Always Adopt Self-Supervised Learning

Making Real AI - Series

(Shaka) Shih-Chia Chen

Founder/CEO
www.libgirl.com

Thesis

Instead of applying classical task-specific machine learning paradigm,

we should (almost) alway use some universal pre-trained model trained from self-supervised learning and do fine-tuning.

Moreover, we only need a lifelong data stream rather than i.i.d. data points.

Yoshua Bengio said: don't shuffle the data, it will destroy contextual information. Any set of data points implies data points can be shuffled.

https://blog.crossminds.ai/post/yoshua-bengio-from-deep-learning-to-consciousness

Problem of Applying Classical Machine Learning Paradigm to Build One Single Task-General Model.

Resupplying context into data as more dimensions requires model redesign and complete retraining

Gender	Age	Overall survival (months)
M	47	8
M	69	
F	73	2
F	39	
F	55	12
M	63	
M	73	12
M	73	14
M	75	32

No context

Gender	Age	Smoking	Overall survival (months)
M	47	6	8
M	69	0	
F	73	0	2
F	39	0	
F	55	0	12
M	63	60	
M	73	9	12
M	73	8	14
M	75	30	32

More context

Gender	Age	Smoking	Pathology	Stage	Overall survival (months)
M	47	6	Ad-Sq	II	8
M	69	0	Ad	IV	
F	73	0	Ad	IV	2
F	39	0	NSCLC	IV	
F	55	0	Ad	III	12
M	63	60	sq	I	
M	73	9	Ad	IV	12
M	73	8	Ad	IV	14
M	75	30	sq	I	32

Even more context

Lung cancer data source (Shan et al., 2017)

An example of resupplying context into a lifelong data stream

Let a formal language sequence $S[t], t \in \mathbb{N}$

Given that

1. We encoded a data point X into S from $S[k]$ to $S[k+m]$
2. with some originally known context of X as CX_0 encoded into S to from $S[(k-g)-c_0]$ to $S[(k-g)-1]$
3. with some encoding delimiter between CX_0 and Xencoded into S from $S[k-g]$ to $S[k-1]$
4. and then we have already trained a language model until $S[k+m]$.

An example of resupplying context into a lifelong data stream

Now if we

1. supply updated contextual information of X as CX_1 encoded into S from $S[l]$ to $S[l+c_1], l > k+m$

2. and resupply the encoding delimiter and X into S from $S[(l+c_1)+1]$ to $S[(l+c_1)+g+m]$, which should be fuzzily equal to $S[k-g]$ to $S[k+m]$

3. and then fine-tune the language model

Conceptually, this self-supervised trained and fine-tuned model can learn the the originally missing but updated contextual information CX_1 of X.

Paradigm Shift

1. Because researchers will produce better self-supervised lifelong data stream learning algorithms and better universal pre-trained models.
2. All classical machine learning problems can be encoded into such universal pre-training and fine-tuning paradigm.
3. Universal pre-training and fine-tuning paradigm is more adaptive to data drift, task specification change, and missing context.

=> We should (almost) always adopt universal pre-training and fine-tuning paradigm.

Goodbye, Classical Machine Learning Paradigm.

Hi, the Domination of Self-Supervised Learning with Fined-Tuning.

Appendix

About Reinforcement Learning

Reinforcement Learning is a special case of such paradigm.

The problem of a pure reinforcement learning algorithm is that

1. We can’t provide data for an agent to imitate, which much reduces training efficiency. Some works (Hester et al., 2017) proposed reinforcement learning from demonstration to accelerate the learning process.
2. Difficult to define the reward function across different tasks.
   // need reference

References

Hester, T., Vecerik, M., Pietquin, O., Lanctot, M., Schaul, T., Piot, B., Horgan, D., Quan, J., Sendonaris, A., Dulac-Arnold, G., Osband, I., Agapiou, J., Leibo, J. Z., & Gruslys, A. (2017). Deep Q-learning from Demonstrations. *ArXiv:1704.03732 [Cs]*. https://arxiv.org/abs/1704.03732