**Q 1.1** Consider an MDP with 2 states {*A*, *B*} and 2 actions: "stay" at current state and "move" to other state. Let **r** be the reward function such that  $\mathbf{r}(A) = 1$ ,  $\mathbf{r}(B) = 0$ . Let  $\gamma$  be the discounting factor. What is the optimal policy  $\pi^*(A)$  and  $\pi^*(B)$ ? What are  $V^*(A)$ ,  $V^*(B)$ ?

- A. Stay, Stay, 1/(1-γ), 1
- B. Stay, Move, 1/(1-γ), 1/(1-γ)
- C. Move, Move, 1/(1-γ), 1
- D. Stay, Move, 1/(1-γ), γ/(1-γ)

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- B. Stay, Move, 1/(1-γ), 1/(1-γ)
- C. Move, Move, 1/(1-γ), 1
- D. Stay, Move, 1/(1-γ), γ/(1-γ) Note: want to stay at A, if at B, move to A. Starting at A, sequence A,A,A,... rewards 1, γ, γ<sup>2</sup>,.... Start at B, sequence B,A,A,... rewards 0, γ, γ<sup>2</sup>,.... Sums to 1/(1-γ), γ/(1-γ).

**Q 2.1** For Q learning to converge to the true Q function, we must

- A. Visit every state and try every action
- B. Perform at least 20,000 iterations.
- C. Re-start with different random initial table values.
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**Q 2.1** For Q learning to converge to the true Q function, we must

- A. Visit every state and try every action
- B. Perform at least 20,000 iterations. (No: this is dependent on the particular problem, not a general constant).
- C. Re-start with different random initial table values. (No: this is not necessary in general).
- D. Prioritize exploitation over exploration. (No: insufficient exploration means potentially unupdated state action pairs).