scikit-uplift

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Contents

scikit-uplift (sklift) is a Python module for basic approaches of uplift modeling built on top of scikit-learn.

Uplift prediction aims to estimate the causal impact of a treatment at the individual level.

More about uplift modelling problem read in russian on habr.com: Part 1 and Part 2.

CHAPTER 1

Features

- Comfortable and intuitive style of modelling like scikit-learn;
- Applying any estimator adheres to scikit-learn conventions;
- All approaches can be used in sklearn.pipeline (see example (EN , RU))
- Almost all implemented approaches solve both the problem of classification and regression;
- A lot of metrics (Such as *Area Under Uplift Curve* or *Area Under Qini Curve*) are implemented to evaluate your uplift model;
- Useful graphs for analyzing the built model.

The package currently supports the following methods:

1. Solo Model (aka Treatment Dummy) approach
2. Class Transformation (aka Class Variable Transformation or Revert Label) approach
3. Two Models (aka naïve approach, or difference score method, or double classifier approach) approach, including Dependent Data Representation

And the following metrics:

1. Uplift@k
2. Area Under Uplift Curve
3. Area Under Qini Curve

CHAPTER 2

Project info

- GitHub repository: https://github.com/maks-sh/scikit-uplift
- Github examples: https://github.com/maks-sh/scikit-uplift/tree/master/notebooks
- License: MIT

2.1 Installation

Install the package by the following command from PyPI:

```
pip install scikit-uplift
```

Or install from source:

```
git clone https://github.com/maks-sh/scikit-uplift.git
cd scikit-uplift
python setup.py install
```

2.2 Quick Start

See the **RetailHero tutorial notebook** (EN , RU) for details.

Train and predict your uplift model

```
# import approaches
from sklift.models import SoloModel, ClassTransformation, TwoModels
# import any estimator adheres to scikit-learn conventions.
from catboost import CatBoostClassifier

# define approach
```

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```
sm = SoloModel(CatBoostClassifier(verbose=100, random_state=777))
# fit model
sm = sm.fit(X_train, y_train, treat_train, estimator_fit_params={'plot': True})

# predict uplift
uplift_sm = sm.predict(X_val)
```

Evaluate your uplift model

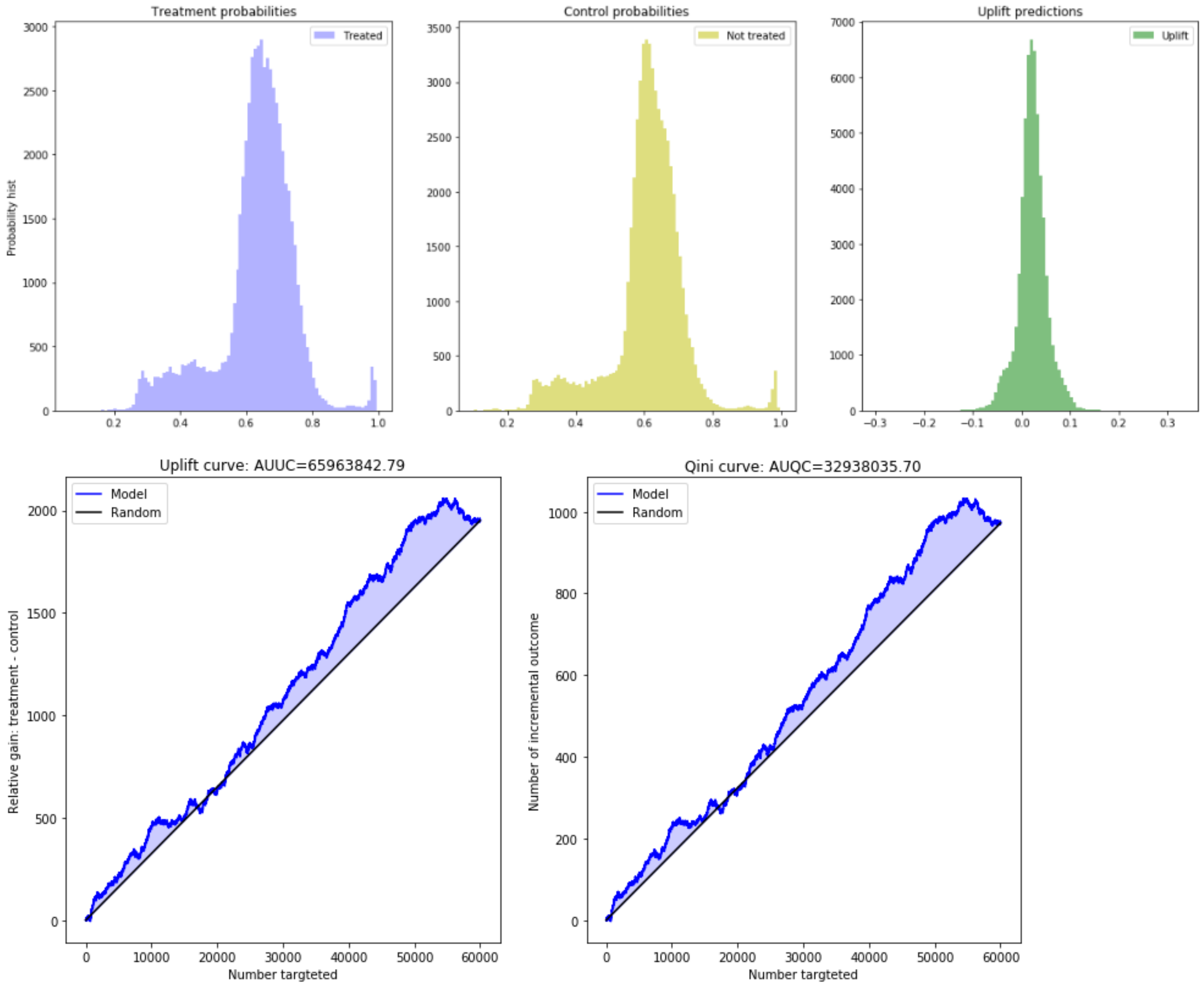
```
# import metrics to evaluate your model
from sklift.metrics import qini_auc_score, uplift_auc_score, uplift_at_k
# Uplift@30%
sm_uplift_at_k = uplift_at_k(y_true=y_val, uplift=uplift_sm, treatment=treat_val, k=0.
↪3)
# Area Under Qini Curve
sm_qini_auc_score = qini_auc_score(y_true=y_val, uplift=uplift_sm, treatment=treat_
↪val)
# Area Under Uplift Curve
sm_uplift_auc_score = uplift_auc_score(y_true=y_val, uplift=uplift_sm,␣
↪treatment=treat_val)
```

Vizualize the results

```
# import vizualisation tools
from sklift.viz import plot_uplift_preds, plot_uplift_qini_curves

# get conditional predictions (probabilities) of performing a target action
# with interaction for each object
sm_trmnt_preds = sm.trmnt_preds_
# get conditional predictions (probabilities) of performing a target action
# without interaction for each object
sm_ctrl_preds = sm.ctrl_preds_

# draw probability distributions and their difference (uplift)
plot_uplift_preds(trmnt_preds=sm_trmnt_preds, ctrl_preds=sm_ctrl_preds);
# draw Uplift and Qini curves
plot_uplift_qini_curves(y_true=y_val, uplift=uplift_sm, treatment=treat_val);
```



2.3 API

2.3.1 Models (sklift.models)

1. Approaches with the same model

1.1 One model with treatment as feature

The simplest and most intuitive solution: the model is trained on union of two groups, with the binary communication flag acting as an additional feature. Each object from the test sample is scored twice: with the communication flag equal to *1* and equal to *0*. Subtracting the probabilities for each observation, we get the required uplift.

The training process:

$$fit\left(\underset{X_{train}}{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nk} \end{matrix}} \quad \underset{W_{train}}{\begin{matrix} w_1 \\ \cdots, \\ w_n \end{matrix}} \quad \underset{Y_{train}}{\begin{matrix} y_1 \\ \cdots \\ y_n \end{matrix}}\right)$$

The process of applying the model:

$$\begin{matrix} predict \\ proba \end{matrix}\left(\underset{X_{test}}{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mk} \end{matrix}} \quad \underset{W_1}{\begin{matrix} 1 \\ \vdots \\ 1 \end{matrix}}\right) - \begin{matrix} predict \\ proba \end{matrix}\left(\underset{X_{test}}{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mk} \end{matrix}} \quad \underset{W_0}{\begin{matrix} 0 \\ \vdots \\ 0 \end{matrix}}\right) = \underset{uplift}{\begin{pmatrix} u_1 \\ \vdots \\ u_m \end{pmatrix}}$$

class sklift.models.models.**SoloModel**(*estimator*)

aka Treatment Dummy approach, or Single model approach, or S-Learner.

Fit solo model on whole dataset with 'treatment' as an additional feature.

For each test example calculate predictions on new set twice: with treatment == '1' and with treatment == '0'. After that calculate uplift as a delta between these predictions.

Return delta of predictions for each example.

See more details about SoloModel in documentation.

Parameters **estimator** (*estimator object implementing 'fit'*) – The object to use to fit the data.

trmnt_preds_

Estimator predictions on samples when treatment.

Type array-like, shape (n_samples,)

ctrl_preds_

Estimator predictions on samples when control.

Type array-like, shape (n_samples,)

Example:

```python
# import approach
from sklift.models import SoloModel
# import any estimator adheres to scikit-learn conventions
from catboost import CatBoostClassifier


sm = SoloModel(CatBoostClassifier(verbose=100, random_state=777))  # define approach
sm = sm.fit(X_train, y_train, treat_train, estimator_fit_params={{'plot': True}) # fit the model
uplift_sm = sm.predict(X_val)  # predict uplift
```

References

Lo, Victor. (2002). The True Lift Model - A Novel Data Mining Approach to Response Modeling in Database Marketing. SIGKDD Explorations. 4. 78-86.

fit (*X*, *y*, *treatment*, *estimator_fit_params=None*)

Fit the model according to the given training data.

For each test example calculate predictions on new set twice: by the first and second models. After that calculate uplift as a delta between these predictions.

Return delta of predictions for each example.

Parameters

- **X** (*array-like, shape (n_samples, n_features)*) – Training vector, where n_samples is the number of samples and n_features is the number of features.
- **y** (*array-like, shape (n_samples,)*) – Target vector relative to X.
- **treatment** (*array-like, shape (n_samples,)*) – Binary treatment vector relative to X.
- **estimator_fit_params** (*dict, optional*) – Parameters to pass to the fit method of the estimator.

Returns self

Return type object

predict (*X*)

Perform uplift on samples in X.

Parameters X (*array-like, shape (n_samples, n_features)*) – Training vector, where n_samples is the number of samples and n_features is the number of features.

Returns uplift

Return type array (shape (n_samples,))

1.2 Class Transformation

Warning: This approach is only suitable for classification problem

Quite an interesting and mathematically confirmed approach to the construction of the model, presented back in 2012. The method is to predict a slightly changed target:

$$z_i = y_i * w_i + (1 - y_i) * (1 - w_i),$$

- z_i - new target for i customer;
- y_i - old target i customer;
- w_i - treatment flag i customer.

In other words, the new class is 1 if we know that on a particular observation, the result in the interaction would be as good as in the control group if we could know the result in both groups:

$$z_i = \begin{cases} 1, & \text{if } w_i = 1 \text{ and } y_i = 1 \\ 1, & \text{if } w_i = 0 \text{ and } y_i = 0 \\ 0, & \text{otherwise} \end{cases}$$

Let's describe in more detail what is the probability of a new target variable:

$$\begin{aligned} P(Z=1|X_1,...,X_m) = \\ = P(Z=1|X_1,...,X_m,W=1) * P(W=1|X_1,...,X_m,)+ \\ +P(Z=1|X_1,...,X_m,W=0) * P(W=0|X_1,...,X_m,) = \\ = P(Y=1|X_1,...,X_m,W=1) * P(W=1|X_1,...,X_m,)+ \\ +P(Y=0|X_1,...,X_m,W=0) * P(W=0|X_1,...,X_m,). \end{aligned}$$

We assume that W does not depend on the attributes of $X_1,...,X_m$, because otherwise the experiment design is not very well designed. Taking this, we have: $P(W|X_1,...,X_m,) = P(W)$ and

$$\begin{aligned} P(Z=1|X_1,...,X_m) = \\ = P^T(Y=1|X_1,...,X_m) * P(W=1)+ \\ +P^C(Y=0|X_1,...,X_m) * P(W=0). \end{aligned}$$

Also assume that $P(W=1) = P(W=0) = \frac{1}{2}$, i.e. during the experiment, the control and treatment groups were divided in equal proportions. Then we get the following:

$$\begin{aligned} P(Z=1|X_1,...,X_m) = \\ = P^T(Y=1|X_1,...,X_m) * \frac{1}{2} + P^C(Y=0|X_1,...,X_m) * \frac{1}{2} \Rightarrow \\ \Rightarrow 2 * P(Z=1|X_1,...,X_m) = \\ = P^T(Y=1|X_1,...,X_m) + P^C(Y=0|X_1,...,X_m) = \\ = P^T(Y=1|X_1,...,X_m) + 1 - P^C(Y=1|X_1,...,X_m) \Rightarrow \\ \Rightarrow P^T(Y=1|X_1,...,X_m) - P^C(Y=1|X_1,...,X_m) = \\ = UPLIFT = 2 * P(Z=1|X_1,...,X_m) - 1 \end{aligned}$$

Thus, by doubling the forecast of the new target and subtracting one from it, we get the value of the uplift itself, i.e.

$$UPLIFT = 2 * P(Z=1) - 1$$

Based on the assumption described above: $P(W=1) = P(W=0) = \frac{1}{2}$, this approach should be used only in cases where the number of clients with whom we have communicated is equal to the number of clients with whom there was no communication.

class `sklift.models.models.`**`ClassTransformation`**(*estimator*)

aka Class Variable Transformation or Revert Label approach.

Redefine target variable, which indicates that treatment make some impact on target or did target is negative without treatment.

Z = Y * W + (1 - Y)(1 - W),

where Y - target, W - communication flag.

Then, Uplift ~ 2 * (Z == 1) - 1

Returns only uplift predictions.

See more details about ClassTransformation in documentation.

Parameters **`estimator`** (*`estimator object implementing 'fit'`*) – The object to use to fit the data.

Example:

```
# import approach
from sklift.models import ClassTransformation
# import any estimator adheres to scikit-learn conventions
from catboost import CatBoostClassifier


ct = ClassTransformation(CatBoostClassifier(verbose=100, random_state=777))  # define approach
ct = ct.fit(X_train, y_train, treat_train, estimator_fit_params={'plot': True})  # fit the model
uplift_ct = ct.predict(X_val)  # predict uplift
```

References

Maciej Jaskowski and Szymon Jaroszewicz. Uplift modeling for clinical trial data. ICML Workshop on Clinical Data Analysis, 2012.

fit (*X*, *y*, *treatment*, *estimator_fit_params=None*)

Fit the model according to the given training data.

Parameters

- **X** (*array-like, shape (n_samples, n_features)*) – Training vector, where n_samples is the number of samples and n_features is the number of features.
- **y** (*array-like, shape (n_samples,)*) – Target vector relative to X.
- **treatment** (*array-like, shape (n_samples,)*) – Binary treatment vector relative to X.
- **estimator_fit_params** (*dict, optional*) – Parameters to pass to the fit method of the estimator.

Returns self

Return type object

predict (*X*)

Perform uplift on samples in X.

Parameters **X** (*array-like, shape (n_samples, n_features)*) – Training vector, where n_samples is the number of samples and n_features is the number of features.

Returns uplift

Return type array (shape (n_samples,))

2. Approaches with two models

The two-model approach can be found in almost any uplift modeling work, and is often used as a baseline. However, the use of two models can lead to some unpleasant consequences: if the training will be used fundamentally different models or the nature of the data of the test and control groups will be very different, then the returned models will not be comparable with each other. As a result, the calculation of the uplift will not be completely correct. To avoid this effect, it is necessary to calibrate the models so that their scores can be interpolated as probabilities. Calibration of model probabilities is well described in the scikit-learn documentation.

2.1 Two independent models

Hint: In sklift this approach corresponds to the *TwoModels* class and the **vanilla** method.

As the name implies, the approach is to model the conditional probabilities of the treatment and control groups separately. The articles argue that this approach is rather weak, since both models focus on predicting the result separately and can therefore skip the "weaker" differences in the samples.

The training process:

$$model^T = fit\left(\underbrace{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{p1} & \cdots & x_{pk} \end{matrix}}_{X_{train\_treat}}, \underbrace{\begin{matrix} y_1 \\ \cdots \\ y_p \end{matrix}}_{Y_{train\_treat}}\right),\ model^C = fit\left(\underbrace{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{q1} & \cdots & x_{qk} \end{matrix}}_{X_{train\_control}}, \underbrace{\begin{matrix} y_1 \\ \cdots \\ y_q \end{matrix}}_{Y_{train\_control}}\right)$$

The process of applying the model:

$$\begin{matrix} model^T \\ predict \\ proba \end{matrix} \underbrace{\begin{pmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mk} \end{pmatrix}}_{X_{test}} - \begin{matrix} model^c \\ predict \\ proba \end{matrix} \underbrace{\begin{pmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mk} \end{pmatrix}}_{X_{test}} = \underbrace{\begin{pmatrix} u_1 \\ \vdots \\ u_m \end{pmatrix}}_{uplift}$$

2.2 Two dependent models

The dependent data representation approach is based on the classifier chain method originally developed for multiclass classification problems. The idea is that if there are L different labels, you can build L different classifiers, each of which solves the problem of binary classification and in the learning process, each subsequent classifier uses the predictions of the previous ones as additional features. The authors of this method proposed to use the same idea to solve the problem of uplift modeling in two stages.

Hint: In sklift this approach corresponds to the *TwoModels* class and the **ddr_control** method.

At the beginning we train the classifier based on control data:

$$P^C = P(Y = 1|X, W = 0),$$

then we will perform the P_C predictions as a new feature for training the second classifier on test data, thus effectively introducing a dependency between the two data sets:

$$P^T = P(Y = 1|X, P_C(X), W = 1)$$

To get the uplift for each observation, calculate the difference:

$$uplift(x_i) = P^T(x_i, P_C(x_i)) - P^C(x_i)$$

Intuitively, the second classifier studies the difference between the expected result in the test and the control, i.e. the uplift itself.

The training process:

$$model^C = fit\left(\underset{X_{train\_control}}{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{q1} & \cdots & x_{qk} \end{matrix}}\ ,\ \underset{Y_{train\_control}}{\begin{matrix} y_1 \\ \cdots \\ y_q \end{matrix}}\right),$$

$$P^C = \begin{matrix} model^c \\ predict \\ proba \end{matrix} \underset{X_{train\_treat}}{\begin{pmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{p1} & \cdots & x_{pk} \end{pmatrix}}, \qquad model^T = fit\left(\underset{X_{train\_treat}}{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{p1} & \cdots & x_{pk} \end{matrix}}\ \underset{P^C}{\begin{matrix} P^C_1 \\ \vdots \\ P^C_p \end{matrix}}\ ,\ \underset{Y_{train\_treat}}{\begin{matrix} y_1 \\ \cdots \\ y_p \end{matrix}}\right),$$

The process of applying the model:

$$\begin{matrix} model^T \\ predict \\ proba \end{matrix}\left(\underset{X_{test}}{\begin{matrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mk} \end{matrix}}\ \underset{P^C(X_{test})}{\begin{matrix} model^c \\ predict \\ proba \end{matrix}\begin{pmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mk} \end{pmatrix}}\right) - \begin{matrix} model^c \\ predict \\ proba \end{matrix}\underset{X_{test}}{\begin{pmatrix} x_{11} & \cdots & x_{1k} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mk} \end{pmatrix}} = \underset{uplift}{\begin{pmatrix} u_1 \\ \vdots \\ u_m \end{pmatrix}}$$

Similarly, you can first train the P_T classifier and then use its predictions as a trait for the P_C classifier.

Hint: In sklift this approach corresponds to the *TwoModels* class and the **ddr_treatment** method.

class sklift.models.models.**TwoModels**(*estimator_trmnt*, *estimator_ctrl*, *method='vanilla'*)

aka naïve approach, or difference score method, or double classifier approach. Fit two separate models: on the treatment data and on the control data.

See more details about TwoModels in documentation.

Parameters

- **estimator_trmnt** (*estimator object implementing 'fit'*) – The object to use to fit the treatment data.
- **estimator_ctrl** (*estimator object implementing 'fit'*) – The object to use to fit the control data.
- **method** (*string, 'vanilla', 'ddr_control' or 'ddr_treatment', default='vanilla'*) – Specifies the approach: * 'vanilla' - two independent models * 'ddr_control' - dependent data representation (First train control estimator) * 'ddr_treatment' - dependent data representation (First train treatment estimator)

trmnt_preds_

Estimator predictions on samples when treatment.

Type array-like, shape (n_samples,)

ctrl_preds_

Estimator predictions on samples when control.

Type array-like, shape (n_samples,)

Example:

```
# import approach
from sklift.models import TwoModels
# import any estimator adheres to scikit-learn conventions
from catboost import CatBoostClassifier


estimator_trmnt = CatBoostClassifier(silent=True, thread_count=2, random_state=42)
estimator_ctrl = CatBoostClassifier(silent=True, thread_count=2, random_state=42)

# define approach
tm_ctrl = TwoModels(
    estimator_trmnt=estimator_trmnt,
    estimator_ctrl=estimator_ctrl,
    method='ddr_control'
)

# fit the models
tm_ctrl = tm_ctrl.fit(
    X_train, y_train, treat_train,
    estimator_trmnt_fit_params={'cat_features': cat_features},
    estimator_ctrl_fit_params={'cat_features': cat_features}
)
uplift_tm_ctrl = tm_ctrl.predict(X_val)  # predict uplift
```

References Betlei, Artem & Diemert, Eustache & Amini, Massih-Reza. (2018). Uplift Prediction with Dependent Feature Representation in Imbalanced Treatment and Control Conditions: 25th International Conference, ICONIP 2018, Siem Reap, Cambodia, December 13–16, 2018, Proceedings, Part V. 10.1007/978-3-030-04221-9_5.

Zhao, Yan & Fang, Xiao & Simchi-Levi, David. (2017). Uplift Modeling with Multiple Treatments and General Response Types. 10.1137/1.9781611974973.66.

fit (*X*, *y*, *treatment*, *estimator_trmnt_fit_params=None*, *estimator_ctrl_fit_params=None*)

Fit the model according to the given training data.

For each test example calculate predictions on new set twice: by the first and second models. After that calculate uplift as a delta between these predictions.

Return delta of predictions for each example.

Parameters

- **X** (*array-like, shape (n_samples, n_features)*) – Training vector, where n_samples is the number of samples and n_features is the number of features.
- **y** (*array-like, shape (n_samples,)*) – Target vector relative to X.
- **treatment** (*array-like, shape (n_samples,)*) – Binary treatment vector relative to X.
- **estimator_trmnt_fit_params** (*dict, optional*) – Parameters to pass to the fit method of the treatment estimator.
- **estimator_ctrl_fit_params** (*dict, optional*) – Parameters to pass to the fit method of the control estimator.

Returns self

Return type object

predict (*X*)

Perform uplift on samples in X.

Parameters **X** (*array-like, shape (n_samples, n_features)*) – Training vector, where n_samples is the number of samples and n_features is the number of features.

Returns uplift

Return type array (shape (n_samples,))

2.3.2 Metrics (sklift.metrics)

sklift.metrics.metrics.**auqc** (*y_true*, *uplift*, *treatment*)

Compute Area Under the Qini Curve (aka Qini coefficient) from prediction scores.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.

Returns Area Under the Qini Curve.

Return type float

> **Warning:** Metric *auqc* was renamed to *qini_auc_score()* in version 0.1.0 and will be removed in 0.2.0

sklift.metrics.metrics.**auuc** (*y_true*, *uplift*, *treatment*)

Compute Area Under the Uplift Curve from prediction scores.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.

Returns Area Under the Uplift Curve.

Return type float

> **Warning:** Metric *auuc* was renamed to *uplift_auc_score()* in version 0.1.0 and will be removed in 0.2.0

sklift.metrics.metrics.**qini_auc_score** (*y_true*, *uplift*, *treatment*)

Compute Area Under the Qini Curve (aka Qini coefficient) from prediction scores.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.

Returns Area Under the Qini Curve.

Return type float

sklift.metrics.metrics.**qini_curve**(*y_true*, *uplift*, *treatment*)

Compute Qini curve.

This is a general function, given points on a curve. For computing the area under the Qini Curve, see *qini_auc_score()*.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.

Returns Points on a curve.

Return type array (shape = [>2]), array (shape = [>2])

See also:

qini_auc_score(): Compute the area under the Qini curve.

plot_uplift_qini_curves(): Plot Uplift and Qini curves.

sklift.metrics.metrics.**response_rate_by_percentile**(*y_true*, *uplift*, *treatment*, *group*, *strategy*, *bins=10*)

Compute response rate (target mean in the control or treatment group) at each percentile.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.
- **group** (*string, ['treatment', 'control']*) – Group type for computing response rate: treatment or control. * 'treatment':

  Values equal 1 in the treatment column.

  – **'control':** Values equal 0 in the treatment column.

- **strategy** (*string, ['overall', 'by_group']*) – Determines the calculating strategy. * 'overall':

  The first step is taking the first k observations of all test data ordered by uplift prediction (overall both groups - control and treatment) and conversions in treatment and control groups calculated only on them. Then the difference between these conversions is calculated.

  – **'by_group':** Separately calculates conversions in top k observations in each group (control and treatment) sorted by uplift predictions. Then the difference between these conversions is calculated

- **bins** (*int*) – Determines the number of bins (and relative percentile) in the test data.

Returns Response rate at each percentile for control or treatment group array: Variance of the response rate at each percentile

Return type array

`sklift.metrics.metrics.`**`treatment_balance_curve`**(*uplift*, *treatment*, *winsize*)

Compute the treatment balance curve: proportion of treatment group in the ordered predictions.

Parameters

- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.
- **winsize** (*int*) – Size of the sliding window for calculating the balance between treatment and control.

Returns Points on a curve.

Return type array (shape = [>2]), array (shape = [>2])

`sklift.metrics.metrics.`**`uplift_at_k`**(*y_true*, *uplift*, *treatment*, *strategy*, *k=0.3*)

Compute uplift at first k percentage of the total sample.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.
- **k** (*float or int*) – If float, should be between 0.0 and 1.0 and represent the proportion of the dataset to include in the computation of uplift. If int, represents the absolute number of samples.
- **strategy** (*string, ['overall', 'by_group']*) – Determines the calculating strategy.
  - **'overall':** The first step is taking the first k observations of all test data ordered by uplift prediction (overall both groups - control and treatment) and conversions in treatment and control groups calculated only on them. Then the difference between these conversions is calculated.
  - **'by_group':** Separately calculates conversions in top k observations in each group (control and treatment) sorted by uplift predictions. Then the difference between these conversions is calculated

Changed in version 0.1.0: Add supporting absolute values for `k` parameter Add parameter `strategy`

- **Returns** Uplift score at first k observations of the total sample.

Return type float

`sklift.metrics.metrics.`**`uplift_auc_score`**(*y_true*, *uplift*, *treatment*)

Compute Area Under the Uplift Curve from prediction scores.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.

Returns Area Under the Uplift Curve.

Return type float

sklift.metrics.metrics.**uplift_curve**(*y_true*, *uplift*, *treatment*)

Compute Uplift curve

This is a general function, given points on a curve. For computing the area under the Uplift Curve, see *uplift_auc_score()*.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.

Returns Points on a curve.

Return type array (shape = [>2]), array (shape = [>2])

See also:

uplift_auc_score(): Compute the area under the Uplift curve.

plot_uplift_qini_curves(): Plot Uplift and Qini curves.

2.3.3 Visualization (sklift.viz)

sklift.viz.base.**plot_treatment_balance_curve**(*uplift*, *treatment*, *random=True*, *winsize=0.1*)

Plot Treatment Balance curve.

Parameters

- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.
- **random** (*bool, default True*) – Draw a random curve.
- **winsize** (*float, default 0.1*) – Size of the sliding window to apply. Should be between 0 and 1, extremes excluded.

Returns Object that stores computed values.

sklift.viz.base.**plot_uplift_by_percentile**(*y_true*, *uplift*, *treatment*, *strategy*, *bins=10*)

Plot Uplift score at each percentile, Treatment response rate (target mean in the treatment group) and Control response rate (target mean in the control group) at each percentile.

Parameters

- **y_true** (*1d array-like*) – Correct (true) target values.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.
- **strategy** (*string, ['overall', 'by_group']*) – Determines the calculating strategy. Defaults to ‘first’. * 'overall':

  > The first step is taking the first k observations of all test data ordered by uplift prediction (overall both groups - control and treatment) and conversions in treatment and control groups calculated only on them. Then the difference between these conversions is calculated.

  - **'by_group':** Separately calculates conversions in top k observations in each group (control and treatment) sorted by uplift predictions. Then the difference between these conversions is calculated

- **bins** (*int*) – Determines the number of bins (and relative percentile) in the test data.

Returns Object that stores computed values.

sklift.viz.base.**plot_uplift_preds**(*trmnt_preds*, *ctrl_preds*, *log=False*, *bins=100*)

Plot histograms of treatment, control and uplift predictions.

Parameters

- **trmnt_preds** (*1d array-like*) – Predictions for all observations if they are treatment.
- **ctrl_preds** (*1d array-like*) – Predictions for all observations if they are control.
- **log** (*bool, default False*) – Logarithm of source samples.
- **bins** (*integer or sequence, default 100*) – Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

Returns Object that stores computed values.

sklift.viz.base.**plot_uplift_qini_curves**(*y_true*, *uplift*, *treatment*, *random=True*, *perfect=False*)

Plot Uplift and Qini curves.

Parameters

- **y_true** (*1d array-like*) – Ground truth (correct) labels.
- **uplift** (*1d array-like*) – Predicted uplift, as returned by a model.
- **treatment** (*1d array-like*) – Treatment labels.
- **random** (*bool, default True*) – Draw a random curve.
- **perfect** (*bool, default False*) – Draw a perfect curve.

Returns Object that stores computed values.

2.4 Tutorials

2.4.1 Basic

It is better to start scikit-uplift from the basic tutorials.

- **The overview of the basic approaches to solving the Uplift Modeling problem**
  - In English: nbviewer | github
  - In Russian: nbviewer | github
- **Example of usage model from sklift.models in sklearn.pipeline**
  - In English: nbviewer | github
  - In Russian: nbviewer | github

2.5 Release History

2.5.1 Legend for changelogs

- something big that you couldn't do before.
- something that you couldn't do before.
- a miscellaneous minor improvement.
- something that previously didn't work as documentated – or according to reasonable expectations – should now work.
- you will need to change your code to have the same effect in the future; or a feature will be removed in the future.

2.5.2 Version 0.1.1

sklift.viz

- Add plot_uplift_by_percentile by @ElisovaIra.
- Fix bug with import plot_treatment_balance_curve.

sklift.metrics

- Add response_rate_by_percentile by @ElisovaIra.
- Fix bug with import uplift_auc_score and qini_auc_score.
- Fix typos in docstrings.

Miscellaneous

- Add tutorial "Example of usage model from sklift.models in sklearn.pipeline".
- Add link to Release History in main Readme.md.

2.5.3 Version 0.1.0

sklift.models

- Fix typo in TwoModels docstring by @spiaz.
- Improve docstrings and add references to all approaches.

sklift.metrics

- Add treatment_balance_curve by @spiaz.
- The metrics `auuc` and `auqc` are now respectively renamed to uplift_auc_score and qini_auc_score. So, `auuc` and `auqc` will be removed in 0.2.0.
- Add a new parameter `startegy` in uplift_at_k.

sklift.viz

- Add plot_treatment_balance_curve by @spiaz.
- fix typo in plot_uplift_qini_curves by @spiaz.

Miscellaneous

- Remove sklift.preprocess submodule.
- Add compatibility of tutorials with colab and add colab buttons by @ElMaxuno.
- Add Changelog.
- Change the documentation structure. Add next pages: Tutorials, Release History and Hall of fame.

2.6 Hall of Fame

Here are the links to the competitions, names of the winners and to their solutions, where scikit-uplift was used.

2.6.1 X5 RetailHero Uplift Modeling contest

2. **Kirill Liksakov** solution

CHAPTER 3

Papers and materials

1. **Gutierrez, P., & Gérardy, J. Y.** Causal Inference and Uplift Modelling: A Review of the Literature. In International Conference on Predictive Applications and APIs (pp. 1-13).

2. **Artem Betlei, Criteo Research; Eustache Diemert, Criteo Research; Massih-Reza Amini, Univ. Grenoble Alpes** Dependent and Shared Data Representations improve Uplift Prediction in Imbalanced Treatment Conditions FAIM'18 Workshop on CausalML.

3. **Eustache Diemert, Artem Betlei, Christophe Renaudin, and Massih-Reza Amini. 2018.** A Large Scale Benchmark for Uplift Modeling. In Proceedings of AdKDD & TargetAd (ADKDD'18). ACM, New York, NY, USA, 6 pages.

4. **Athey, Susan, and Imbens, Guido. 2015.** Machine learning methods for estimating heterogeneous causal effects. Preprint, arXiv:1504.01132. Google Scholar.

5. **Oscar Mesalles Naranjo. 2012.** Testing a New Metric for Uplift Models. Dissertation Presented for the Degree of MSc in Statistics and Operational Research.

6. **Kane, K., V. S. Y. Lo, and J. Zheng. 2014.** Mining for the Truly Responsive Customers and Prospects Using True-Lift Modeling: Comparison of New and Existing Methods. Journal of Marketing Analytics 2 (4): 218–238.

7. **Maciej Jaskowski and Szymon Jaroszewicz.** Uplift modeling for clinical trial data. ICML Workshop on Clinical Data Analysis, 2012.

8. **Lo, Victor. 2002.** The True Lift Model - A Novel Data Mining Approach to Response Modeling in Database Marketing. SIGKDD Explorations. 4. 78-86.

9. **Zhao, Yan & Fang, Xiao & Simchi-Levi, David. 2017.** Uplift Modeling with Multiple Treatments and General Response Types. 10.1137/1.9781611974973.66.

CHAPTER 4

Tags

EN: uplift modeling, uplift modelling, causal inference, causal effect, causality, individual treatment effect, true lift, net lift, incremental modeling

RU: , Uplift

ZH: ,,,,,

CHAPTER 5

Indices and tables

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