modAL: A modular active learning framework for Python

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Abstract
modAL is a modular active learning framework for Python, aimed to make active learning research and practice simpler. Its distinguishing features are (i) clear and modular object oriented design (ii) full compatibility with scikit-learn models and workflows. These features make fast prototyping and easy extensibility possible, aiding the development of real-life active learning pipelines and novel algorithms as well. modAL is fully open source, hosted on GitHub.\(^1\) To assure code quality, extensive unit tests are provided and continuous integration is applied. In addition, a detailed documentation with several tutorials are also available for ease of use. The framework is available in PyPI and distributed under the MIT license.

Keywords: Active Learning, scikit-learn, Machine Learning, Python

1. Introduction
Upon learning patterns from data in real-life applications, labelling examples often consume significant time and money, which makes it infeasible to obtain large training sets. For example, sentiment analysis of texts requires extensive manual annotation, which costs expert time. Another example is the optimization of black box functions, for which the evaluation is costly or derivatives are not available. In these cases, active learning can be used to query labels for the most informative instances. modAL is an active learning framework for Python, designed with modularity, flexibility and extensibility in mind. Built on top of scikit-learn (Pedregosa et al. (2011); Buitinck et al. (2013)), it allows the rapid prototyping of active learning workflows with a large degree of freedom. It was designed to be easily extensible, allowing researchers to implement and test novel active learning strategies with minimal effort.

2. Design principles and features
Our objective with modAL was to create an active learning library which takes advantage of the advanced features of Python and the extensive ecosystem of scikit-learn, making

\(^1\) https://github.com/modAL-python/modAL
the implementation of complex workflows simple and intuitive. Specifically, modAL was
designed with the following goals in mind.

1. **Modularity: separating and recombining parts of a workflow.** In general,
an active learning workflow consists of a learning algorithm and a query strategy.
In modAL, this is represented by the `ActiveLearner` class, for which these compo-
nents are passed upon object creation. Learning algorithms can be used with query
strategies in any combination, making rapid prototyping possible.

2. **Extensibility: simple customization of parts.** In a modAL active learning work-
flow, a query strategy is simply a function, given to the object representing the active
learning algorithm upon initialization. Implementing custom query strategies can be
done without understanding class structures or modAL internals. Thus it requires
minimal effort, allowing researchers to easily test novel strategies and compare them
with existing ones.

3. **Flexibility: compatibility with the scikit-learn ecosystem.** scikit-learn is one
of the most popular machine learning tools in Python, used by researchers and prac-
titioners as well. modAL is built on top of it, allowing the use any of its classifier and
regressor algorithms in active learning pipelines. Objects in modAL also follow the
scikit-learn API, making it possible to insert them into already existing workflows.

modAL supports a wide range of active learning algorithms for both pool-based and
stream-based (Atlas et al. (1990)) scenarios. For multiclass problems, uncertainty sampling
methods such as least confident (Lewis and Catlett (1994)), max margin and max entropy
sampling; committee-based methods such as query by committee (Seung et al. (1992)) and
query by disagreement (Cohn et al. (1994)); ranked batch-mode sampling (Cardoso et al.
(2017)); expected error reduction (Roy and McCallum (2001)) is provided. For multilabel
classification, SVM binary minimum (Brinker (2006)); max loss and mean max loss (Li et al.
(2004)); MinConfidence, AvgConfidence, MinScore, AvgScore (Esuli and Sebastiani (2009))
algorithms are implemented. For density weighting, the information density framework
(McCallum and Nigam (1998)) is available. In addition to classification, active regression.
Moreover, Bayesian optimization is available with probability of improvement, expected
improvement and upper confidence bound strategies (Shahriari et al. (2016)).

3. **Classes and interfaces**

For modularity and easy extensibility, active learning workflows are abstracted and repre-
sented by the `ActiveLearner`, `BayesianOptimizer`, `Committee` and `CommitteeRegressor`
classes. All classes inherit from the `sklearn.base.BaseEstimator` class. `ActiveLearner`
serves as an abstract model for general active learning algorithms, while `Committee` and
`CommitteeRegressor` implements committee-based strategies. Bayesian optimization algo-
rithms are represented by `BayesianOptimizer`. All classes require a learner and a query
strategy upon initialization. In the case of `ActiveLearner` and `BayesianOptimizer`, the
learner is an arbitrary object implementing the scikit-learn API, while the for `Committee`
and `CommitteeRegressor`, a list of `ActiveLearner` instances must be provided. Again,
the query function can be factored into two functions: one calculating the utility for each instance and one selecting the instances to be queried based upon the utility score. This modular design makes easy extensibility and interaction with other libraries possible. The use of `ActiveLearner` is demonstrated below.

```python
from modAL.models import ActiveLearner
from modAL.uncertainty import uncertainty_sampling
from sklearn.ensemble import RandomForestClassifier

# initializing the learner
learner = ActiveLearner(
    estimator=RandomForestClassifier(),
    query_strategy=uncertainty_sampling
)

# training
learner.fit(X_training, y_training)

# query for labels
query_idx, query_inst = learner.query(X_pool)

# obtaining new labels from the Oracle...

# supply label for queried instance
learner.teach(X_pool[query_idx], y_new)
```

4. Comparison with other libraries

To assess the features of modAL, a comparison between libraries is provided. We compare modAL to the Python libraries acton\(^2\), alp\(^3\), libact\(^4\) (Yang et al. (2017)) and the Java library JCLAL (Reyes et al. (2016)) in Tables 1, 2. The comparison is made with respect to supported algorithms, design and support. For Python libraries, a runtime comparison for least confident sampling, query by committee\(^5\) and expected error reduction can be found in Table 3. The runtime data was obtained by averaging the result of 10 runs for each algorithm. During each run, 10 queries were made. The comparison script is available at https://github.com/modAL-python/modAL/blob/master/examples/runtime_comparison.py.

5. Availability

The framework is fully open-source, hosted on GitHub.\(^6\) Besides the core features, detailed documentation and a wealth of examples and tutorials are available at the project website\(^7\), making active learning accessible for a wide range of users. All tutorials and examples

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2. https://github.com/chengsoonong/acton
3. https://github.com/davefernig/alp
4. https://github.com/ntucllab/libact
5. A minor bugfix was applied on alp for QBC to work, see https://github.com/davefernig/alp/issues/1
6. https://github.com/modAL-python/modAL
7. https://modAL-python.github.io
Table 1: Comparison of libraries with respect to supported algorithms.

|              | pool | stream | regression | committee | multilabel | information density | expected error | variance reduction | hierarchical sampling | meta-learning | batch | cost | Bayes optimization | cost sensitive |
|--------------|------|--------|------------|-----------|------------|---------------------|----------------|-------------------|-----------------------|--------------|-------|------|-------------------|---------------|
| modAL        | ✓    | ✓      | ✓          | ✓         | ✓          | ✓                   | X              | X                 | X                     | ✓            | ✓     | ✓    | ✓                 | ✓             |
| acton        | ✓    | X      | ✓          | X         | X          | X                   | X              | X                 | X                     | X            | X     | ✓    | ✓                 | ✓             |
| alp          | ✓    | X      | ✓          | X         | X          | X                   | X              | X                 | X                     | X            | X     | ✓    | ✓                 | ✓             |
| libact       | ✓    | X      | ✓          | ✓         | ✓          | ✓                   | ✓              | ✓                 | ✓                     | ✓            | X     | ✓    | ✓                 | ✓             |
| JCLAL        | ✓    | ✓      | ✓          | ✓         | ✓          | ✓                   | ✓              | ✓                 | ✓                     | ✓            | X     | ✓    | ✓                 | ✓             |

Table 2: Comparison of libraries with respect to design and support.

|              | sklearn model usability | follows sklearn API | actively maintained | Python version | documentation, tutorials |
|--------------|-------------------------|---------------------|---------------------|----------------|-------------------------|
| modAL        | ✓                       | ✓                   | ✓                   | 3              | ✓                       |
| acton        | ✓                       | ✓                   | ✓                   | 3              | ✓                       |
| alp          | ✓                       | ✓                   | ✓                   | 2, 3           | X                       |
| libact       | ✓                       | ✓                   | ✓                   | 2, 3           | ✓                       |
| JCLAL        | ✓                       | –                   | ✓                   | –              | ✓                       |

Table 3: Comparison of Python libraries with respect to runtime. For each algorithm, 10 queries were made in a run and each run was repeated 10 times.

|              | least confident | QBC       | EER  |
|--------------|----------------|-----------|------|
| modAL        | 0.0087 s       | 0.0465 s  | 2.1255 s |
| acton        | 0.1860 s       | 0.5858 s  | –    |
| alp          | 0.0055 s       | 0.0573 s  | –    |
| libact       | 0.0191 s       | 0.0324 s  | 2.8436 s |

on the official website can be downloaded as a Jupyter notebook. To assure code quality, extensive unit tests are provided with 98% code coverage. Continuous integration is applied using Travis-CI. modAL is also available from PyPI.

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