

Importing all the modules required for this project

```
In [1]: import keras
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
# Setting seed for reproducibility
np.random.seed(1234)
PYTHONHASHSEED = 0
from sklearn import preprocessing
from sklearn.metrics import confusion_matrix, recall_score, precision_score
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM, Activation
%matplotlib inline
import pandas as pd
```

Using TensorFlow backend.

Reading data

```
In [2]: #Reading train data
train_df = pd.read_csv('C:\\Users\\Ashish2448311\\
\\Anaconda3\\envs\\tensorflow\\lib\\site-packages\\train_FD004.txt', sep=" ", header=0)
train_df.drop(train_df.columns[[26, 27]], axis=1, inplace=True)
train_df.columns = ['id', 'cycle', 'setting1', 'setting2', 'setting3', 's1', 's2',
                    's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12', 's13',
                    's15', 's16', 's17', 's18', 's19', 's20', 's21']
```

Reading labels

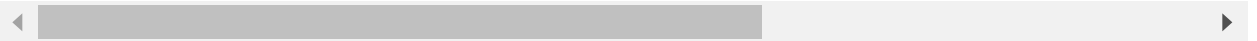
```
In [3]: # reading ground truth data
truth_df = pd.read_csv('C:\\Users\\Ashish2448311\\
\\Anaconda3\\envs\\tensorflow\\lib\\site-packages\\RUL_FD004.txt', sep=" ", header=0)
truth_df.drop(truth_df.columns[[1]], axis=1, inplace=True)
```

```
In [4]: train_df = train_df.sort_values(['id','cycle'])
train_df.head()
```

```
Out[4]:
```

| | id | cycle | setting1 | setting2 | setting3 | s1 | s2 | s3 | s4 | s5 | ... | s12 | s1 |
|---|----|-------|----------|----------|----------|--------|--------|---------|---------|------|-----|--------|--------|
| 0 | 1 | 1 | 42.0049 | 0.8400 | 100.0 | 445.00 | 549.68 | 1343.43 | 1112.93 | 3.91 | ... | 129.78 | 2387.9 |
| 1 | 1 | 2 | 20.0020 | 0.7002 | 100.0 | 491.19 | 606.07 | 1477.61 | 1237.50 | 9.35 | ... | 312.59 | 2387.7 |
| 2 | 1 | 3 | 42.0038 | 0.8409 | 100.0 | 445.00 | 548.95 | 1343.12 | 1117.05 | 3.91 | ... | 129.62 | 2387.9 |
| 3 | 1 | 4 | 42.0000 | 0.8400 | 100.0 | 445.00 | 548.70 | 1341.24 | 1118.03 | 3.91 | ... | 129.80 | 2388.0 |
| 4 | 1 | 5 | 25.0063 | 0.6207 | 60.0 | 462.54 | 536.10 | 1255.23 | 1033.59 | 7.05 | ... | 164.11 | 2028.0 |

5 rows × 26 columns



generation of RUL

```
In [5]: # Data Labeling - generate column RUL
rul = pd.DataFrame(train_df.groupby('id')['cycle'].max()).reset_index()
rul.columns = ['id', 'max']
train_df = train_df.merge(rul, on=['id'], how='left')
train_df['RUL'] = train_df['max'] - train_df['cycle']
train_df.drop('max', axis=1, inplace=True)
train_df.head()
```

```
Out[5]:
```

| | id | cycle | setting1 | setting2 | setting3 | s1 | s2 | s3 | s4 | s5 | ... | s13 | s |
|---|----|-------|----------|----------|----------|--------|--------|---------|---------|------|-----|---------|------|
| 0 | 1 | 1 | 42.0049 | 0.8400 | 100.0 | 445.00 | 549.68 | 1343.43 | 1112.93 | 3.91 | ... | 2387.99 | 8074 |
| 1 | 1 | 2 | 20.0020 | 0.7002 | 100.0 | 491.19 | 606.07 | 1477.61 | 1237.50 | 9.35 | ... | 2387.73 | 8046 |
| 2 | 1 | 3 | 42.0038 | 0.8409 | 100.0 | 445.00 | 548.95 | 1343.12 | 1117.05 | 3.91 | ... | 2387.97 | 8066 |
| 3 | 1 | 4 | 42.0000 | 0.8400 | 100.0 | 445.00 | 548.70 | 1341.24 | 1118.03 | 3.91 | ... | 2388.02 | 8076 |
| 4 | 1 | 5 | 25.0063 | 0.6207 | 60.0 | 462.54 | 536.10 | 1255.23 | 1033.59 | 7.05 | ... | 2028.08 | 7865 |

5 rows × 27 columns



Adding label in data

```
In [6]: # generate label columns for training data
w1 = 30

train_df['label1'] = np.where(train_df['RUL'] <= w1, 1, 0 )

train_df.head()
```

```
Out[6]:
```

| | id | cycle | setting1 | setting2 | setting3 | s1 | s2 | s3 | s4 | s5 | ... | s14 | s |
|---|----|-------|----------|----------|----------|--------|--------|---------|---------|------|-----|---------|-------|
| 0 | 1 | 1 | 42.0049 | 0.8400 | 100.0 | 445.00 | 549.68 | 1343.43 | 1112.93 | 3.91 | ... | 8074.83 | 9.33 |
| 1 | 1 | 2 | 20.0020 | 0.7002 | 100.0 | 491.19 | 606.07 | 1477.61 | 1237.50 | 9.35 | ... | 8046.13 | 9.19 |
| 2 | 1 | 3 | 42.0038 | 0.8409 | 100.0 | 445.00 | 548.95 | 1343.12 | 1117.05 | 3.91 | ... | 8066.62 | 9.40 |
| 3 | 1 | 4 | 42.0000 | 0.8400 | 100.0 | 445.00 | 548.70 | 1341.24 | 1118.03 | 3.91 | ... | 8076.05 | 9.33 |
| 4 | 1 | 5 | 25.0063 | 0.6207 | 60.0 | 462.54 | 536.10 | 1255.23 | 1033.59 | 7.05 | ... | 7865.80 | 10.83 |

5 rows × 28 columns

MinMax normalization

```
In [7]: # MinMax normalization
train_df['cycle_norm'] = train_df['cycle']
cols_normalize = train_df.columns.difference(['id','cycle','RUL','label1','label2'])
min_max_scaler = preprocessing.MinMaxScaler()
norm_train_df = pd.DataFrame(min_max_scaler.fit_transform(train_df[cols_normalize]),
                             columns=cols_normalize,
                             index=train_df.index)
join_df = train_df[train_df.columns.difference(cols_normalize)].join(norm_train_df)
train_df = join_df.reindex(columns = train_df.columns)
train_df.head()
```

```
Out[7]:
```

| | id | cycle | setting1 | setting2 | setting3 | s1 | s2 | s3 | s4 | s5 | ... | s14 | s |
|---|----|-------|----------|----------|----------|----------|----------|----------|----------|----------|-----|-----|---|
| 0 | 1 | 1 | 0.999926 | 0.997625 | 1.0 | 0.000000 | 0.130347 | 0.272082 | 0.212586 | 0.000000 | ... | 0 | 0 |
| 1 | 1 | 2 | 0.476147 | 0.831591 | 1.0 | 0.626985 | 0.647971 | 0.634407 | 0.511781 | 0.507937 | ... | 0 | 0 |
| 2 | 1 | 3 | 0.999900 | 0.998694 | 1.0 | 0.000000 | 0.123646 | 0.271245 | 0.222481 | 0.000000 | ... | 0 | 0 |
| 3 | 1 | 4 | 0.999810 | 0.997625 | 1.0 | 0.000000 | 0.121351 | 0.266168 | 0.224835 | 0.000000 | ... | 0 | 0 |
| 4 | 1 | 5 | 0.595275 | 0.737173 | 0.0 | 0.238089 | 0.005691 | 0.033916 | 0.022025 | 0.293184 | ... | 0 | 0 |

5 rows × 29 columns

```
In [9]: tr= train_df.drop('label1',axis=1)
y = train_df['label1']
```

```
In [ ]:
```

Over sampling using smote

```
In [10]: from imblearn.over_sampling import SMOTE
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import recall_score
from imblearn.over_sampling import SMOTE
from imblearn import under_sampling, over_sampling

sm = SMOTE(random_state=12, ratio = 1.0)
#X_train_sampled, Y_train_sampled = sm.fit_sample(X_train, Y_train)
X_train_sampled, Y_train_sampled = sm.fit_sample(tr, y)
```

C:\Users\Ashish2448311\Anaconda3\envs\tensorflow\lib\site-packages\sklearn\utils\deprecation.py:77: DeprecationWarning: Function _ratio_float is deprecated; Use a float for 'ratio' is deprecated from version 0.2. The support will be removed in 0.4. Use a dict, str, or a callable instead.
warnings.warn(msg, category=DeprecationWarning)

```
In [11]: df=pd.DataFrame(X_train_sampled)
df.columns = ['id', 'cycle', 'setting1', 'setting2', 'setting3', 's1', 's2', 's3',
              's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12', 's13',
              's14', 's15', 's16', 's17', 's18', 's19', 's20', 's21', 'RUL', 'cycle']
```

```
In [12]: unique, counts = np.unique(Y_train_sampled, return_counts=True)
dict(zip(unique, counts))
```

```
Out[12]: {0: 53530, 1: 53530}
```

```
In [13]: label=pd.DataFrame(Y_train_sampled)
label.columns=['label1']
df['label1']=label
```

```
In [ ]:
```

window size of 30

```
In [14]: # pick a window size of 30 cycles
sequence_length = 30
```

function to reshape features into (samples, time steps, features)

```

In [15]: # function to reshape features into (samples, time steps, features)
def gen_sequence(id_df, seq_length, seq_cols):
    """ Only sequences that meet the window-length are considered, no padding is
    we need to drop those which are below the window-length. An alternative would
    we can use shorter ones """
    data_array = id_df[seq_cols].values
    num_elements = data_array.shape[0]
    for start, stop in zip(range(0, num_elements-seq_length), range(seq_length, num_elements)):
        yield data_array[start:stop, :]

# pick the feature columns
sensor_cols = ['s' + str(i) for i in range(1,22)]
sequence_cols = ['setting1', 'setting2', 'setting3', 'cycle_norm']
sequence_cols.extend(sensor_cols)

# generator for the sequences
seq_gen = (list(gen_sequence(df[df['id']==id], sequence_length, sequence_cols))
            for id in train_df['id'].unique())

seq_array = np.concatenate(list(seq_gen)).astype(np.float32)
seq_array.shape

# function to generate labels
def gen_labels(id_df, seq_length, label):
    data_array = id_df[label].values
    num_elements = data_array.shape[0]
    return data_array[seq_length:num_elements, :]

# generate labels
label_gen = [gen_labels(df[df['id']==id], sequence_length, ['label1'])
              for id in df['id'].unique()]
label_array = np.concatenate(label_gen).astype(np.float32)
label_array.shape

```

Out[15]: (90075, 1)

Splitting of data into 20% validation set and 80%training set

```

In [16]: RANDOM_SEED=40
X_train, X_test, y_train, y_test = train_test_split(
    seq_array, label_array, test_size=0.2, random_state=RANDOM_SEED)#split the

```

building the network

```

In [17]: # build the network
nb_features = seq_array.shape[2]
nb_out = label_array.shape[1]

model = Sequential()

model.add(LSTM(
    input_shape=(sequence_length, nb_features),
    units=100,
    return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(
    units=50,
    return_sequences=False))
model.add(Dropout(0.2))

model.add(Dense(units=nb_out, activation='sigmoid'))
epochs = 10
learning_rate = 0.1
decay_rate = learning_rate / epochs
momentum = 0.8
sgd = SGD(lr=learning_rate, momentum=momentum, decay=decay_rate, nesterov=True)
model.compile(loss='binary_crossentropy', optimizer=sgd, metrics=['accuracy'])

```

```

In [18]: print(model.summary())

```

| Layer (type) | Output Shape | Param # |
|--------------------------|-----------------|---------|
| lstm_1 (LSTM) | (None, 50, 100) | 50400 |
| dropout_1 (Dropout) | (None, 50, 100) | 0 |
| lstm_2 (LSTM) | (None, 50) | 30200 |
| dropout_2 (Dropout) | (None, 50) | 0 |
| dense_1 (Dense) | (None, 1) | 51 |
| Total params: 80,651 | | |
| Trainable params: 80,651 | | |
| Non-trainable params: 0 | | |
| None | | |

Fitting the network

```
In [22]: %%time
# fit the network

model.fit(X_train,y_train, epochs=10, batch_size=50,validation_data=(X_test,y_test))
```

Train on 72060 samples, validate on 18015 samples

Epoch 1/10

72060/72060 [=====] - 179s - loss: 0.1627 - acc: 0.937

8 - val_loss: 0.1280 - val_acc: 0.9503

Epoch 2/10

72060/72060 [=====] - 179s - loss: 0.1295 - acc: 0.949

2 - val_loss: 0.1219 - val_acc: 0.9568

Epoch 3/10

72060/72060 [=====] - 179s - loss: 0.1087 - acc: 0.957

3 - val_loss: 0.0889 - val_acc: 0.9636

Epoch 4/10

72060/72060 [=====] - 176s - loss: 0.0933 - acc: 0.963

5 - val_loss: 0.1286 - val_acc: 0.9455

Epoch 5/10

72060/72060 [=====] - 173s - loss: 0.0850 - acc: 0.966

4 - val_loss: 0.1125 - val_acc: 0.9551

Epoch 6/10

72060/72060 [=====] - 175s - loss: 0.0769 - acc: 0.970

3 - val_loss: 0.0681 - val_acc: 0.9742

Epoch 7/10

72060/72060 [=====] - 172s - loss: 0.0727 - acc: 0.971

8 - val_loss: 0.0795 - val_acc: 0.9728

Epoch 8/10

72060/72060 [=====] - 173s - loss: 0.0631 - acc: 0.975

1 - val_loss: 0.0557 - val_acc: 0.9793

Epoch 9/10

72060/72060 [=====] - 173s - loss: 0.0632 - acc: 0.975

5 - val_loss: 0.0464 - val_acc: 0.9830

Epoch 10/10

72060/72060 [=====] - 169s - loss: 0.0653 - acc: 0.974

7 - val_loss: 0.0524 - val_acc: 0.9799

Wall time: 29min 13s

```
Out[22]: <keras.callbacks.History at 0x1afd394fa20>
```

Function for confusion matrix

```

In [98]: import itertools
def plot_confusion_matrix(cm, classes,
                           normalize=False,
                           title='Confusion matrix',
                           cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

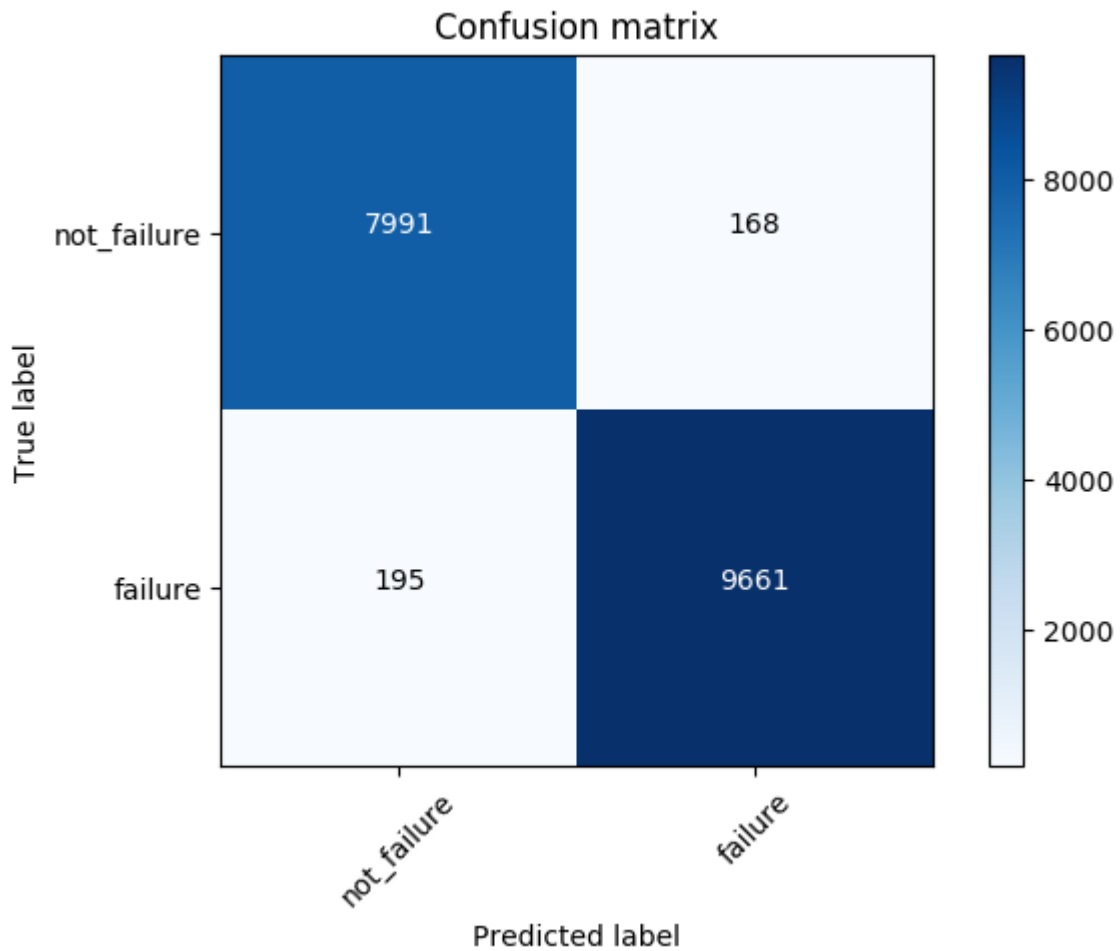
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

class_names = ['not_failure', 'failure']
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cm, classes=class_names,
                      title='Confusion matrix')

plt.show()
# compute precision and recall
precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)
print( 'precision = ', precision, '\n', 'recall = ', recall)

```

```
precision = 0.982907722047  
recall = 0.980215097403
```

In []:

type of learning rate vs val accuracy

```

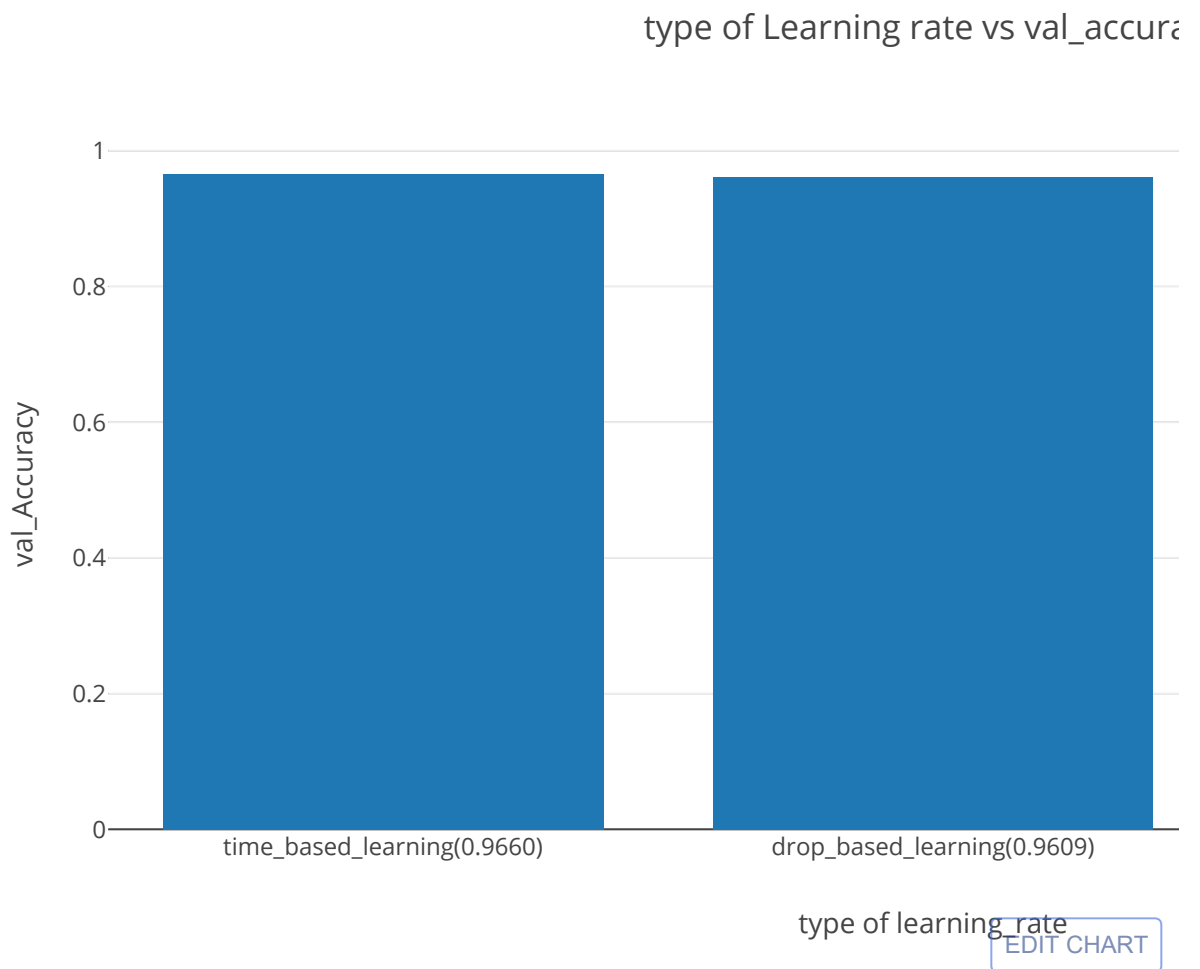
In [86]: import plotly.plotly as py
import plotly.graph_objs as go

data = [go.Bar(
    x=['time_based_learning(0.9660)', 'drop_based_learning(0.9609)', 'con
    y=[0.9660, 0.9609, 0.951]
    )]
layout = dict(title = 'type of Learning rate vs val_accuracy',
    xaxis = dict(title = 'type of learning_rate'),
    yaxis = dict(title = 'val_Accuracy'),
    )

fig = dict(data=data, layout=layout)
py.iplot(fig, filename='basic-bar')

```

Out[86]:



In []:

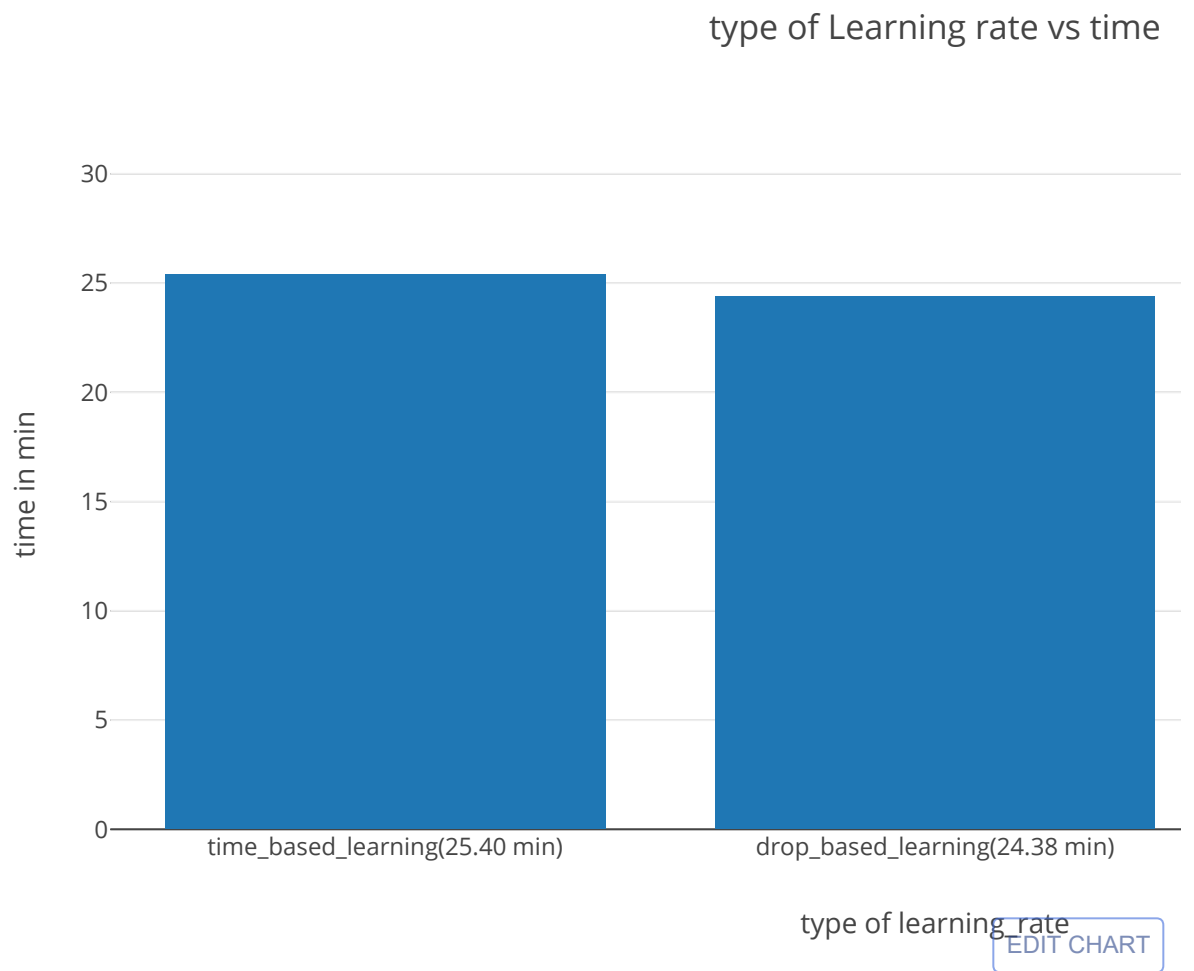
type of learning rate vs time

```
In [89]: import plotly.plotly as py
import plotly.graph_objs as go

data = [go.Bar(
    x=['time_based_learning(25.40 min)', 'drop_based_learning(24.38 min)'],
    y=[25.40, 24.38, 30]
)]
layout = dict(title = 'type of Learning rate vs time',
    xaxis = dict(title = 'type of learning_rate'),
    yaxis = dict(title = 'time in min'),
)

fig = dict(data=data, layout=layout)
py.iplot(fig, filename='basic-bar')
```

Out[89]:



In []:

val accuracy v batch size

In [82]:

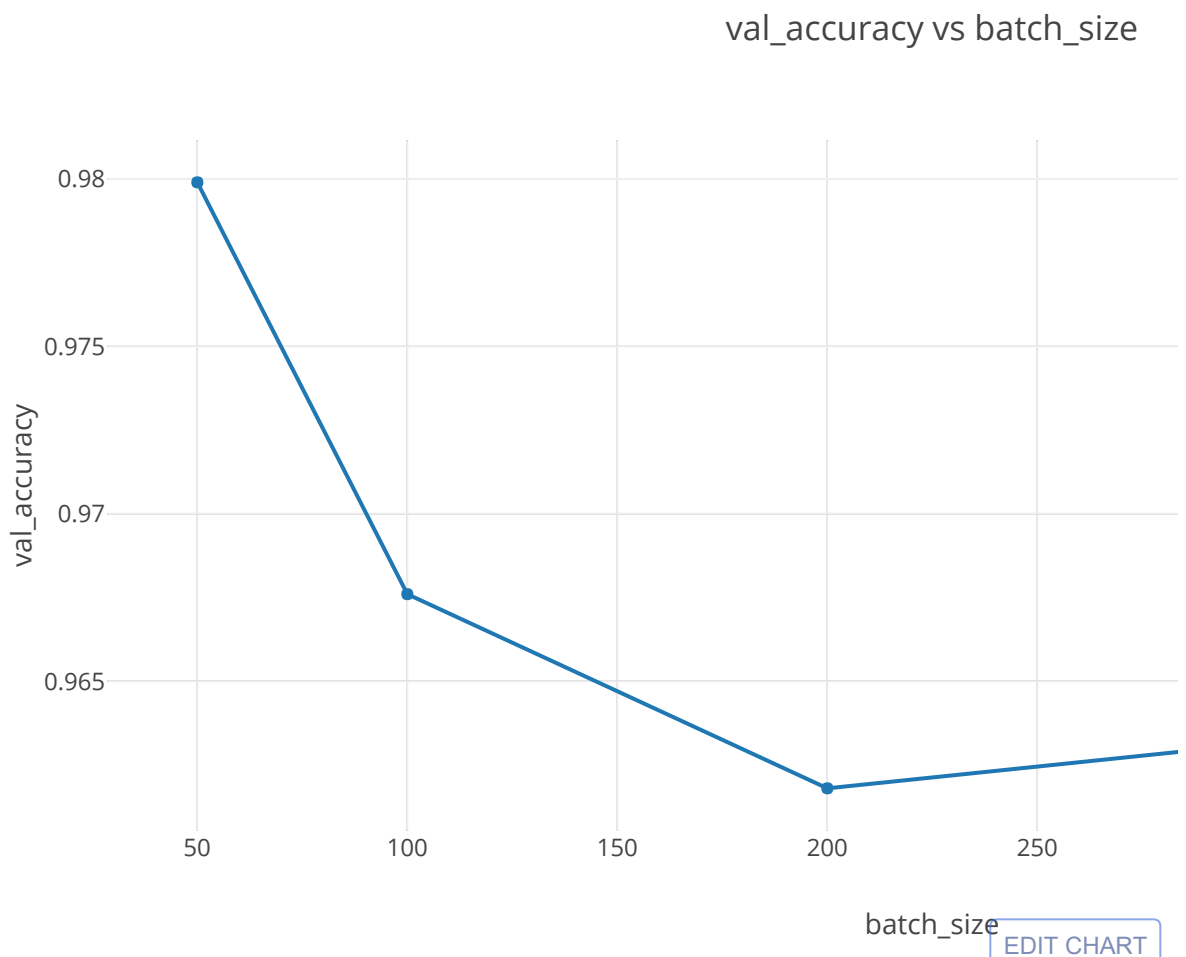
```
import plotly.plotly as py
import plotly.graph_objs as go

trace1 = go.Scatter(
    x=[50,100,200,400],
    y=[0.9799,0.9676,0.9618,0.9644],
    name='accuracy'
)

data = [trace1]
layout = go.Layout(
    title='val_accuracy vs batch_size',
    xaxis = dict(title = 'batch_size'),
    yaxis=dict(
        title='val_accuracy'
    )
)

fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='multiple-axes-double')
```

Out[82]:



In []:

Length sequence vs val accuracy and time

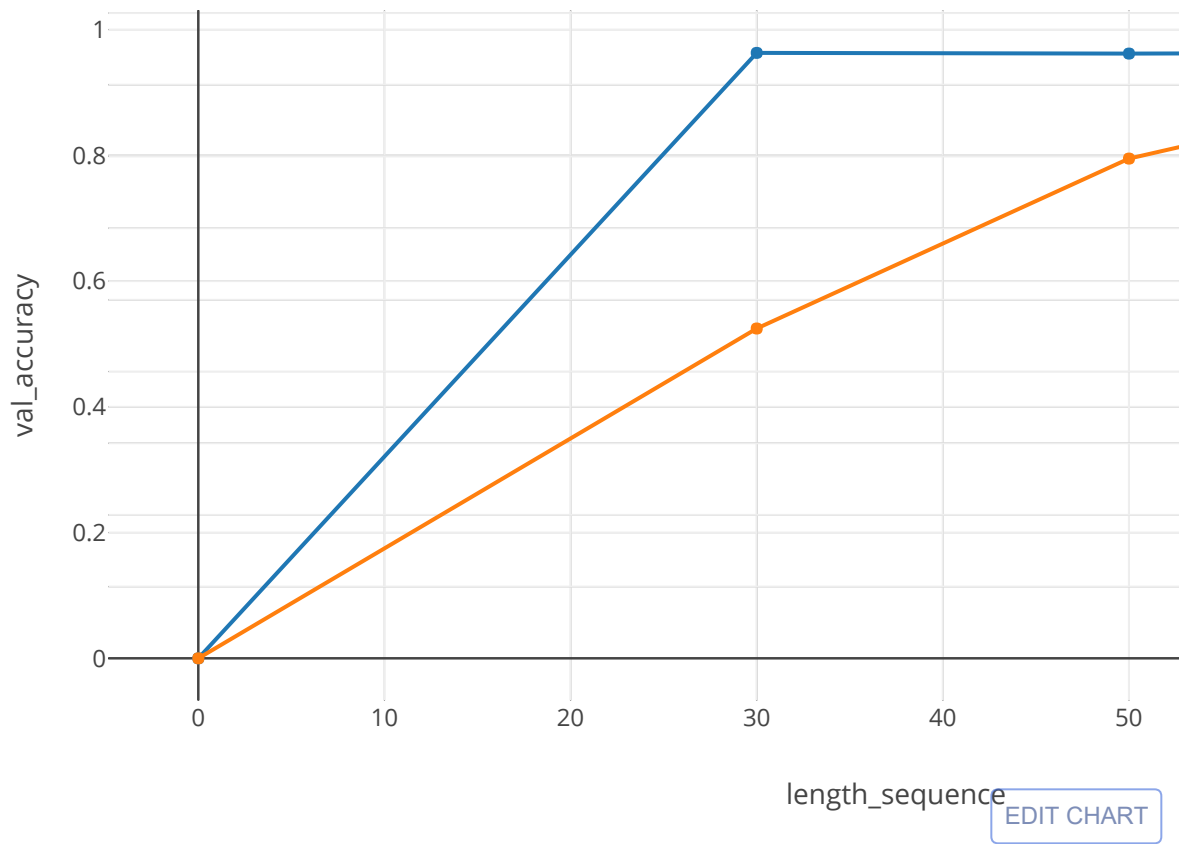
In [90]:

```
import plotly.plotly as py
import plotly.graph_objs as go

trace1 = go.Scatter(
    x=[0,30,50,75],
    y=[0,0.9629,0.9618,0.9638],
    name='accuracy'
)
trace2 = go.Scatter(
    x=[0,30,50,75],
    y=[0,23,34.85,42.26],
    name='time',
    yaxis='y2'
)
data = [trace1, trace2]
layout = go.Layout(
    title='length_sequence vs val_accuracy and time',
    xaxis = dict(title = 'length_sequence'),
    yaxis=dict(
        title='val_accuracy'
    ),
    yaxis2=dict(
        title='time in minutes',
        titlefont=dict(
            color='rgb(148, 103, 189)'
        ),
        tickfont=dict(
            color='rgb(148, 103, 189)'
        ),
        overlaying='y',
        side='right'
    )
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='multiple-axes-double')
```

Out[90]:

length_sequence vs val_accuracy and



In []:

SVM Results

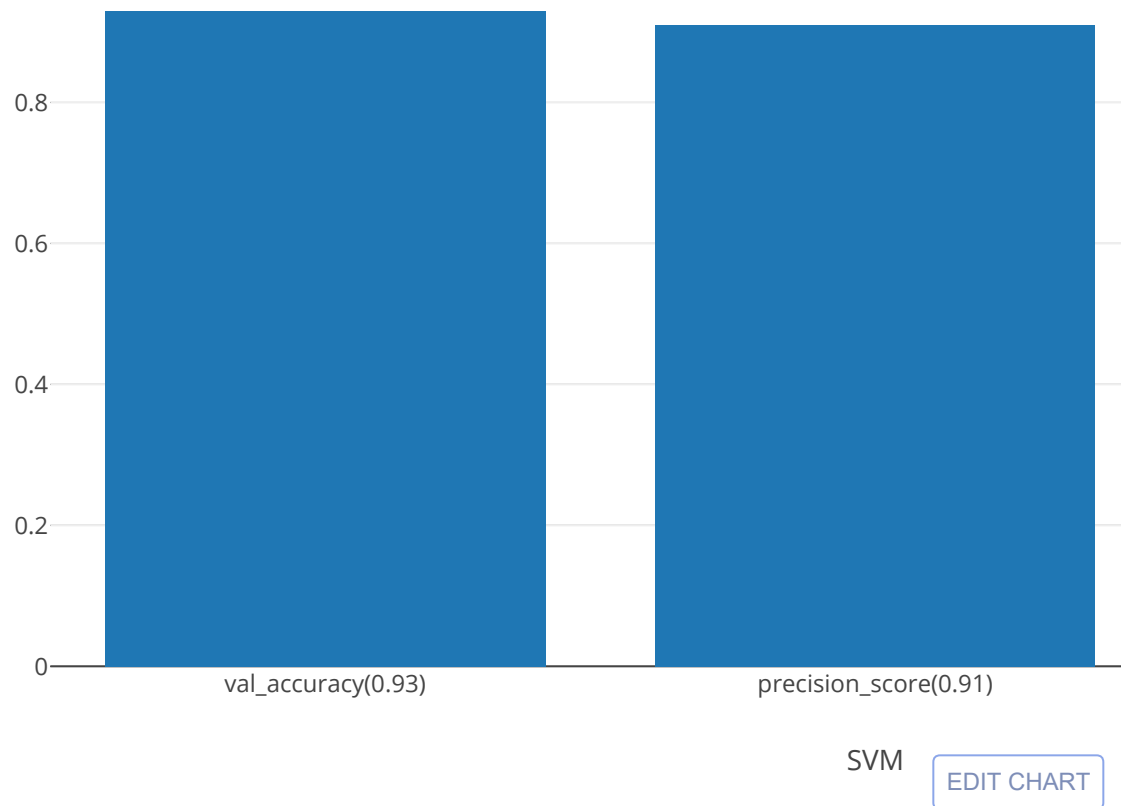
```
In [99]: import plotly.plotly as py
import plotly.graph_objs as go

data = [go.Bar(
    x=['val_accuracy(0.93)', 'precision_score(0.91)', 'recall(0.52)'],
    y=[0.93, 0.91, 0.52]
)]
layout = dict(title = 'SVM results with 90% variance(2 components)',
    xaxis = dict(title = 'SVM')
)

fig = dict(data=data, layout=layout)
py.iplot(fig, filename='basic-bar')
```

Out[99]:

SVM results with 90% variance(2 comp



In []:

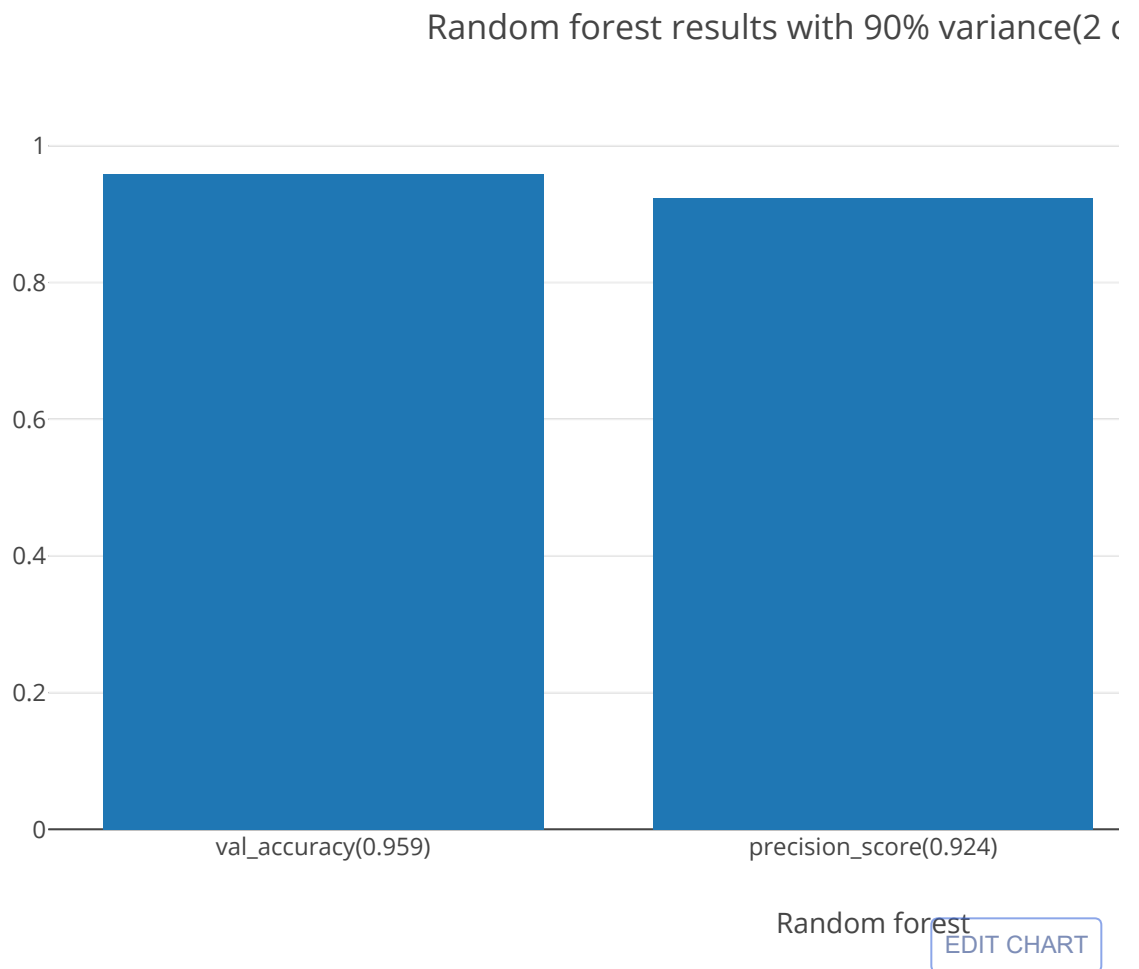
Random forest


```
In [101]: import plotly.plotly as py
import plotly.graph_objs as go

data = [go.Bar(
    x=['val_accuracy(0.959)', 'precision_score(0.924)', 'recall(0.748)'],
    y=[0.959, 0.924, 0.748]
)]
layout = dict(title = 'Random forest results with 90% variance(2 components)',
    xaxis = dict(title = 'Random forest')
)

fig = dict(data=data, layout=layout)
py.iplot(fig, filename='basic-bar')
```

Out[101]:



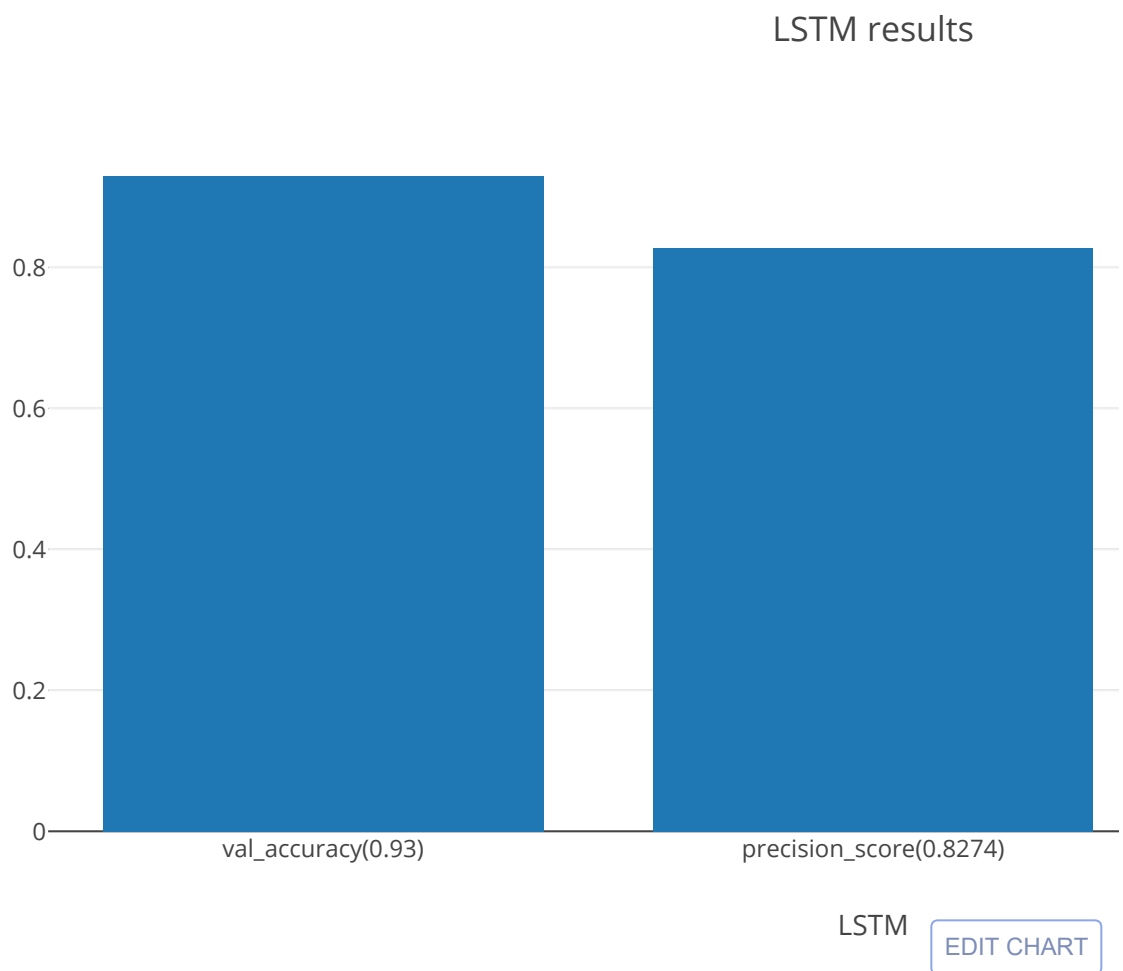
LSTM results

```
In [105]: import plotly.plotly as py
import plotly.graph_objs as go

data = [go.Bar(
    x=['val_accuracy(0.93)', 'precision_score(0.8274)', 'recall( 0.825)']
    y=[0.93, 0.8274, 0.825]
)]
layout = dict(title = 'LSTM results ',
    xaxis = dict(title = 'LSTM')
)

fig = dict(data=data, layout=layout)
py.iplot(fig, filename='basic-bar')
```

Out[105]:



In []:

In []:

In []:

results of all the algorithm

```
In [65]: import plotly.plotly as py
import plotly.graph_objs as go

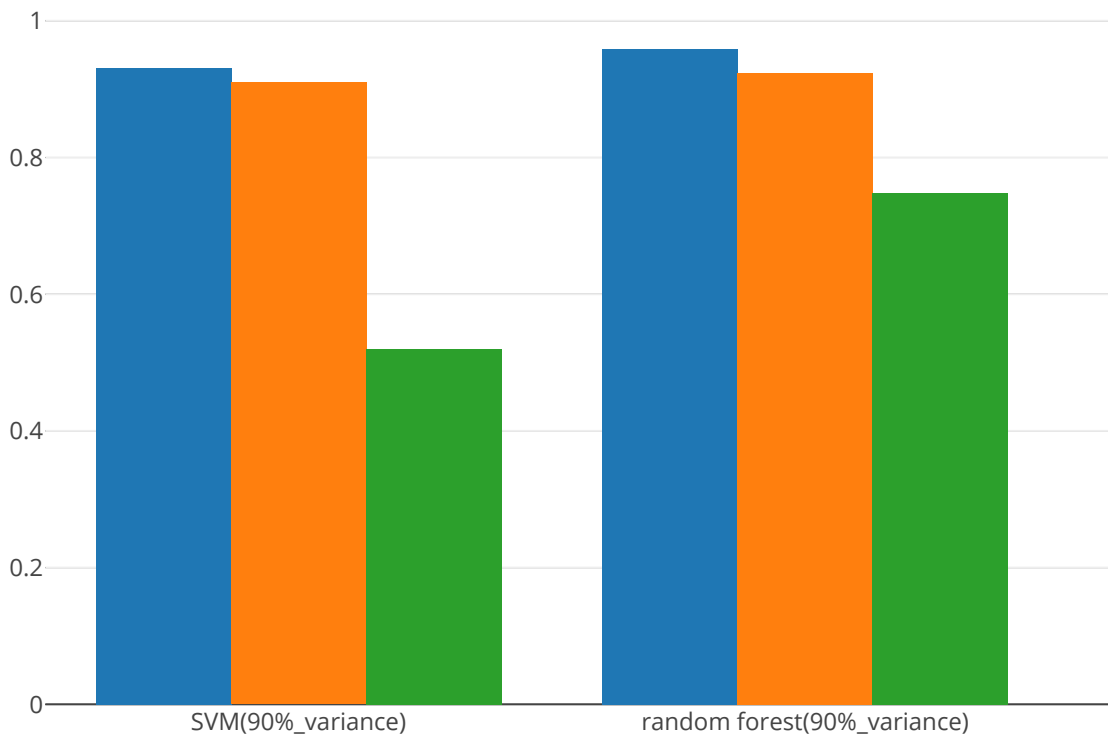
trace1 = go.Bar(
    x=['SVM(90%_variance)', 'random forest(90%_variance)', 'LSTM'],
    y=[0.931, 0.959, 0.9799],
    name='val_accuracy'
)
trace2 = go.Bar(
    x=['SVM(90%_variance)', 'random forest(90%_variance)', 'LSTM'],
    y=[0.91,0.924,0.82],
    name='precision'
)
trace3 = go.Bar(
    x=['SVM(90%_variance)', 'random forest(90%_variance)', 'LSTM'],
    y=[0.52, 0.748,0.825 ],
    name='recall'
)

data = [trace1, trace2,trace3 ]

layout = go.Layout(
    barmode='group',
    title='Results of all the algorithms',
    xaxis = dict(title = 'Algorithms')
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='multiple-axes-double')
```

Out[65]:

Results of all the algorithms



Algorithms

[EDIT CHART](#)

In []:

In []:

Results of all algorithm after sampling

```
In [102]: import plotly.plotly as py
import plotly.graph_objs as go

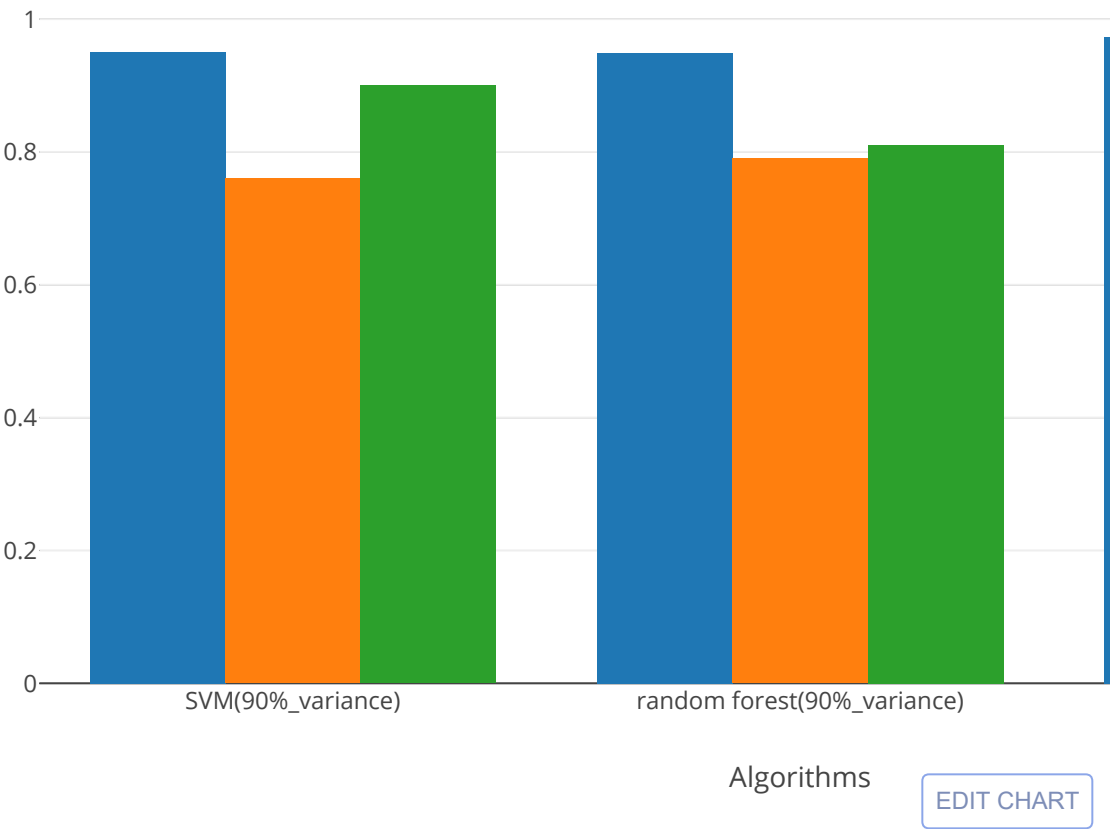
trace1 = go.Bar(
    x=['SVM(90%_variance)', 'random forest(90%_variance)', 'LSTM'],
    y=[0.95, 0.949, 0.9732],
    name='val_accuracy'
)
trace2 = go.Bar(
    x=['SVM(90%_variance)', 'random forest(90%_variance)', 'LSTM'],
    y=[0.76,0.79,0.984],
    name='precision'
)
trace3 = go.Bar(
    x=['SVM(90%_variance)', 'random forest(90%_variance)', 'LSTM'],
    y=[0.90, 0.81,0.974 ],
    name='recall'
)

data = [trace1, trace2,trace3 ]

layout = go.Layout(
    barmode='group',
    title='Results of all the algorithms after oversampling',
    xaxis = dict(title = 'Algorithms')
)
fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='multiple-axes-double')
```

Out[102]:

Results of all the algorithms after overs



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