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CFRL: A Python library for counterfactually fair offline reinforcement learning via data preprocessing

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DOI: 10.xxxxxx/draft

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Submitted: 01 January 1970
Published: unpublished

Summary

Reinforcement learning (RL) aims to learn and evaluate a sequential decision-making rule, often referred to as a "policy", that maximizes expected discounted cumulative rewards to optimize population-level benefit in an environment across possibly infinitely many time steps. RL has gained popularity in fields such as healthcare, banking, autonomous driving, and more recently large language model pre-training. However, the sequential decisions made by an RL algorithm may disadvantage individuals with certain values of a sensitive attribute (e.g., race, ethnicity, gender, education level). An RL algorithm learns an optimal policy that makes decisions based on observed state variables. If certain values of the sensitive attribute influence the state variables in a way that leads the policy to systematically withhold an action from an individual, unfairness will result. For example, Hispanics may under-report their pain levels due to cultural factors, misleading the RL agent to assign less therapist time to them (Piette et al., 2023). Deployment of RL algorithms without careful fairness considerations can raise concerns and erode public trust in high-stake settings.

To formally define and address the unfairness problem in sequential decision making settings, Wang et al. (2025) extended the concept of single-stage counterfactual fairness (CF) in a structural causal framework (Kusner et al., 2018) to the multi-stage setting and proposed a data preprocessing based algorithm that ensures CF. A policy is CF if, at every time step, the probability of assigning any action does not change had the individual's sensitive attribute taken a different value, while holding constant other historical exogenous variables and actions. In this light, the data preprocessing algorithm ensures CF by constructing new state variables that are not impacted by the sensitive attribute(s). The rewards in data are also preprocessed, but the purpose of preprocessing the rewards is to improve the value of the learned optimal policy rather than ensure CF. We refer interested readers to Wang et al. (2025) for more technical details.

The `CFRL` library implements the data preprocessing algorithm proposed by Wang et al. (2025) and provides a suite of tools to evaluate the value and CF level achieved by any given policy. The library produces preprocessed trajectories that can be used by any off-the-shelf offline RL algorithms, such as fitted Q-iteration (FQI) (Riedmiller, 2005), to learn an optimal CF policy. The library can also simply read in any policy following a required format and return its value and CF level in the environment of interest, where the environment can be either pre-specified or learned from the data.

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Statement of Need

Many existing Python libraries implement algorithms that ensure fairness in machine learning. For example, `Fairlearn` (Weerts et al., 2023) and `aif360` (Bellamy et al., 2018) provide tools for mitigating bias in single-stage machine learning predictions under statistical assocoiation-based fairness criterion such as demographic parity and equal opportunity. However, they do not focus on counterfactual fairness, which defines an individual-level fairness concept from a causal perspective, and they cannot be easily extended to the reinforcement learning setting in general. Additionally, `ml-fairness-gym` (D'Amour et al., 2020) allows users to simulate unfairness in sequential decision-making, but it neither implements algorithms that reduce unfairness nor addresses CF. To our knowledge, Wang et al. (2025) is the first work to study CF in RL. Correspondingly, `CFRL` is also the first code library to address CF in the RL setting.

The contribution of CFRL is two-fold. First, it implements a data preprocessing algorithm that ensures CF in offline RL. For each individual in the data, the preprocessing algorithm sequentially estimates the counterfactual states under different sensitive attribute values and concatenates all of the individual's counterfactual states at each time point into a new state vector. The preprocessed data can then be directly used by existing RL algorithms for policy learning, and the learned policy should be counterfactually fair up to finite-sample estimation accuracy. Second, it provides a platform for assessing RL policies based on CF. After passing in any policy and a data trajectory from the environment of interest, users can estimate the value and CF level achieved by the policy in the environment of interest.

High-level Design

The `CFRL` library is composed of 5 major modules. The functionalities of the modules are summarized in the table below.

Module	Functionalities
`reader`	Implements functions that read tabular trajectory data from either a `.csv` file or a `pandas.Dataframe` into an array format required by `CFRL`. Also implements functions that export trajectory data to either a `.csv` file or a `pandas.Dataframe`.
`preprocessor`	Implements the data preprocessing algorithm introduced in Wang et al. (2025).
`agents`	Implements a fitted Q-iteration (FQI) algorithm (Riedmiller, 2005), which learns RL policies and makes decisions based on the learned policy. Users can also pass a preprocessor to the FQI; in this case, the FQI will be able to take in unpreprocessed trajectories, internally preprocess the input trajectories, and directly output counterfactually fair policies.
`environment`	Implements a synthetic environment that produces synthetic data as well as a simulated environment that estimates and simulates the transition dynamics of the unknown environment underlying some real-world RL trajectory data. Also implements functions for sampling trajectories from the synthetic and simulated environments.
`evaluation`	Implements functions that evaluate the value and CF level of a policy. Depending on the user's needs, the evaluation can be done either in a synthetic environment or in a simulated environment.

A general CFRL workflow is as follows: First, simulate a trajectory using `environment` or read in a trajectory using `reader`. Then, train a preprocessor using `preprocessor` and preprocess the training trajectory data. After that, pass the preprocessed trajectory into the FQI algorithm in

agents to learn a counterfactually fair policy. Finally, use functions in `evaluation` to evaluate the value and CF level of the trained policy.

Data Example

We provide a data example to demontrate how `CFRL` learns a counterfactually fair policy from real-world trajectory data with unknown underlying transition dynamics. We also show how `CFRL` evaluates the value and CF level of the learned policy. We note that this is only one of the many workflows that `CFRL` can perform. For example, `CFRL` can also generate synthetic trajectory data and use it to evaluate the value and CF level resulting from some custom data preprocessing methods. We refer interested readers to the "Example Workflows" section of the CFRL documentation for more workflow examples.

Load Data

In this demonstration, we use an offline trajectory generated from a `SyntheticEnvironment` following some pre-specified transition rules. Although it is actually synthesized, we treat it as if it is from some unknown environment for pedagogical convenience.

The trajectory contains 500 individuals (i.e. $N = 500$) and 10 transitions (i.e. $T = 10$). The sensitive attribute variable and the state variable are both univariate. The sensitive attribute is binary (0 or 1). The actions are also binary (0 or 1) and were sampled using a behavior policy that selects 0 or 1 randomly with equal probability. The trajectory is stored in a tabular format in a `.csv` file. We use `read_trajectory_from_csv()` to load the trajectory from the `.csv` format into the array format required by `CFRL`.

```
zs, states, actions, rewards, ids = read_trajectory_from_csv(
    path='../data/sample_data_large_uni.csv', z_labels=['z1'],
    state_labels=['state1'], action_label='action', reward_label='reward',
    id_label='ID', T=10)
```

We then split the trajectory data into a training set (80%) and a testing set (20%) using scikit-learn's `train_test_split()`. The training set is used to train the counterfactually fair policy, while the testing set is used to evaluate the value and CF level achieved by the policy.

```
(zs_train, zs_test, states_train, states_test,
 actions_train, actions_test, rewards_train, rewards_test
) = train_test_split(zs, states, actions, rewards, test_size=0.2)
```

Train Preprocessor & Preprocess Trajectories

We now train a `SequentialPreprocessor` and preprocess the trajectory. The `SequentialPreprocessor` ensures the learned policy is counterfactually fair by constructing new state variables that are not impacted by the sensitive attribute. Due to limited trajectory data, the data to be preprocessed will also be the data used to train the preprocessor, so we set `cross_folds=5` to reduce overfitting. In this case, `train_preprocessor()` will internally divide the training data into 5 folds, and each fold is preprocessed using a model that is trained on the other 4 folds. We initialize the `SequentialPreprocessor`, and `train_preprocessor()` will take care of both preprocessor training and trajectory preprocessing.

```
sp = SequentialPreprocessor(z_space=[[0], [1]], num_actions=2, cross_folds=5,
                            mode='single', reg_model='nn')
states_tilde, rewards_tilde = sp.train_preprocessor(
    zs=zs_train, xs=states_train, actions=actions_train, rewards=rewards_train)
```

Counterfactually Fair Policy Learning

Now we train a counterfactually fair policy using the preprocessed data and `FQI` with `sp` as its internal preprocessor. By default, the input data will first be preprocessed by `sp` before being used for policy learning. However, since the training data `state_tilde` and `rewards_tilde` are already preprocessed in our case, we set `preprocess=False` during training so that the input trajectory will not be preprocessed again by the internal preprocessor (i.e. `sp`).

```
agent = FQI(num_actions=2, model_type='nn', preprocessor=sp)
agent.train(zs=zs_train, xs=states_tilde, actions=actions_train,
            rewards=rewards_tilde, max_iter=100, preprocess=False)
```

`SimulatedEnvironment` Training

Before moving on to the evaluation stage, there is one more thing to do: We need to train a `SimulatedEnvironment` that mimics the transition rules of the true environment that generated the training trajectory, which will be used by the evaluation functions to simulate the true data-generating environment. To do so, we initialize a `SimulatedEnvironment` and train it on the whole trajectory data (i.e. training set and testing set combined).

```
env = SimulatedEnvironment(num_actions=2, state_model_type='nn',
                           reward_model_type='nn')
env.fit(zs=zs, states=states, actions=actions, rewards=rewards)
```

Value and Counterfactual Fairness Evaluation

We now use `evaluate_value_through_fqe()` and `evaluate_fairness_through_model()` to estimate the value and CF level achieved by the trained policy when interacting with the environment of interest, respectively. The CF level is represented by a metric from 0 to 1, with 0 representing perfect fairness and 1 indicating complete unfairness. We use the testing set for evaluation.

```
value = evaluate_reward_through_fqe(zs=zs_test, states=states_test,
    actions=actions_test, rewards=rewards_test, policy=agent, model_type='nn')
cf_metric = evaluate_fairness_through_model(env=env, zs=zs_test, states=states_test,
                                            actions=actions_test, policy=agent)
```

The estimated value is 7.358 and CF metric is 0.042, which indicates our policy is close to being perfectly counterfactually fair. Indeed, the CF metric should be exactly 0 if we know the true dynamics of the environment of interest; the reason why it is not exactly 0 here is because we need to estimate the dynamics of the environment of interest during preprocessing, which can introduce finite-sample errors.

Comparisons Against Baseline Methods

We can compare the sequential data preprocessing method in `CFRL` against a few baselines: Random, which selects each action randomly with equal probability; Full, which uses all variables, including the sensitive attribute, for policy learning; and Unaware, which uses all variables except the sensitive attribute for policy learning. We implemented these baselines and evaluated their values and CF levels as part of the code example of the "Assessing Policies Using Real Data" workflow in the "Example Workflows" section of the CFRL documentation. We summarize below the values and CF metrics calculated in this code example, where "ours" stands for the `SequentialPreprocessor`.

	Random	Full	Unaware	Ours
Value	-1.444	8.606	8.588	7.358
CF Metric	0	0.407	0.446	0.042

By definition, the "random" baseline always achieves perfect CF. On the other hand, "ours" resulted in much fairer policies than "full" and "unaware", which suggests that the `SequentialPreprocessor` can effectively improve CF. Nevertheless, as a trade-off for higher CF, "ours" achieved a lower value than "full" and "unaware".

Conclusions

`CFRL` is a Python library that enables CF reinforcement learning through data preprocessing. It also provides tools to calculate the value and unfairness level of a given policy. To our knowledge, it is the first library to address CF problems in the context of RL. The practical utility of `CFRL` can be further improved via extensions. First, the current `CFRL` implementation requires every individual in the offline dataset to have the same number of time steps. Extending the library to accommodate variable-length episodes can improve its flexibility and usefulness. Second, `CFRL` can further combine the preprocessor with popular offline RL algorithm libraries such as `d3rlpy` (Seno & Imai, 2022), or connect the evaluation functions with established RL environment libraries such as `gym` (Towers et al., 2024). Third, generalization to non-additive counterfactual states reconstruction can make `CFRL` theoretically more versatile. We leave these extensions to future updates.

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