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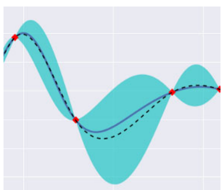
Large-scale Data Processing and Optimisation

Overview



Eiko Yoneki

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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)

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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

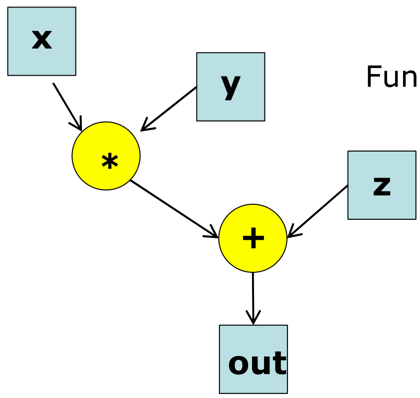
- **Distributed File Systems**: GFS, HDFS, Amazon S3, Flat FS..
- **Operational Store/NoSQL DB**: Big Table, Hbase, Dynamo, Cassandra, Redis, Mongo, Spanner…
- **Logging System/Distributed Messaging Systems**: Kafka, Flume…

Resource Management Layer

- **Resource Management Tools**: Mesos, YARN, Borg, Kubernetes, EC2, OpenStack…

Data Flow Programming

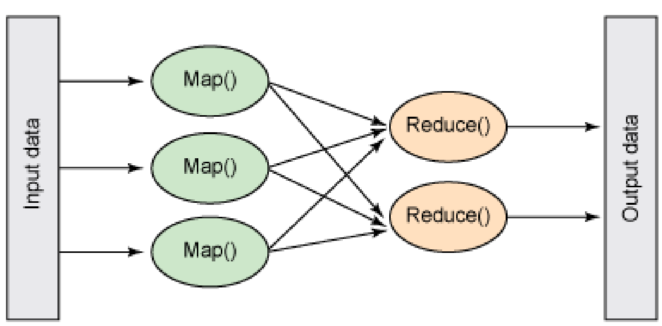
- Non-standard programming models
- Powerful abstraction: mapping computation into dataflow graphs



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

MapReduce Programming

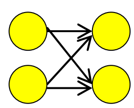
- Target problem needs to be parallelisable
- Split into a set of smaller code (map)
- Next small piece of code executed in parallel
- Results from map operation get synthesised into a result of original problem (reduce)



Data Flow Programming Examples

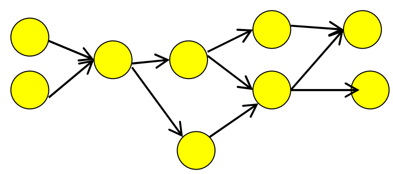
- Data (flow) parallel programming
  - e.g. MapReduce, Dryad/LINQ, NAIAD, Spark, Tensorflow…
  - e.g. ML compiler: computation graphs

MapReduce:
Hadoop

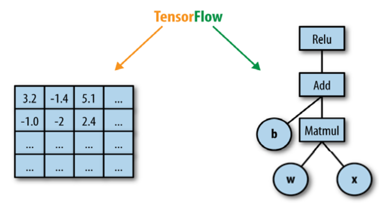


Two-Stage fixed dataflow

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



More flexible dataflow model



Data Flow Programming's Usefulness for ML

- Data flow programming holds the key to natural, modular, streamlined ML specification
- Same language for layer, network, and integration specification
  - For complex NN classes. RL with complex reward, gated networks, attention/transformers, mix of NN and data processing
- Same language for ML algorithmics and compiler design
- Well-established analysis and compilation techniques integrated within existing ML compilers (e.g. MLIR)
  - MLIR (Multi-Level Intermediate Representation) is intended to be a hybrid IR which can support multiple different requirements in a unified infrastructure (https://mlir.llvm.org/)

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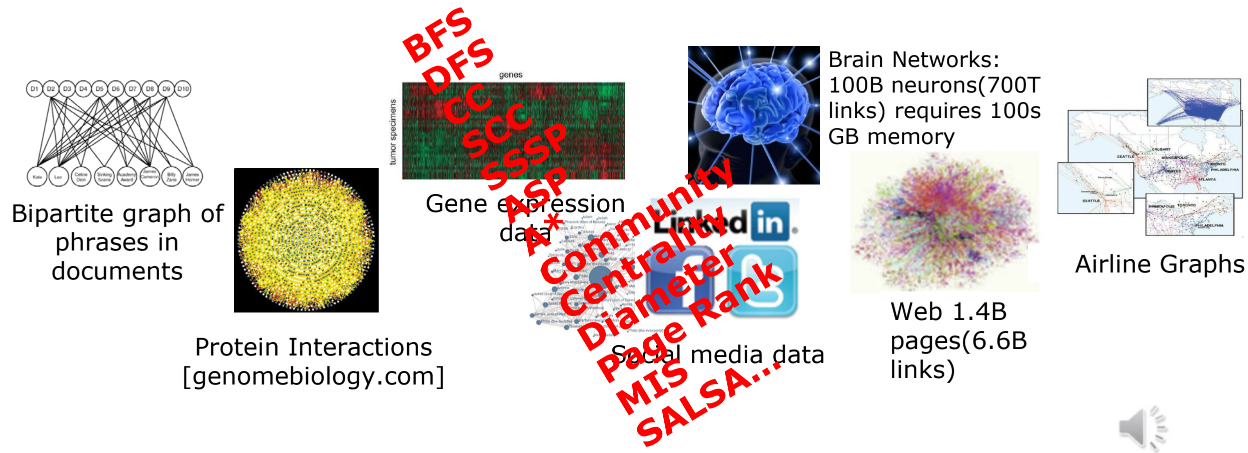
Emerging Massive-Scale Graph Data



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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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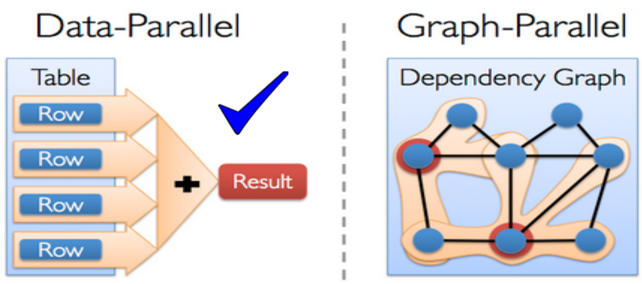
Data-Parallel vs. Graph-Parallel

- *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…

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Bulk synchronous parallel: Example

- Finding the largest value in a connected graph

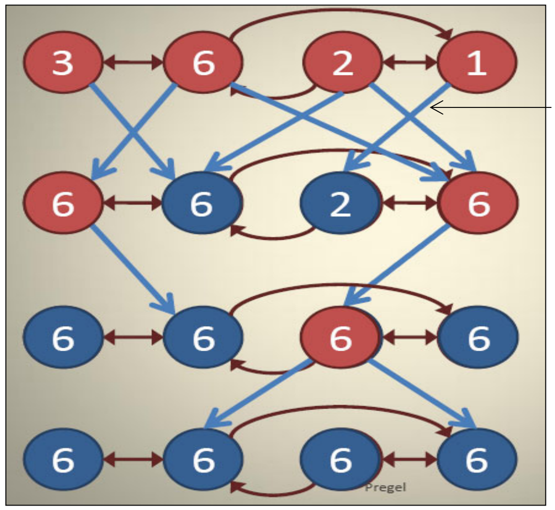
Local Computation

Communication

Local Computation

Communication

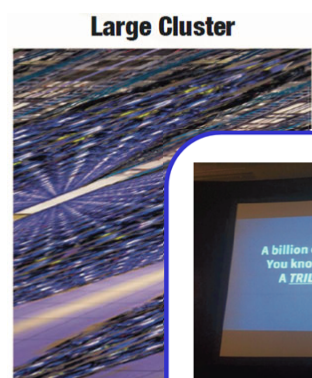
...



Message

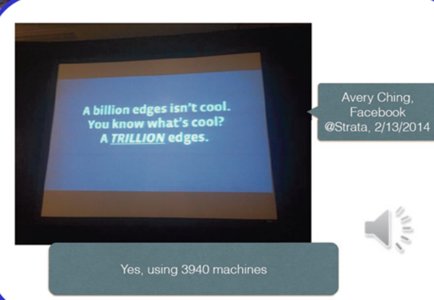
Are Large Clusters and Many cores Efficient?

- 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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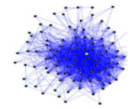
Do we really need large clusters?



- 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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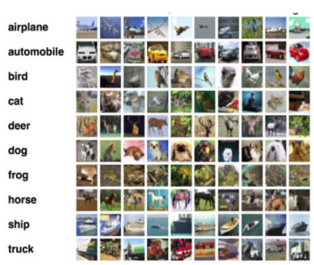
Data Processing Paradigm Change

- 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

Image courtesy: The Guardian

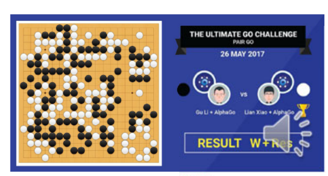


Image courtesy: Twitter - Deep Mind AI

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)

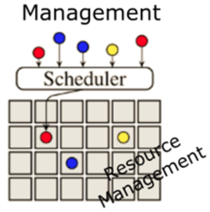
Many systems problems are combinatorial in nature

Tuning Computer Systems is Complex

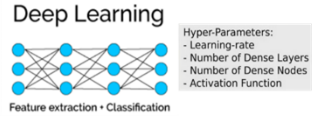
- Complex and High Dimension Parameter Space
- Expensive Objective Functions
- Hand-crafted solutions impractical, often left static or configured through extensive offline analysis
- Not well-tuned system's performance does not scale

→ Necessity of scalable Auto-tuning

Cluster Workload Management

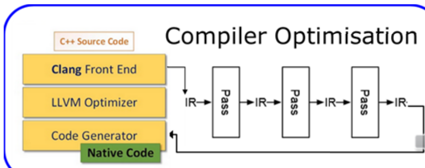


Deep Learning



SoC/ASIC SW/HW Co-Design

Compiler Optimisation



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!

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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Massive Parameter Space in Large-scale Systems

Number of cluster nodes	Coarse	Optimise parameters θ?
ML Hyperparameters		Minimise some cost function f(θ)
Compiler Flags	Fine	...where cost is runtime, memory, I/O, or combination of all...

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

→ Blackbox Optimisation

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Search Parameter Space

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

PetaBricks

Evolution strategies: Evaluate permutations against fitness function

SPEARMINT

Hill Climbing OpenTuner

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

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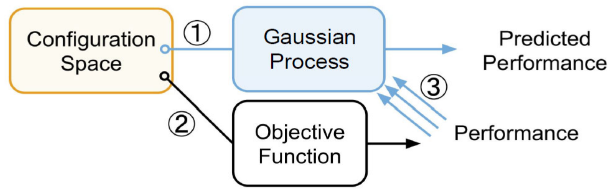
Bayesian Optimisation

- 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

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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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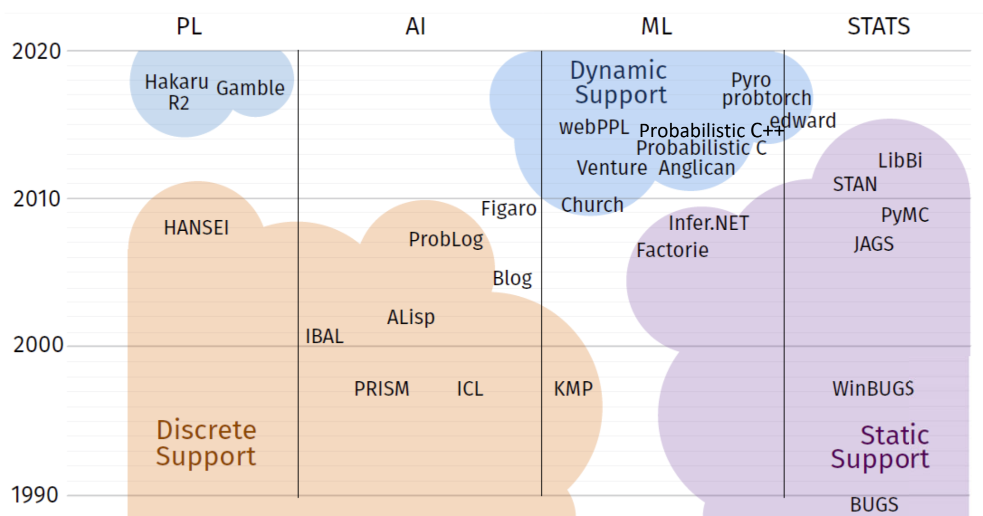
Probabilistic Model

- 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…)

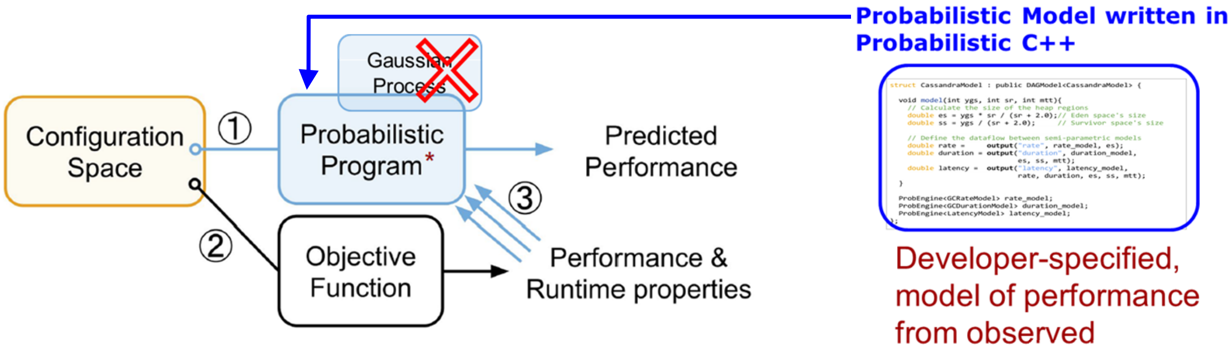
Tutorial: Session 5 – Guest Lecture by Brooks Paige

Probabilistic Programming



B. Paige

Structured Bayesian Optimisation (SBO)



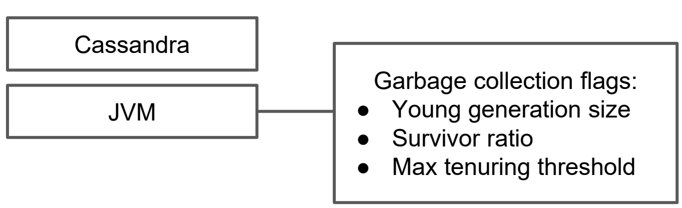
Developer-specified, model of performance from observed performance + arbitrary runtime characteristics

✓ Better convergence
✓ Use all measurements

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

Example: JVM Garbage Collection

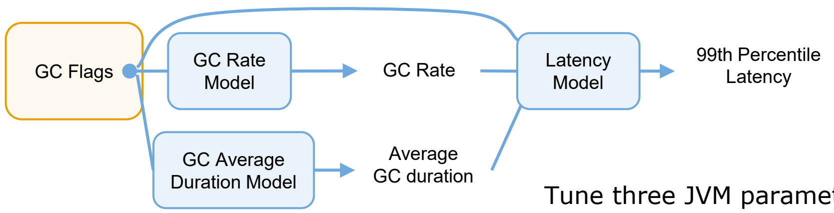
- Cassandra's garbage collection



- Minimise 99th percentile latency of Cassandra

Performance Improvement from Structure

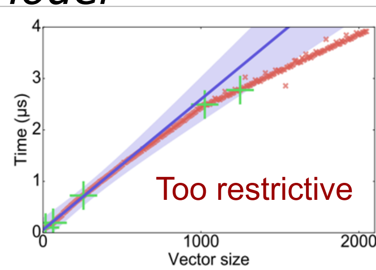
User-given probabilistic model structured in semi-parametric model using Directed Acyclic Graph



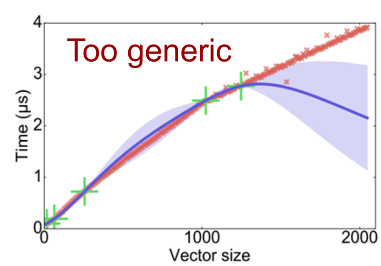
Tune three JVM parameters of database (Cassandra) to minimise latency

Semi-parametric Model

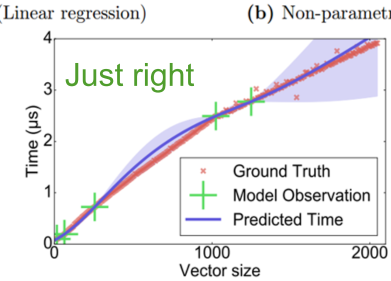
- Easy to use and well suited to SBO
  - Understand general trend of Objective function
  - High precision in region of optimum for finding highest performance



(a) Parametric (Linear regression)



(b) Non-parametric (Gaussian process)



(c) Semi-parametric (Combination)

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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;
};
```

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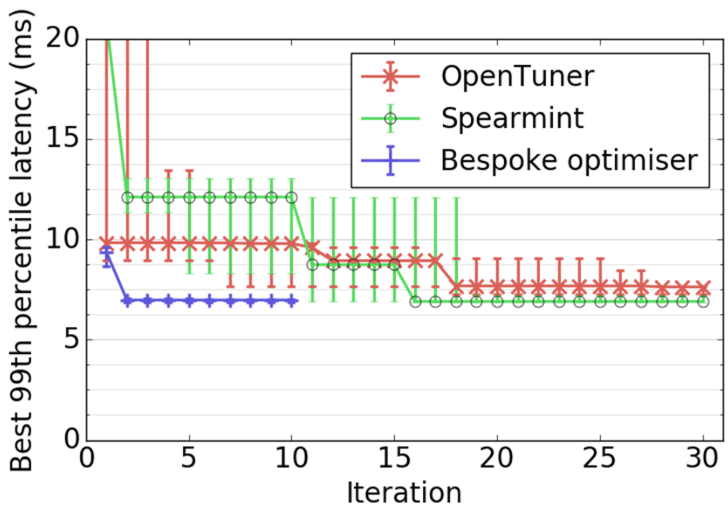
Evaluation: Garbage collection



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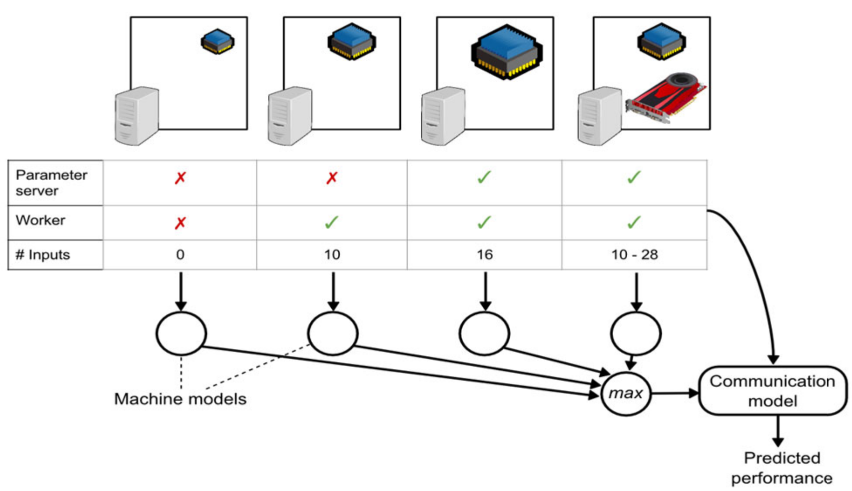
Distributed Scheduling of Neural Networks (SGD)

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



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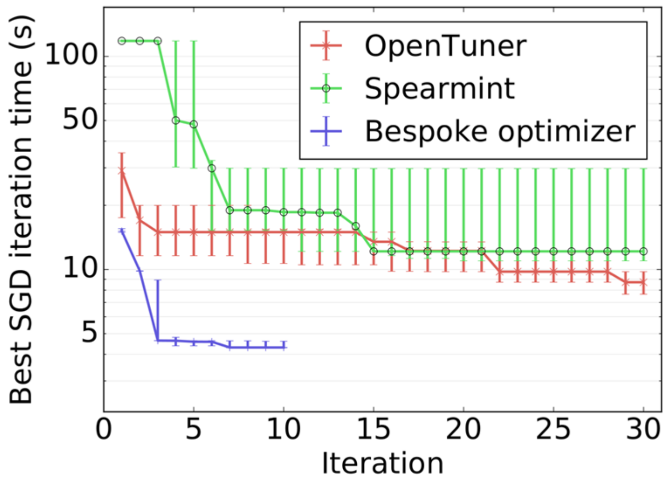
Evaluation: Neural network scheduling



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

Existing systems don't converge!

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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.

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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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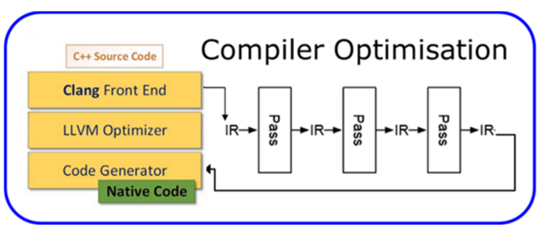
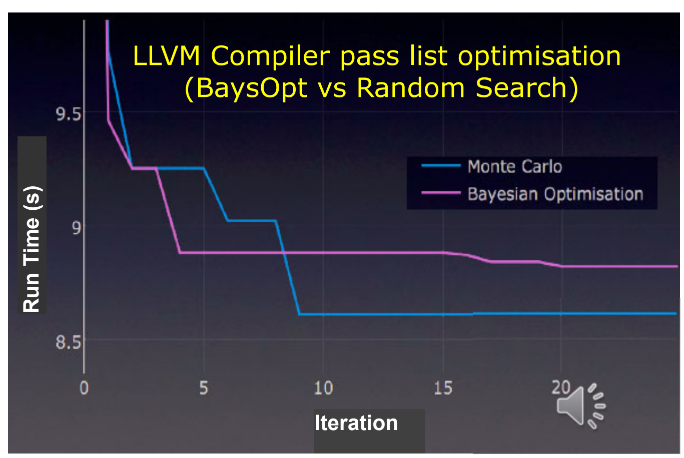
Bayesian Optimisation not for Combinatorial Model





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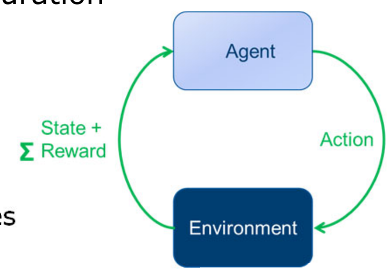
Reinforcement Learning in Computer Systems

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

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

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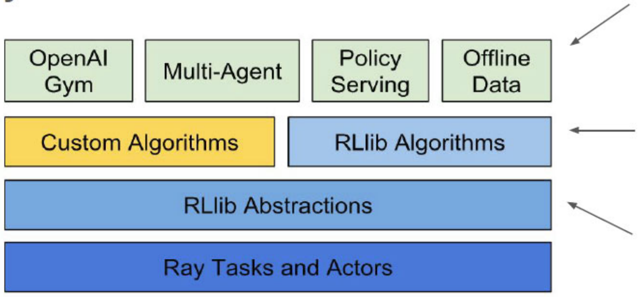
RLlib (UC Berkeley) Architecture

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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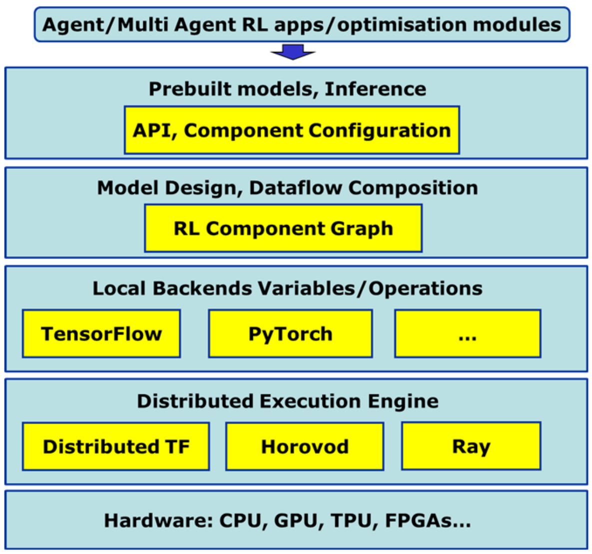
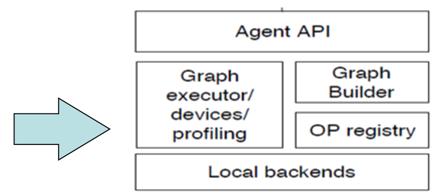
RLgraph: Modular Dataflow Composition





- ... 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 Challenges

- Fast tensor operation capable compilers: Complex optimisation plays a crucial role for LLM processing
  - Use of ML to optimise ML Compiler
  - Superoptimisation: Deal with massive parameter space
    → use of Equality Saturation (ES), MCTS
    → use of reinforcement Learning
  - Many compiler optimisations are phase ordering problem
- Challenge to bridge the gap between ML models and HW
- Existing ML Compiler
  - Apache TVM
  - NVIDIA TensorRT - CuDNN
  - ONNX runtime
  - LLVM
  - Google MLIR
  - TensorFlow XLA
  - Meta Glow
  - PyTorch nvFuser
  - INTEL pLAIDml
  - Open VINO

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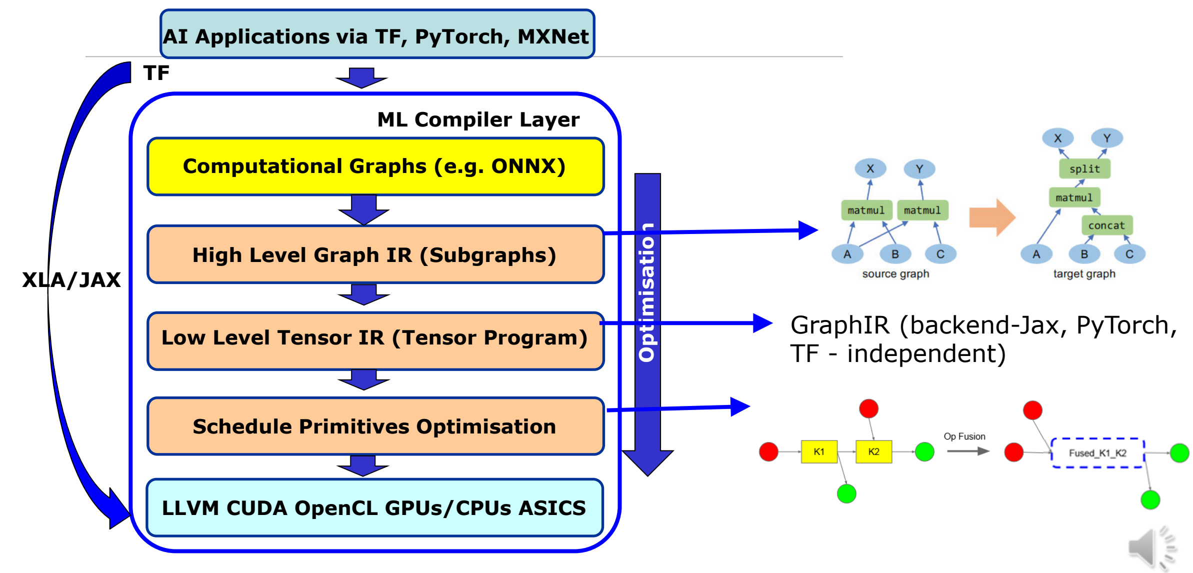
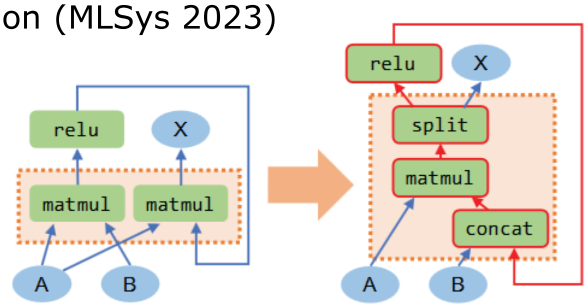


See ML Compiler Tutorial: https://mlc.ai/summer22/schedule
Also Survey: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9222299

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)
- X-RLflow: Graph Reinforcement Learning for Neural Network Subgraph Transformation (MLSys 2023)



(a) before substitution (b) after substitution

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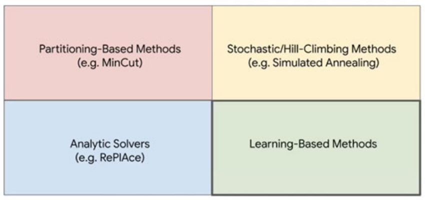
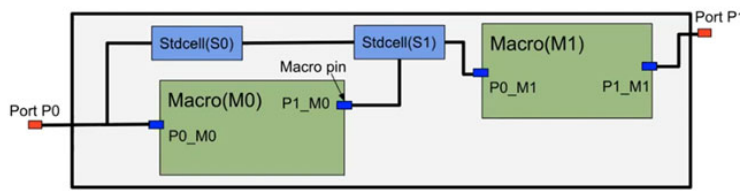
Chip Placement with Reinforcement Learning

- 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

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Course Schedule

https://www.cl.cam.ac.uk/~ey204/teaching/ACS/R244_2023_2024

Session 1: Introduction

Session 2: Data Flow Programming: Map/Reduce to TensorFlow to ML

Session 3: Large-scale Graph Data Processing

Session 4: Hands-on Tutorial: Distributed Data Flow Programing

Session 5: Probabilistic Programming + BO : Guest lecture (Brooks Paige)

Session 6: Optimisation in ML Compiler (Superoptimisation…)

Session 7: Optimisation of Computer Systems (HW design, DB…)

Session 8: Project Study Presentation (2022.11.29 @10:00)

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