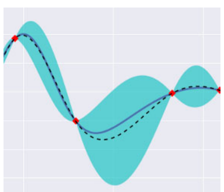
Large-scale Data Processing and Optimisation

Overview

Eiko Yoneki

University of Cambridge Computer Laboratory



Massive Data: Scale-Up vs Scale-Out

- Popular solution for massive data processing
  → scale and build distribution, combine theoretically unlimited number of machines in single distributed storage
  → Parallelisable data distribution and processing is key
- Scale-up: add resources to single node (many cores) in system (e.g. HPC)
- Scale-out: add more nodes to system (e.g. Amazon EC2)

Technologies supporting Cluster Computing

- Distributed infrastructure
  - Cloud (e.g. Infrastructure as a service, Amazon EC2, GCP, Azure)

    cf. Many core (parallel computing)
- Storage
  - Distributed storage (e.g. Amazon S3, Hadoop Distributed File System (HDFS), Google File System (GFS))
- Data model/indexing
  - High-performance schema-free database (e.g. NoSQL DB - Redis, BigTable, Hbase, Neo4J)
- Programming model
  - Distributed processing (e.g. MapReduce)

Data Processing Stack

Data Processing Layer

Streaming Processing
Storm, SEEP, Naiad, Spark Streaming, Flink, Milwheel, Google Dataflow...

Query Language
Pig, Hive, SparkSQL, DryadLINQ...

Machine Learning
Rllib, Caffe, Keras, Torch, MLlib...

Execution Engine
MapReduce, Spark, Tensorflow, Ray, Flumejava...

Graph Processing
Pregel, Giraph, GraphLab, PowerGraph, (Dato), GraphX, X-Stream...

Storage Layer

Distributed File Systems
GFS, HDFS, Amazon S3, Flat FS..

Operational Store/NoSQL DB
Big Table, Hbase, Dynamo, Cassandra, Redis, Mongo, Spanner...

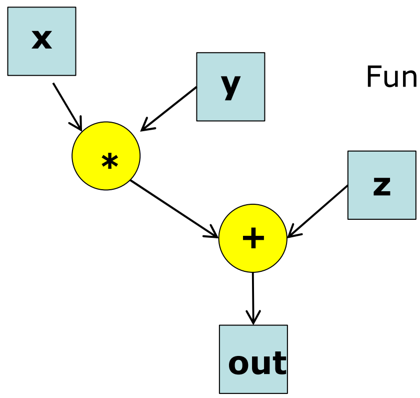
Logging System/Distributed Messaging Systems
Kafka, Flume...

Resource Management Layer

Resource Management Tools
Mesos, YARN, Borg, Kubernetes, EC2, OpenStack...

Data Flow Programming

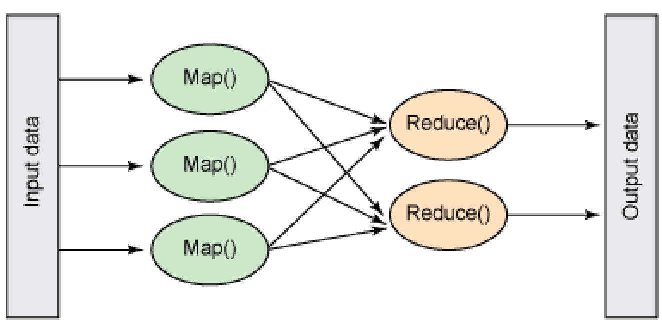
- Non-standard programming models
- Powerful abstraction: mapping computation into dataflow graphs



Function f(x, y, z) = x* y + z

MapReduce Programming

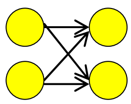
- Target problem needs to be parallelisable
- Split into a set of smaller code (map)
- Next small piece of code executed in parallel
- Results from map operation get synthesised into a result of original problem (reduce)



Data Flow Programming Examples

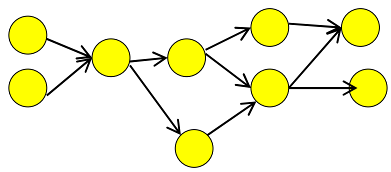
- Data (flow) parallel programming
  - e.g. MapReduce, Dryad/LINQ, NAIAD, Spark, Tensorflow…

MapReduce: Hadoop

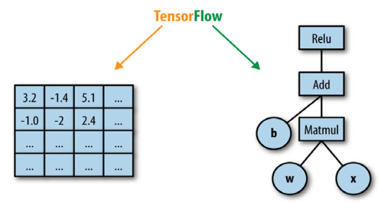


Two-Stage fixed dataflow

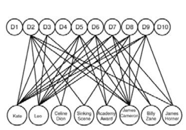
DAG (Directed Acyclic Graph) based: Dryad/Spark…



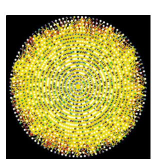
More flexible dataflow model



Emerging Massive-Scale Graph Data



Bipartite graph of phrases in documents

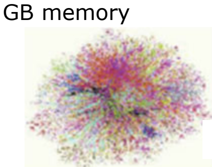


Protein Interactions [genomebiology.com]

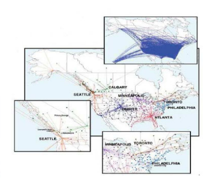
Gene expression data

Brain Networks: 100B neurons(700T links) requires 100s GB memory

Social media data



Web 1.4B pages(6.6B links)



Airline Graphs

BFS
DFS
CC
SCC
SSSP
ASP
A*
Community
Centrality
Diameter
Page Rank
MIS
SALSA…

Graph Computation Challenges

1. Graph algorithms (BFS, Shortest path)
2. Query on connectivity (Triangle, Pattern)
3. Structure (Community, Centrality)
4. ML & Optimisation (Regression, SGD)

- Data driven computation: dictated by graph's structure and parallelism based on partitioning is difficult
- Poor locality: graph can represent relationships between irregular entries and access patterns tend to have little locality
- High data access to computation ratio: graph algorithms are often based on exploring graph structure leading to a large access rate to computation ratio

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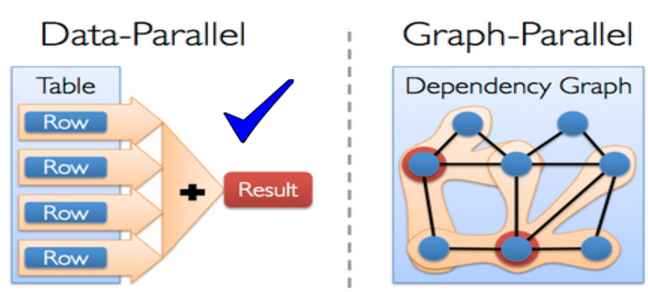
Data-Parallel vs. Graph-Parallel

- *Data-Parallel* for all? *Graph-Parallel* is hard!
  - Data-Parallel (sort/search - randomly split data to feed MapReduce)
  - Not every graph algorithm is parallelisable (interdependent computation)
  - Not much data access locality
  - High data access to computation ratio



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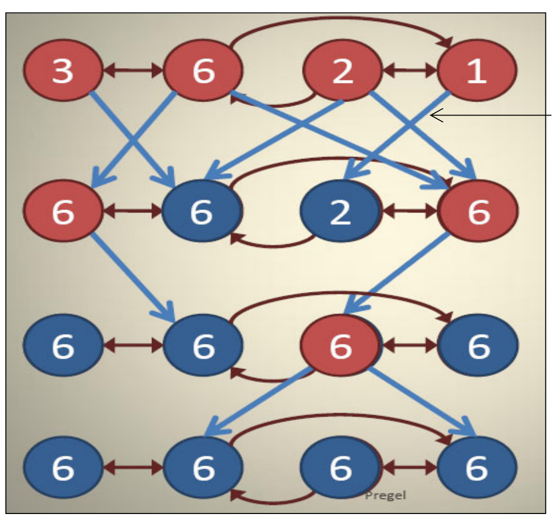
Graph-Parallel

- Graph-Parallel (Graph Specific Data Parallel)
  - Vertex-based iterative computation model
  - Use of iterative Bulk Synchronous Parallel Model
    ➔ Pregel (Google), Giraph (Apache), Graphlab, GraphChi (CMU - Dato)
  - Optimisation over data parallel
    ➔ GraphX/Spark (U.C. Berkeley)
  - Data-flow programming – more general framework
    ➔ NAIAD (MSR), TensorFlow..

Bulk synchronous parallel: Example

- Finding the largest value in a connected graph

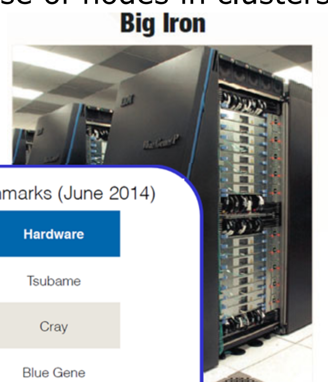
Local Computation
Communication
Local Computation
Communication
...



Message

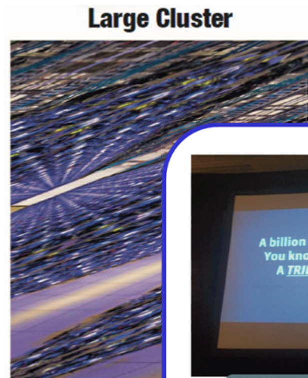
Are Large Clusters and Many cores Efficient?

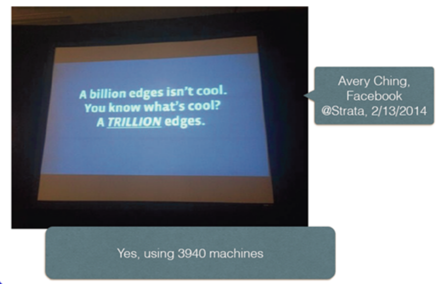
- Brute force approach really efficiently works?
  - Increase of number of cores (including use of GPU)
  - Increase of nodes in clusters



HPC/Graph500 benchmarks (June 2014)

Graph Edges	Hardware
1 trillion	Tsubame
1 trillion	Cray
1 trillion	Blue Gene
1 trillion	NEC





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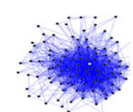
Do we really need large clusters?



- Laptops are sufficient?

Twenty pagerank iterations

System	cores	twitter_rv	uk_2007_05
Spark	128	857s	1759s
Giraph	128	596s	1235s
GraphLab	128	249s	833s
GraphX	128	419s	462s
Single thread	1	300s	651s

Label propagation to fixed-point (graph connectivity)

System	cores	twitter_rv	uk_2007_05
Spark	128	1784s	8000s+
Giraph	128	200s	8000s+
GraphLab	128	242s	714s
GraphX	128	251s	800s
Single thread	1	153s	417s

Fixed-point iteration: All vertices active in each iteration (50% computation, 50% communication)

Traversal: Search proceeds in a frontier (90% computation, 10% communication)

from Frank McSherry HotOS 2015

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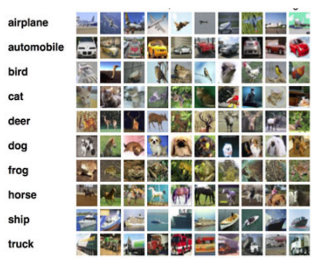
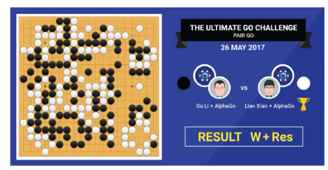
Data Processing Paradigm Change

- Emergence of modern Neural Networks Applications
- Practicalities of training Neural Networks
- Leveraging heterogeneous hardware
- Traditional dataflow programming does not deal with mathematical objects (no deep learning back then), now control flow requires to be numerically differentiable (i.e. TensorFlow)

Image Classification



Reinforcement Learning



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Challenging: Computer Systems Optimisation

- How do we improve performance:
  - Manual tuning
  - Auto-tuning
- What is performance? – objective function of optimisation
  - Resource usage (e.g. time, power)
  - Computational properties (e.g. accuracy, fairness, latency)
  - Large number of parameters
  - Evaluation is slow and expensive
- What is Optimisation Model?
  - Short-term dynamic control (e.g. stream processing: distinct workload or dynamic workload)
  - Combinatorial optimisation (e.g. indexing DB, device assignment)

Many systems problems are combinatorial in nature

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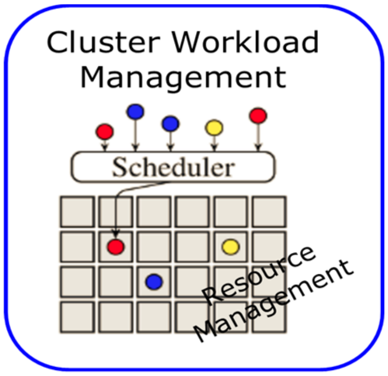
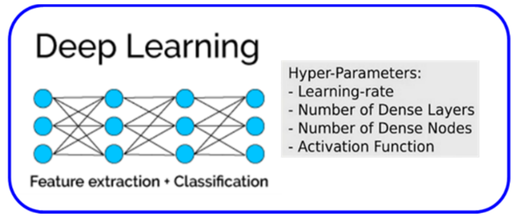
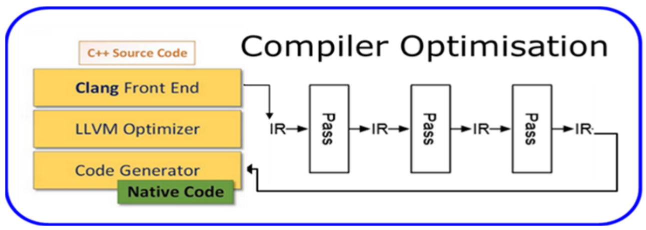
Use of ML based Optimisation Methods

- Increasing data volumes and high-dimension parameter space
- Expensive Objective Functions
- Hand-crafted solutions impractical, often left static or configured through extensive offline analysis







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Machine Learning and Optimisation

- Function Optimisation
  - Find the set of inputs to a target objective function that result in the minimum or maximum of the function
- Function Approximation:
  - Generalise from specific examples to a reusable mapping function for making predictions on new examples
  - ML can be described as function approximation as approximating the unknown underlying function that maps examples of inputs to outputs in order to make predictions on new data
  - Function approximation often uses function optimisation
- At the core of many ML algorithms is an optimisation algorithm!

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Optimisation: Iterative Operation

- Common to use an iterative global search algorithm for optimisation problem
- e.g. Bayesian optimisation algorithm that is capable of simultaneously approximating the target function that is being optimised while optimising it.

- Automated machine learning (AutoML) algorithms being used to choose an algorithm, an algorithm and hyperparameters, or data preparation, algorithm and hyperparameters, with very little user intervention

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Auto-tuning Complex Systems

- Many dimensions
- Expensive objective function
- Hand-crafted solutions impractical (e.g. extensive offline analysis)

➡ Blackbox Optimisation

✓ can surpass human expert-level tuning

- Grid search θ ∈ [1, 2, 3, …]
- Random search
- Evolutionary approaches (e.g. PetaBricks)
- Hill-climbing (e.g. OpenTuner)
- Bayesian optimisation (e.g. SPEARMINT)

1000s of evaluations of objective function

Computation more expensive

Fewer samples

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Search Parameter Space

Random search: No risk of 'getting stuck'
potentially many samples required

Evolution strategies: Evaluate permutations against fitness function

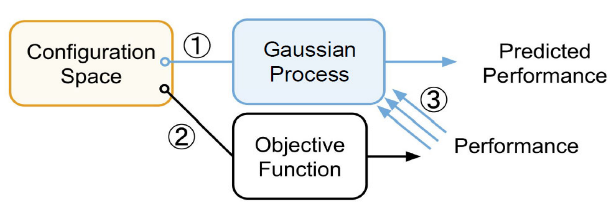
Bayes Opt: Sample efficient, requires continuous function, some configuration

Random Search	Genetic algorithm / Simulated annealing	Bayesian Optimisation
No overhead	Slight overhead	High overhead
High #evaluation	Medium-high #evaluation	Low #evaluation

Bayesian Optimisation

- Iteratively builds probabilistic model of objective function
- Typically Gaussian process as probabilistic model
- Data efficient: converges quickly

Input: Objective function $f()$
Input: Surrogate function initial distribution G
Input: Acquisition function $a()$
for $i = 1, 2, \ldots$ **do**
  Sample point: $\boldsymbol{x}_t \leftarrow \arg\max_{\boldsymbol{x}} a(G, \boldsymbol{x})$
  Evaluate new point: $y_t \leftarrow f(\boldsymbol{x}_t)$
  Update surrogate distribution: $G \leftarrow G \mid (\boldsymbol{x}_t, y_t)$
end for



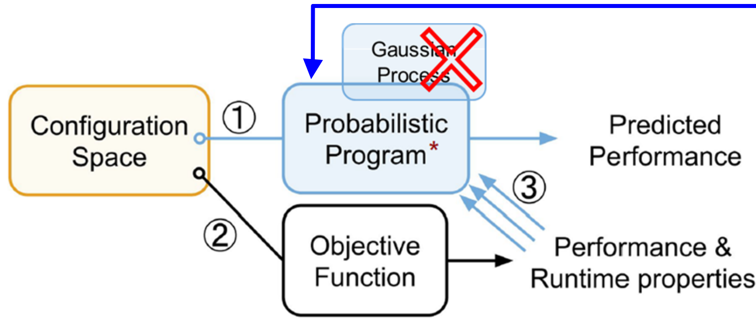
Pros:
✓ Data efficient: converges in few iterations
✓ Able to deal with noisy observations
Cons:
✗ In many dimensions, model does not converge to the objective function

① Find promising point (high performance value in the model)
② Evaluate the objective function at that point
③ Update the model to reflect this new measurement

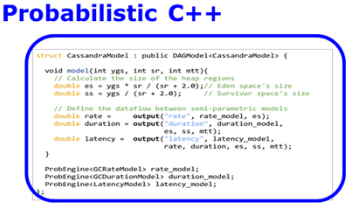
Further Bayesian Optimisation…

- BO overview/Tutorial
  - https://www.cl.cam.ac.uk/~ey204/teaching/ACS/R244_2021_2022/aid/BO_overview_Archambeau.pdf
  - https://www.cl.cam.ac.uk/~ey204/teaching/ACS/R244_2021_2022/aid/BO_overview_adams.pdf
  - https://www.cl.cam.ac.uk/~ey204/teaching/ACS/R244_2021_2022/aid/BO_overview_gonzalez.pdf
- Papers
  - Review paper by Shahriari, et al. (2016): Taking the Human Out of the Loop: A Review of Bayesian Optimization. Proceedings of the IEEE 104(1):148-175, 2016.
  - Slides by Ryan Adams (2014): A Tutorial on Bayesian Optimization for Machine Learning. CIFAR NCAP Summer School.
  - Slides by Peter Frazier (2010): Tutorial: Bayesian Methods for Global and Simulation Optimization. INFORMS Annual Meeting.

Structured Bayesian Optimisation (SBO)



Probabilistic Model written in Probabilistic C++



Developer-specified, model of performance from observed performance + arbitrary runtime characteristics

✓ Better convergence
✓ Use all measurements

BOAT: a framework to build **B**esp**O**ke **A**uto-**T**uners

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Probabilistic Model

- Probabilistic models incorporate random variables and probability distributions into the model
  - Deterministic model gives a single possible outcome
  - Probabilistic model gives a probability distribution
- Used for various probabilistic logic inference (e.g. MCMC-based inference, Bayesian inference…)

Tutorial: Session 5 – Guest Lecture by Brooks Paige

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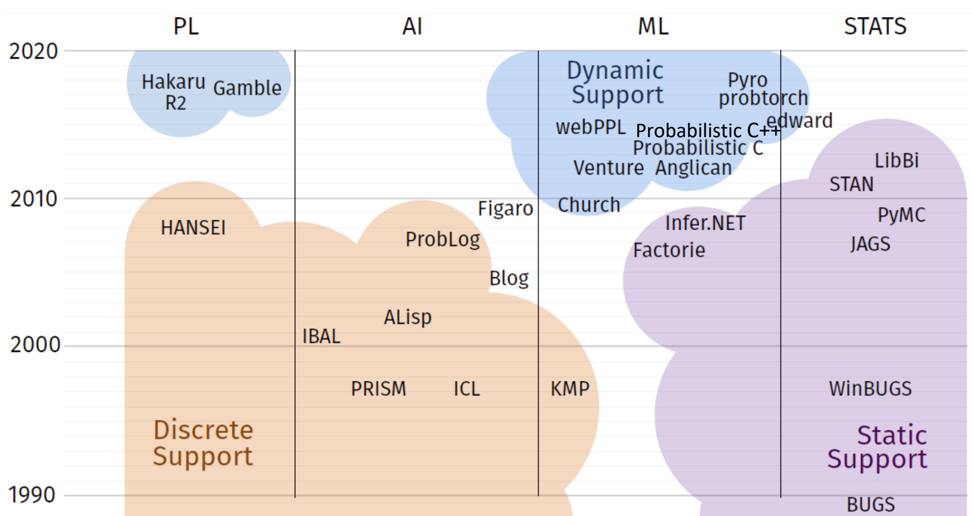
Probabilistic Programming



B. Paige

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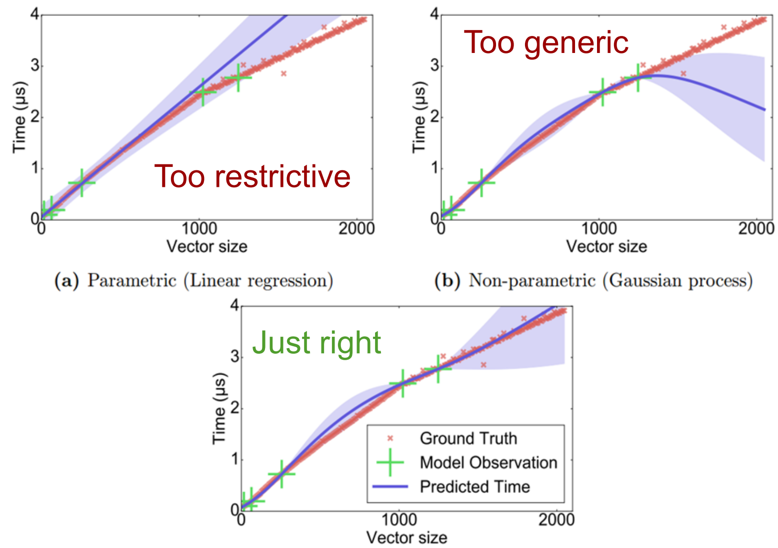
Semi-parametric Model

- Easy to use and well suited to SBO
  - Understand general trend of Objective function
  - High precision in region of optimum for finding highest performance



(a) Parametric (Linear regression)
(b) Non-parametric (Gaussian process)
(c) Semi-parametric (Combination)

Example: JVM Garbage Collection

- Cassandra's garbage collection

Cassandra

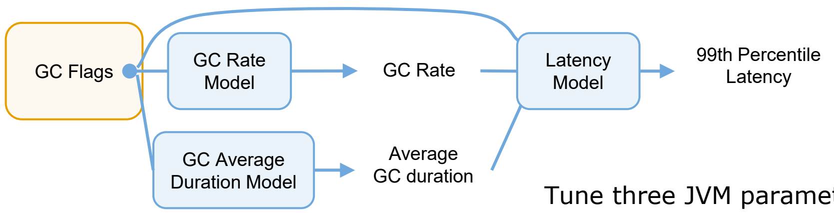
JVM

Garbage collection flags:
- Young generation size
- Survivor ratio
- Max tenuring threshold

- Minimise 99th percentile latency of Cassandra

Performance Improvement from Structure

User-given probabilistic model structured in semi-parametric model using Directed Acyclic Graph



Tune three JVM parameters of database (Cassandra) to minimise latency

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DAG model in BOAT

```
struct CassandraModel : public DAGModel<CassandraModel> {

  void model(int ygs, int sr, int mtt){
    // Calculate the size of the heap regions
    double es = ygs * sr / (sr + 2.0);// Eden space's size
    double ss = ygs / (sr + 2.0);      // Survivor space's size

    // Define the dataflow between semi-parametric models
    double rate =     output("rate", rate_model, es);
    double duration = output("duration", duration_model,
                             es, ss, mtt);
    double latency =  output("latency", latency_model,
                             rate, duration, es, ss, mtt);
  }

  ProbEngine<GCRateModel> rate_model;
  ProbEngine<GCDurationModel> duration_model;
  ProbEngine<LatencyModel> latency_model;
};
```

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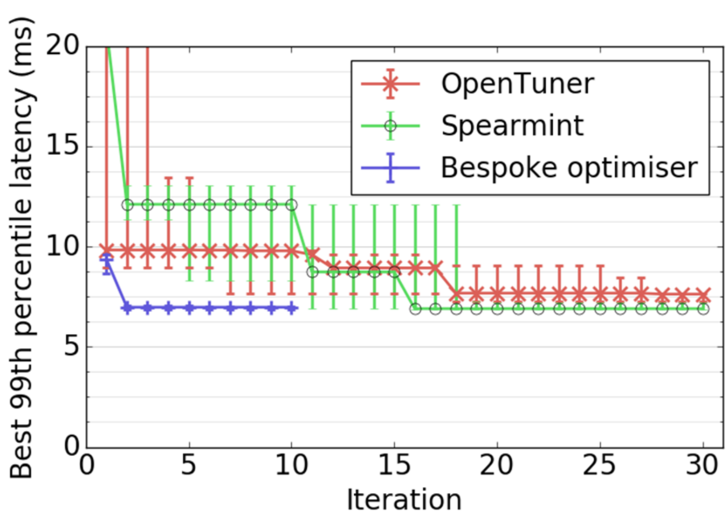
GC Rate Semi-parametric model

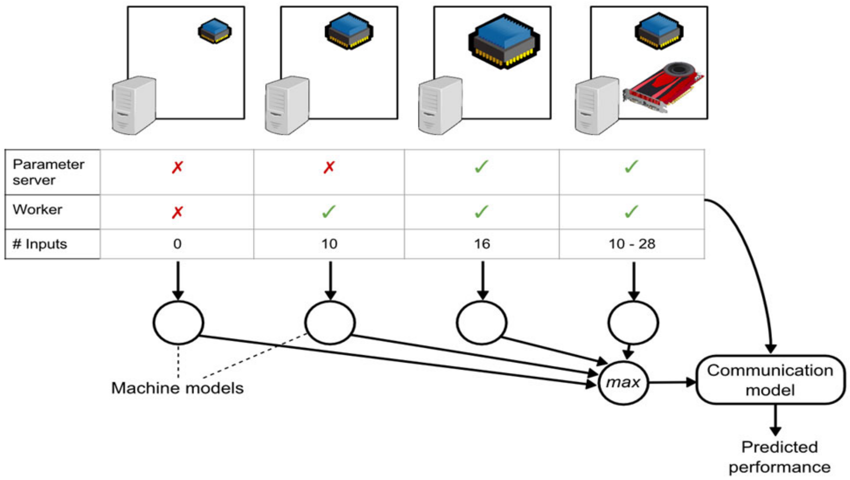
```
struct GCRateModel : public SemiParametricModel<GCRateModel> {

  GCRateModel() {
    allocated_mbs_per_sec =
     std::uniform_real_distribution<>(0.0, 5000.0)(generator);
    // set the GP parameters here
  }

  double parametric(double eden_size) const {
    // Model the rate as inversely proportional to Eden's size
    return allocated_mbs_per_sec / eden_size;
  }

  double allocated_mbs_per_sec;
};
```


Evaluation: Garbage collection



Distributed Scheduling of Neural Networks (SGD)

- Tune scheduling over 10 machines, setting ~30 parameters (e.g. ~10^{53} possible valid configurations)



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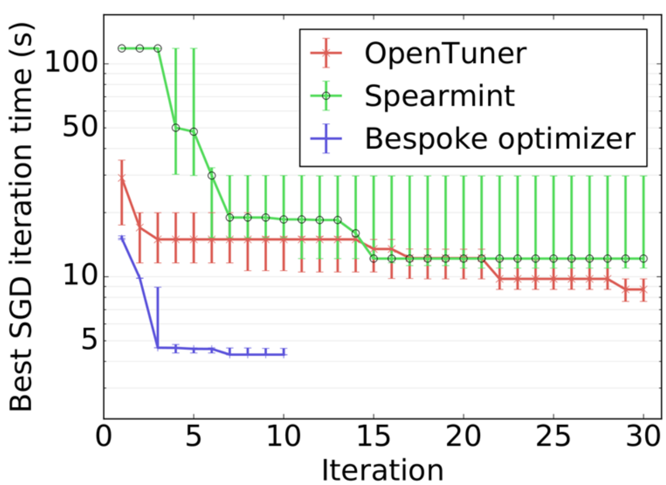
Evaluation: Neural network scheduling



Default configuration: 9.82s
OpenTuner: 8.71s
BOAT: **4.31s**

Existing systems don't converge!

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Auto-Tuning

- Manual Tuning
  - User to learn expert knowledge and not transferable
  - e.g. Ottertune (manually selects limited number of parameters then use BO)
- Automated Tuning
  - Divide-and-diverge sampling to explore the configuration space
  - Use of Gaussian processes, but it struggles to make accurate performance predictions because of high dimensionality

→Generic Auto-Tuning with DAG models

  - Use of DAG models for surrogate model, which mitigates the curse of dimensionality while also retaining all configurable variables
  - Exploit data analysis to identify parameter dependencies
  - Automatic building of DAG models: use of Bayesian Networks

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Surrogate Model in Bayesian Optimisation

Table 2.1: Comparison of surrogate models for BO

Model	Advantages	Disadvantages
Parametric models	• Quickly fit long-distance trends	• Require known structure of f
Gaussian processes	• Expressive • Flexible	• Fitting is $O(n^3)$ in train-data size • Continuous, non-hierarchical configuration space only
Tree-Parzen estimators	• Fitting is $O(n)$ in train-data size • Categorical and hierarchical configuration space supported	• Less sample efficient than GP
Random forests	• Computationally very cheap • Categorical and hierarchical configuration space supported	• Inaccurately extrapolates uncertainty

- Structural information (e.g. DAG model) improves Optimisation.

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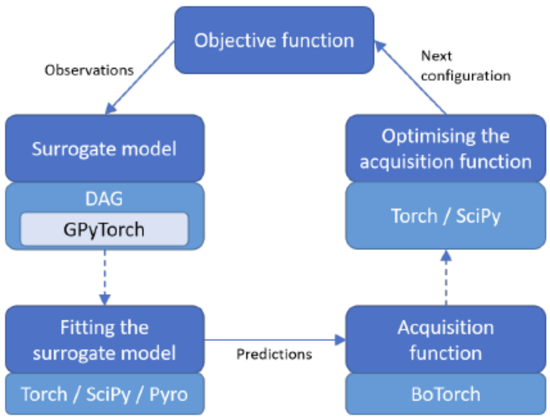
DAG model integration to BoTorch



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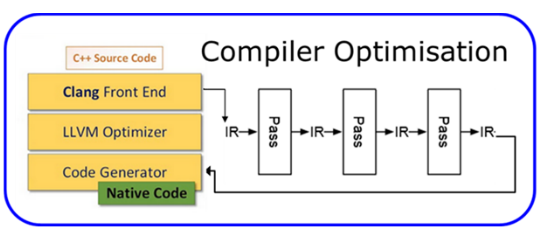
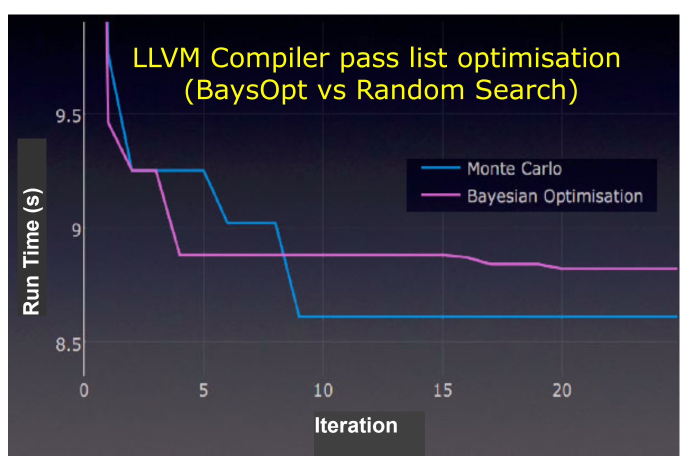
Bayesian Optimisation not for Combinatorial Model





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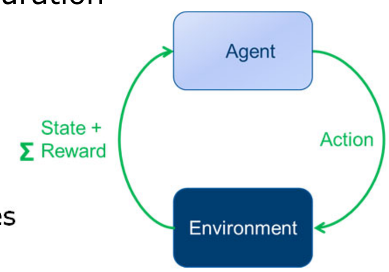
Reinforcement Learning in Computer Systems

- Agent interacts with Dynamic environment
- Goal: Maximise expectations over rewards in agent's lifetime
- Notion of Planning/Control, not single static configuration

What makes RL different from other ML paradigms?

- There is no supervisor, only a reward signal
- Feedback is delayed, not instantaneous
- Time really matters (sequential)
- Agent's actions affect the subsequent data it receives



Practical Consideration:

- Action spaces do not scale
- Exploration in production system not a good idea
- Simulations can oversimplify problem (Expensive to build)
- Online steps take too long

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Reinforcement Learning for Optimisation

Many problems in systems are sequential decision making and/or combinatorial problems

- Compiler Optimisation
- Chip placement
- Datacentre resource allocation
- Network congestion control with multiple connections
- Wide range of signals to make decisions (e.g., VM allocation)
- Database: Query optimiser, Dynamic indexing…

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A brief history of Deep Reinforcement Learning Tools

Gen (2014-16): Loose research scripts (e.g. DQN), high expertise required, only specific simulators

Gen (2016-17): OpenAI gym gives unified task interface, reference implementations

- Good results on some environments (e.g. game), difficult to retool to new domains and execution modes
- Abstractions/Libraries: not fully reusable, customised towards game simulators
- High implementation risk: lack of systematic testing, performance strongly impacted by noisy heuristics

Gen (2017-18): Generic declarative APIs, distributed abstractions (Ray Rllib, RLGraph), some standard *flavours* emerge

Still Problems... Tightly coupled execution/logic, testing, reuse...

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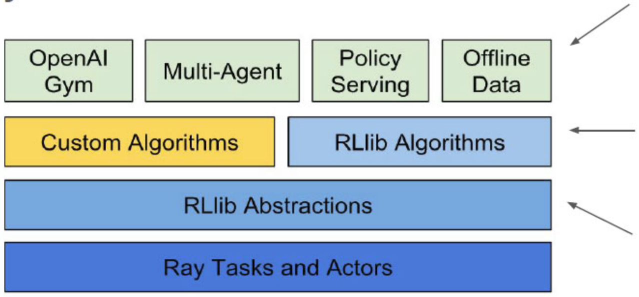
RLlib (UC Berkeley) Architecture

User perspective: three main layers to RLlib:



1. APIs that make RL accessible to a variety of applications
2. Collection of best-in-class reference algorithms
3. Primitives for implementing new RL algorithms

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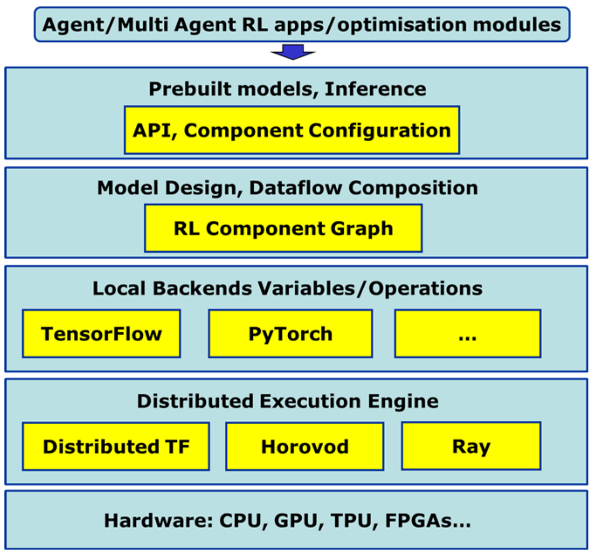
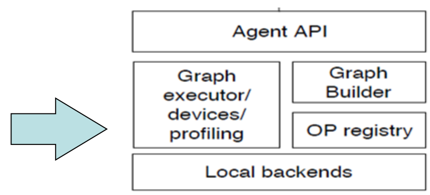
RLgraph: Modular Dataflow Composition





- ... is a programming model to design and execute RL algorithms across execution paradigms
- ... generates incrementally testable, transparently configurable code through a staged build process

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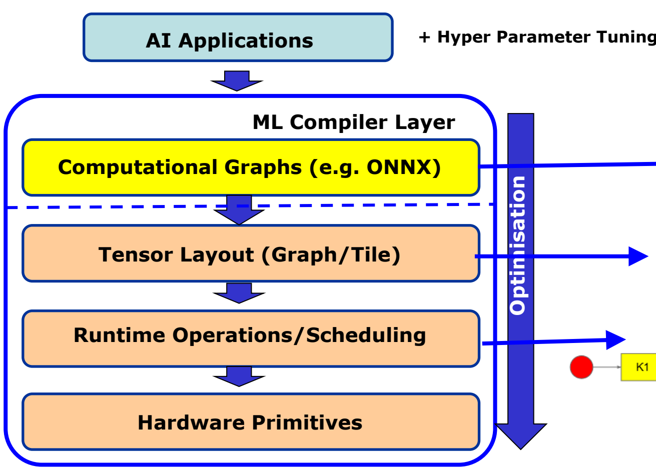
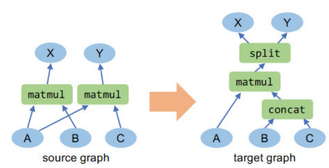
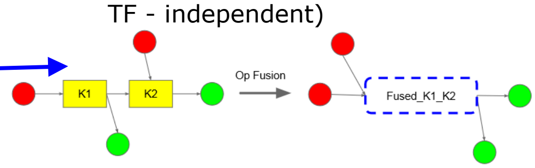
ML Compiler Optimisation





GraphIR (backend-Jax, PyTorch, TF - independent)



TensorFlow, MXNet, and PyTorch

See ML Compiler Tutorial: https://mlc.ai/summer22/schedule
Also Survey: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9222299

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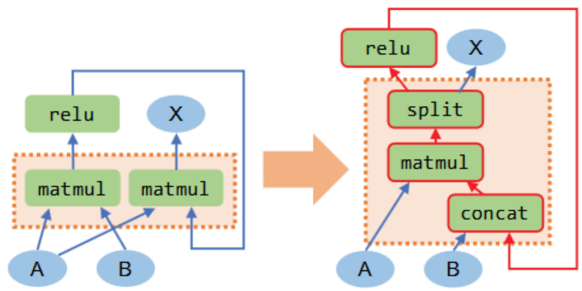
Optimising DNN Computation with Graph Substitutions

- TASO (SOSP, 2019): Performance improvement by transformation of computation graphs
- PET (OSDI, 2021): Optimizing Tensor Programs with Partially Equivalent Transformations and Automated Corrections
- Equality Saturation for Tensor Graph Superoptimization (MLSys 2021)



(a) before substitution (b) after substitution

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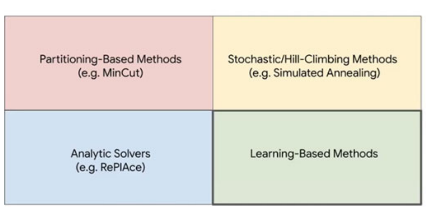
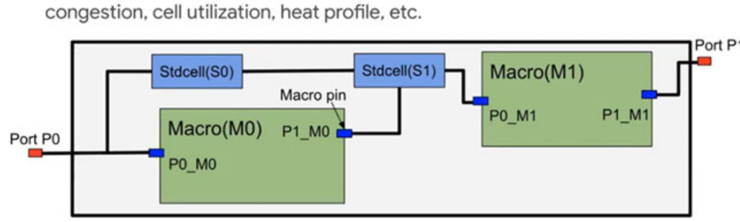
Chip Placement with Reinforcement Learning

- A. Mirhoseini and A. Goldie: A graph placement methodology for fast chip design, Nature, 2021.



- A form of graph resource optimization
- Place the chip components to minimize the latency of computation, power consumption, chip area and cost, while adhering to constraints, such as congestion, cell utilization, heat profile, etc.



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Summary: Massive Data Processing and Optimisation

→ Dataflow is key element used in optimisation

→ Parameter space is complex, large and dynamic/combinatorial

- Systems are nonlinear and difficult to model manually → Exploit ML
- Reinforcement Learning to optimise dynamic combinatorial problem
- Key concept behind is Dataflow (~=Computational Graph) structural transformation/Decomposition

→ Exploit structural information for model decomposition to accelerate optimisation process and/or transform the structure

→ Bayesian Optimisation and Reinforcement Learning are key

Gap between Research and Practice

Device Placement Optimization with Reinforcement Learning

Azalia Mirhoseini [*1 2] Hieu Pham [*1 2] Quoc V. Le [1] Benoit Steiner [1] Rasmus Larsen [1] Yuefeng Zhou [1]
Naveen Kumar [3] Mohammad Norouzi [1] Samy Bengio [1] Jeff Dean [1]

20H with 80GPUs!