GPU RUN TIME PREDICTION

Introduction:

As we are marching towards more technological era, increase of data has increased manifold. With the increase in data, the need for faster processing and manipulation has also increased. In this linear and logistic regression analysis, we are computing the average run time for ideal combination of processors.

This analysis of ideal processors will come under supervised machine learning aiming to predict the fastest combination of processors .Techniques such as Gradient Descent algorithm, linear regression have been applied to get the best results.

Dataset:

The dataset is download at:

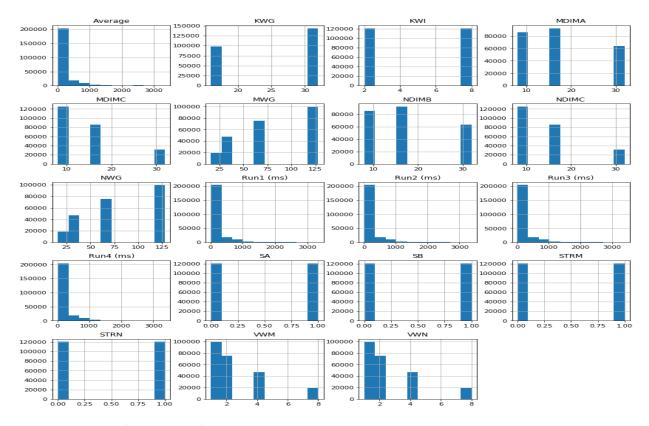
https://archive.ics.uci.edu/ml/datasets/SGEMM+GPU+kernel+performance

There are 14 parameter, the first 10 are ordinal and can only take up to 4 different powers of two values, and the 4 last variables are binary. Out of 1327104 total parameter combinations, only 241600 are feasible (due to various kernel constraints). This data set contains the results for all these feasible combinations. In this data set we don't have any null values present. Please find the screenshot below:

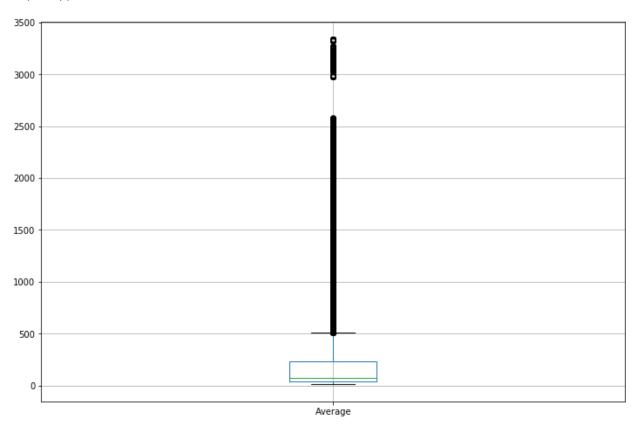
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 241600 entries, 0 to 241599
Data columns (total 18 columns):
MWG
           241600 non-null int64
NWG
           241600 non-null int64
KWG
          241600 non-null int64
MDIMC
          241600 non-null int64
NDIMC
           241600 non-null int64
MDIMA
           241600 non-null int64
NDIMB
           241600 non-null int64
KWI
           241600 non-null int64
VWM
            241600 non-null int64
VWN
           241600 non-null int64
STRM
           241600 non-null int64
           241600 non-null int64
STRN
SA
            241600 non-null int64
SB
           241600 non-null int64
Run1 (ms) 241600 non-null float64
Run2 (ms) 241600 non-null float64
Run3 (ms) 241600 non-null float64
Run4 (ms) 241600 non-null float64
dtypes: float64(4), int64(14)
```

memory usage: 33.2 MB

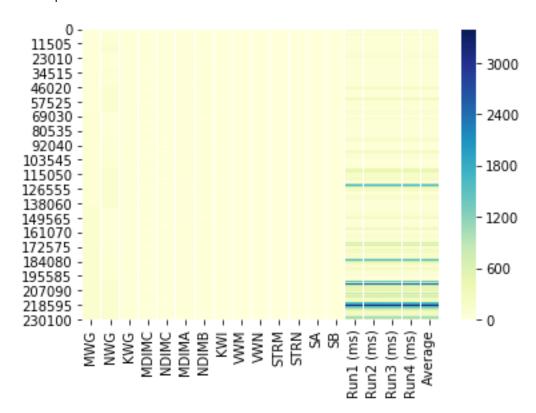
Feature distribution for the above variables is described below:



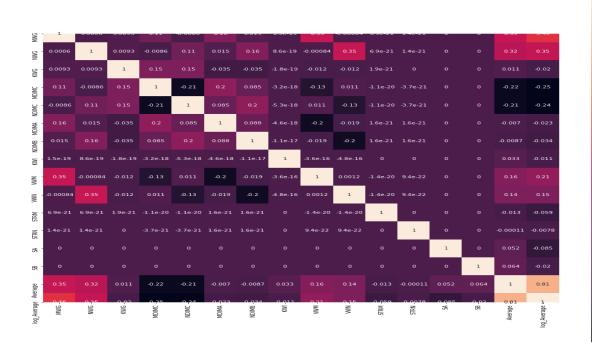
Boxplot Application for the above features:



Heatmap for the above features:



Correlation matrix



0.50

0.25

0.00

Part 1: Download the dataset and partition it randomly into train and test set using a good train/test split percentage.

I have randomly separated the data into testing and training sets using different percentages as 0.8 and 0.2 which means 80 percent of data will be used in training and 20 percent of data will be used to validate the model.

Part 2 :Design a linear regression model to model the average GPU run time. Include your regression model equation in the report.

Part 3: Implement the gradient descent algorithm with batch update rule. Use the same cost function as in the class (sum of squared error). Report your initial parameter values.

I have designed the linear regression model to model the average runtime of processors.

The model equation is

Average=beta0 + beta1*x1+beta2*x2+beta3*x3.....beta14*x4

I have built a custom implementation of the gradient descent function which implements the linear model. The initial parameters that I have got are

| Features | coefficients |
|----------|---------------|
| X1 | 218.0101525 |
| X2 | 141.6565995 |
| Х3 | 130.84711401 |
| X4 | 41.16106933 |
| X5 | -131.56267379 |
| X6 | -128.83840281 |
| X7 | 10.12431447 |
| X8 | 9.50365155 |
| Х9 | 12.39775437 |
| X10 | -2.77959938 |
| X11 | -6.34156052 |

| X12 | -4.59608693 |
|-----|-------------|
| | |
| X13 | 0.27944157 |
| | |
| X14 | 19.46804351 |
| | |
| X15 | 23.84465519 |
| | |

Part 4:

Part 4: Convert this problem into a binary classification problem. The target variable should have two categories. Implement logistic regression to carry out classification on this data set. Report accuracy/error metrics for train and test sets.

I have converted this problem into binary classification problem using the Average column in the dataset and have converted the target variable into 0 and 1. I have taken the mean of log_Average column and have classified the average into two categories that is above mean and below mean as 1 and 0 respectively. Accuracy my model has achieved is 89.9 percent.

EXPERIMENTS:

Experiment 1:

Experiment with various parameters for linear and logistic regression (e.g. learning rate \propto) and report on your findings as how the error/accuracy varies for train and test sets with varying these parameters. Plot the results. Report the best values of the parameters.

1. Linear Regression

I have fixed the threshold at 0.0000001 and have varied learning rate [1,0.8, 0.6, 0.4, 0.2, 0.1, 0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001].

To find the best value of alpha, I tried the different combinations of learning rate Following learning rates were the last batch of learning rates where I got my local minima: [0.00098,0.00096,0.00094,0.00093,0.00092,0.00091,0.00090,0.00089,0.00088,0.00087] I got the minimum RMSE at 0.0009 and that was the best alpha value for the given threshold.

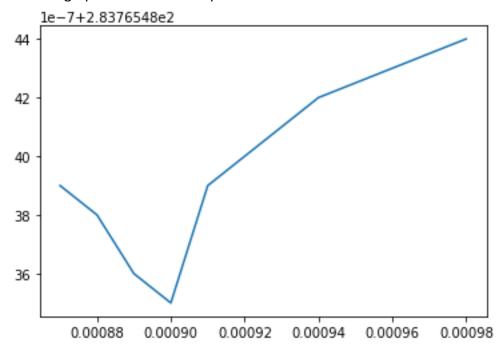
Graphs for Learning Rate:

| Learning Rate | RMSE |
|---------------|-------------|
| 0.00098 | 283.7654844 |
| 0.00096 | 283.7654843 |
| 0.00094 | 283.7654842 |

| 0.00093 | 283.7654841 |
|---------|-------------|
| 0.00092 | 283.7654840 |
| 0.00091 | 283.7654839 |
| 0.00090 | 283.7654835 |
| 0.00089 | 283.7654836 |
| 0.00088 | 283.7654838 |
| 0.00087 | 283.7654839 |

283.7654844,283.7654843,283.7654842,283.7654841,283.7654840,283.7654839,283.7654 835,283.7654836,283.7654838,283.7654839]

The final graph for RMSE and Alpha is below:



2. Logistic Regression

I have fixed threshold at 0.0000001 and have varied learning rate [0.0001, 0.001, 0.005, 0.01, 0.05, 0.075, 0.1, 0.25, 0.5, 0.75, 1].

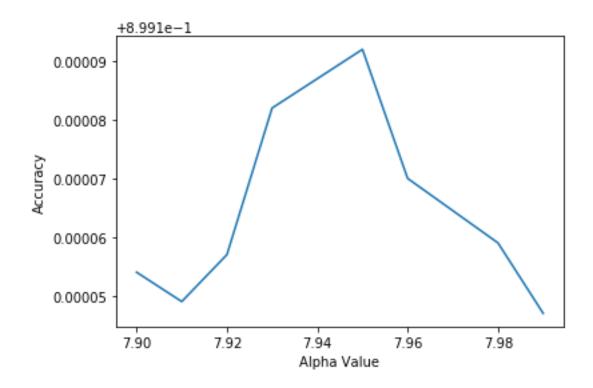
To find the best value of alpha, I have tried the different combinations of alpha. Following were the last batch of alpha. []. I got the minimum RMSE at -----.and that was the best value for the given threshold.

Graphs for Different learning rate:

| Learning Rate | Accuracy |
|---------------|----------|
| 7.9 | 0.899154 |
| 7.91 | 0.899149 |
| 7.92 | 0.899157 |
| 7.93 | 0.899182 |

| 7.95 | 0.899192 |
|------|----------|
| 7.96 | 0.89917 |
| 7.98 | 0.899159 |
| 7.99 | 0.899147 |

Graph for Logistic:



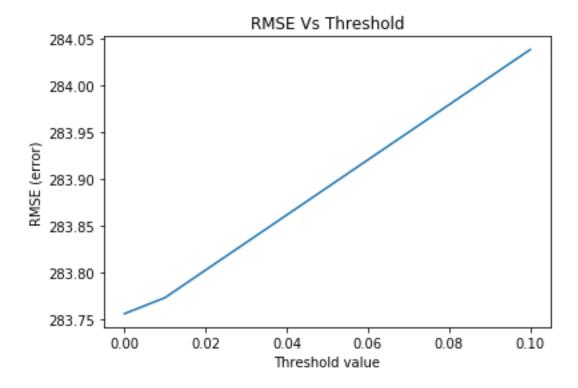
EXPERIMENT 2

Experiment with various thresholds for convergence for linear and logistic regression. Plot error results for train and test sets as a function of threshold and describe how varying the threshold affects error. Pick your best threshold and plot train and test error (in one figure) as a function of number of gradient descent iterations.

For Linear Regression

Changing Threshold values:

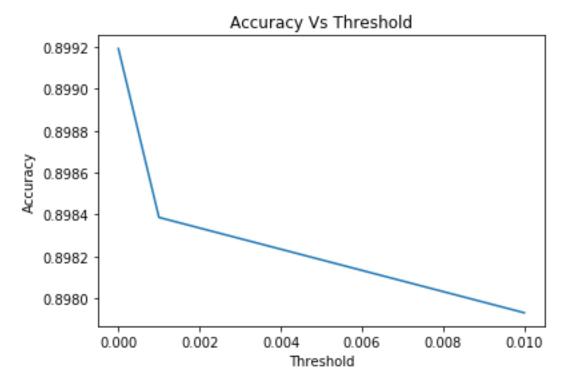
| Threshold Level | RMSE | Learning Rate |
|-----------------|--------------|---------------|
| 0.00001 | 283.75648345 | 0.0009 |
| 0.01 | 283.77357268 | 0.0009 |
| 0.1 | 284.03815423 | 0.0009 |



For Logistic Regression

| Threshold Level | Learning Rate | Accuracy |
|-----------------|---------------|--------------------|
| 0.0000001 | 7.95 | 0.899192 |
| 0.001 | 7.95 | 0.898385761589404 |
| 0.01 | 7.95 | 0.8979304635761589 |

GRAPHS FOR LOGISTIC REGRESSION



EXPERIMENT 3

Pick eight features randomly and retrain your models only on these ten features. Compare train and test error results for the case of using your original set of features (14) and eight random features. Report the ten randomly selected features.

I have randomly taken 8 features and have modeled my linear and logistic models on those features:

8 Features: ["MWG","NWG","KWG","MDIMC","NDIMC","MDIMA","NDIMB","KWI"]

Target Variable: ["Average]

1) Linear Model

| | RMSE | Cost Value | Iterations |
|--------------|--------------|------------|------------|
| Model – 8 | 285.542627 | 40889.511 | 4747 |
| Random | 15 | 7525077 | |
| variables | | | |
| Best Model | 284.03815423 | 40395.446 | 5200 |
| using | | 610390405 | |
| Experiment 1 | | | |
| and 2 | | | |

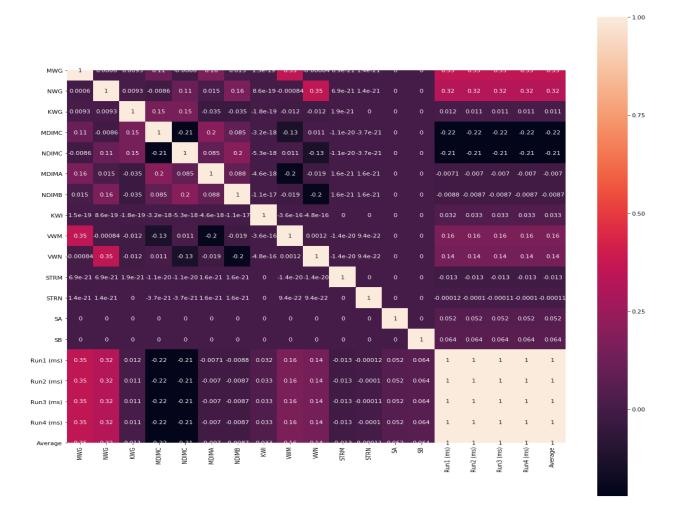
2) Logistic Model

| | Accuracy | Cost Value | Iterations |
|-------------------------------------|------------------------|-------------------------|------------|
| Model-8 Random Variables | 0.92181291390728 48 | 0.3538413131336 6624 | 10000 |
| Best Model Experiment 1 and 2 | 0.899192 | 40395.446 | 10000 |

EXPERIMENT 4

Now pick eight features that you think are best suited to predict the output, and retrain your models using these ten features. Compare to the case of using your original set of features and to the random features case. Did your choice of features provide better results than picking random features? Why? Did your choice of features provide better results than using all features? Why?

According to the correlation matrix described below:



I have taken the best 8 features which are highly co related to the Average i.e the target variable:

The variables I have taken are listed below:

['MWG', 'NWG', 'KWG', 'MDIMC', 'NDIMC', 'VWM', 'SA','VWN']

1) Linear Model

| Models | RMSE | Cost Value | Iterations |
|---------------------|---------------|------------------|------------|
| Randomly selected | 285.542627156 | 40889.5117525077 | 4747 |
| Selected 8 features | 285.542627154 | 40854.0281642906 | 5191 |

When I have taken the random 8 variables and selected 8 features, there is just slight difference between the RMSE between the two models. Cost Value for the selected eight features is less as compared to the randomly selected feature model.

2) Logistic Model

| Models | Accuracy | Cost Value |
|---------------------|--------------------|---------------------|
| Randomly selected | 0.9218129139072848 | 0.35384131313366624 |
| Selected 8 features | 0.8997102649006623 | 0.34832213626441216 |

For logistic Regression, the randomly selected features gave me better resutts as compared to the best selected 8 features.

Discussion:

Describe your interpretation of the results. What do you think matters the most for predicting the GPU run time? What other steps you could have taken with regards to modeling to get better results?

Answer: The pre processing and analysis of the data mattered the most while predicting results through our model.

We could have used PCA (Principal component analysis) to determine which features are most relevant ones. This could have saved us time and gave us better understanding.

We could have used better classification techniques such as KNN, to classify results better.