Contributions to Deep Transfer Learning

From Supervised to Reinforcement Learning

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Presentation outline

1. Part I: Preliminaries
   - Deep Transfer Learning
2. Part II: Supervised Learning
   - On the Transferability of Convolutional Neural Networks
   - On the Transferability of Lottery Winners
3. Part III: Reinforcement Learning
   - A Novel Family of Deep Reinforcement Learning Algorithms
   - On the Transferability of Deep-Q Networks

PART I

Deep Transfer Learning

PART II

We start by defining the components of Supervised Learning:

- An input space $\mathcal{X}$,
- An output space $\mathcal{Y}$,
- A joint probability distribution $P(X, Y)$.
- A loss function $\ell : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}$

The goal is to find a function $f : \mathcal{X} \to \mathcal{Y}$ that minimizes the expected risk:

$$R(f) = \mathbb{E}_{(\vec{x},y)\sim P(X,Y)}\left[\ell(y, f(\vec{x}))\right]$$

On the Transferability of Convolutional Neural Networks

Typically, the only information available to build this function f is a learning sample of input-output pairs $LS_T = \{(x_i, y_i) | i = 1, \ldots, N_T\}$ drawn independently from $P_T(x, y)$.

However, when it comes to Transfer Learning we have an additional dataset LS_S that can be used for finding a better f than when only LS_T is used for training.

On the Transferability of Convolutional Neural Networks

For our first study ...

- We consider f to come in the form of a Convolutional Neural Network
- We define the source domain $\mathcal{D}_S$ to be that of natural images
- We define the target domain $\mathcal{D}_T$ to be that of Digital Heritage
- We assume that labels are available in both the source and target data and that the input spaces $\mathcal{X}_T$ and $\mathcal{X}_S$ match: Inductive Transfer Learning

On the Transferability of Convolutional Neural Networks

We have a CNN pre-trained on the ImageNet dataset as source-task $\mathcal{T}_S$

We have three target-tasks $\mathcal{T}_T$ defined by the Rijksmuseum collection

On the Transferability of Convolutional Neural Networks

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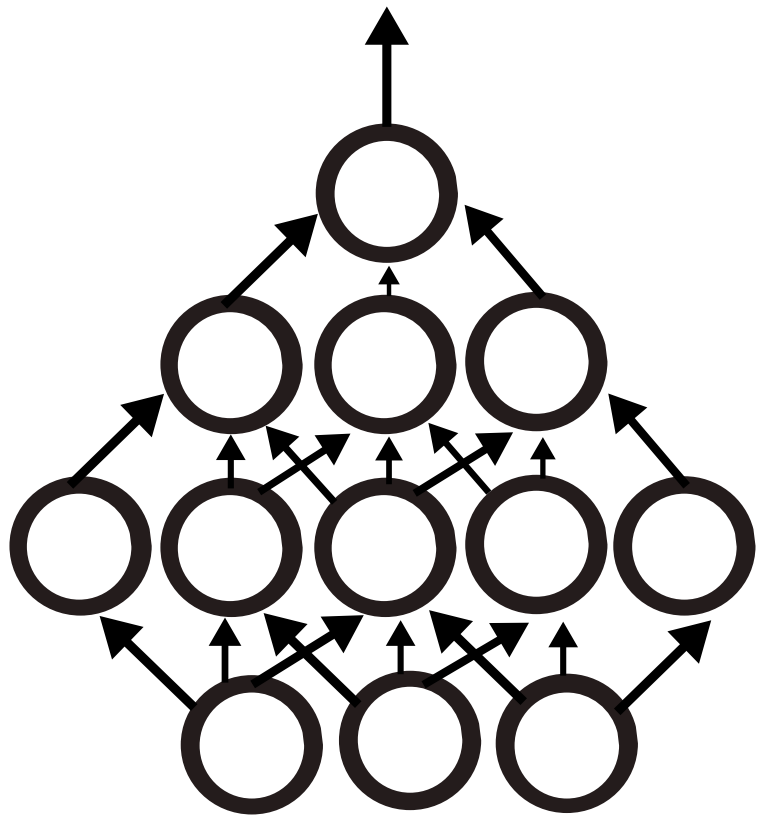
On the Transferability of Lottery Winners

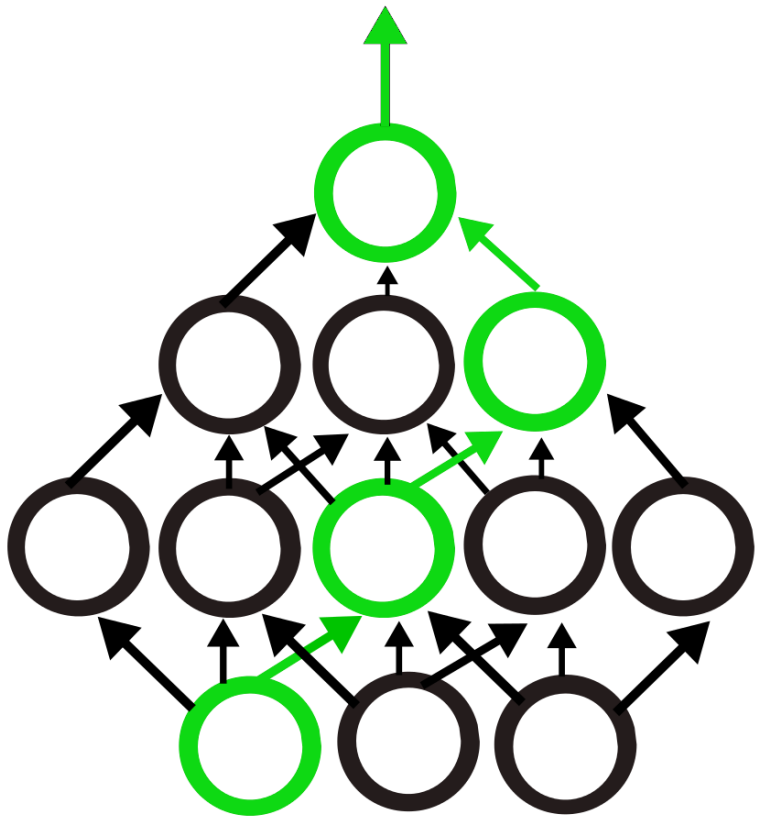
The Lottery Ticket Hypothesis: *"A randomly-initialized dense neural network contains a subnetwork that is initialized such that when trained in isolation it can match the test accuracy of the original network after training for at most the same number of iterations.*[1]*"*

[1] Frankle, Jonathan, and Michael Carbin. "The lottery ticket hypothesis: Finding sparse, trainable neural networks." (2018)

On the Transferability of Lottery Winners



On the Transferability of Lottery Winners



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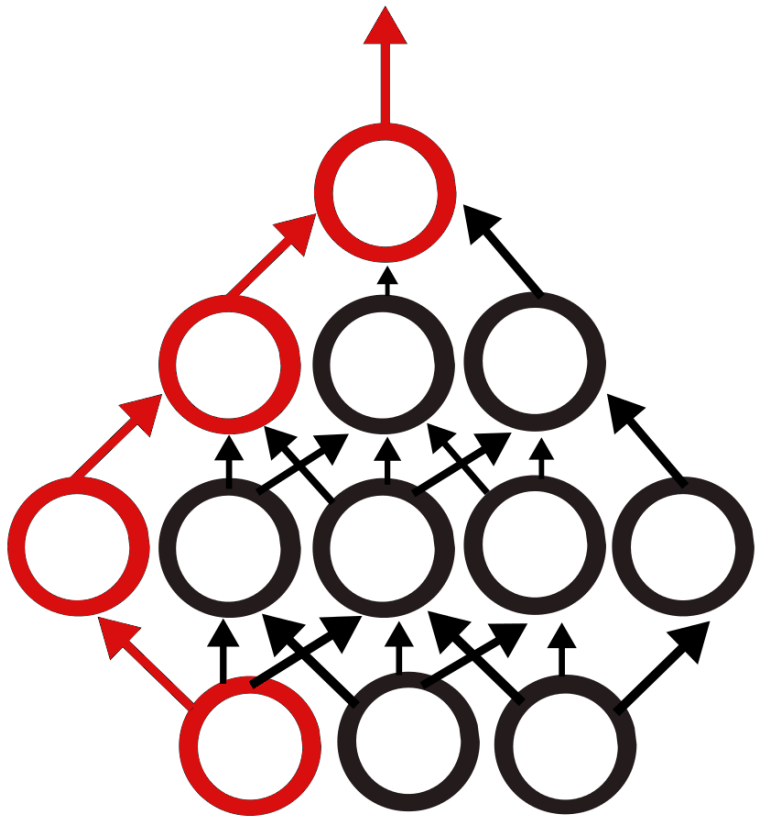

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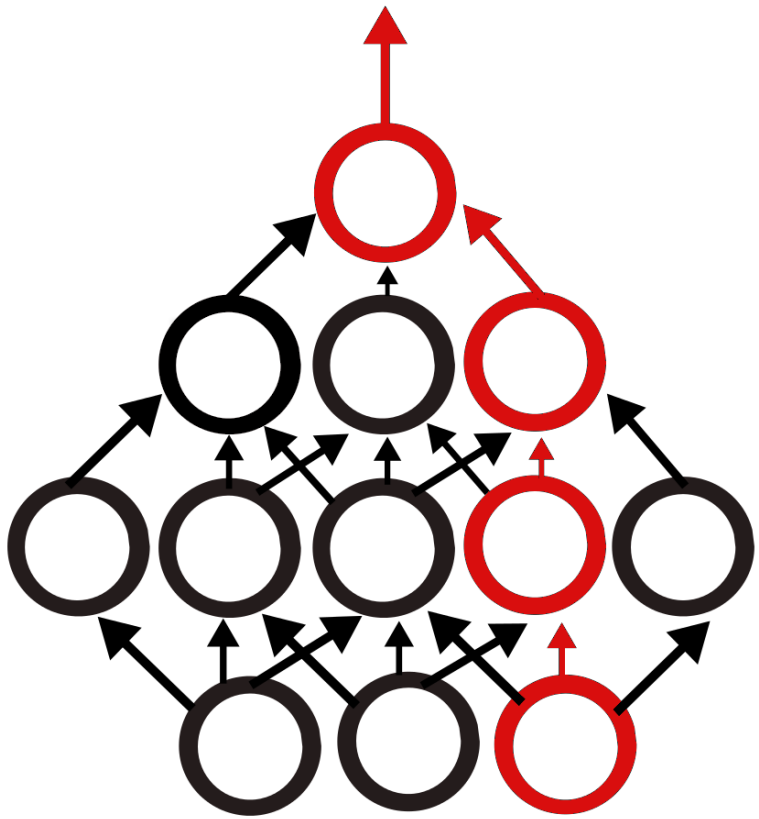


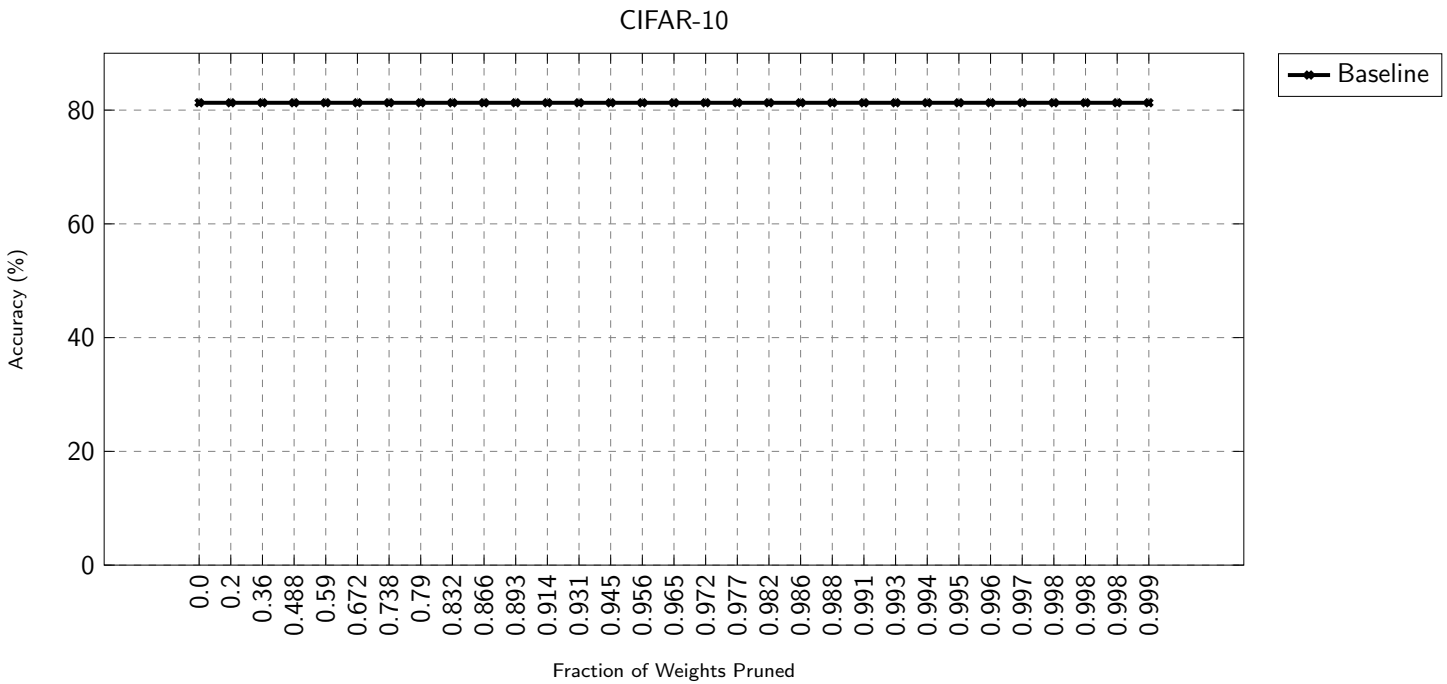
On the Transferability of Lottery Winners

$\Rightarrow$ How does one find a winning ticket?

- Randomly initialize a network $f(x; \theta_0)$ where $\theta_0 \sim \mathcal{D}_\theta$
- We train the network for j iterations
- We prune $p\%$ of the parameters in θ_j creating a mask m
- Reset the remaining parameters to their values at θ_0, creating a winning ticket $f(x; m \odot \theta_0)$

On the Transferability of Lottery Winners

The Lottery Ticket Hypothesis in practice ...



On the Transferability of Lottery Winners

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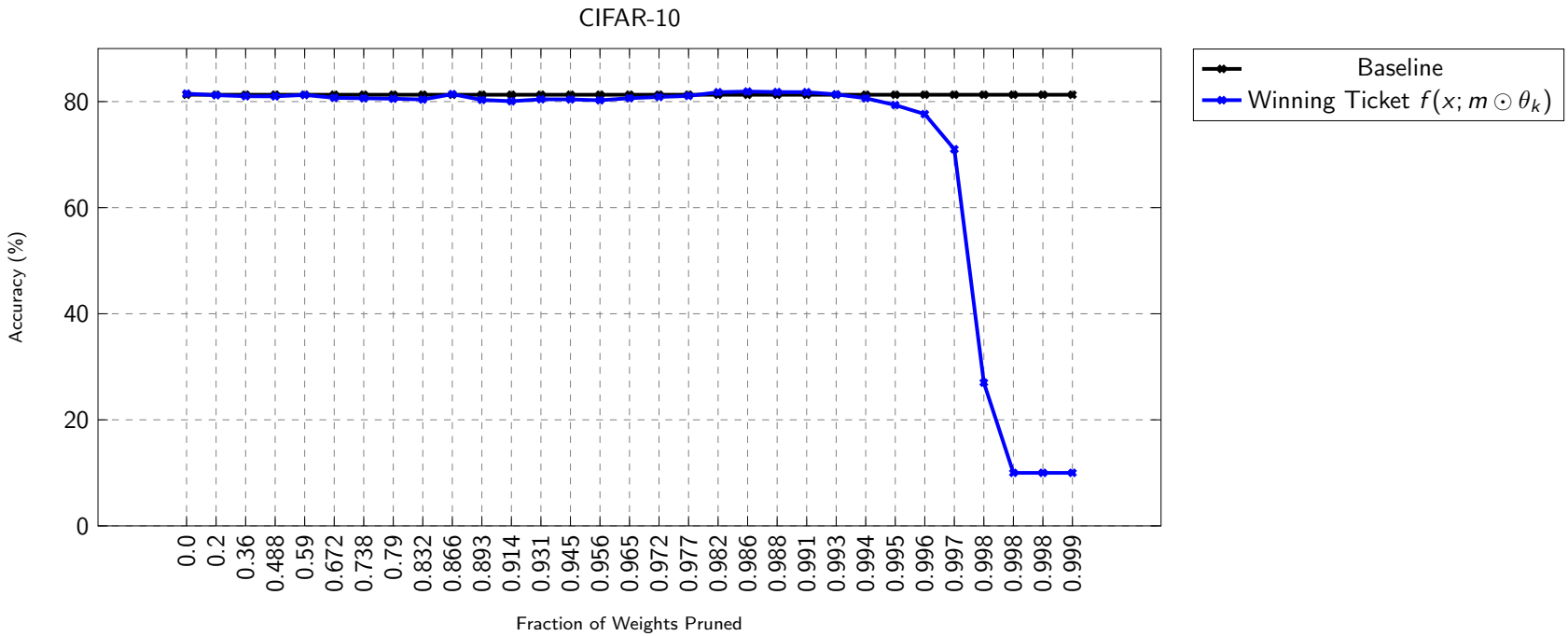

On the Transferability of Lottery Winners

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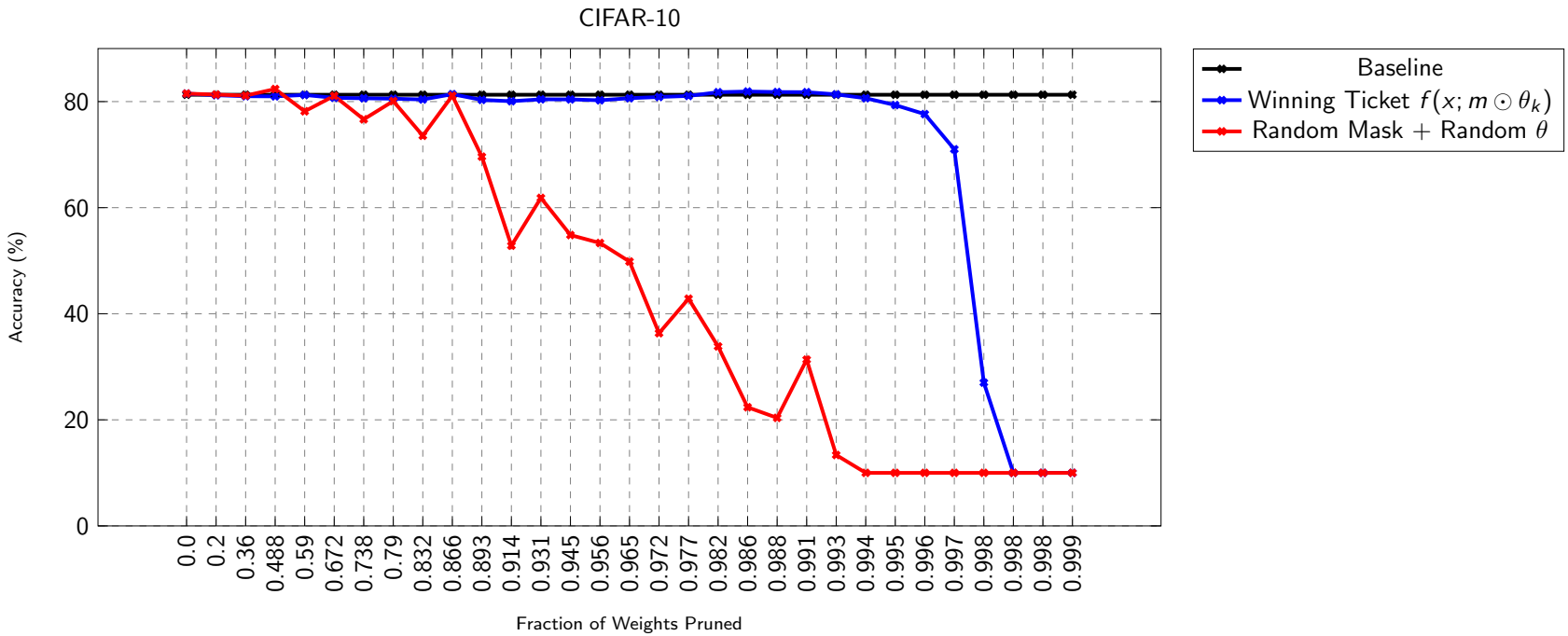


On the Transferability of Lottery Winners

Why are lottery tickets $f(x; m \odot \theta_0)$ so special?

- Train faster
- Faster Inference
- (Sometimes) obtain a better final performance

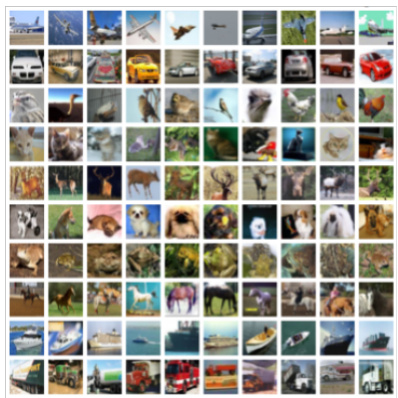
However ...

- Identifying a winning ticket is computationally expensive
- We do not know how and why lottery winners appear throughout learning

On the Transferability of Lottery Winners

$\Rightarrow$ Therefore we study whether winning tickets $f(x; m \odot \theta_0)$ found on natural image datasets can get transferred to the non-natural realm

We use three popular Computer Vision datasets as source domains $\mathcal{D}_S$:



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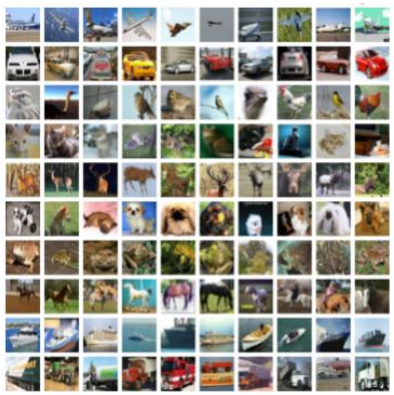

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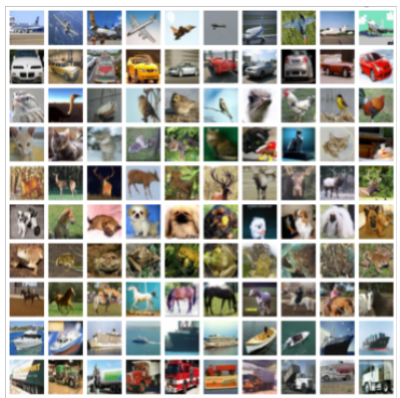
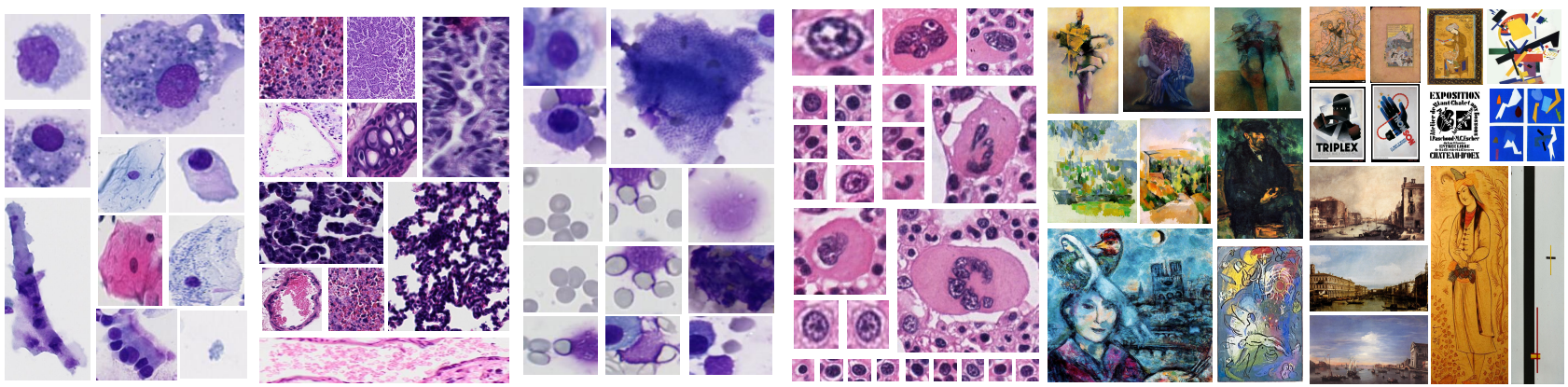


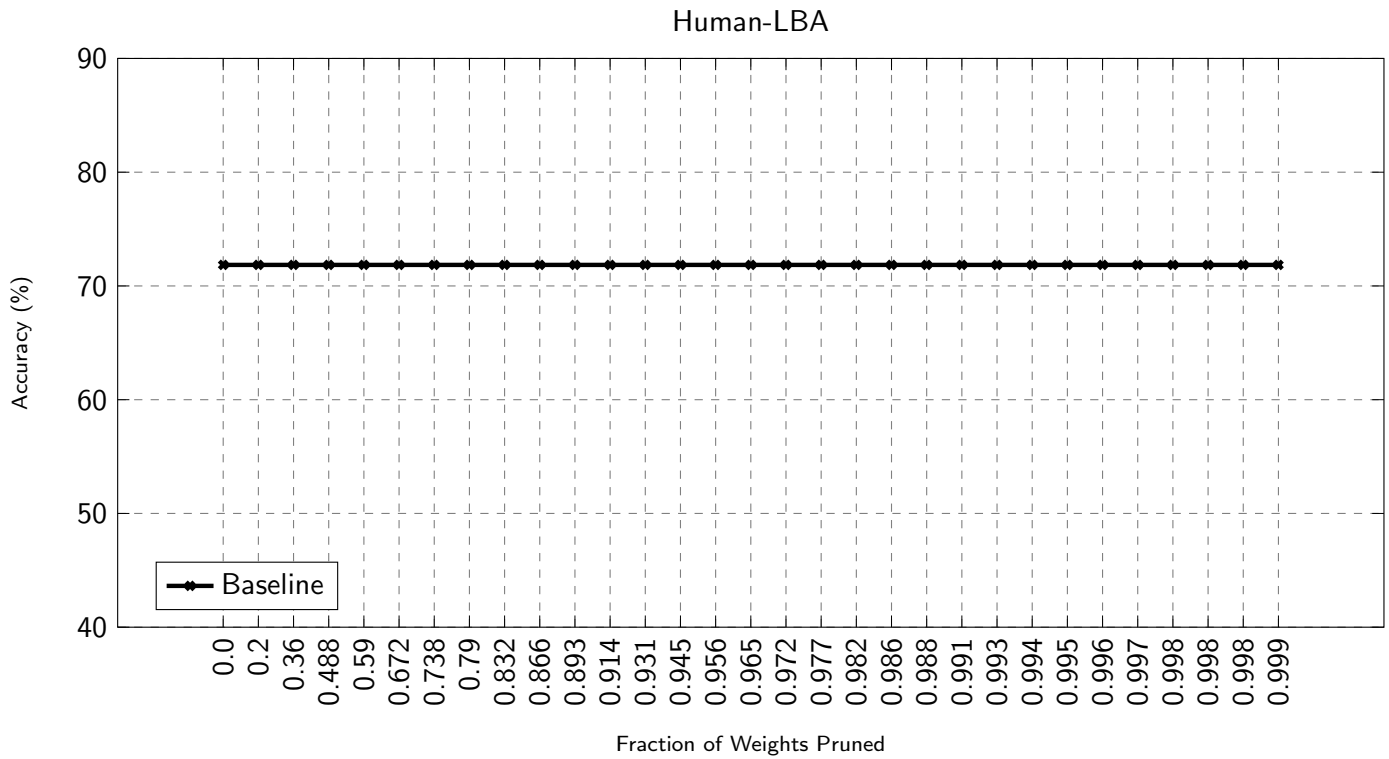
On the Transferability of Lottery Winners

And we use seven datasets of non-natural images as target tasks $\mathcal{T}_T$ coming from the fields of Digital Pathology and Digital Heritage



On the Transferability of Lottery Winners

Transferring lottery winners to the Digital Pathology data ...



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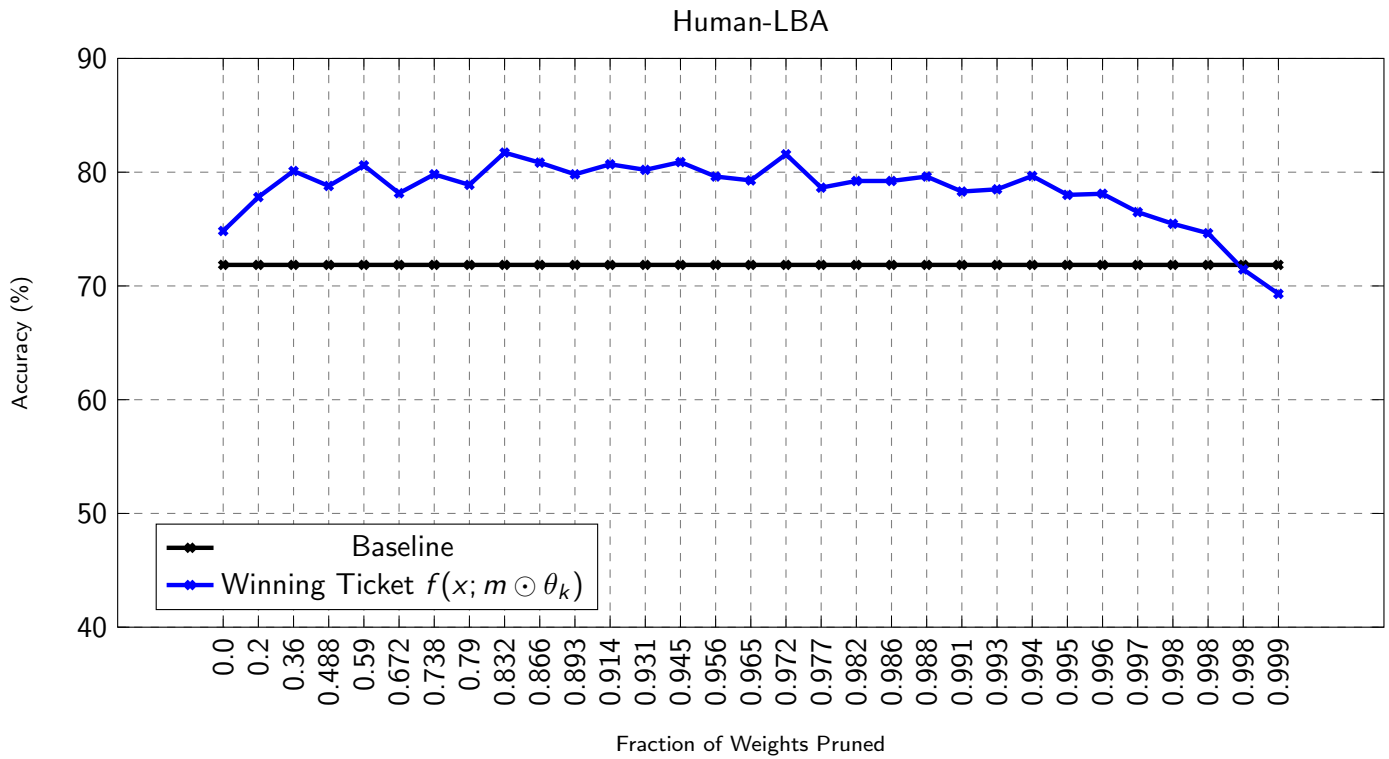

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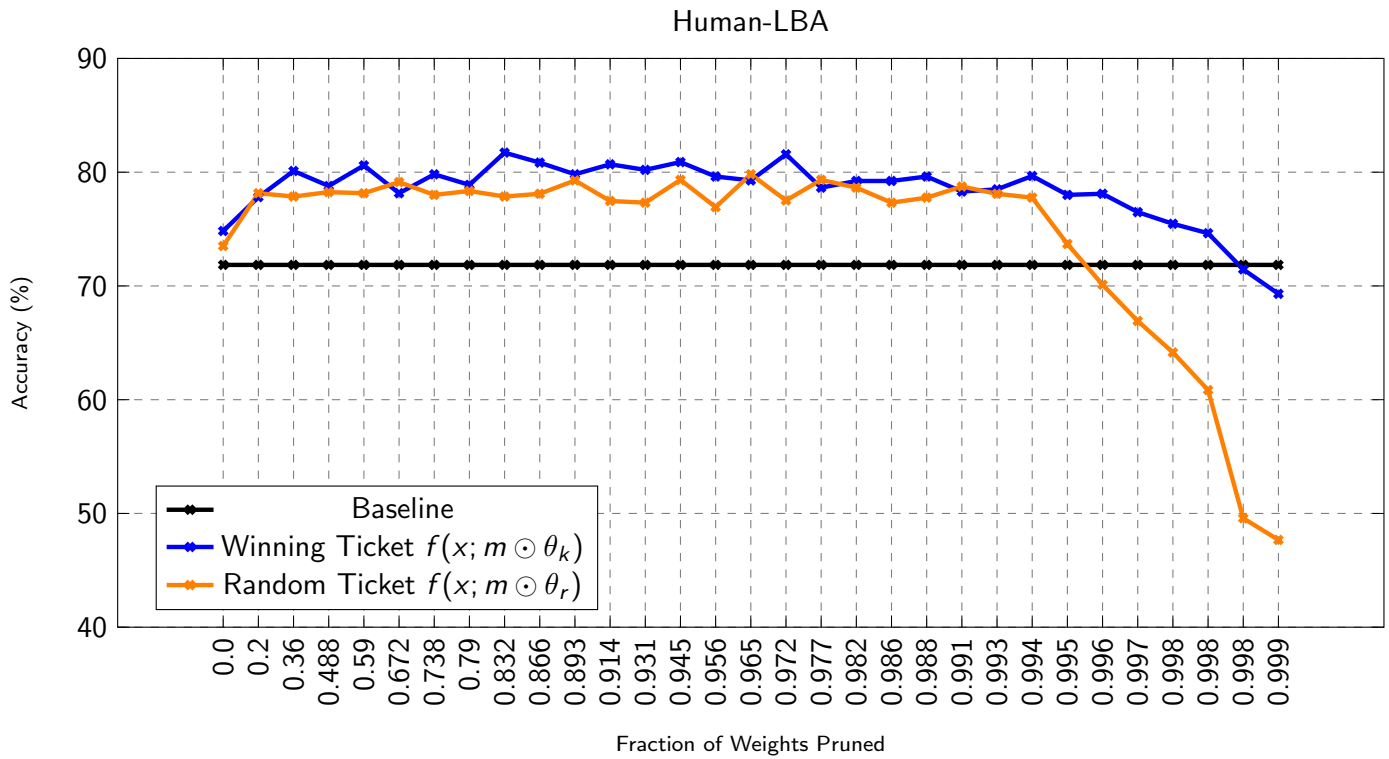

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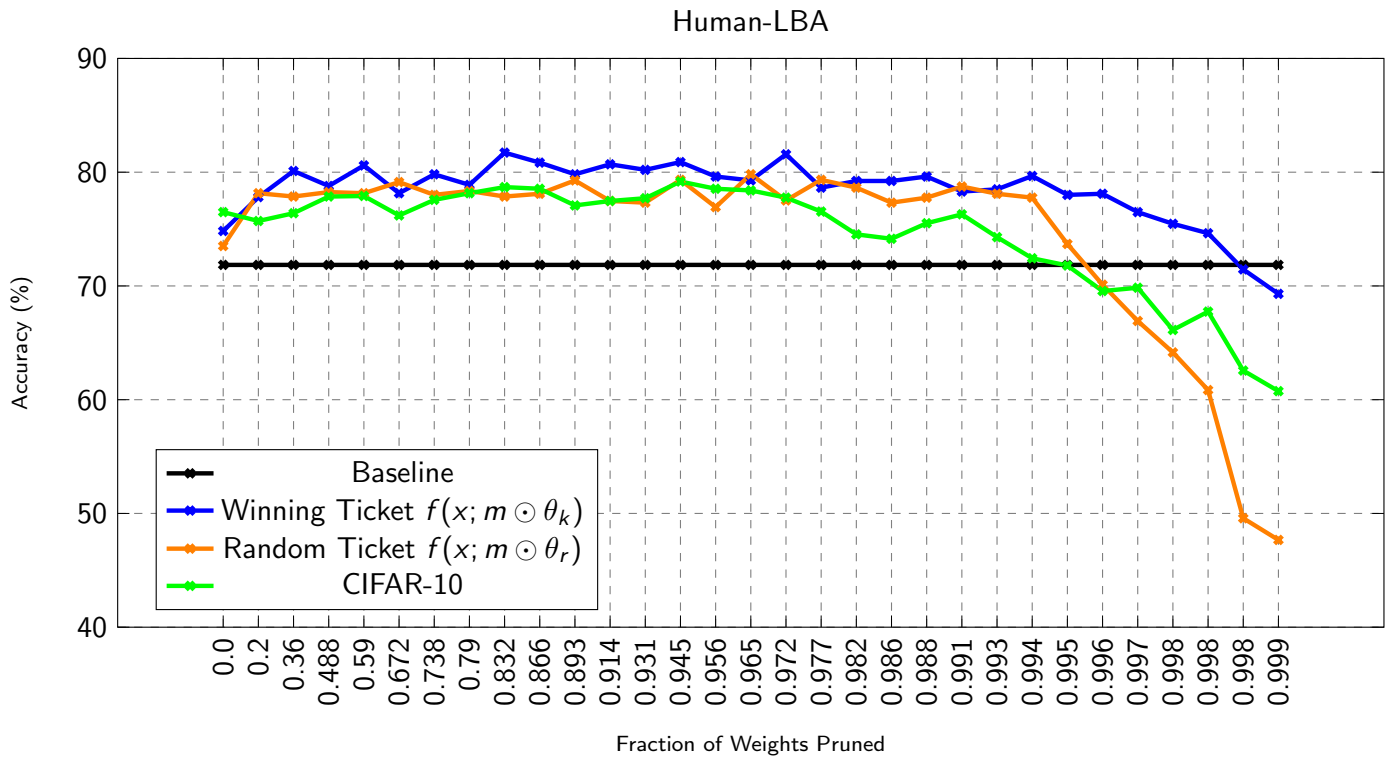

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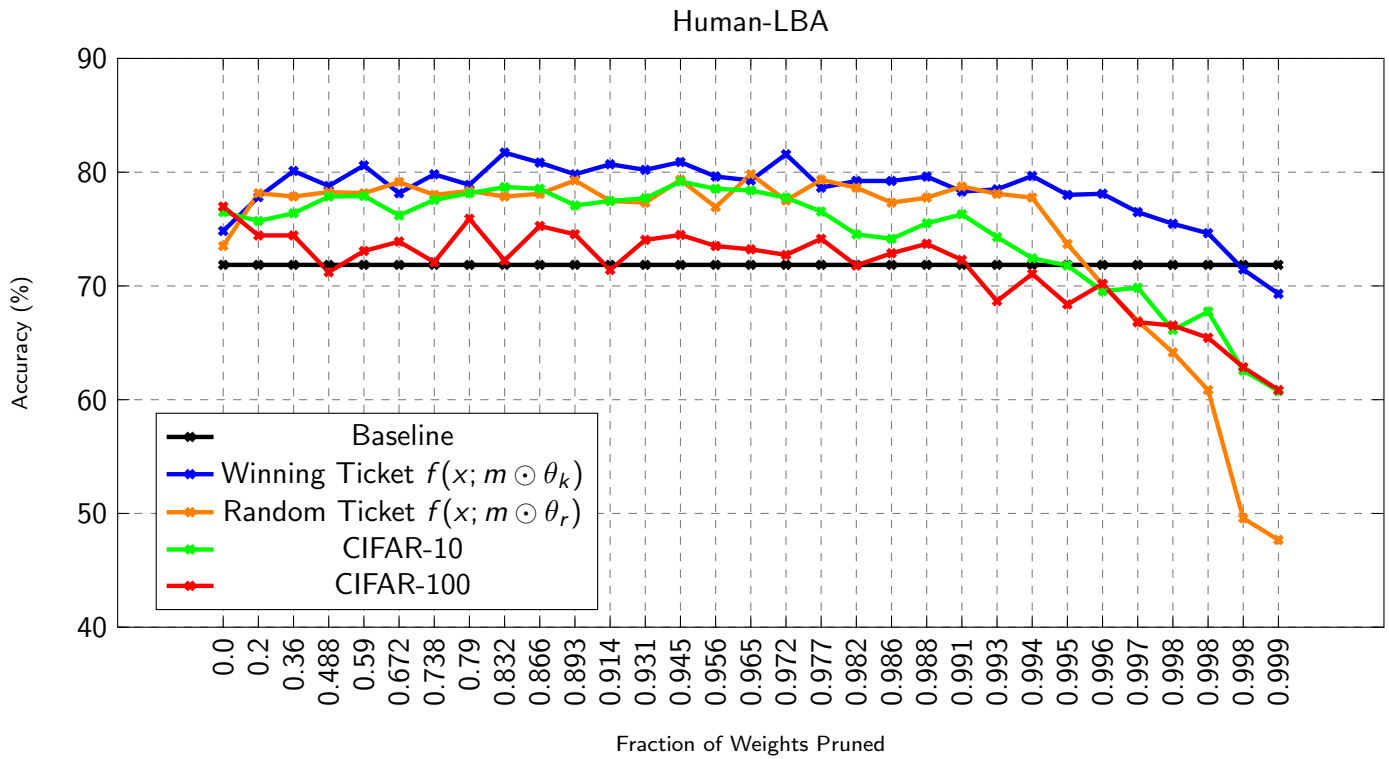

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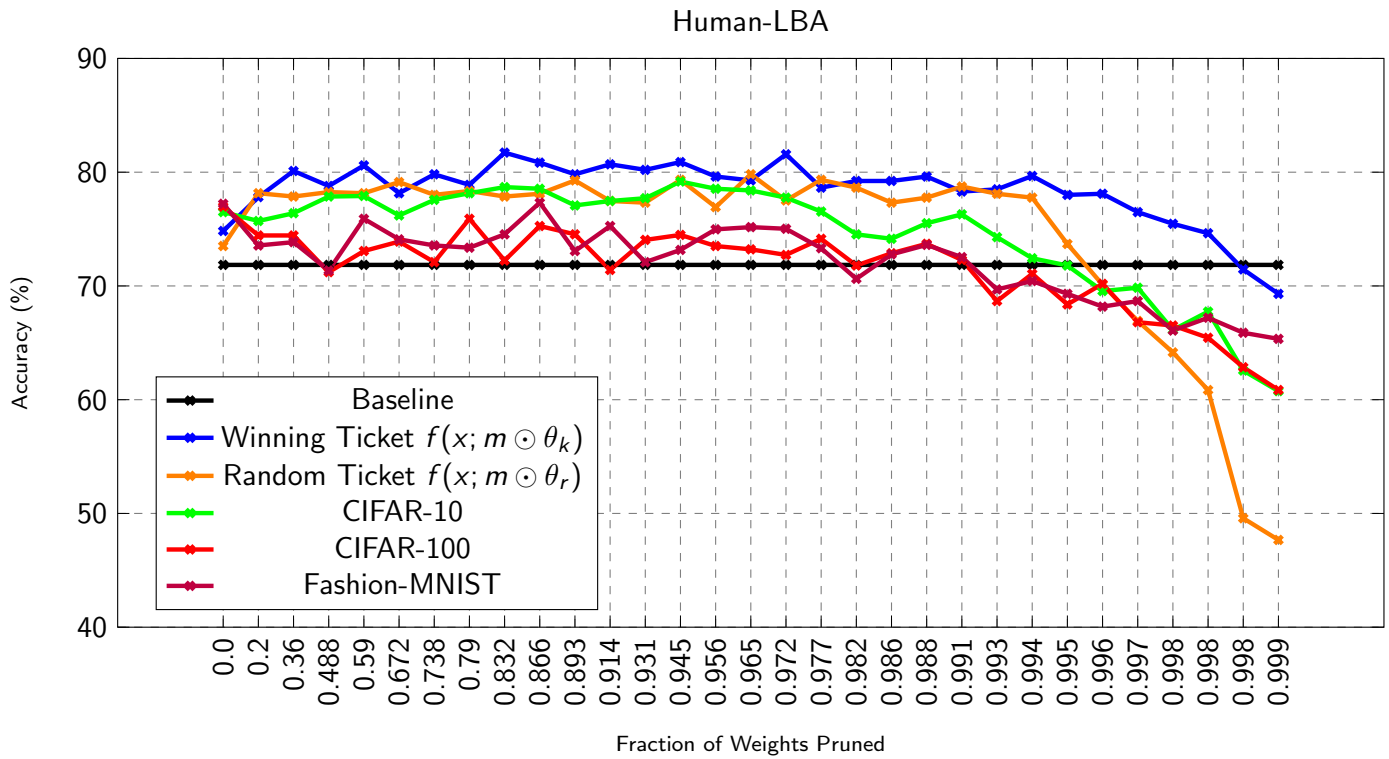
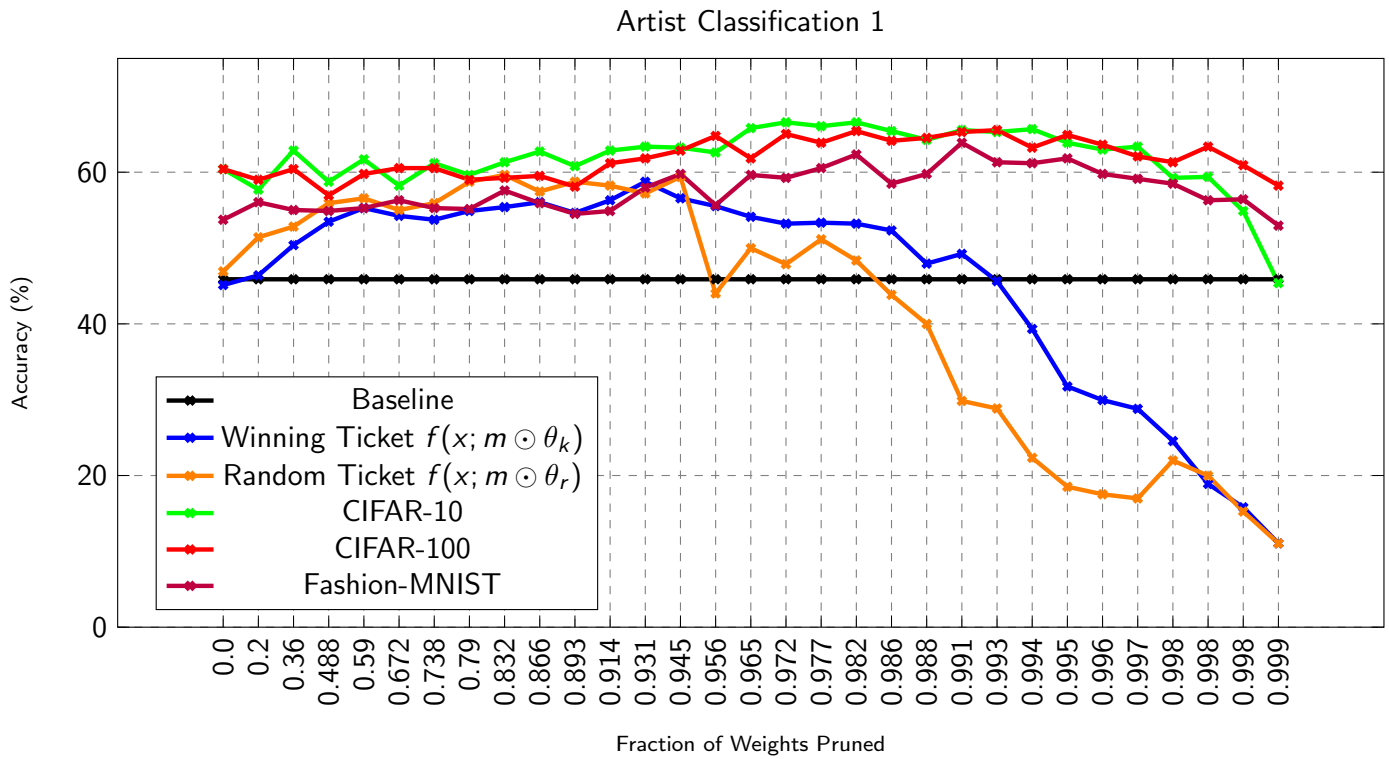


On the Transferability of Lottery Winners

Transferring lottery winners to the Digital Heritage data ...



On the Transferability of Lottery Winners

Our main findings show that on Digital Pathology data

- All lottery winners significantly outperfom unpruned models
- Natural lottery winners contain a generic inductive bias (to some extent)
- Best performance is obtained by identifying a winning ticket directly on the target task $\mathcal{T}_T$

whereas on Digital Heritage data

- Natural lottery winners transfer much better
- They can even outperform target task $\mathcal{T}_T$ tickets

On the Transferability of Lottery Winners

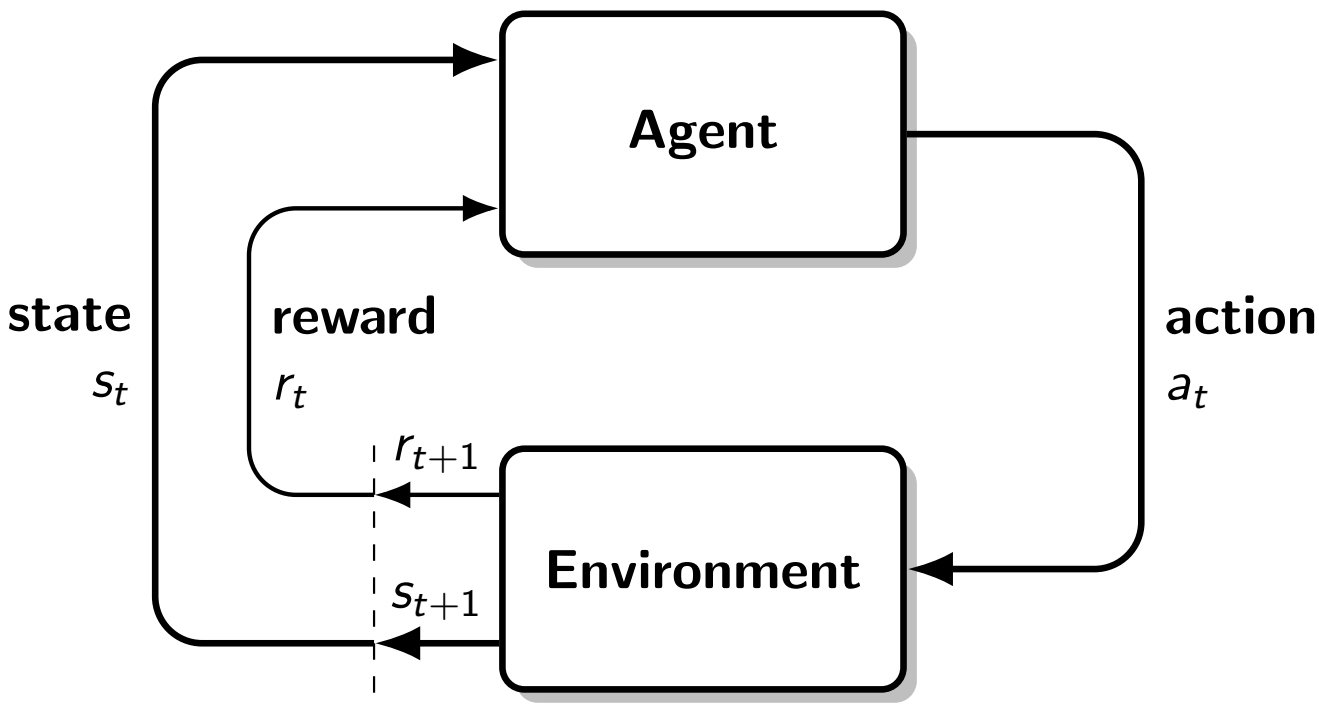
We also provide additional empirical insights into the Lottery Ticket Hypothesis:

- We show that completely pre-trained winning tickets $f(x; m \odot \theta_i)$ overfit on the source task $\mathcal{T}_S$
- The presence of winning tickets does not depend on the size of the training data
- The closer the source task $\mathcal{S}_T$ and the target task $\mathcal{T}_T$ the better the transferability of $f(x; m \odot \theta_k)$

PART III

A Novel Family of Deep Reinforcement Learning Algorithms

We now consider a different machine learning paradigm: Reinforcement Learning (RL), where an agent needs to learn how to interact with its environment



A Novel Family of Deep Reinforcement Learning Algorithms

Such interaction is modeled as a Markov Decision Process (MDP) consisting of the following elements:

- A set of possible states $\mathcal{S}$,
- A set of possible actions $\mathcal{A}$,
- A transition function $\mathcal{P} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0, 1]$,
- A reward function $\mathfrak{R} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$,
- A discount factor denoted as $\gamma \in [0, 1]$.

Therefore we can define an MDP as $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathfrak{R}, \gamma \rangle$.

A Novel Family of Deep Reinforcement Learning Algorithms

The interaction between the agent and the environment is given by the agent's policy π, a probability distribution over $a \in \mathcal{A}(s)$ for each $s \in \mathcal{S}$:

$$\pi(a|s) = \Pr\{a_t = a | s_t = s\}, \text{ for all } s \in \mathcal{S} \text{ and } a \in \mathcal{A}.$$

The goal of the agent is to maximize the expected discounted return as:

$$\begin{aligned} G_t &= r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \\ &= \sum_{k=0}^{\infty} \gamma^k r_{t+k}. \end{aligned}$$

A Novel Family of Deep Reinforcement Learning Algorithms

In RL some components of the MDP are unknown

$$\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle,$$

which in the case of model-free RL can be overcome by learning either the state-value function

$$V^{\pi}(s) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} \middle| s_t = s, \pi \right],$$

or the state-action value function

$$Q^{\pi}(s, a) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} \middle| s_t = s, a_t = a, \pi \right].$$

A Novel Family of Deep Reinforcement Learning Algorithms

- Model-free algorithms are implemented in a tabular fashion, meaning that the state values, or state-action values, are stored within tables of sizes $|\mathcal{S}|$ and $|\mathcal{S} \times \mathcal{A}|$ respectively
- For many problems we typically seek to learn an approximation of the value functions

$$V^{\pi}(s) \approx V^{\pi}(s;\theta) \text{ and } Q^{\pi}(s,a;\theta) \approx Q(s,a;\theta)$$

A Novel Family of Deep Reinforcement Learning Algorithms

This approximation can be represented by a Convolutional Neural Network

A Novel Family of Deep Reinforcement Learning Algorithms

Typical DRL algorithms aim at only learning an approximation of the state-action value function $Q^{\pi}(s, a) \approx Q^{\pi}(s, a; \theta)$

- A policy π can only be derived from $Q^{\pi}(s, a)$
- It is hard to combine RL algorithms with neural networks
- Dealing with one value function is enough

However ...

- Training can be very slow
- Algorithms are prone to diverge
- Do not correctly estimate $Q^{\pi}(s, a)$

A Novel Family of Deep Reinforcement Learning Algorithms

$\Rightarrow$ Therefore we suggest to jointly approximate the state-value function $V^{\pi}(s;\phi)$ alongside the state-action value function $Q^{\pi}(s,a;\theta)$

We can do this by either learning $V^{\pi}(s;\phi)$ with

$$L(\phi) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1}\rangle \sim U(D)}\left[\left(r_t + \gamma V(s_{t+1};\Phi^{-}) - V(s_t;\Phi)\right)^2\right],$$

and $Q^{\pi}(s,a)$ with:

$$L(\theta) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1}\rangle \sim U(D)}\left[\left(r_t + \gamma V(s_{t+1};\Phi^{-}) - Q(s_t,a_t;\theta)\right)^2\right],$$

A Novel Family of Deep Reinforcement Learning Algorithms

... or by learning $V^{\pi}(s;\phi)$ with

$$L(\phi) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1}\rangle \sim U(D)}\left[\left(r_t + \gamma \max_{a \in \mathcal{A}} Q(s_{t+1}, a; \theta^{-}) - V(s_t; \Phi)\right)^2\right],$$

and $Q^{\pi}(s,a)$ with:

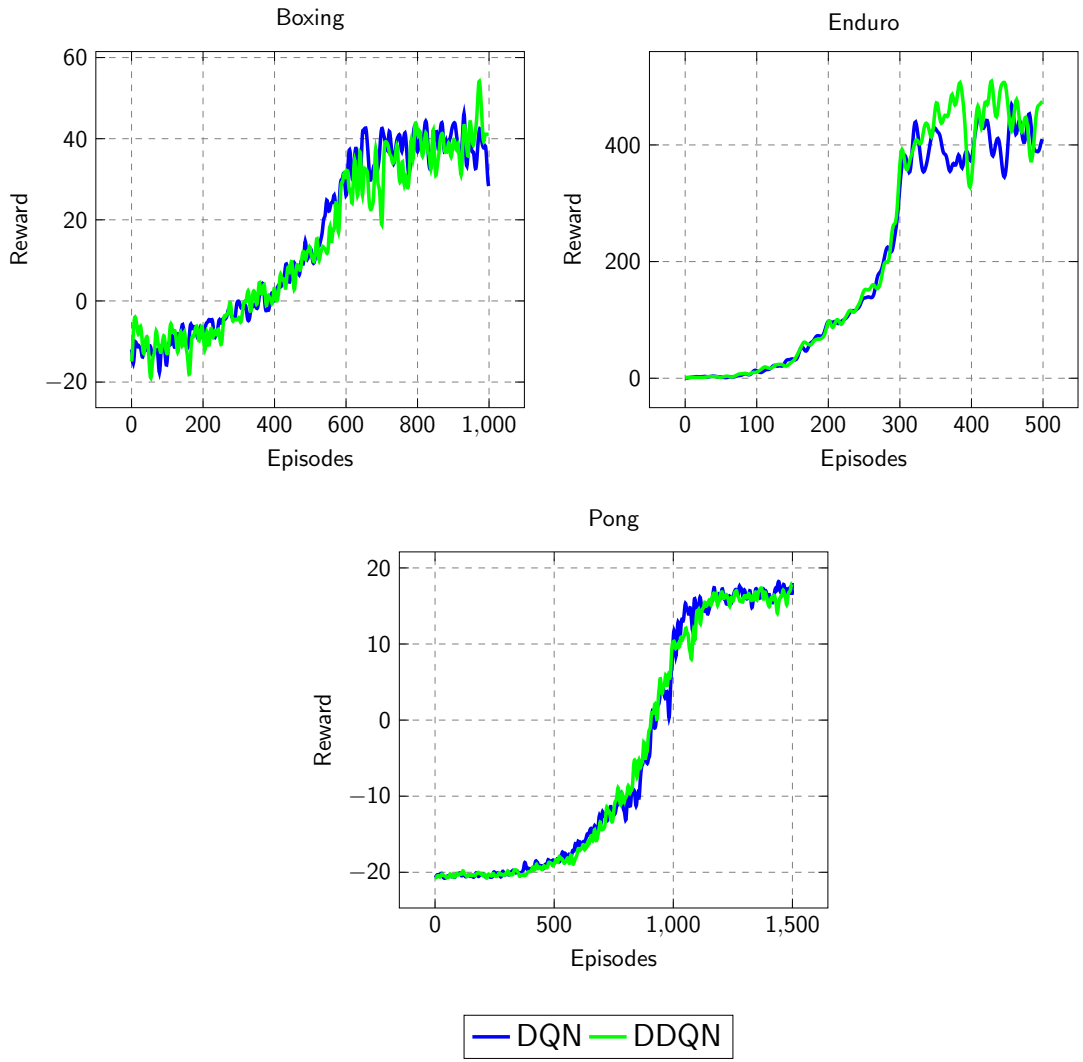
$$L(\theta) = \mathbb{E}_{\langle s_t, a_t, r_t, s_{t+1}\rangle \sim U(D)}\left[\left(r_t + \gamma V(s_{t+1}; \Phi) - Q(s_t, a_t; \theta)\right)^2\right].$$

A Novel Family of Deep Reinforcement Learning Algorithms

The first two objective functions constitute the **DQV-Learning** algorithm, whereas the second two objective functions define the **DQV-Max Learning** algorithm.

We compare their performance to algorithms which only learn an approximation of the state-action value function $Q^{\pi}(s, a)$

A Novel Family of Deep Reinforcement Learning Algorithms



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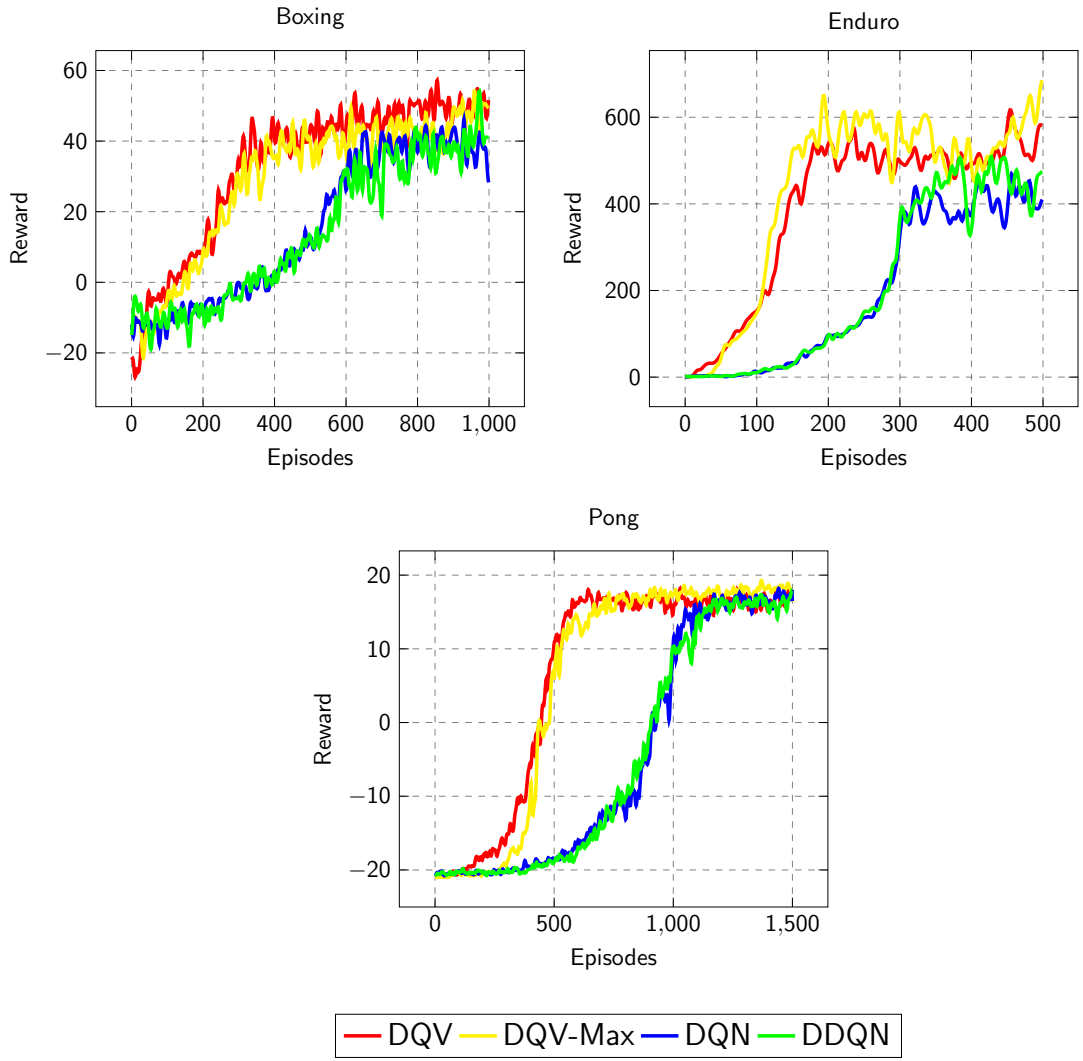
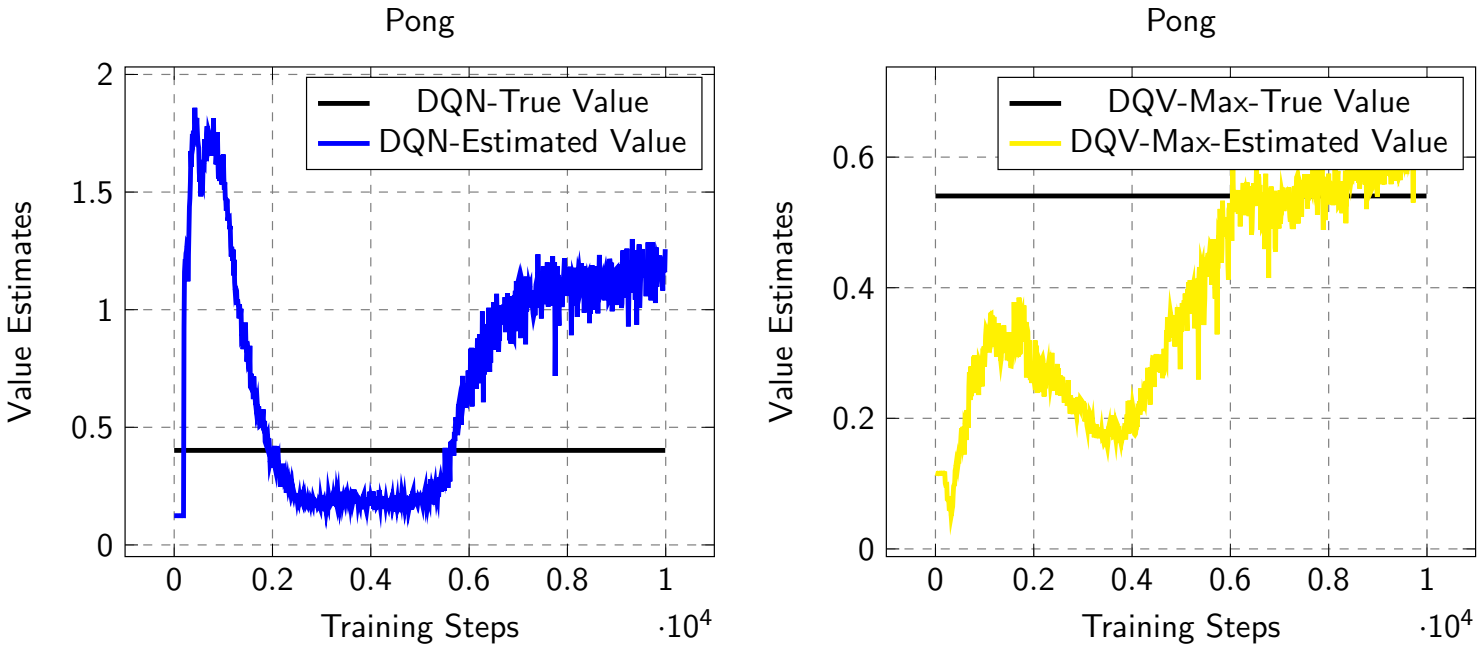


A Novel Family of Deep Reinforcement Learning Algorithms

$\Rightarrow$ Jointly approximating two value functions over one results in faster convergence, but also in accurate value estimates:



A Novel Family of Deep Reinforcement Learning Algorithms

To conclude DQV-Learning and DQV-Max Learning

- Result in faster learning
- Are robust to the "Deadly Triad of DRL"
- Suffer less from the overestimation bias of the Q function
- Scale well to the multi-agent setting [2]

However ...

- Memory wise are twice as expensive as DQN and DDQN
- Do not always result in better policies

[2] Leroy, Pascal, et al. "QVMix and QVMix-Max: Extending the Deep Quality-Value Family of Algorithms to Cooperative Multi-Agent Reinforcement Learning." (2021).

Final References