



Pruning Neural Networks with Lottery Tickets in a MDP Approach

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We propose to modify the Lottery Tickets Hypothesis (a model compression method) with a Markov Decision Process with Q-Learning.





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The Lottery Tickets Hypothesis.

Algorithm 1 Lottery Tickets Hypothesis

Source: adapted from (Frankle et al. 2019)

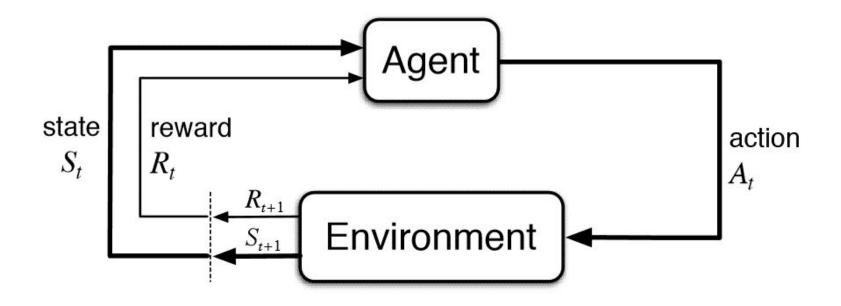
Require: weight matrix W, mask W', pruning rate p

- 1: $W_0 \leftarrow W$
- 2: $train(W, X, Y, n_epochs)$
- 3: while $remaining_weights > total_weights \times p$ do
- 4: $indexes \leftarrow find_smallest_values(|W|, p)$
- 5: $W'[indexes] \leftarrow 0$
- 6: $W \leftarrow W_0$
- 7: $train(W, W', X, Y, n_epochs)$
- 8: end while





Markov Decision Process



Source: Sutton, R. S., Barto, A. G., & Bach, F. (1998). Reinforcement learning: An introduction





Q-Learning

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Q-learning \begin{aligned} & \text{loop} \\ & a \leftarrow \mathsf{Select}_a\{Q(s,a)\} \\ & \text{apply action } a \\ & \text{observe resulting reward } r(s,a) \text{ and next state } s' \\ & Q(s,a) \leftarrow Q(s,a) + \alpha[r(s,a) + \max_{a'}\{Q(s',a')\} - Q(s,a)] \\ & s \leftarrow s' \end{aligned} until termination condition
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Source: Ghallab, M., Nau, D., & Traverso, P. (2016). Automated planning and acting





The Proposed Method

Algorithm 3 Our proposed method

Require: weight matrix W, mask W', pruning rate p

- 1: $W_0 \leftarrow W$
- 2: $train(W, X, Y, n_epochs)$
- 3: while $remaining_weights > total_weights \times p$ do
- 4: $s \leftarrow W'$
- 5: $indexes \leftarrow \pi(s)$
- 6: $W'[indexes] \leftarrow 0$
- 7: $W \leftarrow W_0$
- 8: $train(W, W', X, Y, n_epochs)$
- 9: end while





Some Details

Creating the Q-Table:

- First train LeNet 300-100 by 30 epochs
- The agent will perform a decreasing epsilon-search
 - Total of steps: 1000
 - Number of iterations: 15
 - epsilon decreation [1.0; ...; 0.1]
 - Reward: $r_a(s,s') \leftarrow \frac{-(1-accuracy)*remaining_weights}{total_weights}$

$$Q(s, a) \leftarrow Q(s, a) + \alpha \cdot \left[r_a(s, s') + \max_{a'} \{ Q(s', a') \} - Q(s, a) \right]$$

Q-Table update: or $Q(s,a) \leftarrow (1-\alpha) \cdot Q(s,a) + \alpha \left(r_a(s,s') + \gamma \cdot \max_a Q\left(s',a\right) \right)$







- Pruning the model:
 - Create another LeNet 300-100 from scratch
 - o Iteratively:
 - Train 9 epochs
 - Prune (action which maximizes the Quality based on the state)





Results

Table 1: Train and validation accuracy's

Table 1. Train and varidation accuracy 5						
Q-update	$ \alpha$	γ	Train_Acc	Valid_Acc		
EQ_3	0.5	-	89.68%	89.31%		
EQ_{-3}	0.6	-	90.70%	90.40%		
EQ_3	0.7	_	91.09%	90.86%		
EQ_3	0.8	-	8.85%	0.09%		
EQ_3	0.9	_	90.59%	89.82%		
EQ_3	1.0	-	91.21%	90.86%		
EQ_6	0.9	0.4	9.10%	0.09%		
EQ_6	0.9	0.5	88.98%	88.69%		
EQ_{-6}	0.9	0.6	90.60%	89.94%		
EQ_6	0.9	0.7	89.83%	89.22%		
EQ_6	0.9	0.8	90.09%	89.39%		
EQ_6	0.9	0.9	90.16%	89.79%		
EQ_6	0.9	1.0	9.10%	0.09%		
LTH	-	-	96.86%	95.92%		





Results

Table 2: Test accuracy of the best models

Class	Model 1	Model 2	Model 3	Instances
0	97.44%	97.55%	98.57%	980
1	97.26%	97.18%	98.23%	1135
2	91.08%	88.56%	95.54%	1032
3	88.81%	87.62%	96.33%	1010
4	92.46%	94.80%	95.92%	982
5	83.85%	81.83%	94.05%	892
6	94.67%	94.05%	96.97%	958
7	91.34%	90.66%	96.39%	1028
8	89.73%	86.34%	94.76%	974
9	88%	86.91%	94.84%	1009
Overall	91.6%	90.7%	96.2%	10000





Thank you!

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