Hardware Opportunities in the Machine Learning Lifecycle

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Get the latest slides and links to literature

https://tinyurl.com/isscc-lifecycle

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About Me

- Co-director of the RISE Lab
- Co-founder of Turi Inc.
- Member of the Apache Spark PMC
- Research
  - Artificial Intelligence
  - Data Science
  - Distributed Data Systems
  - Graph Processing Systems
- I don't study processor **architecture**
  - But I probably should …

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Outline

- History and the **Co-evolution** of Hardware and AI
  - The **Feedback Cycle** driving the 3rd wave of AI
- Machine Learning is **not a single workload**
  - Stages of the **Machine Learning Lifecycle**
- **Security** and machine learning

Along the way, I will talk about some of the research in my group addressing interesting aspects of the lifecycle.

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Hardware and the History of AI

- **1950 to 1974:** *Birth of AI*
  - 1951 Marvin Minsky builds first **neural network hardware** (SNARC)
- **1974 to 1980:** *First AI Winter*
  - Limited **processing power** and **data**
- **1980 to 1987:** *Second Wave of AI*
  - XCON (AI for **hardware configuration**) for DEC → boom in AI hardware companies
- **1987 to 1993:** *Second AI Winter*
  - **Brittle** AI and the collapse of the **AI Hardware Market**
- **1993 to 2011:** *AI → Machine Learning*
  - *Confluence of ideas + **Compute** + **Big Data** → AI starts to really work*
- **2011 to 2019:** *Third Wave (Deep Learning)*
  - ***Compute** + **data** + **abstractions** → feedback cycle*

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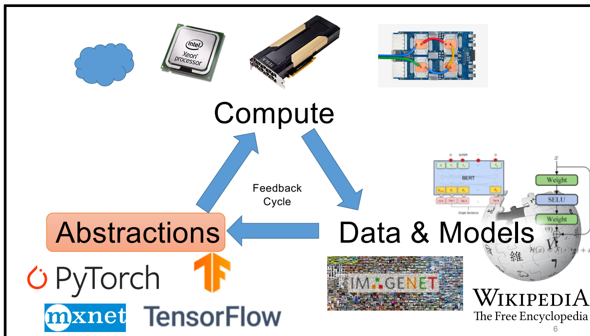

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Abstractions are Enabling Innovation

- Much of machine learning before 2010
  - Research focused on machine learning **algorithms**
  - Programs written using **high-level imperative languages**
    - Matlab/R/C++/Java
  - **Big abstractions:** linear algebra, map-reduce, graph systems
- Today:
  - Research focused on **model design**
  - **Models** written in high-level **DSLs**
    - TensorFlow/Pytorch
  - Big abstractions: **tensor operations**, **loss minimization,** linear algebra, …
- Models written in **TensorFlow** can now run on **hardware** that didn't exist when the models were created.

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How do we make **hardware** for Machine learning?

Machine learning is not a single application.

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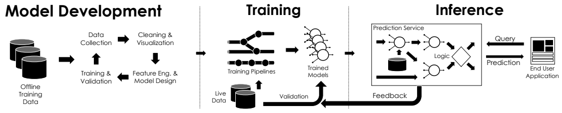
Machine learning is ***multiple applications*** *with* ***different requirements.***



Machine Learning Lifecycle

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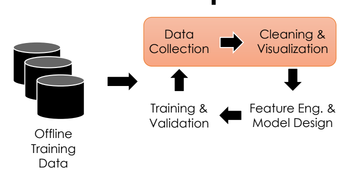
Model Development



Identifying potential sources of data

Joining data from multiple sources

Addressing **missing values** and **outliers**

Plotting trends to identify **anomalies**

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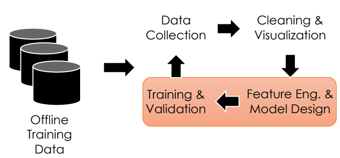
Model Development



Building informative **features functions**

Designing new **model architectures**

Tuning training algos.

Validating prediction accuracy

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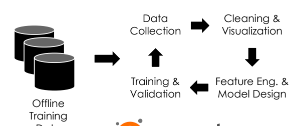
Model Development *Frameworks*



scikit learn, TensorFlow, R, PYTORCH, Keras, jupyter, mxnet, dmlc XGBoost, matplotlib, Caffe2, pandas, NumPy, Apache Spark, DASK, HIVE

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Model Development → Hardware

- Need to test **multiple designs and hyperparameters** quickly
  - May be better to run many parallel experiments than one experiment faster
- **Debug heavy** → sources of error → data, hyperparams., & model
  - **System should not be a source of error**
  - **Avoid** cutting corners (e.g., quantization, async) for increased performance
    - Unless you can make a case for stable convergence …
- **Data preparation** is often a bottleneck
  - Opportunity for **data tooling**
  - Accelerate data transformation and augmentation
- Emerging Trends
  - **Attention Models** and **Graph Neural Networks**: reduced locality, sparsity
  - **Dynamic Networks**: gating, cascades, mixtures, …
  - Increased emphasis on **DNN features** and **Fine-Tuning**
    - Reuse of common architectures and weights

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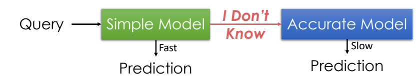
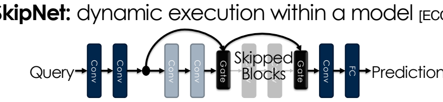
Dynamic Networks for **fast** and **accurate** inference

IDK Cascades: Using the fastest model possible [UAI'18]



SkipNet: dynamic execution within a model [ECCV'18]



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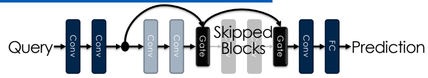
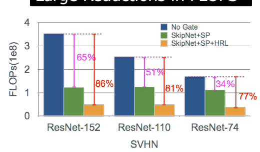
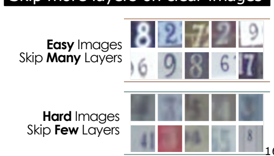


Large Reductions in FLOPS



Skip more layers on clear images



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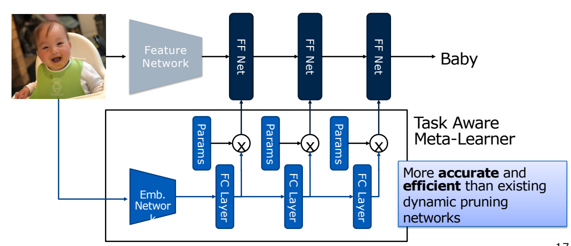
Task Aware Feature Embeddings [CVPR'19]



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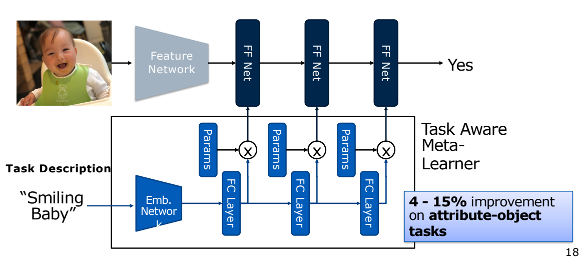

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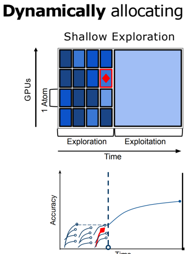
HyperSched [SOCC'19]

Dynamically allocating **parallel resources** to **parallel experiments**.



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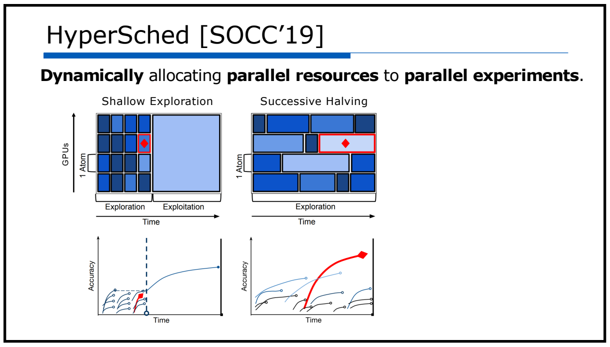

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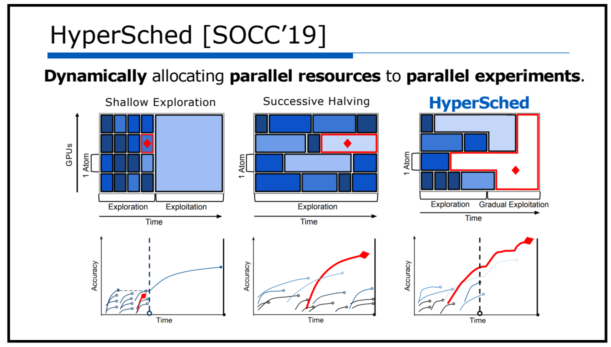

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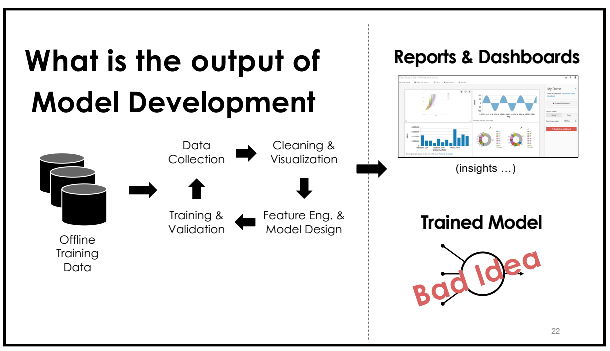

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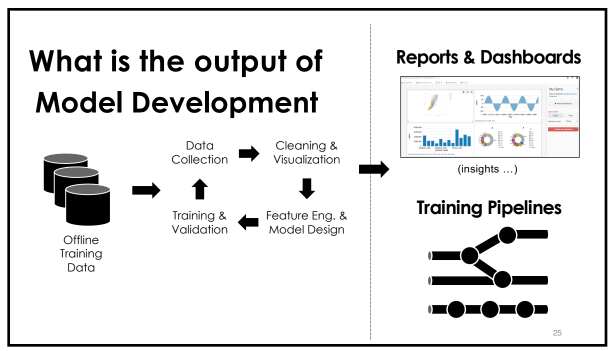

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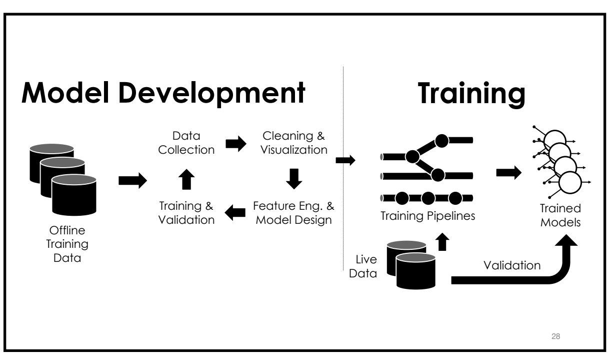

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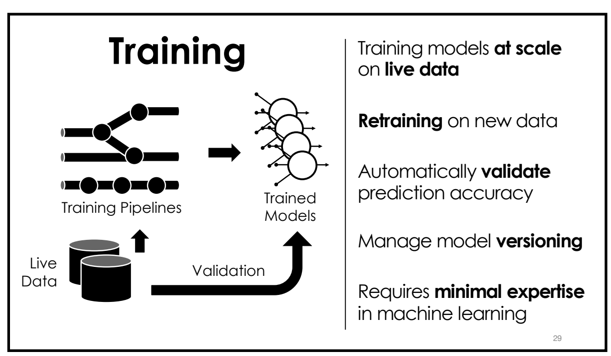

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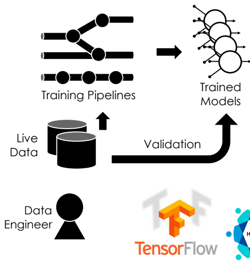
Training *Systems*



Workflow Management:

Apache Airflow
Luigi
Azkaban
Open-source Workflow Manager
Oozie

Scalable Training:

PyTorch
mxnet
TensorFlow
Horovod
Apache Spark
dmlc XGBoost

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Model Training → Hardware

- Fewer models to train → need **distributed training** of **individual models**
  - Often train with **more data**
- **Larger models** and **mini-batch sizes**
  - Need larger on-device memory
  - Counter trends → reversable networks, **optimal checkpointing**, …
- Models and hyperparameters are vetted → focus on **system optimizations**
  - Can **tolerate** some **system error** (quantization and async.)
  - Need adequate stability to meet deadlines
- **Data preparation** is still potentially an issue (as with model dev.)
- Need to deal with **composition** of multiple models

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Do Bigger Models Train Faster?

(Preliminary unpublished work.)

- Studying **pre-training** of large **Transformer Models** for NLP task (e.g., BERT)

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Deeper Models **Reduce Error Faster**

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Do Bigger Models Train Faster?

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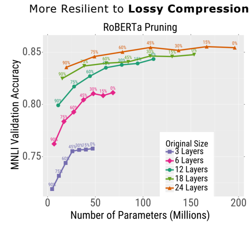
- Studying **pre-training** of large **Transformer Models** for NLP task (e.g., BERT)

Deeper Models **Reduce Error Faster**

More Resilient to **Lossy Compression**



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CheckMate [MLSys 2020]

Scaling deep learning training beyond the GPU memory wall.

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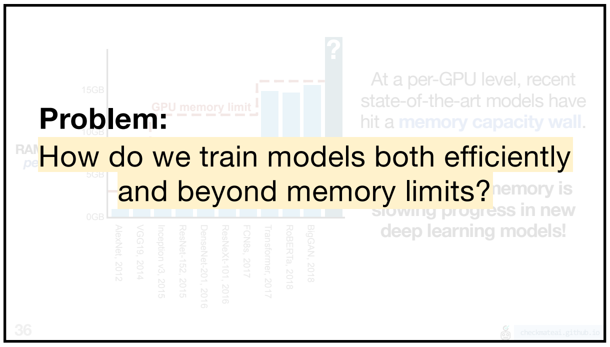

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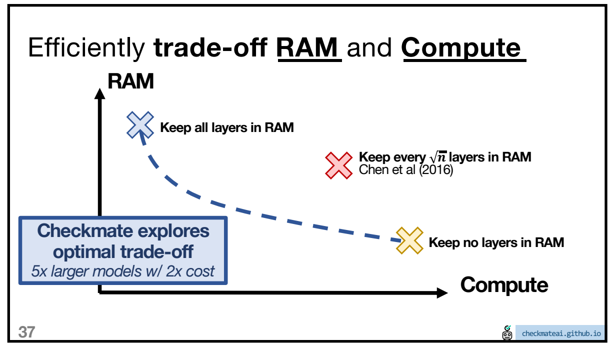

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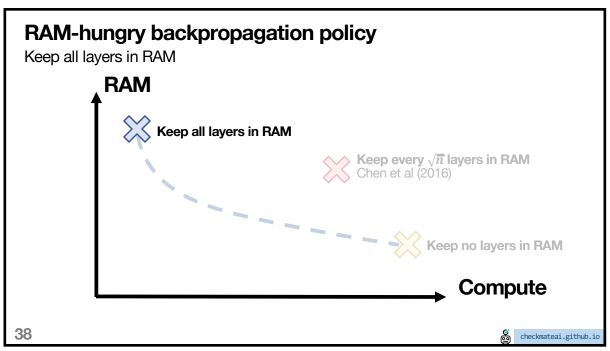

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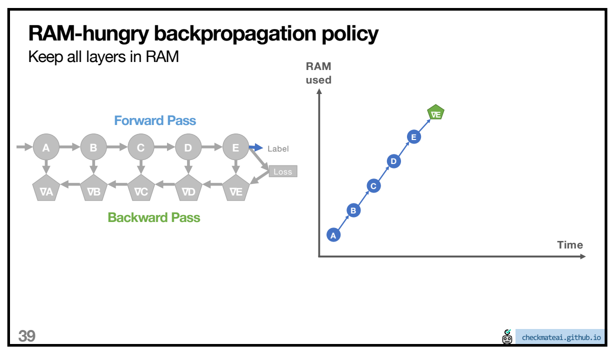

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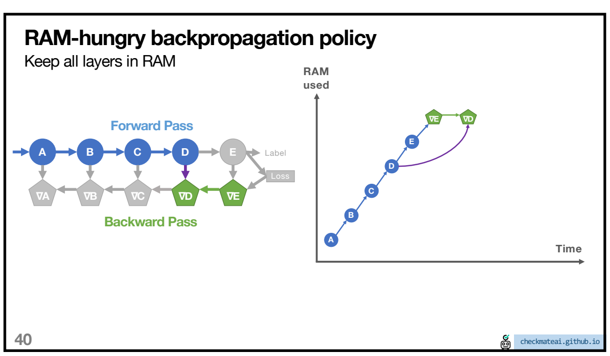

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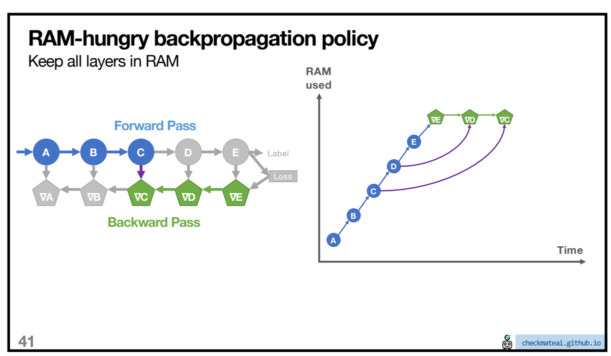

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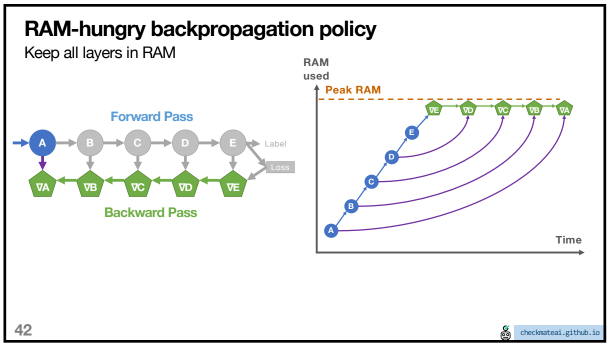

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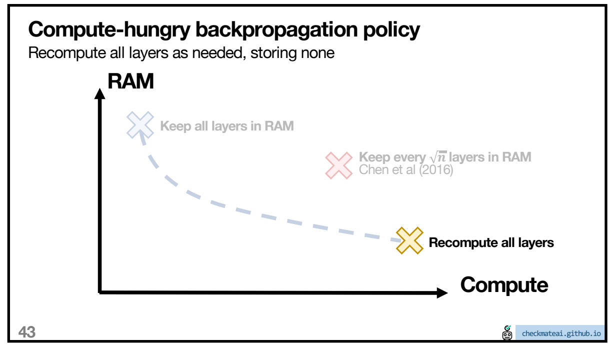

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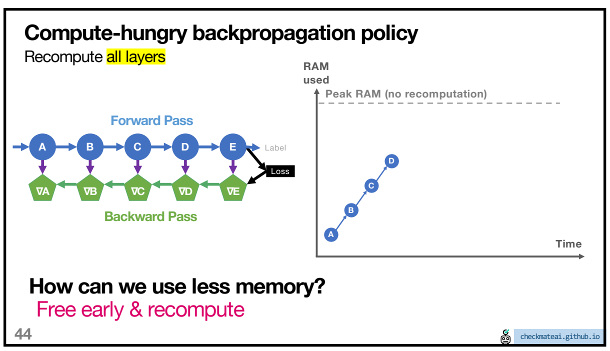

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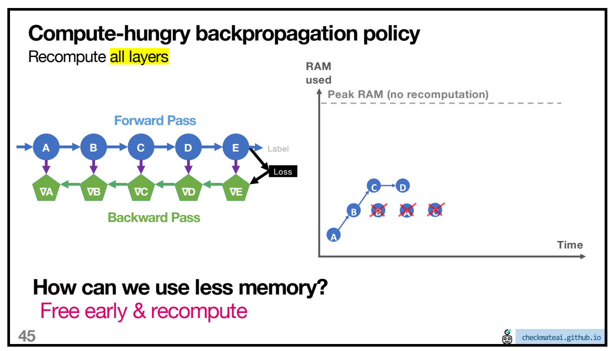

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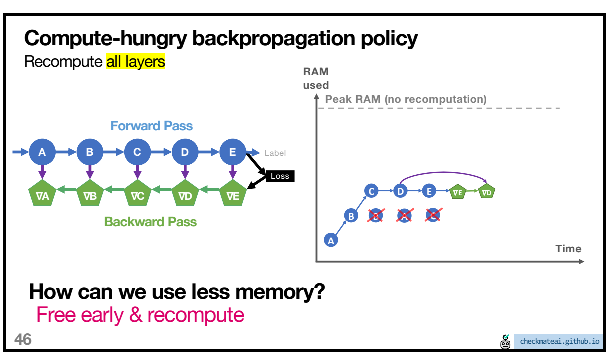

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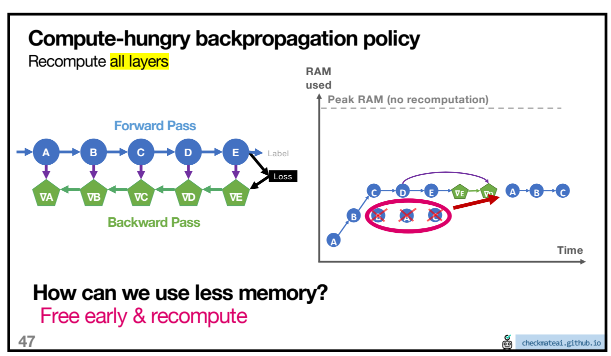

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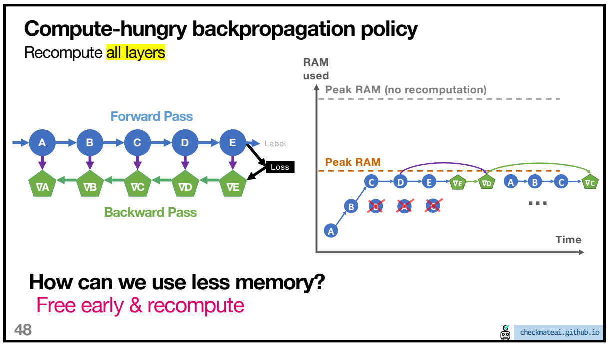

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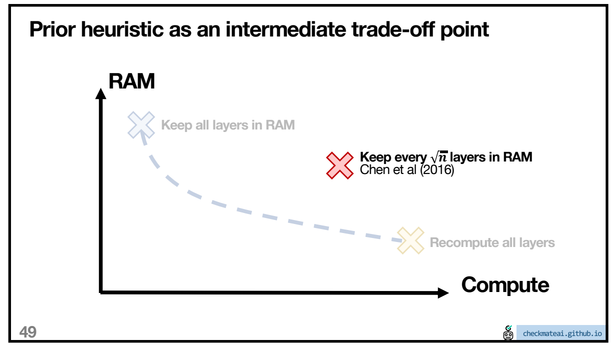

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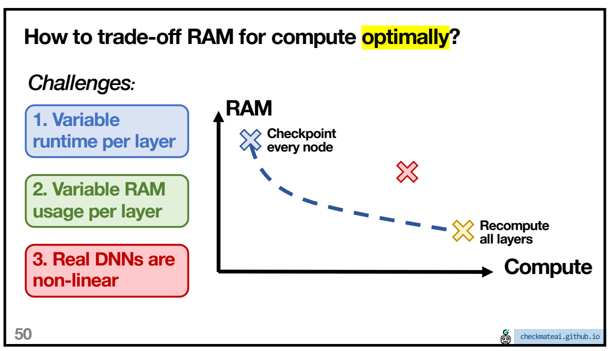

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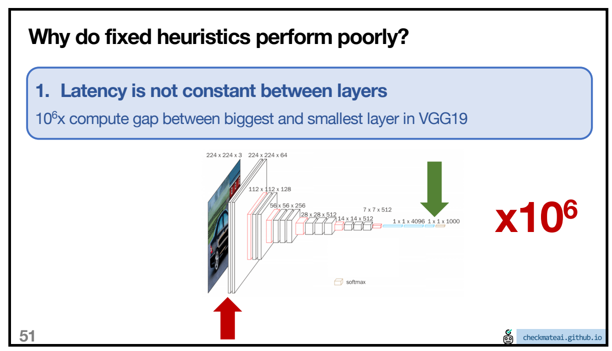

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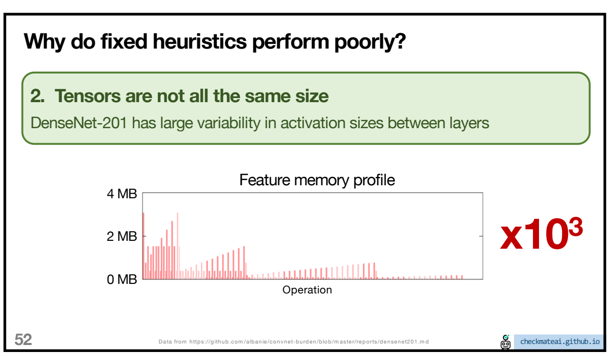

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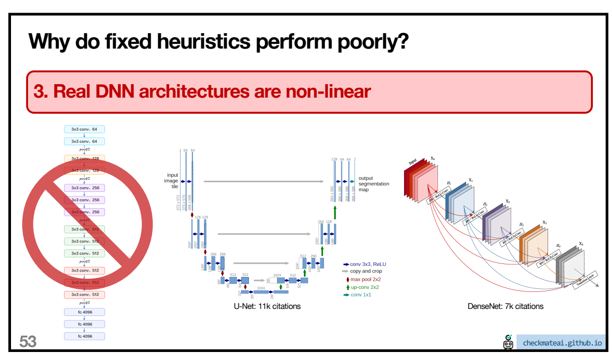

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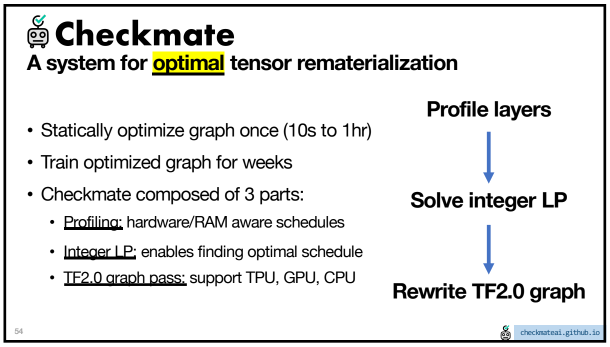

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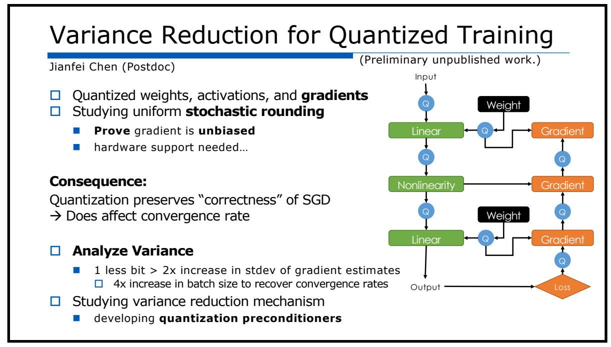

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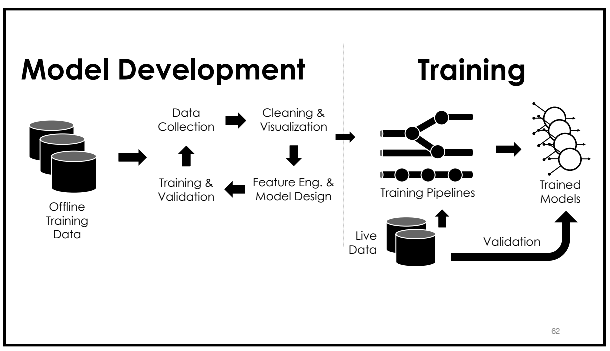

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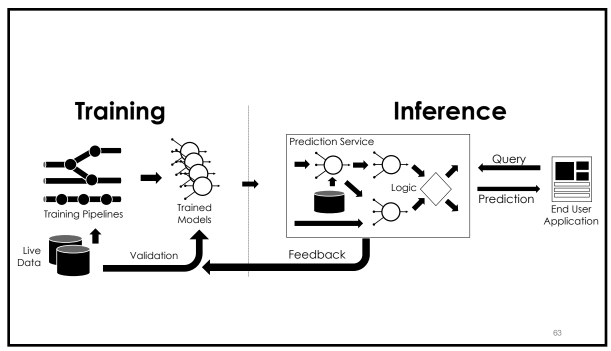

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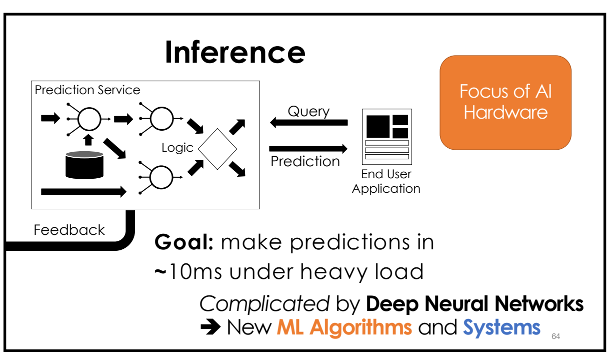

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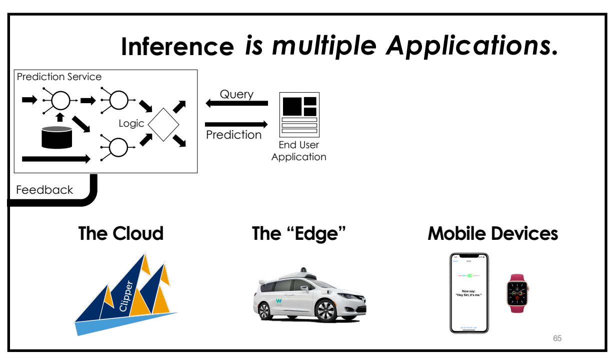

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The Cloud | **The "Edge"** | **Mobile Devices**

Throughput Oriented

Latency Oriented

Variable Load

Predictable Load

Budget

Power

Energy

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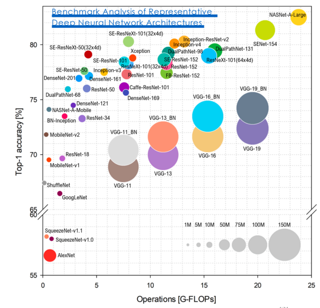
Inference in Deep Learning Models

- **Compute intensive**
- **Less memory intensive** than training



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Inference in Deep Learning Models

- **Compute intensive**
- **Less memory intensive** than training
- Latency vs throughput tradeoff determined by **batch size** and **hardware**
  - **Increase batch size**
    - Increase throughput ☺
    - Increase latency ☹

[Benchmark Analysis of Representative Deep Neural Network Architectures]

TitanXP

FPS	>1000	>250	>125	>62.5	>30	>15	>5	<=5
ms	<1	<4	<8	<16	<33	<66	<200	>=200

DNN	1	2	4	8	16	32	64
AlexNet	1.28	0.70	0.48	0.27	0.18	0.14	0.15
BN-Inception	5.79	3.00	1.64	1.10	0.87	0.77	0.71
CaffeResNet-101	8.20	4.82	3.32	2.54	2.27	2.16	2.08
DenseNet-121 (k=32)	8.93	4.41	2.64	1.96	1.64	1.44	1.39
DenseNet-169 (k=32)	13.03	6.72	3.97	2.73	2.14	1.87	1.75
DenseNet-201 (k=32)	17.15	9.25	5.36	3.66	2.84	2.41	2.27
DenseNet-161 (k=48)	15.50	9.10	5.89	4.45	3.66	3.43	3.24
DPN-68	10.68	5.36	3.24	2.47	1.80	1.59	1.52
DPN-98	22.31	13.84	8.97	6.77	5.59	4.96	4.72
DPN-131	29.70	18.29	11.96	9.12	7.57	6.72	6.37
FBResNet-152	14.55	7.79	5.15	4.31	3.96	3.76	3.65
GoogLeNet	4.54	2.44	1.65	1.06	0.86	0.76	0.72
Inception-ResNet-v2	25.94	14.36	8.82	6.43	5.19	4.88	4.59
Inception-v3	10.10	5.70	3.65	2.54	2.05	1.89	1.80
Inception-v4	18.96	10.61	6.53	4.85	4.10	3.77	3.61
MobileNet-v1	2.45	0.89	0.68	0.60	0.55	0.53	0.53
MobileNet-v2	3.34	1.63	0.95	0.78	0.72	0.63	0.61
NASNet-A-Large	32.30	23.00	19.75	18.49	18.11	17.73	17.77
NASNet-A-Mobile	22.36	11.44	5.60	2.81	1.61	1.75	1.51
ResNet-101	8.90	5.16	3.32	2.69	2.42	2.29	2.21
ResNet-152	14.31	7.36	4.68	3.83	3.50	3.30	3.17
ResNet-18	1.79	1.01	0.70	0.56	0.51	0.41	0.38
ResNet-34	3.11	1.80	1.20	0.96	0.82	0.71	0.67
ResNet-50	5.10	2.87	1.99	1.65	1.49	1.37	1.34
ResNeXt-101 (32x4d)	17.05	9.02	6.27	4.62	3.71	3.25	3.11
ResNeXt-101 (64x4d)	21.05	15.54	10.39	7.80	6.39	5.62	5.29
SE-ResNet-101	15.10	9.26	6.17	4.72	4.03	3.62	3.42
SE-ResNet-152	23.43	13.08	8.74	6.55	5.51	5.06	4.85
SE-ResNet-50	8.32	5.16	3.36	2.62	2.22	2.01	2.06
SE-ResNeXt-101 (32x4d)	24.96	13.86	9.16	6.55	5.29	4.53	4.29
SE-ResNeXt-50 (32x4d)	12.06	7.41	5.12	3.64	2.97	3.01	2.56
SENet-154	53.80	30.30	19.32	13.27	10.45	9.41	8.91
ShuffleNet	5.40	2.67	1.37	0.82	0.66	0.59	0.56
SqueezeNet-v1.0	1.53	0.84	0.66	0.59	0.54	0.52	0.53
SqueezeNet-v1.1	1.60	0.77	0.44	0.37	0.32	0.31	0.30
VGG-11	3.57	4.40	2.89	1.56	1.19	1.10	1.13
VGG-11_BN	3.49	4.60	2.99	1.71	1.33	1.24	1.27
VGG-13	3.88	5.03	3.44	2.25	1.83	1.75	1.79
VGG-13_BN	4.40	5.37	3.71	2.42	2.05	1.97	2.00
VGG-16	5.17	5.91	4.01	2.84	2.20	2.12	2.15
VGG-16_BN	5.04	5.95	4.27	3.06	2.45	2.36	2.41
VGG-19	5.50	6.26	4.71	3.29	2.59	2.52	2.50
VGG-19_BN	6.17	6.67	4.86	3.56	2.88	2.74	2.76
Xception	6.44	5.35	4.90	4.47	4.41	4.41	4.36

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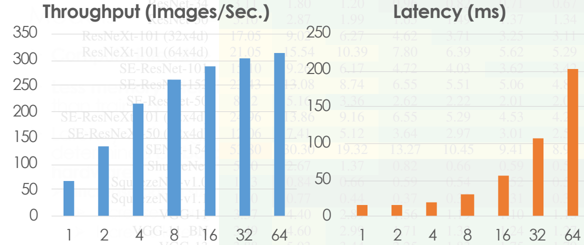
Batch Size.	1	2	4	8	16	32	64
ResNet-152	14.31	7.36	4.68	3.83	3.50	3.30	3.17

Throughput (Images/Sec.) | **Latency (ms)**



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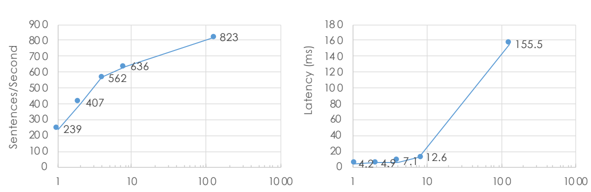
BERT-Large on a V100 (~$10K)



Results included Mixed precision optimizations!

Numbers obtained from: https://developer.nvidia.com/deep-learning-performance-training-inference

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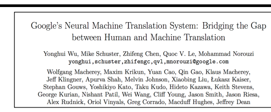
Google Translate


Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi

Serving

140 billion words a day[1]

82,000 GPUs running 24/7

*"If each of the **world's Android phones** used the new Google voice search for just **three minutes a day**, these engineers realized, the company would **need twice as many data centers.**"*
– Wired

Designed New Hardware! Tensor Processing Unit (TPU)

[1] https://www.nytimes.com/2016/12/14/magazine/the-great-ai-awakening.html

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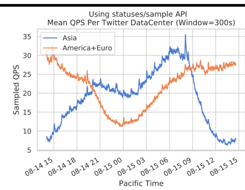
Other Challenges?

- **Bursty load** →
  - overprovision resources →
    - **expensive**
  - TPU reports 28% utilization of vector units in production
  - Solutions
    - statistical multiplexing → hardware not designed for multitenancy
    - could try to predict arrival process → generally difficult to predict
- **Versioning** and **testing models**
- **Prediction pipelines** → more on this soon



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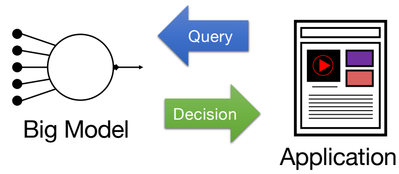
Inference



Two Approaches

- ***Offline:*** Pre-Materialize Predictions
- ***Online:*** Compute Predictions on the fly

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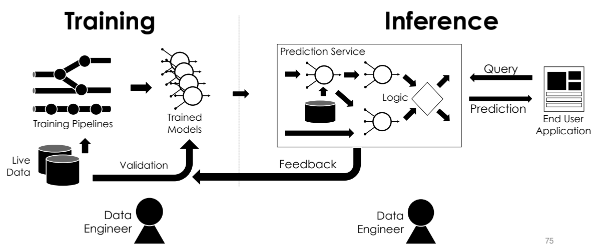
Pre-materialized Predictions



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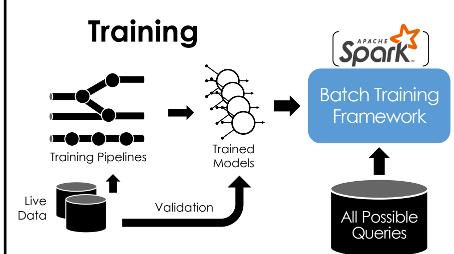
Pre-materialized Predictions



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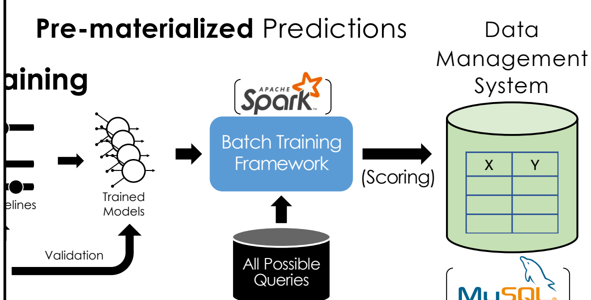
Pre-materialized Predictions



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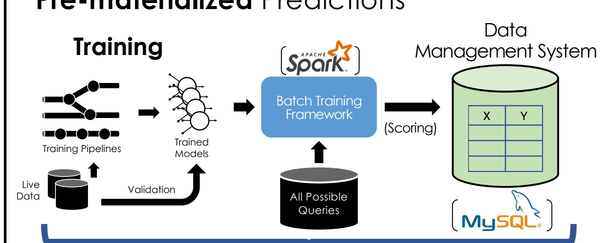
Pre-materialized Predictions



Standard Data Eng. Tools

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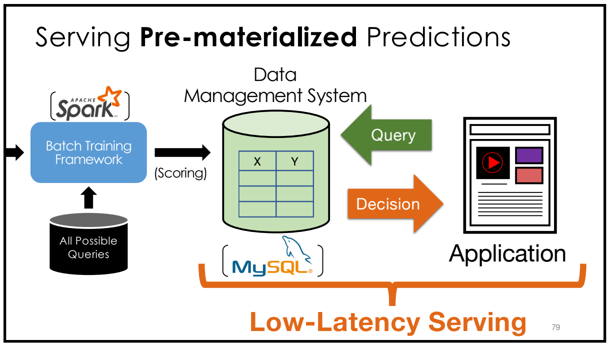

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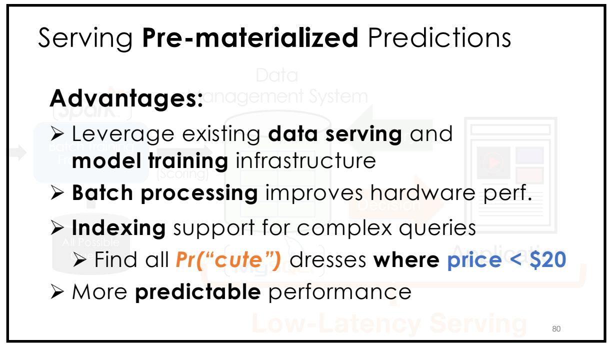

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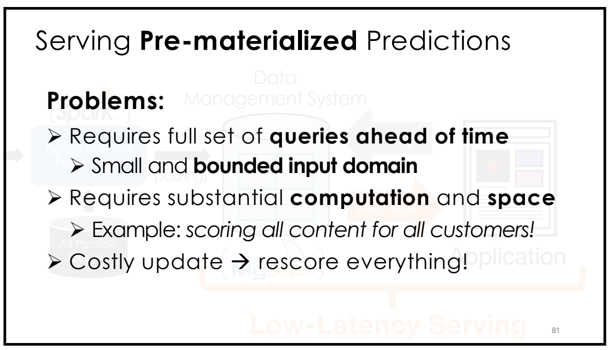

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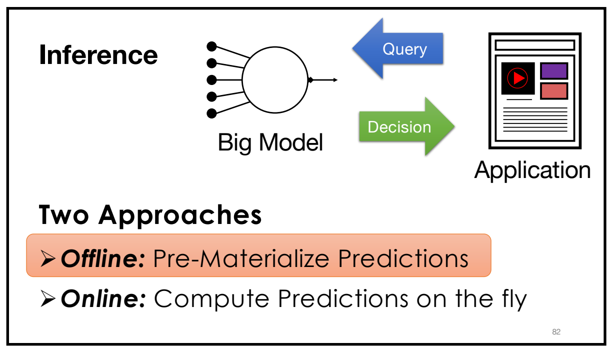

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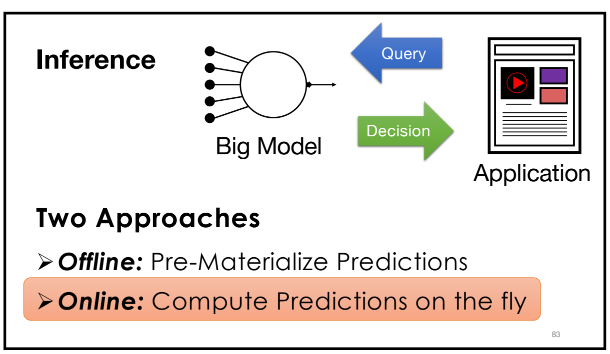

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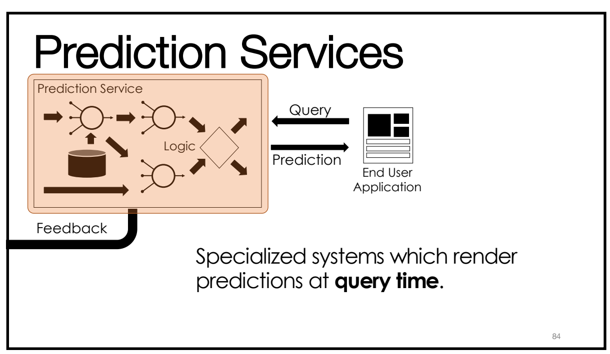

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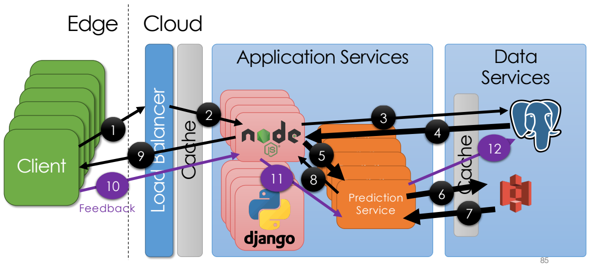
Architecture of a Prediction Service



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Online: Compute Predictions at Query Time

- **Examples**
  - Signals processing: speech recognition & image tagging
  - Ad-targeting based on search terms, available ads, user features
- **Advantages**
  - Compute only necessary queries
  - Enables models to be changed rapidly (e.g., bandit exploration)
  - Queries do not need to be from small ground set
- **Disadvantages**
  - Increases complexity and computation overhead of serving system
  - Requires low and predictable latency from models

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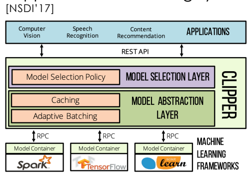
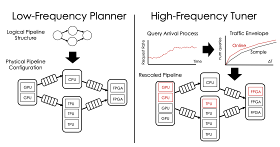
Active Area of Research in my Group

Clipper Prediction Serving System
[NSDI'17]



InferLine Pipeline Provisioning System
[Under review]



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Prediction Serving → Hardware

- Inference requires less memory → **focus on compute**
- Greater emphasis on **latency** instead of throughput
  - Focus on **small batch** inference (batch size = 1)
  - Opportunity to exploit **pipeline parallelism**
  - Need **high availability** → esp. in mission critical settings
- Often runs multiple **concurrent prediction tasks**
  - Cloud → Multitenancy → Performance isolation
  - Edge → supporting multiple data streams
- Tolerate **model compression** and **quantization**
  - As low as 4-bit activations and weights
- **Bursty load**
  - Statistical multiplexing
  - Use inference hardware for background training?

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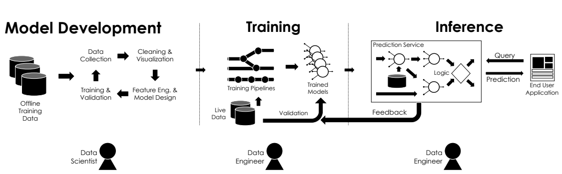
Machine Learning Lifecycle



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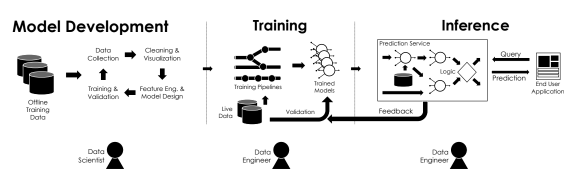

Security?

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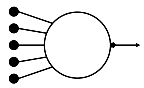
Protect the **data**, the **model**, and the **query**

High-Value **Data** *is* ***Sensitive***

- Medical Info.
- Home video
- Finance

Models capture **value** in data

- Core Asset
- "Contain" the data



Biggest opportunity for hardware in ML.

Queries can be as sensitive as the data

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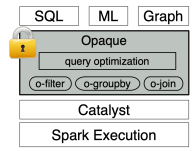
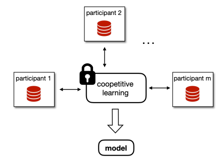
Our recent work in secure ML

Opaque [NSDI'17] | Oblivious Spark over **SGX**



Helen [S&P'19] | **Coopetitive Learning** Using Cryptographic Primitives



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Security and Hardware

- Improved Access to Data
  - User willing to share data with models but **not companies (people)**
  - **Differential Privacy** can increase data sharing incentives
- Better **isolation** of co-tenant models on hardware accelerators
- **Coopetitive Learning**: Secure multiparty computation for ML
  - **Example:** *Competing banks collaborate to construct a shared fraud model without sharing data.*
- Models have access **to more sensitive inputs**
  - **Example:** *Alexa could see where you are when asking to turn on a light.*

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Conclusion

- **History:** AI and Computer Systems have Co-evolved
- **Feedback Cycle:** Hardware, Abstractions, and Data
- **ML is many Applications:** *Machine Learning Lifecycle*
  - *Model Development:* Exploration
  - *Training:* Scale and Composition
  - *Inference:* Cloud – Edge Spectrum
- **Security:** Opportunity for hardware innovation in AI

Thank you!

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