

In [27]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [28]:

```
x_train = pd.read_csv('X_train.csv')
y_train = pd.read_csv('y_train.csv')
x_test = pd.read_csv('X_test.csv')
```

In [29]:

```
print("Shape of dataset")
print("X Train: {} \ny Train: {} \nX Test: {}".format(x_train.shape, y_train.shape, x_test.sh
```

```
Shape of dataset
X Train: (487680, 13)
y Train: (3810, 3)
X Test: (488448, 13)
```

In [66]:

```
print(y_train.sample(5))
```

	series_id	group_id	surface
3602	3602	43	wood
484	484	1	tiled
1834	1834	60	carpet
3533	3533	46	wood
2540	2540	39	concrete

In [31]:

```
x_train.head()
```

Out[31]:

	row_id	series_id	measurement_number	orientation_X	orientation_Y	orientation_Z	orientation
0	0_0	0	0	-0.75853	-0.63435	-0.10488	-0.1
1	0_1	0	1	-0.75853	-0.63434	-0.10490	-0.1
2	0_2	0	2	-0.75853	-0.63435	-0.10492	-0.1
3	0_3	0	3	-0.75852	-0.63436	-0.10495	-0.1
4	0_4	0	4	-0.75852	-0.63435	-0.10495	-0.1

In [32]:

```
x_test.head()
```

Out[32]:

	row_id	series_id	measurement_number	orientation_X	orientation_Y	orientation_Z	orientation_W
0	0_0	0	0	0.91208	-0.38193	-0.050618	0.050618
1	0_1	0	1	0.91220	-0.38165	-0.050573	0.050573
2	0_2	0	2	0.91228	-0.38143	-0.050586	0.050586
3	0_3	0	3	0.91237	-0.38121	-0.050588	0.050588
4	0_4	0	4	0.91247	-0.38096	-0.050546	0.050546

In [33]:

```
x_train.dtypes
```

Out[33]:

```

row_id          object
series_id       int64
measurement_number  int64
orientation_X    float64
orientation_Y    float64
orientation_Z    float64
orientation_W    float64
angular_velocity_X  float64
angular_velocity_Y  float64
angular_velocity_Z  float64
linear_acceleration_X  float64
linear_acceleration_Y  float64
linear_acceleration_Z  float64
dtype: object

```

In [67]:

```
y_train.dtypes
```

Out[67]:

```

series_id      int64
group_id       int64
surface        object
dtype: object

```

OBSERVATIONS:

X_train and X_test datasets have the following entries:

- **series and measurements identifiers** : row_id, series_id, measurement_number: these identify uniquely a series and measurement; there are 3809 series, each with max 127 measurements
- **measurement orientations** : orientation_X, orientation_Y, orientation_Z, orientation_W
- **angular velocities** : angular_velocity_X, angular_velocity_Y, angular_velocity_Z
- **linear accelerations** : linear_acceleration_X, linear_acceleration_Y, linear_acceleration_Z

y_train has the following columns:

- **series_id** - this corresponds to the series in train data
- **group_id**
- **surface** - this is the surface type that need to be predicted

Checking for missing values :

In [34]:

```
print(x_train.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
```

In [35]:

```
print(x_test.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
```

In [36]:

```
print(y_train.isnull().sum())
```

```
series_id      0
group_id       0
surface        0
dtype: int64
```

observation: no missing values in dataset

In [37]:

```
x_train.describe()
```

Out[37]:

	series_id	measurement_number	orientation_X	orientation_Y	orientation_Z	orientation_W
count	487680.000000	487680.000000	487680.000000	487680.000000	487680.000000	487680.000000
mean	1904.500000	63.500000	-0.018050	0.075062	0.012458	-0.000000
std	1099.853353	36.949327	0.685696	0.708226	0.105972	0.000000
min	0.000000	0.000000	-0.989100	-0.989650	-0.162830	-0.989100
25%	952.000000	31.750000	-0.705120	-0.688980	-0.089466	-0.705120
50%	1904.500000	63.500000	-0.105960	0.237855	0.031949	-0.000000
75%	2857.000000	95.250000	0.651803	0.809550	0.122870	0.651803
max	3809.000000	127.000000	0.989100	0.988980	0.155710	0.989100

In [38]:

```
x_test.describe()
```

Out[38]:

	series_id	measurement_number	orientation_X	orientation_Y	orientation_Z	orientation
count	488448.000000	488448.000000	488448.000000	488448.000000	488448.000000	488448.000000
mean	1907.500000	63.500000	0.031996	0.120651	0.018735	0.018735
std	1101.585403	36.949327	0.671977	0.714522	0.108481	0.108481
min	0.000000	0.000000	-0.989720	-0.989810	-0.154680	-0.154680
25%	953.750000	31.750000	-0.648130	-0.744503	-0.112660	-0.112660
50%	1907.500000	63.500000	0.132910	0.397860	0.057271	0.057271
75%	2861.250000	95.250000	0.575270	0.803600	0.124770	0.124770
max	3815.000000	127.000000	0.989320	0.988940	0.154250	0.154250

In [68]:

```
y_train.describe(include='object')
```

Out[68]:

	surface
count	3810
unique	9
top	concrete
freq	779

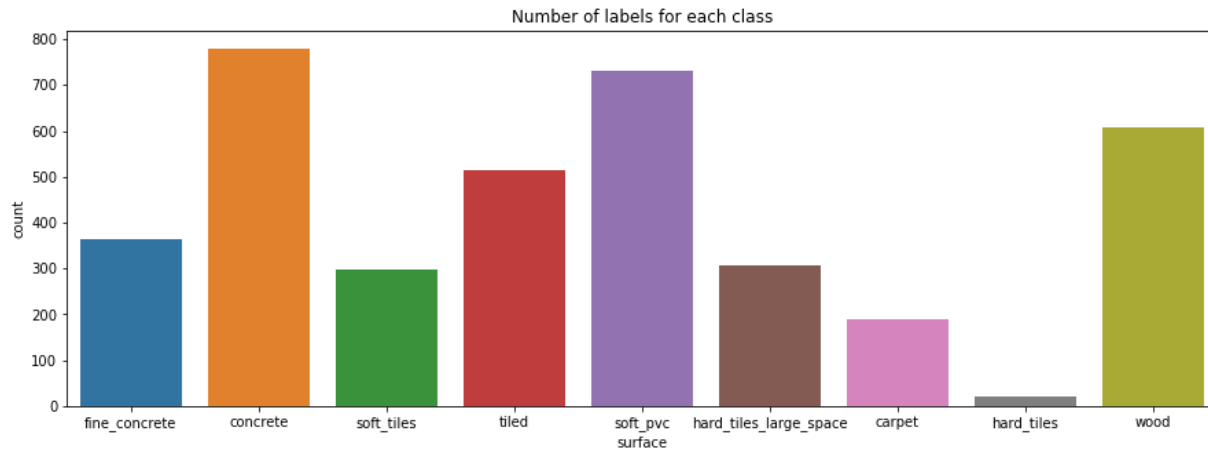
Observation:

There is the same number of series in X_train and y_train, numbered from 0 to 3809 (total 3810). Each series have 128 measurements. Each series in train dataset is part of a group (numbered from 0 to 72, 72 being the half of 128). The number of rows in X_train and X_test differs with 6 x 128, 128 being the number of measurements for each group.

Distribution of target variable:

In [40]:

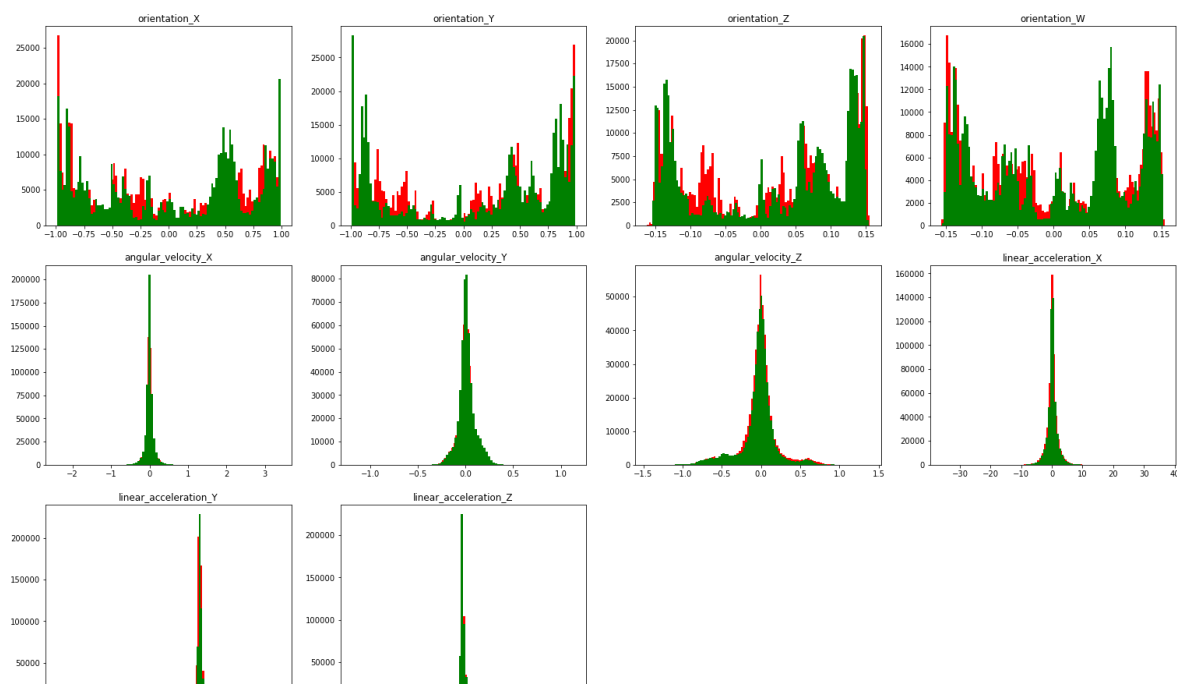
```
import warnings
warnings.filterwarnings('ignore')
f, ax = plt.subplots(1,1, figsize=(15,5))
graph = sns.countplot(y_train['surface'])
graph.set_title("Number of labels for each class")
plt.show()
```



Distribution of Train(red) and Test(green) features:

In [41]:

```
plt.figure(figsize=(26, 16))
for i, col in enumerate(x_train.columns[3:]):
    plt.subplot(3, 4, i+1)
    plt.hist(x_train[col], color='red', bins=100)
    plt.hist(x_test[col], color='green', bins=100)
    plt.title(col)
```

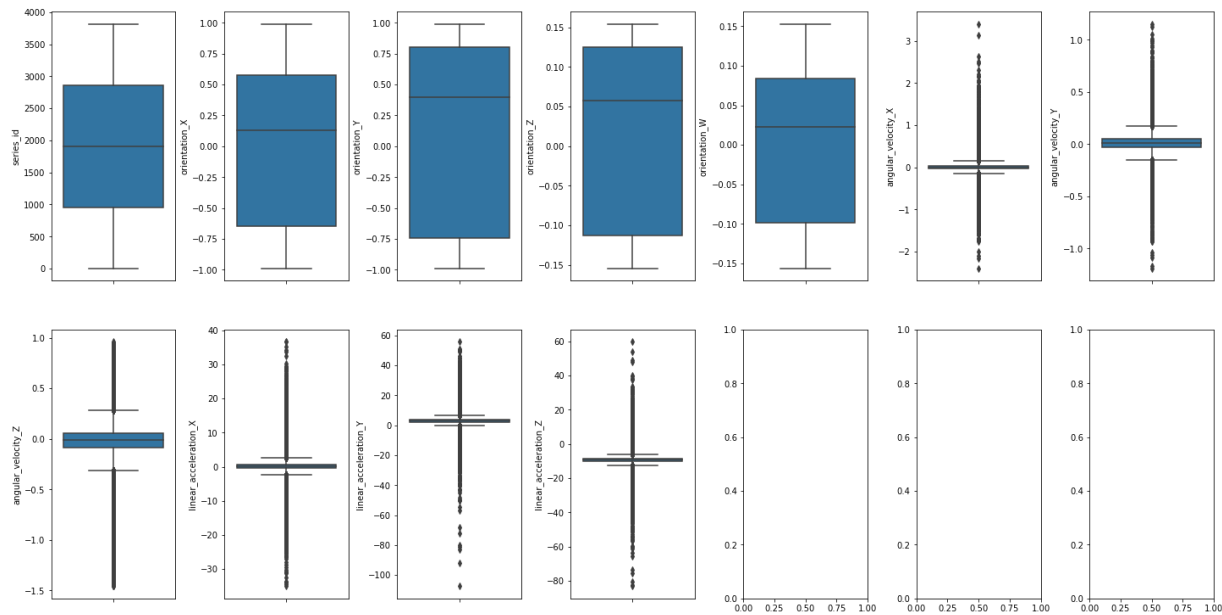


Observations:

- Velocity and acceleration have normal distribution
- Feature distributions in train and test are quite similar.

In [71]:

```
fig, axs = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
axs = axs.flatten()
for k,v in x_test.items():
    sns.boxplot(y=k, data=x_test, ax=axs[index])
    index += 1
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=5.0)
```



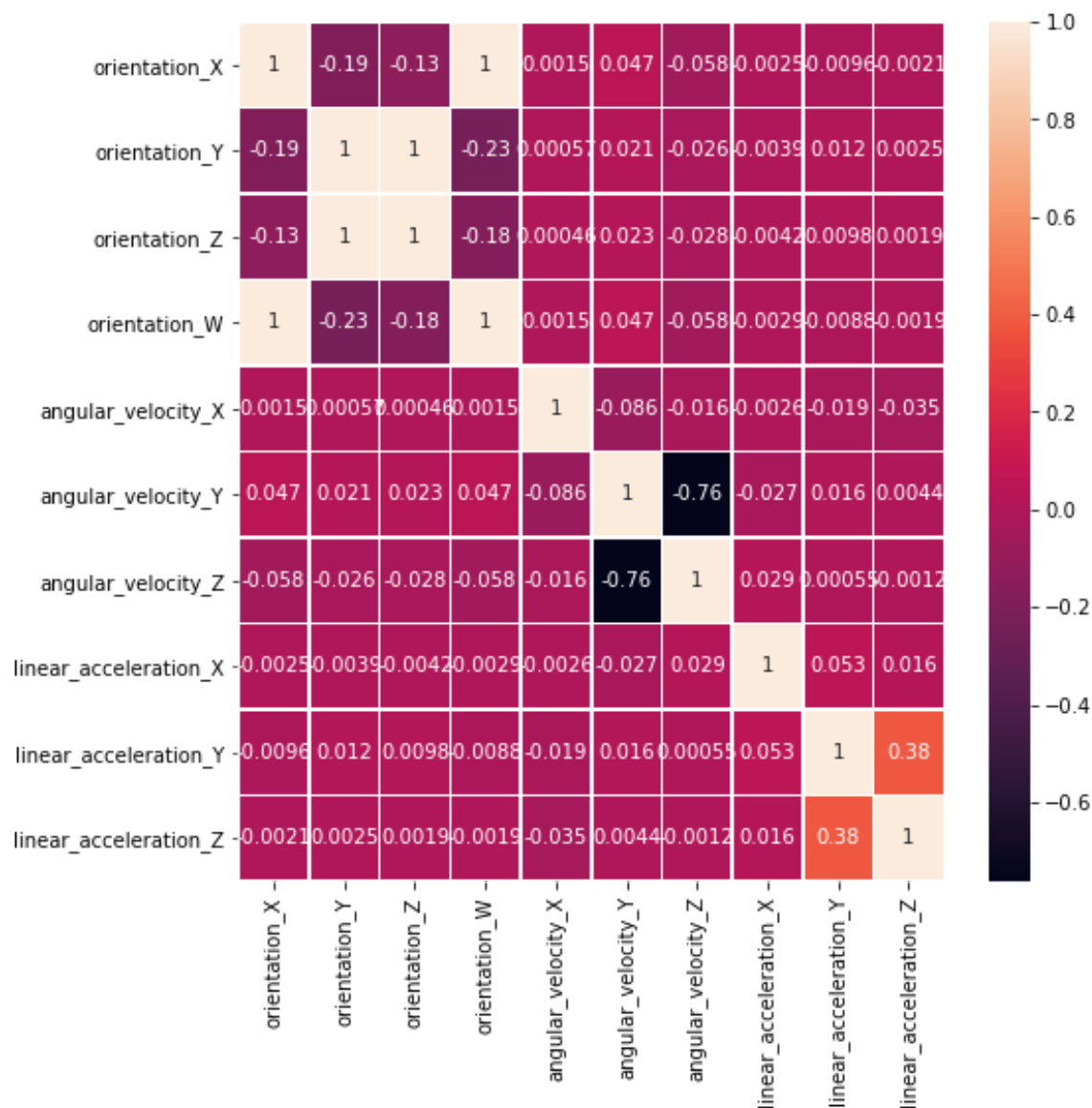
Correlation heatmaps:

In [42]:

```
f,ax = plt.subplots(figsize=(8, 8))
sns.heatmap(x_train.iloc[:,3:].corr(), annot=True, linewidths=.5)
```

Out[42]:

<matplotlib.axes._subplots.AxesSubplot at 0x2a28f171b48>

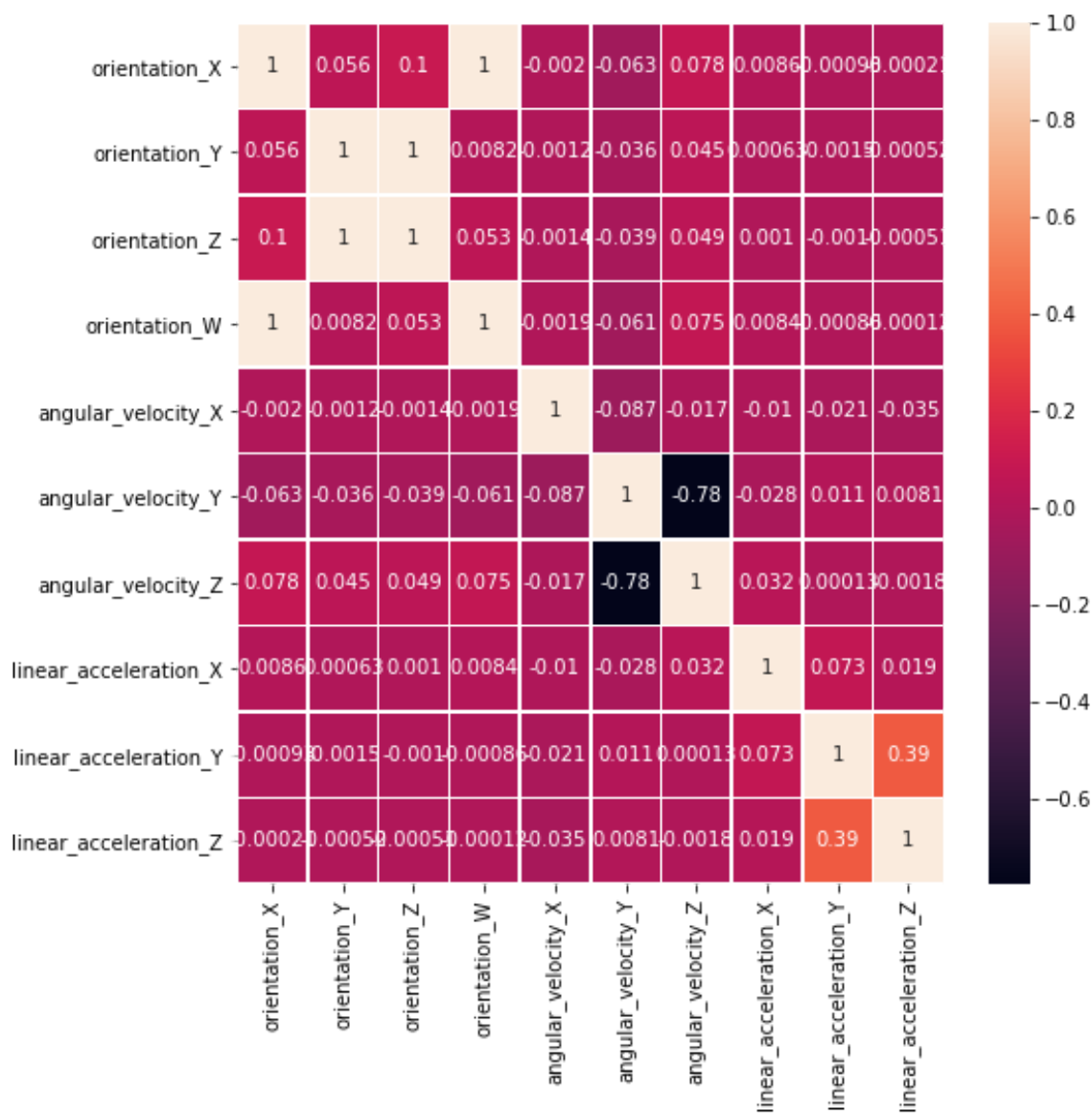


In [43]:

```
f,ax = plt.subplots(figsize=(8, 8))
sns.heatmap(x_test.iloc[:,3:].corr(), annot=True, linewidths=.5)
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2a2939f3608>
```

**Observation:**

There is a strong correlation between:

- angular_velocity_Z and angular_velocity_Y
- orientation_X and orientation_Y
- orientation_Y and orientation_Z

Feature Engineering:

Merging x_train and y_train into a single data-frame

In [44]:

```
df = pd.merge(x_train,y_train,how='left',on='series_id')
df.sample()
```

Out[44]:

	row_id	series_id	measurement_number	orientation_X	orientation_Y	orientation_Z	o
427725	3341_77	3341	77	-0.9848	0.082082	0.007407	

In [45]:

```
df.drop(columns=["row_id","measurement_number","group_id"], inplace=True)
df.sample(2)
```

Out[45]:

	series_id	orientation_X	orientation_Y	orientation_Z	orientation_W	angular_velocity_X
337671	2638	-0.95176	0.26741	0.034794	-0.146390	-0.028428
238244	1861	0.11640	0.98232	0.146260	0.009979	-0.022359

In [46]:

```
just_check = df.groupby("series_id").mean().reset_index()
df = pd.merge(just_check,y_train,how='left',on='series_id')
df.sample(3)
```

Out[46]:

	series_id	orientation_X	orientation_Y	orientation_Z	orientation_W	angular_velocity_X	an
331	331	-0.388866	-0.908631	-0.144438	-0.048040	0.009423	
69	69	0.800486	-0.580899	-0.082066	0.122626	0.004783	
732	732	0.226724	0.961707	0.151068	0.029913	0.000041	

In [47]:

```
df.drop(columns=["series_id","group_id"],inplace=True)
```

Model Building:

Splitting merged data frame into train and test splits:

In [48]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
train = scaler.fit_transform(df[df.columns[:-1]])
train_x, test_x, train_y, test_y = train_test_split(train,df[df.columns[-1]],test_size = 0.
```

In [49]:

```
train_x.shape
```

Out[49]:

```
(3429, 10)
```

Random Forest base model

In [50]:

```
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(train_x, train_y)
target = model.predict(test_x)
mat = confusion_matrix(test_y, target)
print("*****confusion*****\n",mat)
```

```
*****confusion*****
[[11  3  0  0  0  0  1  3  3]
 [ 0 68  3  0  0  7  0  1  4]
 [ 0  2 24  0  0  0  0  0  2]
 [ 0  0  0  2  1  0  0  0  0]
 [ 1  2  1  0 23  1  1  1  2]
 [ 0  1  2  0  1 71  0  1  2]
 [ 0  6  1  0  1  4 21  1  0]
 [ 1  3  0  0  0  4  0 43  3]
 [ 0  5  3  0  1  2  1  2 34]]
```

In [51]:

```
x_test.drop(columns=["row_id", "measurement_number"], inplace=True)
testing = x_test.groupby("series_id").mean().reset_index()
testing.sample(3)
testing.shape
```

Out[51]:

(3816, 11)

In [52]:

```
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
fin_train = scale.fit_transform(df[df.columns[:-1]])
test = scale.transform(testing[testing.columns[1:]])
```

Final model: XG boosted Classifier

In [53]:

```
from xgboost import XGBClassifier

model = XGBClassifier()
model.fit(fin_train, df[df.columns[-1]])
target = model.predict(test)
```

In [54]:

```
a = testing.series_id.tolist()
b = target
submission = pd.DataFrame({"series_id":a, "surface":b})
```

In [55]:

```
submission.surface.value_counts()
```

Out[55]:

```
concrete      1086
wood           702
soft_pvc       569
fine_concrete  378
tiled          334
hard_tiles_large_space  312
soft_tiles     268
carpet         163
hard_tiles       4
Name: surface, dtype: int64
```

In [56]:

```
submission.to_csv("submission_final.csv",index=False)
```

In [57]:

```
import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import confusion_matrix, accuracy_score
from xgboost import XGBClassifier
for i in range(4,10):
    model = XGBClassifier(model_depth = i)
    model.fit(train_x, train_y)
    target = model.predict(test_x)
    print("accuracy : ", accuracy_score(target, test_y))
mat = confusion_matrix(test_y, target)
print("*****confusion matrix*****\n", mat)
```

[07:15:29] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\learner.cc:516:
Parameters: { model_depth } might not be used.

This may not be accurate due to some parameters are only used in language bindings but passed down to XGBoost core. Or some parameters are not used but slip through this verification. Please open an issue if you find above cases.

accuracy : 0.7926509186351706
[07:15:31] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\learner.cc:516:
Parameters: { model_depth } might not be used.

This may not be accurate due to some parameters are only used in language bindings but passed down to XGBoost core. Or some parameters are not used but slip through this verification. Please open an issue if you find above cases.

accuracy : 0.7926509186351706
[07:15:33] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\learner.cc:516:
Parameters: { model_depth } might not be used.

This may not be accurate due to some parameters are only used in language bindings but passed down to XGBoost core. Or some parameters are not used but slip through this verification. Please open an issue if you find above cases.

accuracy : 0.7926509186351706
[07:15:35] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\learner.cc:516:
Parameters: { model_depth } might not be used.

This may not be accurate due to some parameters are only used in language

e bindings but
 passed down to XGBoost core. Or some parameters are not used but slip t
 hrough this
 verification. Please open an issue if you find above cases.

accuracy : 0.7926509186351706
 [07:15:37] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release
 _1.2.0\src\learner.cc:516:
 Parameters: { model_depth } might not be used.

This may not be accurate due to some parameters are only used in languag
 e bindings but
 passed down to XGBoost core. Or some parameters are not used but slip t
 hrough this
 verification. Please open an issue if you find above cases.

accuracy : 0.7926509186351706
 [07:15:39] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release
 _1.2.0\src\learner.cc:516:
 Parameters: { model_depth } might not be used.

This may not be accurate due to some parameters are only used in languag
 e bindings but
 passed down to XGBoost core. Or some parameters are not used but slip t
 hrough this
 verification. Please open an issue if you find above cases.

accuracy : 0.7926509186351706
 *****confusion matrix*****
 [[14 3 0 0 0 0 0 2 2]
 [0 74 2 0 0 4 0 0 3]
 [0 1 25 0 0 0 1 0 1]
 [0 0 0 1 1 1 0 0 0]
 [1 1 1 0 24 2 1 1 1]
 [0 1 2 0 1 69 0 1 4]
 [0 7 1 0 1 3 21 1 0]
 [2 4 0 0 0 3 2 39 4]
 [1 4 3 0 0 3 0 2 35]]

Final accuracy of model : 0.79

This was my first cut solution to the problem . A more detailed solution will be updated here in the future.