Reinforcement Learning for Active Learning

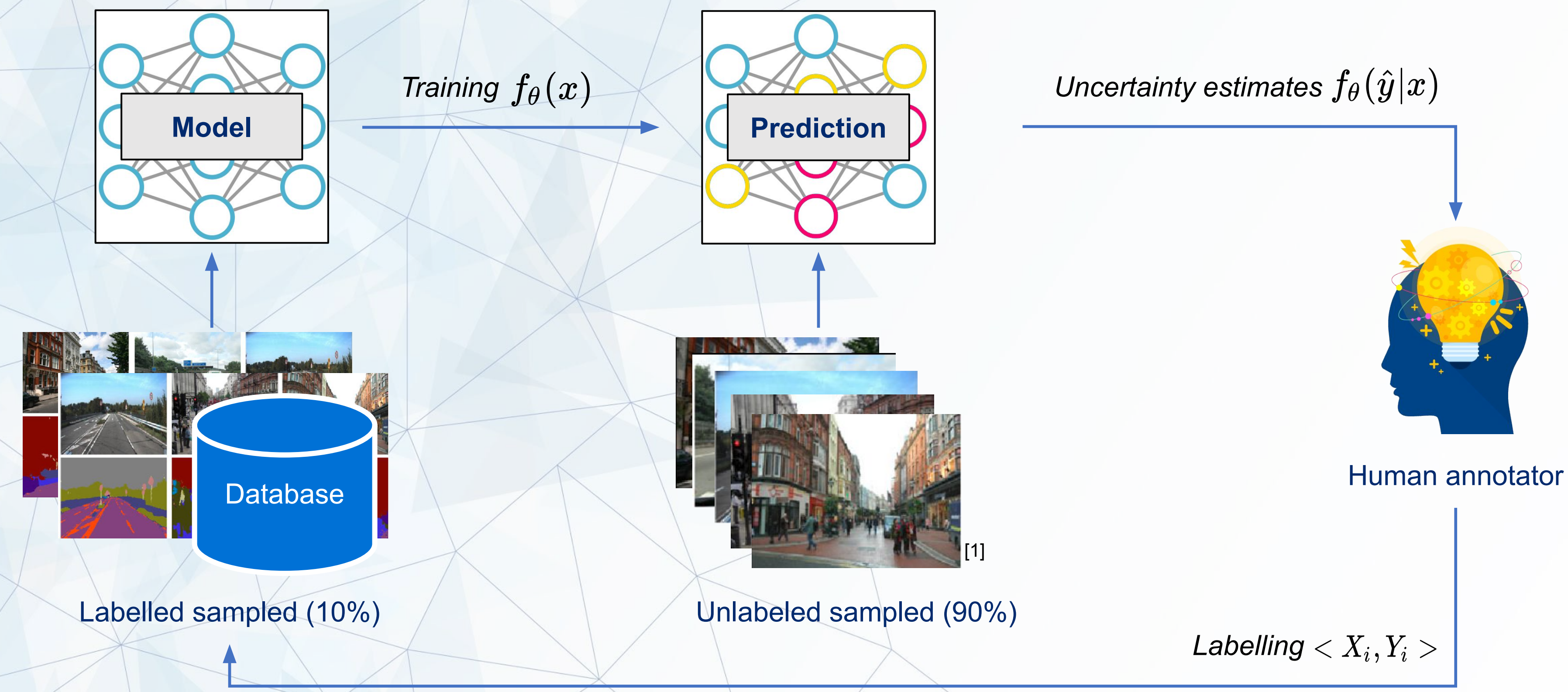
Interdisciplinary Project

Ming Yip, Cheung

Content

- What is *Active Learning* ?
- What is *Reinforcement Learning* ?
- Related Work
- Formulate *Active Learning* as a *Reinforcement Learning* problem
- Full Algorithm
- Challenges
- Result
- Conclusion

Active Learning

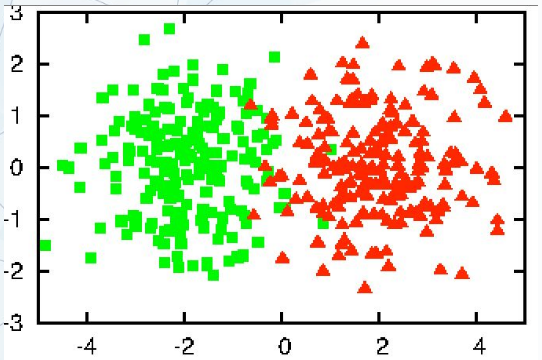


[1] Badrinarayanan, V., Kendall, A., & Cipolla, R. (2015). SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39, 2481-2495.

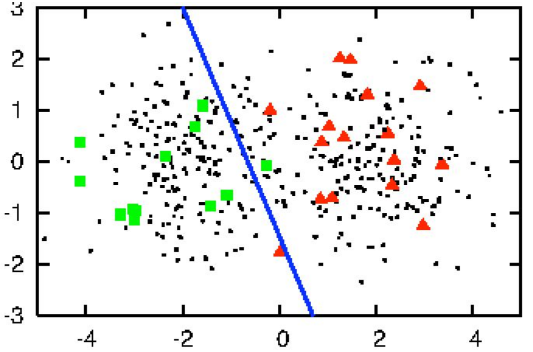
Active Learning

Advantages:

- Requires less training data
- Label efficient learning strategy
- Handle skewed dataset better [3]
- Faster convergence

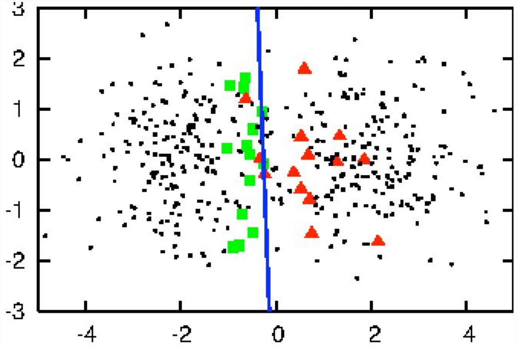


400 instances data from 2 classes



Random sampling

30 data (70% acc)



[2]

Uncertainty sampling

30 data (90% acc)

[2] Settles, B. (2009). Active Learning Literature Survey.
[3] Slotkin, M. (2019, September 30). Accelerate Machine Learning with Active Learning. Retrieved from https://becominghuman.ai/accelerate-machine-learning-with-active-learning-96cea4b72fdb.

Reinforcement Learning [4]

Modeled as a Markov decision process [5]

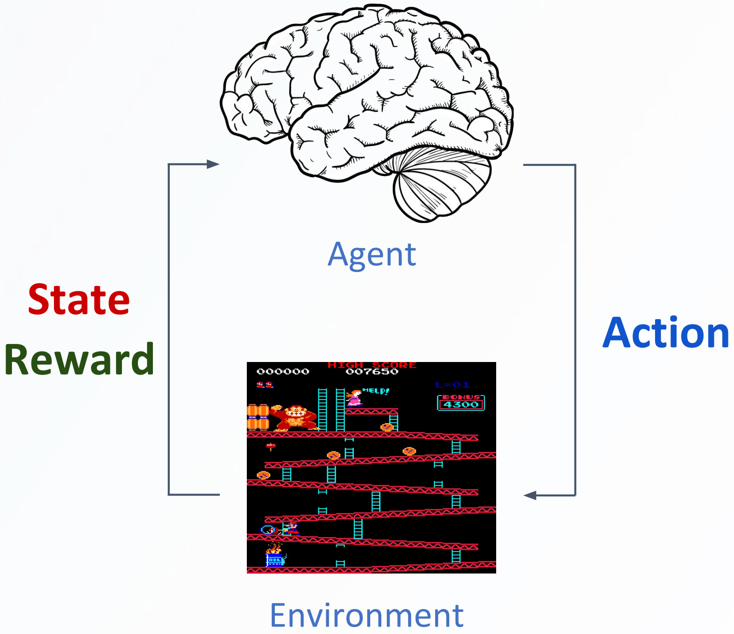
- A set of states S
- A set of actions A
- Reward function $R(s, a, s')$
- Probabilistic transition function $P_r(s_{t+1} = s' | s_t = s, a_t = a)$

Goal: maximize the total expected future reward

$$\pi^* = arg \max_{\pi} \mathbb{E}[G|\pi]$$

where $G = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$

In a **Value-based method,** we learn and predict the $Q(s,a)$ value.
In a **Policy gradient method** [6], we learn policy $\pi(s,a)$.



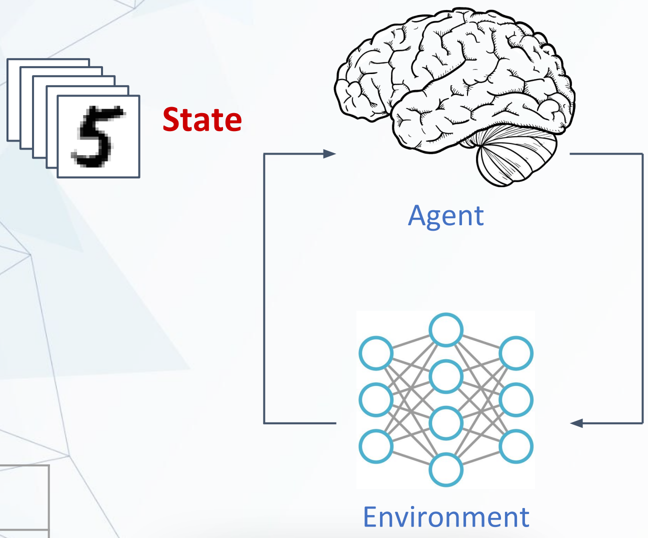
[4] Sutton, R.S., & Barto, A.G. (1988). Reinforcement Learning: An Introduction. IEEE Transactions on Neural Networks, 16, 285-286.
[5] Richard Bellman. A markovian decision process.Indiana Univ. Math. J., 6:679–684,1957
[6] Sutton, R.S., McAllester, D.A., Singh, S.P., & Mansour, Y. (1999). Policy Gradient Methods for Reinforcement Learning with Function Approximation. NIPS.

Reinforcement Learning for Active Learning

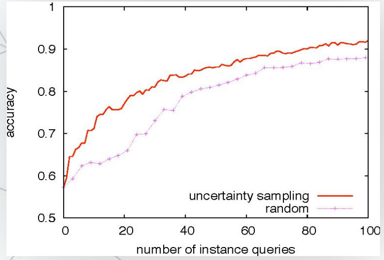
Objective

- Combine RL with AL for classification
- Stream-based active learning
- Neural network as environment

State s_t	images, network weights
Action a_t	select or discard images
Reward R	accuracy



Action



Reward

$56\% \rightarrow 67\%$

Related Work

Related Work

Active Learning Methods:

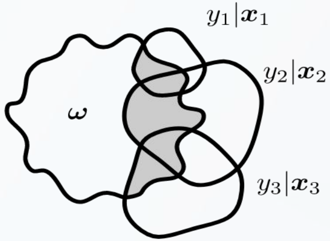
- Uncertainty sampling [7] [8]
- Query-By-Committee [9]
- Variance reduction [10]

Deep Active Learning:

- Studies of AL approaches for neural network
- Uncertainty-based method [11]
- Bayesian uncertainty measure [12]

Reinforcement Learning for:

- Transfer learning [13]
- Named entity recognition (NER) [14]
- Auto data augmentation [15]



$$a_{\text{BatchBALD}}\left(\{x_1, \ldots, x_b\}, \mathrm{p}\left(\boldsymbol{\omega}|\mathcal{D}_{\text{train}}\right)\right) := \mathbb{I}\left(y_1, \ldots, y_b; \boldsymbol{\omega}|x_1, \ldots, x_b, \mathcal{D}_{\text{train}}\right).$$

[7] David D. Lewis and William A. Gale. A sequential algorithm for training text classifiers. In SIGIR, 1994
[8] David D. Lewis and Jason Catlett. Heterogeneous uncertainty sampling for supervised learning. In ICML, 1994
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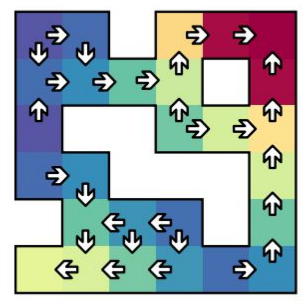
[13] Meng Fang, Yuan Li, and Trevor Cohn. Learning how to active learn: A deep reinforcement learning approach. In EMNLP, 2017
[14] Yanyao Shen, Hyokun Yun, Zachary Chase Lipton, Yakov Kronrod, and Anima Anandkumar. Deep active learning for named entity recognition. In ICLR, 2017.
[15] Ekin Dogus Cubuk, Barret Zoph, Dandelion Man´e, V. Vasudevan, and Quoc V. Le.Autoaugment: Learning augmentation strategies from data. In CVPR, 2019

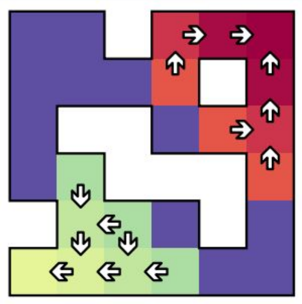
Related Work

Time Limits in Reinforcement Learning [16]

- Time limits are part of the state of the environment
- Include the remaining time as part of the state
- significant performance improvements for agents with time-awareness



(a) Standard

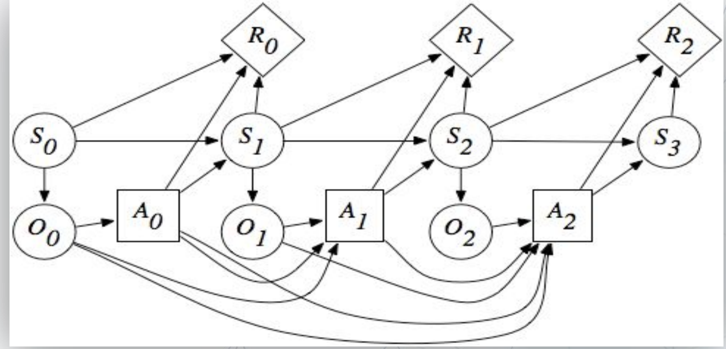


(b) Time-awareness

Partially observable Markov decision process: [17]

- Partially Observable Environments
- Deal with the uncertainty of states
- Beliefs of environment states:

$$S_t^a = (\mathbb{P}[S_t^e = s^1], \ldots, \mathbb{P}[S_t^e = s^n])$$



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[17] Åström, K.J. (1965). "Optimal control of Markov processes with incomplete state information".Journal of Mathematical Analysis and Applications. 10: 174–205

Algorithm

1 Training iteration - step by step

Classification Network f_θ

RL Agent F_ϕ

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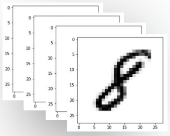
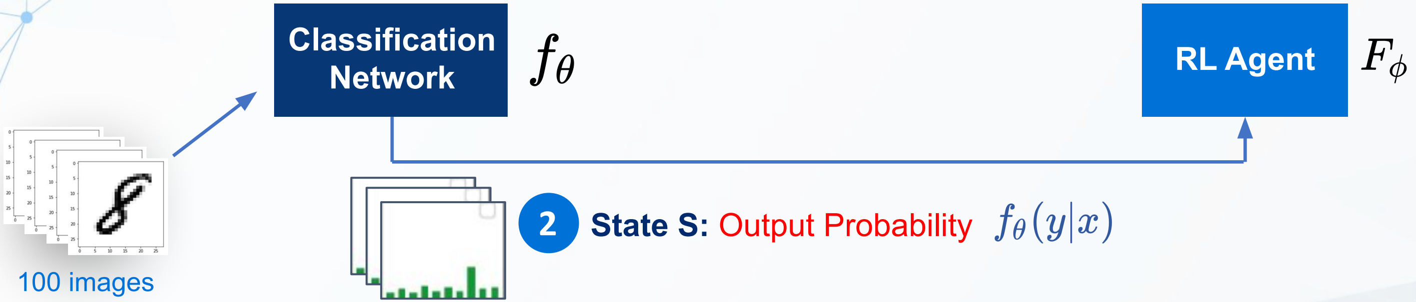


100 images

1 **Select** 100 random images

1 Training iteration - step by step



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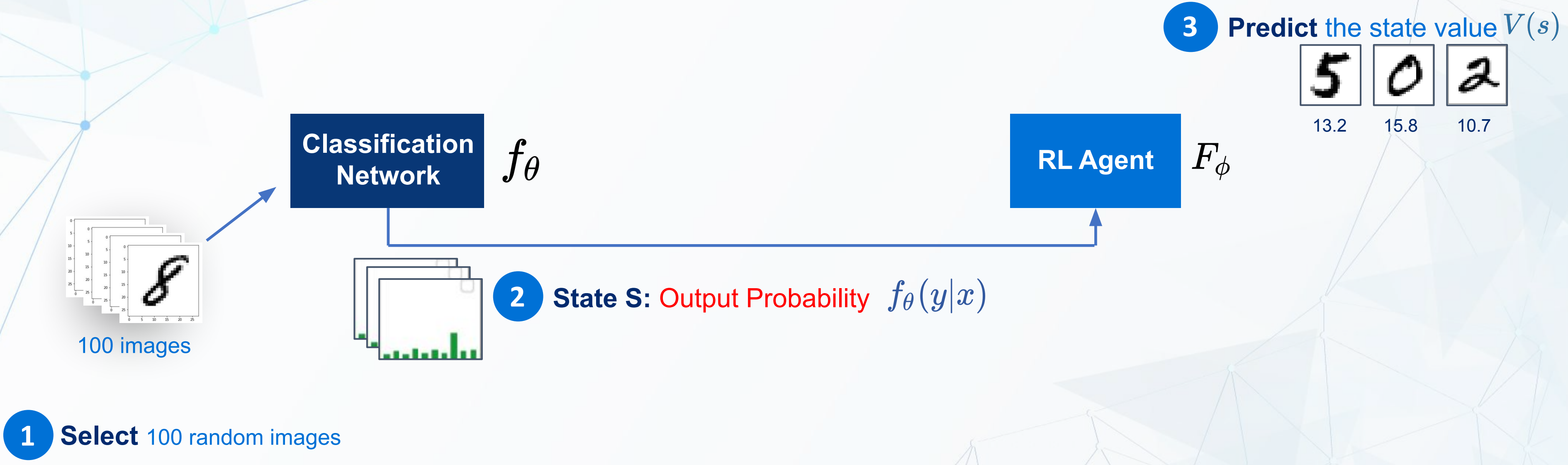

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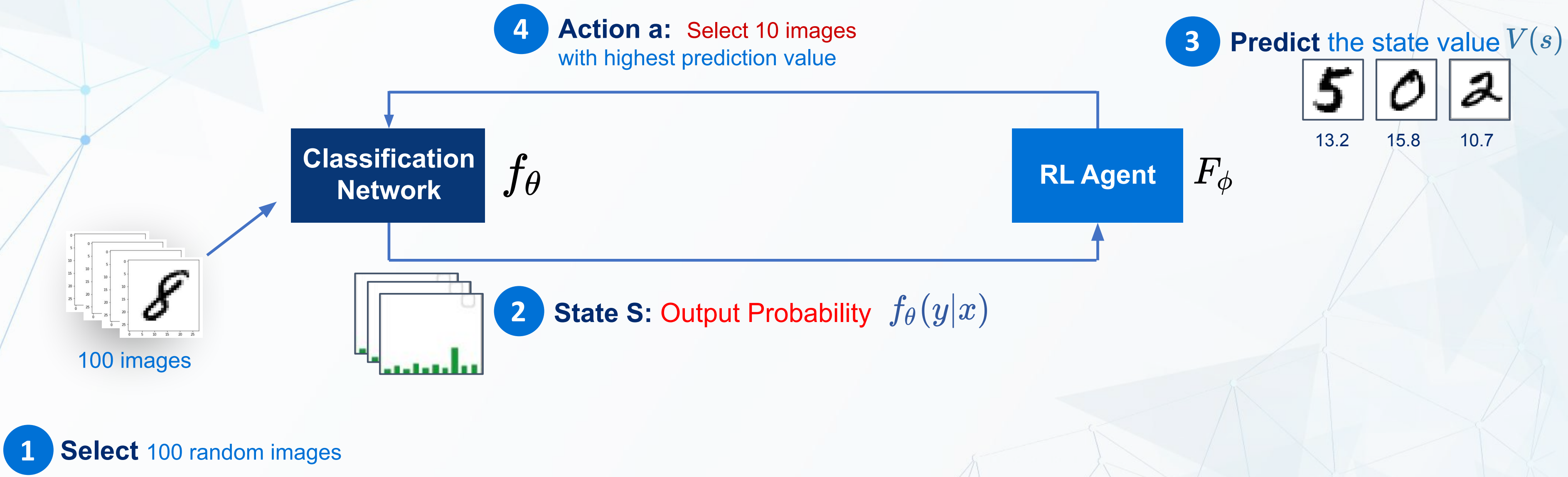

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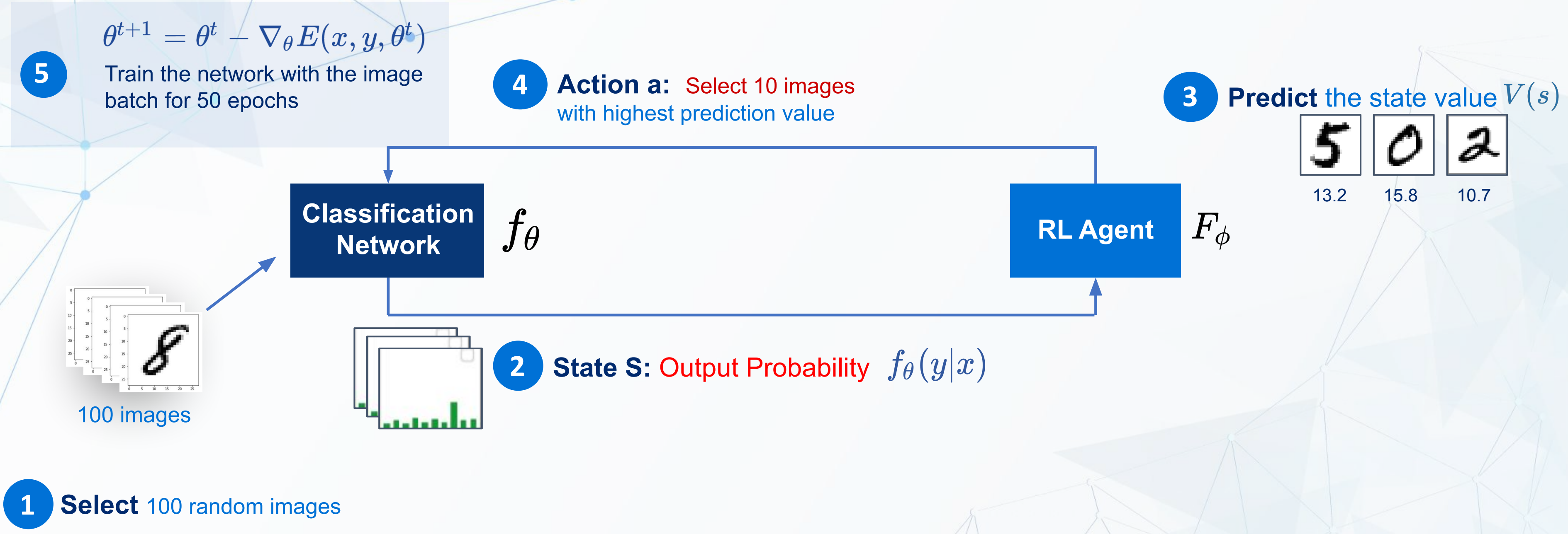


1 Training iteration - step by step

5 $\theta^{t+1} = \theta^t - \nabla_\theta E(x, y, \theta^t)$

Train the network with the image batch for 50 epochs

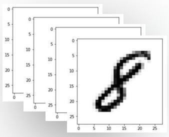
4 **Action a:** Select 10 images with highest prediction value

3 **Predict** the state value $V(s)$

13.2 15.8 10.7

Classification Network f_θ

RL Agent F_ϕ



100 images

2 **State S:** Output Probability $f_\theta(y|x)$

6 **New State S'**

Reward: Accuracy

We evaluate the CNN with Validation set and get the accuracy as **Reward**

1 **Select** 100 random images

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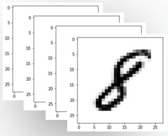

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7 Train RL agent with

$$V(S) \leftarrow V(S) + \alpha(\underbrace{r + \gamma V(S')}_{\text{TD - Target}} - V(S))$$

1 **Select** 100 random images

Algorithm

Algorithm 5: Reinforcement algorithm for training Value function ϕ

Input : data D, budget B, RL selection batch size b, RL network weights ϕ, classification network weights θ

Output: RL network weights ϕ

Train RL network weight ϕ ;

Fix the samples' order of the data-set D

$steps = \frac{|B|}{|b|}$

for *episode in 1 ... episodes* **do**

  Reset the classification weight θ with same initial random weights

  for t = *0, 1, ..., steps* **do**

    Predicted Future Expected Return $V_i(x_t) \leftarrow F_\phi(f_\theta(y|x), T - t, B - i * b)$

    Select top b images $D_t = Top_b\{(x_t, y_t)\}_{i=1}^{b}$

    for *epoch in 1 ... epochs* **do**

      Train Classification Network $\theta \leftarrow \theta - \nabla_\theta L(y_i, f\theta(x_i))$

    end

    Get Validation set Accuracy $R_v = A_i$

    Train RL agent $\phi \leftarrow \phi + \alpha \nabla_\phi F_\phi(S_t, A_t, R_t, S_{t+1}, \gamma)$

  end

  Get Final Validation set Accuracy $R_t = A_i$

  if R_t *is the best Accuracy* **then**

    Store the best Agent ϕ

  end

end

return best RL Agent ϕ

Train RL Agent

Train CNN

Algorithm

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Train CNN

Time awareness [16]

- Remaining episodes (RL)
- Remaining budgets (CNN)

$$V_\pi(s, T-t, B-ss) = \mathbb{E}_\pi[G_{t:T}|S_t = s]$$

[16] Pardo, F., Tavakoli, A., Levdik, V., & Kormushev, P. (2017). Time Limits in Reinforcement Learning. ICML.

Challenges

Split a complete state into a batch

- Evaluate the importanceness of each image
- Incomplete information of the state
- The RL agent observes only part of the state

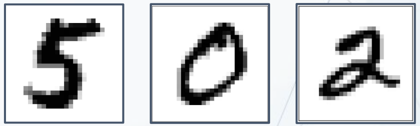
We select the top k images from a batch with M images

- If (M, k) are too large then the RL agent can hardly learn anything.
- If (M, k) are too small then the CNN network learns too slow and with insignificant reward

Markov Decision Process assumption

- $P(S_{t+1} = s_{t+1} | s_t, s_{t-1}, s_{t-2}, \ldots, s_1) = P(S_{t+1} = s_{t+1} | s_t)$
- Naive approach is a stateless environment
- Randomly select images from the date-set
- Each state does not necessary depend on the previous state
- Need to include the information of the CNN network weight
- The output probability may keep the MDP assumption

Predict the state value $V(s)$



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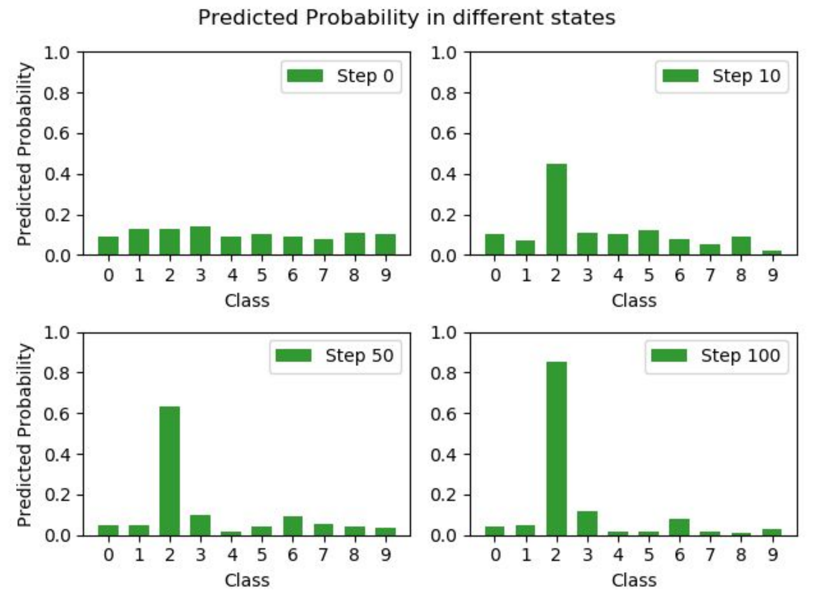
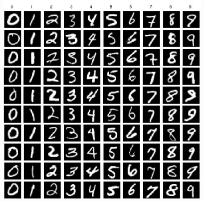


Evaluation

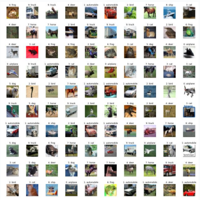
Data sets

Data sets	Num. of Images	Num. of Classes	Num. of Training images	Num. of Validation images	Num. of Test images	Num. of images per class	Dimension
MNIST [18]	70,000	10	50,000	10,000	10,000	~7,000	28x28
CIFAR-10 [19]	60,000	10	48,000	6,000	6,000	~6,000	32x32x3
EMNIST [20]	78,000	26	62,400	7,800	7,800	3,000	28x28

Table1: 3 labeled datasets



MNIST



CIFAR-10

EMNIST

Random Agent

vs

Least Margin Sampling Method (BVSB):

$$x^* = arg\,min P_\phi(\hat{y_1}|x) - P_\phi(\hat{y_2}|x)$$

[18] Yann LeCun, Corinna Cortes, and CJ Burges. Mnist handwritten digit database.ATTLabs [Online]. Available: http://yann. lecun. com/exdb/mnist, 2, 2010.
[19] Alex Krizhevsky. Learning multiple layers of features from tiny images. Technical report, 2009.
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MNIST

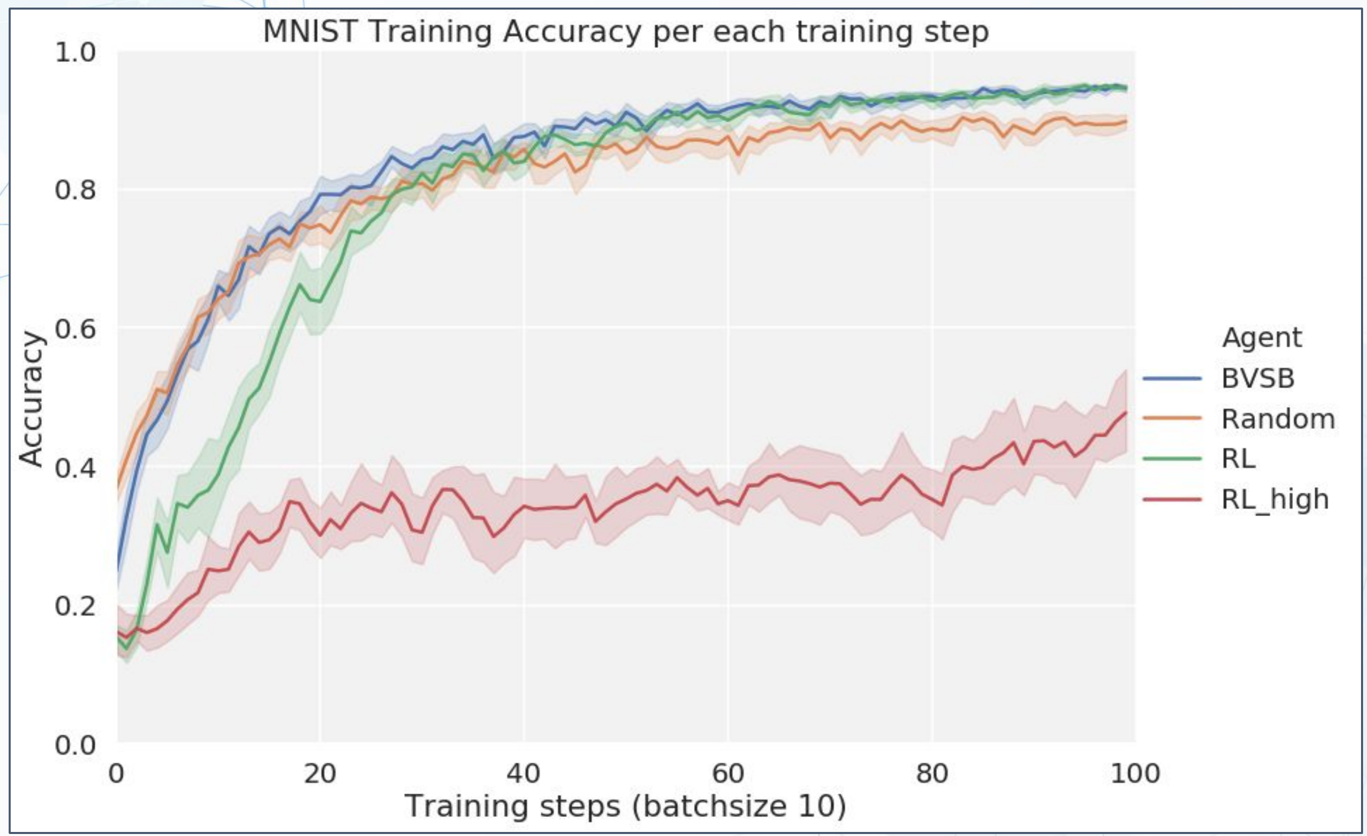


Table 4.2: Average terminal accuracy of 20 experiments on MNIST

Dataset	Random	BVSB	RL-top	RL-low
MNIST	0.8974 ± 0.0240	0.9447 ± 0.0128	0.4924 ± 0.0763	*0.9487 ± 0.00975

EMNIST

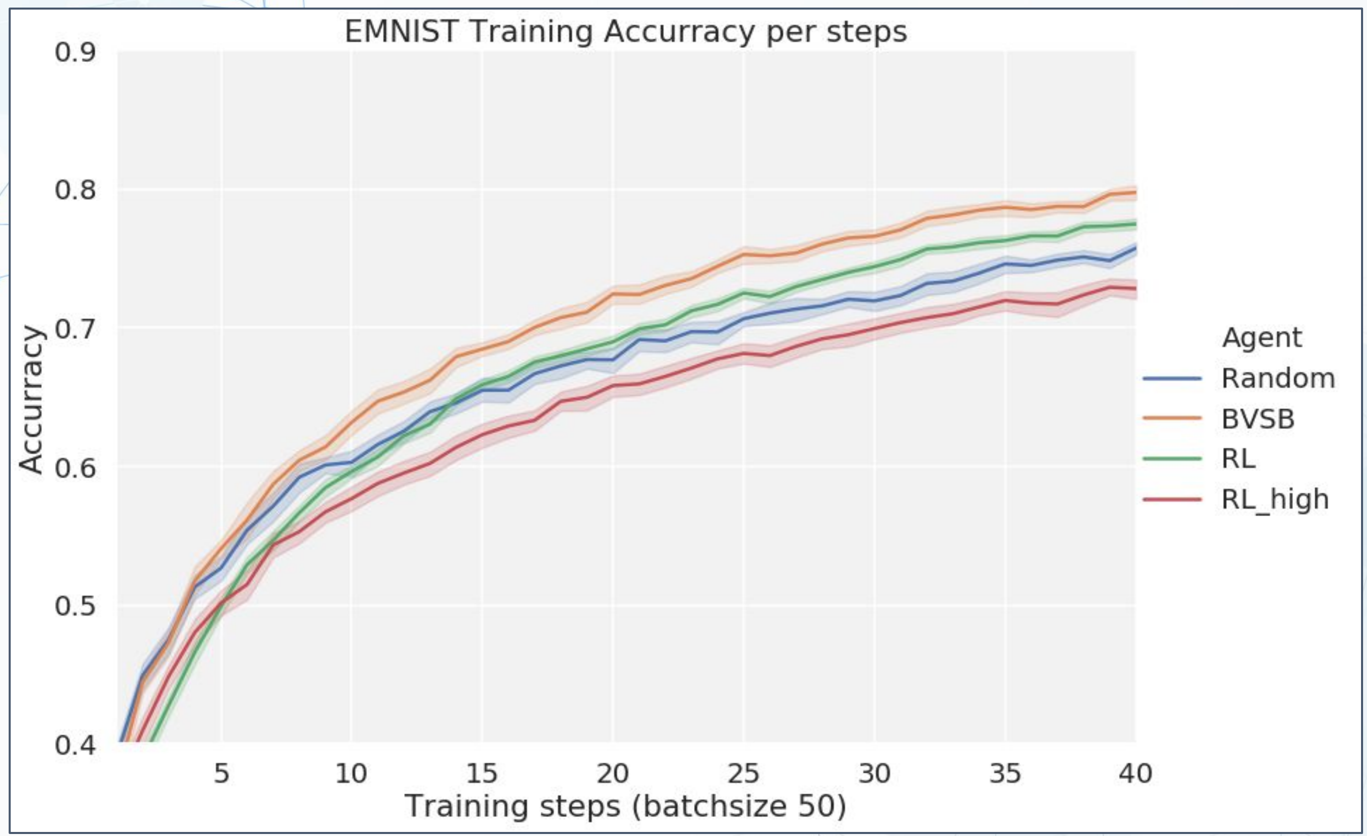


Table 4.2: Average terminal accuracy of 20 experiments on EMNIST

Dataset	Random	BVSB	RL-top	RL-low
EMNIST	0.7574 ± 0.0104	*0.7975 ± 0.0123	0.7282 ± 0.0232	0.7748 ± 0.0150

CIFAR

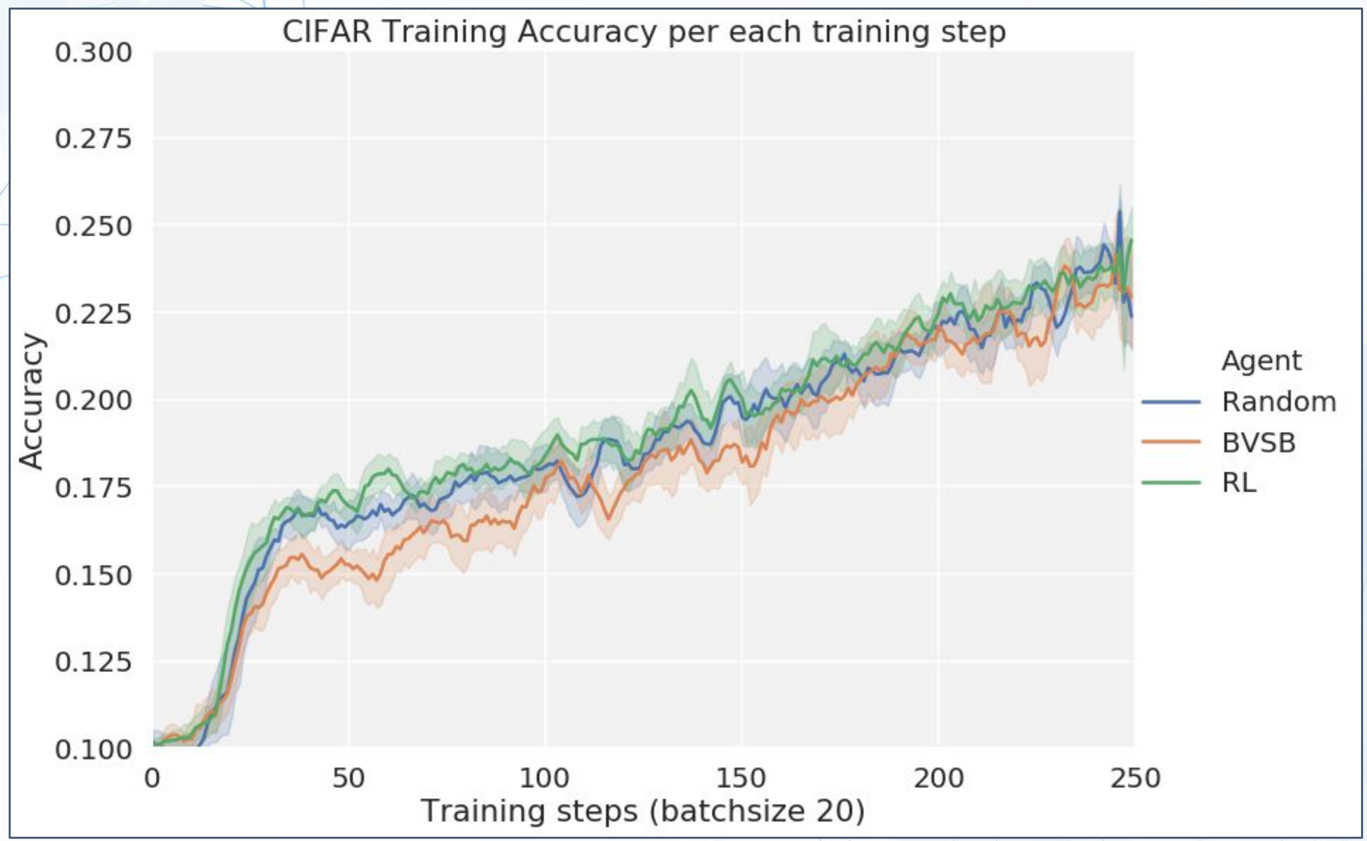
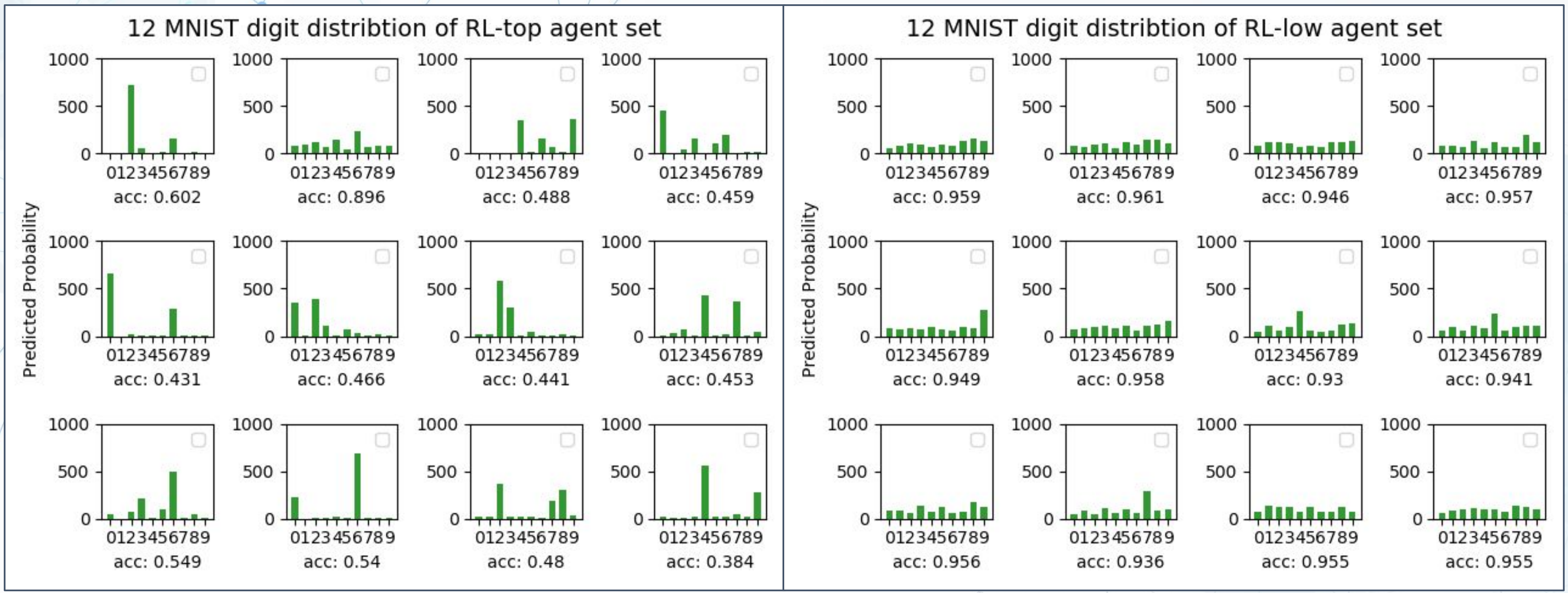


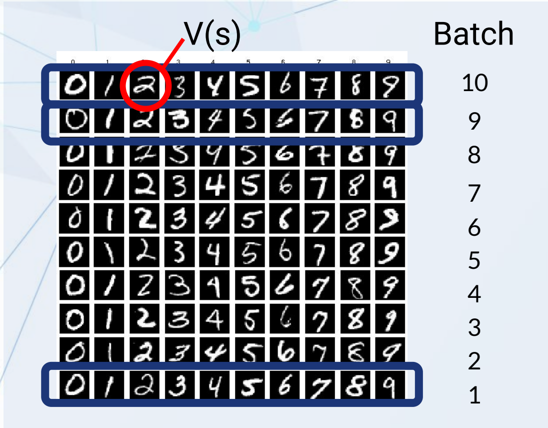
Table 4.2: Average terminal accuracy of 20 experiments on CIFAR

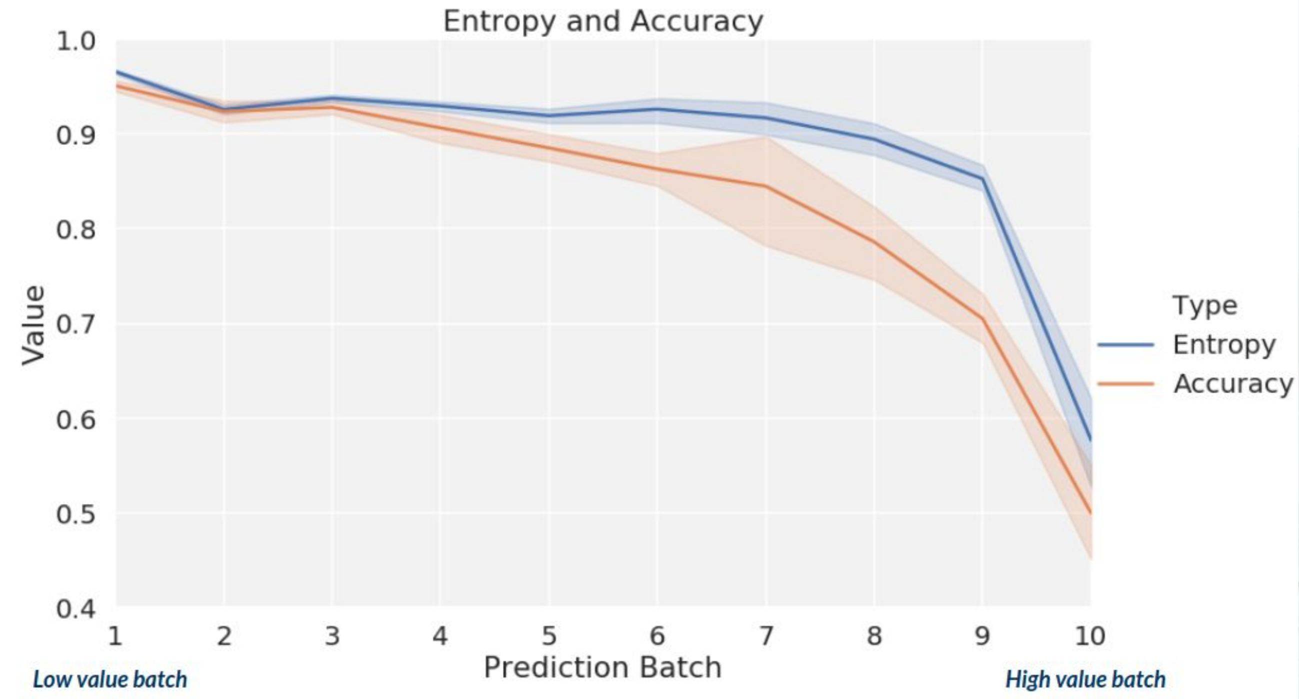
Dataset	Random	BVSB	RL-low
CIFAR[4]	0.2238 ± 0.0173	0.2294 ± 0.0253	*0.245714 ± 0.0161

Selection bias

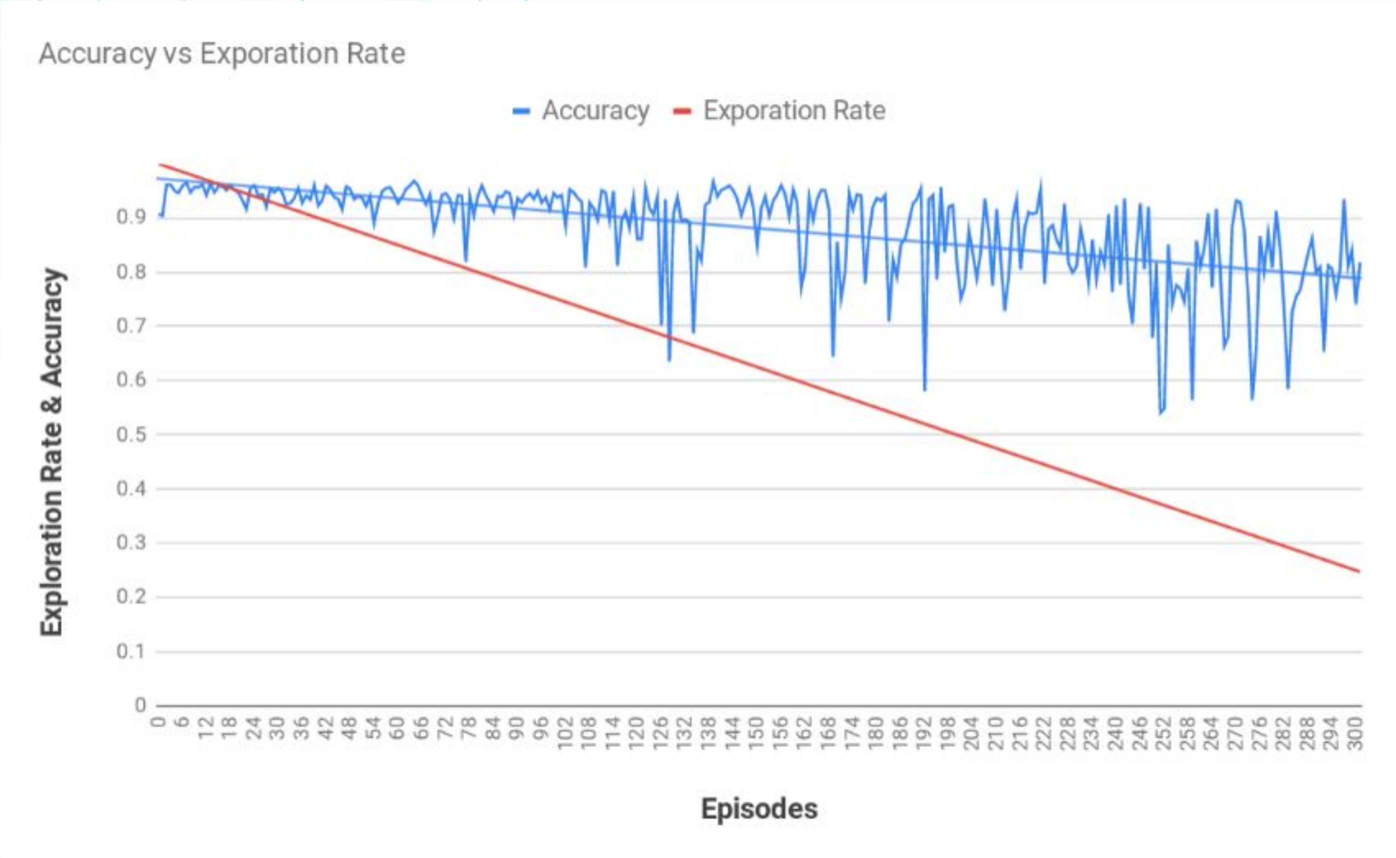


Entropy of the selection distribution





Effect of using exploration rate



Conclusion

- Competitive good result on MNIST and EMNIST
- CIFAR-10
- RL-top agent suffers from the bias selection
- Exploitation hurts the performance

Thank you

Reference

1. Badrinarayanan, V., Kendall, A., & Cipolla, R. (2015). SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39, 2481-2495.
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