Transfer Learning for Healthcare

Hui Wei 11/20/2018

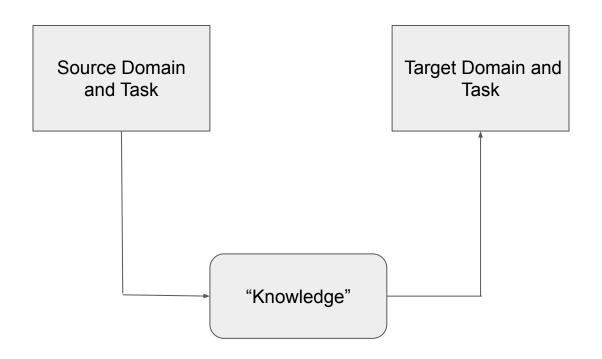
Contents

- Why transfer learning
- What is transfer learning
- How to transfer (a paper)

Why Transfer Learning

- "Transfer Learning will be the next driver of ML." --- Andrew Ng
- Key points to General Al
- Large Parameters, small dataset (especially in Healthcare)

What is Transfer Learning



What is Transfer Learning

Mathematical Definition:

- $D = \{X, P(X)\}$
- $T = \{y, P(y|x)\}$
- D(source) ≠ D(target) and/or T(source) ≠ T(target)
- N(source) >> N(target)
- Note: source and target are different but RELATED!!
- Negative transfer

What is Transfer Learning

Traditional Machine Learning:

Distribution(training) = Distribution(test)

Transfer Learning:

Distribution(training) ≠ Distribution(test)

Note: improve the performance in Target domain/task!! (unlike Multi-task Learning)

How to Transfer

- Instance-based
- Mapping-based
- Network-based
- Adversarial-based

Transfer Learning for Clinical Time Series Analysis using Recurrent Neural Networks Gupta,P et at.

why:

- Transfer Learning and RNN
- Clinical Time Series Analysis Problems
- Effectiveness and Robustness

What:

$$\mathcal{D}_S = \{(\mathbf{x}_S^{(i)}, \mathbf{y}_S^{(i)})\}_{i=1}^{N_S}$$

 N_S : # of instances for N_S patients

$$\mathbf{x} = \mathbf{x}_1 \mathbf{x}_2 \dots \mathbf{x}_t$$

$$\mathbf{x_t} \in \mathbb{R}^n$$

$$\mathbf{y} = [y_1,\ldots,y_K] \in \{0,1\}^K$$

$$\mathcal{D}_T = \{(\mathbf{x}_T^{(i)}, \mathbf{y}_T^{(i)})\}_{i=1}^{N_T}$$

$$N_T \ll N_S$$

$$y_T^{(i)} \in \{0,1\}$$

How:

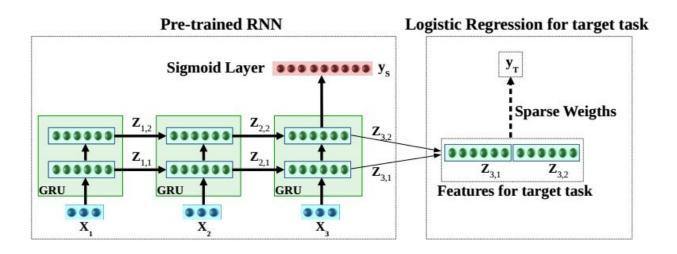


Figure 1: Inference in the proposed transfer learning approach. RNN with L=2 hidden layers is shown unrolled over $\tau=3$ time steps.

Pretrain RNN:

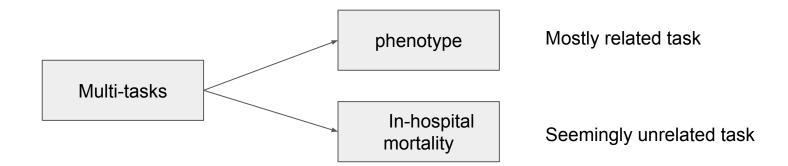
$$\mathbf{z}_{\tau}^{(i)} = f_{E}(\mathbf{x}^{(i)}; \mathbf{W}_{E}), \ \hat{\mathbf{y}}^{(i)} = \sigma(\mathbf{W}_{C} \ \mathbf{z}_{\tau, L}^{(i)} + \mathbf{b}_{C})$$

$$C(y_{k}^{(i)}, \hat{y}_{k}^{(i)}) = y_{k}^{(i)} \cdot log(\hat{y}_{k}^{(i)}) + (1 - y_{k}^{(i)}) \cdot log((1 - \hat{y}_{k}^{(i)}))$$

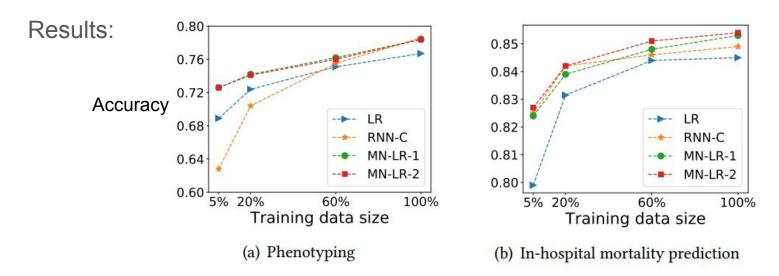
$$\mathcal{L} = -\frac{1}{N_{S} \times K} \sum_{i=1}^{N_{S}} \sum_{k=1}^{K} C(y_{k}^{(i)}, \hat{y}_{k}^{(i)}).$$

Logistic Regression for target task:

$$\mathcal{L}' = -\sum_{i=1}^{N_T} C(y^{(i)}, \hat{y}^{(i)}) + \lambda ||\mathbf{w'}_C||_1$$



- Dataset: MIMIC-III (v1.4)
- n=76
- K = 25, 20 phenotypes for source, 5 for target
- T = 48



- 100% target training data size: MN-LR = RNN-C > LR
- Less data size: MN-LR > RNN-C and MN-LR > LR
- 5%~50%: LR > RNN-C
- General enough and well transferable

Resources

Comprehensive paper lists for transfer learning:

- https://github.com/jindongwang/transferlearning/blob/master/doc/awesome_p aper.md
- https://github.com/artix41/awesome-transfer-learning

References

[1] Yosinski J, Clune J, Bengio Y, and Lipson H. How transferable are features in deep neural networks? In Advances in Neural Information Processing Systems 27 (NIPS '14), NIPS Foundation, 2014.

[2] Pan, S. J. and Yang, Q. (2010). A survey on transfer learning. IEEE TKDE, 22(10):1345–1359

[3] Tan C, Sun F, Kong T, Zhang W, Yang C, and Liu C. A survey on Deep Transfer Learning. arXiv:1808.01974v1

[4] Gupta P, Malhotra P, Vig L, Shroff G. Transfer Learning for Clinical Time Series Analysis using Recurrent Neural Networks. MLMH Workshop, KDD, August 19-23, 2018, London

Thanks