LealdadeClientes

June 22, 2019

0.1 Competição DSA de Machine Learning - Edição Junho/2019

1 MARCIO DE LIMA

2 As submissões para esta competição serão avaliadas pelo RMSE (Root Mean Squared Error).

3

In [ ]:
```
# Nesta competição, você desenvolverá algoritmos para identificar e atender as oportun
# para os indivíduos, revelando sinais de lealdade dos clientes. Sua contribuição melh
# clientes e ajudará a reduzir as campanhas indesejadas, a fim de criar uma e experiên
# para cada cliente e consequentemente aumentar a satisfação e claro, as vendas.
```

In [1]:
```
# Importando as bibliotecas
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from IPython.core.pylabtools import figsize
import seaborn as sns
import warnings

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

In [54]:
```
# Carregando os arquivos
df = pd.read_csv('data/dataset_treino.csv')
df_teste = pd.read_csv('data/dataset_teste.csv')

df.head(5)
```

Out[54]:

	first_active_month	card_id	feature_1	feature_2	feature_3	\
0	2017-06	C_ID_92a2005557	5	2	1	
1	2017-01	C_ID_3d0044924f	4	1	0	
2	2016-08	C_ID_d639edf6cd	2	2	0	
3	2017-09	C_ID_186d6a6901	4	3	0	
4	2017-11	C_ID_cdbd2c0db2	1	3	0	

```
     target
0 -0.820283
1  0.392913
2  0.688056
3  0.142495
4 -0.159749
```

```
In [4]: # Mostrando as estruturas dos Datasets
        df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 201917 entries, 0 to 201916
Data columns (total 6 columns):
first_active_month    201917 non-null object
card_id               201917 non-null object
feature_1             201917 non-null int64
feature_2             201917 non-null int64
feature_3             201917 non-null int64
target                201917 non-null float64
dtypes: float64(1), int64(3), object(2)
memory usage: 9.2+ MB
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 123623 entries, 0 to 123622
Data columns (total 5 columns):
first_active_month    123622 non-null object
card_id               123623 non-null object
feature_1             123623 non-null int64
feature_2             123623 non-null int64
feature_3             123623 non-null int64
dtypes: int64(3), object(2)
memory usage: 4.7+ MB
```

```
In [41]: #Limpando espaços do texto caso existam
         df['first_active_month'] = df['first_active_month'].str.strip()
         df_teste['first_active_month'] = df_teste['first_active_month'].str.strip()
```

```
In [55]: #Checando valores NA nos dados
         df.isna().any()[lambda x: x]
         df_teste.isna().any()[lambda x: x]
```

```
Out[55]: Series([], dtype: bool)
```

```
In [56]: # Ajustando colunas e limpeza dos dados nos DataSets
```

```
#Criando novas colunas
df['Month'] = df.first_active_month.apply(lambda dt: dt[5:7])
df['Year'] = df.first_active_month.apply(lambda dt: dt[:4])
df_teste['Month'] = df_teste.first_active_month.apply(lambda dt: dt[5:7])
df_teste['Year'] = df_teste.first_active_month.apply(lambda dt: dt[:4])

#Ajustando a tipagem da coluna
df['Month'] = df['Month'].apply(pd.to_numeric, downcast='integer')
df['Year'] = df['Year'].apply(pd.to_numeric, downcast='integer')
df_teste['Month'] = df['Month'].apply(pd.to_numeric, downcast='integer')
df_teste['Year'] = df['Year'].apply(pd.to_numeric, downcast='integer')

df.dtypes
```

Out[56]:
```
first_active_month     object
card_id                object
feature_1               int64
feature_2               int64
feature_3               int64
target                float64
Month                   int64
Year                    int64
dtype: object
```

In [65]:
```
# Criando coluna = calculo das features
df['feature_4'] = (df['feature_1'] * df['feature_1'].mean()) + (df['feature_2']  * df
df_teste['feature_4'] = (df_teste['feature_1'] * df_teste['feature_1'].mean()) + (df_
df.head(5)
```

Out[65]:

	first_active_month	card_id	feature_1	feature_2	feature_3	target	Month	Year	feature_4
0	2017-06	C_ID_92a2005557	5	2	1	-0.820283	6	2017	19.582942
1	2017-01	C_ID_3d0044924f	4	1	0	0.392913	1	2017	14.166653
2	2016-08	C_ID_d639edf6cd	2	2	0	0.688056	8	2016	9.701442
3	2017-09	C_ID_186d6a6901	4	3	0	0.142495	9	2017	17.657473
4	2017-11	C_ID_cdbd2c0db2	1	3	0	-0.159749	11	2017	8.341541

In [66]:
```
# Correlação com a Variavel TARGET
df[df.columns.drop('target')].corrwith(df.target)
```

Out[66]:
```
feature_1   -0.014251
feature_2   -0.006242
feature_3   -0.008125
```

```
Month        0.031512
Year         0.040341
feature_4   -0.016069
dtype: float64
```

In [68]:
```
# Dados estatisticos
df.describe()
```

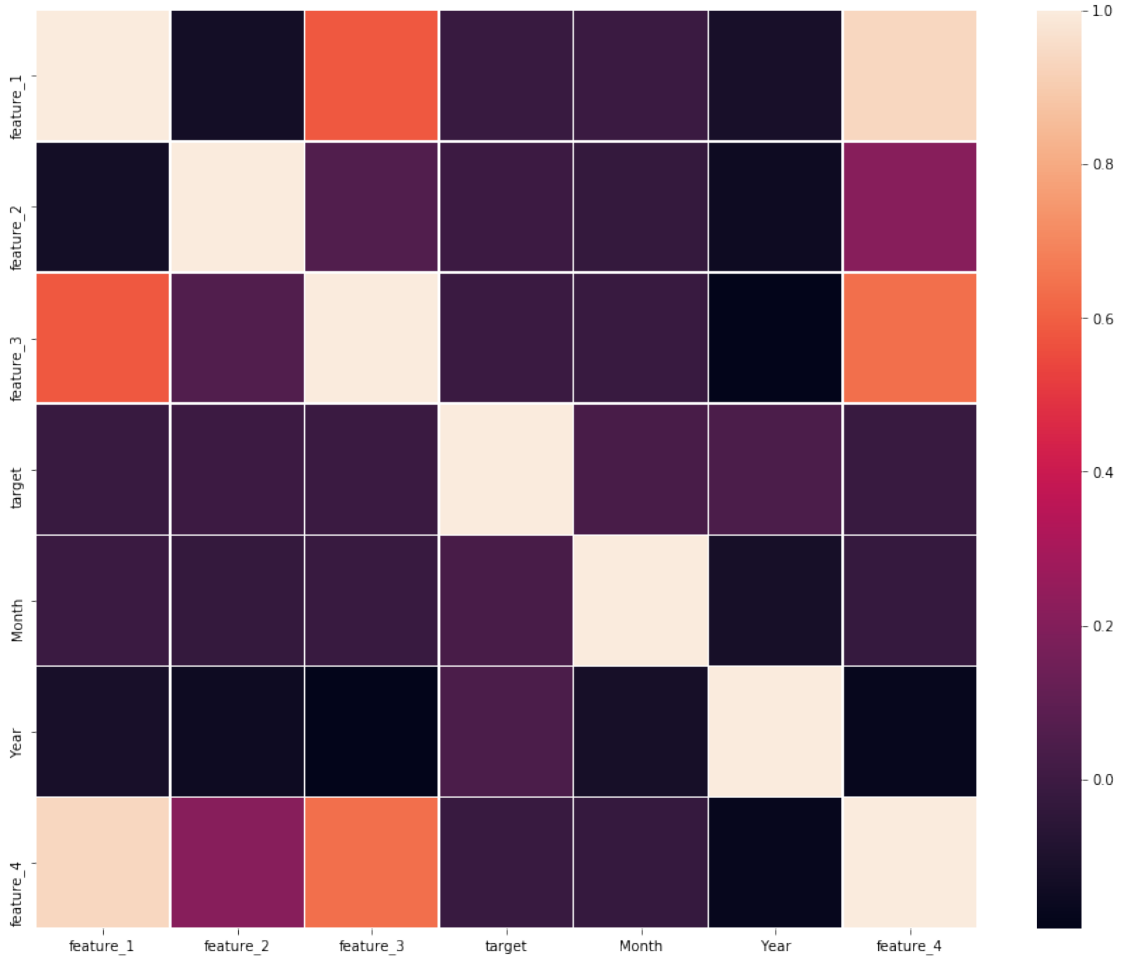
Out[68]:

	feature_1	feature_2	feature_3	target
count	201917.000000	201917.000000	201917.000000	201917.000000
mean	3.105311	1.745410	0.565569	-0.393636
std	1.186160	0.751362	0.495683	3.850500
min	1.000000	1.000000	0.000000	-33.219281
25%	2.000000	1.000000	0.000000	-0.883110
50%	3.000000	2.000000	1.000000	-0.023437
75%	4.000000	2.000000	1.000000	0.765453
max	5.000000	3.000000	1.000000	17.965068

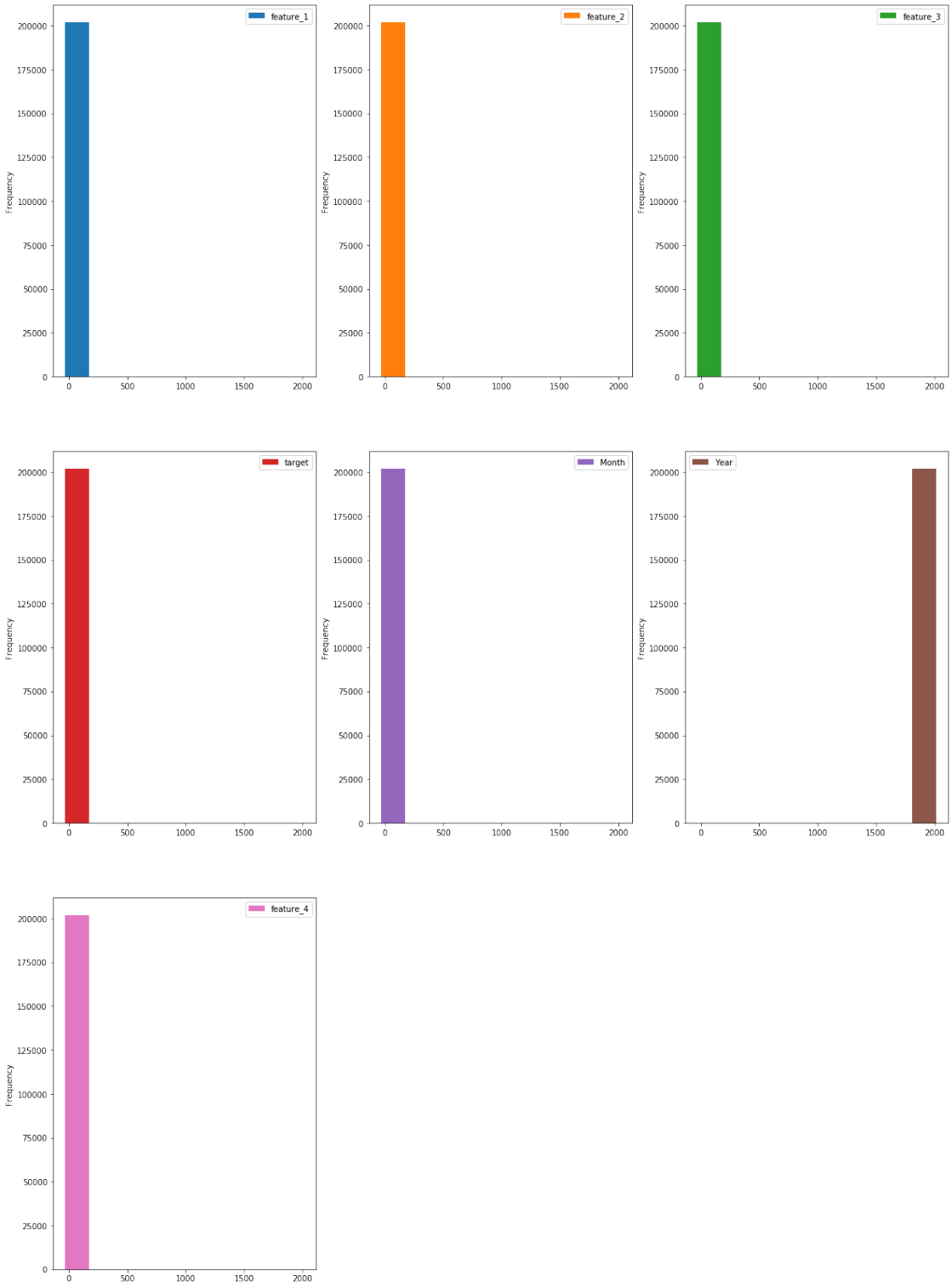
	Month	Year	feature_4
count	201917.000000	201917.000000	201917.000000
mean	7.378745	2016.509298	13.009279
std	3.340718	0.788199	3.917852
min	1.000000	2011.000000	4.850721
25%	5.000000	2016.000000	9.701442
50%	8.000000	2017.000000	13.372321
75%	10.000000	2017.000000	15.912063
max	12.000000	2018.000000	19.582942

In [69]:
```
#Construindo um gráfico de HEATMAP
f, ax = plt.subplots(figsize=(15, 12))
sns.heatmap(df.corr(),linewidths=.5, ax=ax)
```

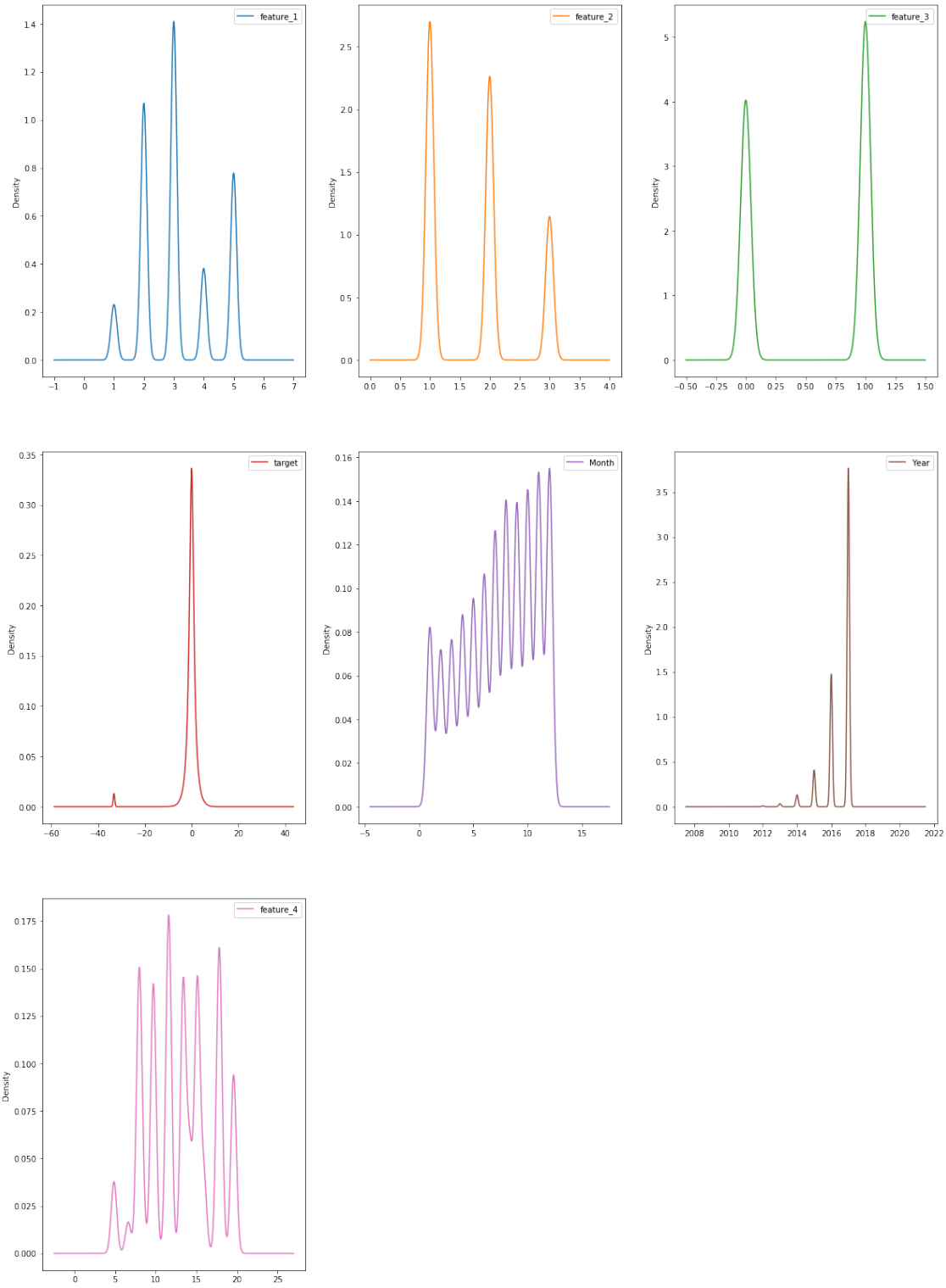
Out[69]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f677d8c9438>
```



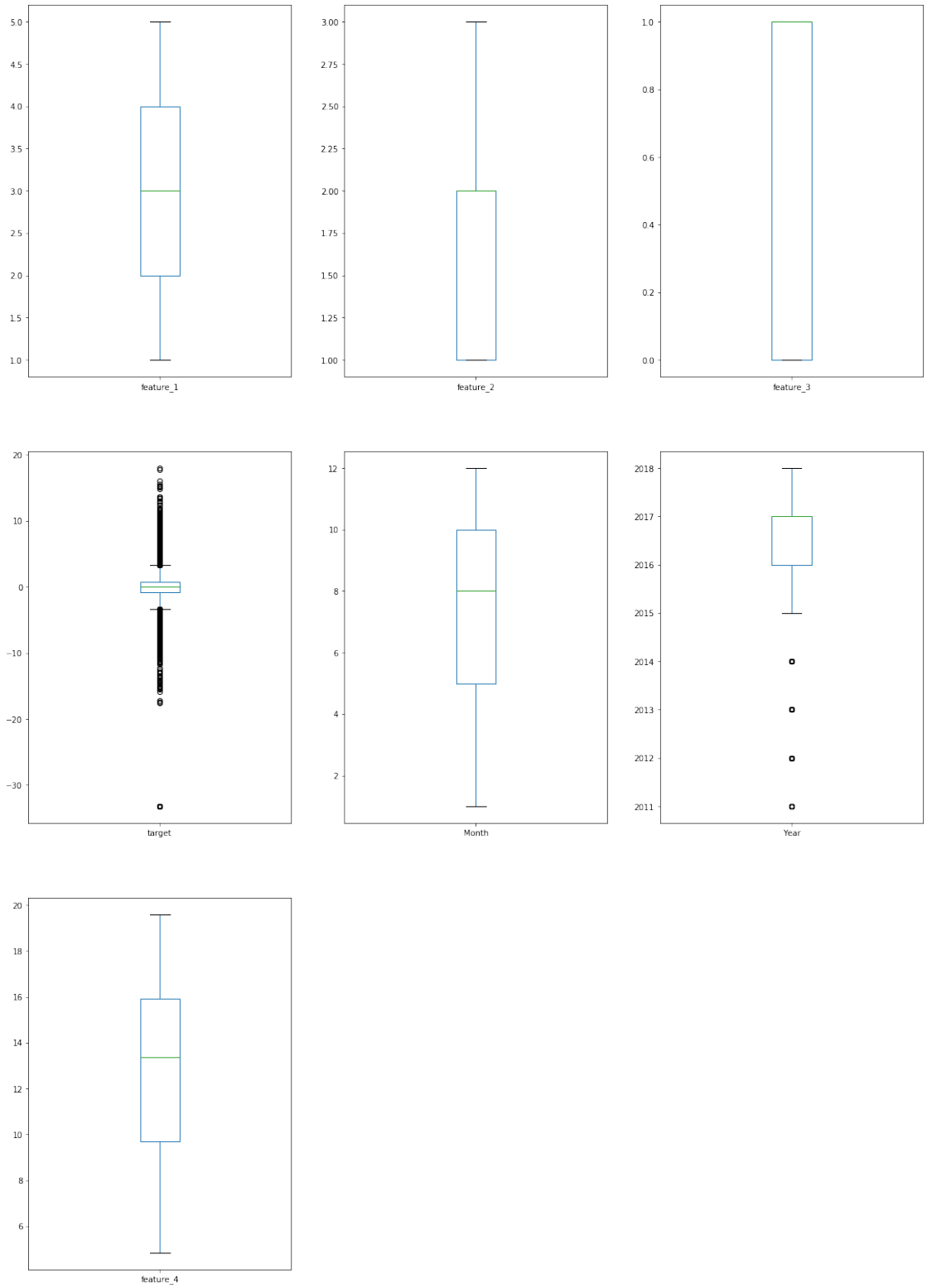
In [76]:
```
#Gerando gráficos para analise das variaveis

#Histogramas
df.plot(kind = 'hist', subplots = True, layout = (7,3), sharex = False, figsize=(20,7
plt.show()
```




```
In [78]: df.plot(kind = 'density', subplots = True, layout = (7,3), sharex = False, figsize=(20
         plt.show()
```




```
In [80]: df.plot(kind = 'box', subplots = True, layout = (7,3), sharex = False, sharey = False
         plt.show()
```



In [142]: *#Funcoes utilitárias para medir a performance dos modelos*

```
            from sklearn.metrics import mean_squared_error
            from math import sqrt

            def rmspe(y_test, y_pred):

                mse = mean_squared_error(y_test, y_pred)
                rmspe = sqrt(mse)

                return rmspe

            # Treinamento e resultado do modelo - funcao generica
            def treine_e_avalie(model, X, y, X_test, y_test):


                # Predicao
                model_pred = treino_e_predicao(model, X, y, X_test)
                #Performance
                model_rmspe = rmspe(y_test, model_pred)

                # Retorno da Performance do modelo
                return model_rmspe

            def treino_e_predicao(model, X, y, X_test):

                # FIT
                model.fit(X, y)
                # Predicao
                return model.predict(X_test)
```

```
In [85]: df.shape
```

```
Out[85]: (201917, 9)
```

```
In [88]: #Gerando dados de Treino e de Teste para os modelos
         from sklearn.model_selection import train_test_split

         seed = 1313

         array = df.values
         X = array[:,6:9]
         Y = df.target.values

         X_treino, X_teste, y_treino, y_teste = train_test_split(X, Y, test_size = 0.30, rando
```

```
In [96]: X_treino
```

```
Out[96]: array([[12, 2017, 6.596131083564039],
                [1, 2017, 13.372321300336276],
                [10, 2017, 11.62691105751373],
```

```
       ...,
       [8, 2015, 15.117731543158822],
       [12, 2016, 17.837532253351625],
       [12, 2016, 8.341541326386585]], dtype=object)
```

```
In [91]: # Importando os modelos

         from sklearn.svm import SVR
         from sklearn.linear_model import LinearRegression
         from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
         from sklearn.neighbors import KNeighborsRegressor
```

```
In [102]: # Modelo 1 - Regressao Linear Simples

          lr = LinearRegression()
          lr_rmspe = treine_e_avalie(lr, X_treino, y_treino, X_teste, y_teste)

          print('Modelo 1 - Regressao Linear => RMSPE = %0.4f' % lr_rmspe)
```

```
Modelo 1 - Regressao Linear => RMSPE = 3.8569
```

```
In [106]: # Modelo 2 - KNN
          knn = KNeighborsRegressor(n_neighbors=5)
          knn_rmspe = treine_e_avalie(knn, X_treino, y_treino, X_teste, y_teste)

          print('Modelo 2 - KNN => RMSPE = %0.4f' % knn_rmspe)
```

```
Modelo 2 - KNN => RMSPE = 4.3201
```

```
In [143]: # Modelo 3 - GradientBoostingRegressor
          gradient_boosted = GradientBoostingRegressor(random_state=60)
          gradient_boosted_rmspe = treine_e_avalie(gradient_boosted, X_treino, y_treino, X_tes

          print('Modelo 3 - GradientBoostingRegressor = %0.4f' % gradient_boosted_rmspe)
```

```
Modelo 3 - GradientBoostingRegressor = 3.8544
```

3.1 Melhor modelo - GradientBoostingRegressor - 3.8544

```
In [171]: # Otimizando o modelo 3 - Otimização de Hyperparâmetro
          from sklearn.model_selection import RandomizedSearchCV

          #Modelo para testar a otimização
          gbr = GradientBoostingRegressor(random_state=13)
          #Parametros da otimização
          param_grid = {
```

```
                'n_estimators': [100, 200, 500],
                'max_features': ['auto', 'sqrt', 'log2', None],
                'max_depth': [2, 3, 5, 10, 15],
                'learning_rate': [0.1],
                'loss': ['ls', 'lad', 'huber'],
                'subsample': [1]
            }

            #Modelo para melhor scoring para o RMSE
            modelo_otm = RandomizedSearchCV(estimator=gbr,
                                            param_distributions=param_grid,
                                            cv=2, n_iter=1,
                                            scoring = 'neg_mean_absolute_error',
                                            n_jobs = -1, verbose = 1,
                                            return_train_score = True,
                                            random_state=60)
```

In [172]:
```
#Treinando o modelo otimizado
modelo_otm.fit(X_treino, y_treino)
```

```
Fitting 2 folds for each of 1 candidates, totalling 2 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done   2 out of   2 | elapsed:   10.5s finished
```

Out[172]:
```
RandomizedSearchCV(cv=2, error_score='raise-deprecating',
                   estimator=GradientBoostingRegressor(alpha=0.9, criterion='friedman_mse', in
                      learning_rate=0.1, loss='ls', max_depth=3, max_features=None,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_sampl...te=13, subsample=1.0, tol=0.0001,
                      validation_fraction=0.1, verbose=0, warm_start=False),
                   fit_params=None, iid='warn', n_iter=1, n_jobs=-1,
                   param_distributions={'n_estimators': [100, 200, 500], 'max_features': ['aut
                   pre_dispatch='2*n_jobs', random_state=60, refit=True,
                   return_train_score=True, scoring='neg_mean_absolute_error',
                   verbose=1)
```

In [173]:
```
#Resultado do modelo otimizado
print('Melhores Params:')
print(modelo_otm.best_params_)
print('Melhor CV Score:')
print(-modelo_otm.best_score_)
```

```
Melhores Params:
{'subsample': 1, 'n_estimators': 500, 'max_features': 'sqrt', 'max_depth': 2, 'loss': 'lad', 'l
Melhor CV Score:
```

```
1.5433707250438624
```

```
In [203]: # Modelo 4 - GradientBoostingRegressor Otimizado
          # Melhores parameters
          #gradient_boosted1_otm = GradientBoostingRegressor(max_depth=2, max_features='sqrt',
          #                                                  n_estimators=500, loss='lad', ran
          #                                                  learning_rate=0.1, verbose=1, sub

          gradient_boosted1_otm = GradientBoostingRegressor( max_depth=3, max_features='sqrt',
                                                             n_estimators=100,
                                                             criterion='mse',
                                                             learning_rate=0.05,
                                                             random_state=60)

          modelo_pred_otm = treino_e_predicao(gradient_boosted1_otm, X_treino, y_treino, X_tes
          gradient_boosted_rmspe_otm = rmspe(y_teste, modelo_pred_otm)

          print('Modelo 4 - GradientBoostingRegressor - Otimizado = %0.4f' % gradient_boosted_

Modelo 4 - GradientBoostingRegressor - Otimizado = 3.8540
```

```
In [212]: #Gerando os dados para o Arquivo de submissao
          array = df_teste.values
          X_teste1 = array[:,5:9]

In [215]: X_teste1

Out[215]: array([[6, 2017, 15.117542852058275],
                 [1, 2017, 11.443906069258958],
                 [8, 2016, 17.852470818537],
                 ...,
                 [6, 2017, 17.852470818537],
                 [9, 2017, 7.960314828146866],
                 [11, 2017, 17.852470818537]], dtype=object)

In [216]: #Gerando Arquivo de Submissao
          df_submission = pd.DataFrame()
          df_submission['card_id'] = df_teste['card_id']

          resultado_otm = gradient_boosted1_otm.predict(X_teste1)

In [217]: resultado_otm

Out[217]: array([-0.33643612, -0.55861594, -0.76771115, ..., -0.32270524,
                 -0.0777886 , -0.09971289])

In [218]: df_submission['target'] = resultado_otm
```

```
In [221]: df_submission.head(10)
```

```
Out[221]:            card_id    target
          0  C_ID_0ab67a22ab -0.336436
          1  C_ID_130fd0cbdd -0.558616
          2  C_ID_b709037bc5 -0.767711
          3  C_ID_d27d835a9f -0.077789
          4  C_ID_2b5e3df5c2 -0.099713
          5  C_ID_5814b4f13c -0.666733
          6  C_ID_a1b3c75277 -0.661761
          7  C_ID_f7cada36d3 -0.066085
          8  C_ID_9d2bc8dfc4 -0.252309
          9  C_ID_6d8dba8475 -0.767711
```

```
In [222]: #Gravando Arquivo de Submissao
          df_submission.to_csv('data/submission.csv', index=False)
```

3.2 FIM

3.3 Obrigado