Self-accelerating Processing Workflows Progress Presentation

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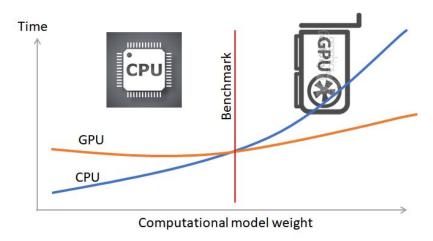
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Introduction

A particular task can be executed in both CPU or GPU but the execution time may vary depending on many factors.



... Introduction

- Profit from different processing units for the tasks are varying and depending on various factors such as properties of the accelerators, deployment environment, time of the day, complexity of the tasks and system's current state influence significantly, e.g. contention [14][19].
- Hence, the tasks cannot be pre-classified whether they are efficient to run on GPU or CPU during the programming period.

... Introduction

- ❖ Inappropriate scheduling of computations into wrong processors are inefficient and time consuming [17].
- * Many applications utilize GPUs to seek gain but leave CPUs sitting idle [18].
- ❖ At this moment Programmer has to switch the application manually.

Problem Statement

❖ Create a solution (library) that predicts the optimal processor at runtime which has less latency and high throughput for computations at different instances in a heterogeneous environment.

<u>NB</u>

Our research scope is to detect computational intensive problem type that can be executed on CPU faster rather than on a GPU in a real time system.

Research Motivation

- Appropriate selection of optimal processor reduces the overall execution times of the computations.
- **\Delta** Low latency and high throughput can be achieved.
- **\Delta** It can also prevent starvation of data stream in some instances.
- The overall performance of the system can be improved like by the branch predictor in CPU hardware.

Objectives and Expected Outcomes

- A hardware independent library that predicts optimal processing units using a selection strategy by evaluating some properties given by the programmer related to the task and through obtaining some performance matrices during runtime.
- * It should be able to integrate new computational models defined by the programmer.
- The solution should adapt to the nature of input streams and avoid them being assigned to wrong units.

Literature Review - Selection mechanism

Document	Methods	Key Points	
Seamlessly Portable Applications [14]	DLS will look the performance database to analyse the history runs of that particular implementation and compare the time taken to execute with the other implementation for that particular problem size.	Once the platform is selected, it wont switch to other platform during runtime. Only history based runs are selected	
Adaptive runtime selection for GPU [17]	Whichever the version that finishes the tasks first will kill the other run	Using resource for redundant calculation.	
Toward an Analytical Performance Model [16]	Machine-Learning-based algorithms may achieve high degrees of accuracy, but may also suffer from some drawbacks that limit their applications.	Applicability of such solutions is often limited in production systems. The need for runtime-available parameters in ML solutions leads to overhead for inference at runtime.	

Literature Review - Selection mechanism

Document	Methods	Key Points
STARPU A Unified Platform for Task Scheduling on Heterogeneous Multicore Architectures [18]	Providing user selectable scheduling mechanism	Once selected, same mechanism is used throughout the run.
Workload Partitioning for Accelerating Applications on Heterogeneous Platforms [19]	Workload partitioning using online and offline profiling	Function nature is not considered. Only data transfer and hardware computational capacity is considered.
Automatic task mapping and heterogeneity-aware fault tolerance [15]	Using performance database to select the accelerator based on previous run.	Won't be effective if there are no previous run.

Literature Review - Experimental Mechanism

Document	Methods	Key Points
Runtime Coordinated Heterogeneous Tasks in Charm++ [22]	Use Accel framework to select the strategy	Limited to the selection strategies presented in the framework.
Cost-Aware Function Migration in Heterogeneous Systems	The idea is based on online learning of the implementations which assist in guided execution of the best implementation.	This technique is similar to the history based selection.

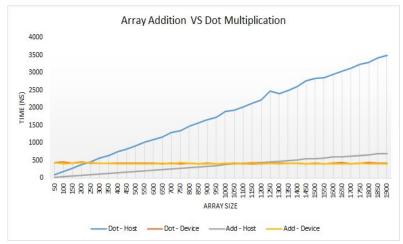
Methodology

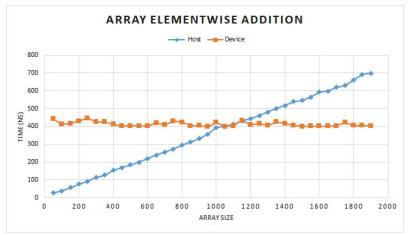
We conducted the experiment in following approaches,

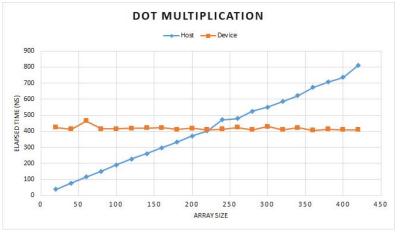
- 1. Dive into the context
- 2. Execution time based analysis
 - Last N Average Time Comparison
 - Sampling Execution Time Algorithm
 - Sampling Algorithm with Varying Revise Count
- 3. Input based analysis
 - Machine Learning (ML)
- 4. Hybrid Analysis

Methodology - Dive into the context









Methodology - Deployment System Experiment

Array Size	Host Time	Time Device Time	
100	0.00212042	0.00039633	
200	0.00444981	0.00023719	
800	0.01605261	0.000225	
900	0.0176719	0.00022228	
1000	0.01917692	0.0002281	
1100	0.02090968	0.00022673	
1200	0.02668534	0.00022467	
1300	0.02593127	0.00026113	

Array Size	Host Time Device Time		
100	0.00032395	0.00247511	
200	0.00047535	0.00152941	
800	0.00105543	0.00149808	
900	0.00123664	0.00152057	
1000	0.00199642	0.00166710	
1100	0.00270865	0.00209979	
1200	0.00233752	0.00320343	
1300	0.00300046	0.00151011	

Methodology - Error Boundary

$$n = \left(\frac{zs}{r\bar{x}}\right)^2$$

z – standard deviation for required confidence interval from normal curve

 \bar{x} – sample mean

s - sample standard deviation

r - required accuracy

$$\Rightarrow$$
 z = 1.960 (95% confidence interval)

$$\Rightarrow$$
 r = 0.05 (5%)

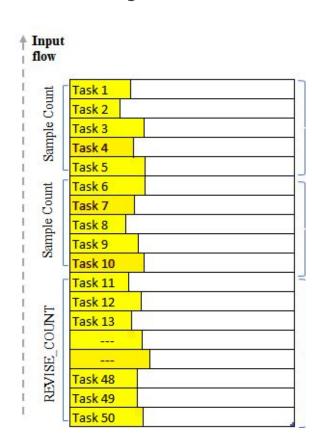
$$n = \left(\frac{196 \, s}{5 \, \bar{x}}\right)^2$$

Methodology - Execution Time Based Analysis

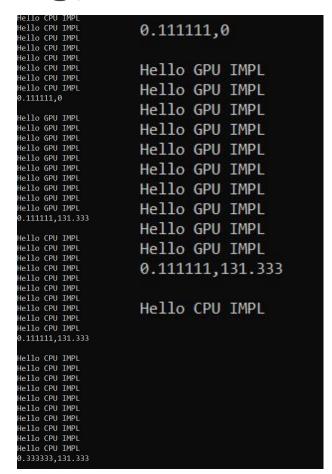
We experimented based on raw execution time after we had implemented a framework.

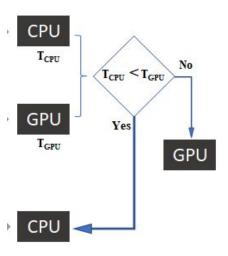
We have followed various approaches.

- Last N Average Time Comparison
- Sample Execution Time Algorithm
- Sample Algorithm with Varying Revise Count



Methodology - Last N Average Time Comparison



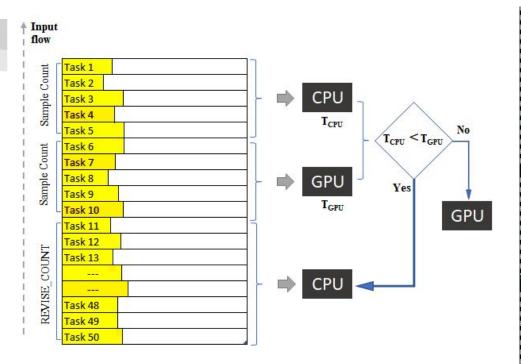


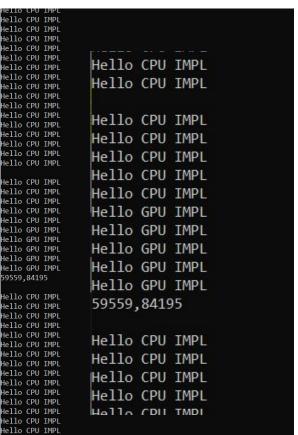
Methodology - Last N Average Time Comparison

Problem: There may be instances one processor sitting idle if execution time has raised to high value due to some unexpected issues.

Therefore, the other accelerator continues the execution forever which makes this approach inefficient.

Methodology - Sample Execution Time Algorithm





Methodology - Sample Execution Time Algorithm

Lacks in this approach:

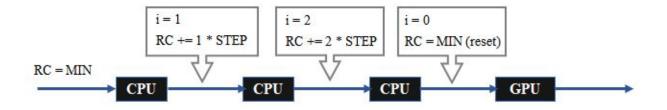
- It is hard to select the most appropriate REVISE_COUNT value.
- It is waste to evaluate samples unwantedly if one accelerator specific problems are arriving continuously.
- Evaluating the samples every fixed count adding overhead to the processing and it recoup the gain over the latency from the algorithm.

Methodology - Sample Algo with Varying Revise Count

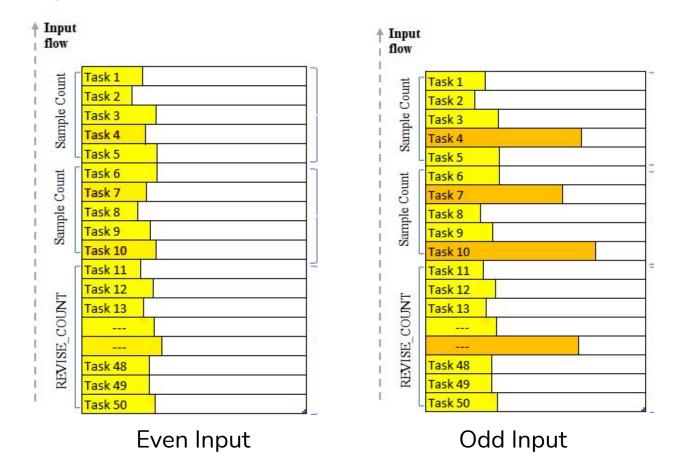
```
Microsoft Visual Studio Debug Console
Hello CPU IMPL
Hello GPU IMPL
1,3639,29402
Hello CPU IMPL
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Hello CPU IMPL
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Hello CPU IMPL
Hello CPU IMPL
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2,14313,59743
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                 2,14313,59743
Hello CPU IMPL
 Hello CPU IMPL
```

Methodology - Sample Algo with Varying Revise Count

- Problems in this version of selection algorithm is it cannot tackle with all kind of the nature of the input data.
- We need to consider the results from the Task Based Experiment with current version of algorithm to determine solution for this issue.



Methodology - Nature of Input Data



Methodology - Nature of Input Data

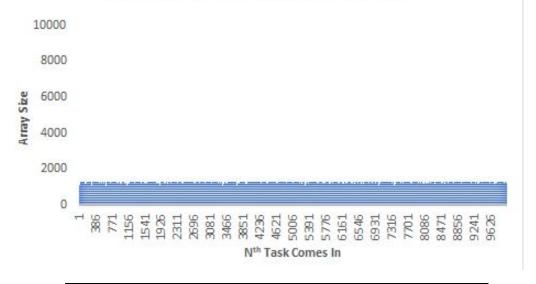
In this analysis, we experimented with 5 nature of input data

- 1. CPU Specific Input Stream
- 2. GPU Specific Input Stream
- 3. Square Aligned Wave Input Stream
- 4. Binary Aligned Input Stream
- 5. Odd Input Stream

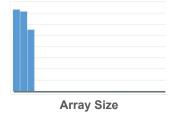
Methodology

CPU Specific Input Stream







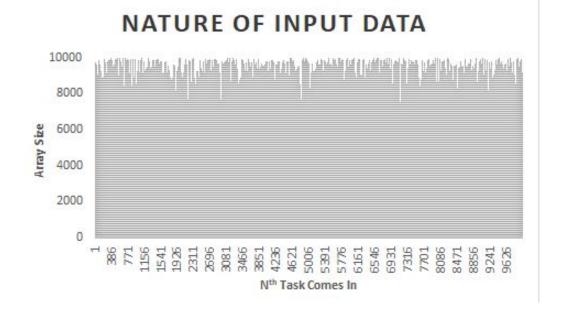


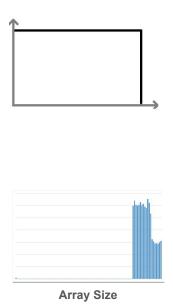
Self Flow Time: 1925 ms

CPU Only Time: 263 ms

GPU Only Time: 34406 ms

GPU Specific Input Stream



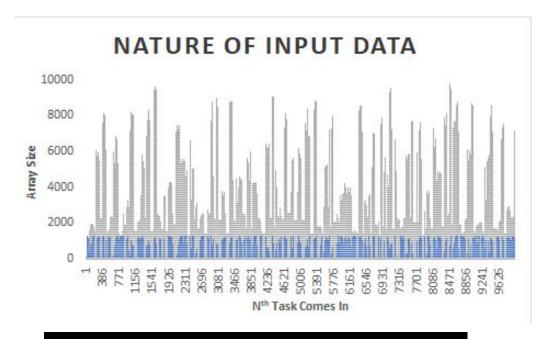


Self Flow Time: 34084 ms

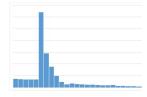
CPU Only Time: 34101 ms

GPU Only Time: 30389 ms

Square Aligned Wave Input Stream





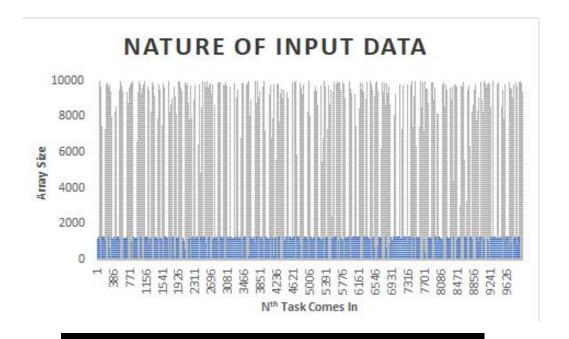


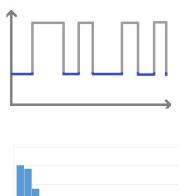
Self Flow Time: 2062 ms

CPU Only Time: 785 ms

GPU Only Time: 35921 ms

Binary Aligned Input Stream



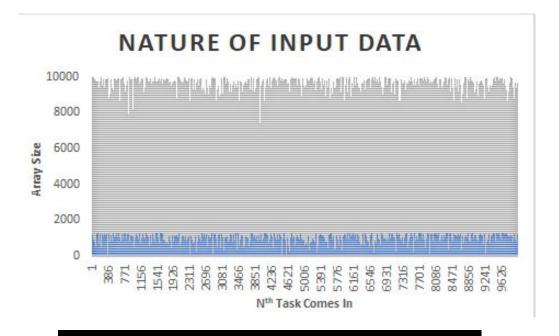


Self Flow Time: 2436 ms

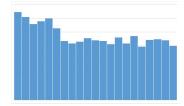
CPU Only Time: 2936 ms

GPU Only Time: 41697 ms

Odd Input Stream







Self Flow Time: 10545 ms

CPU Only Time: 16579 ms

GPU Only Time: 55062 ms

Outlier Issues

- The sampling algorithm cannot handle all input patterns.
- It can create a worse case scenario to the algorithm.
- Outliers issue means a sudden surge in input size among small inputs.
- It will be sent it to the wrong processor.
- we introduced machine learning model to decrease the effects.

Machine Learning Approach

Why machine learning?

- Tasks and number of attributes impact execution of the tasks are not known in advance.
- Dataset can be summarised using ML model with less human interventions.
- The relationship between the attributes and execution time does not converge to a general equation for all problem types.

Dataset Generation

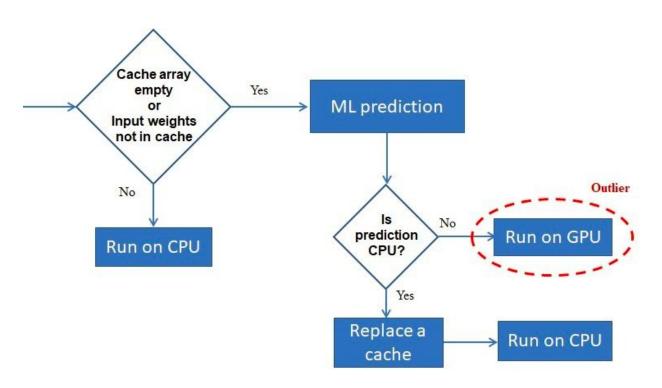
0	32	32	32
0	64	32	32
0	96	32	32
0	128	32	32
0	160	32	32
0	32	64	32
0	64	64	32
0	96	64	32
0	128	64	32
0	160	64	32
0	32	96	32
0	64	96	32
0	96	96	32
0	128	96	32
0	160	96	32
222	222	222	222
300	***		
222	222	222	222
360			
2000	222	222	222
307	***		
1	64	160	160
1	96	160	160
1	128	160	160
1	160	160	160

- Need dataset that represents weights of inputs and the decisions to train an ml model.
- It can only be obtained by executing inputs in both processors and comparing corresponding execution times.
- An input stream containing all possible combinations of the weights, within a range generated and the dataset created.

Technical Details

- XGboost machine learning algorithm used here.
- XGboost has less prediction time.
- Predictions are cached to reduce prediction overhead further.
- The model would use attributes that are given by programmer for training and predictions.
- The model must be trained manually once at the beginning, when deployed.

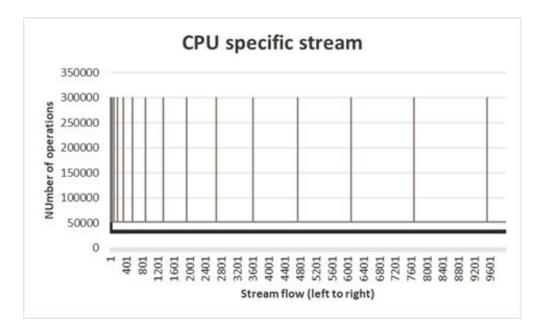
Caching Mechanisms



How AI is used to solve outlier issue

- Every problem is evaluated before execution if it is CPU turn.
- Al decision used as boundary just to prevent hike streams hit the CPU.
- Therefore the prediction need not be much accurate.
- The characteristics of input are collected using an abstract method getAttributes() that must be implemented by the developer for new models.
- Consequent catches leads next batch to the GPU automatically.

CPU input stream



CPU only: 577.8 ms

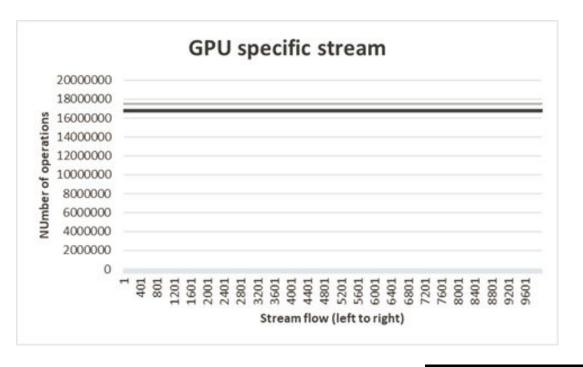
GPU only: 2586.8 ms

Hybrid model: 623.6 ms

Automated Hybrid Execution started

Code:

GPU input stream

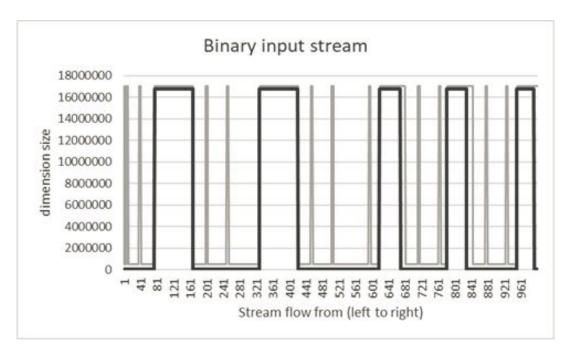


CPU only: 184447.6 ms

GPU only: 22167 ms

Hybrid model: 22199.8 ms

Binary input stream

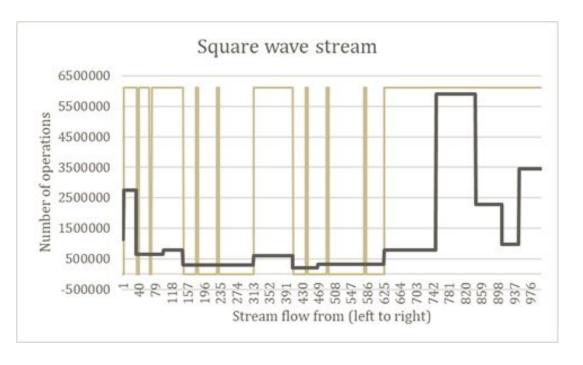


CPU only: 64144.8 ms

GPU only: 9432.4 ms

Hybrid model: 8332.4 ms

Square wave input stream

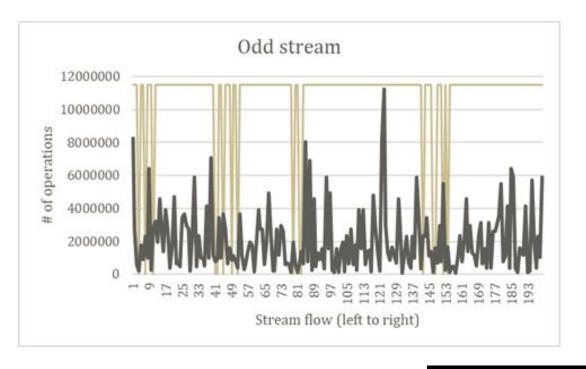


CPU only: 32303.4 ms

GPU only: 7694.2 ms

Hybrid model: 7681.4 ms

Random input stream



CPU only: 34750.2 ms

GPU only: 9122.6 ms

Hybrid model: 9217.6 ms

Elapsed Time Averages

	СРИ	GPU	Self-flow	ML	Hybrid	
Binary	64144.8	9432.4	45824	8061.2	8332.4	13.2%
Square	32303.4	7694.2	8508	8023.4	7681.4	0.17%
GPU favor	184447.6	22167	24035	22161.8	22199.8	-0.15
CPU favor	577.8	2586.8	613	600.8	623.6	314.81%
Random	34750.2	9122.6	9151	9361	9217.6	-1.03%

CONCLUSION

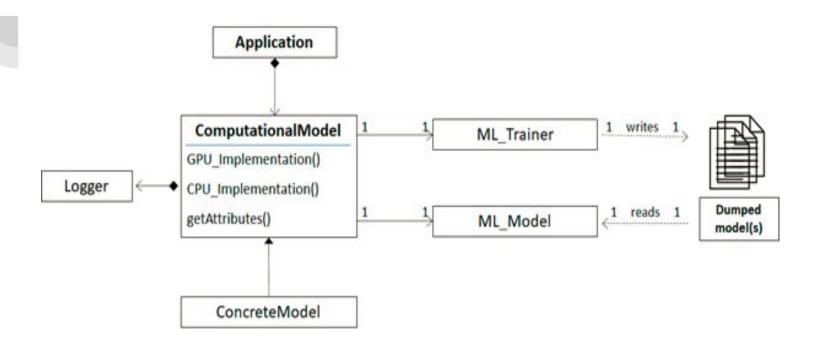
- Towards the progress to the solution we came up with mainly three algorithms.
 - Time based sampling model
 - Problem weights based ML model
 - A hybrid model containing both above
- Time based model has the issue of outlier.
- ML is time consuming and not considering the present loads in the processors.
- So, we combined the both models along with a caching mechanism which would handle both the outlier and present loads of the server.
- Hence we were able to obtain better performance.

Future Tasks

- Multiple threads to make predictions faster and parallel.
- Evaluating inputs in batch in the ML model may reduce the prediction time further.
- Increase the performance of the CPU.
- Dump and reuse the ML model without training it every time when the server starts.

Timeline and Future Tasks

Month	Task breakdown	Status
April	Extracting features	Completed
	Prioritizing features	In progress
	Set the features into classe	In progress
May	Group the features for functions Implement related algorithm	Completed
June	 Measuring the impacts of the features Create models and design of the Library 	In progress
July	Implement and code the Library	In progress
August	Prepare for mid evaluation	Completed



Summary

- Evaluate processing problems in relation to their execution time determining factors.
- A library of functions predicts which processor would offer less execution time.
- The framework switch processor evaluating few samples runtime periodically.
- * This solution can be scaled up to other complex computations.
- This research will push the heterogeneous computings into another dimension.

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