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Appendix A

Supplementary Information

A.1 Additional Technical Information

This section contains some additional technical information about the thesis. Table A.1 contains the technical specifications of the Atari 2600 games utilized in the thesis. Table A.2 provides the hyperparameter used for training DQN on RET simulator. Table A.3 gives the technical details of Experiment 4.

Game	Size per frame (state space)	Number of actions (action space)	Reward range
amidar	(250, 160, 3)	10	$(-\infty, \infty)$
assault	(250, 160, 3)	7	$(-\infty, \infty)$
asterix	(210, 160, 3)	9	$(-\infty, \infty)$
asteroids	(210, 160, 3)	14	$(-\infty, \infty)$
atlantis	(210, 160, 3)	4	$(-\infty, \infty)$
enduro	(210, 160, 3)	9	$(-\infty, \infty)$
frostbite	(210, 160, 3)	18	$(-\infty, \infty)$
gravitar	(210, 160, 3)	18	$(-\infty, \infty)$
kangaroo	(210, 160, 3)	18	$(-\infty, \infty)$
seaquest	(210, 160, 3)	18	$(-\infty, \infty)$
skiing	(250, 160, 3)	3	$(-\infty, \infty)$
venture	(210, 160, 3)	18	$(-\infty, \infty)$
zaxxon	(210, 160, 3)	18	$(-\infty, \infty)$
beamrider	(210, 160, 3)	9	$(-\infty, \infty)$
qbert	(210, 160, 3)	6	$(-\infty, \infty)$
spaceinvaders	(210, 160, 3)	6	$(-\infty, \infty)$

Table A.1 – Specification of Atari 2600 games used for the experiments.