Large-scale Open Dataset and Pipeline for Bandit Algorithms

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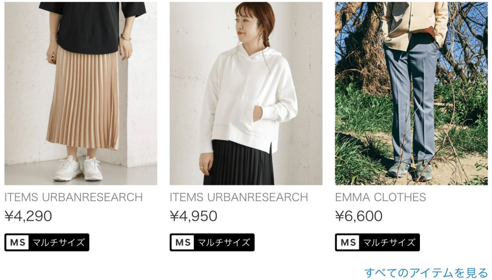
Outline

- overview of *off-policy evaluation* (just briefly)
- ***open bandit project*** (on-going)
    - open bandit dataset v1 (v2 will be released)
    - open bandit pipeline
    - example analysis with the data and pipeline
    - limitations and future work
- Q & A

Machine Learning for Decision Making (Bandit / RL)

We often use machine learning to make **decisions, not predictions**

decide which items to show



a coming user

often multiple items are recommended at the same time

observe reward (e.g., click)

Many Applications of "Machine Decision Making"

- news recommendation (by Yahoo)
- music/playlist recommendation (by Spotify)
- artwork personalization (by Netflix)
- ad allocation optimization (by Criteo)
- medicine
- education

We want to evaluate the performance of a *new decision making policy* using data generated by a *behavior, past policy*

Data Generating Process (contextual bandit setting)

Observes X (context vector, e.g., a user visit)

A *policy* π selects an *action* A (e.g., a fashion item)

Observes Y (e.g., a click indicator)

a ***policy*** interacts with the environment and produces the log data

Logged Bandit Feedback

We can use the *logged bandit feedback* collected by a *behavior (or past) policy* to estimate the policy value of a new policy

$$\mathcal{D} = \{(X_i, A_i, Y_i)\}_{i=1}^{n}$$

$$A_i \sim \pi_b(a \mid X_i)$$

action choice by behavior policy

$$Y_i = Y_i(A_i)$$

observed reward

Estimation Target in Off-Policy Evaluation

In OPE, we aim to estimate the following *policy value*

of an *evaluation (or new)* policy

$$V(\pi_e) := \mathbb{E}_{(Y(\cdot),X)}[\sum_{a=0}^{m} Y(a)\pi_e(a \mid X)]$$

➡ expected reward obtained by running π_e on a real system

Benefits of Off-Policy Evaluation

Accurately estimating the policy value of an evaluation policy

$$V(\pi_e) \approx \hat{V}(\underline{\pi_e; \mathcal{D}})$$

an estimated policy value of π_e using historical data $\mathcal{D}$

- avoid deploying poor performing policies
- identify promising new policies among many candidates

Direct Method (DM)

DM first estimates the expected reward and uses it to estimate the policy value

$$\hat{V}_{DM}(\pi_e; \mathcal{D}) = \mathbb{E}_n[\sum_{a=0}^{m} \pi(a \mid X_i) \underbrace{\hat{\mu}(X_i, a)}_{\text{estimated expected reward}}]$$

- **High bias** when the model is mis-specified
- **Low variance**

$$\mathbb{E}[Y(a) \mid X = x] \approx \hat{\mu}(x, a)$$

Inverse Probability Weighting (IPW)

IPW re-weighs observed rewards by importance weights

$$\hat{V}_{IPW}(\pi_e; \mathcal{D}) = \mathbb{E}_n \left[Y_i \underbrace{\frac{\pi_e\left(A_i \mid X_i\right)}{\pi_b\left(A_i \mid X_i\right)}}_{\text{importance weight}} \right]$$

- **Consistent**
- **High variance** when old and new policies are largely different

Doubly Robust (DR)

DR uses DM as a baseline and applies IPW to shifted rewards

$$\hat{V}_{DR}(\pi_e; \mathcal{D}) = \underbrace{\hat{V}_{DM}(\pi_e; \mathcal{D})}_{\text{baseline}} + \mathbb{E}_n \left[\underbrace{(Y_i - \hat{\mu}(X_i, A_i)) \frac{\pi_e(A_i|X_i)}{\pi_b(A_i|X_i)}}_{\text{weighted shifted reward}} \right]$$

$$\mathbb{E}[Y(a) \mid X = x] \approx \hat{\mu}(x, a)$$

- Consistent
- Locally Efficient

Theoretical/Methodological Advances in OPE

- Self-Normalized IPW [Swaminathan and Joachims 2015]
- Switch Doubly Robust Estimator [Wang+ 2017]
- More Robust Doubly Robust Estimator [Farajtabar+ 2018]
- Hirano-Imbence-Ridder Estimator [Narita+ 2019]
- REG and EMP [Kallus & Uehara 2019]
- Doubly Robust with Shrinkage [Su+ 2020]

It seems the OPE community have made great progress over the years!

There are many other estimators in the reinforcement learning setting

Issues with the current experimental procedures

Experiments in every OPE paper rely on

- Synthetic or classification data (unrealistic)

or

- (Real, but) Unpublished data (irreproduceble)

We need real-world data enabling the *"evaluation of OPE"*

Project's Goal and Components

We enable *realistic* and *reproducible* experiments on

- Bandit Algorithms
- Off-Policy Evaluation (OPE)

➡ ***"Open Bandit Dataset"***

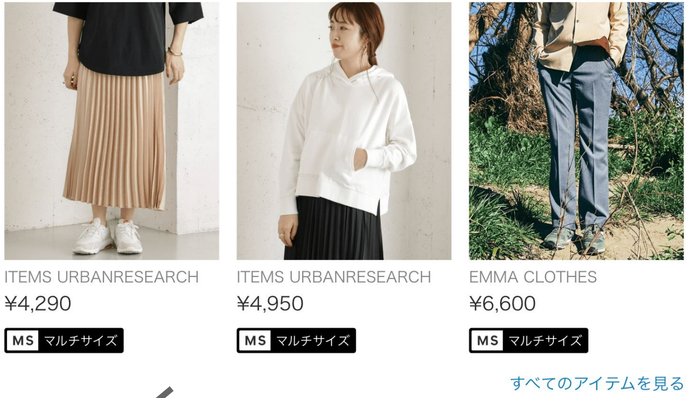
and ***"Open Bandit Pipeline"***

Overview of Open Bandit Dataset

user

Behavior policy

ZOZOTOWN recommendation



$$\mathcal{D} = \{(X_i, A_i, Y_i)\}_{i=1}^{n}$$

Schema of Open Bandit Dataset

	A		$\pi_b(\cdot \mid X)$	Y	X	
timestamp	**item_id**	**position**	**propensity _score**	**click indicator**	**features**	**...**
2019-11-xx	25	1	0.0002	0	e2500f3f	...
2019-11-xx	32	2	0.043	1	7c414ef7	...
2019-11-xx	11	3	0.167	0	60bd4df9	...
2019-11-xx	40	1	0.0011	0	7c20d9b5	...
...	...	...	...	...	...	...

Essential Features of Open Bandit Dataset

- over 25M records collected by online experiments of bandit algorithms on a large-scale fashion e-commerce (*ZOZOTOWN*)

- **logged bandit feedback collected by *multiple* bandit policies**
  - *Uniform Random* (fixed)
  - *Bernoulli Thompson Sampling* (pre-trained before collection)

➡ **enabling realistic experiments on OPE for the first time**

Protocol for the Evaluation of OPE with Open Bandit Dataset

1. **Prepare *two* logged bandit feedback data collected by different policies**

$$\mathcal{D}^{(1)} = \left\{ \left(X_i^{(1)}, A_i^{(1)}, Y_i^{(1)} \right) \right\}_{i=1}^{n}$$

collected by $\pi^{(1)}$

$$\mathcal{D}^{(2)} = \left\{ \left(X_i^{(2)}, A_i^{(2)}, Y_i^{(2)} \right) \right\}_{i=1}^{n}$$

collected by $\pi^{(2)}$

Protocol for the Evaluation of OPE with Open Bandit Dataset

2. Regard one policy as an *evaluation policy* and the other as a *behavior policy*. Then, estimate the performance of the evaluation policy by OPE

$$V(\pi^{(1)}) \approx \hat{V}(\pi^{(1)}; \mathcal{D}^{(2)})$$

$\pi^{(1)}$: evaluation policy

$\pi^{(2)}$: behavior policy

- The task here is to evaluate the accuracy of $\hat{V}$

Protocol for the Evaluation of OPE with Open Bandit Dataset

3. Regard the *on-policy estimation* of the policy value of the evaluation policy as the ground-truth policy value

$$V(\pi^{(1)}) = \mathbb{E}_{n^{(1)}}[Y^{(1)}]$$

we can do this on-policy estimation because we have $\mathcal{D}^{(1)}$ in our data

Protocol for the Evaluation of OPE with Open Bandit Dataset

4. Compare the estimated policy value with the ground-truth to evaluate the OPE estimator, for example, using the *relative estimation error*

$$\textit{relative estimation error of } \hat{V} = \left| \frac{\hat{V}\left(\pi^{(1)}; \mathcal{D}^{(2)}\right) - V\left(\pi^{(1)}\right)}{V\left(\pi^{(1)}\right)} \right|$$

By applying this procedure to several estimators, we can compare them

Comparison with Existing Real-World Bandit Datasets

Table 2: Comparison of Currently Available Large-scale Bandit Datasets

	Criteo Data (Lefortier et al. 2016)	**Yahoo! Data** (Li et al. 2010)	**Open Bandit Dataset** (ours)
Domain	Display Advertising	News Recommendation	Fashion E-Commerce
#Data	>= 103M	>= 40M	>= 26M (will increase)
#Behavior Policies	1	1	2 (will increase)
Random A/B Test Data	✗	✓	✓
Behavior Policy Code	✗	✗	✓
Evaluation of Bandit Algorithms	✓	✓	✓
Evaluation of OPE	✗	✗	✓
Pipeline Implementation	✗	✗	✓

Our Open Bandit Dataset

- contains *multiple behavior policies*
- enables *the evaluation of OPE for the first time*
- *comes with the pipeline implementations* (Open Bandit Pipeline)

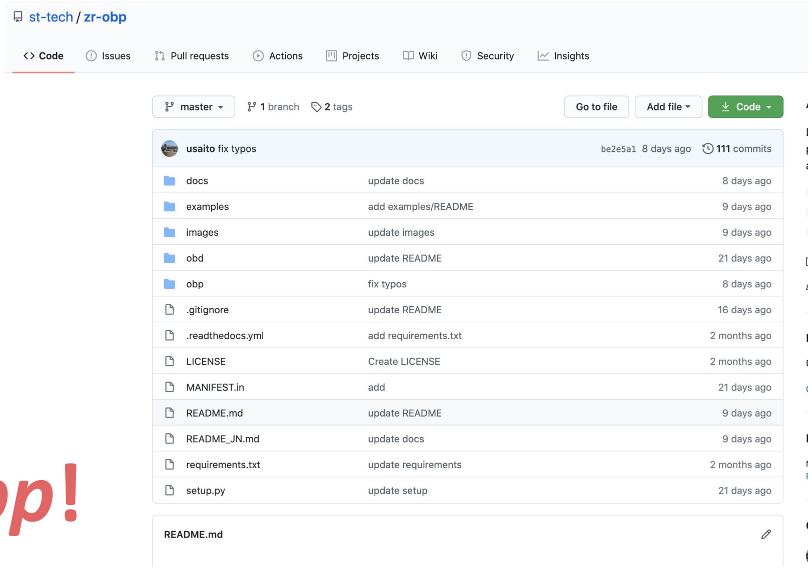
Open Bandit Pipeline (OBP)

We have implemented ***Open Bandit Pipeline (OBP)***

to streamline and standardize experiments on OPE

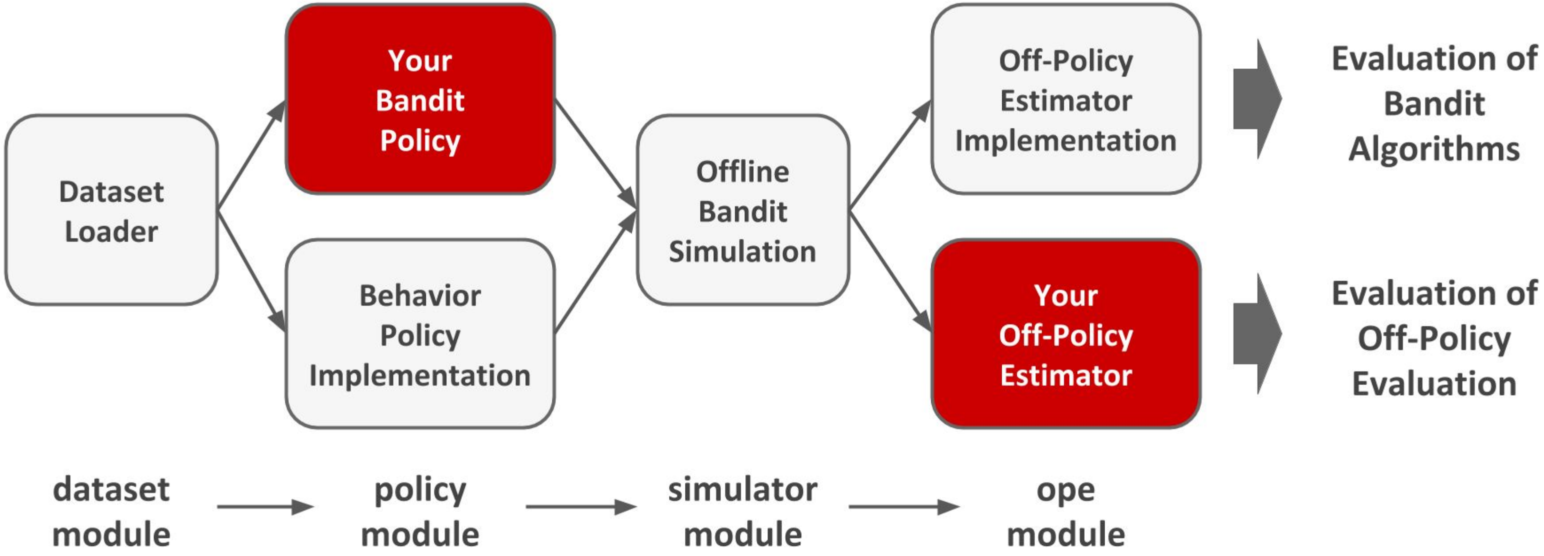
OPEN
BANDIT
PIPELINE™

find out *zr-obp*!



Structure of Open Bandit Pipeline

OBP consists of **four main modules** (dataset, policy, simulator, and ope)



Proof of Concept Demo with Our Data and Pipeline

Let me now run a [quickstart example]() of OBP

Other Nice Features

We can easily implement experiments on OPE or OPE itself with our OBP

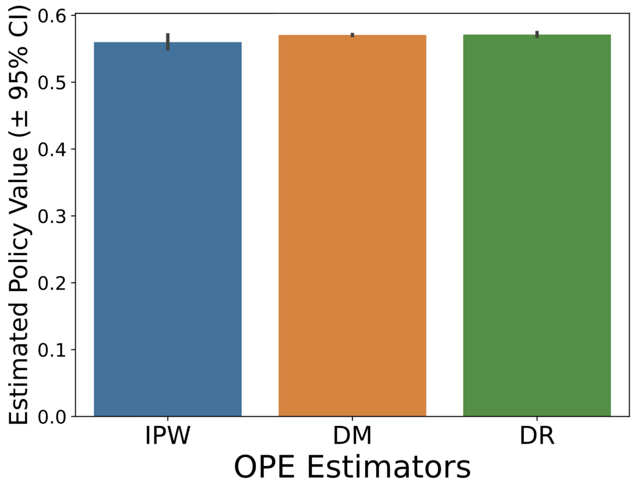
```python
# a case for implementing OPE of the BernoulliTS policy using log data generated by the Random policy
from obp.dataset import OpenBanditDataset
from obp.policy import BernoulliTS
from obp.simulator import run_bandit_simulation
from obp.ope import OffPolicyEvaluation, ReplayMethod

# (1) Data loading and preprocessing
dataset = OpenBanditDataset(behavior_policy='random', campaign='women')
bandit_feedback = dataset.obtain_batch_bandit_feedback()

# (2) Offline Bandit Simulation
counterfactual_policy = BernoulliTS(n_actions=dataset.n_actions, len_list=dataset.len_list)
selected_actions = run_bandit_simulation(bandit_feedback=bandit_feedback, policy=counterfactual_policy)

# (3) Off-Policy Evaluation
ope = OffPolicyEvaluation(bandit_feedback=bandit_feedback, ope_estimators=[ReplayMethod()])
estimated_policy_value = ope.estimate_policy_values(selected_actions=selected_actions)

# estimated performance of BernoulliTS relative to the ground-truth performance of Random
relative_policy_value_of_bernoulli_ts = estimated_policy_value['rm'] / bandit_feedback['reward'].mean()
print(relative_policy_value_of_bernoulli_ts) # 1.120574...
```

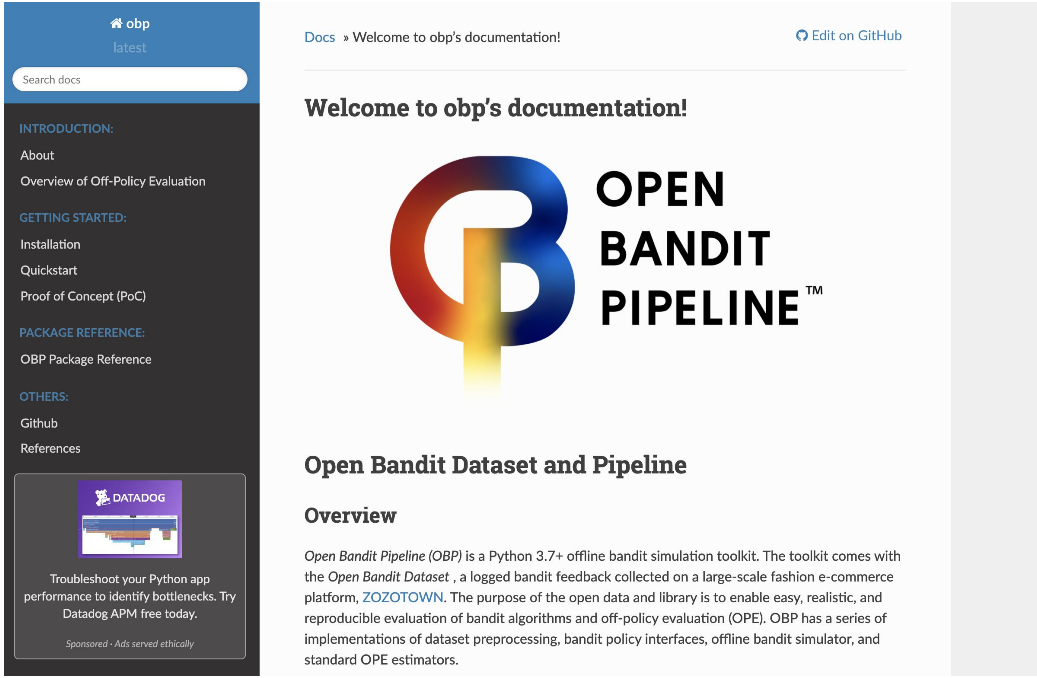


Potential Users

- *Researchers* can compare their own method with others in an easy, realistic, and reproducible manner

- *Practitioners (engineers, data scientists)* can evaluate candidate policies and identify the best one immediately using our pipeline and their own data

Other Nice Features



We built a detailed documentation of Open Bandit Pipeline

Comparison with Existing Bandit Packages

Table 3: Comparison of Currently Available Packages of Bandit Algorithms

	contextualbandits	**RecoGym** (Rohde et al. 2018)	**Open Bandit Pipeline** (ours)
Synthetic Data Generator	✗	✓	✓
Support for Real-World Data	✗	✗	✓
Implementation of Bandit Algorithms	✓	✓	✓
Implementation of Basic Off-Policy Estimators	✓	✗	✓
Implementation of Advanced Off-Policy Estimators	✗	✗	✓
Evaluation of OPE	✗	✗	✓

Our Open Bandit Pipeline

- can *handle real-world bandit data* (including ours)
- implements *advanced OPE estimators* (SNIPW, Switch, MRDR, and DML)
- streamline *the evaluation of OPE*

Benchmark Results of Some OPE Methods

We performed benchmark comparison on basic OPE estimators

Table 4: Comparing Relative-Estimation Errors of OPE Estimators (**Random** → **Bernoulli TS**)

	Campaigns		
Estimators	All	Men's	Women's
DM	0.23879 [0.22998, 0.24988]	0.24155 [0.22656, 0.25592]	0.22884 [0.22224, 0.23423]
IPW	0.03477 [0.01147, 0.06592]	0.09806 [0.07485, 0.12151]	0.03252 [0.01708, 0.04912]
SNIPW	0.03381 [0.01005, 0.06662]	0.08153 [0.05677, 0.10592]	0.03179 [0.01562, 0.04825]
DR	0.03487 [0.01094, 0.06784]	0.08528 [0.06186, 0.10876]	0.03224 [0.01605, 0.04843]

IPW, SNIPW, and DR seem accurate, but this is a very simple task

Some Limitations...

We now assume that the **click of an item (reward) depends only on that item and position**

$$\mathcal{A} = \mathcal{I} \times \mathcal{K}$$

action set

item set (total of 80 items)

position set (total of 3 positions)

Some Limitations...

- <u>assumption on the action decomposition might be too strict</u>

$$\mathcal{A} = \mathcal{I} \times \mathcal{K}$$

because it ignores the interactions among items in the same list

$\longrightarrow$ We will compare other estimators relying on other reasonable assumptions (e.g., estimators for the slate setting)

Some Limitations...

- **the current data contains only context-free policies**
  → we will run another experiment to collect more useful bandit datasets (open bandit dataset v2)

- **current benchmark analysis is simple, primitive**
  → we are now conducting extensive experiments to answer
  - Can OPE estimates the performance of a new policy in the future environment (out-sample policy value)?
  - How does the performance of OPE change with different settings?

Thank you!

Please come to our poster for further discussions!

github: https://github.com/st-tech/zr-obp

docs: https://zr-obp.readthedocs.io/en/latest/

dataset: https://research.zozo.com/data.html