- $\epsilon_i > 0$ for all time steps i, and
- ϵ_i decays to zero in the limit as the time step i approaches infinity (that is, $\lim_{i\to\infty} \epsilon_i = 0$).

For example, to ensure convergence to the optimal policy, we could set $\epsilon_i = \frac{1}{i}$. (You are encouraged to verify that $\epsilon_i > 0$ for all i, and $\lim_{i\to\infty} \epsilon_i = 0$.)

Setting the Value of ϵ, in Practice

As you read in the above section, in order to guarantee convergence, we must let ϵ_i decay in accordance with the GLIE conditions. But sometimes "guaranteed convergence" *isn't good enough* in practice, since this really doesn't tell you how long you have to wait! It is possible that you could need trillions of episodes to recover the optimal policy, for instance, and the "guaranteed convergence" would still be accurate!

> Even though convergence is **not** guaranteed by the mathematics, you can often get better results by either:
>
> - using fixed ϵ, or
> - letting ϵ_i decay to a small positive number, like 0.1.

This is because one has to be very careful with setting the decay rate for ϵ; letting it get too small too fast can be disastrous. If you get late in training and ϵ is really small, you pretty much want the agent to have already converged to the optimal policy, as it will take way too long otherwise for it to test out new actions!

As a famous example in practice, you can read more about how the value of ϵ was set in the famous DQN algorithm by reading the Methods section of the research paper:

> *The behavior policy during training was epsilon-greedy with epsilon annealed linearly from 1.0 to 0.1 over the first million frames, and fixed at 0.1 thereafter.*

When you implement your own algorithm for MC control later in this lesson, you are strongly encouraged to experiment with setting the value of ϵ to build your intuition.