aramco-technaton-challenge1

October 28, 2018

1 Challenge #1. Reservoir Evaluation

Aramco Upstream Solutions Technathon MSU Science Park - 26-28 Oct 2018

Let's assume that we know nothing about underlying physics and learn from the data using just machine learning

In [57]:
```
import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import lightgbm as lgb
from sklearn.model_selection import KFold
import multiprocessing

random_state = 2018
```

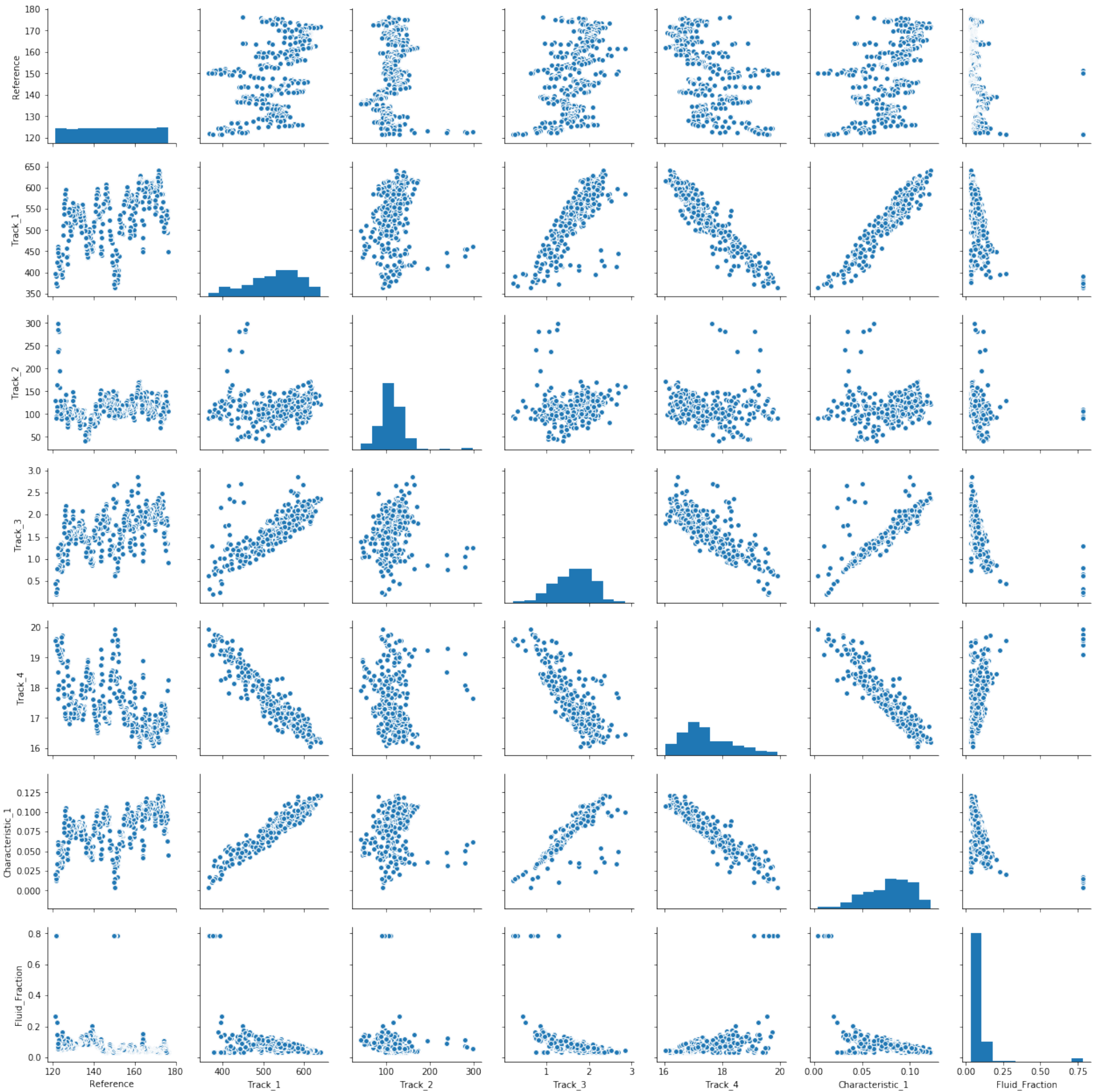
In [58]:
```
train_b = pd.read_csv('aramco-data/task1/2. Training/Logs-B.csv')
train_c = pd.read_csv('aramco-data/task1/2. Training/Logs-C.csv')
train_d = pd.read_csv('aramco-data/task1/2. Training/Logs-D_Lost_Sections.csv')

test_a = pd.read_csv('aramco-data/task1/3. Testing/Logs-A.csv')
test_d = pd.read_csv('aramco-data/task1/3. Testing/Logs-D_Lost_Sections.csv')
```

In [59]:
```
train_b.head()
```

Out[59]:
```
    Reference    Track_1    Track_2   Track_3   Track_4  Characteristic_1  \
0  176.151735  449.52114  106.79179  0.924423  18.24576          0.044960
1  176.009779  494.77735  124.72322  1.356370  17.91681          0.062602
2  175.854890  530.24547  126.32411  1.759663  16.71797          0.090488
3  175.690536  545.80115  122.55946  1.916755  16.60101          0.097377
4  175.527445  546.45174  115.30063  1.916755  16.54253          0.098116

   Fluid_Fraction
0         0.03132
1         0.03132
2         0.03132
3         0.03132
4         0.03132
```

Let's look at feature correlations

In [60]:
```
import seaborn as sns
sns.pairplot(train_b);
```



In [61]:
```
train_b['Fluid_Fraction'].mean()
```

Out[61]: 0.08742102017971018

In [62]:
```
train_c.head()
```

Out[62]:
```
    Reference     Track_1    Track_2   Track_3   Track_4  Characteristic_1  \
0  216.661514  561.846600  84.884451  1.536635  16.73990          0.093360
1  216.502524  558.706224  88.596469  1.383191  16.74721          0.092437
```

```
   2  216.343533  553.657207   95.754421  1.547037  16.74721           0.090931
   3  216.184227  568.184370  100.570249  1.655613  16.99575           0.095192
   4  216.025237  583.821922  104.431391  1.630941  16.77645           0.099540

      Fluid_Fraction
   0        0.042590
   1        0.042286
   2        0.042204
   3        0.039533
   4        0.037631
```

```
In [63]: train_c['Fluid_Fraction'].mean()
```

```
Out[63]: 0.08436770301748256
```

```
In [64]: train_d.head()
```

```
Out[64]:     Reference    Track_1    Track_2   Track_3    Track_4  Characteristic_1  \
         0  316.847634  349.04519  89.279954  0.269666  19.049860          0.000038
         1  316.737539  352.48089  95.623572  0.245251  18.443130          0.000038
         2  316.621136  355.55840  98.238359  0.240397  17.652042          0.000038
         3  316.499369  358.84790  98.267599  0.276530  17.345972          0.000472
         4  316.372240  355.59495  96.231764  0.338862  17.444365          0.000038

            Fluid_Fraction
         0           0.783
         1           0.783
         2           0.783
         3           0.783
         4           0.783
```

```
In [65]: train_d['Fluid_Fraction'].mean()
```

```
Out[65]: 0.12046181560057474
```

```
In [66]: train = train_b.append(train_c).append(train_d)
```

```
In [67]: X_train = train.drop('Fluid_Fraction', axis=1)
         y_train = train['Fluid_Fraction']

         X_test_a = test_a
         X_test_d = test_d
```

2 Permutation importance

eli5 provides a way to compute feature importances for any black-box estimator by measuring how score decreases when a feature is not available; the method is also known as “permutation importance” or “Mean Decrease Accuracy (MDA)”.

In [68]:
```
from sklearn.model_selection import train_test_split

X_tr, X_va, y_tr, y_va = train_test_split(X_train, y_train, test_size=0.5, random_state
```

In [69]:
```
from sklearn.ensemble import RandomForestRegressor

reg = RandomForestRegressor(criterion="mae").fit(X_tr.fillna(-1), y_tr)
```

In [70]:
```
import eli5
from eli5.sklearn import PermutationImportance

perm = PermutationImportance(reg).fit(X_va.fillna(-1), y_va)
eli5.show_weights(perm, feature_names = X_va.columns.tolist())
```

Out[70]: <IPython.core.display.HTML object>

we see that all features bring information to the model, there are no random/pure noise features

In [71]:
```
train['Fluid_Fraction'].mean()
```

Out[71]: 0.09827387829826342

In [72]:
```
params = {
    'objective' : 'mae',
    'metric': 'mae',
    #'feature_fraction': .8,
    #'learning_rate': 0.001
    }
n_fold = 3
n_estimators = 50000
nthread = multiprocessing.cpu_count()
folds = KFold(n_splits=n_fold, shuffle=True, random_state=random_state)
model = lgb.LGBMRegressor(**params, n_estimators = n_estimators, nthread = nthread, n_j
```

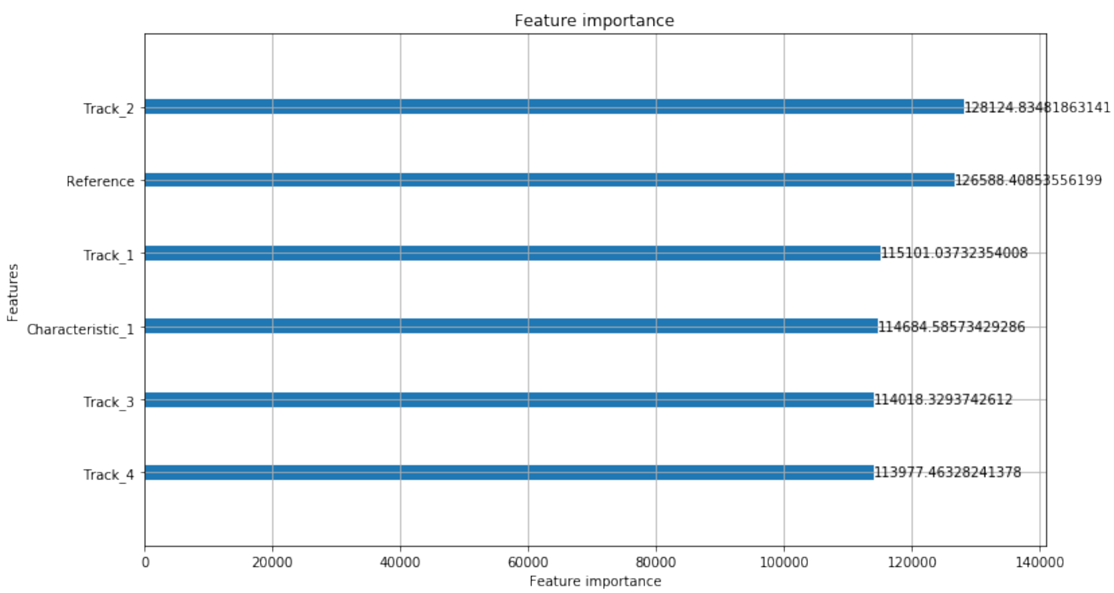
In [73]:
```
%%time

prediction_a = np.zeros(X_test_a.shape[0])
prediction_d = np.zeros(X_test_d.shape[0])

for fold_n, (train_index, test_index) in enumerate(folds.split(X_train)):
    print('Fold:', fold_n)
    X_tr, X_va = X_train.iloc[train_index], X_train.iloc[test_index]
    y_tr, y_va = y_train.iloc[train_index], y_train.iloc[test_index]

    model.fit(X_tr, y_tr,
            eval_set=[(X_tr, y_tr), (X_va, y_va)],
            verbose=250, early_stopping_rounds=100)
```

```
            y_pred_a = model.predict(X_test_a, num_iteration=model.best_iteration_)
            y_pred_d = model.predict(X_test_d, num_iteration=model.best_iteration_)
            prediction_a += y_pred_a
            prediction_d += y_pred_d

        prediction_a /= n_fold
        prediction_d /= n_fold
```

```
Fold: 0
Training until validation scores don't improve for 100 rounds.
[250]	training's l2: 0.00156422	valid_1's l2: 0.00255552
[500]	training's l2: 0.000965945	valid_1's l2: 0.00183363
[750]	training's l2: 0.0008902	valid_1's l2: 0.00174847
[1000]	training's l2: 0.000875846	valid_1's l2: 0.00173469
[1250]	training's l2: 0.000865499	valid_1's l2: 0.00172815
[1500]	training's l2: 0.000860064	valid_1's l2: 0.00172279
[1750]	training's l2: 0.000856403	valid_1's l2: 0.00172135
Early stopping, best iteration is:
[1738]	training's l2: 0.000856278	valid_1's l2: 0.00172008
Fold: 1
Training until validation scores don't improve for 100 rounds.
[250]	training's l2: 0.00465503	valid_1's l2: 0.00511517
[500]	training's l2: 0.00451262	valid_1's l2: 0.00507116
[750]	training's l2: 0.00446918	valid_1's l2: 0.00505939
Early stopping, best iteration is:
[702]	training's l2: 0.00447797	valid_1's l2: 0.00505763
Fold: 2
Training until validation scores don't improve for 100 rounds.
[250]	training's l2: 0.00169297	valid_1's l2: 0.00291367
[500]	training's l2: 0.00151146	valid_1's l2: 0.00274579
[750]	training's l2: 0.00142898	valid_1's l2: 0.00266867
[1000]	training's l2: 0.00137229	valid_1's l2: 0.00262378
[1250]	training's l2: 0.00132071	valid_1's l2: 0.00257297
[1500]	training's l2: 0.00127534	valid_1's l2: 0.00252954
[1750]	training's l2: 0.00124727	valid_1's l2: 0.00250696
[2000]	training's l2: 0.00122338	valid_1's l2: 0.00248699
[2250]	training's l2: 0.00120712	valid_1's l2: 0.00247621
[2500]	training's l2: 0.0011921	valid_1's l2: 0.00246295
[2750]	training's l2: 0.00118262	valid_1's l2: 0.00245338
[3000]	training's l2: 0.00117172	valid_1's l2: 0.00244159
[3250]	training's l2: 0.00116809	valid_1's l2: 0.00243872
[3500]	training's l2: 0.0011636	valid_1's l2: 0.00243503
[3750]	training's l2: 0.0011605	valid_1's l2: 0.00243284
[4000]	training's l2: 0.00115467	valid_1's l2: 0.0024276
[4250]	training's l2: 0.00114998	valid_1's l2: 0.00242261
[4500]	training's l2: 0.00114719	valid_1's l2: 0.00242023
[4750]	training's l2: 0.00114398	valid_1's l2: 0.00241677
[5000]	training's l2: 0.00113896	valid_1's l2: 0.00241164
```

```
[5250]	training's l2: 0.00113643	valid_1's l2: 0.00241002
[5500]	training's l2: 0.00113272	valid_1's l2: 0.00240737
[5750]	training's l2: 0.00113117	valid_1's l2: 0.00240582
[6000]	training's l2: 0.00112834	valid_1's l2: 0.00240343
[6250]	training's l2: 0.0011257	valid_1's l2: 0.00240021
[6500]	training's l2: 0.00112348	valid_1's l2: 0.00239848
[6750]	training's l2: 0.00112218	valid_1's l2: 0.00239727
[7000]	training's l2: 0.00112109	valid_1's l2: 0.00239628
[7250]	training's l2: 0.00111897	valid_1's l2: 0.0023943
[7500]	training's l2: 0.0011159	valid_1's l2: 0.00239156
[7750]	training's l2: 0.00111442	valid_1's l2: 0.00239049
[8000]	training's l2: 0.00111364	valid_1's l2: 0.00238989
[8250]	training's l2: 0.00111215	valid_1's l2: 0.00238834
[8500]	training's l2: 0.00111068	valid_1's l2: 0.00238724
[8750]	training's l2: 0.00110891	valid_1's l2: 0.00238553
[9000]	training's l2: 0.00110812	valid_1's l2: 0.00238496
[9250]	training's l2: 0.00110566	valid_1's l2: 0.002383
[9500]	training's l2: 0.00110186	valid_1's l2: 0.00237888
[9750]	training's l2: 0.00109968	valid_1's l2: 0.00237655
[10000]	training's l2: 0.00109875	valid_1's l2: 0.00237577
[10250]	training's l2: 0.00109796	valid_1's l2: 0.00237507
Early stopping, best iteration is:
[10353]	training's l2: 0.0010978	valid_1's l2: 0.00237498
CPU times: user 51 s, sys: 1.07 s, total: 52.1 s
Wall time: 14 s
```

In [74]:
```
%matplotlib inline
lgb.plot_importance(model, importance_type='gain', figsize=(12,7));
```



```
In [75]: test_a.head()
```

```
Out[75]:     Reference     Track_1    Track_2   Track_3    Track_4  Characteristic_1
         0  226.575710  397.220283  58.885559  0.449736  20.657621          0.025308
         1  226.563407  420.739477  62.158392  0.793581  19.482100          0.038290
         2  226.541010  436.382146  77.639510  1.150514  18.644520          0.046150
         3  226.489905  445.895380  86.846455  1.417029  18.059136          0.050661
         4  226.419558  441.466251  92.864047  1.274250  18.644520          0.048585
```

```
In [76]: test_a['Fluid_Fraction'] = prediction_a
         test_d['Fluid_Fraction'] = prediction_d
```

```
In [77]: test_a.head()
```

```
Out[77]:     Reference     Track_1    Track_2   Track_3    Track_4  Characteristic_1  \
         0  226.575710  397.220283  58.885559  0.449736  20.657621          0.025308
         1  226.563407  420.739477  62.158392  0.793581  19.482100          0.038290
         2  226.541010  436.382146  77.639510  1.150514  18.644520          0.046150
         3  226.489905  445.895380  86.846455  1.417029  18.059136          0.050661
         4  226.419558  441.466251  92.864047  1.274250  18.644520          0.048585

            Fluid_Fraction
         0        0.149652
         1        0.094111
         2        0.074702
         3        0.072238
         4        0.070949
```

```
In [78]: test_d.head()
```

```
Out[78]:     Reference    Track_1    Track_2   Track_3   Track_4  Characteristic_1  \
         0  308.571924  612.39525  94.665231  1.811031  15.64340          0.106913
         1  308.419243  608.00194  93.844318  1.893699  15.73843          0.105824
         2  308.266562  606.68614  93.175453  1.948597  15.80422          0.105495
         3  308.104101  606.60573  92.503664  1.946580  15.82615          0.105476
         4  307.938170  607.56334  91.593569  1.914906  15.76036          0.105715

            Fluid_Fraction
         0        0.031647
         1        0.031710
         2        0.031581
         3        0.031587
         4        0.031404
```

```
In [79]: !mkdir aramco-data/output
```

```
mkdir: cannot create directory aramco-data/output: File exists
```

Save calculated data to the files

```
In [80]: test_a.to_csv('aramco-data/output/Logs-A--solved.csv', index=False)
         test_d.to_csv('aramco-data/output/Logs-D_Lost_Sections--solved.csv', index=False)
```

3 Comparison of real Fluid_Fraction with one calculated from the model

strictly speaking, that is not correct in terms of ML, because we have model trained on this data, just for the illustraion

In [81]:
```
train.head()
```

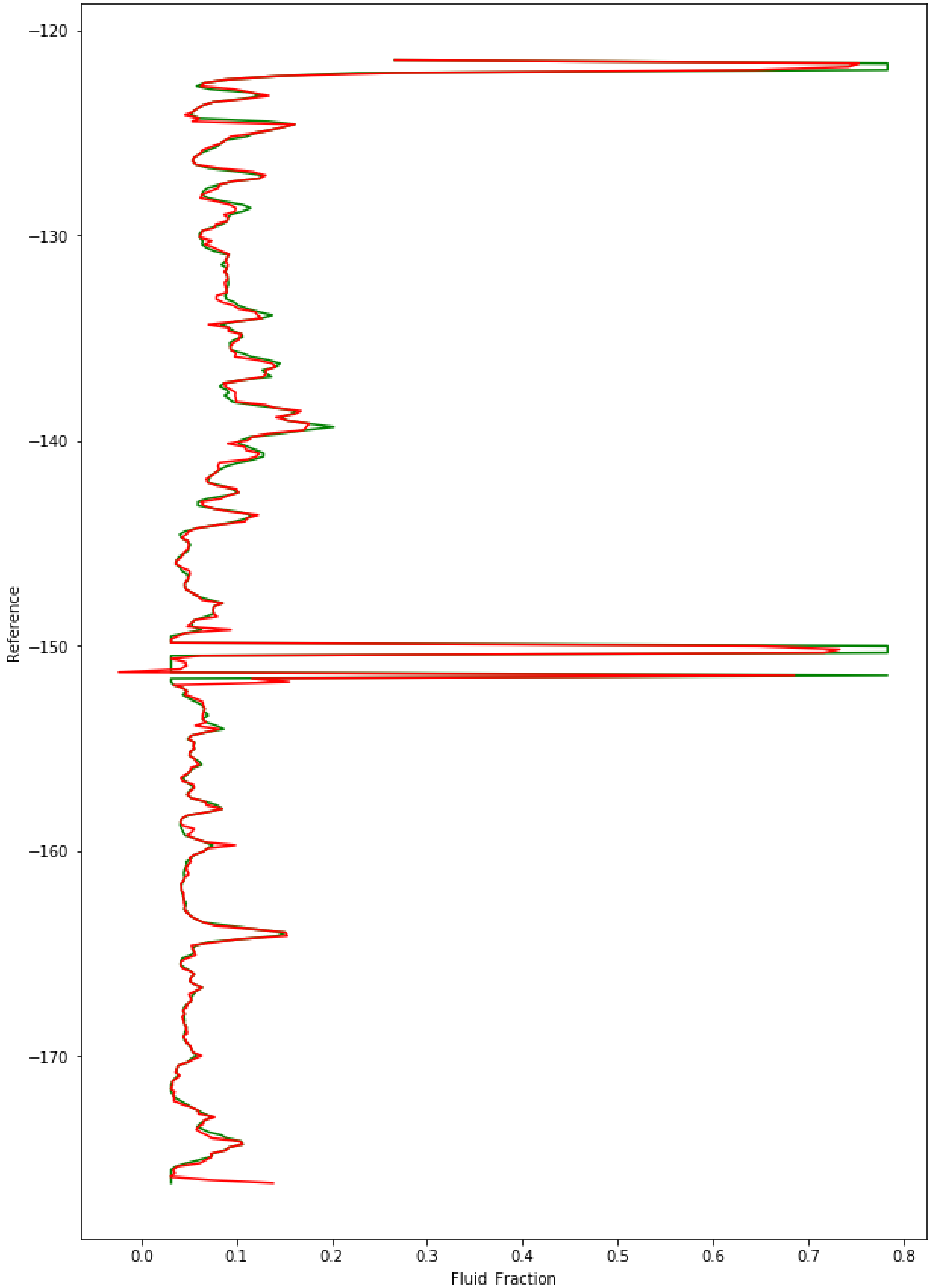
Out[81]:
```
    Reference    Track_1    Track_2   Track_3   Track_4  Characteristic_1  \
0  176.151735  449.52114  106.79179  0.924423  18.24576          0.044960
1  176.009779  494.77735  124.72322  1.356370  17.91681          0.062602
2  175.854890  530.24547  126.32411  1.759663  16.71797          0.090488
3  175.690536  545.80115  122.55946  1.916755  16.60101          0.097377
4  175.527445  546.45174  115.30063  1.916755  16.54253          0.098116

   Fluid_Fraction
0         0.03132
1         0.03132
2         0.03132
3         0.03132
4         0.03132
```

In [82]:
```
train_b['Predicted_Fluid_Fraction'] = model.predict(train_b.copy().drop('Fluid_Fraction
```

In [83]:
```
train_b.head()
```

Out[83]:
```
    Reference    Track_1    Track_2   Track_3   Track_4  Characteristic_1  \
0  176.151735  449.52114  106.79179  0.924423  18.24576          0.044960
1  176.009779  494.77735  124.72322  1.356370  17.91681          0.062602
2  175.854890  530.24547  126.32411  1.759663  16.71797          0.090488
3  175.690536  545.80115  122.55946  1.916755  16.60101          0.097377
4  175.527445  546.45174  115.30063  1.916755  16.54253          0.098116

   Fluid_Fraction  Predicted_Fluid_Fraction
0         0.03132                  0.138450
1         0.03132                  0.073302
2         0.03132                  0.030827
3         0.03132                  0.035043
4         0.03132                  0.033542
```

In [84]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,15))

plt.plot(train_b['Fluid_Fraction'], -train_b['Reference'], 'g')
plt.plot(train_b['Predicted_Fluid_Fraction'], -train_b['Reference'], 'r')

plt.xlabel('Fluid_Fraction')
plt.ylabel('Reference');
```


−120
−130
−140
−150
−160
−170
Reference
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Fluid_Fraction