Conducting Research Experiments with QuaPy

Quantification: Predicting Class Frequencies via Supervised Learning

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Consiglio Nazionale delle Ricerche

Learning to Quantify: Methods and Applications (LQ 2024)
@ECML-PKDD, Vilnius, Lithuania
September 13, 2024

Introduction

- QuaPy is a Python-based, open-source software library for quantification
- Installation:

```
! pip install quapy
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting quapy
  Downloading QuaPy-0.1.7-py3-none-any.whl (99 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 99.1/99.1 KB 2.8 MB/s eta 0:00:00
Requirement already satisfied: pandas in /usr/local/lib/python3.8/dist-packages (from quapy) (1.3.5)
Requirement already satisfied: tqdm in /usr/local/lib/python3.8/dist-packages (from quapy) (4.64.1)
Requirement already satisfied: xlrd in /usr/local/lib/python3.8/dist-packages (from quapy) (1.2.0)
Requirement already satisfied: joblib in /usr/local/lib/python3.8/dist-packages (from quapy) (1.2.0)
Collecting abstention
  Downloading abstention-0.1.3.1.tar.gz (24 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.8/dist-packages (from quapy) (1
Requirement already satisfied: matplotlib in /usr/local/lib/python3.8/dist-packages (from quapy) (3.2
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Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.8/dist-packages (from m
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.8/d
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.8/dist-packages (from matp
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/dist-packages (from matplotli
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-packages (from pandas->q
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-packages (from python-dateut
Building wheels for collected packages: abstention
  Building wheel for abstention (setup.py) ... done
  Created wheel for abstention: filename=abstention-0.1.3.1-py3-none-any.whl size=25454 sha256=1b42c5
  Stored in directory: /root/.cache/pip/wheels/a0/dc/ed/2ddd390de2a6b43aa30f75155b50dfea2bc3b8ed9a5c6
Successfully built abstention
Installing collected packages: abstention, quapy
Successfully installed abstention-0.1.3.1 quapy-0.1.7
```
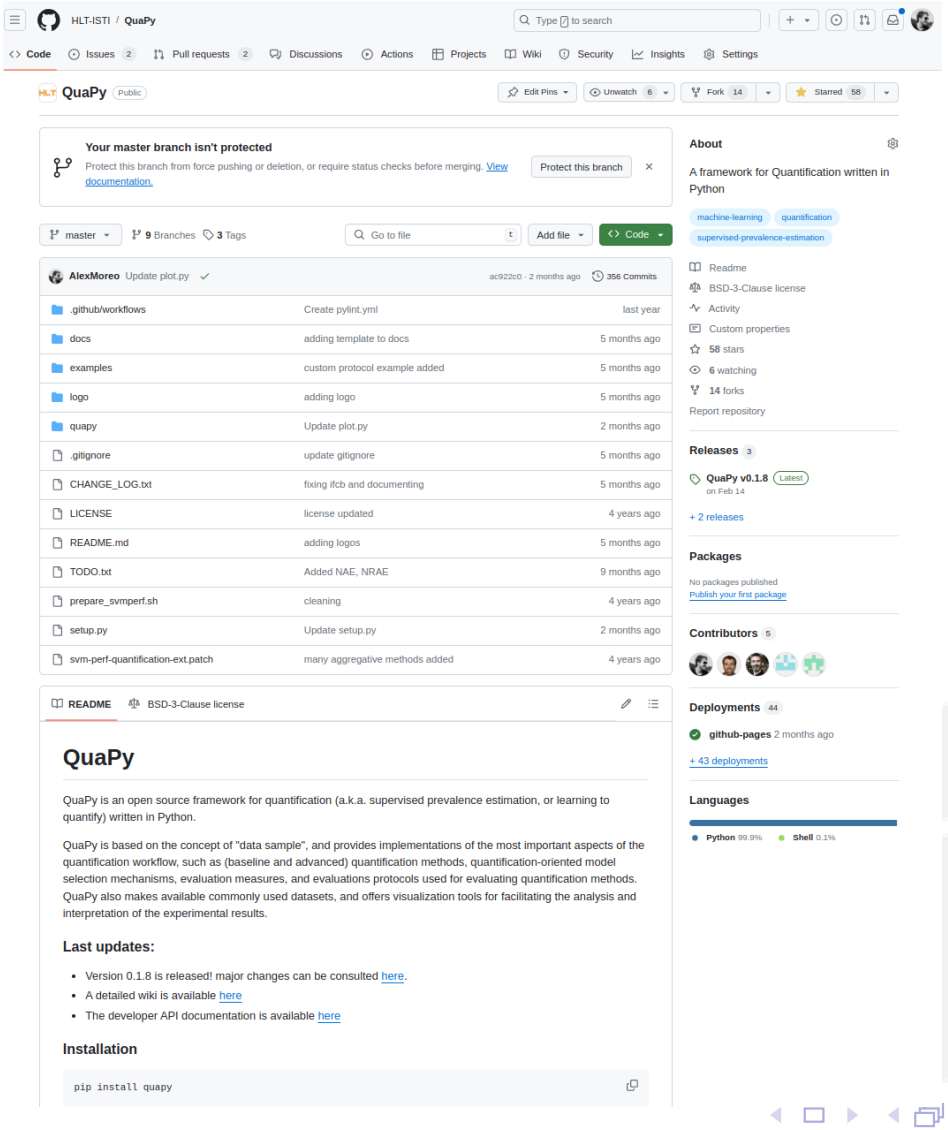
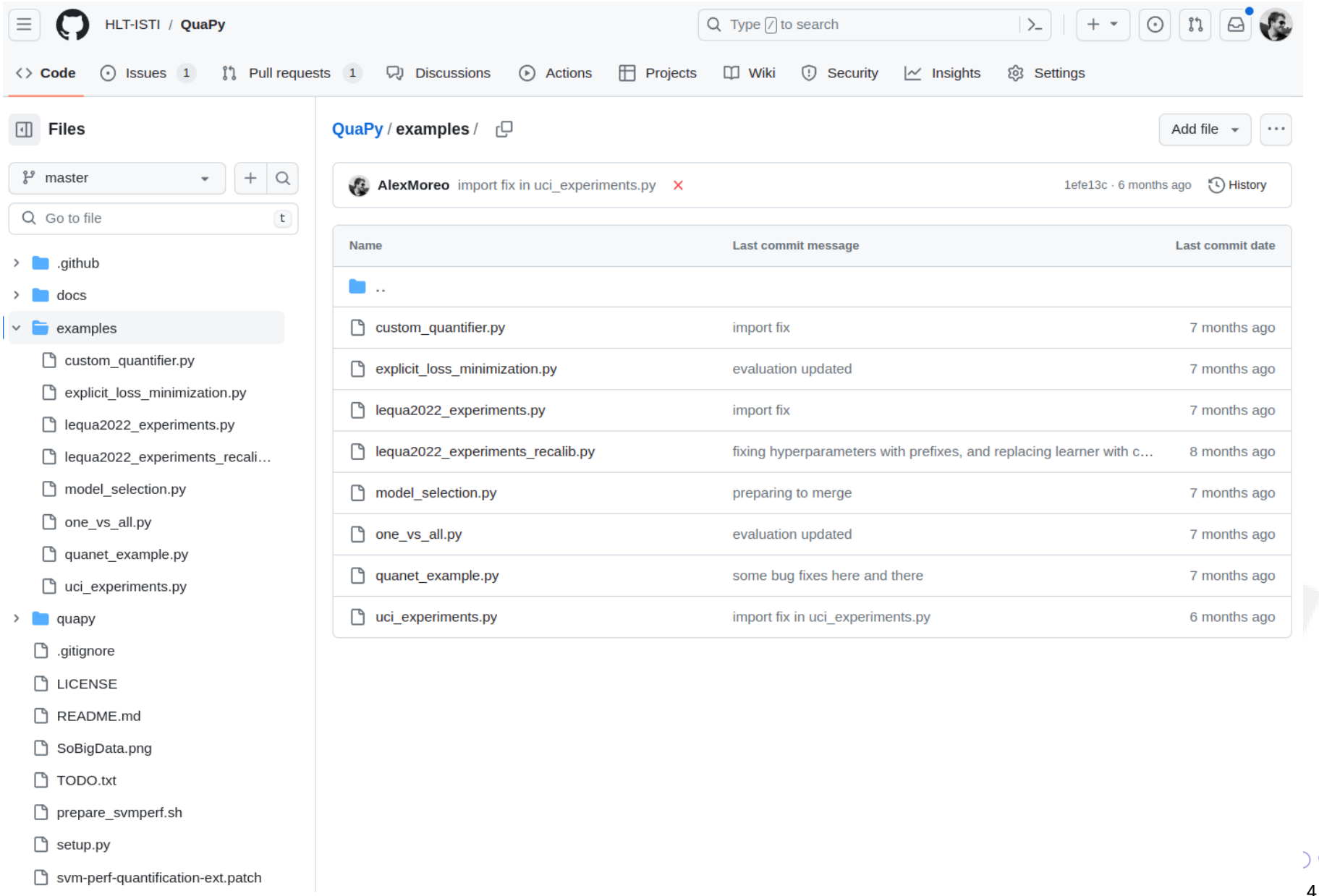

GitHub repository

- QuaPy v0.1.8 available at https://github.com/HLT-ISTI/QuaPy



GitHub repository: Examples



Online API documentation

quapy.functional

quapy.functional.**HellingerDistance**(*P*, *Q*)

Computes the Hellingher Distance (HD) between (discretized) distributions *P* and *Q*. The HD for two discrete distributions of *k* bins is defined as:

$$HD(P,Q) = \frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{k}(\sqrt{p_i}-\sqrt{q_i})^2}$$

Parameters:
- **P** – real-valued array-like of shape *(k,)* representing a discrete distribution
- **Q** – real-valued array-like of shape *(k,)* representing a discrete distribution

Returns: float

quapy.functional.**TopsoeDistance**(*P*, *Q*, *epsilon=1e-20*)

Topsoe distance between two (discretized) distributions *P* and *Q*. The Topsoe distance for two discrete distributions of *k* bins is defined as:

$$Topsoe(P,Q) = \sum_{i=1}^{k}\left(p_i \log\left(\frac{2p_i+\epsilon}{p_i+q_i+\epsilon}\right) + q_i \log\left(\frac{2q_i+\epsilon}{p_i+q_i+\epsilon}\right)\right)$$

Parameters:
- **P** – real-valued array-like of shape *(k,)* representing a discrete distribution
- **Q** – real-valued array-like of shape *(k,)* representing a discrete distribution

Returns: float

quapy.functional.**adjusted_quantification**(*prevalence_estim*, *tpr*, *fpr*, *clip=True*)

Implements the adjustment of ACC and PACC for the binary case. The adjustment for a prevalence estimate of the positive class *p* comes down to computing:

$$ACC(p) = \frac{p - fpr}{tpr - fpr}$$

Parameters:
- **prevalence_estim** – float, the estimated value for the positive class
- **tpr** – float, the true positive rate of the classifier
- **fpr** – float, the false positive rate of the classifier
- **clip** – set to True (default) to clip values that might exceed the range [0,1]

Returns: float, the adjusted count

Online API documentation

quapy.data.datasets

quapy.data.datasets.**fetch_UCIDataset**(*dataset_name*, *data_home=None*, *test_split=0.3*, *verbose=False*) → Dataset

Loads a UCI dataset as an instance of **quapy.data.base.Dataset**, as used in Pérez-Gállego, P., Quevedo, J. R., & del Coz, J. J. (2017). Using ensembles for problems with characterizable changes in data distribution: A case study on quantification. Information Fusion, 34, 87-100. and Pérez-Gállego, P., Castano, A., Quevedo, J. R., & del Coz, J. J. (2019). Dynamic ensemble selection for quantification tasks. Information Fusion, 45, 1-15.. The datasets do not come with a predefined train-test split (see **fetch_UCILabelledCollection()** for further information on how to use these collections), and so a train-test split is generated at desired proportion. The list of valid dataset names can be accessed in *quapy.data.datasets.UCI_DATASETS*

Parameters:
- **dataset_name** – a dataset name
- **data_home** – specify the quapy home directory where collections will be dumped (leave empty to use the default ~/quay_data/ directory)
- **test_split** – proportion of documents to be included in the test set. The rest conforms the training set
- **verbose** – set to True (default is False) to get information (from the UCI ML repository) about the datasets

Returns: a **quapy.data.base.Dataset** instance

quapy.data.datasets.**fetch_UCILabelledCollection**(*dataset_name*, *data_home=None*, *verbose=False*) → Dataset

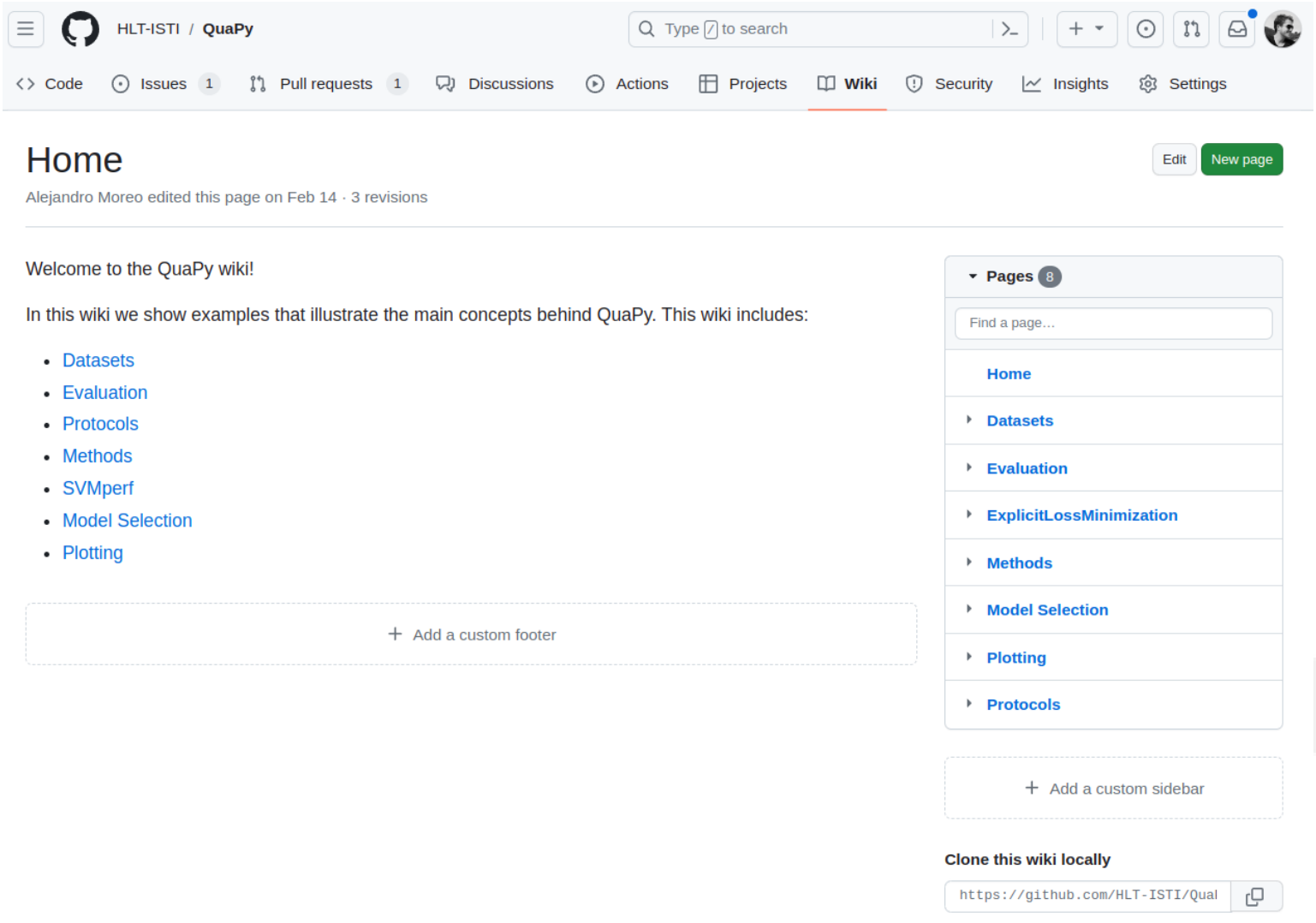
Loads a UCI collection as an instance of **quapy.data.base.LabelledCollection**, as used in Pérez-Gállego, P., Quevedo, J. R., & del Coz, J. J. (2017). Using ensembles for problems with characterizable changes in data distribution: A case study on quantification. Information Fusion, 34, 87-100. and Pérez-Gállego, P., Castano, A., Quevedo, J. R., & del Coz, J. J. (2019). Dynamic ensemble selection for quantification tasks. Information Fusion, 45, 1-15.. The datasets do not come with a predefined train-test split, and so Pérez-Gállego et al. adopted a 5FCVx2 evaluation protocol, meaning that each collection was used to generate two rounds (hence the x2) of 5 fold cross validation. This can be reproduced by using **quapy.data.base.Dataset.kFCV()**, e.g.:

```
>>> import quapy as qp
>>> collection = qp.datasets.fetch_UCILabelledCollection("yeast")
>>> for data in qp.data.Dataset.kFCV(collection, nfolds=5, nrepeats=2):
>>>     ...
```

The list of valid dataset names can be accessed in *quapy.data.datasets.UCI_DATASETS*

Parameters:
- **dataset_name** – a dataset name
- **data_home** – specify the quapy home directory where collections will be dumped (leave empty to use the default ~/quay_data/ directory)

Online Wiki


HLT-ISTI / QuaPy
Type / to search
Code
Issues 1
Pull requests 1
Discussions
Actions
Projects
Wiki
Security
Insights
Settings
Home
Edit
New page
Alejandro Moreo edited this page on Feb 14 · 3 revisions
Welcome to the QuaPy wiki!
In this wiki we show examples that illustrate the main concepts behind QuaPy. This wiki includes:
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Protocols
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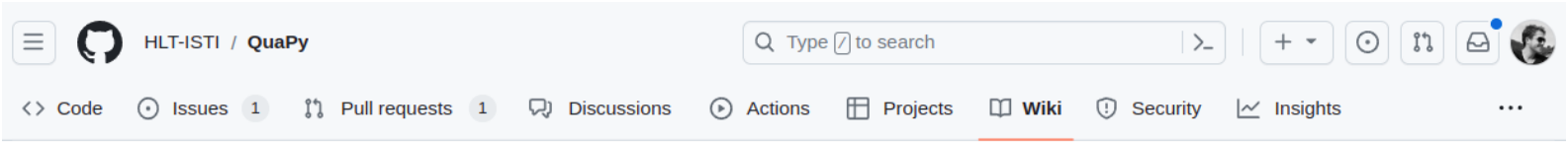

Datasets

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Alejandro Moreo edited this page on Feb 14 · 8 revisions

Datasets

QuaPy makes available several datasets that have been used in quantification literature, as well as an interface to allow anyone import their custom datasets.

A *Dataset* object in QuaPy is roughly a pair of *LabelledCollection* objects, one playing the role of the training set, another the test set. *LabelledCollection* is a data class consisting of the (iterable) instances and labels. This class handles most of the sampling functionality in QuaPy. Take a look at the following code:

```
import quapy as qp
import quapy.functional as F

instances = [
    '1st positive document', '2nd positive document',
    'the only negative document',
    '1st neutral document', '2nd neutral document', '3rd neutral document'
]
labels = [2, 2, 0, 1, 1, 1]

data = qp.data.LabelledCollection(instances, labels)
print(F.strprev(data.prevalence(), prec=2))
```

Output the class prevalences (showing 2 digit precision):

```
[0.17, 0.50, 0.33]
```

One can easily produce new samples at desired class prevalence values:

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Online Wiki

Meta Models

By *meta* models we mean quantification methods that are defined on top of other quantification methods, and that thus do not squarely belong to the aggregative nor the non-aggregative group (indeed, *meta* models could use quantifiers from any of those groups). *Meta* models are implemented in the *qp.method.meta* module.

Ensembles

QuaPy implements (some of) the variants proposed in:

- *Pérez-Gállego, P., Quevedo, J. R., & del Coz, J. J. (2017). Using ensembles for problems with characterizable changes in data distribution: A case study on quantification. Information Fusion, 34, 87-100.*
- *Pérez-Gállego, P., Castano, A., Quevedo, J. R., & del Coz, J. J. (2019). Dynamic ensemble selection for quantification tasks. Information Fusion, 45, 1-15.*

The following code shows how to instantiate an Ensemble of 30 *Adjusted Classify & Count* (ACC) quantifiers operating with a *Logistic Regressor* (LR) as the base classifier, and using the *average* as the aggregation policy (see the original article for further details). The last parameter indicates to use all processors for parallelization.

```
import quapy as qp
from quapy.method.aggregative import ACC
from quapy.method.meta import Ensemble
from sklearn.linear_model import LogisticRegression

dataset = qp.datasets.fetch_UCIDataset('haberman')

model = Ensemble(quantifier=ACC(LogisticRegression()), size=30, policy='ave', n_jobs=-1)
model.fit(dataset.training)
estim_prevalence = model.quantify(dataset.test.instances)
```

Other aggregation policies implemented in QuaPy include:

- 'ptr' for applying a dynamic selection based on the training prevalence of the ensemble's members
- 'ds' for applying a dynamic selection based on the Hellinger Distance
- *any valid quantification measure* (e.g., 'mse') for performing a static selection based on the performance estimated for each member of the ensemble in terms of that evaluation metric.

Features

- The most important features of QuaPy include:
  - QuaPy provides implementations of many methods (basic and advanced) implementing the same interface
  - QuaPy implements standard evaluation protocols
  - Provides implementations of the most important evaluation metrics
  - Access to many popular datasets for quantification
  - QuaPy provides native support to multiclass quantification
  - Automatic optimization of hyperparameters (model selection)
  - Visualization tools

Example: binary quantification

```
from sklearn.linear_model import LogisticRegression

dataset = qp.datasets.fetch_reviews('kindle', tfidf=True, min_df=5)
training, test = dataset.train_test

# create an "Adjusted Classify & Count" quantifier
model = qp.method.aggregative.ACC(LogisticRegression())
model.fit(training)

estim_prevalence = model.quantify(test.instances)
true_prevalence  = test.prevalence()

error = qp.error.mae(true_prevalence, estim_prevalence)

print(f'Mean Absolute Error (MAE)={error:.3f}')
```

```
loading /root/quapy_data/reviews/kindle/train.txt: 100%|██████████| 3821/3821 [00:00<00:00, 316371.59it/s]
loading /root/quapy_data/reviews/kindle/test.txt: 100%|██████████| 21591/21591 [00:00<00:00, 562546.00it/s]
Mean Absolute Error (MAE)=0.006
```

Example: multiclass quantification

```
dataset = qp.datasets.fetch_twitter('hcr')
training, test = dataset.train_test

# create an "Adjusted Classify & Count" quantifier
model = qp.method.aggregative.ACC(LogisticRegression())
model.fit(training)

estim_prevalence = model.quantify(test.instances)
true_prevalence  = test.prevalence()

error = qp.error.mae(true_prevalence, estim_prevalence)

print(f'Mean Absolute Error (MAE)={error:.3f}')
```

```
Downloading https://zenodo.org/record/4255764/files/tweet_sentiment_quantification_snam.zip
downloaded 238.17 MB / 238.17 MB
loading /root/quapy_data/tweet_sentiment_quantification_snam/train/hcr.train+dev.feature.txt: 100%
\-- filling matrix of shape (1594, 222046): 100%|██████████| 1594/1594 [00:01<00:00, 1040.91it/s]
loading /root/quapy_data/tweet_sentiment_quantification_snam/test/hcr.test.feature.txt: 100%|████
\-- filling matrix of shape (798, 222046): 100%|██████████| 798/798 [00:00<00:00, 1908.64it/s]
Mean Absolute Error (MAE)=0.038
```

Evaluation Protocols

- QuaPy implements most important evaluation protocols (example: APP)
- Results can be stored as a pandas' dataframe

```python
# evaluation measures typically used in quantification literature
from quapy.protocol import UPP
import quapy.functional as F
import pandas as pd

qp.environ['SAMPLE_SIZE'] = 100

report = qp.evaluation.evaluation_report(model, protocol=UPP(test), error_metrics=['mae', 'mrae', 'kld', 'nkld'])

pd.set_option('display.expand_frame_repr', False)
report['estim-prev'] = report['estim-prev'].map(F.strprev)
print(report)

print('Averaged values:')
print(f"MAE={report['mae'].mean():.3f}")
print(f"MRAE={report['mrae'].mean():.3f}")
print(f"KLD={report['kld'].mean():.3f}")
print(f"NKLD={report['nkld'].mean():.3f}")
```

```
                              true-prev                                    estim-prev       mae      mrae       kld      nkld
0    [0.44, 0.12, 0.0, 0.05, 0.04, 0.07, 0.28]  [0.432, 0.116, 0.000, 0.062, 0.053, 0.113, 0.224]  0.019464  0.189856  0.018309  0.009154
1    [0.39, 0.05, 0.09, 0.26, 0.1, 0.07, 0.04]  [0.429, 0.048, 0.000, 0.234, 0.239, 0.050, 0.000]  0.050600  0.520629  0.305042  0.151349
2   [0.02, 0.05, 0.02, 0.48, 0.27, 0.09, 0.07]  [0.081, 0.049, 0.000, 0.506, 0.185, 0.102, 0.078]  0.030468  0.550649  0.068955  0.034464
3    [0.46, 0.32, 0.0, 0.02, 0.07, 0.11, 0.02]  [0.470, 0.320, 0.000, 0.006, 0.032, 0.150, 0.021]  0.014838  0.212554  0.027286  0.013642
4     [0.12, 0.03, 0.27, 0.1, 0.12, 0.3, 0.06]  [0.138, 0.030, 0.246, 0.102, 0.180, 0.300, 0.005]  0.022825  0.226465  0.082289  0.041121
..                                         ...                                              ...       ...       ...       ...       ...
95  [0.04, 0.14, 0.13, 0.09, 0.52, 0.03, 0.05]  [0.013, 0.139, 0.157, 0.099, 0.574, 0.018, 0.000]  0.025756  0.324492  0.104496  0.052201
96   [0.16, 0.0, 0.29, 0.21, 0.23, 0.02, 0.09]  [0.163, 0.000, 0.272, 0.168, 0.272, 0.079, 0.045]  0.029729  0.470370  0.053128  0.026558
97   [0.04, 0.02, 0.02, 0.17, 0.19, 0.26, 0.3]  [0.030, 0.020, 0.049, 0.152, 0.142, 0.196, 0.411]  0.039911  0.333049  0.044520  0.022256
98  [0.06, 0.47, 0.14, 0.07, 0.16, 0.01, 0.09]  [0.000, 0.471, 0.163, 0.072, 0.263, 0.014, 0.016]  0.038178  0.401266  0.200046  0.099691
99    [0.3, 0.06, 0.02, 0.09, 0.51, 0.02, 0.0]  [0.335, 0.057, 0.022, 0.110, 0.458, 0.019, 0.000]  0.016266  0.087341  0.006745  0.003372

[100 rows x 6 columns]
Averaged values:
MAE=0.032
MRAE=0.414
KLD=0.089
NKLD=0.044
```

Model Selection

```python
import quapy as qp
from quapy.protocol import UPP
from quapy.method.aggregative import DistributionMatchingY
from sklearn.linear_model import LogisticRegression
import numpy as np

model = DistributionMatchingY(LogisticRegression())

qp.environ['SAMPLE_SIZE'] = 100
qp.environ['N_JOBS'] = -1  # explore hyper-parameters in parallel

training, test = qp.datasets.fetch_UCIMulticlassDataset('digits').train_test

model.fit(training)
mae_score = qp.evaluation.evaluate(model, protocol=UPP(test), error_metric='mae')
print(f'MAE (not optimized)={mae_score:.5f}')


training, validation = training.split_stratified(train_prop=0.7)
protocol = UPP(validation, repeats=100)

param_grid = {
    'classifier__C': np.logspace(-3,3,7),
    'nbins': [4, 8, 10, 16],
}

model = qp.model_selection.GridSearchQ(
    model=model,
    param_grid=param_grid,
    protocol=protocol,
    error='mae',  # the error to optimize is the MAE (a quantification-oriented loss)
    refit=True,   # retrain on the whole labelled set once done
    verbose=True, # show information as the process goes on
).fit(training)

print(f'model selection ended: best hyper-parameters={model.best_params_}')
model = model.best_model_

# evaluation in terms of MAE
# we use the same evaluation protocol (APP) on the test set
mae_score = qp.evaluation.evaluate(model, protocol=UPP(test), error_metric='mae')

print(f'MAE (optimized)={mae_score:.5f}')
```

Comparing different models: Plots

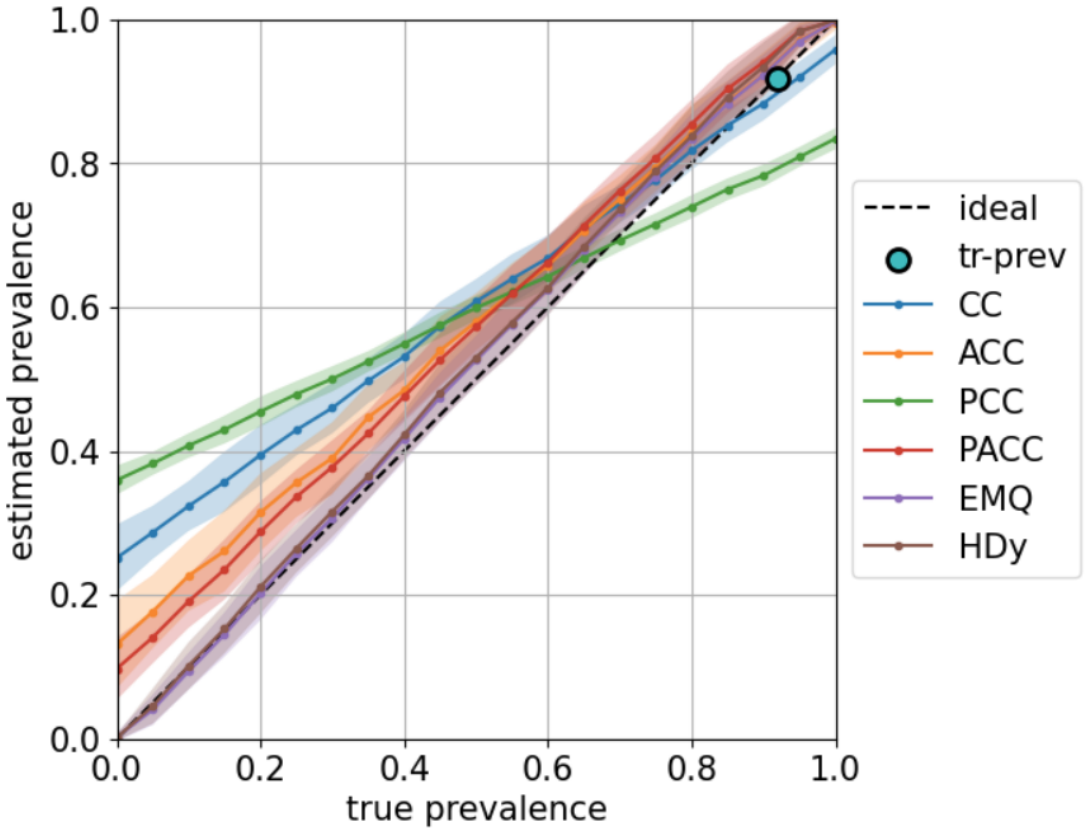
```
from quapy.method.aggregative import CC, ACC, PCC, PACC, EMQ, DistributionMatching
from sklearn.calibration import CalibratedClassifierCV
from tqdm import tqdm

def base_classifier():
  return LogisticRegression(class_weight='balanced')

def models():
  yield 'CC', CC(base_classifier())
  yield 'ACC', ACC(base_classifier())
  yield 'PCC', PCC(base_classifier())
  yield 'PACC', PACC(base_classifier())
  yield 'EMQ', EMQ(CalibratedClassifierCV(base_classifier()))
  yield 'HDy', DistributionMatching(base_classifier())

training, test = qp.datasets.fetch_reviews('kindle', tfidf=True, min_df=5).train_test

method_names, true_prevs, estim_prevs, tr_prevs = [], [], [], []

for method_name, model in tqdm(models(), 'generating results', total=6):
    model.fit(training)
    true_prev, estim_prev = qp.evaluation.prediction(model, APP(test, repeats=100, random_state=0))

    method_names.append(method_name)
    true_prevs.append(true_prev)
    estim_prevs.append(estim_prev)
    tr_prevs.append(training.prevalence())
```

```
loading /root/quapy_data/reviews/kindle/train.txt: 100%|██████████| 3821/3821 [00:00<00:00, 253671.14it/s]
loading /root/quapy_data/reviews/kindle/test.txt: 100%|██████████| 21591/21591 [00:00<00:00, 278491.22it/s]
generating results: 100%|██████████| 6/6 [00:15<00:00,  2.63s/it]
```

Comparing different models: Plots

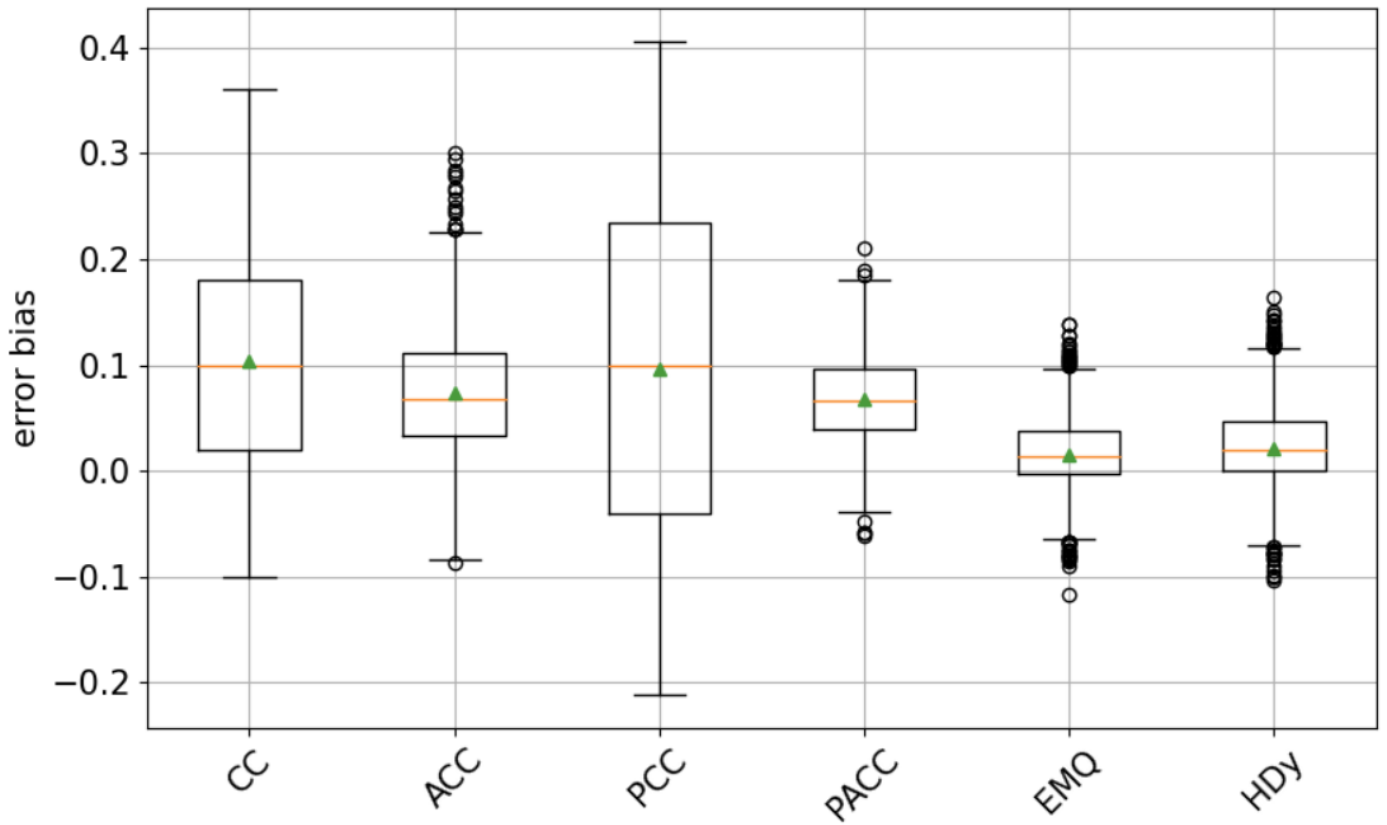
```
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10, 6]
plt.rcParams['figure.dpi'] = 100
plt.rcParams['font.size'] = 15
```

```
qp.plot.binary_diagonal(method_names, true_prevs, estim_prevs, train_prev=tr_prevs[0])
```



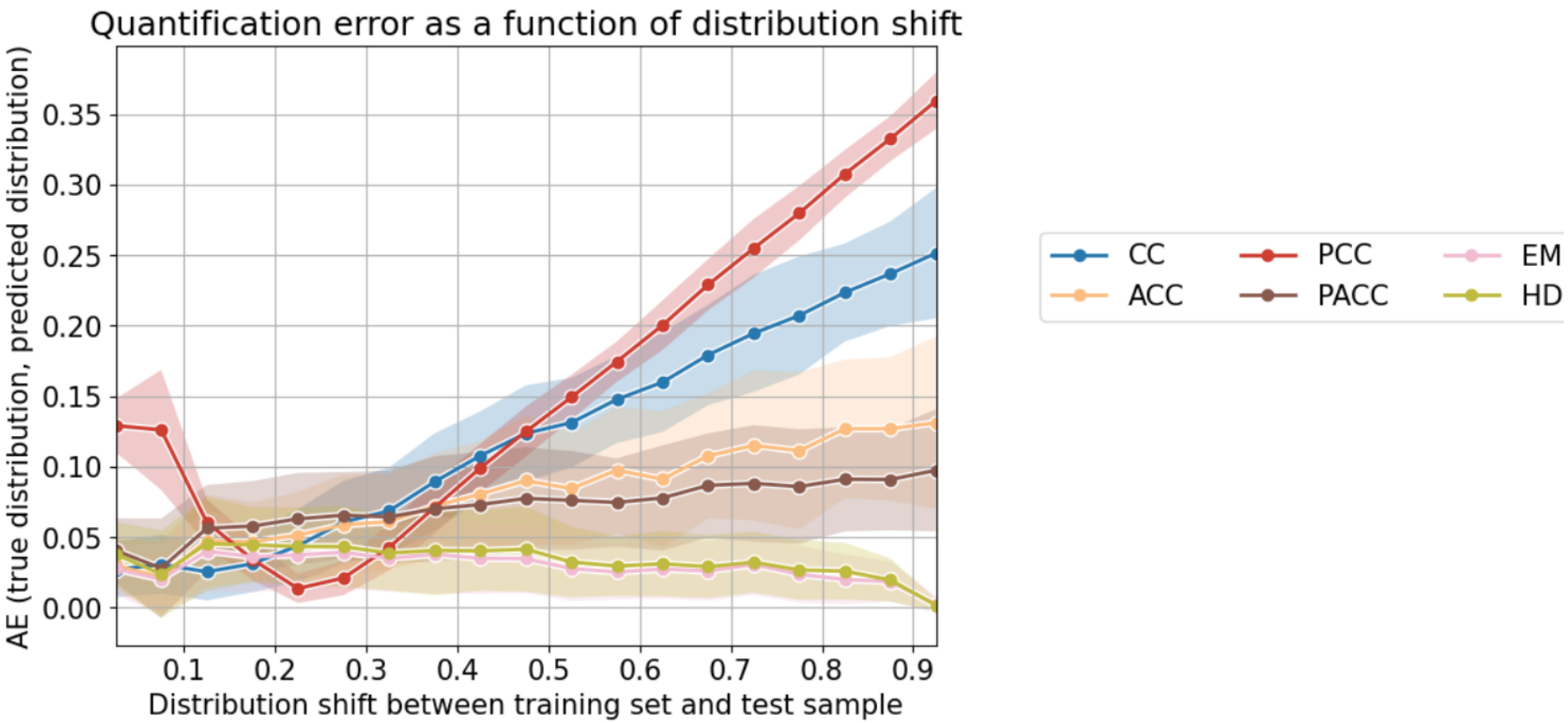
Comparing different models: Plots

```
qp.plot.binary_bias_global(method_names, true_prevs, estim_prevs)
```



Comparing different models: Plots

```
qp.plot.error_by_drift(method_names, true_prevs, estim_prevs, tr_prevs, show_density=False, show_std=True)
```



Full Example: T1A@LeQua

```python
import numpy as np
from sklearn.linear_model import LogisticRegression
import quapy as qp
import quapy.functional as F
from quapy.data.datasets import LEQUA2022_SAMPLE_SIZE, fetch_lequa2022
from quapy.evaluation import evaluation_report
from quapy.method.aggregative import EMQ
from quapy.model_selection import GridSearchQ
import pandas as pd

task = 'T1A'  # there are 4 tasks (T1A, T1B, T2A, T2B)
qp.environ['SAMPLE_SIZE'] = LEQUA2022_SAMPLE_SIZE[task]
qp.environ['N_JOBS'] = -1

training, val_generator, test_generator = fetch_lequa2022(task=task)

quantifier = EMQ(classifier=LogisticRegression())

# model selection
param_grid = {
    'classifier__C': np.logspace(-3, 3, 7),
}

model_selection = GridSearchQ(quantifier, param_grid, protocol=val_generator, error='mrae', refit=False)
quantifier = model_selection.fit(training)

# evaluation
report = evaluation_report(quantifier, protocol=test_generator, error_metrics=['mae', 'mrae'])

# printing results
pd.set_option('display.expand_frame_repr', False)
report['estim-prev'] = report['estim-prev'].map(F.strprev)
print(report)

print('Averaged values:')
print(report.mean())
```

Full Example: T1A@LeQua

```python
import quapy as qp
from quapy.data import LabelledCollection
from quapy.method.base import BaseQuantifier


class PCA_LR(BaseQuantifier):

    def fit(self, data: LabelledCollection):
        pass

    def quantify(self, instances):
        pass
```

Full Example: T1A@LeQua

```python
import quapy as qp
import quapy.functional as F
from quapy.data import LabelledCollection
from quapy.method.base import BaseQuantifier
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression


class PCA_LR(BaseQuantifier):

    def __init__(self, n_components=50, C=1.):
        self.n_components = n_components
        self.C = C

    def fit(self, data: LabelledCollection):
        self.classes_ = data.classes_
        self.pca = PCA(n_components=self.n_components)
        X = self.pca.fit_transform(data.X)
        self.classifier = LogisticRegression(C=self.C).fit(X, data.y)
        return self

    def quantify(self, X):
        X = self.pca.transform(X)
        y_hat = self.classifier.predict(X)
        return F.prevalence_from_labels(y_hat, classes=self.classes_)
```

Full Example: T1A@LeQua

```python
import quapy as qp
import quapy.functional as F
from quapy.data.datasets import LEQUA2022_SAMPLE_SIZE, fetch_lequa2022
from quapy.evaluation import evaluation_report
from quapy.method.aggregative import EMQ
from quapy.model_selection import GridSearchQ
import pandas as pd

from mymethods import PCA_LR

task = 'T1A'  # there are 4 tasks (T1A, T1B, T2A, T2B)
qp.environ['SAMPLE_SIZE'] = LEQUA2022_SAMPLE_SIZE[task]
qp.environ['N_JOBS'] = -1

training, val_generator, test_generator = fetch_lequa2022(task=task)

# quantifier = EMQ(classifier=LogisticRegression())
quantifier = PCA_LR()

# model selection
param_grid = {
    'C': [0.1, 1, 10],
    'n_components': [50, 100]
}

model_selection = GridSearchQ(quantifier, param_grid, protocol=val_generator, error='mrae', refit=False, verbose=True)
quantifier = model_selection.fit(training)

# evaluation
report = evaluation_report(quantifier, protocol=test_generator, error_metrics=['mae', 'mrae'], verbose=True)

# printing results
pd.set_option('display.expand_frame_repr', False)
report['estim-prev'] = report['estim-prev'].map(F.strprev)
print(report)

print('Averaged values:')
print(report.mean())
```

Full Example: Output

```
[GridSearchQ:PCA_LR]: hyperparams={'C': 1, 'n_components': 50}    got mrae score 2.24224 [took 7.7348s]
[GridSearchQ:PCA_LR]: hyperparams={'C': 0.1, 'n_components': 50}  got mrae score 2.26135 [took 7.8331s]
[GridSearchQ:PCA_LR]: hyperparams={'C': 10, 'n_components': 50}   got mrae score 2.26711 [took 7.8997s]
[GridSearchQ:PCA_LR]: hyperparams={'C': 1, 'n_components': 100}   got mrae score 1.97783 [took 7.9226s]
[GridSearchQ:PCA_LR]: hyperparams={'C': 10, 'n_components': 100}  got mrae score 1.97374 [took 7.9275s]
[GridSearchQ:PCA_LR]: hyperparams={'C': 0.1, 'n_components': 100} got mrae score 1.99763 [took 7.9820s]
[GridSearchQ:PCA_LR]: optimization finished: best params {'C': 10, 'n_components': 100} (score=1.97374)
[took 9.4701s]

predicting: 5000it [01:00, 82.73it/s]
           true-prev      estim-prev    mae      mrae
0     [0.308, 0.692]  [0.216, 0.784]  0.092  0.214670
1     [0.896, 0.104]  [0.576, 0.424]  0.320  1.687608
2     [0.848, 0.152]  [0.456, 0.544]  0.392  1.503316
3     [0.016, 0.984]  [0.088, 0.912]  0.072  2.036511
4     [0.728, 0.272]  [0.488, 0.512]  0.240  0.602340
...              ...             ...    ...       ...
4995  [0.720, 0.280]  [0.416, 0.584]  0.304  0.749533
4996  [0.868, 0.132]  [0.508, 0.492]  0.360  1.550180
4997  [0.292, 0.708]  [0.216, 0.784]  0.076  0.182773
4998  [0.240, 0.760]  [0.184, 0.816]  0.056  0.152448
4999  [0.948, 0.052]  [0.604, 0.396]  0.344  3.366238

[5000 rows x 4 columns]
Averaged values:
mae     0.189446
mrae    1.686049
dtype: float64
```

Wrapping up

- QuaPy is a Python-based open-source tool that supports research and development in quantification
- Automates typical tasks of the quantification workflow
- A rich suite of methods, datasets, and protocols available
- Fully documented

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https://github.com/HLT-ISTI/QuaPy