Aramco Upstream Solutions Technathon

26-28.10.18

Challenge #1

Reservoir Evaluation

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Pure ML solution

Let's assume that we know nothing about underlying physics and learn from the data using quite powerful machine learning model that can deal with non-linearities.

So if we have data prepared using the same process,
we can train the model on dataset with known target
(Fluid_Fraction)
and then make a prediction for other dataset

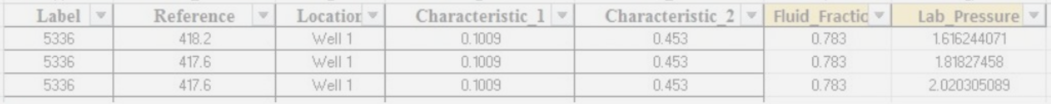
Technathon

Data Structure

1 Clustering

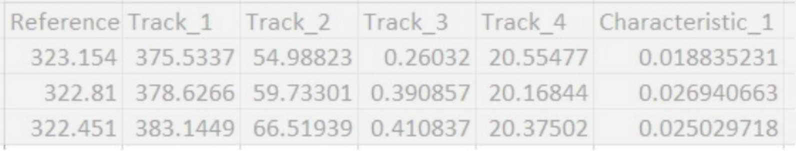
- Lab_Curves
- Logs-5
- Logs-4

Lab_Curves



Label	Reference	Locatior	Characteristic_1	Characteristic_2	Fluid_Fractic	Lab_Pressure
5336	418.2	Well 1	0.1009	0.453	0.783	1.616244071
5336	417.6	Well 1	0.1009	0.453	0.783	1.81827458
5336	417.6	Well 1	0.1009	0.453	0.783	2.020305089

Logs

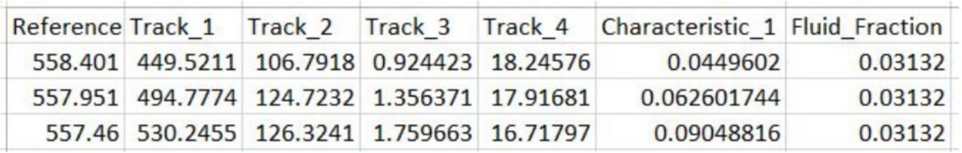


Reference	Track_1	Track_2	Track_3	Track_4	Characteristic_1
323.154	375.5337	54.98823	0.26032	20.55477	0.018835231
322.81	378.6266	59.73301	0.390857	20.16844	0.026940663
322.451	383.1449	66.51939	0.410837	20.37502	0.025029718

2 Training

- Logs-B
- Logs-C
- Logs-D_Lost_Sections

Logs

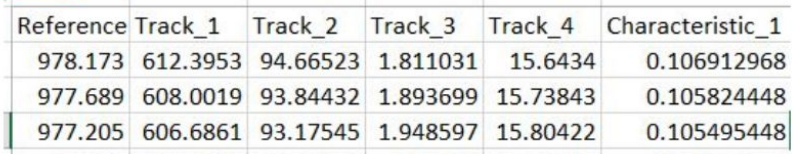


Reference	Track_1	Track_2	Track_3	Track_4	Characteristic_1	Fluid_Fraction
558.401	449.5211	106.7918	0.924423	18.24576	0.0449602	0.03132
557.951	494.7774	124.7232	1.356371	17.91681	0.062601744	0.03132
557.46	530.2455	126.3241	1.759663	16.71797	0.09048816	0.03132

3 Testing

- Logs-A
- Logs-D_Lost_Sections

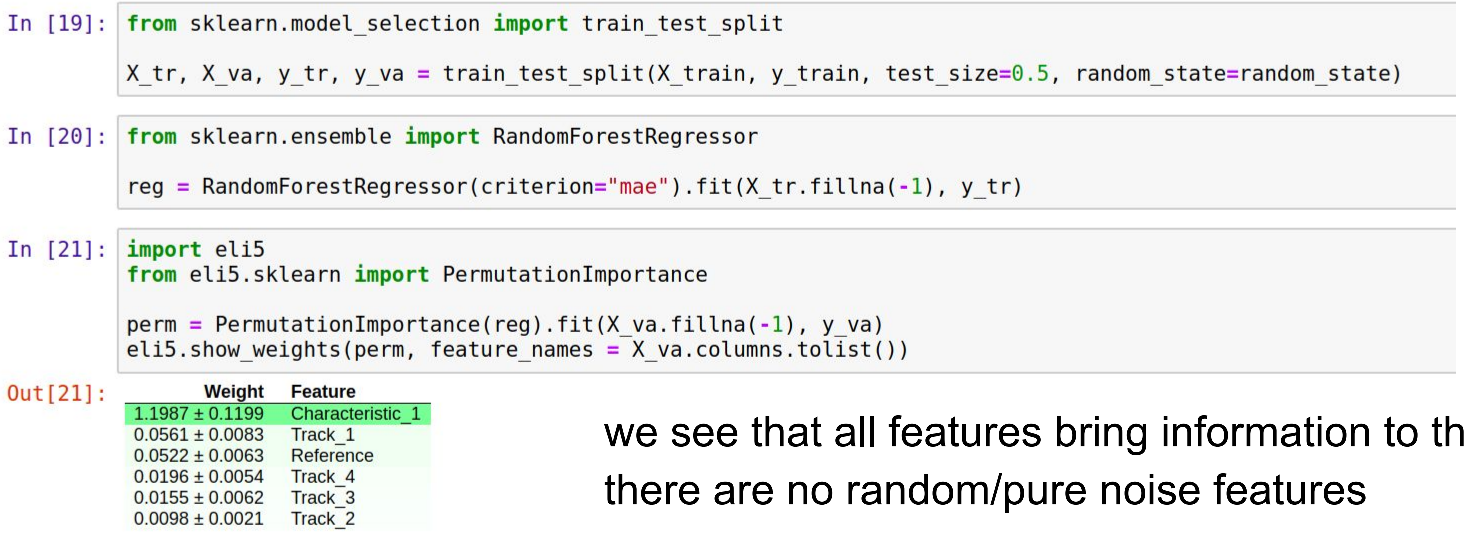
Logs



Reference	Track_1	Track_2	Track_3	Track_4	Characteristic_1
978.173	612.3953	94.66523	1.811031	15.6434	0.106912968
977.689	608.0019	93.84432	1.893699	15.73843	0.105824448
977.205	606.6861	93.17545	1.948597	15.80422	0.105495448

Permutation importance / Mean Decrease Accuracy (MDA)

black-box estimator measuring how score decreases when a feature is not available



```
In [19]: 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=random_state)
```

```
In [20]: from sklearn.ensemble import RandomForestRegressor

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

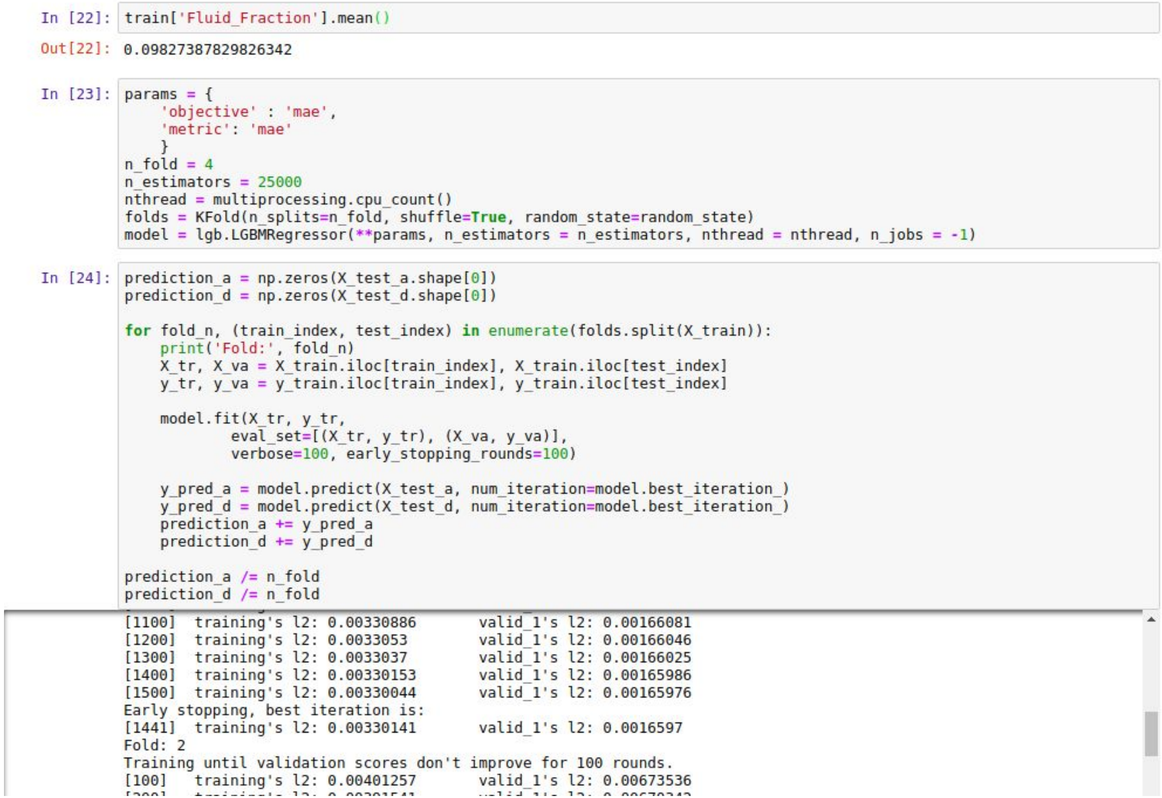
```
In [21]: import eli5
         from eli5.sklearn import PermutationImportance

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

Out[21]:

Weight	Feature
1.1987 ± 0.1199	Characteristic_1
0.0561 ± 0.0083	Track_1
0.0522 ± 0.0063	Reference
0.0196 ± 0.0054	Track_4
0.0155 ± 0.0062	Track_3
0.0098 ± 0.0021	Track_2

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

Model



```
In [22]: train['Fluid_Fraction'].mean()

Out[22]: 0.09827387829826342

In [23]: params = {
             'objective' : 'mae',
             'metric': 'mae'
             }
         n_fold = 4
         n_estimators = 25000
         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_jobs = -1)

In [24]: 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=100, 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
```

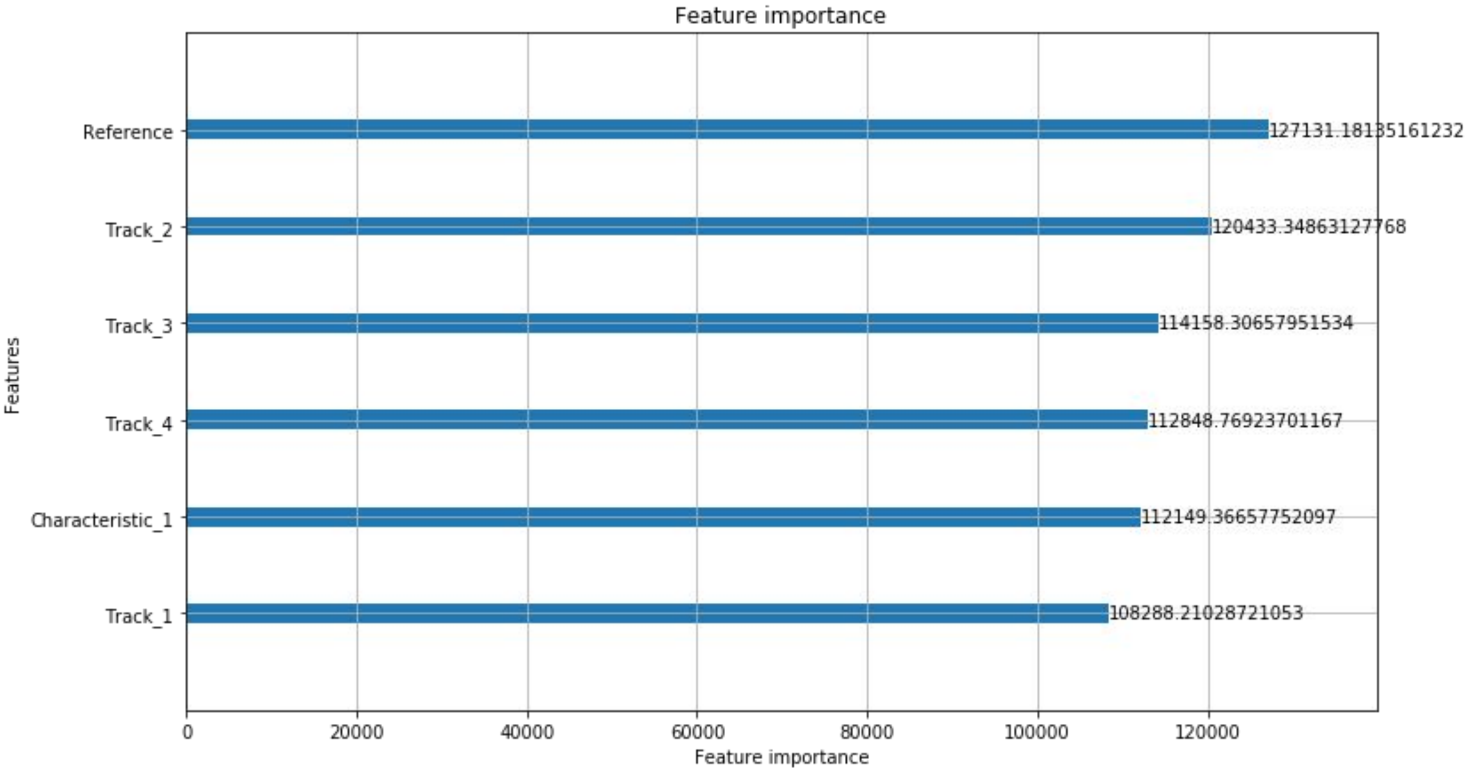
```
[1100]  training's l2: 0.00330886       valid_1's l2: 0.00166081
[1200]  training's l2: 0.0033053        valid_1's l2: 0.00166046
[1300]  training's l2: 0.0033037        valid_1's l2: 0.00166025
[1400]  training's l2: 0.00330153       valid_1's l2: 0.00165986
[1500]  training's l2: 0.00330044       valid_1's l2: 0.00165976
Early stopping, best iteration is:
[1441]  training's l2: 0.00330141       valid_1's l2: 0.0016597
Fold: 2
Training until validation scores don't improve for 100 rounds.
[100]   training's l2: 0.00401257       valid_1's l2: 0.00673536
```

Model:
Gradient boosting
Cross-validation:
4 folds
Metric:
Mean absolute error

$$mae = \frac{\sum_{i=1}^{n} abs\left(y_i - \lambda(x_i)\right)}{n}$$

early stopping to prevent overfitting

Feature importance


Feature importance
Reference
Track_2
Track_3
Track_4
Characteristic_1
Track_1
Features
Feature importance