

IBM ADVANCED DATA SCIENCE CAPSTONE PROJECT

ALEX BRAGA

IMU BASED SURFACE DETECTION

BASE DATASET

- ▶ Objective: Recognition of floor surface based on IMU data from robot
- ▶ Based on Kaggle CarrerCon 2019: Help Navigate robots competition
- ▶ <https://www.kaggle.com/c/career-con-2019/data>
- ▶ Data was collected from a robot in 9 different surfaces taking IMU data(10 channels), each data series have 128 measurements and refer to a single surface category
- ▶ Special thanks to Tampere University in Finland, Department of Signal Processing and Department of Automation and Mechanics Engineering for making the data available

ROBOT SURFACE CLASSIFICATION

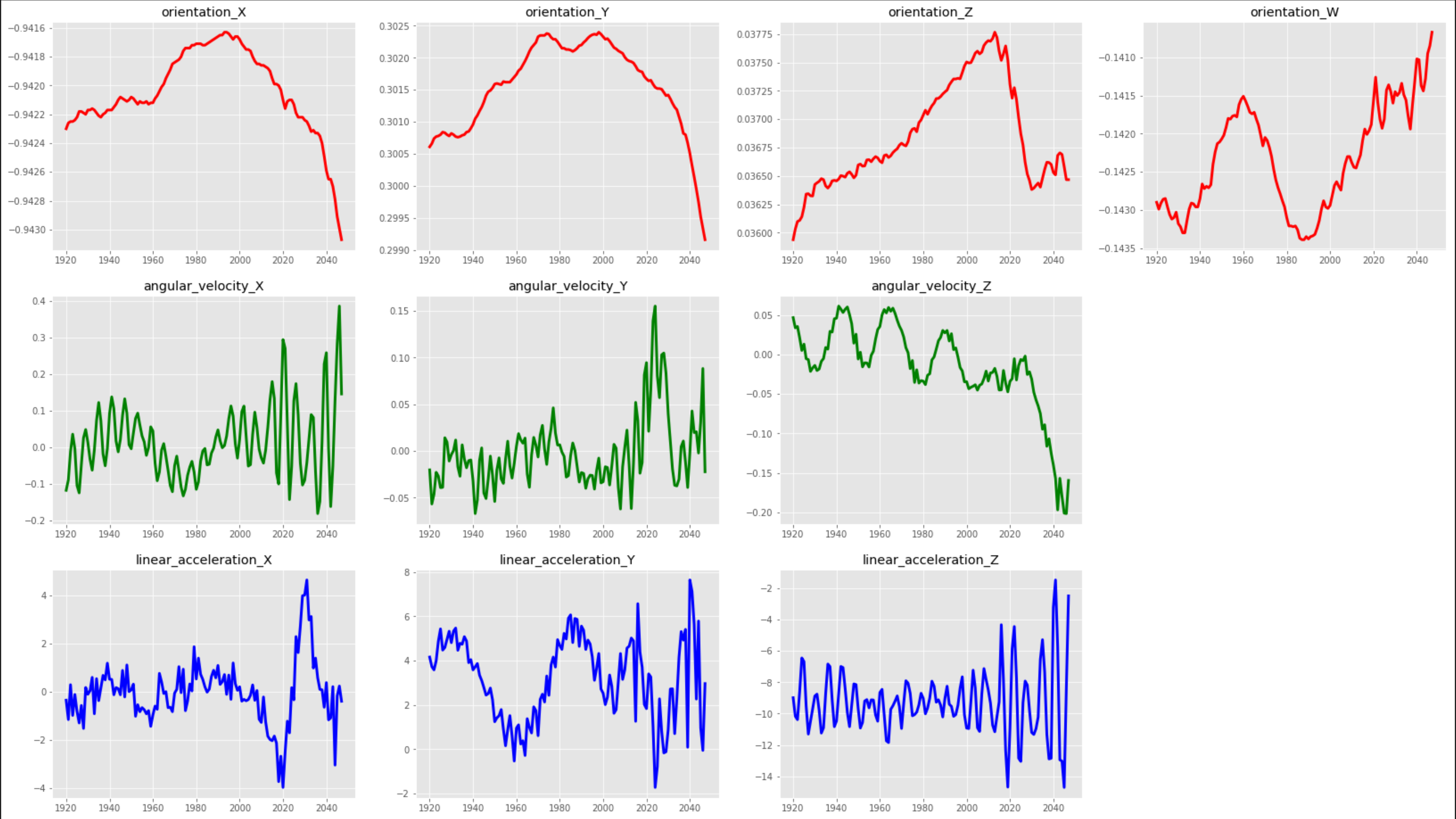
- ▶ Data consists of 2 files
- ▶ X
 - ▶ Row_ID: ID of a given row
 - ▶ Series_ID: ID of an 128 measurement series
 - ▶ Measurement_Number: Step of a measurement on a single series
 - ▶ Orientation X,Y,Z,W: Quaternion based location
 - ▶ Angular Velocity X,Y,Z: IMU data for rotation speed
 - ▶ Linear Acceleration X,Y,Z: IMU data for robot acceleration
- ▶ Y
 - ▶ Series ID: External reference to X data series
 - ▶ Group ID: Target ID for surface category
 - ▶ Surface: Surface Name

INITIAL DATA EXPLORATION

X DATA

```
X_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 487680 entries, 0 to 487679
Data columns (total 13 columns):
row_id                487680 non-null object
series_id             487680 non-null int64
measurement_number    487680 non-null int64
orientation_X         487680 non-null float64
orientation_Y         487680 non-null float64
orientation_Z         487680 non-null float64
orientation_W         487680 non-null float64
angular_velocity_X    487680 non-null float64
angular_velocity_Y    487680 non-null float64
angular_velocity_Z    487680 non-null float64
linear_acceleration_X 487680 non-null float64
linear_acceleration_Y 487680 non-null float64
linear_acceleration_Z 487680 non-null float64
dtypes: float64(10), int64(2), object(1)
memory usage: 48.4+ MB
```



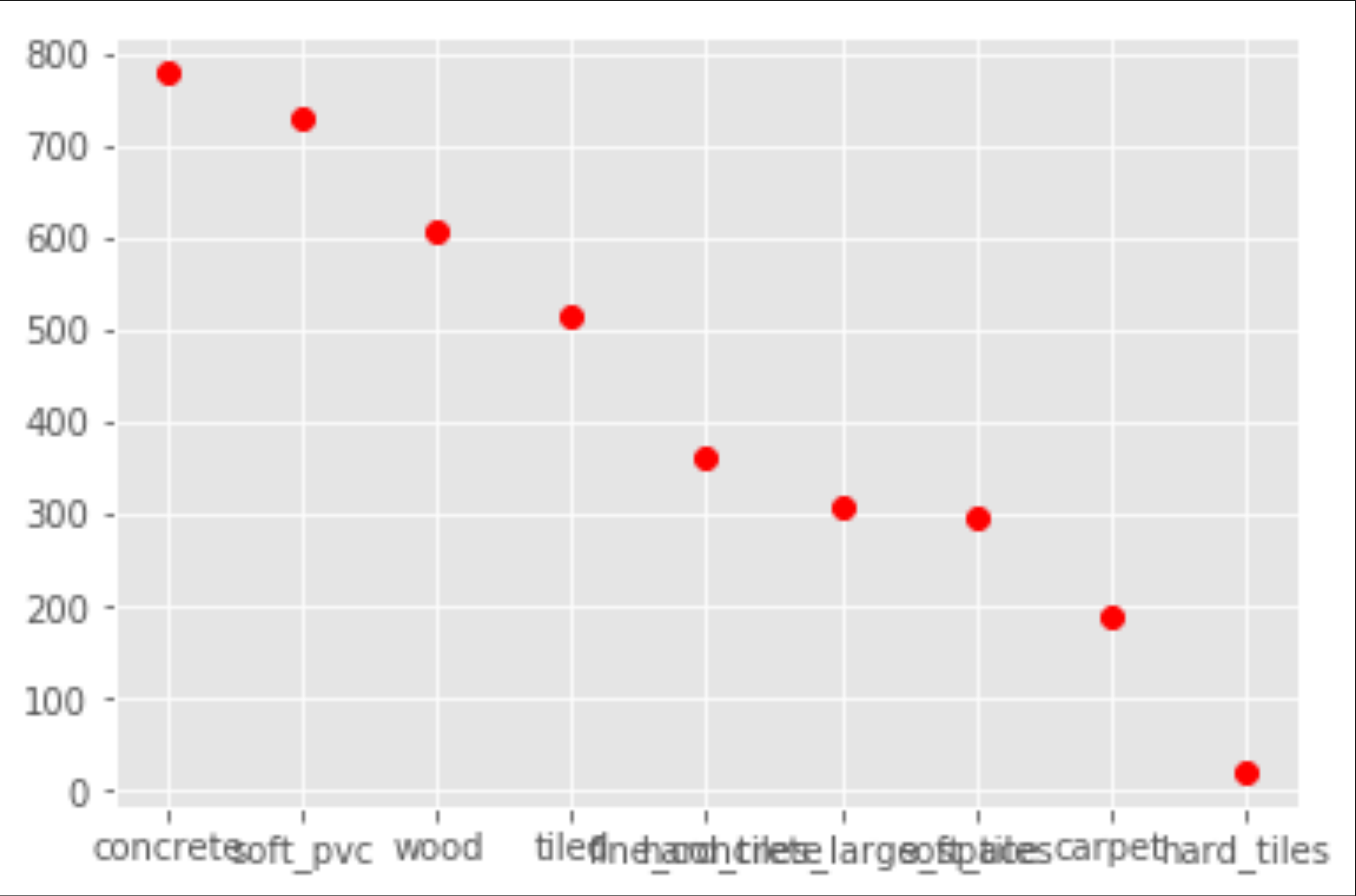
INITIAL DATA EXPLORATION

X DATA

```
Y_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3810 entries, 0 to 3809
Data columns (total 3 columns):
series_id    3810 non-null int64
group_id     3810 non-null int64
surface      3810 non-null object
dtypes: int64(2), object(1)
memory usage: 89.4+ KB
```

Y_data.head()			
	series_id	group_id	surface
0	0	13	fine_concrete
1	1	31	concrete
2	2	20	concrete
3	3	31	concrete
4	4	22	soft_tiles



DATA CLEANING

X_data.isnull().sum()

row_id	0
series_id	0
measurement_number	0
orientation_X	0
orientation_Y	0
orientation_Z	0
orientation_W	0
angular_velocity_X	0
angular_velocity_Y	0
angular_velocity_Z	0
linear_acceleration_X	0
linear_acceleration_Y	0
linear_acceleration_Z	0
dtype:	int64

Y_data.isnull().sum()

series_id	0
group_id	0
surface	0
dtype:	int64

X_data.duplicated().value_counts()

False 487680
dtype: int64

X_data.shape

(487680, 13)

Y_data.duplicated().value_counts()

False 3810
dtype: int64

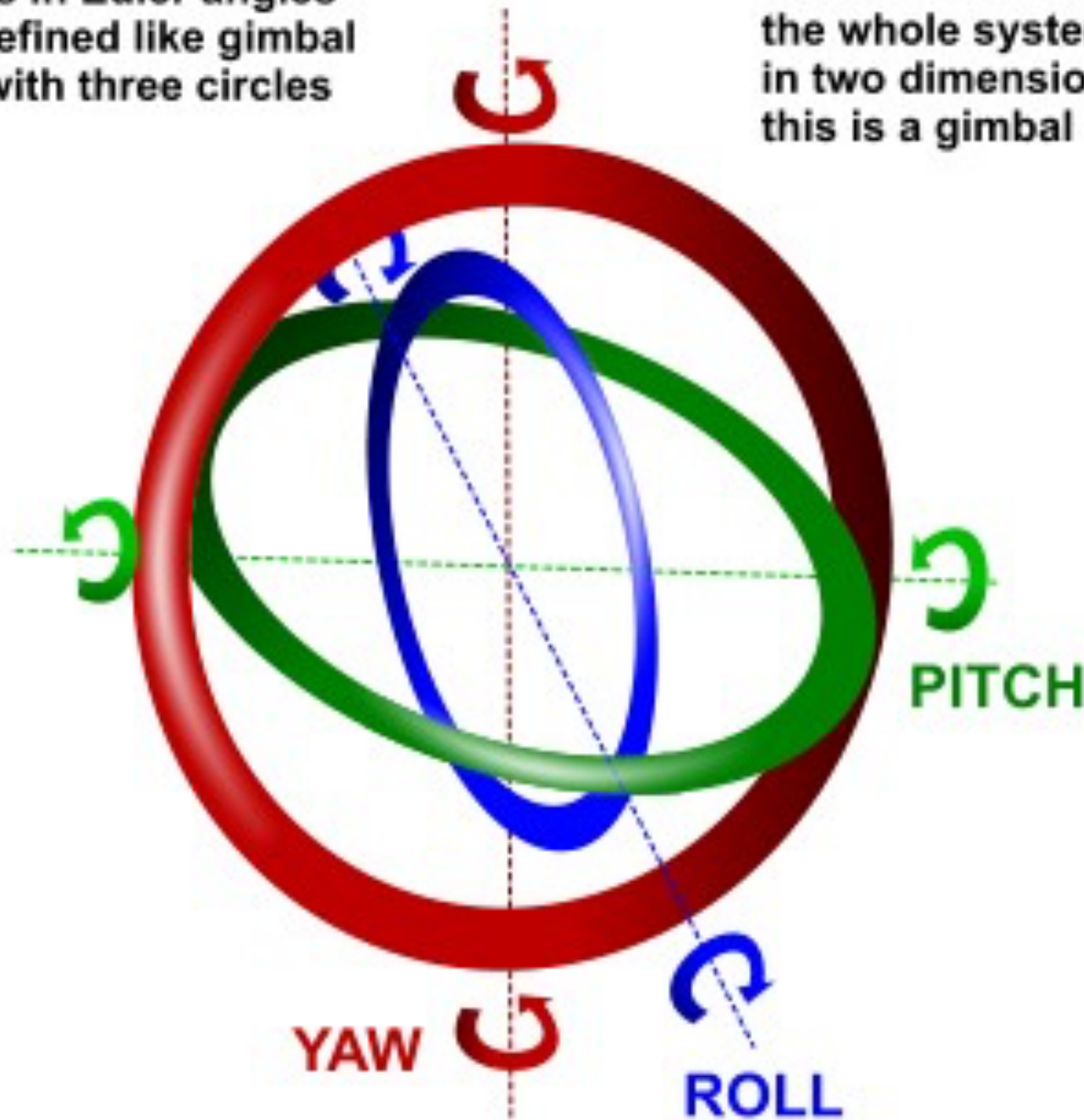
Y_data.shape

(3810, 3)

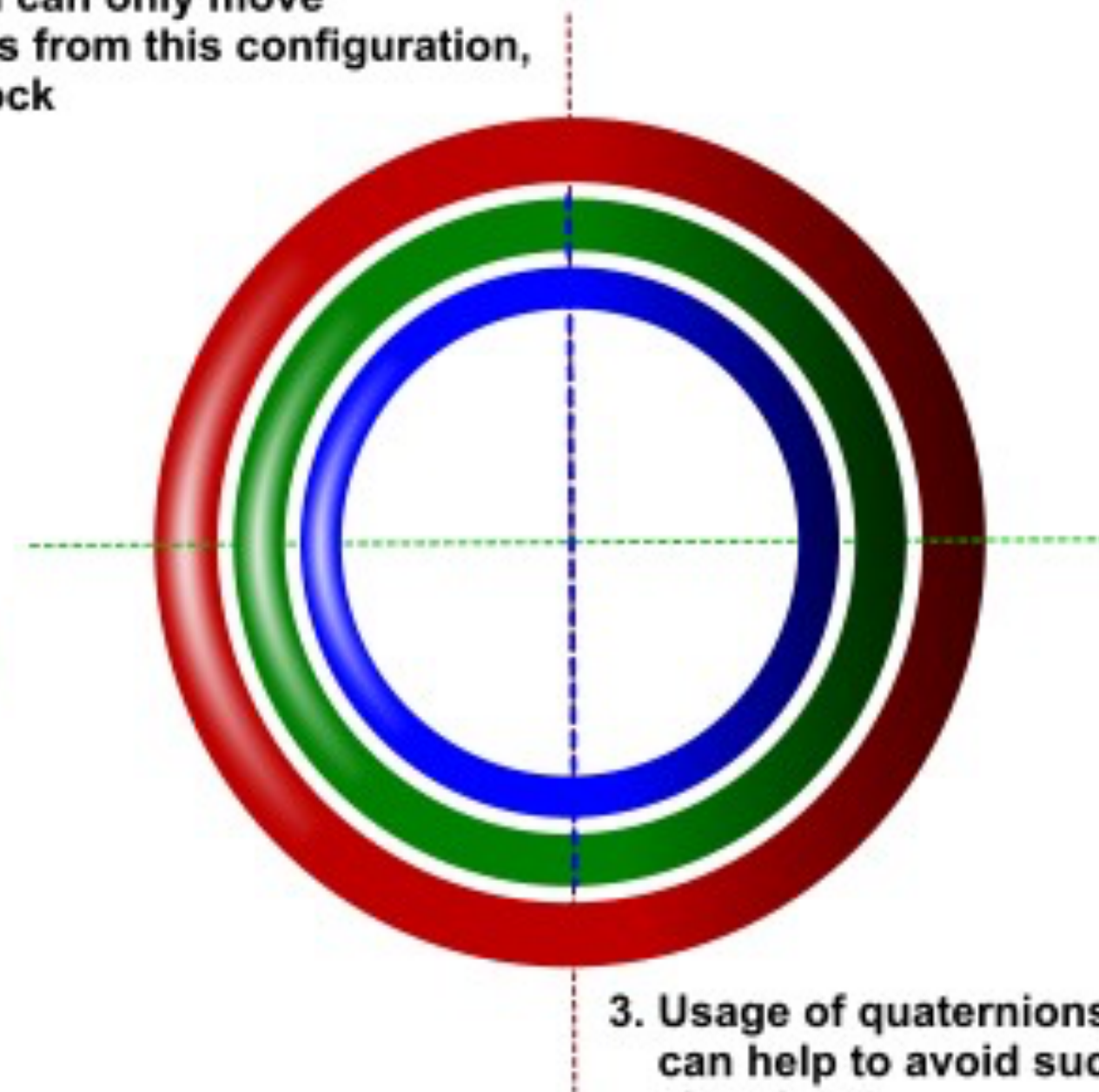
```
X_data.fillna(0, inplace = True)
X_data.replace(-np.inf, 0, inplace = True)
X_data.replace(np.inf, 0, inplace = True)
Y_data.fillna(0, inplace = True)
Y_data.replace(-np.inf, 0, inplace = True)
Y_data.replace(np.inf, 0, inplace = True)
```

QUATERNION TO EULER

1. Rotations in Euler angles can be defined like gimbal system with three circles



2. When all three circles are lined up, the whole system can only move in two dimensions from this configuration, this is a gimbal lock

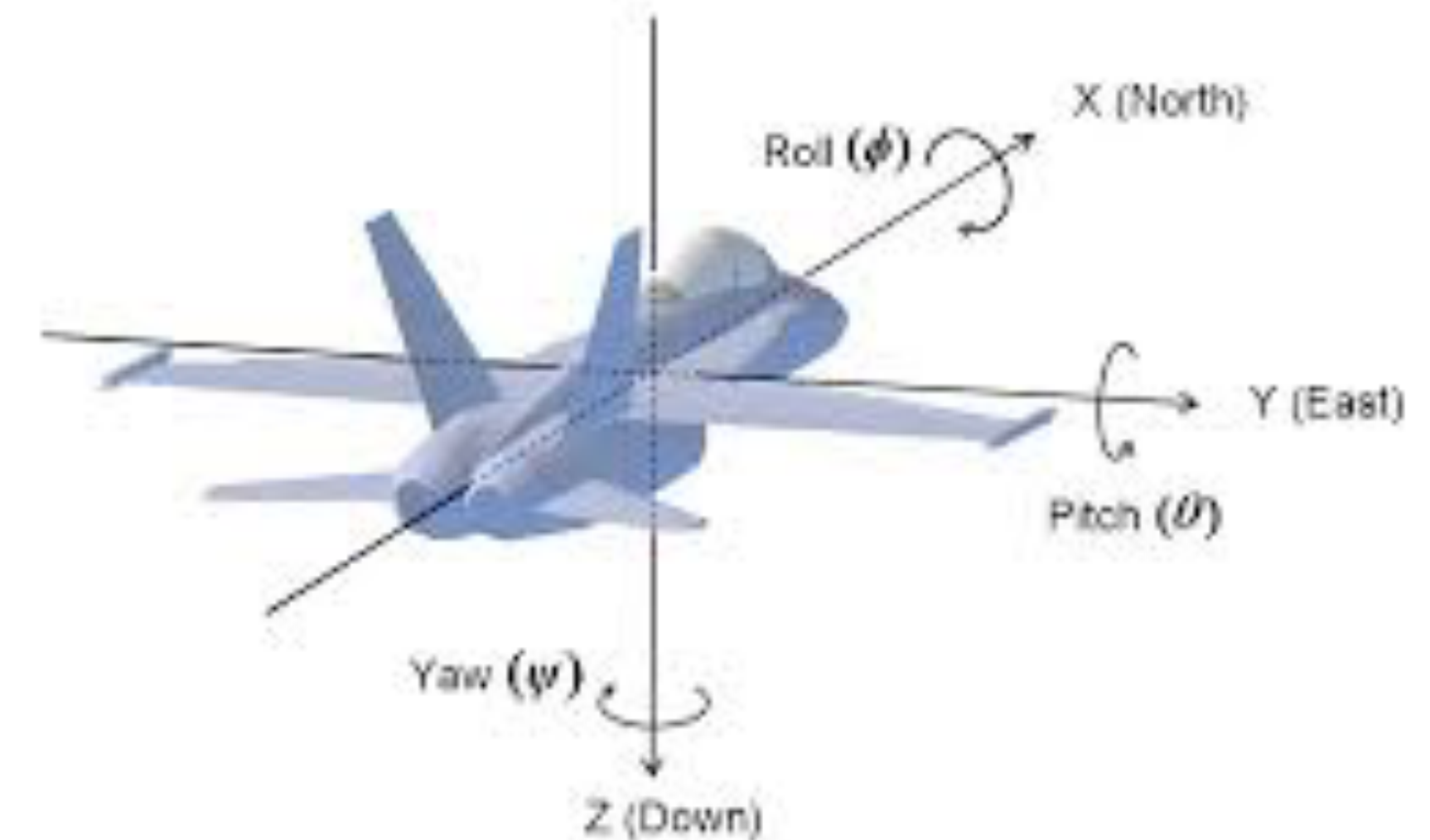


3. Usage of quaternions can help to avoid such situations

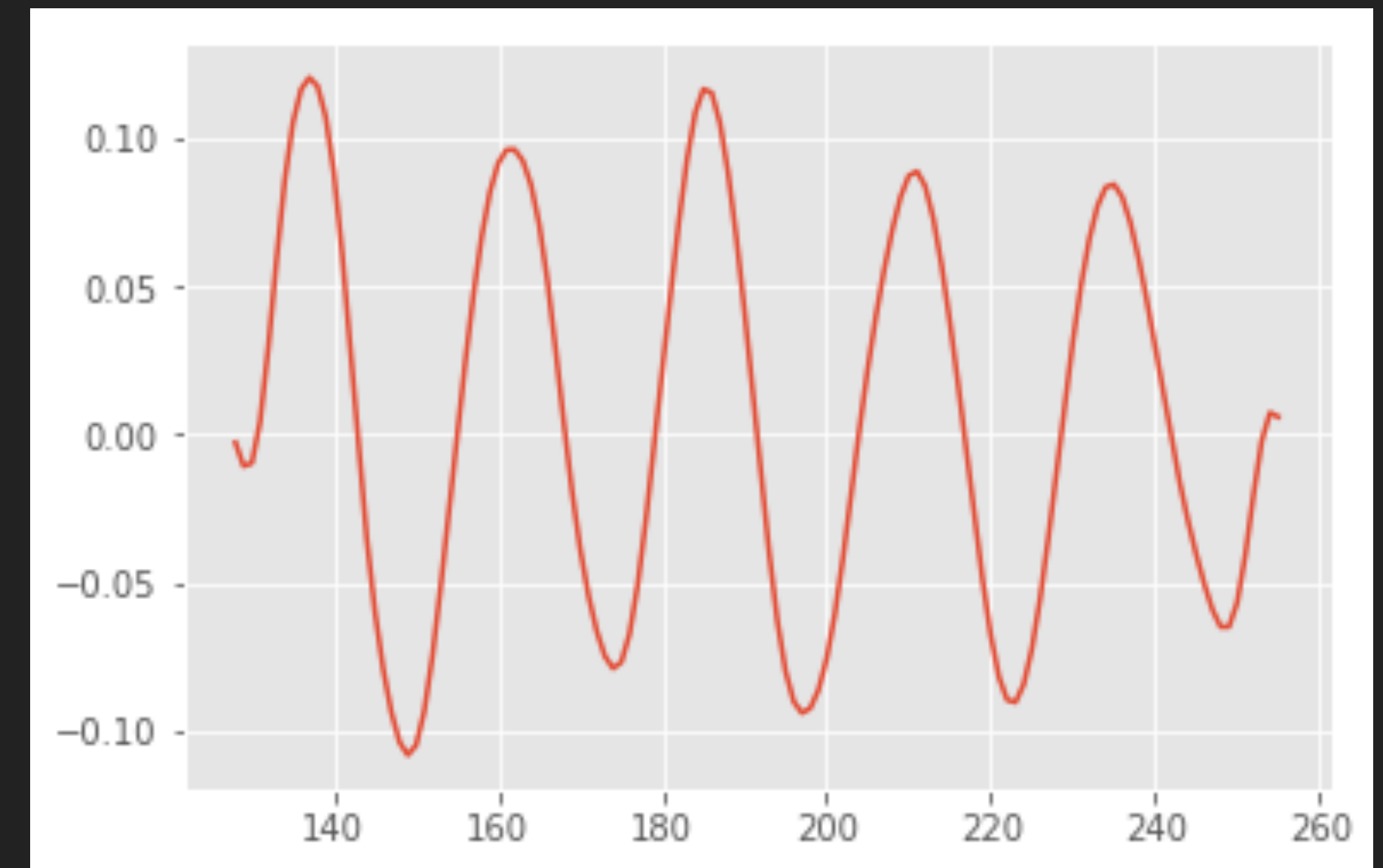
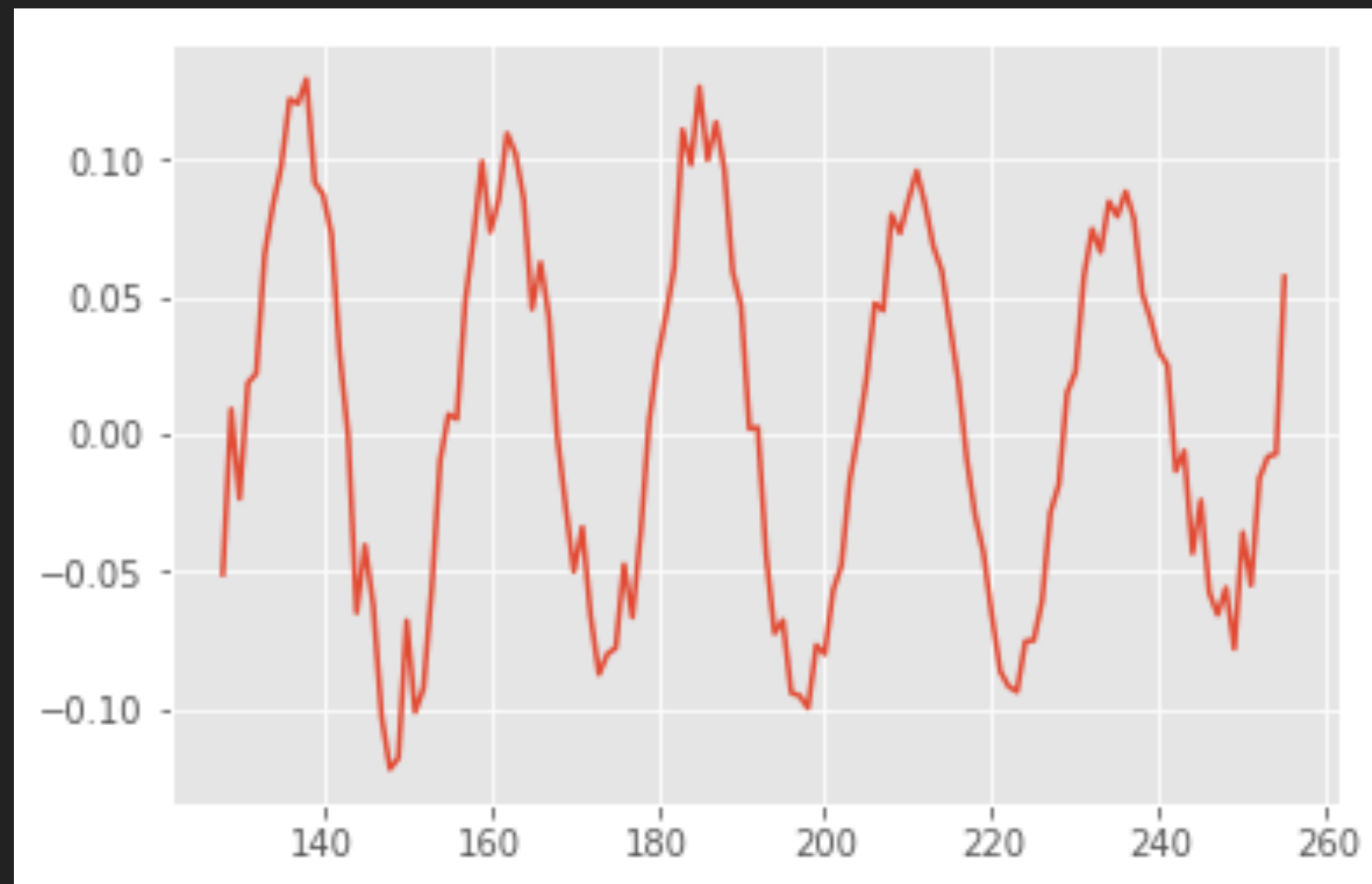
$$\phi = \arctan\left(\frac{2(ab+cd)}{a^2-b^2-c^2+d^2}\right),$$

$$\theta = -\arcsin(2(bd-ac)), \text{ and}$$

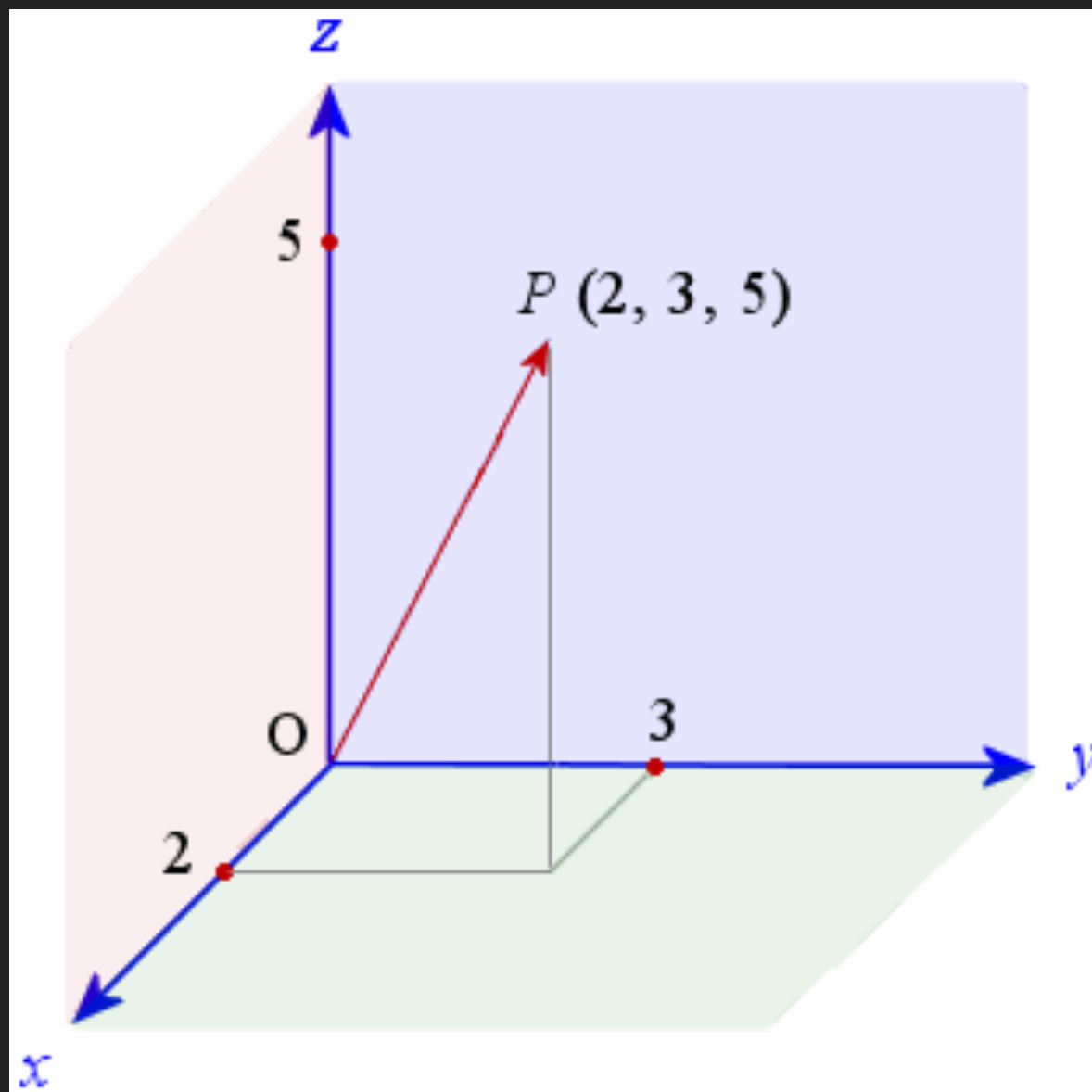
$$\psi = \arctan\left(\frac{2(ad+bc)}{a^2+b^2-c^2-d^2}\right).$$



NOISE REDUCTION



MAGNITUDE AND RELATION



```
X_data['total_angular_vel'] = (X_data['angular_velocity_X']**2 + X_data['a  
ngular_velocity_Y']**2 + X_data['angular_velocity_Z']**2)** 0.5  
X_data['total_linear_acc'] = (X_data['linear_acceleration_X']**2 + X_data[  
'linear_acceleration_Y']**2 + X_data['linear_acceleration_Z']**2)**0.5  
X_data['total_orientation'] = (X_data['orientation_X']**2 + X_data['orient  
ation_Y']**2 + X_data['orientation_Z']**2)**0.5  
X_data['acc_vs_vel'] = X_data['total_linear_acc'] / X_data['total_angular_  
vel']  
X_data['total_angle'] = (X_data['euler_x'] ** 2 + X_data['euler_y'] ** 2 +  
X_data['euler_z'] ** 2) ** 0.5  
X_data['angle_vs_acc'] = X_data['total_angle'] / X_data['total_linear_acc']  
]  
X_data['angle_vs_vel'] = X_data['total_angle'] / X_data['total_angular_vel  
']
```

FROM TIME TO MEASUREMENT DOMAIN

Series	Measurement	X	Y	Z	...
1	1				
1	2				
1	3				
1	...				
1	128				
2	1				
2	2				
2	3				
2	...				
2	128				
...	...				

DATA



Series	X_mean	X_max	X_min	...
1				
2				
3				
...				

DATA

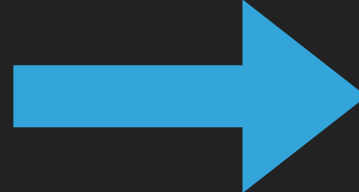


```
x = Input.values
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(x)
Input = pd.DataFrame(x_scaled)
```

LABEL ENCODING

Y_data.head()

	series_id	group_id	surface
0	0	13	fine_concrete
1	1	31	concrete
2	2	20	concrete
3	3	31	concrete
4	4	22	soft_tiles

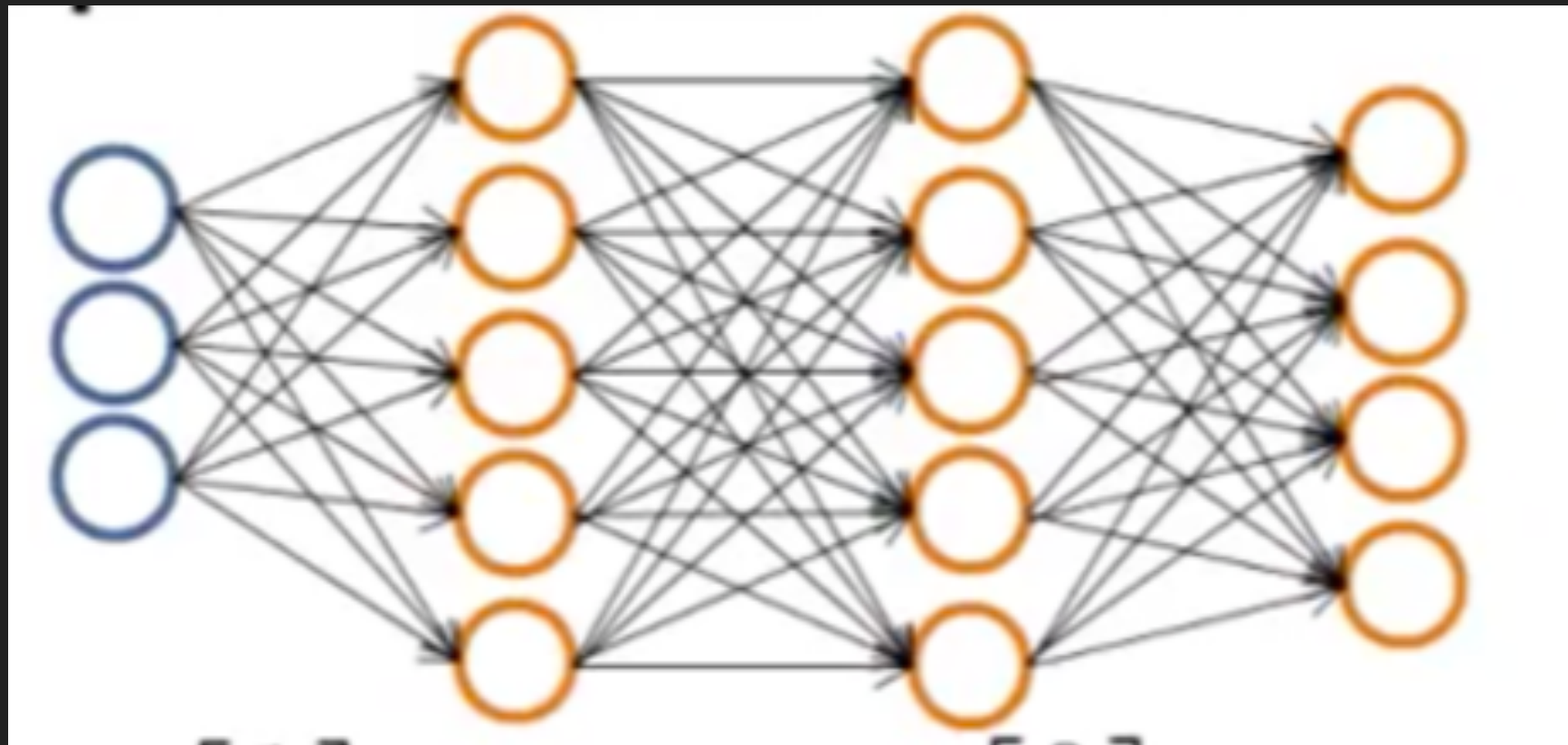


	series_id	group_id	surface
0	0	13	2
1	1	31	1
2	2	20	1
3	3	31	1
4	4	22	6



	0	1	2	3	4	5	6	7	8
0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
1	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
3	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0

SEQUENTIAL NEURAL NETWORK



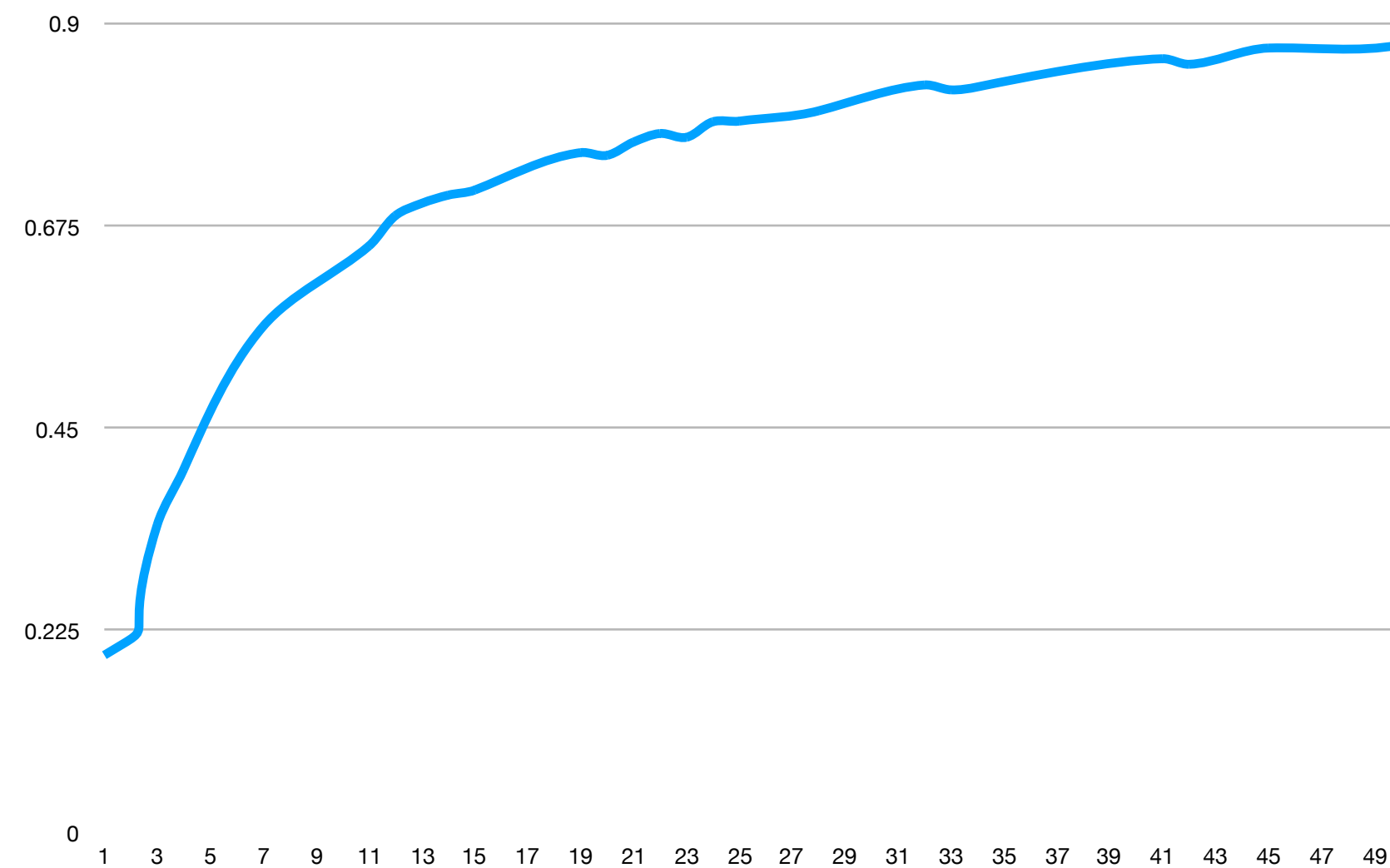
Let's divide the data in test and train using 80/20 ratio given then small dataset.

```
: xTrain, xTest, yTrain, yTest = train_test_split(Input, Y_data, test_size=0.2, random_state = 0)
```

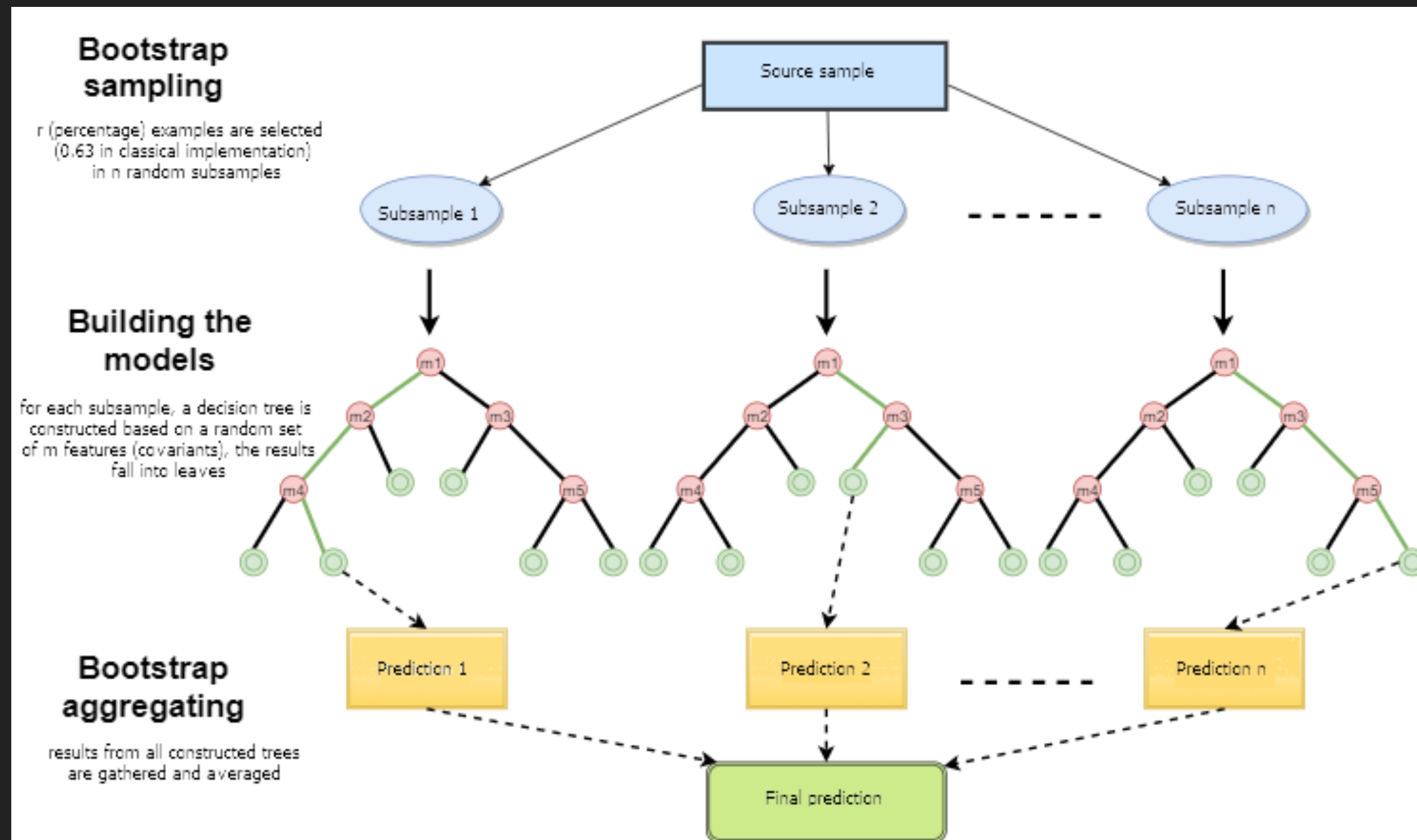
```
model = keras.Sequential()  
model.add(keras.layers.Dense(64, input_shape=(100,), activation=tf.nn.sigmoid))  
model.add(keras.layers.Dense(32, activation=tf.nn.sigmoid))  
model.add(keras.layers.Dense(16, activation=tf.nn.sigmoid))  
model.add(keras.layers.Dense(9, activation=tf.nn.softmax))  
  
model.compile(optimizer=tf.train.RMSPropOptimizer(0.01),  
              loss=tf.keras.losses.categorical_crossentropy,  
              metrics=[tf.keras.metrics.categorical_accuracy])  
  
model.fit(xTrain, yTrainOHE, epochs=50)
```

```
model.evaluate(xTest, yTestOHE)
```

```
762/762 [=====] - 0s 85us/sample - loss: 0.5579  
- categorical_accuracy: 0.8163
```



RANDOM FOREST



```

folds = StratifiedKFold(n_splits=5, shuffle=True, random_state=60)
predicted = np.zeros((xTest.shape[0],9))
measured= np.zeros((Input.shape[0]))
score = 0

for times, (trn_idx, val_idx) in enumerate(folds.split(Input.values,Y_data
['surface'].values)):
    model2 = RandomForestClassifier(n_estimators=300, max_depth=5, min_sam
ples_split=5, n_jobs=-1)
    model2.fit(Input.iloc[trn_idx],Y_data['surface'][trn_idx])
    measured[val_idx] = model2.predict(Input.iloc[val_idx])
    predicted += model2.predict_proba(xTest)/folds.n_splits
    score += model2.score(Input.iloc[val_idx],Y_data['surface'][val_idx])
    print("Fold: {} score: {}".format(times,model2.score(Input.iloc[val_id
x],Y_data['surface'][val_idx])))

gc.collect()

```

```

Fold: 0 score: 0.7023498694516971
Fold: 1 score: 0.7633986928104575
Fold: 2 score: 0.6968503937007874
Fold: 3 score: 0.6934210526315789
Fold: 4 score: 0.7357992073976222

```

```

print('Average score', score / folds.n_splits)

```

Average score 0.7183638431984287

ADDITIONAL FEATURES

```
Input2=Input.copy()
for col in X_data.columns:
    if col in ['row_id','series_id','measurement_number']:
        continue
    print ("FE on column ", col, "...")
    Input2[col + '_mad'] = X_data.groupby(['series_id'])[col].apply(lambda x: np.median(np.abs(np.diff(x))))
    Input2[col + '_abs_max'] = X_data.groupby(['series_id'])[col].apply(lambda x: np.max(np.abs(x)))
    Input2[col + '_abs_min'] = X_data.groupby(['series_id'])[col].apply(lambda x: np.min(np.abs(x)))
    Input2[col + '_abs_avg'] = (Input2[col + '_abs_min'] + Input2[col + '_abs_max'])/2
    Input2[col + '_skew'] = X_data.groupby(['series_id'])[col].skew()
    Input2[col + '_mad'] = X_data.groupby(['series_id'])[col].mad()
    Input2[col + '_q25'] = X_data.groupby(['series_id'])[col].quantile(0.25)
    Input2[col + '_q75'] = X_data.groupby(['series_id'])[col].quantile(0.75)
    Input2[col + '_q95'] = X_data.groupby(['series_id'])[col].quantile(0.95)
    Input2[col + '_iqr'] = Input2[col + '_q75'] - Input2[col + '_q25']
    Input2[col + '_SSC'] = X_data.groupby(['series_id'])[col].apply(SSC)
    Input2[col + '_skewness'] = X_data.groupby(['series_id'])[col].apply(skewness)
    Input2[col + '_wave_lenght'] = X_data.groupby(['series_id'])[col].apply(wave_length)
    Input2[col + '_norm_entropy'] = X_data.groupby(['series_id'])[col].apply(norm_entropy)
    Input2[col + '_SRAV'] = X_data.groupby(['series_id'])[col].apply(SRAV)
    Input2[col + '_kurtosis'] = X_data.groupby(['series_id'])[col].apply(_kurtosis)
    Input2[col + '_zero_crossing'] = X_data.groupby(['series_id'])[col].apply(zero_crossing)
```


MODEL

NEURAL NETWORK

```
model3 = keras.Sequential()
model3.add(keras.layers.Dense(256, input_shape=(420,), activation=tf.nn.sigmoid))
model3.add(keras.layers.Dense(128, activation=tf.nn.sigmoid))
model3.add(keras.layers.Dense(64, activation=tf.nn.sigmoid))
model3.add(keras.layers.Dense(32, activation=tf.nn.sigmoid))
model3.add(keras.layers.Dense(9, activation=tf.nn.softmax))

model3.compile(loss='categorical_crossentropy', optimizer='adam', metrics=[ 'accuracy' ])

model3.fit(xTrain2, yTrainOHE2, epochs=200)
```

```
model3.evaluate(xTest2,yTestOHE2)
```

```
762/762 [=====] - 0s 126us/sample - loss: 0.3634
- acc: 0.9094
```

```
[0.3634368342364554, 0.9094488]
```

RANDOM FOREST

```
fold2 = StratifiedKFold(n_splits=10, shuffle=True, random_state=60)
predicted2 = np.zeros((xTest.shape[0],9))
measured2= np.zeros((Input.shape[0]))
score2 = 0

for times, (trn_idx, val_idx) in enumerate(fold2.split(Input2.values,Y_data2[ 'surface' ].values)):
    model4 = RandomForestClassifier(n_estimators=700, max_depth=20, min_samples_split=5, n_jobs=-1)
    model4.fit(Input2.iloc[trn_idx],Y_data2[ 'surface' ][trn_idx])
    measured2[val_idx] = model4.predict(Input2.iloc[val_idx])
    predicted2 += model4.predict_proba(xTest2)/fold2.n_splits
    score2 += model4.score(Input2.iloc[val_idx],Y_data2[ 'surface' ][val_idx])

    print("Fold: {} score: {}".format(times,model4.score(Input2.iloc[val_idx],Y_data2[ 'surface' ][val_idx])))

gc.collect()
```

```
print('Average score', score2 / fold2.n_splits)
```

```
Average score 0.9097169076841908
```



THANKS

Alex Braga