Convergence and Spectral Radius COMP 767 - Reinforcement Learning

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Policy Evaluation: Iterative Method (Matrix Form)

Bellman equation

$$v_{k+1}(s) = \sum_{a} \pi(a|s) \sum_{s',r} p(s',r|s,a) [r + \gamma v_k(s')]$$

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Optimal Solution

$$v^* = (I - \gamma P_\pi)^{-1} R_\pi$$

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$$v^* - v_{k+1} = R_{\pi} + \gamma P_{\pi} v^* - R_{\pi} - \gamma P_{\pi} v_k$$

$$v^* - v_{k+1} = \gamma P_{\pi} (v^* - v_k)$$

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Convergence

$$\lim_{k\to\infty} v_k = v^* \text{ if } \lim_{k\to\infty} (\gamma P_\pi)^k = 0$$

Spectral Radius

For a linear operator T, the spectral radius is the maximal magnitude of its eigenvalues.

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In our case,

$$\rho(\gamma P_{\pi}) = \gamma < 1$$

because P_{π} is stochastic!

Assume the eigenvectors of P_{π} form a basis of the vector space. We can express the original error, e_0 as a linear combination of the eigenvectors.

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This assumption is not necessary, but it helps visualize the proof. Without this assumption, the proof would be essentially the same, at a more abstract level.

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When we multiply...

$$e_1 = \gamma P_{\pi}(c_1 x_1 + \ldots + c_N x_N)$$

= $c_1 \gamma P_{\pi} x_1 + \ldots + c_N \gamma P_{\pi} x_N$
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Again...

$$e_k = c_1 \lambda_1^k x_1 + \ldots + c_N \lambda_N^k x_N$$

To Infinity!

$$\lim_{k \to \infty} ||e_k|| = \lim_{k \to \infty} ||c_1 \lambda_1^k x_1 + \ldots + c_N \lambda_N^k x_N||$$

$$\leq |c_1| \left(\lim_{k \to \infty} |\lambda_1|^k\right) ||x_1|| + \ldots + |c_N| \left(\lim_{k \to \infty} |\lambda_N|^k\right) ||x_N||$$

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Use the spectral radius

$$\rho(\gamma P_{\pi}) < 1 \qquad \Leftrightarrow \\
|\lambda_i| < 1 \qquad \forall i \qquad \Leftrightarrow \\
\lim_{k \to \infty} |\lambda_i|^k = 0 \qquad \forall i$$

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$$\begin{aligned}
\rho(\gamma P_{\pi}) &< 1 & \Leftrightarrow \\
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\end{aligned}$$

Conclusion

$$\lim_{k \to \infty} ||e_k|| \le |c_1| \times 0 \times ||x_1|| + \ldots + |c_N| \times 0 \times ||x_N|| = 0$$

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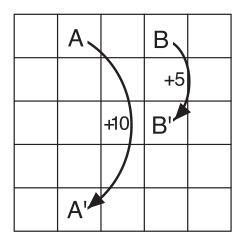
• Relies on the powers of the matrix becoming smaller and smaller.

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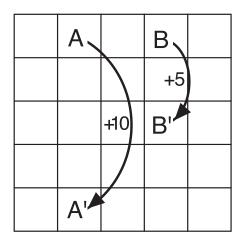
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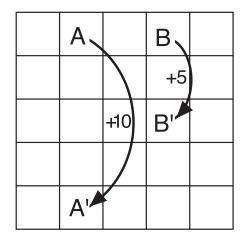
- Relies on the powers of the matrix becoming smaller and smaller.
- Convergence is linear at worst (and in the general case)
- Small spectral radius $(\gamma) = \text{Fast convergence}$



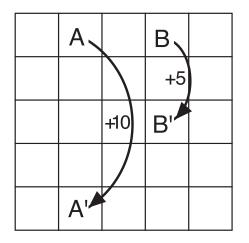
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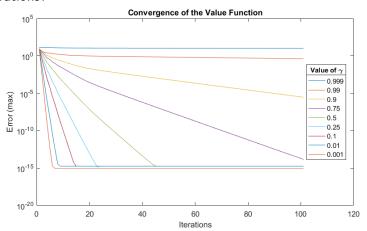
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- v_0 : all zeros
- γ : variable

Successive Iterations of the Algorithm

Depending on γ , how does the error evolves for successive iterations?

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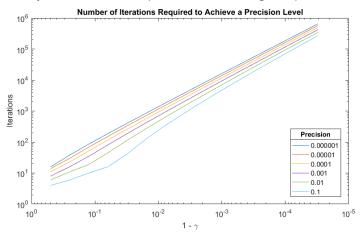


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Proof of Convergence (General Case)

Relies on the following result

$$\rho(M) < 1 \qquad \Leftrightarrow \qquad \lim_{k \to \infty} M^k = 0$$

Then,

$$\lim_{k\to\infty} e_k = \lim_{k\to\infty} (\gamma P_\pi)^k e_0 = 0$$

Proof of Convergence (General Case)

Express M in its Jordan normal form

$$M = VJV^{-1}$$

$$M^{k} = VJ^{k}V^{-1}$$

$$\lim_{k \to \infty} J^{k} = 0$$

$$\lim_{k \to \infty} M^{k} = 0$$