

## Time series forecasting of positions of basket ball players

I have interpreted this as a state space problem hence not tried out Vector Autoregression (VAR) method (although, it would be among my next steps to try out.) Hence, the options I had were Kalman filter, RNN, particle filter, extended Kalman filter, generative RNNs or Variational Autoencoder. Since, this is a complex system, the underlying dynamical process can't be linear (and known before hand say for example Newtonian mechanics), hence there is no point trying out Kalman filter. Witnessing the tremendous success of RNN in object tracking and time series, I decided to implement a simple architecture of RNN to predict the next time step given past (25 and 100) time steps. Future time steps can be further computed by applying the learnt model from past known steps along with predicted previous step(s). Following is my implementation:

### single time series

I have experimented with only one time series '2019040102\_nba-bos\_TRACKING.csv' in a way that player ID or jersey number and team ID are not a part of the training set and the information is implicit from the data structure used as training and test data. This gives rise to 3 features (x, y, z) and hence  $11 \times 3$  states at each time step of the time series.

### Understanding dataset

In [1]:

```
import pandas as pd
from pandas.plotting import autocorrelation_plot
import matplotlib.pyplot as plt
import os
import keras
```

```
C:\Users\verma_k\anaconda3\lib\site-packages\numpy\_distributor_init.py:30: UserWarning: loaded more than 1 DLL from .libs:
C:\Users\verma_k\anaconda3\lib\site-packages\numpy\.libs\libopenblas.GK7GX5KEQ4F6UYO3P26ULGBQYHGQ07J4.gfortran-win_amd64.dll
C:\Users\verma_k\anaconda3\lib\site-packages\numpy\.libs\libopenblas.wcdjnk7yvmpzq2me2zzhjrrj3jikndb7.gfortran-win_amd64.dll
  warnings.warn("loaded more than 1 DLL from .libs:")
```

In [2]:

```
os.chdir('C:/kinexon_task')
nba_bos = pd.read_csv('2019040102_nba-bos_TRACKING.csv')
nba_bos.head(11)
```

Out[2]:

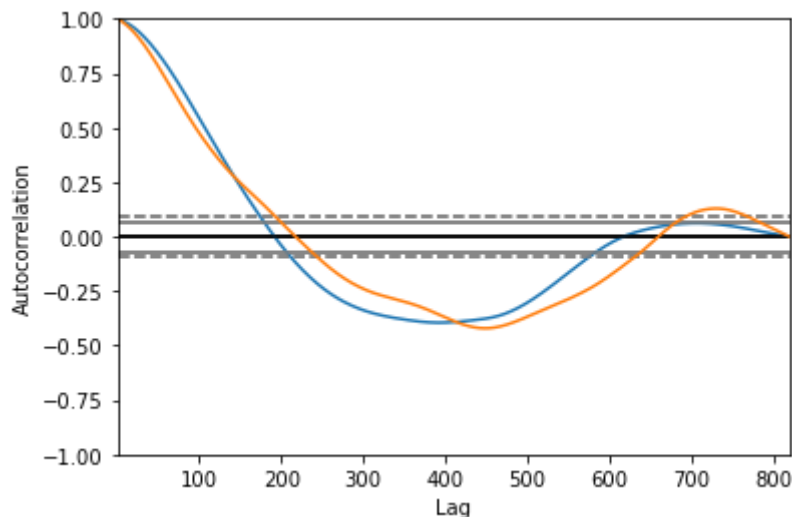
	ts	player_id	jersey_nr	team	x	y	z
0	40:56.2	986b713a-b20b-4eb0-919e-c859d0508af7	0	team_0	0.182882	2.953548	0.000000
1	40:56.2	ff4221b5-89ef-11e6-b799-a45e60e298d3	11	team_0	6.647769	-0.234699	0.000000
2	40:56.2	ff411907-89ef-11e6-9c68-a45e60e298d3	36	team_0	0.438917	-2.990124	0.000000
3	40:56.2	ff427c2e-89ef-11e6-8d2a-a45e60e298d3	42	team_0	3.313216	-0.268227	0.000000
4	40:56.2	ff413e73-89ef-11e6-a5df-a45e60e298d3	46	team_0	0.143258	0.082297	0.000000
5	40:56.2	ff4024b0-89ef-11e6-a1ae-a45e60e298d3	11	team_1	-0.448061	-2.962692	0.000000

	ts	player_id	jersey_nr	team	x	y	z
6	40:56.2	61fc6b15-5ce2-4613-a67b-f15bada3aa57	13	team_1	-0.579127	-0.271275	0.000000
7	40:56.2	0511e7cf-e543-4547-aa9d-1c80e0ec3ad8	5	team_1	-0.871739	2.950500	0.000000
8	40:56.2	ff41920c-89ef-11e6-b546-a45e60e298d3	7	team_1	-7.135455	-0.091441	0.000000
9	40:56.2	ff426326-89ef-11e6-a607-a45e60e298d3	9	team_1	-4.572056	1.874543	0.000000
10	40:56.2	ball	ball	team_ball	-0.012192	-0.368812	1.868447

```
In [3]: time_steps = nba_bos['ts']
player_id = nba_bos['player_id']
jersey_nr = nba_bos['jersey_nr']
team = nba_bos['team']
x = nba_bos['x']
y = nba_bos['y']
z = nba_bos['z']
```

From the following autocorrelation graph, one can interpret that the number of past time steps to forecast next time steps should be less than around 200. Hence, I started with 100.

```
In [6]: autocorrelation_plot(x[0:9001:11])
autocorrelation_plot(x[1:9001:11])
plt.show()
```

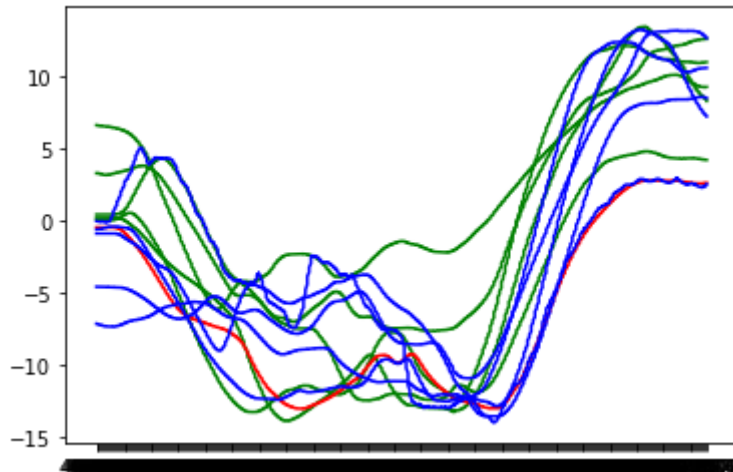


From the following plots, I can assume that the time series I am dealing with is stationary ie., shows no significant trends or seasonality. Hence, I proceed with the data as it is without any preprocessing steps like detrending or deseasonalising.

```
In [7]: plt.plot(time_steps[0:9000:11], x[0:9001:11], color='green')
plt.plot(time_steps[1:9000:11], x[1:9001:11], color='green')
plt.plot(time_steps[2:9000:11], x[2:9001:11], color='green')
plt.plot(time_steps[3:9000:11], x[3:9001:11], color='green')
plt.plot(time_steps[4:9000:11], x[4:9001:11], color='green')
plt.plot(time_steps[5:9000:11], x[5:9001:11], color='red')
plt.plot(time_steps[6:9000:11], x[6:9001:11], color='blue')
plt.plot(time_steps[7:9000:11], x[7:9001:11], color='blue')
```

```
plt.plot(time_steps[8:9000:11], x[8:9000:11], color='blue')
plt.plot(time_steps[9:9000:11], x[9:9000:11], color='blue')
plt.plot(time_steps[10:9000:11], x[10:9000:11], color='blue')
```

Out[7]: [<matplotlib.lines.Line2D at 0x2acc3c36df0>]



## Implementation

The Jupyter file contains an interactive implementation. If you like, you can run the python script that I have sent, in terminal. Following is a sample command:

```
python3 training_and_evaluation.py -episodes 50 -num_past_steps 25 -batch_size 64 -begin 0 -end 1000 -load_model 1
```

I would recommend to load the pre-trained models, one corresponding to number of past time steps 100 and the other one 25.

```
In [4]: import numpy as np
import os
import pandas as pd
from pandas.plotting import autocorrelation_plot
import matplotlib.pyplot as plt

from keras.utils import np_utils
from keras.models import Model
from keras.layers import LSTM, Activation, Dense, Dropout, Input, Embedding, BatchNormalisation
from tensorflow.python.keras.callbacks import History
```

```
In [7]: #Normalization
#x = (x-np.mean(x))/np.std(x)
#y = (y-np.mean(y))/np.std(y)
#z = (z-np.mean(z))/np.std(z)
```

```
In [9]: num_time_steps = time_steps.shape[0]
data = np.concatenate((x,y,z))
data = data.reshape(3, num_time_steps)
player=[]
for i in range (11):
    player1 = data[:, i:num_time_steps:11]
    player.append(player1)
```

```
In [10]: data = np.array(player)
```

```
In [11]: data.shape
```

```
Out[11]: (11, 3, 95325)
```

```
In [12]: data=data.reshape(33, 95325)
```

```
In [12]: #in my previous implementation I used reshape instead of transpose and that created
def create_dataset(num_past_steps, data):
    x = []
    y = []
    for i in range(95224): #num_time_steps/11 = 95325
        #print(i)
        p = np.matrix.transpose(data[:,i:i+num_past_steps]) #training data
        x.append(p)
        q = np.matrix.transpose(data[:,i+num_past_steps]) #test data
        y.append(q)

    return np.array(x), np.array(y)
```

```
In [51]: data_X, label = create_dataset(25, data)
```

```
In [52]: train_x, train_label = data_X[0:95000][:][:], label[0:95000][:][:]
```

```
In [53]: test_x, test_label = data_X[95000:][:][:], label[95000:][:][:]
```

```
In [56]: test_label.shape
```

```
Out[56]: (224, 33)
```

```
In [60]: train_label=train_label.reshape(95000,1,33)
test_label=test_label.reshape(224,1,33)
```

## Training

```
In [44]: def RNN(past_time_steps):
    inputs = Input(name='inputs',shape=(past_time_steps, 33))
    #Layer = BatchNormalization()(inputs)
    layer = LSTM(64, return_sequences=True)(inputs)
    layer = Activation('relu')(layer)
    layer = Dropout(0.2)(layer)
    #Layer = LSTM(32, return_sequences=False)(layer)
    layer = Dense(128,name='FC2')(layer)
    layer = Activation('relu')(layer)

    layer = Dense(33,name='out_layer')(layer)
    model = Model(inputs=inputs,outputs=layer)
    return model

#Compile the model
model_25_ = RNN(25) #or 100
model_25_.summary(25) #or 100
```

```
model_25_.compile(loss='mse',optimizer='adam',metrics=['accuracy']) #or 100

#Fit on training data
#model1.fit(trainx_array_new,label_array_new,batch_size=64,epochs=10, validation_spl
```

Model: "model\_5"

Layer (typ Output Sh Para

inputs (In [(None, 2 0

lstm\_5 (LS (None, 25 2508

activation (None, 25 0

dropout\_1 (None, 25 0

FC2 (Dense (None, 25 8320

activation (None, 25 0

out\_layer (None, 25 4257

Total params: 37,665

Trainable params: 37,665

Non-trainable params: 0

In [45]: `model_25_.fit(train_x, train_label,batch_size=64,epochs=100, validation_split=0.2, s`

Epoch 1/100

1188/1188 [=====] - 36s 24ms/step - loss: 9.4564 - accurac  
y: 0.2410 - val\_loss: 3.0982 - val\_accuracy: 0.5603

Epoch 2/100

1188/1188 [=====] - 33s 28ms/step - loss: 3.0189 - accurac  
y: 0.4494 - val\_loss: 2.9364 - val\_accuracy: 0.5545

Epoch 3/100

1188/1188 [=====] - 30s 26ms/step - loss: 2.6847 - accurac  
y: 0.4675 - val\_loss: 2.9820 - val\_accuracy: 0.5587

Epoch 4/100

1188/1188 [=====] - 32s 27ms/step - loss: 2.4826 - accurac  
y: 0.4777 - val\_loss: 2.8698 - val\_accuracy: 0.5666

Epoch 5/100

1188/1188 [=====] - 32s 27ms/step - loss: 2.3076 - accurac  
y: 0.4877 - val\_loss: 2.9338 - val\_accuracy: 0.5507

Epoch 6/100

1188/1188 [=====] - 36s 30ms/step - loss: 2.2094 - accurac  
y: 0.4958 - val\_loss: 2.9588 - val\_accuracy: 0.5322

Epoch 7/100

1188/1188 [=====] - 33s 28ms/step - loss: 2.1440 - accurac  
y: 0.5002 - val\_loss: 3.0362 - val\_accuracy: 0.5451

Epoch 8/100

1188/1188 [=====] - 33s 28ms/step - loss: 2.0792 - accurac  
y: 0.5052 - val\_loss: 3.0341 - val\_accuracy: 0.5330

Epoch 9/100

1188/1188 [=====] - 33s 28ms/step - loss: 2.0157 - accurac  
y: 0.5081 - val\_loss: 3.1002 - val\_accuracy: 0.5184

Epoch 10/100

1188/1188 [=====] - 36s 30ms/step - loss: 1.9770 - accurac  
y: 0.5130 - val\_loss: 3.0878 - val\_accuracy: 0.5247

Epoch 11/100

1188/1188 [=====] - 33s 28ms/step - loss: 1.9191 - accurac  
y: 0.5169 - val\_loss: 3.1539 - val\_accuracy: 0.5019

Epoch 12/100

1188/1188 [=====] - 33s 28ms/step - loss: 1.9176 - accurac  
y: 0.5171 - val\_loss: 3.1709 - val\_accuracy: 0.5261

Epoch 13/100

1188/1188 [=====] - 36s 30ms/step - loss: 1.8744 - accurac

y: 0.5201 - val\_loss: 3.2502 - val\_accuracy: 0.5224  
Epoch 14/100  
1188/1188 [=====] - 34s 28ms/step - loss: 1.8488 - accurac  
y: 0.5233 - val\_loss: 3.3340 - val\_accuracy: 0.5071  
Epoch 15/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.8272 - accurac  
y: 0.5252 - val\_loss: 3.3380 - val\_accuracy: 0.5085  
Epoch 16/100  
1188/1188 [=====] - 34s 29ms/step - loss: 1.8045 - accurac  
y: 0.5266 - val\_loss: 3.3752 - val\_accuracy: 0.5066  
Epoch 17/100  
1188/1188 [=====] - 35s 30ms/step - loss: 1.7906 - accurac  
y: 0.5289 - val\_loss: 3.4727 - val\_accuracy: 0.5040  
Epoch 18/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.7653 - accurac  
y: 0.5298 - val\_loss: 3.3544 - val\_accuracy: 0.4875  
Epoch 19/100  
1188/1188 [=====] - 35s 29ms/step - loss: 1.7487 - accurac  
y: 0.5316 - val\_loss: 3.4259 - val\_accuracy: 0.4955  
Epoch 20/100  
1188/1188 [=====] - 36s 30ms/step - loss: 1.7221 - accurac  
y: 0.5319 - val\_loss: 3.4890 - val\_accuracy: 0.4855  
Epoch 21/100  
1188/1188 [=====] - 34s 29ms/step - loss: 1.7212 - accurac  
y: 0.5353 - val\_loss: 3.6947 - val\_accuracy: 0.5017  
Epoch 22/100  
1188/1188 [=====] - 34s 28ms/step - loss: 1.7063 - accurac  
y: 0.5351 - val\_loss: 3.5286 - val\_accuracy: 0.4794  
Epoch 23/100  
1188/1188 [=====] - 34s 28ms/step - loss: 1.6982 - accurac  
y: 0.5354 - val\_loss: 3.6237 - val\_accuracy: 0.4884  
Epoch 24/100  
1188/1188 [=====] - 39s 33ms/step - loss: 1.6777 - accurac  
y: 0.5371 - val\_loss: 3.7282 - val\_accuracy: 0.4895  
Epoch 25/100  
1188/1188 [=====] - 38s 32ms/step - loss: 1.6597 - accurac  
y: 0.5391 - val\_loss: 3.6482 - val\_accuracy: 0.4832  
Epoch 26/100  
1188/1188 [=====] - 35s 30ms/step - loss: 1.6600 - accurac  
y: 0.5372 - val\_loss: 3.5184 - val\_accuracy: 0.4991  
Epoch 27/100  
1188/1188 [=====] - 58s 49ms/step - loss: 1.6488 - accurac  
y: 0.5401 - val\_loss: 3.4778 - val\_accuracy: 0.4811  
Epoch 28/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.6387 - accurac  
y: 0.5395 - val\_loss: 3.6605 - val\_accuracy: 0.4891  
Epoch 29/100  
1188/1188 [=====] - 30s 25ms/step - loss: 1.6401 - accurac  
y: 0.5415 - val\_loss: 3.6223 - val\_accuracy: 0.4953  
Epoch 30/100  
1188/1188 [=====] - 31s 26ms/step - loss: 1.6100 - accurac  
y: 0.5437 - val\_loss: 3.5956 - val\_accuracy: 0.4848  
Epoch 31/100  
1188/1188 [=====] - 30s 25ms/step - loss: 1.6038 - accurac  
y: 0.5437 - val\_loss: 3.6245 - val\_accuracy: 0.4885  
Epoch 32/100  
1188/1188 [=====] - 31s 26ms/step - loss: 1.6026 - accurac  
y: 0.5456 - val\_loss: 3.8042 - val\_accuracy: 0.4851  
Epoch 33/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.5994 - accurac  
y: 0.5447 - val\_loss: 3.7163 - val\_accuracy: 0.4916  
Epoch 34/100  
1188/1188 [=====] - 40s 33ms/step - loss: 1.5717 - accurac  
y: 0.5468 - val\_loss: 3.6695 - val\_accuracy: 0.4831  
Epoch 35/100  
1188/1188 [=====] - 31s 26ms/step - loss: 1.5740 - accurac  
y: 0.5468 - val\_loss: 3.6818 - val\_accuracy: 0.4827s: 1.5740 - ac  
Epoch 36/100  
1188/1188 [=====] - 36s 30ms/step - loss: 1.5567 - accurac

y: 0.5473 - val\_loss: 3.6870 - val\_accuracy: 0.4903  
Epoch 37/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.5814 - accurac  
y: 0.5464 - val\_loss: 3.6975 - val\_accuracy: 0.4878  
Epoch 38/100  
1188/1188 [=====] - 37s 31ms/step - loss: 1.5472 - accurac  
y: 0.5477 - val\_loss: 3.7310 - val\_accuracy: 0.4725  
Epoch 39/100  
1188/1188 [=====] - 31s 26ms/step - loss: 1.5549 - accurac  
y: 0.5464 - val\_loss: 3.6649 - val\_accuracy: 0.4862  
Epoch 40/100  
1188/1188 [=====] - 35s 29ms/step - loss: 1.5438 - accurac  
y: 0.5495 - val\_loss: 3.6745 - val\_accuracy: 0.4873  
Epoch 41/100  
1188/1188 [=====] - 39s 33ms/step - loss: 1.5406 - accurac  
y: 0.5478 - val\_loss: 3.7103 - val\_accuracy: 0.5024  
Epoch 42/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.5288 - accurac  
y: 0.5501 - val\_loss: 3.6992 - val\_accuracy: 0.4912  
Epoch 43/100  
1188/1188 [=====] - 36s 30ms/step - loss: 1.5226 - accurac  
y: 0.5506 - val\_loss: 3.6695 - val\_accuracy: 0.4897  
Epoch 44/100  
1188/1188 [=====] - 43s 36ms/step - loss: 1.5234 - accurac  
y: 0.5517 - val\_loss: 3.6613 - val\_accuracy: 0.4991  
Epoch 45/100  
1188/1188 [=====] - 38s 32ms/step - loss: 1.5168 - accurac  
y: 0.5533 - val\_loss: 3.6994 - val\_accuracy: 0.4950  
Epoch 46/100  
1188/1188 [=====] - 41s 35ms/step - loss: 1.5091 - accurac  
y: 0.5530 - val\_loss: 3.6555 - val\_accuracy: 0.4910  
Epoch 47/100  
1188/1188 [=====] - 34s 28ms/step - loss: 1.5044 - accurac  
y: 0.5533 - val\_loss: 3.6537 - val\_accuracy: 0.4948  
Epoch 48/100  
1188/1188 [=====] - 33s 27ms/step - loss: 1.5055 - accurac  
y: 0.5554 - val\_loss: 3.6330 - val\_accuracy: 0.4856  
Epoch 49/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.4810 - accurac  
y: 0.5565 - val\_loss: 3.6557 - val\_accuracy: 0.4918  
Epoch 50/100  
1188/1188 [=====] - 31s 26ms/step - loss: 1.4872 - accurac  
y: 0.5549 - val\_loss: 3.6496 - val\_accuracy: 0.4893  
Epoch 51/100  
1188/1188 [=====] - 34s 29ms/step - loss: 1.4965 - accurac  
y: 0.5537 - val\_loss: 3.6375 - val\_accuracy: 0.4832  
Epoch 52/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.4776 - accurac  
y: 0.5591 - val\_loss: 3.6736 - val\_accuracy: 0.4879  
Epoch 53/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.4767 - accurac  
y: 0.5594 - val\_loss: 3.6988 - val\_accuracy: 0.4938  
Epoch 54/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.4718 - accurac  
y: 0.5602 - val\_loss: 3.6602 - val\_accuracy: 0.4916  
Epoch 55/100  
1188/1188 [=====] - 31s 26ms/step - loss: 1.4656 - accurac  
y: 0.5603 - val\_loss: 3.7002 - val\_accuracy: 0.4849  
Epoch 56/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.4548 - accurac  
y: 0.5597 - val\_loss: 3.6292 - val\_accuracy: 0.4943  
Epoch 57/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.4558 - accurac  
y: 0.5606 - val\_loss: 3.6778 - val\_accuracy: 0.5030  
Epoch 58/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.4596 - accurac  
y: 0.5611 - val\_loss: 3.6834 - val\_accuracy: 0.4938  
Epoch 59/100  
1188/1188 [=====] - 34s 29ms/step - loss: 1.4483 - accurac

y: 0.5618 - val\_loss: 3.6913 - val\_accuracy: 0.4931  
Epoch 60/100  
1188/1188 [=====] - 32s 27ms/step - loss: 1.4615 - accurac  
y: 0.5621 - val\_loss: 3.6860 - val\_accuracy: 0.4942  
Epoch 61/100  
1188/1188 [=====] - 34s 29ms/step - loss: 1.4345 - accurac  
y: 0.5638 - val\_loss: 3.6660 - val\_accuracy: 0.4930  
Epoch 62/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.4366 - accurac  
y: 0.5617 - val\_loss: 3.7378 - val\_accuracy: 0.4860  
Epoch 63/100  
1188/1188 [=====] - 33s 27ms/step - loss: 1.4183 - accurac  
y: 0.5638 - val\_loss: 3.7161 - val\_accuracy: 0.4854  
Epoch 64/100  
1188/1188 [=====] - 34s 28ms/step - loss: 1.4331 - accurac  
y: 0.5637 - val\_loss: 3.7203 - val\_accuracy: 0.4969  
Epoch 65/100  
1188/1188 [=====] - 39s 33ms/step - loss: 1.4170 - accurac  
y: 0.5646 - val\_loss: 3.8863 - val\_accuracy: 0.5020  
Epoch 66/100  
1188/1188 [=====] - 35s 30ms/step - loss: 1.4471 - accurac  
y: 0.5619 - val\_loss: 3.7467 - val\_accuracy: 0.4980  
Epoch 67/100  
1188/1188 [=====] - 37s 31ms/step - loss: 1.4227 - accurac  
y: 0.5644 - val\_loss: 3.8000 - val\_accuracy: 0.5025  
Epoch 68/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.4146 - accurac  
y: 0.5654 - val\_loss: 3.7707 - val\_accuracy: 0.5037  
Epoch 69/100  
1188/1188 [=====] - 36s 30ms/step - loss: 1.4156 - accurac  
y: 0.5667 - val\_loss: 3.7729 - val\_accuracy: 0.4913  
Epoch 70/100  
1188/1188 [=====] - 35s 29ms/step - loss: 1.4102 - accurac  
y: 0.5667 - val\_loss: 3.7685 - val\_accuracy: 0.5022  
Epoch 71/100  
1188/1188 [=====] - 36s 30ms/step - loss: 1.4108 - accurac  
y: 0.5645 - val\_loss: 3.7973 - val\_accuracy: 0.5060  
Epoch 72/100  
1188/1188 [=====] - 39s 33ms/step - loss: 1.3969 - accurac  
y: 0.5651 - val\_loss: 3.8227 - val\_accuracy: 0.4984  
Epoch 73/100  
1188/1188 [=====] - 37s 31ms/step - loss: 1.4002 - accurac  
y: 0.5655 - val\_loss: 3.7701 - val\_accuracy: 0.5146  
Epoch 74/100  
1188/1188 [=====] - 36s 30ms/step - loss: 1.4171 - accurac  
y: 0.5670 - val\_loss: 3.8178 - val\_accuracy: 0.5038  
Epoch 75/100  
1188/1188 [=====] - 39s 33ms/step - loss: 1.4100 - accurac  
y: 0.5664 - val\_loss: 3.8543 - val\_accuracy: 0.5061  
Epoch 76/100  
1188/1188 [=====] - 35s 30ms/step - loss: 1.4056 - accurac  
y: 0.5679 - val\_loss: 3.8036 - val\_accuracy: 0.5112  
Epoch 77/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.3887 - accurac  
y: 0.5666 - val\_loss: 3.7686 - val\_accuracy: 0.5061  
Epoch 78/100  
1188/1188 [=====] - 36s 30ms/step - loss: 1.3918 - accurac  
y: 0.5675 - val\_loss: 3.8103 - val\_accuracy: 0.5016  
Epoch 79/100  
1188/1188 [=====] - 39s 33ms/step - loss: 1.3902 - accurac  
y: 0.5686 - val\_loss: 3.8197 - val\_accuracy: 0.5104  
Epoch 80/100  
1188/1188 [=====] - 37s 31ms/step - loss: 1.3918 - accurac  
y: 0.5667 - val\_loss: 3.8420 - val\_accuracy: 0.5146  
Epoch 81/100  
1188/1188 [=====] - 35s 30ms/step - loss: 1.3760 - accurac  
y: 0.5709 - val\_loss: 3.8599 - val\_accuracy: 0.5208  
Epoch 82/100  
1188/1188 [=====] - 33s 28ms/step - loss: 1.3757 - accurac



```

y: 0.5711 - val_loss: 3.8374 - val_accuracy: 0.5189
Epoch 83/100
1188/1188 [=====] - 36s 30ms/step - loss: 1.3771 - accurac
y: 0.5710 - val_loss: 3.8606 - val_accuracy: 0.5190
Epoch 84/100
1188/1188 [=====] - 36s 31ms/step - loss: 1.3799 - accurac
y: 0.5715 - val_loss: 3.7874 - val_accuracy: 0.5186
Epoch 85/100
1188/1188 [=====] - 37s 31ms/step - loss: 1.3734 - accurac
y: 0.5721 - val_loss: 3.8072 - val_accuracy: 0.5231curacy: 0.57
Epoch 86/100
1188/1188 [=====] - 35s 29ms/step - loss: 1.3637 - accurac
y: 0.5714 - val_loss: 3.8323 - val_accuracy: 0.5179
Epoch 87/100
1188/1188 [=====] - 34s 29ms/step - loss: 1.3737 - accurac
y: 0.5708 - val_loss: 3.8727 - val_accuracy: 0.5122
Epoch 88/100
1188/1188 [=====] - 35s 29ms/step - loss: 1.3639 - accurac
y: 0.5717 - val_loss: 3.7914 - val_accuracy: 0.5093
Epoch 89/100
1188/1188 [=====] - 37s 31ms/step - loss: 1.3725 - accurac
y: 0.5707 - val_loss: 3.8461 - val_accuracy: 0.5123
Epoch 90/100
1188/1188 [=====] - 35s 29ms/step - loss: 1.3633 - accurac
y: 0.5724 - val_loss: 3.8100 - val_accuracy: 0.5207
Epoch 91/100
1188/1188 [=====] - 35s 30ms/step - loss: 1.3596 - accurac
y: 0.5712 - val_loss: 3.7470 - val_accuracy: 0.5152
Epoch 92/100
1188/1188 [=====] - 37s 31ms/step - loss: 1.3553 - accurac
y: 0.5715 - val_loss: 3.7624 - val_accuracy: 0.5097
Epoch 93/100
1188/1188 [=====] - 40s 34ms/step - loss: 1.3650 - accurac
y: 0.5728 - val_loss: 3.9057 - val_accuracy: 0.5108
Epoch 94/100
1188/1188 [=====] - 30s 25ms/step - loss: 1.3587 - accurac
y: 0.5738 - val_loss: 3.8598 - val_accuracy: 0.5131
Epoch 95/100
1188/1188 [=====] - 32s 27ms/step - loss: 1.3514 - accurac
y: 0.5723 - val_loss: 3.8271 - val_accuracy: 0.5068
Epoch 96/100
1188/1188 [=====] - 33s 28ms/step - loss: 1.3492 - accurac
y: 0.5731 - val_loss: 3.8154 - val_accuracy: 0.5084
Epoch 97/100
1188/1188 [=====] - 36s 30ms/step - loss: 1.3576 - accurac
y: 0.5717 - val_loss: 3.8459 - val_accuracy: 0.5023
Epoch 98/100
1188/1188 [=====] - 35s 29ms/step - loss: 1.3470 - accurac
y: 0.5728 - val_loss: 3.8606 - val_accuracy: 0.5198
Epoch 99/100
1188/1188 [=====] - 37s 31ms/step - loss: 1.3457 - accurac
y: 0.5751 - val_loss: 3.8252 - val_accuracy: 0.5046
Epoch 100/100
1188/1188 [=====] - 35s 30ms/step - loss: 1.3445 - accurac
y: 0.5748 - val_loss: 3.7688 - val_accuracy: 0.5113

```

Out[45]: <keras.callbacks.History at 0x1977d92a9a0>

```

In [61]: #Test result:
         model_25_.evaluate(test_x, test_label)

```

```

7/7 [=====] - 5s 7ms/step - loss: 3.7754 - accuracy: 0.7379

```

Out[61]: [3.7754178047180176, 0.7378571629524231]

```

In [62]: #Data preparation for model_100_

```

```
In [21]: data_X, label = create_dataset(100, data)
train_x, train_label = data_X[0:95000][:][:], label[0:95000][:][:]
test_x, test_label = data_X[95000:][:][:], label[95000:][:][:]
train_label=train_label.reshape(95000,1,33)
```

```
In [26]: test_label=test_label.reshape(224,1,33)
```

```
In [20]: test_label=test_label.reshape(224,1,3)
```

-----

ValueError

Traceback (most recent call last)

<ipython-input-20-43d8ef69b2c7> in <module>

----> 1 test\_label=test\_label.reshape(224,1,3)

ValueError: cannot reshape array of size 7392 into shape (224,1,3)

```
In [16]: import keras
model_100_ = keras.models.load_model("my_model100")
```

```
In [48]: #Compile the model
model_100_ = RNN(100)
model_100_.summary(100)
model_100_.compile(loss='mse',optimizer='adam',metrics=['accuracy'])
model_100_.fit(train_x, train_label,batch_size=64,epochs=100, validation_split=0.2,
```

Model: "model\_7"

Layer (type) Param #	Output Shape
=====	=====
inputs (InputLayer) 0	[(None, 100, 33)]
=====	=====
lstm_7 (LSTM) 25088	(None, 100, 64)
=====	=====
activation_10 (Activation) 0	(None, 100, 64)
=====	=====
dropout_3 (Dropout) 0	(None, 100, 64)
=====	=====
FC2 (Dense) 8320	(None, 100, 128)
=====	=====
activation_11 (Activation) 0	(None, 100, 128)
=====	=====
out_layer (Dense) 4257	(None, 100, 33)
=====	=====
Total params: 37,665	
Trainable params: 37,665	

Non-trainable params: 0

---

Epoch 1/100  
1188/1188 [=====] - 131s 96ms/step - loss: 12.1563 - accuracy: 0.1731 - val\_loss: 11.3957 - val\_accuracy: 0.3487  
Epoch 2/100  
1188/1188 [=====] - 115s 97ms/step - loss: 5.5186 - accuracy: 0.3357 - val\_loss: 11.8278 - val\_accuracy: 0.3074  
Epoch 3/100  
1188/1188 [=====] - 121s 102ms/step - loss: 4.8076 - accuracy: 0.3621 - val\_loss: 12.1690 - val\_accuracy: 0.3052  
Epoch 4/100  
1188/1188 [=====] - 117s 98ms/step - loss: 4.4408 - accuracy: 0.3747 - val\_loss: 12.9700 - val\_accuracy: 0.2880  
Epoch 5/100  
1188/1188 [=====] - 121s 102ms/step - loss: 4.1417 - accuracy: 0.3840 - val\_loss: 13.4743 - val\_accuracy: 0.2632  
Epoch 6/100  
1188/1188 [=====] - 118s 100ms/step - loss: 3.9686 - accuracy: 0.3931 - val\_loss: 13.7336 - val\_accuracy: 0.2685  
Epoch 7/100  
1188/1188 [=====] - 119s 100ms/step - loss: 3.7665 - accuracy: 0.3984 - val\_loss: 13.3627 - val\_accuracy: 0.2608  
Epoch 8/100  
1188/1188 [=====] - 125s 105ms/step - loss: 3.7010 - accuracy: 0.4043 - val\_loss: 13.5105 - val\_accuracy: 0.2720  
Epoch 9/100  
1188/1188 [=====] - 135s 113ms/step - loss: 3.5891 - accuracy: 0.4096 - val\_loss: 14.2213 - val\_accuracy: 0.2346  
Epoch 10/100  
1188/1188 [=====] - 130s 109ms/step - loss: 3.4924 - accuracy: 0.4118 - val\_loss: 13.8957 - val\_accuracy: 0.2374  
Epoch 11/100  
1188/1188 [=====] - 122s 103ms/step - loss: 3.4124 - accuracy: 0.4151 - val\_loss: 13.6711 - val\_accuracy: 0.2456  
Epoch 12/100  
1188/1188 [=====] - 125s 105ms/step - loss: 3.3109 - accuracy: 0.4197 - val\_loss: 13.9854 - val\_accuracy: 0.2379  
Epoch 13/100  
1188/1188 [=====] - 124s 105ms/step - loss: 3.2600 - accuracy: 0.4213 - val\_loss: 13.9211 - val\_accuracy: 0.2379  
Epoch 14/100  
1188/1188 [=====] - 125s 105ms/step - loss: 3.2312 - accuracy: 0.4226 - val\_loss: 13.7727 - val\_accuracy: 0.2358  
Epoch 15/100  
1188/1188 [=====] - 123s 103ms/step - loss: 3.1851 - accuracy: 0.4267 - val\_loss: 14.0479 - val\_accuracy: 0.2346  
Epoch 16/100  
1188/1188 [=====] - 129s 109ms/step - loss: 3.1439 - accuracy: 0.4276 - val\_loss: 13.7969 - val\_accuracy: 0.2413  
Epoch 17/100  
1188/1188 [=====] - 120s 101ms/step - loss: 3.1007 - accuracy: 0.4291 - val\_loss: 13.7476 - val\_accuracy: 0.2401  
Epoch 18/100  
1188/1188 [=====] - 127s 107ms/step - loss: 3.1259 - accuracy: 0.4280 - val\_loss: 14.1215 - val\_accuracy: 0.2283  
Epoch 19/100  
1188/1188 [=====] - 119s 100ms/step - loss: 3.0431 - accuracy: 0.4304 - val\_loss: 14.1177 - val\_accuracy: 0.2309  
Epoch 20/100  
1188/1188 [=====] - 121s 102ms/step - loss: 3.0091 - accuracy: 0.4326 - val\_loss: 13.9611 - val\_accuracy: 0.2252  
Epoch 21/100  
1188/1188 [=====] - 125s 105ms/step - loss: 3.0402 - accuracy: 0.4333 - val\_loss: 14.1823 - val\_accuracy: 0.2283  
Epoch 22/100  
1188/1188 [=====] - 125s 105ms/step - loss: 2.9907 - accuracy: 0.4363 - val\_loss: 14.6518 - val\_accuracy: 0.2352

```

Epoch 23/100
1188/1188 [=====] - 118s 99ms/step - loss: 2.9713 - accuracy: 0.4332 - val_loss: 14.3322 - val_accuracy: 0.2238
Epoch 24/100
1188/1188 [=====] - 127s 107ms/step - loss: 2.9178 - accuracy: 0.4371 - val_loss: 14.5957 - val_accuracy: 0.2184
Epoch 25/100
1188/1188 [=====] - 123s 104ms/step - loss: 2.8987 - accuracy: 0.4378 - val_loss: 14.8738 - val_accuracy: 0.2231
Epoch 26/100
1188/1188 [=====] - 130s 109ms/step - loss: 2.9033 - accuracy: 0.4397 - val_loss: 14.7893 - val_accuracy: 0.2256
Epoch 27/100
1188/1188 [=====] - 123s 104ms/step - loss: 2.8921 - accuracy: 0.4395 - val_loss: 15.1844 - val_accuracy: 0.2135
Epoch 28/100
1188/1188 [=====] - 129s 109ms/step - loss: 2.9727 - accuracy: 0.4356 - val_loss: 15.0634 - val_accuracy: 0.2131
Epoch 29/100
1188/1188 [=====] - 125s 106ms/step - loss: 2.8672 - accuracy: 0.4397 - val_loss: 15.2148 - val_accuracy: 0.2109
Epoch 30/100
1188/1188 [=====] - 122s 102ms/step - loss: 2.8185 - accuracy: 0.4448 - val_loss: 15.2125 - val_accuracy: 0.2062
Epoch 31/100
1188/1188 [=====] - 127s 107ms/step - loss: 2.8577 - accuracy: 0.4415 - val_loss: 15.2733 - val_accuracy: 0.2087
Epoch 32/100
1188/1188 [=====] - 121s 102ms/step - loss: 2.8096 - accuracy: 0.4439 - val_loss: 15.3282 - val_accuracy: 0.2151
Epoch 33/100
1188/1188 [=====] - 122s 103ms/step - loss: 2.8480 - accuracy: 0.4432 - val_loss: 15.3400 - val_accuracy: 0.2146
Epoch 34/100
1188/1188 [=====] - 123s 104ms/step - loss: 2.7770 - accuracy: 0.4447 - val_loss: 15.6134 - val_accuracy: 0.2094
Epoch 35/100
1188/1188 [=====] - 127s 107ms/step - loss: 2.7769 - accuracy: 0.4464 - val_loss: 15.6778 - val_accuracy: 0.2037
Epoch 36/100
1188/1188 [=====] - 126s 106ms/step - loss: 2.7833 - accuracy: 0.4452 - val_loss: 15.0316 - val_accuracy: 0.2233
Epoch 37/100
1188/1188 [=====] - 122s 102ms/step - loss: 2.8310 - accuracy: 0.4423 - val_loss: 15.6454 - val_accuracy: 0.2077
Epoch 38/100
1188/1188 [=====] - ETA: 1:46 - loss: 2.9058 - accuracy: 0.4367

```

KeyboardInterrupt

Traceback (most recent call last)

```

<ipython-input-48-9fd62560dd82> in <module>
      3 model_100.summary(100)
      4 model_100.compile(loss='mse',optimizer='adam',metrics=['accuracy'])
----> 5 model_100.fit(train_x, train_label,batch_size=64,epochs=100, validation_split=0.2, shuffle='True')

```

```

~\AppData\Roaming\Python\Python38\site-packages\keras\engine\training.py in fit(self, x, y, batch_size, epochs, verbose, callbacks, validation_split, validation_data, shuffle, class_weight, sample_weight, initial_epoch, steps_per_epoch, validation_steps, validation_batch_size, validation_freq, max_queue_size, workers, use_multiprocessing)

```

```

    1156         _r=1):
    1157             callbacks.on_train_batch_begin(step)
-> 1158             tmp_logs = self.train_function(iterator)
    1159             if data_handler.should_sync:
    1160                 context.async_wait()

```

```

~\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\eager\def_function.py in __call__(self, *args, **kwargs)

```

```

887
888     with OptionalXlaContext(self._jit_compile):
--> 889         result = self._call(*args, **kws)
890
891         new_tracing_count = self.experimental_get_tracing_count()

~\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\eager\def_function.py in _call(self, *args, **kws)
915     # In this case we have created variables on the first call, so we run
the
916     # defunned version which is guaranteed to never create variables.
--> 917     return self._stateless_fn(*args, **kws) # pylint: disable=not-callable
le
918     elif self._stateful_fn is not None:
919         # Release the lock early so that multiple threads can perform the call

~\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\eager\function.py
in __call__(self, *args, **kwargs)
3021         (graph_function,
3022          filtered_flat_args) = self._maybe_define_function(args, kwargs)
-> 3023     return graph_function._call_flat(
3024         filtered_flat_args, captured_inputs=graph_function.captured_inputs)
# pylint: disable=protected-access
3025

~\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\eager\function.py
in _call_flat(self, args, captured_inputs, cancellation_manager)
1958         and executing_eagerly):
1959         # No tape is watching; skip to running the function.
-> 1960     return self._build_call_outputs(self._inference_function.call(
1961         ctx, args, cancellation_manager=cancellation_manager))
1962     forward_backward = self._select_forward_and_backward_functions(

~\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\eager\function.py
in call(self, ctx, args, cancellation_manager)
589     with _InterpolateFunctionError(self):
590     if cancellation_manager is None:
--> 591         outputs = execute.execute(
592             str(self.signature.name),
593             num_outputs=self._num_outputs,

~\AppData\Roaming\Python\Python38\site-packages\tensorflow\python\eager\execute.py i
n quick_execute(op_name, num_outputs, inputs, attrs, ctx, name)
57     try:
58         ctx.ensure_initialized()
--> 59     tensors = pywrap_tfe.TFE_Py_Execute(ctx._handle, device_name, op_name,
60                                           inputs, attrs, num_outputs)
61 except core._NotOkStatusException as e:

```

**KeyboardInterrupt:**

```

In [27]: #Test results:
         model_100_.evaluate(test_x, test_label)

```

```

7/7 [=====] - 9s 23ms/step - loss: 6.7734 - accuracy: 0.1204

```

```

Out[27]: [6.773382663726807, 0.12044642865657806]

```

```

In [50]: model_100_.save('my_model100')
         model_25_.save('my_model25')

```

WARNING:absl:Found untraced functions such as lstm\_cell\_7\_layer\_call\_and\_return\_conditional\_losses, lstm\_cell\_7\_layer\_call\_fn, lstm\_cell\_7\_layer\_call\_fn, lstm\_cell\_7\_layer\_call\_and\_return\_conditional\_losses, lstm\_cell\_7\_layer\_call\_and\_return\_conditional\_losses while saving (showing 5 of 5). These functions will not be directly callable after loading.

```
INFO:tensorflow:Assets written to: my_model100\assets
INFO:tensorflow:Assets written to: my_model100\assets
WARNING:absl:Found untraced functions such as lstm_cell_5_layer_call_and_return_conditional_losses, lstm_cell_5_layer_call_fn, lstm_cell_5_layer_call_fn, lstm_cell_5_layer_call_and_return_conditional_losses, lstm_cell_5_layer_call_and_return_conditional_losses while saving (showing 5 of 5). These functions will not be directly callable after loading.
INFO:tensorflow:Assets written to: my_model125\assets
INFO:tensorflow:Assets written to: my_model125\assets
```

## Variance Test

```
In [5]: nba_uta = pd.read_csv('2019040129_nba-uta_TRACKING.csv')
```

```
In [6]: nba_gsw = pd.read_csv('2019051610_nba-gsw_TRACKING.csv')
```

```
In [8]: def data_preprocessing(raw_data):

    #team = raw_data['team']
    #data = 0

    #for i in range (len(raw_data['ts'])):
    #    if team[i]=='team_ball':
    #        team[i]='team_2'

    #team = np.array(team)
    #team_processed = np.zeros([len(team)])
    #for i in range (len(team)):
    #    team_processed[i] = int(team[i][5])

    num_time_steps = time_steps.shape[0]
    data = np.concatenate((raw_data['x'],raw_data['y'],raw_data['z']))
    data = data.reshape(3, num_time_steps)
    player=[]
    for i in range (11):
        player1 = data[:, i:num_time_steps:11]
        player.append(player1)

    data = np.array(player)

    return data
```

```
In [18]: data = data_preprocessing(nba_gsw)
```

```
In [19]: data=data.reshape(33,95325)
```

```
In [25]: x, y = create_dataset(25, data)
```

```
In [28]: len(y)
```

```
Out[28]: 95224
```

```
In [26]: y=y.reshape(95224,1,33)
```

## NBA\_UTA

```
In [44]: model_25_.evaluate(x[0:6000], y[0:6000], batch_size=64)

94/94 [=====] - 6s 8ms/step - loss: 3.1988 - accuracy: 0.5074
Out[44]: [3.198753595352173, 0.5073666572570801]
```

```
In [16]: model_100_.evaluate(x[0:6000], y[0:6000], batch_size=64)

94/94 [=====] - 17s 26ms/step - loss: 12.2466 - accuracy: 0.2411
Out[16]: [12.246556282043457, 0.24110166728496552]
```

## NBA\_GSW

```
In [22]: model_100_.evaluate(x[0:6000], y[0:6000], batch_size=64)

94/94 [=====] - 3s 27ms/step - loss: 15.7371 - accuracy: 0.2476
Out[22]: [15.73711109161377, 0.24758833646774292]
```

```
In [27]: model_25_.evaluate(x[0:6000], y[0:6000], batch_size=64)

94/94 [=====] - 2s 8ms/step - loss: 3.1692 - accuracy: 0.4347
Out[27]: [3.1692137718200684, 0.434746652841568]
```

## Further steps:

1. First of all, training the same model with around 200 to 400 epochs as there is a clear scope of increasing the training accuracy.
2. Combining all the three time series and evaluating with the same RNN architecture.
3. Architectural tweaks, like batch normalization, adding LSTM layers etc.
4. Predicting more than 1 future time steps either in a regressive way (feeding network outputs to the model and predicting the next step), or by directly making labels 2-dimensional.
5. Model player interactions like euclidean distances, playing position etc. (giving rise to a graph), and then apply min-cost flow for time series forecasting.
6. Trying out generative RNNs and Variational Autoencoders, to perform uncertainty quantification and generate scenarios that were never seen before, but have the same posterior distribution  $p(z|x)$ ,  $z$ :=latent variables describing space dynamics,  $x$ :=states. This can also be used for data augmentation.
7. In case the underlying dynamics can also be learnt, then particle filter is also a solution. I am not sure how else to model the underlying dynamics.

```
In [ ]:
```