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

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Summary

Reinforcement learning (RL) aims to learn and evaluate a sequential decision rule, often referred to as a "policy", that maximizes expected discounted cumulative rewards to optimize the 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, income, gender, education level). An fairness-unaware RL algorithm learns an optimal policy that makes decisions based on the *observed* state variables. However, if certain values of the sensitive attribute influence the state variables and lead the policy to systematically withhold certain actions from an individual, unfairness will result. For example, Hispanics may under-report their pain levels due to cultural factors, misleading a fairness-unaware RL agent to assign less therapist time to these individuals (Piette et al., 2023). Deployment of RL algorithms without careful fairness considerations can raise concerns and erode public trust in high-stakes settings.

To formally define and address the fairness problem in the novel 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 algorithm that ensures CF. A policy is counterfactually fair 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). Reward preprocessing is also conducted but with a different purpose to improve the value of the learned optimal policy rather than to 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 functionalities to evaluate the value (expected discounted cumulative reward) and counterfactual unfairness level achieved by any given policy. Here, "CFRL" stands for "Counterfactual Fairness in Reinforcement Learning". The library produces preprocessed trajectories that can be used by an off-the-shelf offline RL algorithm, 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 counterfactual unfairness level in the environment of interest, where the environment can be either pre-specified or learned

₄₄ from the data.

Statement of Need

₄₆ Many existing `Python` libraries implement algorithms designed to ensure fairness in machine
₄₇ learning. For example, `Fairlearn` (Weerts et al., 2023) and `aif360` (Bellamy et al., 2018)
₄₈ provide tools for mitigating bias in single-stage machine learning predictions under statistical
₄₉ association-based fairness criteria such as demographic parity and equal opportunity. However,
₅₀ existing libraries do not focus on counterfactual fairness, which defines an individual-level
₅₁ fairness concept from a causal perspective, and they cannot be easily extended to the general
₅₂ reinforcement learning setting. Scripts available from `ml-fairness-gym` (D'Amour et al., 2020)
₅₃ allow users to simulate unfairness in sequential decision-making, but they neither implement
₅₄ algorithms that reduce unfairness nor address CF. To our knowledge, Wang et al. (2025) is
₅₅ the first work to study CF in RL. Correspondingly, CFRL is also the first code library to address
₅₆ CF in the RL setting.

₅₇ The contribution of CFRL is two-fold. First, CFRL implements a data preprocessing algorithm
₅₈ that ensures CF in offline RL. For each individual in the data, the preprocessing algorithm
₅₉ sequentially estimates and concatenates the counterfactual states under different sensitive
₆₀ attribute values with the observed state at each time point into a new state vector. The
₆₁ preprocessed data can then be directly used by existing RL algorithms for policy learning, and
₆₂ the learned policy will be counterfactually fair up to finite-sample estimation accuracy. Second,
₆₃ CFRL provides a platform for assessing RL policies based on CF. After passing in any policy
₆₄ and a data trajectory from the environment of interest, users can estimate the value and
₆₅ counterfactual unfairness level achieved by the policy in the environment of interest.

High-level Design

₆₇ The `CFRL` library is composed of 5 major modules. The functionalities of the modules are
₆₈ 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 counterfactual unfairness 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.

₆₉ A general CFRL workflow is as follows: First, simulate trajectories using `environment` or read

70 in trajectories using `reader`. Then, train a preprocessor using `preprocessor` and preprocess the
71 training trajectory data. After that, pass the preprocessed trajectories into the FQI algorithm in
72 `agents` to learn a counterfactually fair policy. Finally, use functions in `evaluation` to evaluate
73 the value and counterfactual unfairness level of the trained policy.

74 In addition, CFRL also provides tools to check for potential non-convergence that may arise
75 during the training of neural networks, FQI, or fitted-Q evaluation (FQE). More discussions
76 about the sources, checks, and fixes of non-convergence in CFRL can be found in the "Common
77 Issues" section of the documentation.

Data Example

79 We provide a data example showing how CFRL learns counterfactually fair policies from real-
80 world trajectory data with unknown underlying transition dynamics. The example demonstrates
81 policy learning and evaluation of both value and unfairness levels. This represents just one of
82 many possible workflows. CFRL can also generate synthetic trajectory data and evaluate custom
83 preprocessing methods. See the "Example Workflows" documentation for more examples.

84 We recorded the computing times of different workflows under different combinations of the
85 number of individuals (N) and the number of transitions (T) in the "Computing Times"
86 section of the CFRL documentation. For example, under $N = 500$ and $T = 10$, the workflow
87 presented in this data example ("real data workflow" in the documentation) ran for 378.6
88 seconds on average in our computing environment.

89 Load Data

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

93 The trajectory contains 500 individuals (i.e. $N = 500$) and 10 transitions (i.e. $T = 10$). The
94 sensitive attribute variable and the state variable are both univariate. The sensitive attribute
95 is binary (0 or 1). The actions are also binary (0 or 1) and were sampled using a behavior
96 policy that selects 0 or 1 randomly with equal probability. The trajectory is stored in a tabular
97 format in a `.csv` file. We use `read_trajectory_from_csv()` to load the trajectory from the
98 `.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)
```

99 We then split the trajectory data into a training set (80%) and a testing set (20%) using
100 scikit-learn's `train_test_split()`. The training set is used to train the counterfactually fair
101 policy, while the testing set is used to evaluate the value and counterfactual unfairness level
102 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)
```

103 Train Preprocessor & Preprocess Trajectories

104 We now train a `SequentialPreprocessor` and preprocess the trajectory. The `SequentialPreprocessor`
105 ensures the learned policy is counterfactually fair by constructing new state variables that
106 are not impacted by the sensitive attribute. Due to limited trajectory data, the data to be
107 preprocessed will also be the data used to train the preprocessor, so we set `cross_folds=5`
108 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.

```python
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

Next, 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`).

```python
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 step: 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 via Monte Carlo. To do so, we initialize a `SimulatedEnvironment` and train it on the whole trajectory data (i.e. training set and testing set combined).

```python
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 Unfairness Level Evaluation

We now use `evaluate_value_through_fqe()` and `evaluate_fairness_through_model()` to estimate the value and counterfactual unfairness level achieved by the trained policy when interacting with the environment of interest, respectively. The counterfactual unfairness 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.

```python
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 the 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 that 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 counterfactual unfairness 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 outputs from the `SequentialPreprocessor`.

	Random	Full	Unaware	Ours
Value	−1.444	8.606	8.588	7.358
Counterfactual Unfairness Level	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 better CF, "ours" achieved a lower value than "full" and "unaware".

Conclusions

CFRL is a `Python` library that enables counterfactually fair 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 more versatile. We leave these extensions to future updates.

References

Bellamy, R. K. E., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K., Lohia, P., Martino, J., Mehta, S., Mojsilovic, A., Nagar, S., Ramamurthy, K. N., Richards, J., Saha, D., Sattigeri, P., Singh, M., Varshney, K. R., & Zhang, Y. (2018). *AI Fairness 360: An extensible toolkit for detecting, understanding, and mitigating unwanted algorithmic bias.*

D'Amour, A., Srinivasan, H., Atwood, J., Baljekar, P., Sculley, D., & Halpern, Y. (2020). Fairness is not static: Deeper understanding of long term fairness via simulation studies. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 525–534. https://doi.org/10.1145/3351095.3372878

Kusner, M. J., Loftus, J. R., Russell, C., & Silva, R. (2018). *Counterfactual Fairness.* https://arxiv.org/abs/1703.06856

Piette, J. D., Thomas, L., Newman, S., Marinec, N., Krauss, J., Chen, J., Wu, Z., & Bohnert, A. S. B. (2023). An automatically adaptive digital health intervention to decrease opioid-related risk while conserving counselor time: Quantitative analysis of treatment decisions based on artificial intelligence and patient-reported risk measures. *J Med Internet Res*, *25*, e44165. https://doi.org/10.2196/44165

Riedmiller, M. (2005). Neural fitted Q iteration – first experiences with a data efficient neural reinforcement learning method. In J. Gama, R. Camacho, P. B. Brazdil, A. M. Jorge, & L. Torgo (Eds.), *Machine learning: ECML 2005* (pp. 317–328). Springer Berlin Heidelberg. ISBN: 978-3-540-31692-3

Seno, T., & Imai, M. (2022). d3rlpy: An offline deep reinforcement learning library. *Journal of Machine Learning Research*, *23*(315), 1–20.

182 Towers, M., Kwiatkowski, A., Terry, J., Balis, J. U., De Cola, G., Deleu, T., Goulão, M.,
183   Kallinteris, A., Krimmel, M., KG, A., & others. (2024). Gymnasium: A standard interface
184   for reinforcement learning environments. *arXiv Preprint arXiv:2407.17032*.

185 Wang, J., Shi, C., Piette, J. D., Loftus, J. R., Zeng, D., & Wu, Z. (2025). *Counterfactually fair*
186   *reinforcement learning via sequential data preprocessing*. https://arxiv.org/abs/2501.06366

187 Weerts, H., Dudík, M., Edgar, R., Jalali, A., Lutz, R., & Madaio, M. (2023). Fairlearn:
188   Assessing and improving fairness of AI systems. In *Journal of Machine Learning Research*
189   (No. 257; Vol. 24, pp. 1–8).