DeepSched: A Deep Representation Of Scheduling Policies For Heterogeneous Distributed Systems

Team #10

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Demonstration Audio

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Introduction

- **Task scheduling** is a very critical factor to the performance of all systems.
- **Heterogeneity** of the systems adds extra layers of complexity to the scheduling problem.
- Heterogeneous task scheduling is divided into **Heuristic** and **Approximate** methods.

Introduction

- We study the approximation of heuristic methods using predictive models, specifically **neural networks**.
- We use **HEFT** as our heuristic baseline, **genetic algorithms** as our approximate baseline.

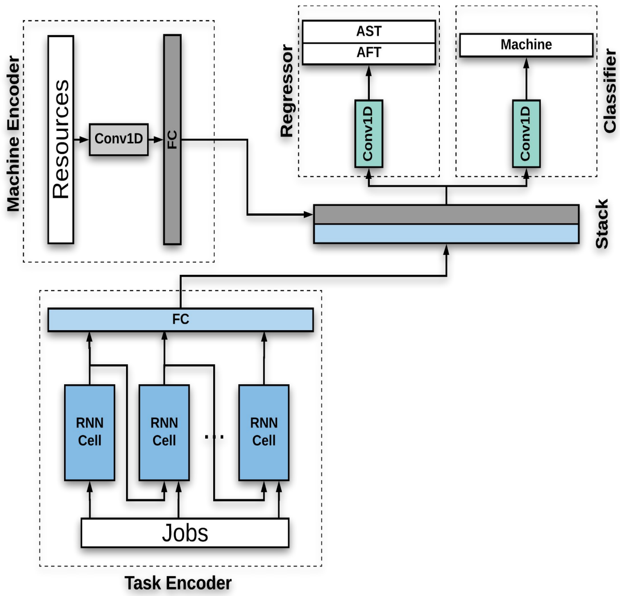
Proposed network

The network consists of 4 main blocks:

1. Task Encoder.
2. Machine Encoder.
3. Classification Module.
4. Regression Module.

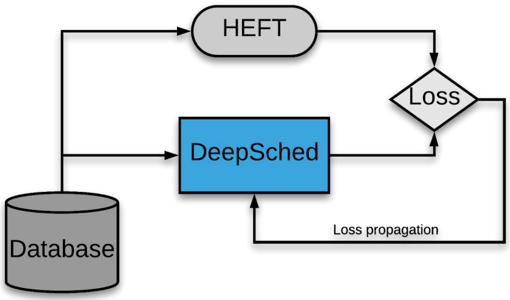
The network dimensions are adjusted on the **maximum** number of tasks and resources.

Full network code is available at:
https://github.com/DarkGeekMS/deepsched



Training Framework

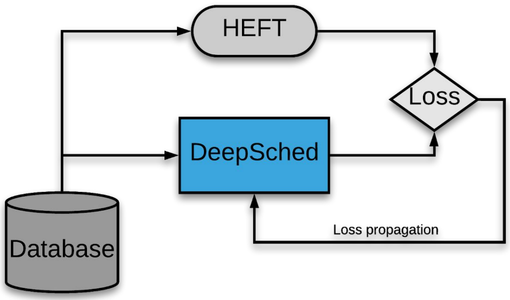
- A database of tasks and resources is provided to both **DeepSched** network and **HEFT**.
- The network is trained on the loss between its predicted schedules and the schedules produced by HEFT.



Training Framework

The **network loss** is mainly composed of two parts:

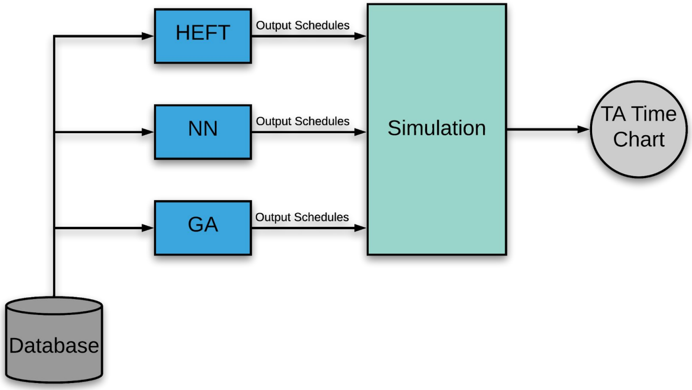
- **Classification loss** of the running machine for each task.
- **Regression loss** for actual start and finish time of each task (to add some constraints on the loss function).



The **summation** of these two losses is used to train the network.

Evaluation Framework

- A database of both **seen** and **unseen** data is provided to the **three** discussed methods.
- The output schedules of the three methods are passed to a **simulation stub** that runs the schedules and calculates the **average turnaround time**.
- This is repeated on **multiple input sizes**.

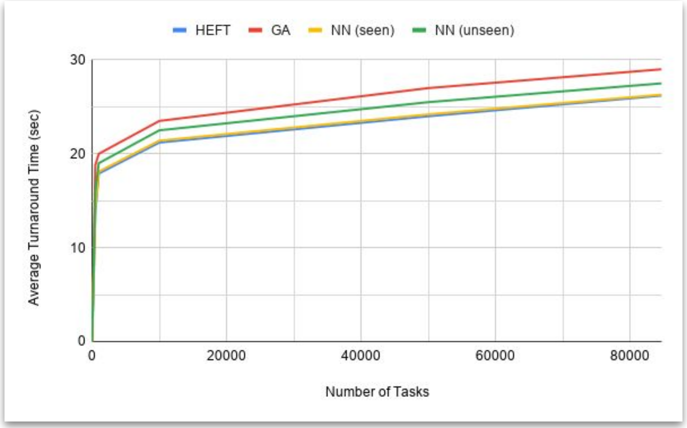


Results Discussion

Our results are divided into two parts:

1) **Performance** analysis:

- The opposite graph shows the **average turnaround time** for different input sizes.
- We can see that the network can offer the **same performance** as HEFT on **seen** data and **slightly lower performance** on **unseen** data. However, it still outperforms GA.



Results Discussion

Our results are divided into two parts:

2) **Time** analysis:

- We can see in the opposite table that the execution time of the **network** is **constant** over different input sizes, while the execution time of **HEFT** and **GA grows rapidly**.

Input Size	HEFT	GA	NN
486	31.5	67.5	0.125
10000	305.5	602.5	0.125
84654	670.0	3967.0	0.125

Future work and limitations

- This work can be improved in **two** possible ways:

1) **Approximation** of other scheduling algorithms, where we can go with some **optimal algorithms**.
2) Dealing with **dynamic** scenarios through **online network optimization** or **reinforcement learning environments**, because **static scenarios** and **maximum predefined input size** are the main **drawbacks** of the proposed method.