1. Finer discritization is indeed a better representation of reality. And it will give better result if we train our agent long enough.

for (5, 5, 5, 5) bins,

No of states = 5^4

So total action state pair $= 2 \times 5^4$

$= 1250$

for (50, 50, 50, 50) bins,

No of states $= 50^4$

So total action-state pair $= 2 \times 50^4$

$= 12.5 \times 10^6$

If we train our agent for only 1K episodes,

We update the Q-table for max

$200 \times 10^3 = 2 \times 10^5$ times.

So we can see that for (5, 5, 5, 5) bins the agent will be better trained. But in case of (50, 50, 50, 50) bins 1K episodes is not sufficient enough to train the agent properly and it will be worse to initial values. So, for less no of episodes coarse discretization gives better result than finer discretization.

(2) As we increase our training episode to 10 K,

Total no of steps increase $\approx 2\times10^6$

So the advantages of finer discretization start to appear and it outperforms the coarse discretization

(3) Discretization is not always a good method. It has some serious disadvantages. In some cases this method starts to break. For example —

(i) <u>Edge cases</u> :-

Discretization has a serious problem in edge cases. For values present at the edge two very close values can be present in two different states. Although almost identical, they are present in different state. On the other hand two d[illegible]ant values can be part of the same state.

(ii) Dementionality Problem :-

If we increase the no of bins the no of states increase as a power of no. of bins. So very fine discretization becomes practically impossible.

④ If we make 5000 bins, theoretically it may give better result but it will be impractical. In this case the size of Q-table will be

$$2 \times 5000^4 = 1.25 \times 10^{15}$$

Even if we train the model long enough, we will get memory infeasibility. In short making Q-table this big is an impractical thing to do.