Machine Learning Engineer Nano-Degree

Capstone Project

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Domain Background

Virtualisation of application environments and containerisation of applications is a trending topic these days. Different solutions are provided to virtualise an operating system or containerise an application; and implement a cluster of nodes for managing or maintaining applications. One of the common topics within these clustering solutions is about distributing the load based on the available infrastructure resources, for example processing power and memory. For distributing the load, a component needs to keep monitoring the environment and provide the information to a scheduler to maintain the environment and organise future application deployments. The scheduler has an important role for improving and enhancing the environment or applications stability. One of the key metrics that scheduler has to consider is CPU utilisation. This project is going to look into providing a model for predicting the CPU utilisation.

Problem Statement

Improving the stability and performance of distributed applications a cross the globe is a challenging topic for enterprises. An application environment can get unstable when there is a heavy load on specific applications or nodes. Users often face high response time and low performance in case of any environment instability and this can have a huge impact on the branding or business of targeted enterprises and organisations. Today's competitive market requires organisations to provide stable and well preforming application environment to their customers, but providing such stability based on a limited visibility on utilisation of infrastructure resources is very challenging. On this project I'm focusing on improving the visibility of system metrics by providing a model for predicting the CPU utilisation based on the previous infrastructure monitoring records. Beside improving the stability, saving energy and costs are also other use cases on such model.

Datasets and Inputs

Following provided dataset from Burn CPU Burn competition on Kaggle will be used:
https://www.kaggle.com/c/model-t4/data

The goal is to predict the load on the CPUs in a cluster of servers based on the applications behaviour running on these servers. There are two CPUs per each server and in total there are seven servers in a cluster.

“The dataset consists of a set of variables that were measured over about a one month period. Measurements were taken in one minute intervals and on each server. Measurements are usually the average or sum over that one minute interval. For instance the number of packets received, the average number of IO operations, etc.”

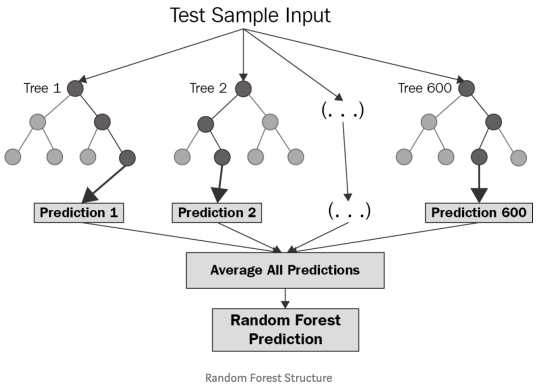
This dataset is from a real cluster that is used to control train traffic in a geographical area spanning several cities. These fields are available on provided CSV files:

- sample time: the date and time the data was sampled.
- m_id: the ID of the server the data was sampled at.
- appxxxx: data about specific application.
- pagexxx: data on memory usage of the server.
- syst_xxx: data on page fault rate, number of processes, etc.

- state_xxx: data on the state the system is in.
- io_xxx: data about general IO usage, (file IO, direct IO).
- tcp_xxx: data on incoming and outgoing TCP traffic.
- llxxx, ewxxx: data on incoming and outgoing network traffic.
- cpu_01_busy: the variable we are trying to predict.

Solution Statement

The solution is to collect the system related metrics like the usage of memory, I/O, network traffic and train a model which can link the recorded data to the CPU utilisation and can provide the estimation in case the system behaviour is similar. This trained model for our prediction needs to be based on a supervised learning. Different regression algorithm can be used to train the model. As a first idea I would like to try on Random Forests and Extra Trees methods since the data set has so many different fields and it might be better to try ensemble learning methods.



Random Forest Structure

Random Forest Regressor:
https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html

Extra Trees Regressor:
https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.ExtraTreesRegressor.html

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Benchmark Model

Based on the information provided on https://www.kaggle.com/c/model-t4/leaderboard the benchmark model is a Two Variable Random Forest model which have been evaluated and scored as 11.18079. For our case here, I think Two Variable model is a very basic model and I'm looking to get better results since there are more than 2 variables to be considered according to our datasets.

Evaluation Metrics

Based on the information provided on https://www.kaggle.com/c/model-t4/data the evaluation metric is the Root Mean Square Error:

$$S = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{l}_i - l_i)^2}$$

* l hat is the predicted load and l the actual load.

“For every line in the test set, submission files should contain two columns: Id and Prediction. Prediction is a real number in the range of 0 to 100 predicting how busy CPU 1 was in the given machine on the given date.”

To compare this evaluation metric with Mean Squared Error (MSE) and Mean Absolute Error (MAE) , MSE is not a good metric when dealing with noisy data as it would make errors to impact result even worse. About MEA, it’s a linear score which would make the comparison of models behaviour difficult as the difference between 10 and 0 will be twice the difference between 5 and 0. Therefore RMSE is still a better evaluation metric.

Analysis

To apply the basic analysis we first would need to download and then explore the data. The train has 178780 records and test data has 50000 records which each entry has 89 attributes including the sample time and different related system metrics.

In[2]:
```
train.head()
```

Out[2]:

	sample_time	m_id	syst_direct_ipo_rate	syst_buffered_ipo_rate	syst_page_fault_rate	syst_page_read_ipo_rate	syst_process_count	syst_other_states	page_page_write_ipo_rate	page_global_valid_fault_rate	...	tc
0	2010-11-24 00:01:00	a	80.48	1261.97	15.55	2.10	271	12	6.23	4.67	...	
1	2010-11-24 00:01:00	b	73.80	624.38	6.43	0.45	317	10	5.47	1.10	...	
2	2010-11-24 00:01:00	c	40.57	466.18	6.40	0.45	258	22	10.90	1.10	...	
3	2010-11-24 00:01:00	d	68.75	495.10	6.50	0.45	224	10	2.58	1.10	...	
4	2010-11-24 00:01:00	e	47.45	436.65	6.42	0.45	253	10	2.48	1.10	...	

5 rows × 89 columns

In[20]:
```
train.tail()
```

Out[20]:

	sample_time	m_id	syst_direct_ipo_rate	syst_buffered_ipo_rate	syst_page_fault_rate	syst_page_read_ipo_rate	syst_process_count	syst_other_states	page_page_write_ipo_rate	page_global_valid_fault_rate	.
178775	2010-12-13 23:59:00	3	0.0	0.0	0.0	0.0	260	22	0.0	0.0	.
178776	2010-12-13 23:59:00	4	0.0	0.0	0.0	0.0	225	10	0.0	0.0	.
178777	2010-12-13 23:59:00	5	0.0	0.0	0.0	0.0	247	10	0.0	0.0	.
178778	2010-12-13 23:59:00	6	0.0	0.0	0.0	0.0	172	10	0.0	0.0	.
178779	2010-12-13 23:59:00	7	0.0	0.0	0.0	0.0	218	2	0.0	0.0	.

5 rows × 94 columns

In[3]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178780 entries, 0 to 178779
Data columns (total 89 columns):
sample_time                    178780 non-null object
m_id                           178780 non-null object
syst_direct_ipo_rate           178780 non-null float64
syst_buffered_ipo_rate         178780 non-null float64
syst_page_fault_rate           178780 non-null float64
syst_page_read_ipo_rate        178780 non-null float64
syst_process_count             178780 non-null int64
syst_other_states              178780 non-null int64
page_page_write_ipo_rate       178780 non-null float64
page_global_valid_fault_rate   178780 non-null float64
page_free_list_size            178780 non-null int64
page_modified_list_size        178780 non-null int64
io_mailbox_write_rate          178780 non-null float64
```

In[14]:
```
test.info()
```

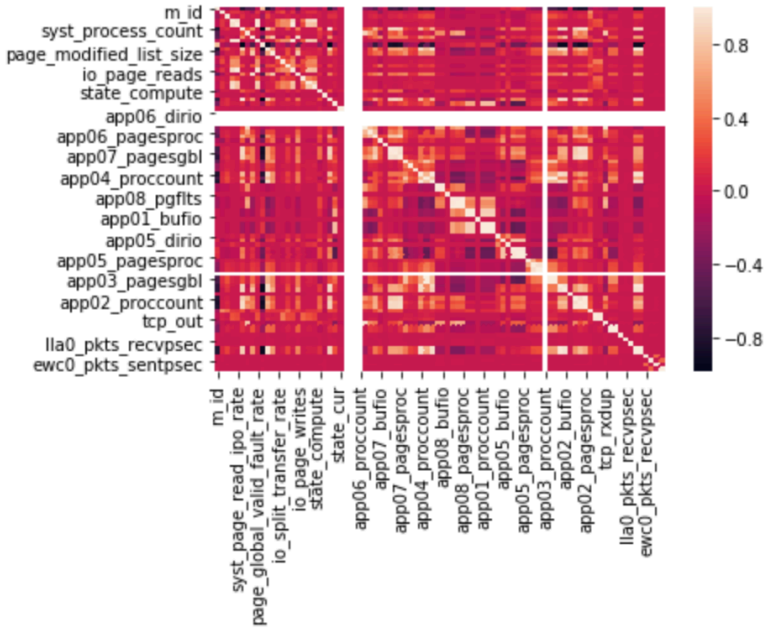
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 94 columns):
sample_time                    50000 non-null object
m_id                           50000 non-null int64
syst_direct_ipo_rate           50000 non-null float64
syst_buffered_ipo_rate         50000 non-null float64
syst_page_fault_rate           50000 non-null float64
syst_page_read_ipo_rate        50000 non-null float64
syst_process_count             50000 non-null int64
syst_other_states              50000 non-null int64
page_page_write_ipo_rate       50000 non-null float64
page_global_valid_fault_rate   50000 non-null float64
page_free_list_size            50000 non-null int64
page_modified_list_size        50000 non-null int64
io_mailbox_write_rate          50000 non-null float64
```

Data Correlation

Following plots show how different attributes within train data are correlated to each other:

In[13]:

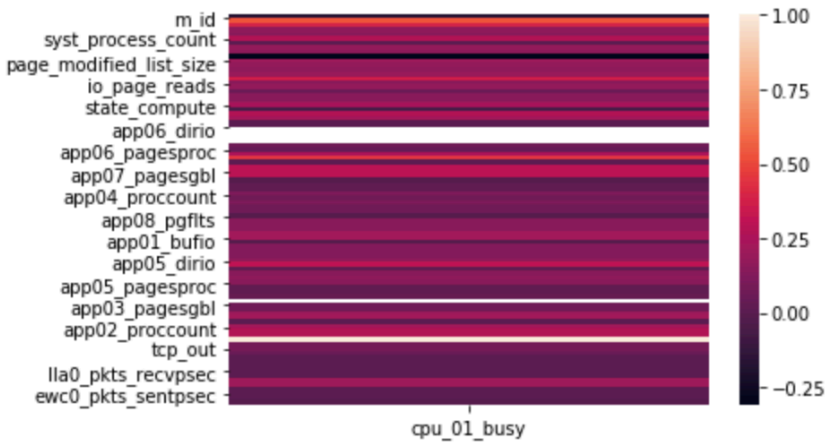
```
import seaborn as sns

sns.heatmap(train.corr());
```



The correlation of cpu usage attribute with other fields is also available on following heatmap:

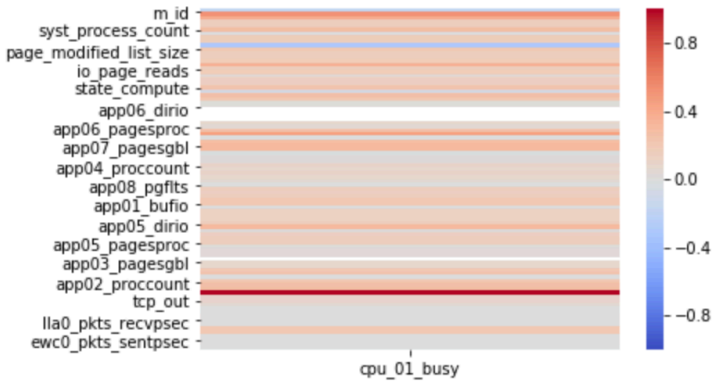
In[32]:

```
sns.heatmap(train.corr()[["cpu_01_busy"]]);
```



In[46]:

```
sns.heatmap(train.corr()[["cpu_01_busy"]],
            vmin=-1,
            vmax=1,
            cmap='coolwarm',
            annot=False);
```



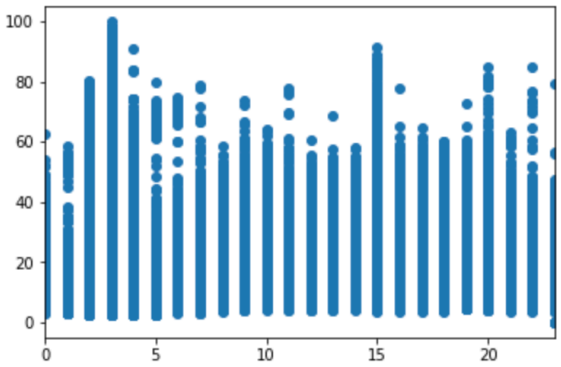
Following visualisation also shows the cpu usage picks during the day. The consumption is high around 3am, 3pm and 8pm.

In[27]:

```
import matplotlib.pyplot as plt

fig, ax = plt.subplots()
train["sample_time"] = pd.to_datetime(train["sample_time"])
ax.scatter(train["sample_time"].dt.hour, train["cpu_01_busy"])
ax.set_xlim(train["sample_time"].dt.hour.min(),
            train["sample_time"].dt.hour.max())
```

Out[27]:

```
(0, 23)
```



Algorithms

In this project I've used two following algorithms which I'm going to explain:

1. Random Forest:

Random forest is a supervised learning algorithm and is an ensemble method with the use of multiple decision trees and bootstrap aggregation technique, also known as bagging. Bagging

would run each model independently and then aggregates the outputs without preference to any model. This can be used to reduce the variance for those algorithm that have high variance, like decision trees.

2. Extra Tree:
The Extra-Tree or extremely randomised trees method is used to further randomising tree building comparing to random forests. This would help it to perform better in presence of noisy features. Although when all the variables are relevant, both algorithms would achieve very similar results. Extra-Tree drops the idea of using bootstrap copies of the learning sample, and instead of trying to find an optimal cutpoint for each one of the randomly chosen features at each node, it selects a cutpoint at random.

Implementation

For implementation I've used Python programming language, panda and scikit libraries; as well as the RandomForest and ExtraTrees algorithms. At the beginning after loading the train and test data, entries had to be normalised or preprocessed on date, time and on the ID of the server the data was sampled at

Preprocessing functions:

```
23  def splitSampleTime(data):
24
25      sub = pd.DataFrame(data.sample_time.str.split(' ').tolist(), columns="date time".split())
26      date = pd.DataFrame(sub.date.str.split('-').tolist(), columns="year month day".split())
27      time = pd.DataFrame(sub.time.str.split(':').tolist(), columns="hour minute second".split())
28
29      data['year'] = date['year']
30      data['month'] = date['month']
31      data['day'] = date['day']
32
33      data['hour'] = time['hour']
34      data['minute'] = time['minute']
35
36      return data
37
38  def mapID(data):
39
40      coded = {'a': 1, 'b': 2, 'c': 3, 'd': 4, 'e': 5, 'f': 6, 'g': 7}
41      data['m_id'] = data['m_id'].astype(str).map(coded)
42
43      return data
```

Then the following classification algorithms could be called:

```
2   import pandas as pd
3   from sklearn.ensemble import RandomForestRegressor
4   from sklearn.ensemble import ExtraTreesRegressor
5
6   def createRandomForest():
7       clf = RandomForestRegressor(n_estimators=50)
8       return clf
9
10  def createExtraTree():
11      clf = ExtraTreesRegressor(n_estimators=50)
12      return clf
13
14  def classify(clf, train, features, target, test, filePath):
15
16      clf.fit(train[features], train[target])
17
18      with open(filePath, "w") as outfile:
19          outfile.write("Id,Prediction\n")
20          for index, value in enumerate(list(clf.predict(test[features]))):
21              outfile.write("%s,%s\n" % (test['Id'].loc[index], value))
22
```

And here is the main function:

```
45  train=pd.read_csv("./input/train.csv")
46  test=pd.read_csv("./input/test.csv")
47
48  train = splitSampleTime(train)
49  train = mapID(train)
50
51  test = splitSampleTime(test)
52  test = mapID(test)
53
54  target = 'cpu_01_busy'
55  features = [col for col in train.columns if col not in ['cpu_01_busy', 'sample_time']]
56
57  clf = createExtraTree()
58  classify(clf, train, features, target, test, "./output/extratree.csv")
59
60  clf = createRandomForest()
61  classify(clf, train, features, target, test, "./output/randomforest.csv")
```

Results

Following table shows the results of above Random Forest and Extra Tree regressors and also compares the outcome with the Two Variable Random Forest model which is used as a benchmark model:

Method	Evaluation Score
Extra Tree	3.39807
Random Forest	3.78130
Two Variable Random Forest	11.18079
All Zero	27.40211

Conclusion

Both Extra Tree and Random Forest have been performed better than the benchmark model. Extra Tree is performing sightly better than Random Forest on the problem specifics and data set here. It seems that the train and test data are quite clean and we don't have much noice there, that's why the Random Forest method appears to be biased on local optimum while Extra Randomised Trees is trying to jump out of local optimum and trying to reach to global optimum.