# OpenML in Python

OpenML is an online collaboration platform for machine learning:

- Share/reuse machine learning datasets, algorithms, models, experiments
- Well documented/annotated datasets, uniform access
- APIs in Java, R, Python\*,... to download/upload everything
- Better reproducibility of experiments, reuse of machine learning models
- · Works well with machine learning libraries such as scikit-learn
- Large scale benchmarking, compare to state of the art

```
<IPython.core.display.HTML object>
```

### **Authentication**

- Create an OpenML account (free) on http://www.openml.org.
- After logging in, open your account page (avatar on the top right)
- Open 'Account Settings', then 'API authentication' to find your API key.

There are two ways to authenticate:

- Create a plain text file ~/.openml/config with the line 'apikey=MYKEY', replacing MYKEY with your API key.
- Run the code below, replacing 'MYKEY' with your API key.

```
[67]: # If you don't keep your API key in the config file, you can also specify
# oml.config.apikey = MYKEY
```

## Data sets

We can list, select, and download all OpenML datasets

#### List datasets

First 10 of 2518 active datasets...

	did	name	NumberOfInstances	NumberOfFeatures	NumberOfClasses
2	2	anneal	898	39	5
3	3	kr-vs-kp	3196	37	2
4	4	labor	57	17	2
5	5	arrhythmia	452	280	13
6	6	letter	20000	17	26
7	7	audiology	226	70	24
8	8	liver-disorders	345	7	16
9	9	autos	205	26	6

```
      10
      10
      lymph
      148
      19
      4

      11
      11
      balance-scale
      625
      5
      3
```

# There are many properties that we can query

```
[69]: list(datalist)
     datalist = datalist[['did','name','NumberOfInstances',
                     'NumberOfFeatures','NumberOfClasses']]
['name',
 'NumberOfFeatures',
'format',
 'NumberOfNumericFeatures',
 'NumberOfClasses',
 'NumberOfSymbolicFeatures',
'NumberOfInstances',
'MinorityClassSize',
 'NumberOfInstancesWithMissingValues',
 'MajorityClassSize',
 'did',
'status',
 'NumberOfMissingValues',
 'MaxNominalAttDistinctValues']
```

#### and we can filter or sort on all of them

	did	name	NumberOfInstances
23515	23515	sulfur	10081
981	981	kdd_internet_usage	10108
372	372	internet_usage	10108
1536	1536	volcanoes-b6	10130
4562	4562	InternetUsage	10168
1531	1531	volcanoes-b1	10176
1534	1534	volcanoes-b4	10190
1459	1459	artificial-characters	10218
1478	1478	har	10299
1533	1533	volcanoes-b3	10386
1532	1532	volcanoes-b2	10668
1053	1053	jm1	10885
1414	1414	<pre>Kaggle_bike_sharing_demand_challange</pre>	10886
1044	1044	eye_movements	10936
1019	1019	pendigits	10992
32	32	pendigits	10992
4534	4534	PhishingWebsites	11055
399	399	ohscal.wc	11162
310	310	mammography	11183
1568	1568	nursery	12958

	NumberOfFeatures	NumberOfClasses
23515	7	-1
981	69	2
372	72	46
1536	4	5
4562	72	-1
1531	4	5
1534	4	5
1459	8	10
1478	562	6
1533	4	5
1532	4	5
1053	22	2
1414	12	822
1044	28	3
1019	17	2
32	17	10
4534	31	2
399	11466	10
310	7	2
1568	9	4

# or find specific ones

```
[71]: datalist.query('name == "MagicTelescope"')
       did
                             NumberOfInstances
                                                 NumberOfFeatures
                       name
     1120
                                          19020
                                                                12
1120
           MagicTelescope
      NumberOfClasses
1120
                     2
[72]: datalist.query('NumberOfClasses > 50')
         did
                                                      NumberOfInstances
                                                name
190
         190
                                            mbagrade
                                                                       61
1092
        1092
                                               Crash
                                                                     352
1414
        1414
              Kaggle_bike_sharing_demand_challange
                                                                   10886
1491
        1491
                          one-hundred-plants-margin
                                                                    1600
1492
        1492
                           one-hundred-plants-shape
                                                                    1600
1493
        1493
                         one-hundred-plants-texture
                                                                    1599
4546
        4546
                                              Plants
                                                                   44940
4552
        4552
                                  BachChoralHarmony
                                                                    5665
40601
      40601
                                           RAM_price
                                                                     333
                                                                 5465575
40753
      40753
                            delays_zurich_transport
40916
       40916
                                 HappinessRank_2015
                                                                     158
41021
       41021
                                           Moneyball
                                                                    1232
41022
       41022
                          Short_Track_Speed_Skating
                                                                    5125
```

NumberOfFeatures NumberOfClasses

190	3	57
1092	14	307
1414	12	822
1491	65	100
1492	65	100
1493	65	100
4546	16	57
4552	17	102
40601	3	219
40753	15	4082
40916	12	157
41021	15	87
41022	27	2954

### Download a specific dataset. This is done based on the dataset ID (called 'did').

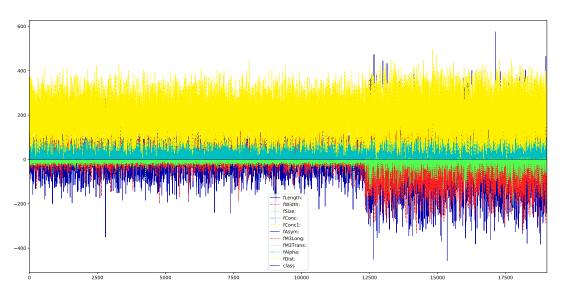
### Convert the data to a DataFrame for easier processing/plotting

[74]: X, y, attribute\_names = dataset.get\_data(

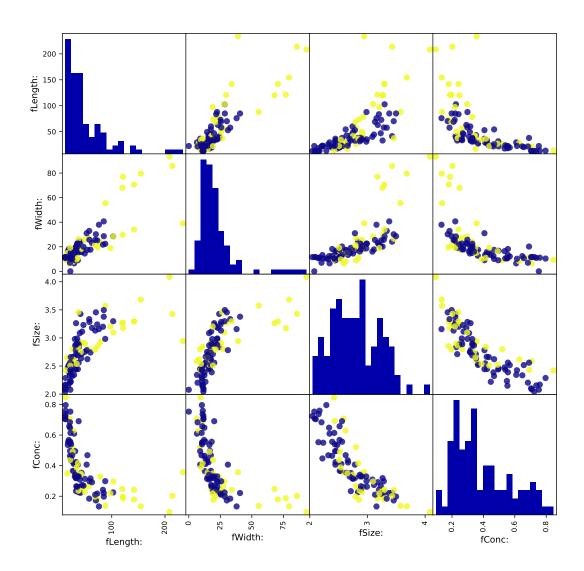
```
target=dataset.default_target_attribute,
           return_attribute_names=True)
      magic = pd.DataFrame(X, columns=attribute_names)
      magic['class'] = y
      print (magic[:10])
   fLength:
              fWidth:
                        fSize:
                                fConc:
                                                 fM3Trans:
                                                             fAlpha:
                                                                       fDist:
                                                                               class
                                         . . .
0
      28.80
                          2.64
                                   0.39
                                                     -8.20
                                                               40.09
                                                                                    0
                16.00
                                                                        81.88
                                         . . .
1
      31.60
                          2.52
                                                     -9.96
                                                                                    0
                11.72
                                   0.53
                                         . . .
                                                                6.36 205.26
2
     162.05
               136.03
                          4.06
                                   0.04
                                                    -45.22
                                                               76.96
                                                                      256.79
                                                                                    0
                 9.57
3
      23.82
                          2.34
                                  0.61
                                                     -7.15
                                                               10.45
                                                                      116.74
                                                                                    0
                                         . . .
4
      75.14
                30.92
                         3.16
                                  0.32
                                                     21.84
                                                                4.65
                                                                      356.46
                                         . . .
5
      51.62
                21.15
                         2.91
                                   0.24
                                                                                    0
                                                      9.81
                                                                3.61
                                                                      238.10
                                         . . .
6
      48.25
                17.36
                         3.03
                                  0.25
                                                     10.59
                                                                4.79 219.09
                                                                                    0
7
      26.79
                13.76
                          2.55
                                   0.42
                                                     -2.93
                                                                0.81 237.13
                                                                                    0
      96.23
                                                                      248.23
8
                46.52
                         4.15
                                   0.08
                                                     43.18
                                                                4.85
                                                                                    0
                                         . . .
      46.76
9
                15.20
                          2.58
                                  0.34
                                         . . .
                                                     -6.68
                                                                7.88
                                                                      102.25
```

```
[10 rows x 11 columns]
```

```
[75]: magic.plot(figsize=(20,10))
    pd.DataFrame(y).plot(figsize=(20,1));
```







# **Train models**

Train a scikit-learn model on the data manually

```
[77]: from sklearn import ensemble
   from sklearn import model_selection

X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y)
   clf = ensemble.RandomForestClassifier(n_estimators=100)
   clf.fit(X_train, y_train)
   pd.DataFrame(clf.predict(X)).plot(figsize=(20,1));
```

And evaluate

```
[78]: kfold = model_selection.StratifiedKFold(n_splits=5, shuffle=True, random_s
    results = model_selection.cross_val_score(clf, X, y, cv=kfold)
    print("Accuracy: %.3f%% (+- %.3f)" % (results.mean(), results.std()))
Accuracy: 0.880% (+- 0.002)
```

Note: You can also ask which features are categorical to do your own encoding

```
[79]: from sklearn import preprocessing
      dataset = oml.datasets.get_dataset(10) # Lymph dataset
      X, y, categorical = dataset.get_data(
          target=dataset.default_target_attribute,
          return_categorical_indicator=True)
      print("Categorical features: %s" % categorical)
      enc = preprocessing.OneHotEncoder(categorical_features=categorical)
      X = enc.fit_transform(X)
      clf.fit(X, y)
Categorical features: [True, True, True, True, True, True, True, False, Fa
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

## **Tasks**

To run benchmarks consistently (also across studies and tools), OpenML offers Tasks, which include specific train-test splits and other information to define a scientific task. Tasks are typically created via the website by the dataset provider.

### Listing tasks

```
'source_data_labeled', 'status', 'target_feature',
       'target_feature_event', 'target_feature_left', 'target_feature_right',
       'target_value', 'task_type', 'tid', 'ttid'],
     dtype='object')
[81]: mytasks = mytasks[['tid','did','name','task_type','estimation_procedure','
     print(mytasks.head())
                                      task_type estimation_procedure
 tid did
                name
   2
2
              anneal Supervised Classification 10-fold Crossvalidation
           kr-vs-kp Supervised Classification 10-fold Crossvalidation
   3
       3
3
   4
     4
               labor Supervised Classification 10-fold Crossvalidation
4
5
   5 5 arrhythmia Supervised Classification 10-fold Crossvalidation
              letter Supervised Classification 10-fold Crossvalidation
  evaluation measures
2 predictive_accuracy
3
                  NaN
4 predictive_accuracy
5 predictive_accuracy
                  NaN
```

### Search for the tasks you need

```
[82]: print(mytasks.query('name=="MagicTelescope"'))
```

	tid	did	name	task_type \	
3954	3954	1120	MagicTelescope	Supervised Classification	
4659	4659	1120	MagicTelescope	Supervised Classification	
7228	7228	1120	MagicTelescope	Supervised Data Stream Classification	
10067	10067	1120	MagicTelescope	Learning Curve	
	estimation_procedure evaluation_measures				
3954	10-fold Crossvalidation NaN				
4659	10 times 10-fold Crossvalidation predictive_accuracy				
7228	Interleaved Test then Train NaN				
10067	10-fold Learning Curve NaN				

#### **Download tasks**

# **Runs: Train models on tasks**

We can run (many) scikit-learn algorithms on (many) OpenML tasks.

Share the run on the OpenML server \* Note: if the exact same experiment has already been done (probably by you), it will just return the run ID from the previous run

# It also works with pipelines

```
flow = oml.flows.sklearn_to_flow(pipe)
    run = oml.runs.run_flow_on_task(task, flow)
    myrun = run.publish()
    print("Uploaded to http://www.openml.org/r/" + str(myrun.run_id))

Uploaded to http://www.openml.org/r/8872326
```

# All together

Train any model on any OpenML dataset and upload to OpenML in a few lines of code

[87]: from sklearn.linear\_model import LogisticRegression

```
task = oml.tasks.get_task(3954)
      clf = LogisticRegression()
      flow = oml.flows.sklearn_to_flow(clf)
      run = oml.runs.run_flow_on_task(task, flow)
      run.model
      myrun = run.publish()
      print("Uploaded to http://www.openml.org/r/" + str(myrun.run_id))
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='12', random_state=45647, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
Uploaded to http://www.openml.org/r/8872327
  • You can (of course) evaluate models in a loop
  • E.g. for easy benchmarking:
[89]: import openml as oml
      from sklearn import neighbors
      for task_id in [14951,10103,9945]:
          task = oml.tasks.get_task(task_id)
          data = oml.datasets.get_dataset(task.dataset_id)
          clf = neighbors.KNeighborsClassifier(n_neighbors=10)
          flow = oml.flows.sklearn_to_flow(clf)
          run = oml.runs.run_flow_on_task(task, flow)
          myrun = run.publish()
          print("kNN on %s: http://www.openml.org/r/%d" % (data.name, myrun.run_
kNN on eeg-eye-state: http://www.openml.org/r/8872328
kNN on volcanoes-al: http://www.openml.org/r/8872329
kNN on walking-activity: http://www.openml.org/r/8872330
```

### Download everyone else's results on the same dataset

Check whether other people built better models on the same task by downloading their evaluations (computed on the OpenML server) and comparing directly against them.

```
[90]: myruns = oml.runs.list_runs(task=[3954], size=10000) # This can take a while
scores = []
for id, _ in myruns.items():
    run = oml.runs.get_run(id)
    if str.startswith(run.flow_name, 'sklearn'):
        scores.append(("flow":run.flow_name, "score":run.evaluations['pred

[94]: import seaborn as sns
fig, ax = plt.subplots(figsize=(8, 12))
    sns.violinplot(x="score", y="flow", data=pd.DataFrame(scores), scale="widt")
```