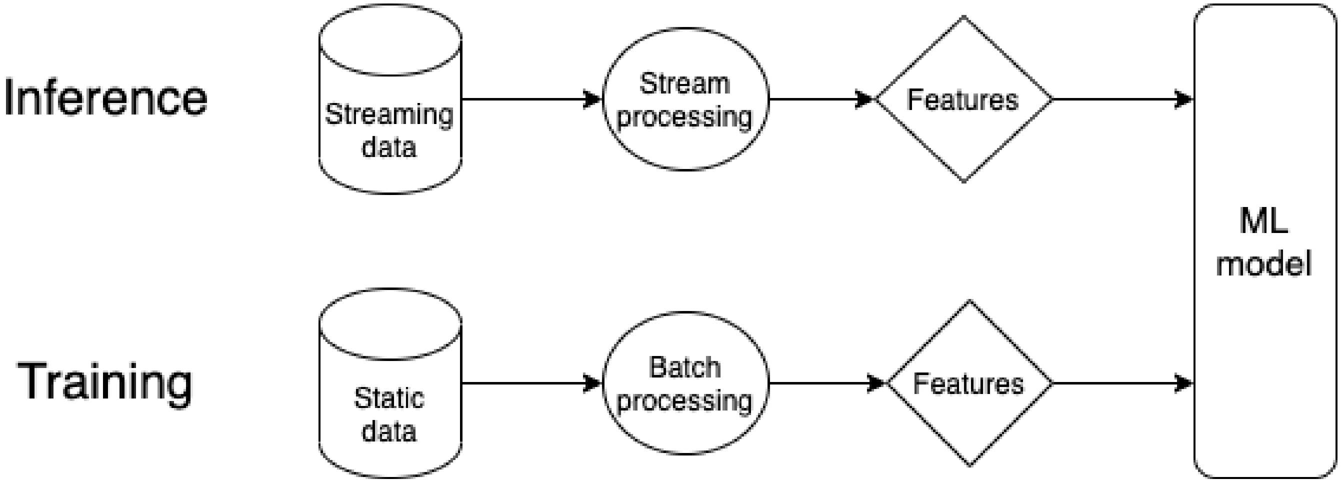
Stream processing



Batch processing vs. stream processing

Historical data	Streaming data
Databases, data warehouses	Kafka, Kinesis, Pulsar, etc.
Batch features: ● age, gender, job, city, income ● when account was created	Dynamic features ● locations in the last 10 minutes ● recent activities
Bounded: know when a job finishes	Unbounded: never finish
Processing kicked of periodically, in batch ● e.g. MapReduce, Spark	Processing can be kicked off as events arrive ● e.g. Flink, Samza, Spark Streaming

One model, two pipelines



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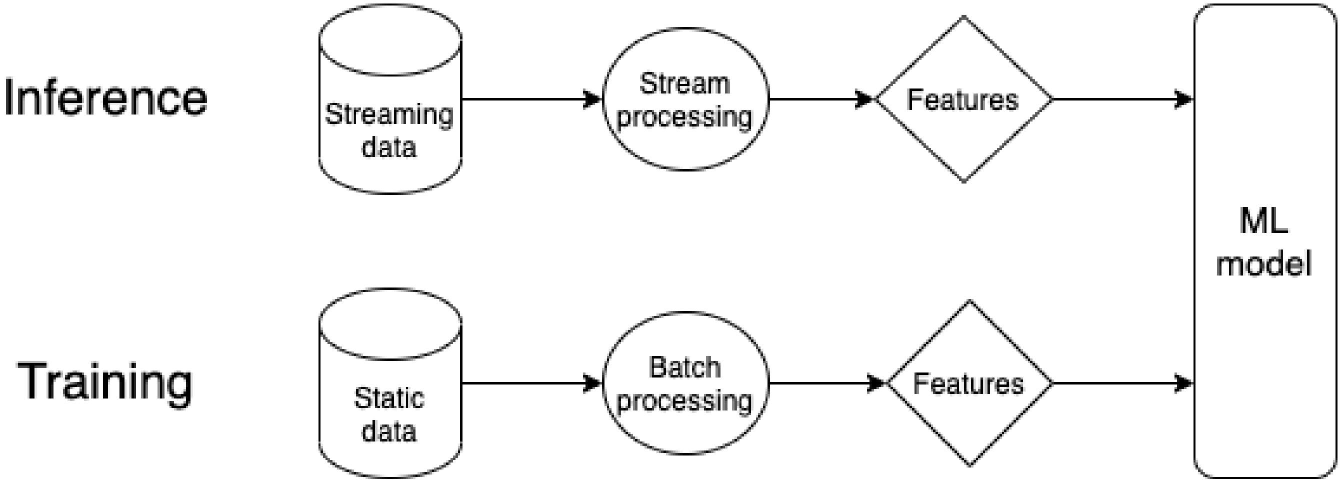


⚠⚠ A common source of errors in production ⚠⚠

Stream & batch processing

- Batch is a special case of streaming

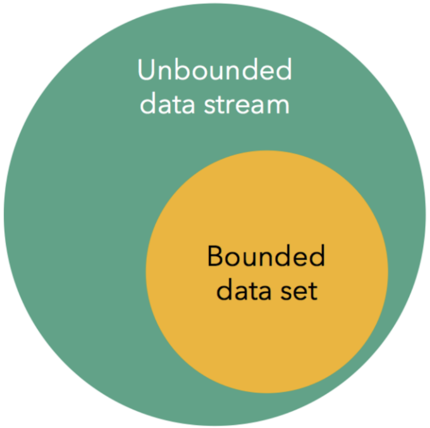
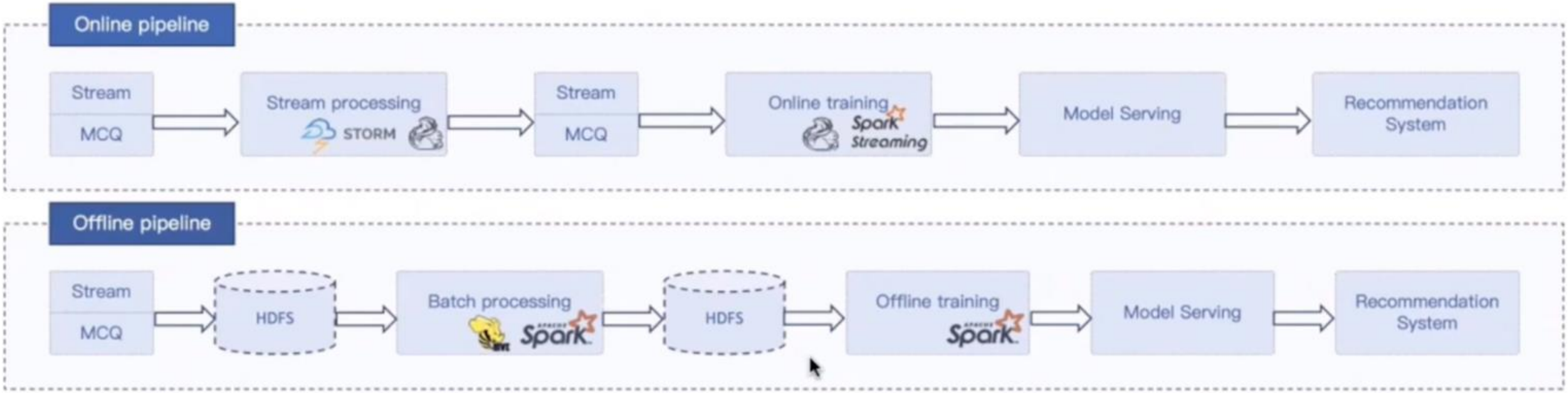


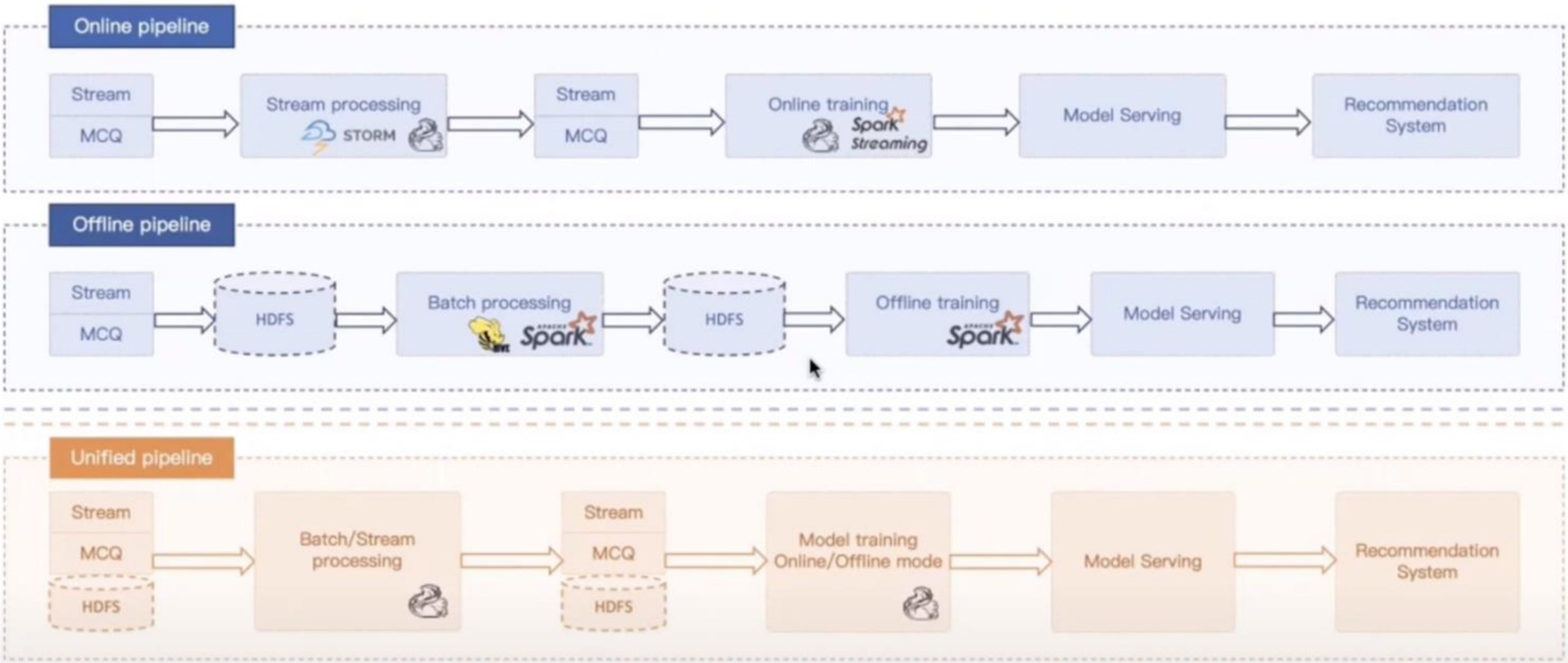
Image by Kostas Tzoumas (Ververica)

One model, two pipelines: example



Machine learning with Flink in Weibo (Qian Yu, QCon 2019)

Apply unified Flink APIs to both online and offline ML pipelines



Machine learning with Flink in Weibo (Qian Yu, QCon 2019)

Barriers to stream processing

1. Companies don’t see the benefits of streaming
    - Systems not at scale
    - Batch predictions work fine
    - Online predictions would work better but they don’t know that

Barriers to stream processing

1. Companies don’t see the benefits of streaming
2. High initial investment on infrastructure
3. Mental shift
4. Python incompatibility

How to serve your model?

1. Batch prediction vs. online prediction
2. Cloud computing vs. edge computing

⚠️⚠️ The dangers of categorical thinking ⚠️⚠️

- Seemingly different ways of doing things might be fundamentally similar
- Choices don't have to be mutually exclusive
- Choices can evolve over time

The Dangers of Categorical Thinking

We're hardwired to sort information into buckets—and that can hamper our ability to make good decisions. by Bart de Langhe and Philip Fernbach

Batch prediction vs. online prediction

Separation: causes of many MLOps problems

- Development environment vs. production environment
- Batch pipeline vs. streaming pipeline
- Development vs. monitoring

Batch prediction vs. online prediction

- Batch prediction
  - Generate predictions periodically, before requests arrive
  - Predictions are stored (e.g. SQL tables, CSV files) and retrieved when requests arrive
- Online prediction
  - Generate predictions after requests arrive
  - Predictions are returned as responses

⚠ Misnomer ⚠

- Both can do one or more samples (batch) at a time
- If you do compute on the cloud, then both are technically "online" - over the Internet

Batch prediction vs. online prediction

- Batch prediction
  - Generate predictions periodically before requests arrive
  - Predictions are stored (e.g. SQL tables) and retrieved when requests arrive
  - Asynch
- Online prediction
  - Generate predictions after requests arrive
  - Predictions are returned as responses
  - Sync when using requests like REST / RPC
    - HTTP prediction
  - Async [with low latency) with real-time transports like Kafka / Kinesis
    - Streaming prediction

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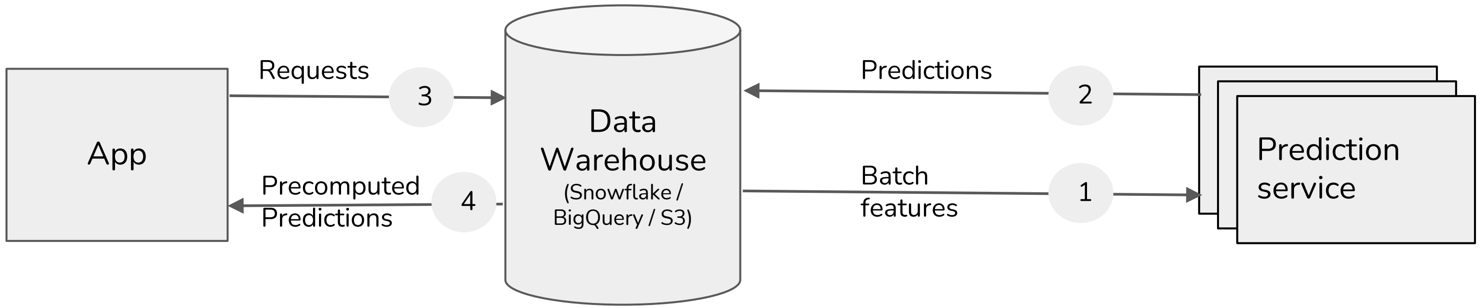
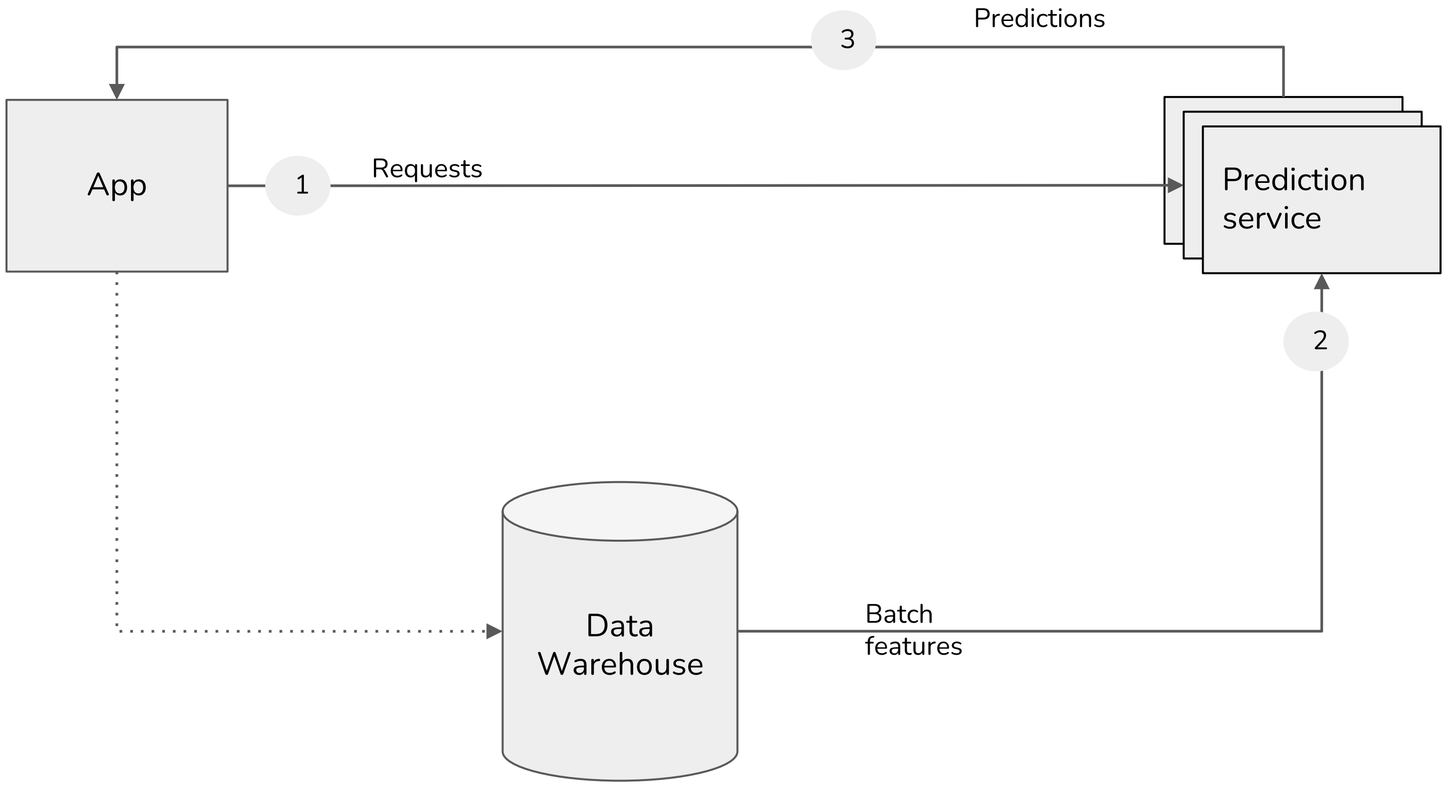
Offered by major cloud providers

Still challenging

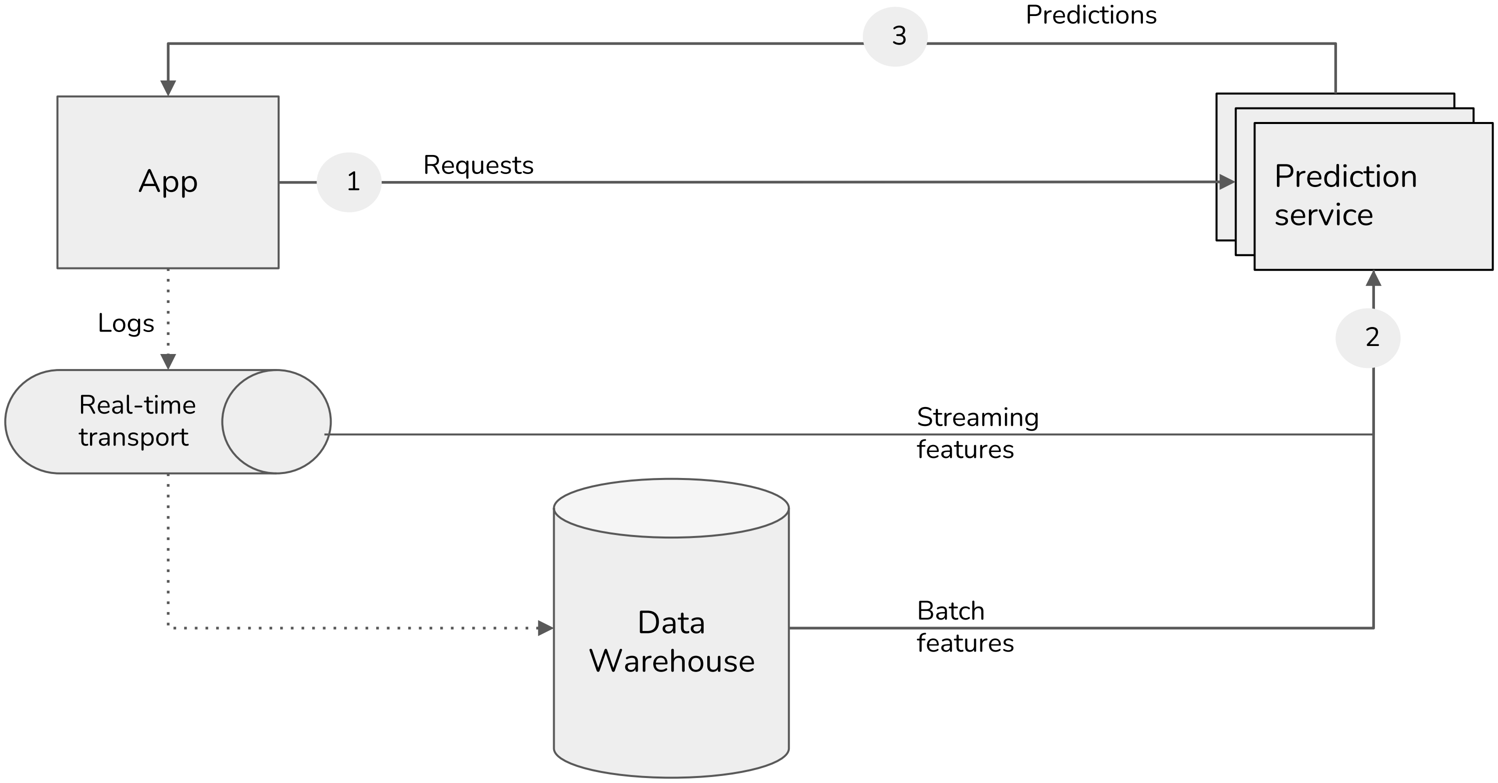
Batch prediction



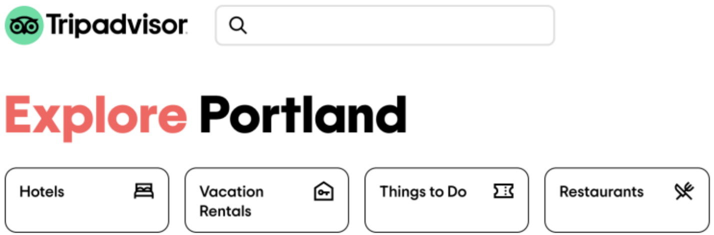
Online prediction (HTTP)

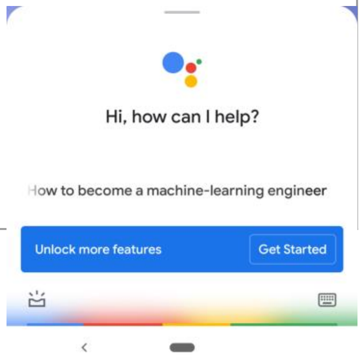


Online prediction (streaming)



	Batch prediction (async)	Online prediction (generally sync)
Frequency	Periodical (e.g. every 4 hours)	As soon as requests come
Useful for	Processing accumulated data when you don't need immediate results (e.g. recommendation systems)	When predictions are needed as soon as data sample is generated (e.g. fraud detection)
Optimized	High throughput	Low latency
Input space	Finite: need to know how many predictions to generate	Can be infinite
Examples	• TripAdvisor hotel ranking • Netflix recommendations	• Google Assistant speech recognition • Twitter feed





Hybrid: batch & online prediction

- Online prediction is default, but common queries are precomputed and stored

  DOORDASH

  - Restaurant recommendations use batch predictions
  - Within each restaurant, item recommendations use online predictions

  NETFLIX

  - Title recommendations use batch predictions
  - Row orders use online predictions

Cloud computing vs. edge computing

	Cloud computing	**Edge computing**
Computations	Done on cloud (servers)	Done on edge devices (browsers, phones, tablets, laptops, smart watches, activity watchers, cars, etc.)
Examples	● Most queries to Alexa, Siri, Google Assistant ● Google Translate for rare language pairs (e.g. English - Yiddish)	● Wake words for Alexa, Siri, Google Assistant ● Google Translate for popular language pairs (e.g. English - Spanish) ● Predictive text ● Unlocking with fingerprints, faces

Benefits of edge computing

- Can work without (Internet) connections or with unreliable connections
  - Many companies have strict no-Internet policy
  - **Caveat**: devices are capable of doing computations but apps need external information
    - e.g. ETA needs external real-time traffic information to work well

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    - Network latency might be a bigger problem than inference latency
    - Many use cases are impossible with network latency
        - e.g. predictive texting

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- Fewer concerns about privacy
  - Don’t have to send user data over networks (which can be intercepted)
  - Cloud database breaches can affect many people
  - Easier to comply with regulations (e.g. GDPR)
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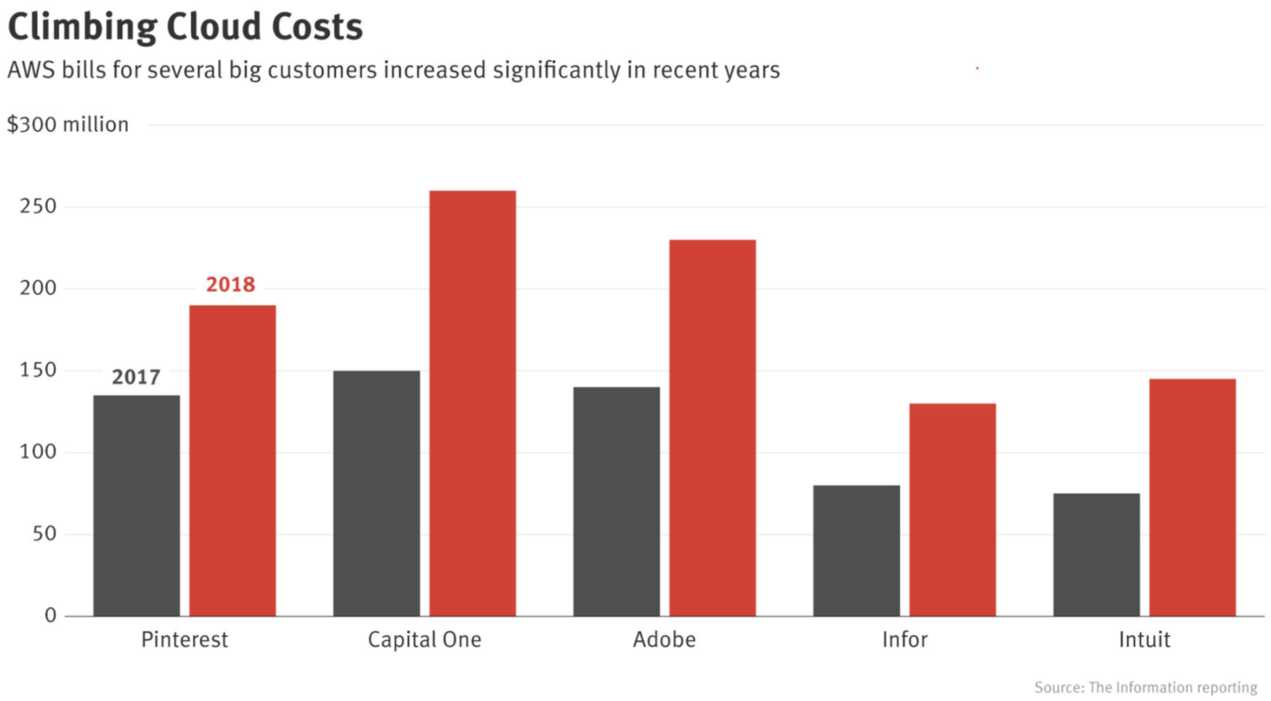
  - **Caveat**: edge computing might make it easier to steal user data by just taking the device
- Cheaper
  - The more computations we can push to the edge, the less we have to pay for servers

A cloud mistake can bankrupt your startup!



Hybrid

- Common predictions are precomputed and stored on device
- Local data centers: e.g. each warehouse has its own server rack
- Predictions are generated on cloud and cached on device

Challenges of ML on the edge

- Device not powerful enough to run models
  - Energy constraint
  - Computational power constraint
  - Memory constraint

Challenges of ML on the edge

1. Hardware: Make hardware more powerful
2. Model compression: Make models smaller
3. Model optimization: Make models faster

Make hardware more powerful: big companies

Musk Boasts Tesla Has 'Best Chip in the World'

The CEO's newest big prediction: that Tesla will have self-driving cars on the road next year.

Bloomberg
APR 23, 2019

⚠ unreliable narrator ⚠

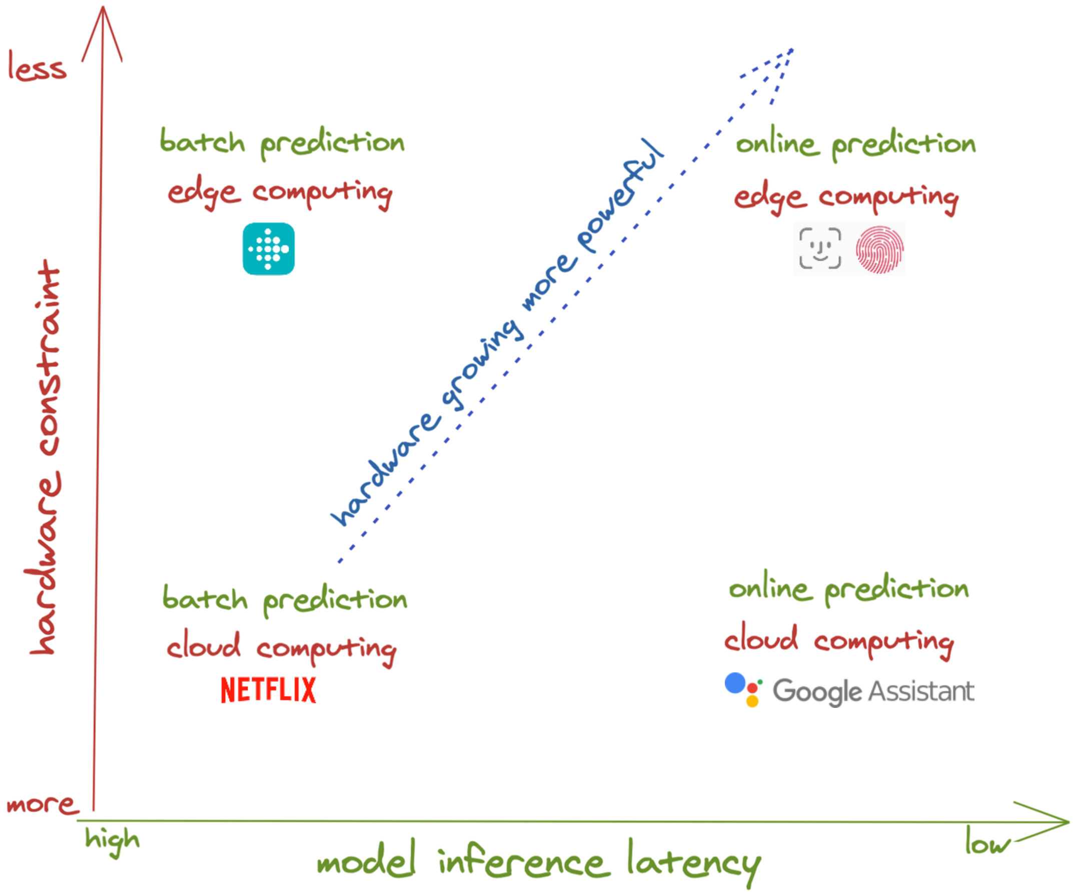
Apr 14, 2020 - Technology

Scoop: Google readies its own chip for future Pixels, Chromebooks

Make hardware more powerful: startups

Hardware startup	Raised ($M)	Year founded	Location
SambaNova	1100	2017	Bay Area
Graphcore	682	2016	UK
Groq	362	2016	Bay Area
Nuvia	293	2019	Bay Area
Wave Computing	203	2008	Bay Area
Cambricon	200	2016	China
Cerebras	112	2016	Bay Area
Hailo	88	2017	Israel
Habana Labs	75	2016	Israel
Kneron	73	2015	San Diego
Prophesee	65	2014	France
Syntiant	65	2017	LA
Groq	62	2016	Bay Area
EdgeQ	53	2018	Bay Area
LeapMind	50	2012	Japan

Future of ML: online and on-device

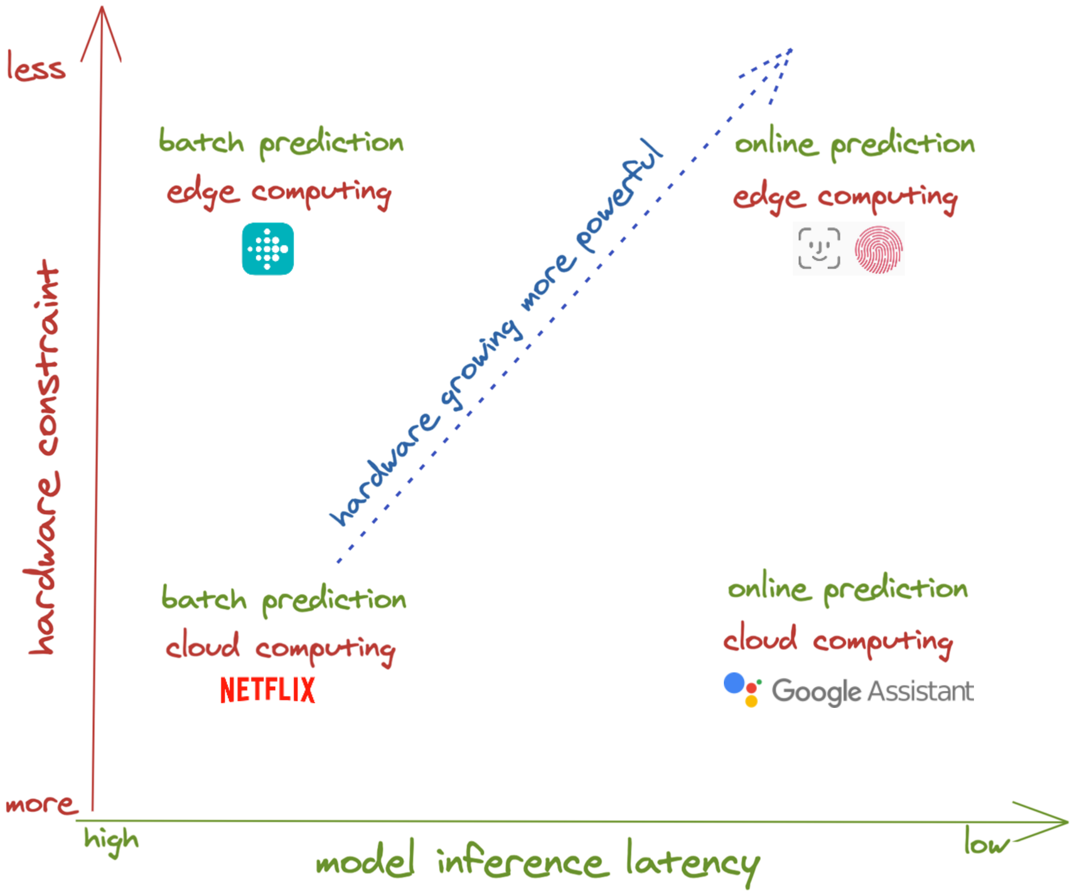


Breakout exercise

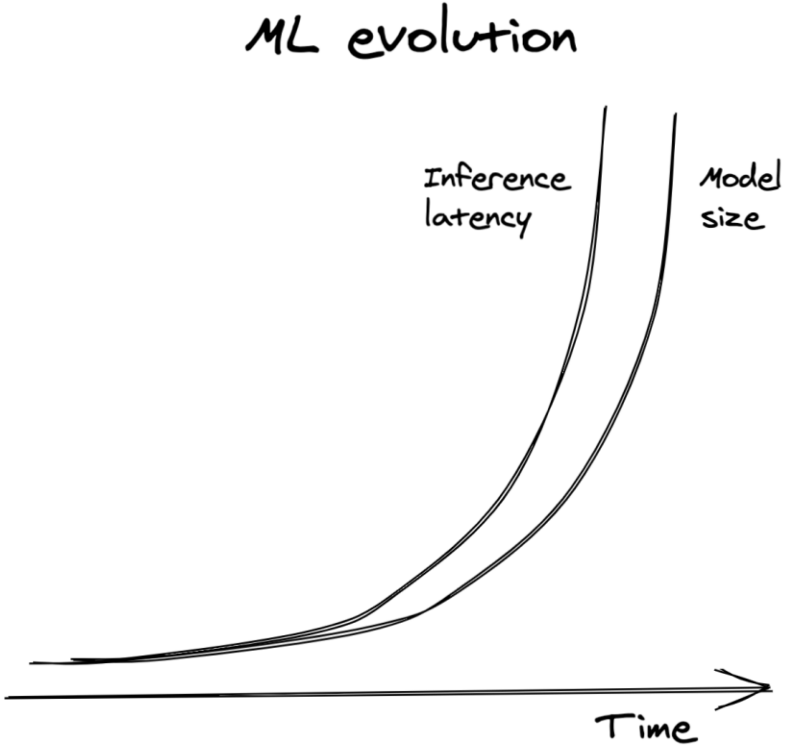
Group of 4, 10 minutes

Identify 3 applications for each quadrant.

- How do you determine:
  - Batch vs. online prediction
  - Edge vs. cloud
- Hints: Look at some of the applications on your phone.



Model Compression



Bigger, better, slower

Model compression

1. Quantization
2. Knowledge distillation
3. Pruning
4. Low-ranked factorization

Model compression: active research/development

The Top 121 Model Compression Open Source Projects on Github

Categories > Machine Learning > **Model Compression**

Nni 10910
An open source AutoML toolkit for automate machine learning lifecycle, including feature engineering, neural architecture search, model compression and hyper-parameter tuning.

Pocketflow 2676
An Automatic Model Compression (AutoMC) framework for developing smaller and faster AI applications.

Neuronblocks 1404
NLP DNN Toolkit - Building Your NLP DNN Models Like Playing Lego

Ghostnet 1823
CV backbones including GhostNet, TinyNet and TNT, developed by Huawei Noah's Ark Lab.

Channel Pruning 1021
Channel Pruning for Accelerating Very Deep Neural Networks (ICCV'17)

Model Optimization 1189
A toolkit to optimize ML models for deployment for Keras and TensorFlow, including quantization and pruning.

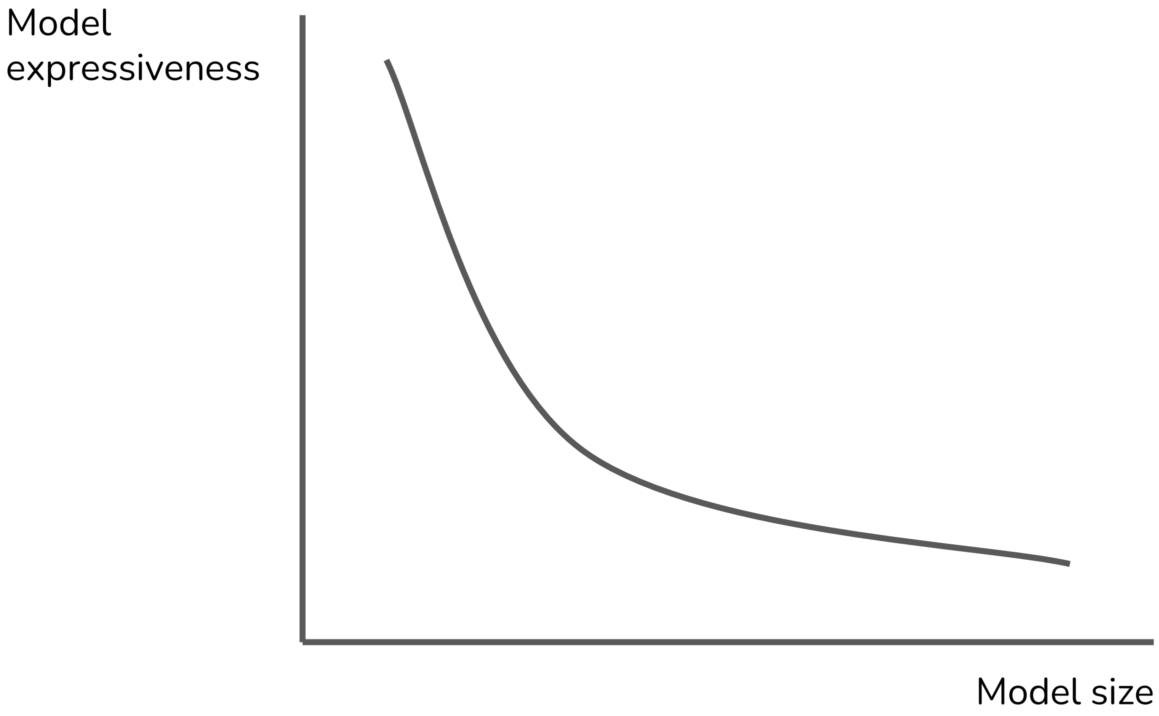
Knowledge Distillation Pytorch 1291
A PyTorch implementation for exploring deep and shallow knowledge distillation (KD) experiments with flexibility

Awesome Pruning 1361
A curated list of neural network pruning resources.

Awesome Knowledge Distillation 1612
Awesome Knowledge-Distillation. 分类整理的知识蒸馏paper(2014-2021)。

https://opensourcelibs.com/libs/model-compression | https://awesomeopensource.com/projects/model-compression

No free lunch!



Model compression: quantization

- Reduces the size of a model by using fewer bits to represent parameter values
  - E.g. half-precision (16-bit) or integer (8-bit) instead of full-precision (32-bit)

100M params

32-bit
400MB

16-bit
200MB

Model compression: quantization

- Reduces the size of a model by using fewer bits to represent parameter values
  - E.g. half-precision (16-bit) or integer (8-bit) instead of full-precision (32-bit)
  - 1-bit representation: BinaryConnect, Xnor-Net

Exclusive: Apple acquires Xnor.ai, edge AI spin-out from Paul Allen's AI2, for price in $200M range

BY ALAN BOYLE, TAYLOR SOPER & TODD BISHOP on January 15, 2020 at 10:44 am

Model compression: quantization

Pros	

1. Reduce memory footprint
2. Increase computation speed
    a. Bigger batch size
    b. Computation on 16 bits is faster than on 32 bits	

BFloat16: The secret to high performance on Cloud TPUs

Model compression: quantization

Pros	Cons

1. Reduce memory footprint
2. Increase computation speed
    a. Bigger batch size
    b. Computation on 16 bits is faster than on 32 bits
	1. Smaller range of values
	2. Values rounded to 0
	
	Need efficient rounding/scaling techniques

Model compression: quantization

- Post-training quantization

```
torch.quantization.convert(model, inplace=True)
```

- Quantization-aware training

Model compression: knowledge distillation

- Train a small model (“student”) to mimic the results of a larger model (“teacher”)
  - Teacher & student can be trained at the same time.
  - E.g. DistillBERT, reduces size of BERT by 40%, and increases inference speed by 60%, while retaining 97% language understanding.

DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter (Sanh et al., 2019)

Model compression: knowledge distillation

- Train a small model (“student”) to mimic the results of a larger model (“teacher”)
- Pros:
  - Fast to train student network if teacher is pre-trained.
  - Teacher and student can be completely different architectures.
- Cons:
  - If teacher is not pre-trained, may need more data & time to first train teacher.
  - Sensitive to applications and model architectures.

Model compression: pruning

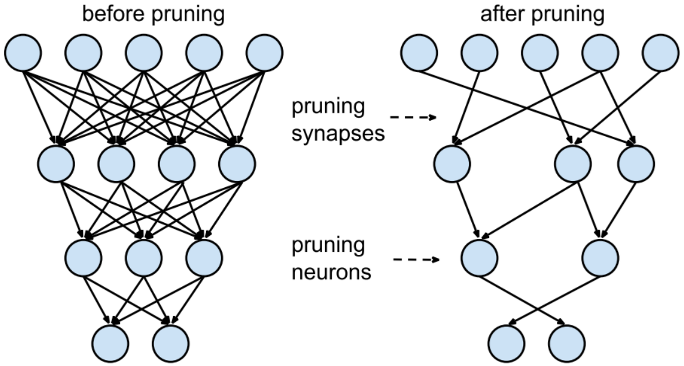
- Originally used for decision trees to remove uncritical sections
- Neural networks: reducing over-parameterization

Model compression: pruning methods

1. Remove nodes
    a. Changing architectures & reducing number of params

Model compression: pruning methods

1. Remove nodes
2. Find least useful params & set to 0
   a. Number of params remains the same
   b. Reducing number of non-zero params



Learning both Weights and Connections for Efficient Neural Networks (Han et al., 2015)

Model compression: pruning methods

1. Remove nodes

???

2. Find least useful params & set to 0
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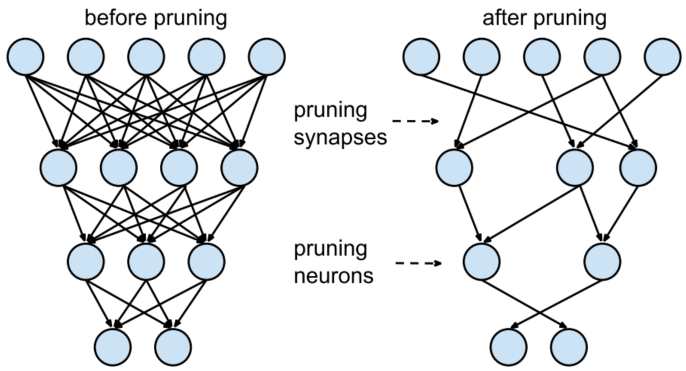

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Model compression: pruning methods

1. Remove nodes
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Makes models more sparse

- lower memory footprint
- increased inference speed

The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks (Frankle et al., ICLR 2019)

Model compression: pruning methods

1. Remove nodes
2. Find least useful params & set to 0
    a. Number of params remains the same
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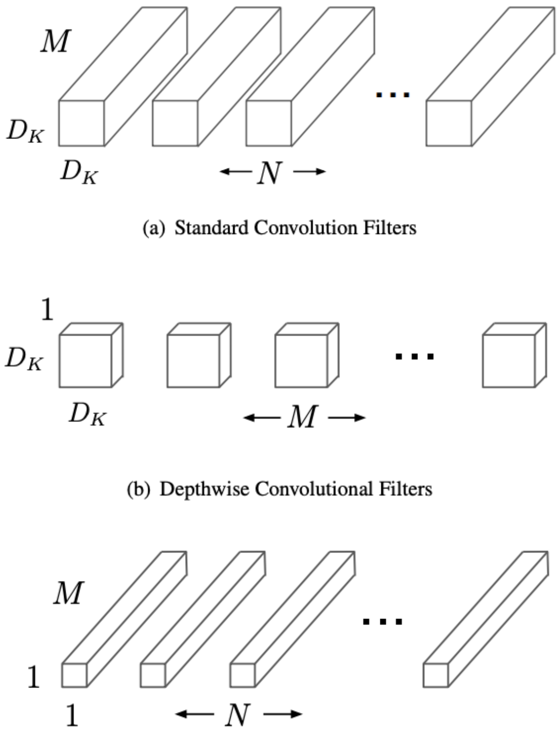
Can be used for architecture search

Model compression: factorization

- 3 x 3 matrix can be written as a product of 3 x 1 and 1 x 1
    - 6 params instead of 9
- Replace convolution filters (many parameters) with compact blocks
    - E.g. MobileNets:
        - (a) are replaced by depthwise convolution
        - (b) and pointwise convolution
        - (c) to build a depthwise separable filter



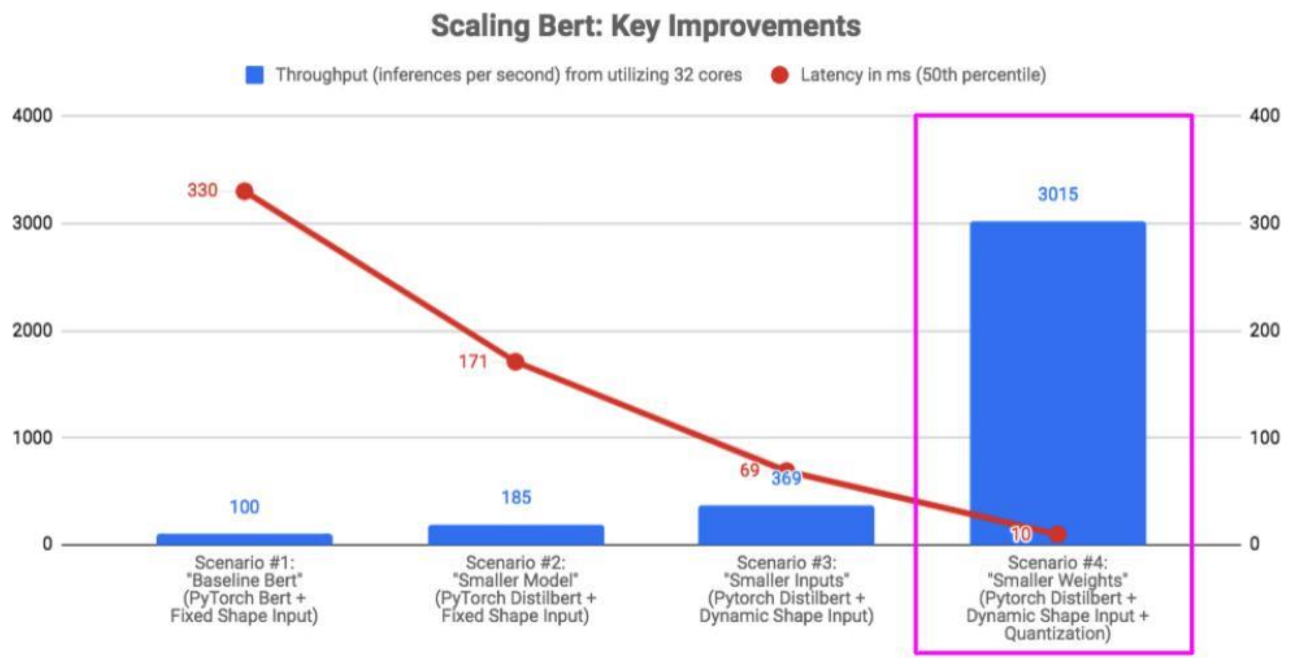
(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications (Howard et al., 2017)

Make models smaller: case study



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

Compiling & optimizing models for edge devices

"With PyTorch and TensorFlow, you've seen the frameworks sort of converge. The reason quantization comes up, and a bunch of other lower-level efficiencies come up, is because the next war is compilers for the frameworks — XLA, TVM, PyTorch has Glow, a lot of innovation is waiting to happen," he said. "For the next few years, you're going to see ... how to quantize smarter, how to fuse better, how to use GPUs more efficiently, [and] how to automatically compile for new hardware."

Soumith Chintala, creator of PyTorch (VentureBeat, 2020)

How to run model on different hardware backends?

classifier

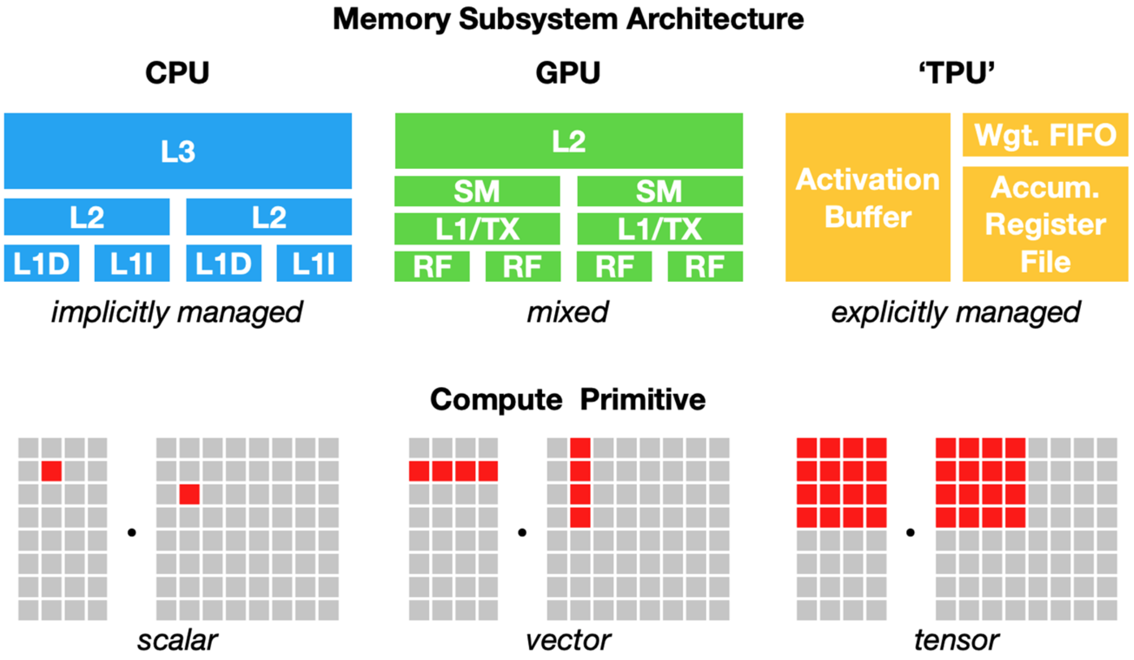
"tabby cat"

PyTorch
TensorFlow
scikit learn
LightGBM
mxnet

Thanks Chris Hoge for the cute slide!

Backends: memory layout + compute primitives

Deep learning models	high-dim instructions
Hardware backend	low-dim compute primitives



TVM: An Automated End-to-End Optimizing Compiler for Deep Learning (Chen et al., 2018)

1. Compatibility

Growing →

Backend / Frontend										
PyTorch	?	?	?	?	?	?	?	?	?	?
TensorFlow	?	?	?	?	?	?	?	?	?	?
scikit learn	?	?	?	?	?	?	?	?	?	?
LightGBM	?	?	?	?	?	?	?	?	?	?
mxnet	?	?	?	?	?	?	?	?	?	?
JAX	?	?	?	?	?	?	?	?	?	?

Growing ↓

2. Performance across frameworks

```
df = pd.read_csv(“train.csv”)
filtered = df.dropna()
features = np.mean(filtered)
model.fit(features)
```

PyTorch pandas scikit learn NumPy TensorFlow

No end-to-end optimization across frameworks

2. Performance

```
df = pd.read_csv("train.csv")
filtered = df.dropna()
features = np.mean(filtered)
model.fit(features)
```

Typical data science workloads using NumPy, Pandas and TensorFlow run 23× slower one thread compared to hand-optimized code
(Palkar et al., '18)

Evaluating End-to-End Optimization for Data Analytics Applications in Weld (Palkar et al., VLDB 2018). Slide inspired by Palkar's talk.

Frontend & backend

Backend

Frontend

PyTorch

TensorFlow

scikit learn

LightGBM

mxnet

- Framework developers:
  - Offer support across a narrow range of server-class hardware
- Hardware vendors:
  - Offer their own SDK / kernel libraries for a narrow range of frameworks (CUDA, OpenVino toolkit, etc.)

→ Hardware lock-in

Optimizing compilers: lowering & optimizing

Generating

Compatibility	**Lowering** hardware-native code for your models
Performance	**Optimizing** your models to run on that hardware

Compatibility

Growing

Backend

Frontend

Frontend \ Backend										
PyTorch	?	?	?	?	?	?	?	?	?	?
TensorFlow	?	?	?	?	?	?	?	?	?	?
scikit learn	?	?	?	?	?	?	?	?	?	?
LightGBM	?	?	?	?	?	?	?	?	?	?
mxnet	?	?	?	?	?	?	?	?	?	?
JAX	?	?	?	?	?	?	?	?	?	?

Growing

Compatibility: bridging frontend & backend

PyTorch
TensorFlow
scikit learn
LightGBM
mxnet

Common language

Intermediate Representations

Machine code

Compatibility: different IR levels

PyTorch
TensorFlow
scikit learn
LightGBM
mxnet

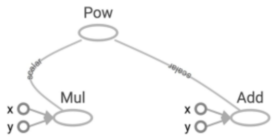
Intermediate Representations

High-level IRs → Tuned IRs → Low-level IRs → Machine code

Computation graphs
Hardware agnostic
E.g.: XLA HLO, TensorFlowLite, TensorRT

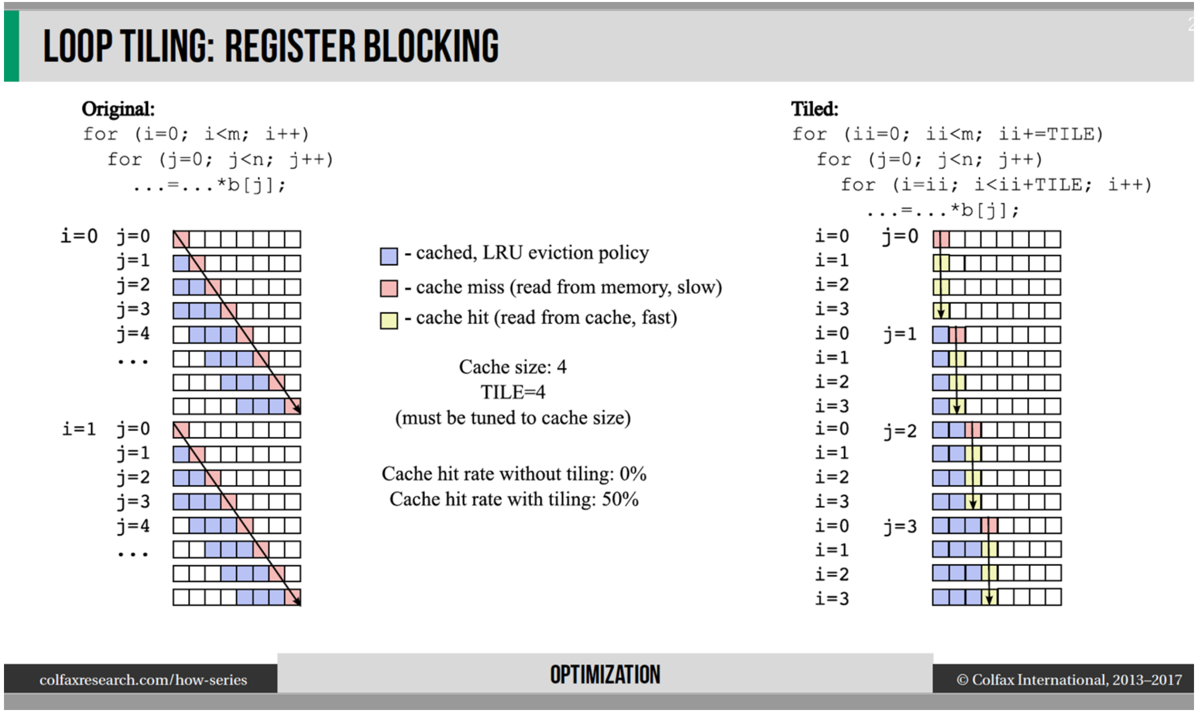
- Hand-tuned
- ML-based

Language agnostic
E.g.: LLVM, NVCC



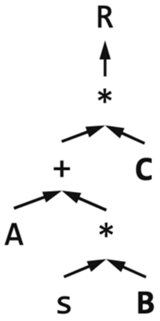
Performance: how to optimize your models

- Standard optimizations
    - vectorization
    - loop tiling
    - explicit parallelism
    - cache
    - etc.



https://colfaxresearch.com/how-series/#ses-10

Operator fusion




```
for( i in 1:n )
  tmp1[i,1] = s * B[i,1];
for( i in 1:n )
  tmp2[i,1] = A[i,1] + tmp1[i,1];
for( i in 1:n )
  R[i,1] = tmp2[i,1] * C[i,1];
```

```
for( i in 1:n )
  R[i,1] = (A[i,i] + s*B[i,1]) * C[i,1];
```

Operator fusion

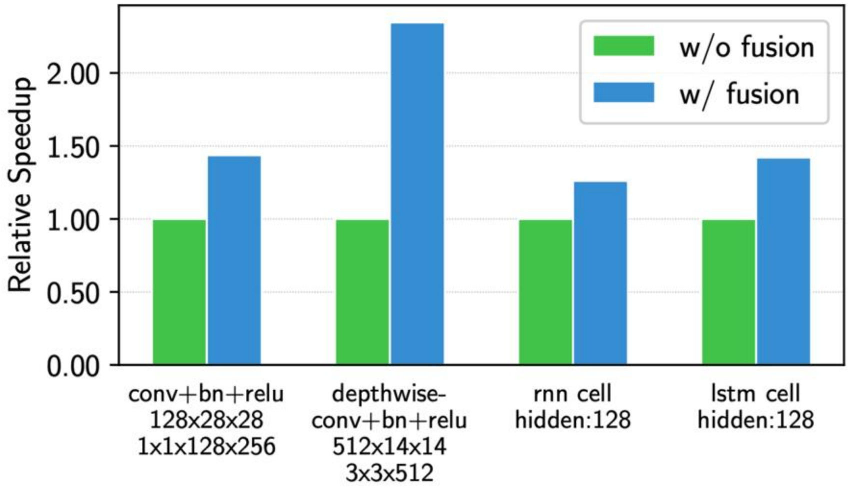
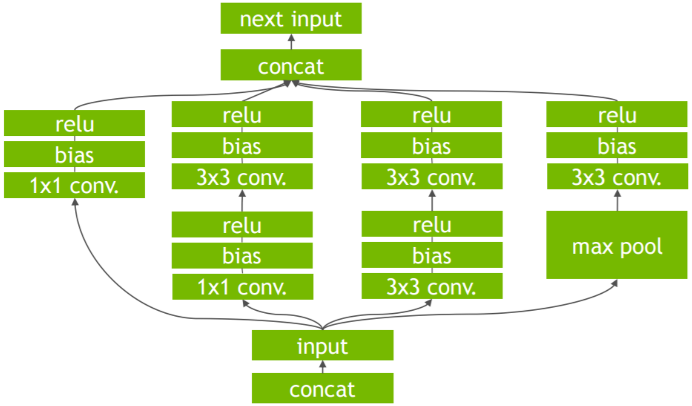


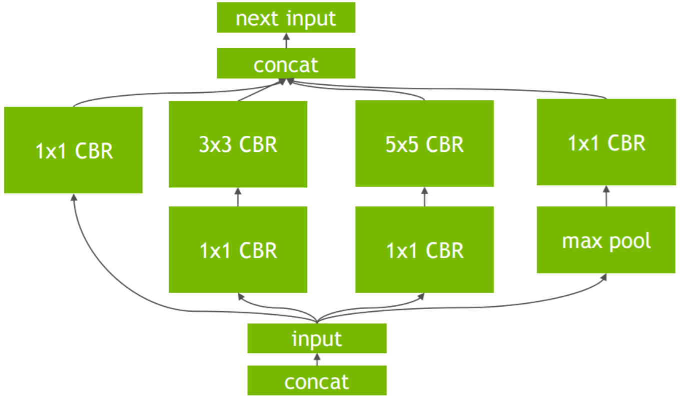
Figure 4: Performance comparison between fused and non-fused operations. TVM generates both operations. Tested on NVIDIA Titan X.

[TVM: An Automated End-to-End Optimizing Compiler for Deep Learning](#) (Chen et al., 2018)

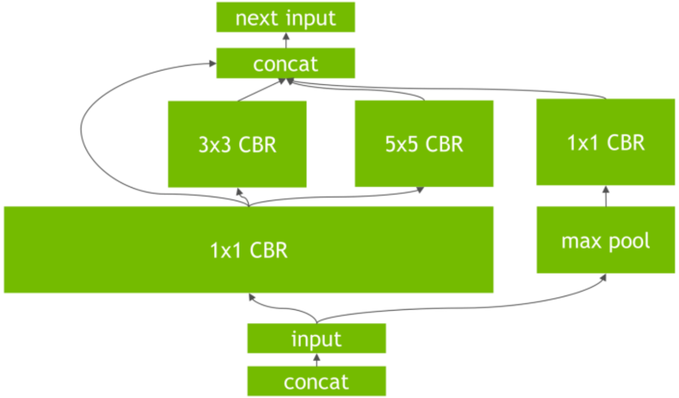
Graph optimization



Original graph



Vertical fusion



Horizontal fusion

https://developer.nvidia.com/tensorrt

Why is it hard?

- Hardware-dependent
  - Different processing/memory/cache/latency hiding
  - Different compute primitives
  - Different instruction sets (RISC-V, ARM, x86, etc.)
- Operator-dependent
- New models being developed all the time
- Many possible paths to execute a graph

Why is it hard?

- Hardware-dependent
  - Different processing/memory/cache/latency hiding
  - Different compute primitives
  - Different instruction sets
- Operator-dependent
- New models being developed all the time
- Many possible paths to execute a graph

Hand-tuned:

- Heuristics-based (non-optimal)
- Non-adaptive
  - **Custom hardware? New framework? New model?**

Idea: automate the optimization process

- What if we explore all possible paths to find the optimal path?
    - Run each path end-to-end to find out how long it takes to execute the path
    - Too slow because of too many possible paths

Idea: automate the optimization process

- What if we explore all possible paths to find the optimal path?
  - Run each path end-to-end to find out how long it takes to execute the path
  - Too slow because of too many possible paths

Combinatorial search problem

AutoScheduler

- What if we explore all possible paths to find the optimal path?
    - ~~Run each path end-to-end to find out how long it takes to execute the path~~
    - ~~Too slow because of too many possible paths~~
    - Use ML to solve it: narrow down the search space to find approximately the optimal one

AutoScheduler

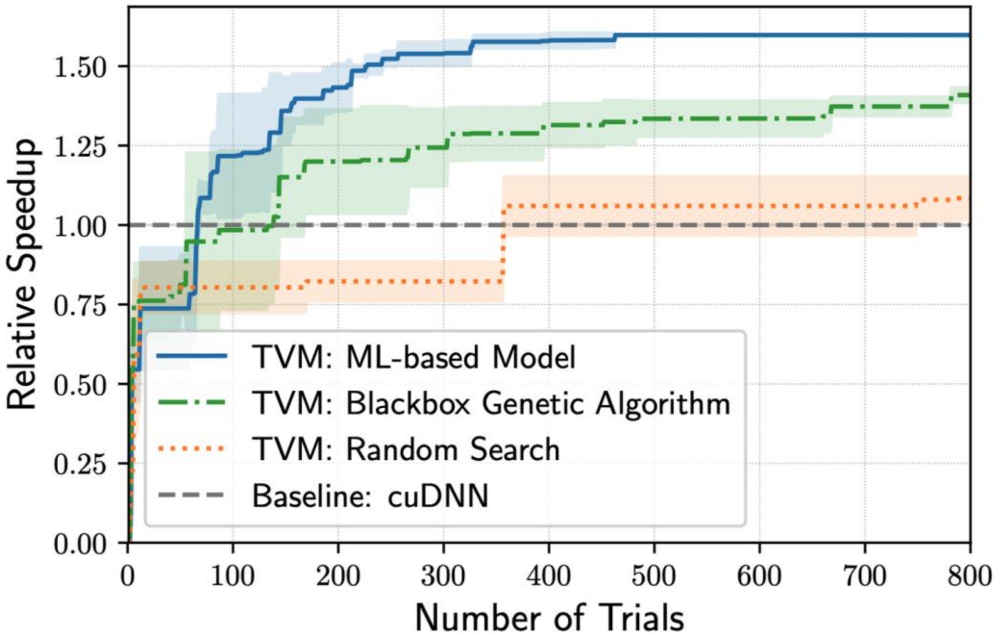
1. Break the graph into subgraphs
2. Predict how big each subgraph is
3. Allow time for each subgraph
4. Stitch them together

AutoScheduler

- cuDNN autotune:
  - for PyTorch on GPU
  - operator-level (only selecting convolutional operator)
- TVM’s autoscheduler:
  - multiple frameworks / multiple hardware
    - automatically adapt to hardware type
  - subgraph-level

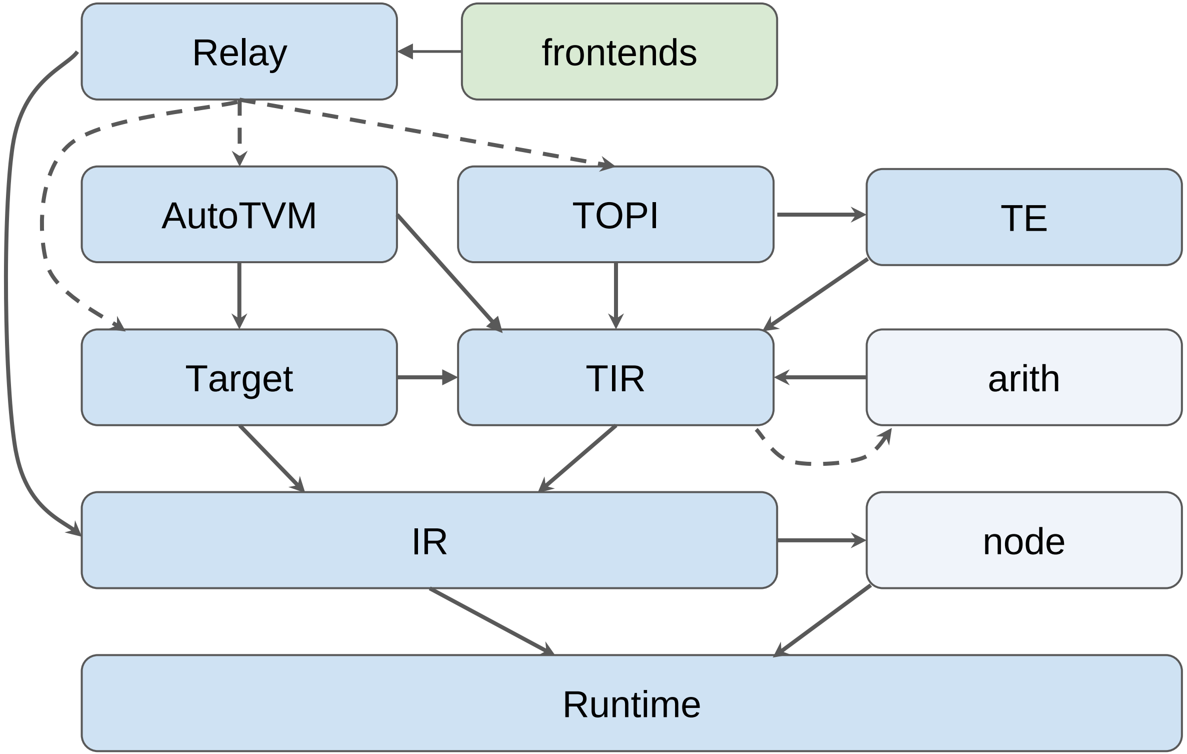
AutoTVM: GPUs

Conv2d operator in ResNet-18 on TITAN X



TVM: An Automated End-to-End Optimizing Compiler for Deep Learning (Chen et al., 2018)

TVM: compiler stack



https://tvm.apache.org/

TVM: Apache OSS

- Compile time:
  - might be slow (lots of paths to explore/evaluate)
  - hours, even days
- Compile once, no need to update even when weights are updated
  - especially useful when you have multiple copies of models on multiple machines

Install TVM the Easy Way - tlcpack.ai

About TLCPack

TLCPack – Tensor learning compiler binary package. It is a community maintained binary builds of deep learning compilers. TLCPack does not contain any additional source code release. It takes source code from Apache TVM and build the binaries by turning on different build configurations. Please note that additional licensing conditions may apply(e.g. CUDA EULA for the cuda enabled package) when you use the binary builds.

TLCPack is not part of Apache and is run by thirdparty community volunteers. Please refer to the official Apache TVM website for Apache source releases.

Licenses for TVM and its dependencies can be found in the github repository.

Build	0.8.dev107+g7b11b9217	Nightly	
Your OS	Linux	Mac	Windows
Package	Conda	Pip	Source
CUDA	10.0	None	
Run this Command:	`conda install tlcpack-nightly -c tlcpack`		

Compatibility: browsers

PyTorch

TensorFlow

scikit learn

LightGBM

mxnet

Browser

ML in browsers

- Compile models to JavaScript
  - TensorFlow.js, Synaptic, and brain.js

ML in browsers

- Compile models to JavaScript
- Compile models to WASM (WebAssembly)
    - Open standard that allows running executable programs in browsers
    - Supported by 93%

https://caniuse.com/wasm

Machine Learning Systems Design

Next class

Universidad Popular del Cesar