# qml4omics

Code overview

- It controls everything!
  - Parameters passed as arguments throughout the code base
- 1) Input data sets

config.yaml

```
# specify output directory where input datasets are located
folder_path: 'tutorial_test_data/lower_dim_datasets'
file_dataset: 'ALL'
# or use a list as below, to only select a few datasets
# file_dataset: ['file1', 'file2', 'file3', etc]
```

qml4omics-profiler.py (main function)

```
# Begin the main function and instatiate Hydra class
@hydra.main(config_path='./configs/', config_name='config.yaml', version_base='1.1')
def main(args):
    beg_time = time.time()
    log = logging.getLogger(__name__)
    log.info(f"Main program initiated")
    log.info(f"The number of ML methods being parallelized is {min(args['n_jobs'], len(args['model']))}")
    log.info(f"Chosen backend for quantum algorithms is: {args['backend']}")
   path to input = os.path.join(current_dir, 'data', args['folder_path'])
    if args['file dataset'] == 'ALL':
        input_files = [file for file in os.listdir(path_to_input) if file.endswith('csv')]
        input files = [file for file in os.listdir(path to input) if file in args['file dataset'] and file.endswith('csv')]
    # need to populate raw data evaluation for each file, so start an empty list
    appended_raw_data_eval = []
   # start looping over datasets
    file_count = 0
    for file in sorted(input files):
```

2) Complexity evaluation (on raw and embedded data)

```
qml4omics-profiler.py (main function)
              config.yaml
                                                                                            # call and run evaluation functions
  # specify output directory where input datasets are located
                                                                                            df dataset = pd.DataFrame(X)
  folder path: 'tutorial test data/lower dim datasets'
  file dataset: 'ALL'
                                                                                             raw data eval = evaluate(df dataset, y encoded, file)
  # or use a list as below, to only select a few datasets
                                                                                            appended raw data eval.append(raw data eval)
  # file_dataset: ['file1', 'file2', 'file3', etc]
                                                                                 # call and run evalution functions again if data is embedded, save
   evaluate(df, y, file):
                                                                                  df dataset = pd.DataFrame(X train emb)
    ""Takes a pandas DataFrame as an input and returns a transposed DataFrame with the calculated mean, median
   standard deviation, variation, skewness, coefficient of variation as percentage, mean/median difference,
                                                                                  evaluate data = evaluate(df dataset, y train, file)
   and kurtosis for each numeric column.""
   df_numeric = df.select_dtypes(include=[np.number])
                                                                                  evaluate_data_listofdict = evaluate_data.to_dict(orient='records')
   n_features, n_samples, feature_sample_ratio = get_dimensions(df_numeric)
   intrinsic_dim = get_intrinsic_dim(df_numeric)
   condition_number = get_condition_number(df_numeric)
   fdr = get_fdr(df_numeric, y)
gml4omics/evaluation/dataset evaluation.py
```

#### 3) Quantum backend

#### config.yaml

# # choose a backend for the QML methods # backend: 'ibm\_cleveland' # backend: 'ibm\_least' backend: 'simulator' # IBM runtime credentials - they should be in qiskit\_json\_path: '~/.qiskit/qiskit-ibm.json'

#### qml4omics/utils/qutils.py

```
def get_backend_session( args: dict, primitive : str, num_qubits : int ):
    backend = None
    session = None
    prim = None

if args['backend'] == 'simulator':

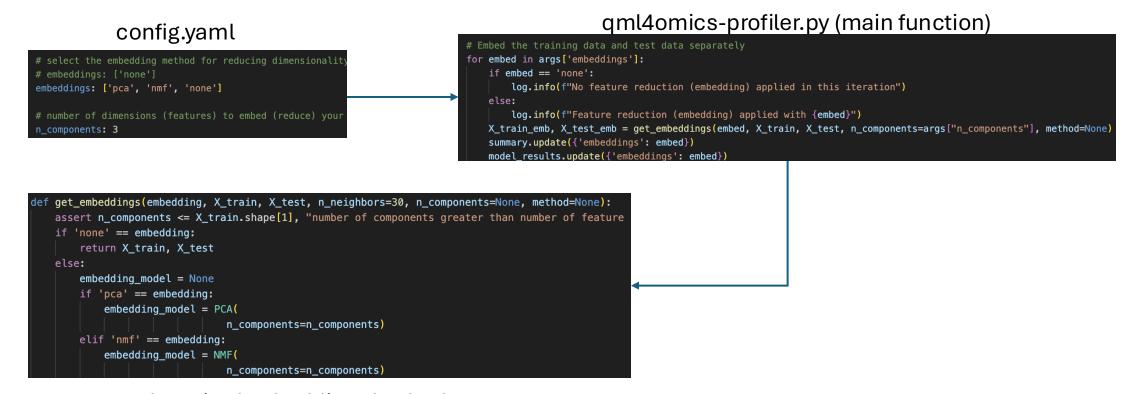
    if primitive == 'estimator':

        # Estimator primitive
        prim = StatevectorEstimator(seed=args['seed'])
    else:
        prim = StatevectorSampler(seed = args['seed'], default_shots=args['shots'])
    elif 'ibm' in args['backend']:

        service = instantiate_runtime_service[args]

        if args['backend'] == 'ibm_least':
            backend = service.least_busy(simulator=False, operational=True, min_num_qubits=num_qubits)
        else:
        backend = service.backend(name=args['backend'])
```

4) Embedding the data (reducing dimensions/features)



qml4omics/embeddings/embed.py

#### 5) Splitting the data

#### config.yaml

```
# This sets the number of times you will perform a train-test split
# For each split, models are generated for every model-embedding com
iter: 2
# set the ratio of train:test the data is split into, in this case 70:30
test_size: 0.3
stratify: ['y']
scaling: ['True']
# ML models to generate
model: ['svc', 'dt', 'lr', 'nb', 'rf', 'mlp', 'qsvc', 'vqc', 'qnn', 'pqk']
average: 'weighted'
multi_class: 'raise'
```

#### qml4omics-profiler.py (main function)

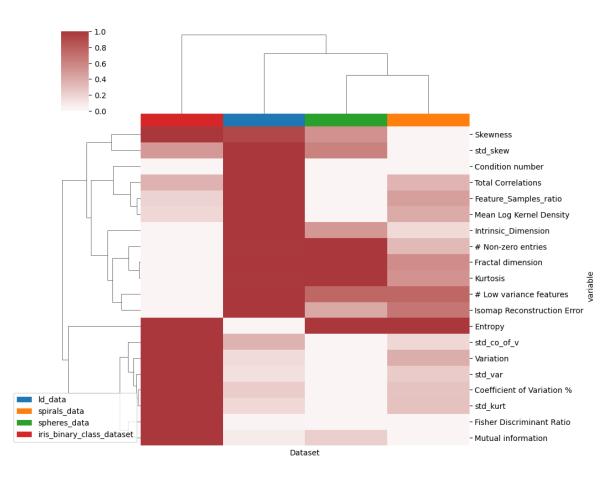
```
stratify = args['stratify']
test_size = args['test_size']
iter = 0
# makes number of iterations an argument from config
for iter in range(args['iter']):
## run all this in a loop N times, while leaving the seed fixed above. The train test split will change
    iter=iter+1
    # track iteration time
    iter_start_time = time.time()
    X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, stratify=y, test_size=test_size)
    log.info(f"Begin processing iteration (split) {iter} of {args['iter']}")
    #Scale the features
    if 'True' in args['scaling']:
        X_train = scaler_fn(X_train, scaling='MinMaxScaler')
        X_test = scaler_fn(X_test, scaling='MinMaxScaler')
summary.update({'iteration': iter})
model_results.update({'iteration': iter})
data_key = '_'.join( [re.sub( '\..*', '', file ), embed, str(args["n_components"]), str(iter)])
summary.update(model_run(X_train_emb, X_test_emb, y_train, y_test, data_key, args))
```

5) Run models (with and without grid search/hyperparameter tuning)

config.yaml qml4omics-profiler.py (main function) # ML models to generate summary.update({'iteration': iter}) model: ['svc', 'dt', 'lr', 'nb', 'rf', 'mlp', 'qsvc', 'vqc', 'qnn', 'pqk'] model results.update({'iteration': iter}) data\_key = '\_'.join( [re.sub( '\..\*', '', file ), embed, str(args["n\_components"]), str(iter)]) average: 'weighted' summary.update(model\_run(X\_train\_emb, X\_test\_emb, y\_train, y\_test, data\_key, args)) multi\_class: 'raise' # this turns on a grid search (hyperparameter tuning) for the CML methods grid search: False # Run classical and quantum models n\_jobs = len(args['model']) if 'n jobs' in args.keys(): n\_jobs = min(args['n\_jobs'], len(args['model'])) grid search = False if 'grid\_search' in args.keys(): grid search = args['grid search'] if grid search: results = Parallel(n\_jobs=n\_jobs)(delayed(compute\_ml\_dict[method+ '\_opt'])(X\_train, X\_test, y\_train, y\_test, args, model= cv = args['cross\_validation'], \*\*args['gridsearch\_' + method + '\_args'], verbose=False) for method in args['model']) else: results = Parallel(n\_jobs=n\_jobs)(delayed(compute\_ml\_dict[method])(X\_train, X\_test, y\_train, y\_test, args, model=method, \*\*args[method+'\_args'], verbose=False) for method in args['model']) gml4omics/evaluation/model run.py

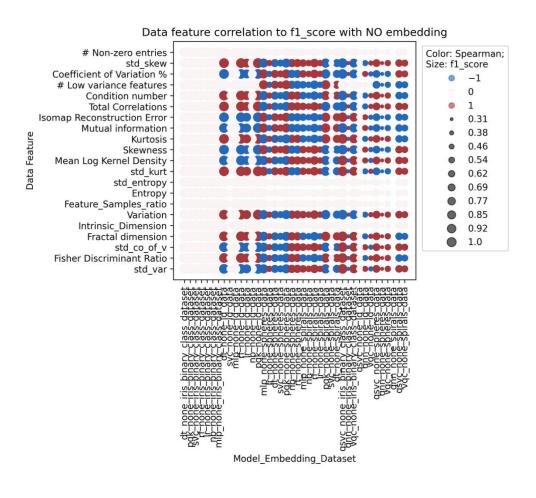
### Understanding the Analyses

- 1) Hierarchical clustering heat maps
- What it's doing here:
  - Complexity measure range is normalized between 0 and 1.
  - Euclidean distance is calculated between columns and rows, clustering together those with the shortest distance similar intensities for complexity measures.
  - The dendogram branches create a pairing hierarchy.
  - Outlier has longest branch.
  - Helps answer: *Is there some structure or pattern in my data?*



### Understanding the Analyses

- 1) Spearman Rank Correlations
- What it's doing here:
  - Correlates data complexity measure to model performance (F1-score)
  - Red = positive correlated
  - Blue = anti-correlated
  - Size of sphere = magnitude of F1score
  - Helps answer: What complexity measures influence your model score the most?



### Understanding the Analyses

- 1) Box-and-whisker plots
- What it's doing here:
  - Plots distribution of median F1scores per datasets, across all splits of data, per model.
  - Top and bottom of box = upper and lower quartiles (Q3 and Q1)
  - Whiskers denote range in F1- scores
  - Helps answer: What is the locality, spread, and skewness groups in my data (F1-scores) based on their quartiles?

