CompeticaoDSA-Set19

September 26, 2019

1 Competição DSA de Machine Learning - Edição Setembro/2019

1.1 MARCIO DE LIMA

2 Problema

Cada vez mais os robôs estão presentes em nosso dia a dia. Mas para que os robôs possam entender e navegar adequadamente por um local, eles precisam de informações sobre seu ambiente.

Nesta competição, você ajudará robôs (especificamente veículos autônomos terrestres) a reconhecer a superfície do piso em que estão, usando os dados coletados por sensores IMU (Inertial Measurement Units).

Os dados usados nesta competição foram coletados pelo Departamento de Processamento de Sinais da Tampere University na Finlândia. A coleta dos dados foi feita com um pequeno robô móvel equipado com sensores IMU sobre diferentes superfícies do piso nas instalações da universidade. A tarefa é prever em qual dos nove tipos de piso (carpete, ladrilhos, concreto, etc. . .) o robô está usando dados do sensor, como aceleração e velocidade. Tenha sucesso nesta competição e você ajudará a melhorar a navegação dos robôs autônomos em muitas superfícies diferentes.

** SE ESSE CODIGO FOR UTIL, VOTE , POR FAVOR **

3 Carregando os dados

In [1]:
```
# Importando as bibliotecas
import os
path = os.getcwd()

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from IPython.core.pylabtools import figsize
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, MinMaxScaler, StandardSc
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier as xgb

import gc
```

```
import seaborn as sns
import warnings

%matplotlib inline
warnings.filterwarnings("ignore")
```

In [2]:
```
# Importando os datasets
df_treino = pd.read_csv('data/X_treino.csv', low_memory=False)
df_treino_y = pd.read_csv('data/y_treino.csv', low_memory=False)
```

In [3]:
```
# Efetuando Merge dos dataSets de Treino - Chave: series_id

df = pd.merge(df_treino, df_treino_y, on='series_id', how='left')
df.shape
```

Out[3]: (487680, 15)

In [4]:
```
df.head(20)
```

Out[4]:

	row_id	series_id	measurement_number	orientation_X	orientation_Y	\
0	0_0	0	0	-0.75853	-0.63435	
1	0_1	0	1	-0.75853	-0.63434	
2	0_2	0	2	-0.75853	-0.63435	
3	0_3	0	3	-0.75852	-0.63436	
4	0_4	0	4	-0.75852	-0.63435	
5	0_5	0	5	-0.75853	-0.63439	
6	0_6	0	6	-0.75853	-0.63441	
7	0_7	0	7	-0.75852	-0.63444	
8	0_8	0	8	-0.75851	-0.63445	
9	0_9	0	9	-0.75851	-0.63443	
10	0_10	0	10	-0.75848	-0.63443	
11	0_11	0	11	-0.75847	-0.63444	
12	0_12	0	12	-0.75846	-0.63448	
13	0_13	0	13	-0.75846	-0.63445	
14	0_14	0	14	-0.75842	-0.63447	
15	0_15	0	15	-0.75838	-0.63447	
16	0_16	0	16	-0.75835	-0.63447	
17	0_17	0	17	-0.75835	-0.63451	
18	0_18	0	18	-0.75835	-0.63453	
19	0_19	0	19	-0.75833	-0.63456	

	orientation_Z	orientation_W	angular_velocity_X	angular_velocity_Y	\
0	-0.10488	-0.10597	0.107650	0.017561	
1	-0.10490	-0.10600	0.067851	0.029939	
2	-0.10492	-0.10597	0.007275	0.028934	
3	-0.10495	-0.10597	-0.013053	0.019448	
4	-0.10495	-0.10596	0.005135	0.007652	
5	-0.10483	-0.10580	0.059664	0.013043	
6	-0.10481	-0.10569	0.082140	0.044356	

7	-0.10480	-0.10561	0.056218	0.038162
8	-0.10485	-0.10559	-0.012846	0.039004
9	-0.10489	-0.10567	-0.090082	0.027299
10	-0.10497	-0.10575	-0.088418	0.011778
11	-0.10499	-0.10573	0.000671	0.022855
12	-0.10495	-0.10570	0.040139	-0.003868
13	-0.10504	-0.10573	-0.014728	0.001884
14	-0.10512	-0.10582	-0.097677	0.008167
15	-0.10525	-0.10597	-0.156020	0.012320
16	-0.10536	-0.10607	-0.123310	0.012997
17	-0.10518	-0.10598	-0.008814	-0.030847
18	-0.10511	-0.10595	0.050935	-0.024422
19	-0.10512	-0.10596	-0.005211	0.005175

	angular_velocity_Z	linear_acceleration_X	linear_acceleration_Y	\
0	0.000767	-0.748570	2.103000	
1	0.003385	0.339950	1.506400	
2	-0.005978	-0.264290	1.592200	
3	-0.008974	0.426840	1.099300	
4	0.005245	-0.509690	1.468900	
5	-0.013231	-0.447450	0.992810	
6	-0.002696	-0.141630	0.734970	
7	-0.022931	-0.121600	0.075417	
8	-0.007831	1.600000	0.816110	
9	-0.009970	0.474960	0.909600	
10	-0.016589	1.594300	0.372050	
11	-0.005791	0.936820	0.126510	
12	-0.030181	0.672260	0.851970	
13	-0.010793	1.497800	1.620500	
14	-0.026073	0.091442	1.244900	
15	-0.026409	1.656300	2.153600	
16	-0.011022	0.396550	1.948800	
17	-0.021756	0.327960	1.219600	
18	-0.018136	0.774420	2.607700	
19	-0.026287	0.438190	3.672600	

	linear_acceleration_Z	group_id	surface
0	-9.7532	13	fine_concrete
1	-9.4128	13	fine_concrete
2	-8.7267	13	fine_concrete
3	-10.0960	13	fine_concrete
4	-10.4410	13	fine_concrete
5	-10.4020	13	fine_concrete
6	-9.4296	13	fine_concrete
7	-8.6088	13	fine_concrete
8	-7.6426	13	fine_concrete
9	-8.8120	13	fine_concrete
10	-11.2160	13	fine_concrete

```
11              -11.2730        13  fine_concrete
12               -9.3933        13  fine_concrete
13               -7.8959        13  fine_concrete
14               -8.1673        13  fine_concrete
15               -9.7079        13  fine_concrete
16              -11.8300        13  fine_concrete
17              -12.5120        13  fine_concrete
18               -9.5633        13  fine_concrete
19               -6.8334        13  fine_concrete
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 487680 entries, 0 to 487679
Data columns (total 15 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
group_id                 487680 non-null int64
surface                  487680 non-null object
dtypes: float64(10), int64(3), object(2)
memory usage: 59.5+ MB
```

In [6]:
```
# Sumário estatístico
df.describe()
```

Out[6]:
```
           series_id  measurement_number  orientation_X  orientation_Y  \
count  487680.000000       487680.000000  487680.000000  487680.000000
mean     1904.500000           63.500000      -0.018050       0.075062
std      1099.853353           36.949327       0.685696       0.708226
min         0.000000            0.000000      -0.989100      -0.989650
25%       952.000000           31.750000      -0.705120      -0.688980
50%      1904.500000           63.500000      -0.105960       0.237855
75%      2857.000000           95.250000       0.651803       0.809550
max      3809.000000          127.000000       0.989100       0.988980

       orientation_Z  orientation_W  angular_velocity_X  angular_velocity_Y  \
count  487680.000000  487680.000000       487680.000000       487680.000000
```

```
mean         0.012458      -0.003804            0.000178            0.008338
std          0.105972       0.104299            0.117764            0.088677
min         -0.162830      -0.156620           -2.371000           -0.927860
25%         -0.089466      -0.106060           -0.040752           -0.033191
50%          0.031949      -0.018704            0.000084            0.005412
75%          0.122870       0.097215            0.040527            0.048068
max          0.155710       0.154770            2.282200            1.079100

       angular_velocity_Z  linear_acceleration_X  linear_acceleration_Y  \
count       487680.000000          487680.000000          487680.000000
mean            -0.019184               0.129281               2.886468
std              0.229153               1.870600               2.140067
min             -1.268800             -36.067000            -121.490000
25%             -0.090743              -0.530833               1.957900
50%             -0.005335               0.124980               2.879600
75%              0.064604               0.792263               3.798800
max              1.387300              36.797000              73.008000

       linear_acceleration_Z       group_id
count          487680.000000  487680.000000
mean               -9.364886      37.601312
std                 2.845341      20.980011
min               -75.386000       0.000000
25%               -10.193000      19.000000
50%                -9.365300      39.000000
75%                -8.522700      55.000000
max                65.839000      72.000000
```

4 Tratamento e Verificação dos Dados

In [7]:
```
#Verificando se existem dados null
df.isnull().values.any()
```

Out[7]:
```
False
```

In [8]:
```
#Checando valores NA nos dados
df.isna().any()[lambda x: x]
```

Out[8]:
```
Series([], dtype: bool)
```

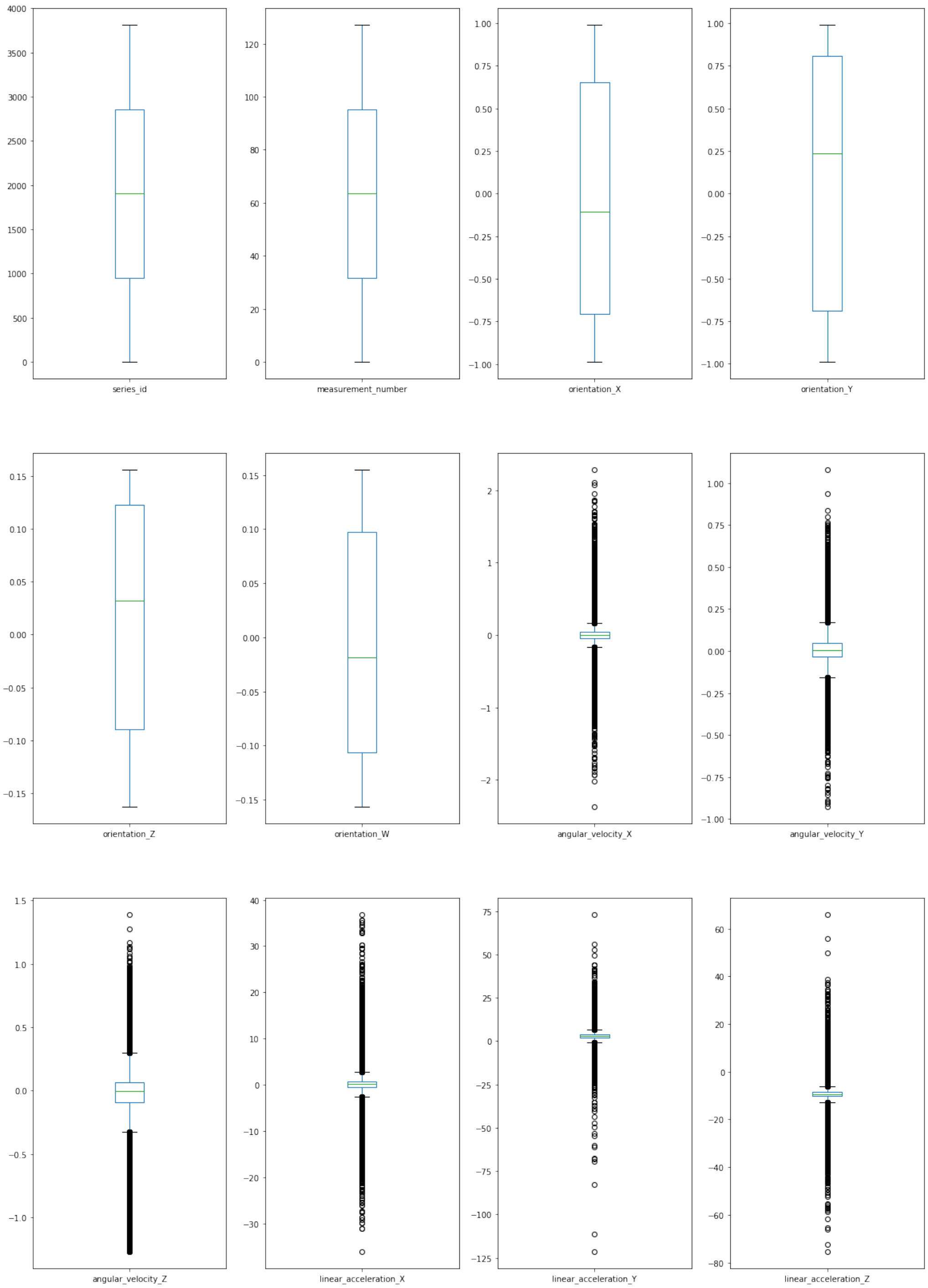
In [9]:
```
#Eliminando coluna sem utilidade
df = df.drop('row_id', axis=1)
df = df.drop('group_id', axis=1)
```

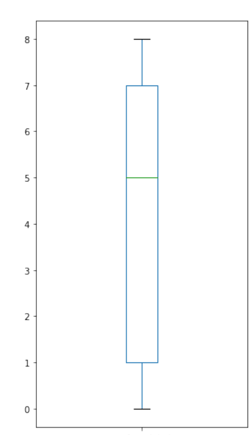
In [10]:
```
# Transformando a varíavel Target em Números com o LabelEncoder
labelencoder_surface = LabelEncoder()
df['surface_label'] = labelencoder_surface.fit_transform(df['surface'])

df.head(5)
```

```
Out[10]:    series_id  measurement_number  orientation_X  orientation_Y  orientation_Z  \
         0          0                   0       -0.75853       -0.63435       -0.10488
         1          0                   1       -0.75853       -0.63434       -0.10490
         2          0                   2       -0.75853       -0.63435       -0.10492
         3          0                   3       -0.75852       -0.63436       -0.10495
         4          0                   4       -0.75852       -0.63435       -0.10495

            orientation_W  angular_velocity_X  angular_velocity_Y  angular_velocity_Z  \
         0       -0.10597            0.107650            0.017561            0.000767
         1       -0.10600            0.067851            0.029939            0.003385
         2       -0.10597            0.007275            0.028934           -0.005978
         3       -0.10597           -0.013053            0.019448           -0.008974
         4       -0.10596            0.005135            0.007652            0.005245

            linear_acceleration_X  linear_acceleration_Y  linear_acceleration_Z  \
         0               -0.74857                 2.1030                -9.7532
         1                0.33995                 1.5064                -9.4128
         2               -0.26429                 1.5922                -8.7267
         3                0.42684                 1.0993               -10.0960
         4               -0.50969                 1.4689               -10.4410

                  surface  surface_label
         0  fine_concrete              2
         1  fine_concrete              2
         2  fine_concrete              2
         3  fine_concrete              2
         4  fine_concrete              2
```

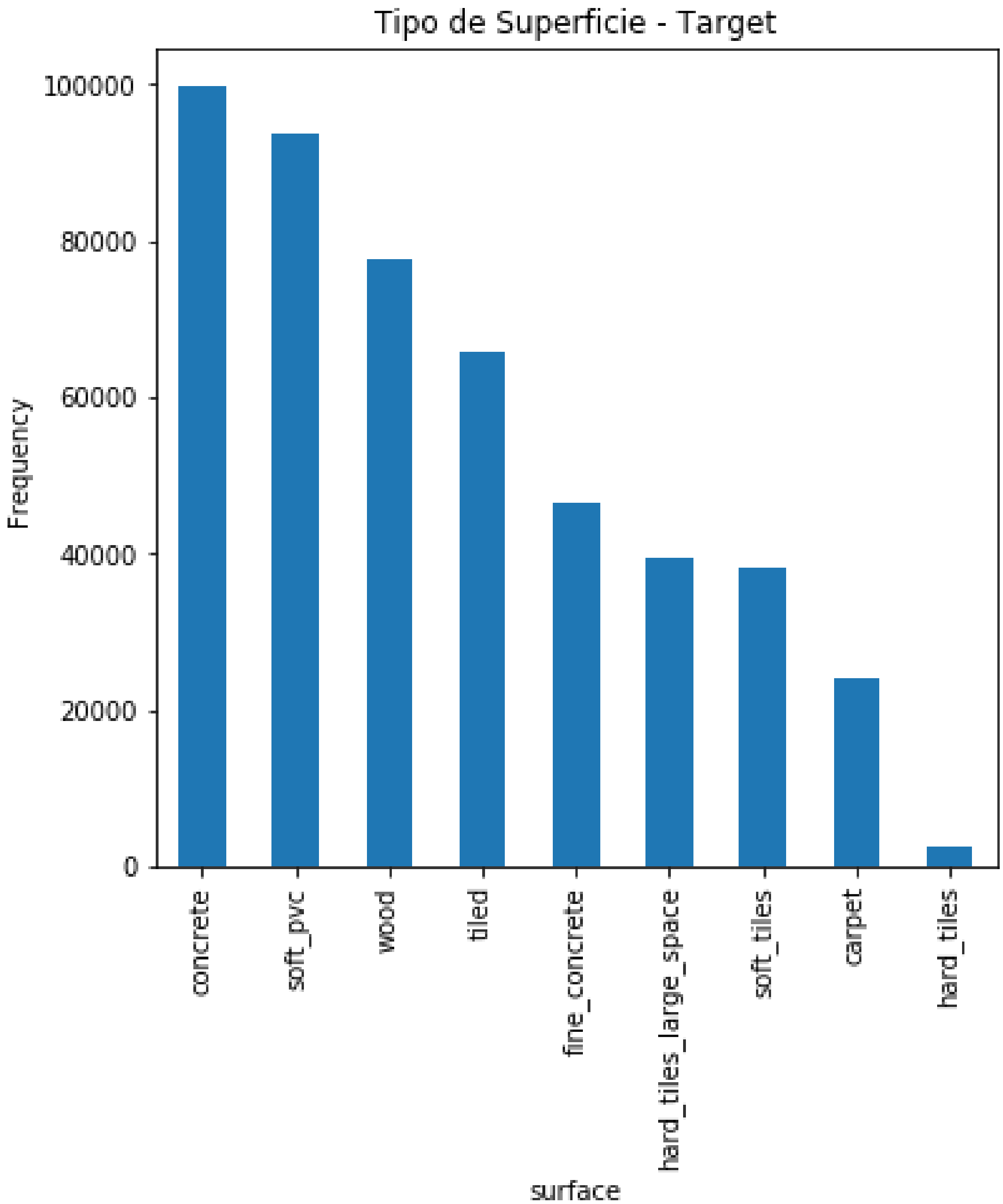
5 Explorando os dados

```
In [11]: # Box-Plot
         df.plot(kind = 'box', subplots = True, layout = (7,4), sharex = False, sharey = False
         plt.show()
```


series_id
measurement_number
orientation_X
orientation_Y
orientation_Z
orientation_W
angular_velocity_X
angular_velocity_Y
angular_velocity_Z
linear_acceleration_X
linear_acceleration_Y
linear_acceleration_Z


surface_label

```
In [12]: df['surface'].value_counts().plot(kind='bar', figsize=(6,6))
         plt.title('Tipo de Superficie - Target')
         plt.xlabel('surface')
         plt.ylabel('Frequency')
         plt.show()
```

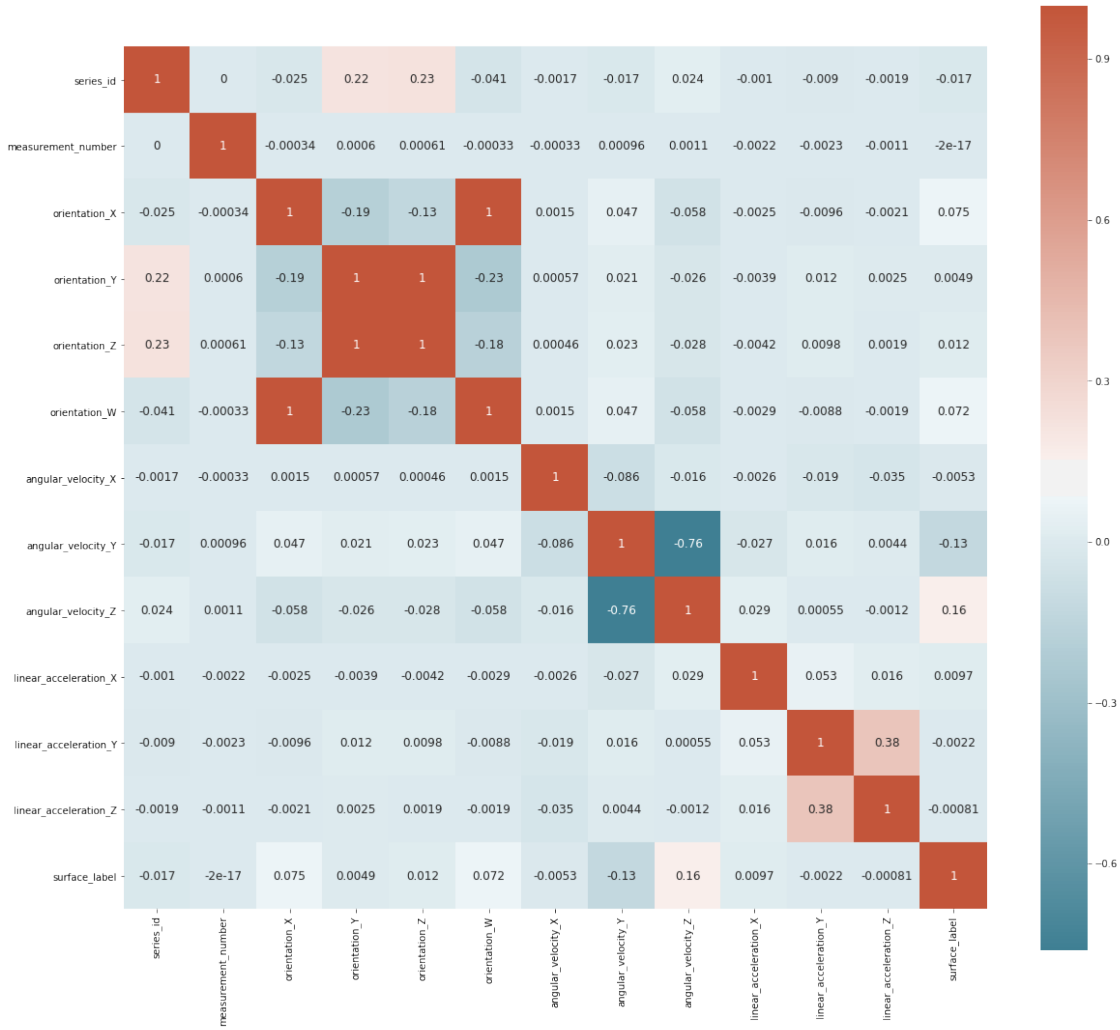


In [13]:
```
# Verificando o skew de cada atributo
df.skew()
```

Out[13]:
```
series_id                 0.000000
measurement_number        0.000000
orientation_X             0.027906
orientation_Y            -0.180998
orientation_Z            -0.175208
orientation_W             0.039368
angular_velocity_X        0.052843
angular_velocity_Y        0.112263
angular_velocity_Z       -0.275458
linear_acceleration_X     0.111975
linear_acceleration_Y    -1.093905
linear_acceleration_Z    -0.065355
surface_label            -0.159903
dtype: float64
```

6 Correlação entre as variáveis

In [14]:
```
corr = df.corr()
_ , ax = plt.subplots( figsize =( 20 , 20 ) )
cmap = sns.diverging_palette( 220 , 20 , as_cmap = True )
_ = sns.heatmap(corr, cmap = cmap, square=True, cbar_kws={ 'shrink' : .9 }, ax=ax, ann
```




```
In [15]: # Correlação com a variavel TARGET
         correlations_data = df[df.columns.drop('surface_label')].corrwith(df.surface_label).s
         # Correlacao Negativa - Primeiros 5
         print(correlations_data.head(5))
         print('\n')
         #Correlação Positiva - Ultimos 5
         print(correlations_data.tail(5))
```

```
angular_velocity_Y       -0.126276
series_id                -0.017232
angular_velocity_X       -0.005343
linear_acceleration_Y    -0.002226
linear_acceleration_Z    -0.000807
dtype: float64
```

```
linear_acceleration_X     0.009695
orientation_Z             0.012337
orientation_W             0.072415
orientation_X             0.074993
angular_velocity_Z        0.158000
dtype: float64
```

In [16]:
```
# Limpando a memoria - Force
gc.collect()
```

Out[16]:
```
52318
```

7 Modelagem dos Dados

In [17]:
```
seed = 1313
df.surface.value_counts()
```

Out[17]:
```
concrete                  99712
soft_pvc                  93696
wood                      77696
tiled                     65792
fine_concrete             46464
hard_tiles_large_space    39424
soft_tiles                38016
carpet                    24192
hard_tiles                 2688
Name: surface, dtype: int64
```

In [18]:
```
df.columns
```

Out[18]:
```
Index(['series_id', 'measurement_number', 'orientation_X', 'orientation_Y',
       'orientation_Z', 'orientation_W', 'angular_velocity_X',
       'angular_velocity_Y', 'angular_velocity_Z', 'linear_acceleration_X',
       'linear_acceleration_Y', 'linear_acceleration_Z', 'surface',
       'surface_label'],
      dtype='object')
```

In [19]:
```
# Montagem dos dados
array = df.values
X = array[:,0:12]
Y_texto = df.surface.values
Y = df.surface_label.values
```

In [20]:
```
X.shape , Y.shape
```

Out[20]:
```
((487680, 12), (487680,))
```

In [21]:
```
# Igualando a escala dos dados
X = MinMaxScaler(feature_range = (0, 1)).fit_transform(X)
```

```
In [22]: # Padronizando os dados
         X = StandardScaler().fit_transform(X)

In [23]: X

Out[23]: array([[-1.73159626, -1.71857161, -1.07989683, ..., -0.46928895,
                 -0.36609528, -0.13647385],
                [-1.73159626, -1.69150749, -1.07989683, ...,  0.11262123,
                 -0.64487185, -0.01683956],
                [-1.73159626, -1.66444337, -1.07989683, ..., -0.21039847,
                 -0.60477961,  0.2242917 ],
                ...,
                [ 1.73159626,  1.66444337,  0.94350897, ...,  1.37684263,
                  0.64284601,  0.42897738],
                [ 1.73159626,  1.69150749,  0.94368397, ...,  1.28927705,
                  0.85349381, -0.02762914],
                [ 1.73159626,  1.71857161,  0.94385898, ...,  0.37134063,
                  0.64887386, -0.39823535]])
```

8 Dividindo os dados de Treino e Teste

```
In [24]: X_treino, X_teste, Y_treino, Y_teste = train_test_split(X, Y, test_size=0.30, random_s

In [25]: X_treino.shape, Y_treino.shape, X_teste.shape, Y_teste.shape

Out[25]: ((341376, 12), (341376,), (146304, 12), (146304,))
```

9 Feature selection com Random Forest

```
In [26]: # Feature selection com Random Forest
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.feature_selection import SelectFromModel

         clf = RandomForestClassifier(random_state=seed)
         selector = clf.fit(X_treino, Y_treino)
         fs = SelectFromModel(selector, prefit=True)

         X_treino_new = fs.transform(X_treino)
         X_teste_new = fs.transform(X_teste)

         feature_idx = fs.get_support()
         feature_idx = np.append(feature_idx, [False, False])
         colunasSelecionadas = df.columns[feature_idx]

         print(X_treino_new.shape, X_teste_new.shape)

(341376, 6) (146304, 6)
```

```
In [27]: colunasSelecionadas
```

```
Out[27]: Index(['series_id', 'orientation_X', 'orientation_Y', 'orientation_Z',
                'orientation_W', 'angular_velocity_Z'],
               dtype='object')
```

```
In [28]: df.columns
```

```
Out[28]: Index(['series_id', 'measurement_number', 'orientation_X', 'orientation_Y',
                'orientation_Z', 'orientation_W', 'angular_velocity_X',
                'angular_velocity_Y', 'angular_velocity_Z', 'linear_acceleration_X',
                'linear_acceleration_Y', 'linear_acceleration_Z', 'surface',
                'surface_label'],
               dtype='object')
```

10 Treinando vários modelos juntos - Modelos de Classificacao Basicos

```
In [29]: from sklearn.tree import DecisionTreeClassifier
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.naive_bayes import GaussianNB
         from sklearn.model_selection import KFold
         from sklearn.model_selection import cross_val_score

         # Definindo os valores para o número de folds
         num_folds = 15

         # Preparando a lista de modelos
         modelos = []
         modelos.append(('NB', GaussianNB()))
         modelos.append(('KNN', KNeighborsClassifier()))
         modelos.append(('CART', DecisionTreeClassifier()))

         # Avaliando cada modelo em um loop
         for nome, modelo in modelos:
             kfold = KFold(num_folds, True, random_state = seed)
             cv_results = cross_val_score(modelo, X, Y, cv = kfold, scoring = 'accuracy')
             msg = "%s: %f (%f)" % (nome, cv_results.mean() * 100, cv_results.std())
             print(msg)
```

```
NB: 37.957677 (0.002535)
KNN: 82.649688 (0.001646)
CART: 98.898048 (0.000692)
```

11 Primeira Versao do Modelo com Features Selection

```
In [30]: #Criando o Modelo - Versao 1
         from xgboost import XGBClassifier
```

```
        modelo = XGBClassifier(n_estimators=110, nthread=-1, seed=seed, objective='multi:softm

        # Treinando o modelo
        modelo.fit(X_treino_new, Y_treino, eval_metric="auc", verbose = False)

        # Fazendo previsões
        y_pred = modelo.predict(X_teste_new)
        previsoes = [round(value) for value in y_pred]

        #Resultado do Modelo - Versao 1
        resultado = accuracy_score(Y_teste, previsoes)
        print("Acuracia do Modelo 1: %.2f" % (resultado * 100.0))

Acuracia do Modelo 1: 79.53
```

12 Segunda Versao do Modelo sem Features Selection

```
In [31]: #Criando o Modelo - Versao 2
        from xgboost import XGBClassifier
        modelo2 = XGBClassifier(learning_rate=0.005, n_estimators=110, nthread=-1, seed=seed,

        # Treinando o modelo
        modelo2.fit(X_treino, Y_treino, eval_metric="auc", verbose = False)

        # Fazendo previsões
        y_pred2 = modelo2.predict(X_teste)
        previsoes2 = [round(value) for value in y_pred2]

        #Resultado do Modelo - Versao 1
        resultado2 = accuracy_score(Y_teste, previsoes2)
        print("Acuracia do Modelo 2: %.2f" % (resultado2 * 100.0))

Acuracia do Modelo 2: 61.15
```

13 Algoritmos de Classificacao MultiVariada

```
In [33]: from sklearn.multiclass import OneVsRestClassifier
        from sklearn.preprocessing import MultiLabelBinarizer

        clf = OneVsRestClassifier(XGBClassifier(n_estimators=150, objective='multi:softmax', n
        clf.fit(X_treino, Y_treino)

Out[33]: OneVsRestClassifier(estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsampl
               colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
               max_delta_step=0, max_depth=3, min_child_weight=1, missing=None,
```

```
              n_estimators=150, n_jobs=1, nthread=None, num_class=9,
              objective='multi:softmax', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
              subsample=1, verbosity=1),
                 n_jobs=None)
```

```
In [34]: y_pred3 = clf.predict(X_teste)
         previsoes3 = [round(value) for value in y_pred3]

         #Resultado do Modelo - Versao 1
         resultado3 = accuracy_score(Y_teste, previsoes3)
         print("Acuracia do Modelo 3: %.2f" % (resultado3 * 100.0))

         from sklearn.metrics import classification_report
         report = classification_report(Y_teste, previsoes3)

         # Imprimindo o relatório
         print(report)
```

```
Acuracia do Modelo 3: 81.21
              precision    recall  f1-score   support

           0       0.94      0.61      0.74      7251
           1       0.89      0.77      0.83     29902
           2       0.93      0.78      0.85     13993
           3       0.97      0.91      0.94       814
           4       0.94      0.77      0.85     11785
           5       0.95      0.79      0.86     28044
           6       0.93      0.89      0.91     11351
           7       0.95      0.84      0.89     19859
           8       0.52      0.93      0.67     23305

   micro avg       0.81      0.81      0.81    146304
   macro avg       0.89      0.81      0.84    146304
weighted avg       0.86      0.81      0.82    146304
```

13.1 Escolhido o modelo de DecisionTreeClassifier - Melhor acurácia.

14 Modelo DecisionTreeClassifier otimizado com Features Selection

```
In [35]: clf1 = OneVsRestClassifier(DecisionTreeClassifier(criterion='entropy',random_state=se

         clf1.fit(X_treino_new, Y_treino)
         y_pred4 = clf1.predict(X_teste_new)
         previsoes4 = [round(value) for value in y_pred4]
```

```
#Resultado do Modelo - Versao 1
resultado4 = accuracy_score(Y_teste, previsoes4)
print("Acuracia do Modelo 4: %.2f" % (resultado4 * 100.0))

from sklearn.metrics import classification_report
report = classification_report(Y_teste, previsoes4)

# Imprimindo o relatório
print(report)
```

```
Acuracia do Modelo 4: 99.49
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      7251
           1       1.00      0.99      0.99     29902
           2       1.00      1.00      1.00     13993
           3       1.00      0.99      1.00       814
           4       1.00      0.99      0.99     11785
           5       1.00      1.00      1.00     28044
           6       1.00      0.99      1.00     11351
           7       1.00      1.00      1.00     19859
           8       0.98      1.00      0.99     23305

   micro avg       0.99      0.99      0.99    146304
   macro avg       1.00      0.99      0.99    146304
weighted avg       0.99      0.99      0.99    146304
```

15 Preparando os dados

```
In [36]: # Dados de Teste - Limpeza e preparação dos dados para a predição

         # Carregando o DataSet de Teste
         df_final = pd.read_csv('data/X_teste.csv', low_memory=False)

         # O modelo no DataSet de Teste para alguns seriesID, classifica surfaces diferentes
         # para o mesmo series_id cuja diferença são em algumas medições do sensor (temos 128 p
         # Testei várias soluções, mas optei por classificar a surface pela última análise do s
         # Exemplo de duplicação - series_id=6
         df_final = df_final[df_final.measurement_number == 127]

         #Eliminando as colunas sem utilidade
         df_final = df_final.drop('row_id', axis=1)
         #Features Selection
         df_final = df_final.drop('measurement_number', axis=1)
         df_final = df_final.drop('angular_velocity_X', axis=1)
```

```
df_final = df_final.drop('angular_velocity_Y', axis=1)
df_final = df_final.drop('linear_acceleration_X', axis=1)
df_final = df_final.drop('linear_acceleration_Y', axis=1)
df_final = df_final.drop('linear_acceleration_Z', axis=1)

#Padronizacao / Escala
X_predicao_final = df_final.values
X_predicao_final = MinMaxScaler(feature_range = (0, 1)).fit_transform(X_predicao_final
X_predicao_final = StandardScaler().fit_transform(X_predicao_final)

# Fazendo as previsoes - Modelo 4 Otimizado
predicao_final = clf1.predict(X_predicao_final)
predicao_final_prob = clf1.predict_proba(X_predicao_final)

# Voltando a transformacao da variavel target em formato texto
predicao_final_texto = labelencoder_surface.inverse_transform(predicao_final)
```

In [37]:
```
predicao_final
```

Out[37]:
```
array([7, 7, 8, ..., 4, 7, 5])
```

In [38]:
```
predicao_final_texto
```

Out[38]:
```
array(['tiled', 'tiled', 'wood', ..., 'hard_tiles_large_space', 'tiled',
       'soft_pvc'], dtype=object)
```

In [39]:
```
predicao_final_prob
```

Out[39]:
```
array([[0.        , 0.        , 0.        , ..., 0.        , 1.        ,
        0.        ],
       [0.33333333, 0.        , 0.        , ..., 0.        , 0.33333333,
        0.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        1.        ],
       ...,
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.14285714, 0.        , 0.        , ..., 0.        , 0.85714286,
        0.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.42857143]])
```

In [40]:
```
df_final.shape, predicao_final_texto.shape, predicao_final_prob.shape
```

Out[40]:
```
((3816, 6), (3816,), (3816, 9))
```

In [41]:
```
predicao_final_prob
```

```
Out[41]: array([[0.        , 0.        , 0.        , ..., 0.        , 1.        ,
          0.        ],
         [0.33333333, 0.        , 0.        , ..., 0.        , 0.33333333,
          0.        ],
         [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
          1.        ],
         ...,
         [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
          0.        ],
         [0.14285714, 0.        , 0.        , ..., 0.        , 0.85714286,
          0.        ],
         [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
          0.42857143]])
```

```
In [42]: predicao_final_prob[:,0]
```

```
Out[42]: array([0.        , 0.33333333, 0.        , ..., 0.        , 0.14285714,
         0.        ])
```

16 Montando DataFrame Final com as predições

```
In [43]: #DataFrame do arquivo
         df_submission = pd.DataFrame({
             "series_id": df_final.series_id,
             "surface": predicao_final_texto
         })

         df_submission.head(50)
```

Out[43]:

	series_id	surface
127	0	tiled
255	1	tiled
383	2	wood
511	3	wood
639	4	wood
767	5	wood
895	6	concrete
1023	7	soft_tiles
1151	8	fine_concrete
1279	9	wood
1407	10	soft_tiles
1535	11	tiled
1663	12	soft_tiles
1791	13	soft_tiles
1919	14	wood
2047	15	wood
2175	16	wood
2303	17	wood

```
2431          18                wood
2559          19            soft_pvc
2687          20          soft_tiles
2815          21            concrete
2943          22          soft_tiles
3071          23          soft_tiles
3199          24       fine_concrete
3327          25               tiled
3455          26               tiled
3583          27                wood
3711          28                wood
3839          29  hard_tiles_large_space
3967          30            concrete
4095          31          soft_tiles
4223          32               tiled
4351          33          soft_tiles
4479          34                wood
4607          35          soft_tiles
4735          36               tiled
4863          37               tiled
4991          38          soft_tiles
5119          39            soft_pvc
5247          40               tiled
5375          41            concrete
5503          42            soft_pvc
5631          43                wood
5759          44          soft_tiles
5887          45                wood
6015          46                wood
6143          47            soft_pvc
6271          48            soft_pvc
6399          49              carpet
```

In [44]:
```
#Grava o arquivo
df_submission.to_csv('data/submission.csv', index=False)
```

17 Obrigado

In [ ]: