Vandre.Tasks_I_II

November 20, 2017

In [1]:
```
# Task I - Data Exploration
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
from sklearn import datasets, linear_model
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
```

In [2]:
```
plt.rcParams['figure.figsize'] = (12.0, 4.0)
X = pd.read_csv('../data/X.csv')
Y = pd.read_csv('../data/Y.csv')
```

In [3]:
```
# 1. Compute the following statistics for each component of X and Y:
# mean, maximum, minimum, 25th percentile, 90th percentile, and standard
deviation.
metrics = pd.merge(X, Y, on='TimeStamp')
metrics.iloc[:,1:].describe(percentiles=[.25, .90])
```

Out[3]:

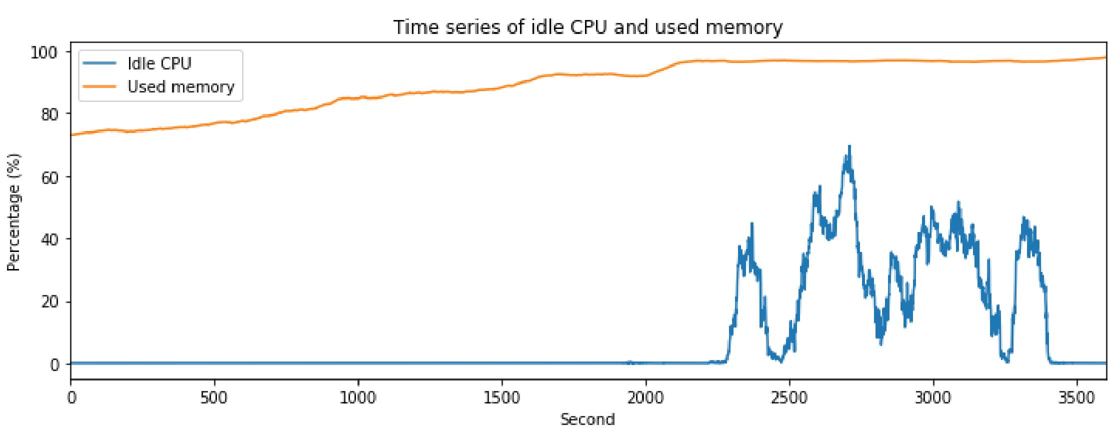
	all_..idle	X..memused	proc.s	cswch.s	file.nr
count	3600.000000	3600.000000	3600.000000	3600.000000	3600.000000
mean	9.064981	89.137517	7.683303	54045.874022	2656.333333
std	16.122822	8.183662	8.532606	19497.811540	196.110748
min	0.000000	73.030000	0.000000	11398.000000	2304.000000
25%	0.000000	82.965000	0.000000	31302.000000	2496.000000
50%	0.000000	92.175000	6.000000	63908.000000	2688.000000
90%	38.621000	96.770000	20.000000	72135.100000	2880.000000
max	69.540000	97.840000	48.000000	83880.000000	2976.000000

	sum_intr.s	ldavg.1	tcpsck	pgfree.s	DispFrames
count	3600.000000	3600.000000	3600.000000	3600.000000	3600.000000
mean	19978.040747	75.875772	48.997500	72872.154569	18.818394
std	4797.271325	43.862445	15.871155	19504.321175	5.219756
min	10393.000000	11.130000	21.000000	15928.000000	0.000000
25%	16678.000000	28.200000	34.000000	61601.750000	13.390000
50%	18109.000000	75.390000	47.000000	71686.500000	19.120001
90%	28228.400000	127.993000	71.000000	97532.500000	24.610000
max	35536.000000	147.470000	87.000000	145874.000000	30.390000

In [4]:
```python
# 2. Compute the following quantities:

# (a) the number of observations with memory usage larger than 80%;
a = metrics[metrics['X..memused'] > 80].count()['X..memused']
print 'a) Number of observations:', a

# (b) the average number of used TCP sockets for observations
# with more than 18000 interrupts/sec;
b = metrics[metrics['sum_intr.s'] > 18000].mean()['tcpsck']
print 'b) Average number of used TCP sockets: %.2f' % b

# (c) the minimum memory utilization for observations
# with CPU idle time lower than 20%.
c = metrics[metrics['all_..idle'] < 20].min()['X..memused']
print 'c) Minimum memory utilization: %.2f' % c
```

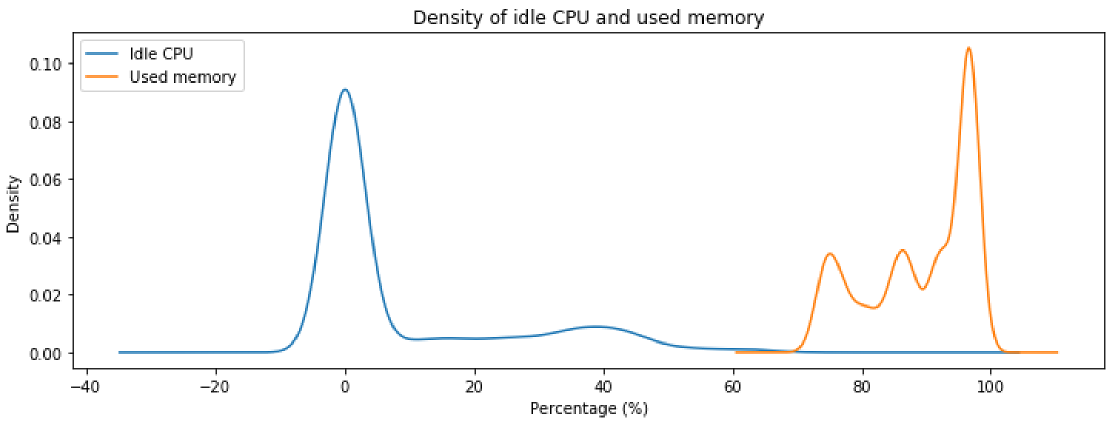
```
a) Number of observations: 2875
b) Average number of used TCP sockets: 46.35
c) Minimum memory utilization: 73.03
```

In [5]:
```python
# 3. Produce the following plots:

# (a) Time series of percentage of idle CPU and of used memory
# (both in a single plot);
series = pd.DataFrame(metrics, columns=['all_..idle', 'X..memused']);
ts = series.plot(title = 'Time series of idle CPU and used memory')
ts.legend(['Idle CPU', 'Used memory'])
ts.set_xlabel("Second")
ts.set_ylabel("Percentage (%)")
fig = ts.get_figure()
plt.show()
```



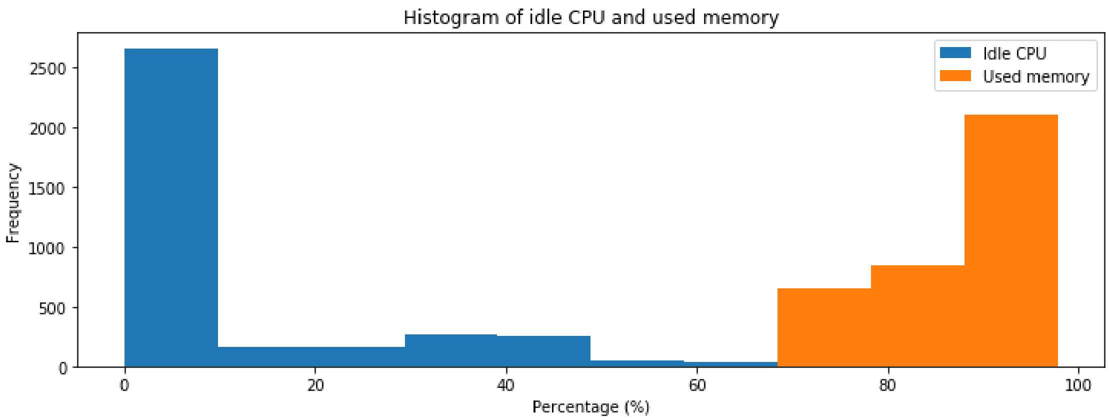
```
In [6]: plt.close(fig)
```

```
In [7]: # (b) Density plots, histograms, and box plots of idle CPU and of used memory.
        kde = series.plot.kde(title = 'Density of idle CPU and used memory')
        kde.legend(['Idle CPU', 'Used memory'])
        kde.set_xlabel("Percentage (%)")
        fig = kde.get_figure()
        plt.show()
```



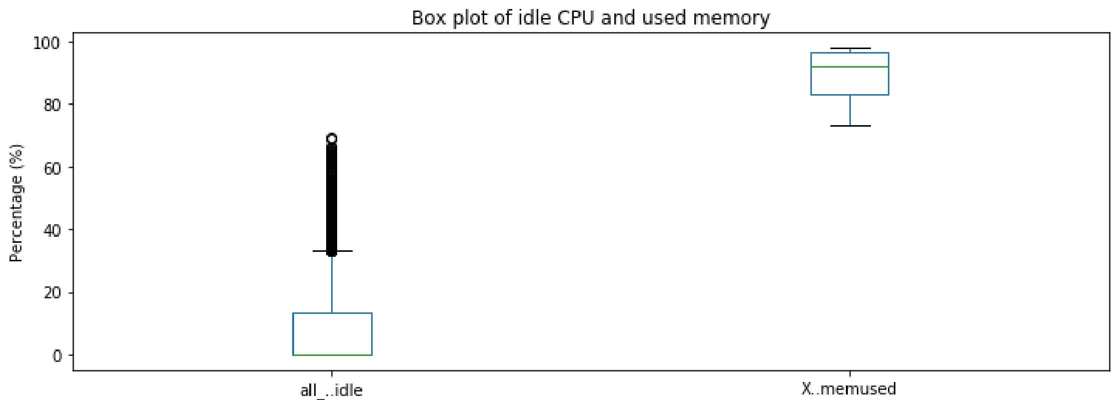

```
In [8]: plt.close(fig)
```

```
In [9]: hist = series.plot.hist(title = 'Histogram of idle CPU and used memory')
        hist.legend(['Idle CPU', 'Used memory'])
        hist.set_xlabel("Percentage (%)")
        fig = hist.get_figure()
        plt.show()
```



In [10]:
```
plt.close(fig)
```

In [11]:
```
bp = series.plot.box(title = 'Box plot of idle CPU and used memory')
bp.set_ylabel("Percentage (%)")
fig = bp.get_figure()
plt.show()
```



In [12]:
```
plt.close(fig)
```

In [13]:
```
# Task II - Estimating Service Metrics from Device Statistics
def nmae(y_test, y_pred):
    y_test = pd.DataFrame(y_test)
    y_pred = pd.DataFrame(y_pred)

    sum = 0.0
    m = len(y_test)
    average = np.mean(y_test)

    for i in range(m):
        sum += abs(y_test.iloc[i, 0] - y_pred.iloc[i, 0])
        i += 1

    nmae = (sum / m) / average
    return nmae
```

In [14]:
```
# 1. Evaluate the Accuracy of Service Metric Estimation
# (a) Model Training - use linear regression to train a model M
# with the training set. Provide the coefficients of your model M.
X = X.iloc[:, X.columns != 'TimeStamp']
Y = Y.iloc[:, Y.columns != 'TimeStamp']

X_train, X_test, y_train, y_test = train_test_split(X, Y, train_size=0.7,
test_size=0.3)
```

```
lm = linear_model.LinearRegression()
model = lm.fit(X_train, y_train)
y_pred = lm.predict(X_test)

print 'Coefficients:', lm.coef_
```

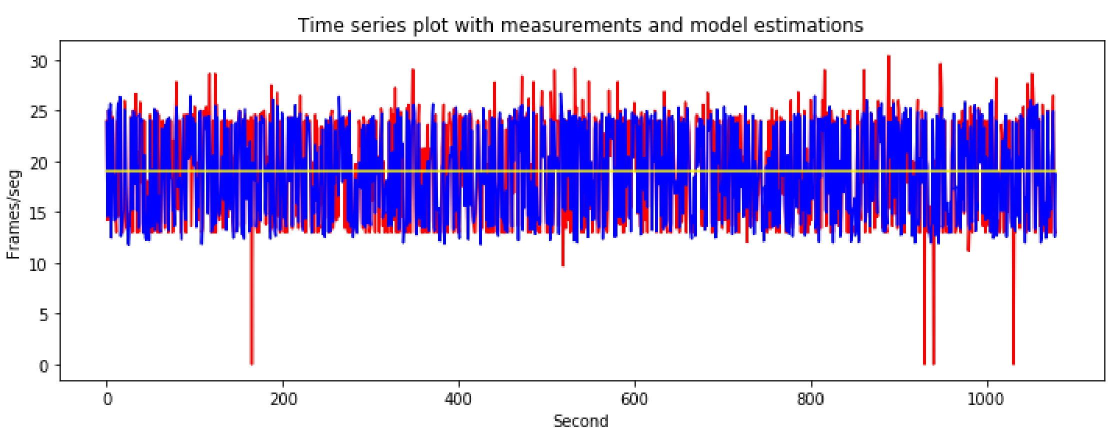
```
Coefficients: [[ -8.63879476e-02  -7.72699183e-02  -1.33623558e-02
-9.87963259e-05
   -3.54053585e-03   2.15181648e-05  -5.89256394e-02  -5.60887870e-02
   -1.58745163e-05]]
```

```
In [15]: # (b) Accuracy of Model M - compute the estimation error of M over the test set.
         # Explained variance score: 1 is perfect prediction
         print 'Accuracy score: %.4f' % model.score(X_test, y_test)
         print 'Normalized Mean Absolute Error: %0.4f ' % nmae(y_test, y_pred)
```

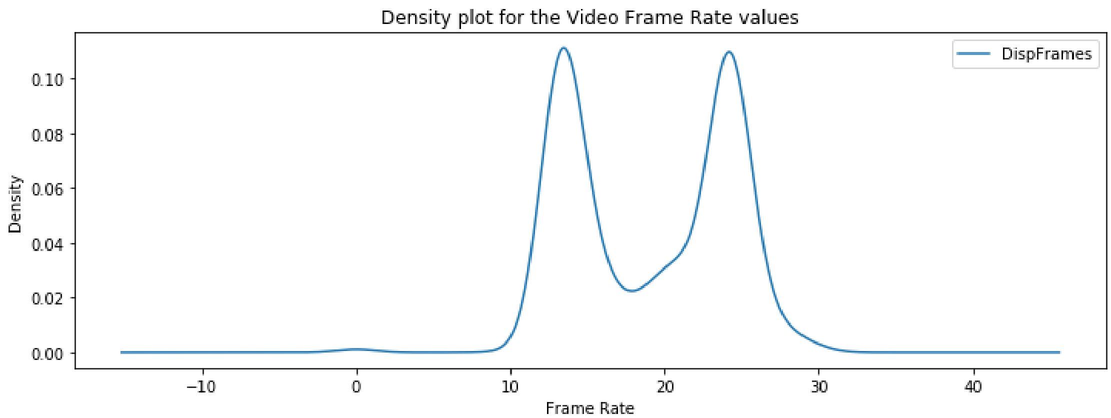
```
Accuracy score: 0.7282
Normalized Mean Absolute Error: 0.1012
```

```
In [16]: plt.clf()
```

```
In [17]: # (c) Produce a time series plot that shows both the measurements and
         # the model estimations for M for the Video Frame Rate values in the
         # test set (see example of such a plot in Figure 4(a) of [1]).
         # Show also the prediction of the a naive method.
         interval = np.arange(0, 1080, 1)

         naive_pred = [np.mean(y_test) for i in range(len(y_test))]
         naive_pred = pd.DataFrame(naive_pred)

         plt.plot(interval, y_test, 'red', interval, y_pred, 'blue', interval,
         naive_pred, 'yellow')
         plt.title('Time series plot with measurements and model estimations')
         plt.ylabel('Frames/seg')
         plt.xlabel('Second')
         plt.show()
```

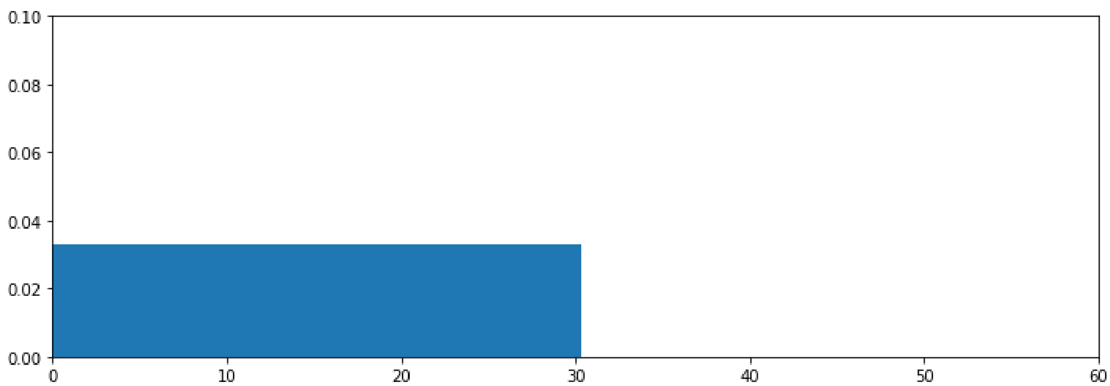


In [18]:
```
# (d) Produce a density plot and a histogram for the Video Frame Rate values
# in the test set. Set the bin size of the histogram to 1 frame.
kde = y_test.plot.kde(title = 'Density plot for the Video Frame Rate values')
kde.set_xlabel("Frame Rate")
fig = kde.get_figure()
plt.show()
```



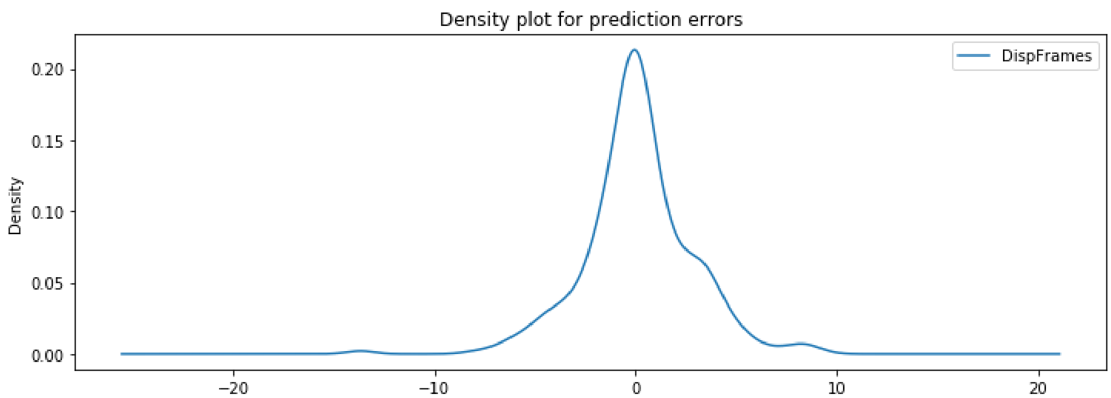
In [19]:
```
plt.close(fig)
```

In [20]:
```
plt.hist(y_test.DispFrames, bins=1, normed=1)
plt.axis([0, 60, 0, 0.1])
fig = hist.get_figure()
plt.show()
```



In [21]:
```
plt.close(fig)
```

In [22]:
```
# (e) Produce a density plot for the prediction errors in the test set.
dy = pd.DataFrame(y_test)

residuals = [dy.iloc[i] - y_pred[i] for i in range(len(y_pred))]
residuals = pd.DataFrame(residuals)

kde = residuals.plot.kde(title = 'Density plot for prediction errors')
fig = kde.get_figure()
plt.show()
```



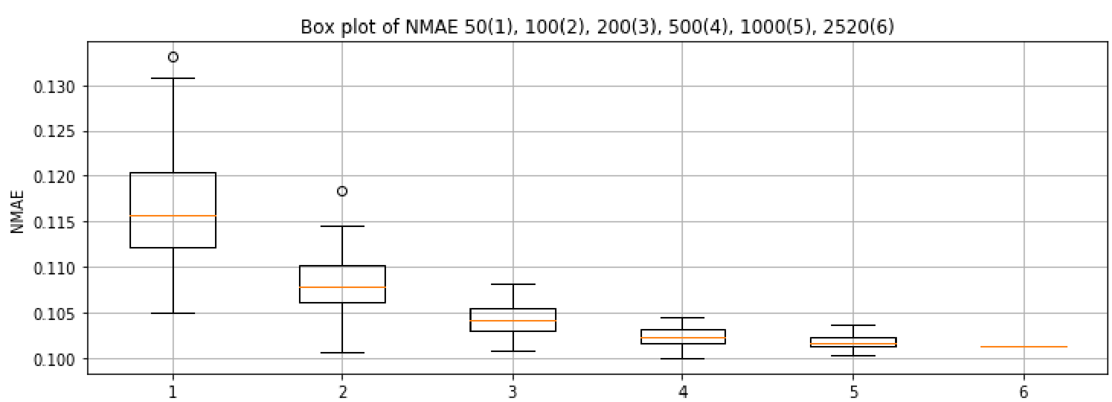
In [23]:
```
# (f) Based on the above figures and graphs, discuss the accuracy of
# estimating the Video Frame Rate.

# Considering the figures and graphs above, especially the time series plot,
# it's noticeable that estimates are not so accurate but generally close to
# the real frame rate. On the other hand, the deviation is usually high when
# a frame rate drop happens.
```

In [24]:
```
plt.close(fig)
plt.clf()
```

In [25]:
```
# 2. Study the Relationship between Estimation Accuracy and the Size of
# the Training Set (a) From the above training set with 2520 observations,
# create six training sets by selecting uniformly at random 50, 100, 200,
# 500, 1000, and 2520 observations (which is the original set).
# (b) Train a linear model and compute the NMAE for each model for the
# original test set with 1080 observations. (c) Perform the above 50 times,
# so you train models for 50 different subsets of a given size.

NMAE = {}
group_sizes = [2520, 1000, 500, 200, 100, 50]
rounds = 50
```

```
for size in group_sizes:
    group_results = []

    for i in range(rounds):
        if(size == 2520):
            gX_train = X_train
            gy_train = y_train
        else:
            gX_train, gX_test, gy_train, gy_test = train_test_split(X_train,
y_train, train_size=size, test_size=0)

        lm = linear_model.LinearRegression()
        model = lm.fit(gX_train, gy_train)
        y_pred = lm.predict(X_test)

        res = nmae(y_test, y_pred)
        group_results.append([i, res])

    NMAE[size] = np.array(group_results)
```

In [26]:
```
# (d) Produce a plot that shows NMAE for M against the size of
# the training set. Use error bars or box plots to show the
# range of the NMAE values for a given set size.

data = [NMAE[50][:,1], NMAE[100][:,1], NMAE[200][:,1], NMAE[500][:,1],
NMAE[1000][:,1], NMAE[2520][:,1]]

plt.title('Box plot of NMAE 50(1), 100(2), 200(3), 500(4), 1000(5), 2520(6)')
plt.ylabel('NMAE');
plt.grid(True)
plt.boxplot(data)
plt.show()
```



In [27]:
```
# (e) Based on the above, discuss the relationship between the accuracy
# of the model estimations and the training set.

# Estimations are more accurate when the amount of observations in
# a training set is closer to the total amount of observations.
```