Username:	[your email username]
Name:	[your first and last name]

By turning in this assignment, I agree by the honor code of USC Columbia.

Submission. You need to submit the following files to Blackboard:

- A pdf file named as assignment1_$\langle username \rangle$.pdf, where you replace $\langle username \rangle$ with your email username. This pdf file contains your anwsers to the written problems, including problems 1, 2, and 3(c). You can either edit the assignment1.tex file to fill in your answers and submit the pdf file generated from the edited tex file, or scan and submit your hand-written answers.

- A zip file named as assignment1_$\langle username \rangle$.zip, where you replace $\langle username \rangle$ with your email username. This zip file contains a single file specified in problem 3.

1 Bellman Optimality Operator Is a Contraction [25pt]

Recall the definition of the Bellman optimality operator $T^* : \mathbb{R}^{|S|} \to \mathbb{R}^{|S|}$, where $|S|$ is the number of states in state space S:

$$(T^*V)(s) := \max_a \left\{ R(s,a) + \gamma \sum_{s'} P(s'|s,a)V(s') \right\}$$

for each $s \in S$. Suppose $\gamma < 1$. Prove that T^* is a γ-contraction in the infinity norm $\| \cdot \|_\infty$, i.e. for any $V, V' \in \mathbb{R}^{|S|}$

$$\|T^*V' - T^*V\|_\infty \leq \gamma \|V' - V\|_\infty$$

where $\|V\|_\infty := \max_{s \in S} |V(s)|$.

Hint: Since it is the infinity norm, we need to show the inequality holds for each $s \in S$, i.e. $|T^*V'(s) - T^*V(s)| \leq \gamma \|V' - V\|_\infty$. For any $s \in S$. Let

$$a_s^* = \arg\max_a \left\{ R(s,a) + \gamma \sum_{s'} P(s'|s,a)V(s') \right\}$$

$$a_s'^* = \arg\max_a \left\{ R(s,a) + \gamma \sum_{s'} P(s'|s,a)V'(s') \right\}$$

be the actions selected by the T^* operator for V and V', respectively.

If $(T^*V')(s) \geq (T^*V)(s)$, try to show that the following holds:

$$
\begin{aligned}
|(T^*V')(s) - (T^*V)(s)| =& (T^*V')(s) - (T^*V)(s) \qquad \text{(Since we assumed } (T^*V')(s) \geq (T^*V)(s)) \\
=& R(s, a_s'^*) + \gamma \sum_{s'} P(s'|s, a_s'^*)V'(s') - (R(s, a_s^*) + \gamma \sum_{s'} P(s'|s, a_s^*)V(s')) \\
\leq& \gamma \|V' - V\|_\infty
\end{aligned}
$$

What if $(T^*V')(s) < (T^*V)(s)$ instead?

Your answer here.

2   Performance Difference Lemma and Policy Improvement Theorem [25pt]

(a) Let's first prove a useful lemma, called Performance Difference Lemma: For any policies π, π', and any state $s \in S$,

$$V^{\pi'}(s) - V^{\pi}(s) = \mathbb{E}_{s' \sim d_s^{\pi'}}[A^{\pi}(s', \pi')]$$

where $d_s^{\pi'}$ is the discounted occupancy induced by policy π' by starting from state s, defined as

$$d_s^{\pi'}(s') := \sum_{t=0}^{\infty} \gamma^t \Pr(s_t = s' | s_0 = s, \pi')$$

and $A^{\pi}(s', \pi')$ is defined as

$$A^{\pi}(s', \pi') := \mathbb{E}_{a' \sim \pi'(s')}[Q^{\pi}(s', a')] - V^{\pi}(s').$$

A^{π} is referred to as the advantage function of π.

Hint: To prove this lemma, consider a sequence of (possibly non-stationary) policies $\{\pi_i\}_{i \geq 0}$, where $\pi_0 = \pi$, $\pi_{\infty} = \pi'$. For any intermediate i, π_i is the non-stationary policy that follows π' for the first i time steps (i.e. time steps t such that $0 \geq t < i$) and then switches to π for time steps $t \geq i$, as shown in the figure below comparing of $\pi_{i=1}$ and $\pi_{i=2}$.
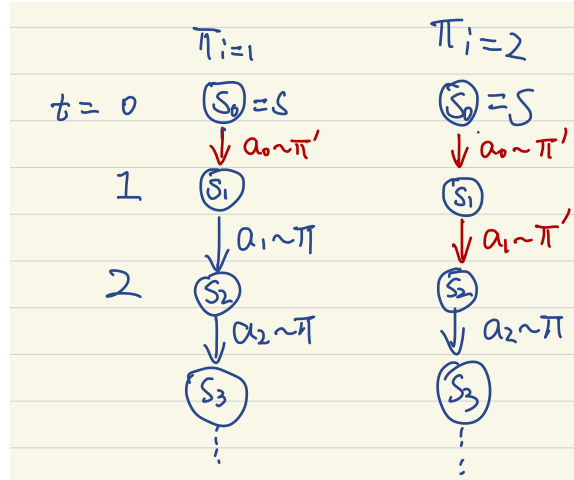
Now we can rewrite the LHS of the statement as:

$$V^{\pi'}(s) - V^{\pi}(s) = \sum_{i=0}^{\infty} (V^{\pi_{i+1}}(s) - V^{\pi_i}(s))$$

For each term $(V^{\pi_{i+1}}(s) - V^{\pi_i}(s))$ on the RHS, observe that π_{i+1} and π_i are both identical to π' for the first i time steps, which induces the same state distribution ate time step i, $\Pr(s_i | s_0 = s, \pi')$. They are also both identical to π starting from state s_{i+1} at time step $i+1$; so conditioned on $(s_i = s, a_i = a)$, the expected total reward for the remainder of the trajectory is $\gamma^i Q^{\pi}(s, a)$. Therefore, we have

$$V^{\pi_{i+1}}(s) - V^{\pi_i}(s) = \gamma^i \sum_{s'} \Pr(s_i = s' | s_0 = s, \pi')(\mathbb{E}_{a_i \sim \pi'(s')}[Q^{\pi}(s', a_i)] - \mathbb{E}_{a_i \sim \pi(s')}[Q^{\pi}(s', a_i)]).$$

because the difference between $V^{\pi_{i+1}} - V^{\pi_i}$ only starts from s_i at time step i, where π_{i+1} and π_i choose action a_i according π' and π, respectively.

Your answer here.

(b) Using the performance difference lemma, prove the policy improvement theorem, i.e. prove $V^{\pi_{k+1}}(s) \geq V^{\pi_k}(s)$, where π_{k+1} and π_k are consecutive policies in policy iteration.

Your answer here.

3   Frozen Lake MDP [50pt]

Implement value iteration and policy iteration for the Frozen Lake environment from OpenAI Gym. We have provided custom versions of this environment in the starter code in folder `assignment1_coding`.
   Make sure you use Python 3 and have installed the dependencies in `requirements.txt`.
   This problem is credited to Emma Brunskill.

(a) **(coding)** Read through `vi_and_pi.py` and implement `policy_evaluation`, `policy_improvement` and `policy_iteration`. The stopping tolerance (defined as $\max_s |V_{old}(s) - V_{new}(s)|$) is tol $= 10^{-3}$. Use $\gamma = 0.9$. Return the optimal value function and the optimal policy.

(b) **(coding)** Implement `value_iteration` in `vi_and_pi.py`. The stopping tolerance is tol $= 10^{-3}$. Use $\gamma = 0.9$. Return the optimal value function and the optimal policy.

(c) **(written)** Run both methods on the Deterministic-4x4-FrozenLake-v0 and Stochastic-4x4-FrozenLake-v0 environments. In the second environment, the dynamics of the world are stochastic. How does stochasticity affect the number of iterations required, and the resulting policy?

Your answer to (c) is here. For (a) and (b), submit the assignment1_⟨*username*⟩.zip file containing your implemented `vi_and_pi.py`.