Self-guided Approximate Linear Programs

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Topics: approximate dynamic programming, approximate linear programming, model-based reinforcement learning, random Fourier features, inventory management, options pricing.

Introduction

This repository hosts algorithm implementations and benchmarks discussed in the paper **Self-Guided Approximate Linear Programs: Randomized Multi-Shot Approximation of Discounted Cost Markov Decision Processes** authored by Parshan Pakiman, Selva Nadarajah, Negar Soheili, and Qihang Lin, available at Management Science. Specifically, this repository includes implementations of the following algorithms for computing control policies in Markov decision processes (MDPs):

- Feature-based Approximate Linear Program (FALP)
- Self-guided FALP
- Policy-guided FALP
- Least Squares Monte Carlo (Longstaff and Schwartz 2001)

Furthermore, the repository includes implementations of two algorithms for computing lower bounds on the optimal policy cost of MDPs:

- Information Relaxation and Duality (Brown et al. 2010)
- A heuristic based on Constraint Violation Learning (Lin et al. 2020)

Integrating lower bounds with the upper bounds derived from simulating control policies enables the computation of optimality gaps. The optimality gap of a policy is the difference between the cost of this policy and the lower bound, expressed as a percentage of the lower bound. This repository implements MDPs associated with the following applications:

- Perishable inventory control
- Bermudan options pricing

Note: The code in this repository is relatively general and can be extended to other MDPs to compute control policies and lower bounds.

Instruction

The following steps are tailored for macOS and Ubuntu users. Windows users may adapt and create similar instructions suitable for their operating system.

1. Download the repository on your local system and extract the zip file. For ease of reference, we assume the extracted files are stored in the following path: `/Desktop/Self-Guided-ALPs-Discounted-Cost-master`.
2. Open `Terminal` on your machine and run the following code:

   ```
   cd  /Desktop/Self-Guided-ALPs-Discounted-Cost-master
   ```

3. Please check the version of your Python. For example, run the code below:

   ```
   python3 --version
   ```

4. Please confirm that `Python 3.10` or above is installed on your machine. There are different ways to install Python. We leave this step to the user's discretion.
5. Create a virtual Python environment and name it `ALP`. For example, use the following code:

   ```
   python -m venv ALP
   ```

6. Activate the `ALP` environment as follows:

   ```
   source ALP/bin/activate
   ```

7. This code relies on several Python packages. We utilize `pip` for their installation, but users can explore alternative methods. If choosing `pip`, please use the following code for its update:

   ```
   pip install --upgrade pip
   ```

8. Please install the following libraries on the ALP environment:
    - numpy
    - pandas
    - scipy
    - numba
    - tqdm
    - emcee
    - sampyl
    - importlib
    - sampyl_mcmc
    - nengo
    - gurobipy

    For instance, run the following command to install all the above libraries:

    ```
    python -m pip install numpy pandas scipy numba tqdm e
    ```

9. This repository uses Gurobi for solving large-scale linear programs. Please ensure that Gurobi (`gurobipy`) is installed along with its corresponding license. If you are affiliated with academia, Gurobi provides a free academic license, accessible through this page. In some cases, an error might occur when running the `grbgetkey` code to activate your license. Refer to this troubleshooting page for assistance with resolving this issue. If the issue persists, consider installing Gurobi using `conda` instead of `pip`. You can use the following code as an example:

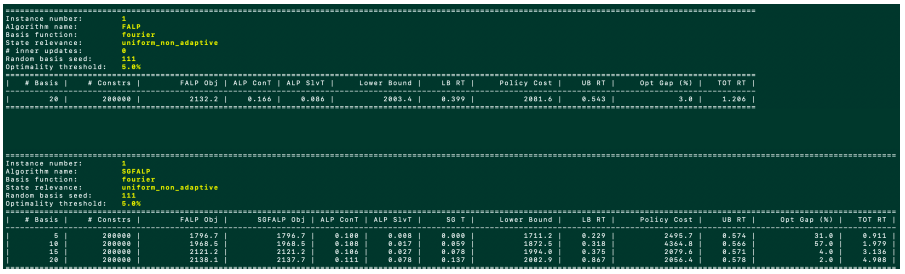
    ```
    conda install -c gurobi gurobi
    grbgetkey xxxxxxxx-xxxx-xxxx-xxxx-xxxxxxxxxxxx
    ```

10. Provided that the ALP environment and Gurobi are correctly installed, you can use the following code to solve test instances of perishable inventory control applications. Please run the following code:

    ```
    ./run_PIC.sh
    ```

    The `run_PIC.sh` file solves the first instance of the perishable inventory control problem using the FALP algorithm with 20 random Fourier features, where FALP is formulated using a uniform state-relevance distribution (refer to the paper and code for details). You can find the specifications (e.g., cost parameters) of this instance under

the path `MDP/PIC/Instances/instance_1.py`. To solve this instance using an alternate algorithm, you can modify the file `run_PIC.sh`. For instance, changing the `algo_name` from `FALP` to `SG-FALP` in this file and rerunning `run_PIC.sh` will display the output for the self-guided FALP algorithm applied to this instance. A screenshot of the output of these algorithms is attached below:



```
Instance number:        1
Algorithm name:         FALP
Basis function:         fourier
State relevance:        uniform_non_adaptive
# inner updates:        0
Random basis seed:      111
Optimality threshold:   5.0%
```

# Basis	# Constrs	FALP Obj	ALP ConT	ALP SlvT	Lower Bound	LB RT	Policy Cost	UB RT	Opt Gap (%)	TOT RT
20	200000	2132.2	0.166	0.086	2003.4	0.399	2081.6	0.543	3.8	1.286

```
Instance number:        1
Algorithm name:         SGFALP
Basis function:         fourier
State relevance:        uniform_non_adaptive
Random basis seed:      111
Optimality threshold:   5.0%
```

# Basis	# Constrs	FALP Obj	SGFALP Obj	ALP ConT	ALP SlvT	SG T	Lower Bound	LB RT	Policy Cost	UB RT	Opt Gap (%)	TOT RT
5	200000	1796.7	1796.7	0.188	0.008	0.000	1711.2	0.229	2495.7	0.574	31.0	0.911
10	200000	1968.5	1968.5	0.188	0.017	0.059	1872.5	0.318	4364.8	0.566	57.0	1.979
15	200000	2121.2	2121.2	0.186	0.027	0.078	1994.0	0.375	2079.6	0.571	4.0	3.136
20	200000	2138.1	2137.7	0.111	0.078	0.137	2002.9	0.867	2056.4	0.578	2.0	4.908

11. Running file `run_BerOpt.sh` produces the output of the algorithms for Instance 1 of the Bermudan options pricing.

Replication

The code in this repository can be directly used to replicate the tables and figures in the paper. For perishable inventory control problem instances, we consider four methods:

- $\mathrm{ALP}^{\mathrm{LNS}}$: the standard ALP model formulated using basis functions described in Lin et al. 2020.
- FALP: a randomized ALP model described in $\S 3$ of the paper.
- $\mathrm{FALP}^{\mathrm{PG}}$: policy-guided FALP model described in Algorithm 1 of the paper.
- $\mathrm{FALP}^{\mathrm{SG}}$: self-guided FALP model described in Algorithm 2 of the paper.

For the Bermudan options pricing problem, we consider methods FALP and $\mathrm{FALP}^{\mathrm{SG}}$, in addition to the following ones:

- LSM: Least quares Monte Carlo (Longstaff and Schwartz 2001) that is implemented in file `LSM.py`.
- $\mathrm{ALP}^{\mathrm{DFM}}$: the standard ALP model formulated using basis functions described in Desai et al. 2012.

We test these methods on different sets of instances described in the paper. To obtain the tables and figures in the paper, the parameters of two files, `run_PIC.sh` and `run_BerOpt.sh`, should be modified. We compute the lower and upper bounds for each instance-method pair across ten different

trials. Each of these trials is specified by the value of parameter **seed** that is varied in {111, 222, 333, 444, 555, 666, 777, 888, 999, 1010}. For each method-instance-trial, we compute the lower and upper bounds and then the averages of these bounds across the trials for each method-instance pair. Below, we describe the other parameters in `run_PIC.sh` and `run_BerOpt.sh` to obtain each table and figur in the paper.

- **Table 2:** Compares $\mathrm{ALP}^{\mathrm{LNS}}$ and FALP with on 12 instances. To replicate this table, please run `run_PIC.sh` after modifying the following parameters:

Parameter name in `run_PIC.sh`	$\mathrm{ALP}^{\mathrm{LNS}}$	FALP
algo_name	FALP	FALP
basis_func_type	lns	fourier
max_basis_num	150	150
batch_size	150	150
state_relevance_inner_itr	0	0
instance_number	{1, 2, ..., 12}	{1, 2, ..., 12}

  Please note that `main.py` atomatically sets the value of parameters **max_basis_num** and **batch_size** for each instance.

- **Table 3:** Compares four models $\mathrm{ALP}^{\mathrm{LNS}}$, FALP, $\mathrm{FALP}^{\mathrm{PG}}$, and $\mathrm{FALP}^{\mathrm{SG}}$ on 6 instances. To replicate this table, please run `run_PIC.sh` after modifying the following parameters:

Parameter name in `run_PIC.sh`	$\mathrm{ALP}^{\mathrm{LNS}}$	FALP	$\mathrm{FALP}^{\mathrm{PG}}$	$\mathrm{FALP}^{\mathrm{SG}}$
algo_name	FALP	FALP	PG-FALP	SG-FALP
basis_func_type	lns	fourier	fourier	fourier
max_basis_num	300	300	300	300
batch_size	300	300	50	300
state_relevance_inner_itr	0	0	0	5
instance_number	{13, 14,...,18}	{13, 14,...,18}	{13, 14,...,18}	{13, 14,...,18}

- **Table 4:** Compares four models $\mathrm{ALP}^{\mathrm{LNS}}$, FALP with 600 random basis functions, FALP with 1000 random basis functions, and $\mathrm{FALP}^{\mathrm{SG}}$ on 6 instances. To replicate this table, please run `run_PIC.sh` after modifying the following parameters:

Parameter name in `run_PIC.sh`	$\mathrm{ALP}^{\mathrm{LNS}}$	FALP_{600}	FALP_{1000}	$\mathrm{FALP}^{\mathrm{SG}}$
algo_name	FALP	FALP	PG-FALP	SG-FALP
basis_func_type	lns	fourier	fourier	fourier
max_basis_num	600	600	1000	600
batch_size	600	600	1000	100
state_relevance_inner_itr	0	0	0	0
instance_number	{19, 20, ..., 24}	{19, 20, ..., 24}	{19, 20, ..., 24}	{19, 20, ..., 24}

- **Figure 2:** Depicts the violin plot of upper and lower bounds across 10 trials for 6 iterations of algorithm $\mathrm{FALP}^{\mathrm{SG}}$ on two instances: Instance 19 and Instance 20. Upon running this algorithm on these instances, several files will be generated under the paths `Output/PIC/instance_19` and `Output/PIC/instance_20`. Then, one can use the plotting function in `SG_FALP_progress_plot.py` to obtain Figure 2 based on these files.

- **Table 5:** Presents performance of LSM, $\mathrm{ALP}^{\mathrm{DFM}}$, FALP, and $\mathrm{FALP}^{\mathrm{SG}}$ on 9 instances. To obtain this table, please modify file `run_BerOpt.sh` by letting **instance_number** take values in {1, 2, ..., 9} and **instance_number** take values in {1, 2, ..., 9} and **seed** to take values in {111, 222, 333, 444, 555, 666, 777, 888, 999, 1010}.

Appendix

This code has undergone testing on two systems:

- 2021 MacBook Pro:
  - CPU: M1 Pro
  - Memory: 16 GB

    - OS: Mac OS 14.1.2
- 2022 Mac Studio:
    - CPU: M1 Max
    - Memory: 64 GB
    - OS: Mac OS 14.1.1

Below is the list of Python package versions utilized during the testing phase of this repository:

Package	Version
autograd	1.6.2
emcee	3.1.4
future	0.18.3
gurobipy	11.0.0
importlib	1.0.4
llvmlite	0.41.1
nengo	4.0.0
numba	0.58.1
numpy	1.26.2
pandas	2.1.4
pip	23.3.1
python-dateutil	2.8.2
pytz	2023.3.post1
sampyl-mcmc	0.3
scipy	1.11.4
setuptools	63.2.0
six	1.16.0
tqdm	4.66.1
tzdata	2023.3