Lecture 1: Introduction

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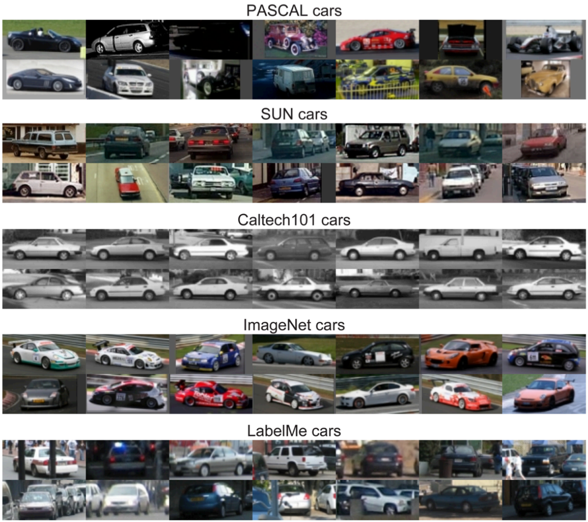
Overview I

§1.1: Why, when, and where

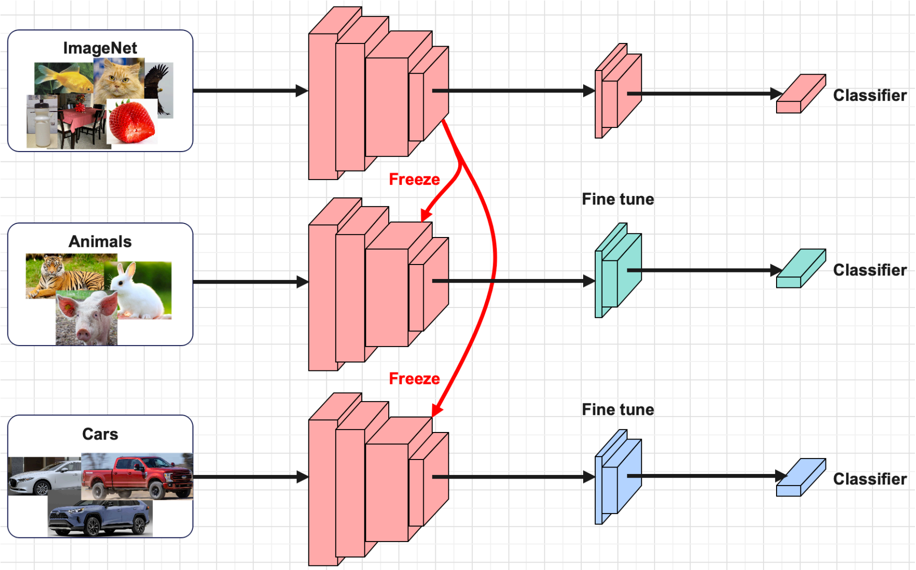
Transfer learning in computer vision



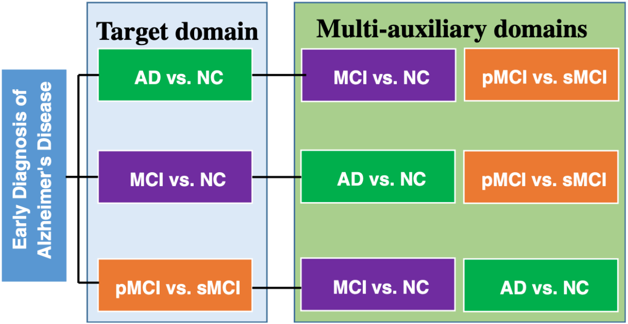
Car images across datasets

Torralba, A., & Efros, A. A. (2011, June). Unbiased look at dataset bias. In CVPR 2011 (pp. 1521-1528). IEEE.

Transfer learning in computer vision



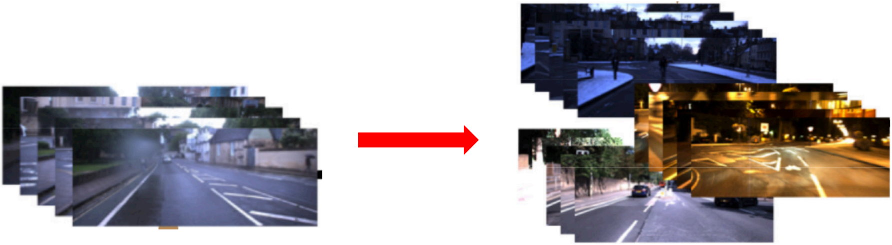
Transfer learning in disease diagnosis



- AD: Alzheimer's Disease
- MCI: mild cognitive impairment
  - pMCI: progressive MCI
  - sMCI: stable MCI
- NC: normal controls

Cheng, B., Liu, M., Shen, D., Li, Z., Zhang, D., & Alzheimer's Disease Neuroimaging Initiative. (2017). Multi-domain transfer learning for early diagnosis of Alzheimer's disease. Neuroinformatics, 15, 115-132.

Transfer learning in autonomous driving



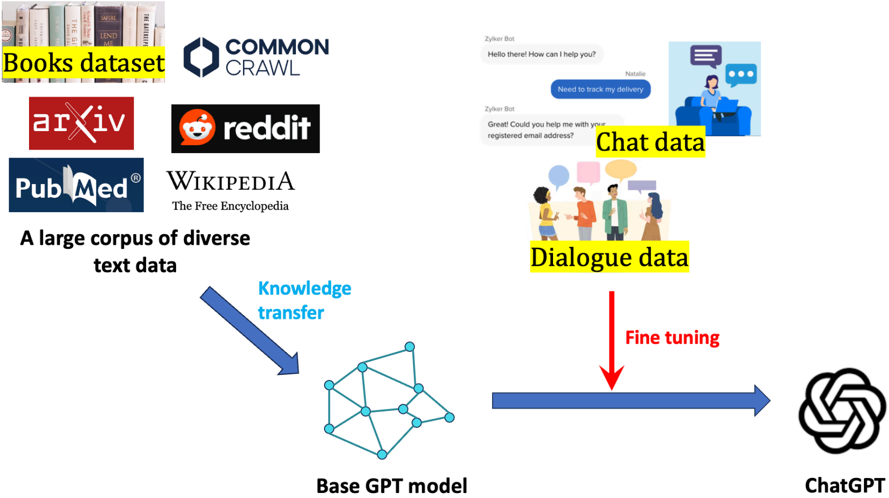
Training scenario

Real application scenario

Image source:
https://nbviewer.org/github/vistalab-technion/cs236605-tutorials/blob/master/tutorial6/tutorial6-TL_DA.ipyn

Akhauri, S., Zheng, L. Y., & Lin, M. C. (2020, October). Enhanced transfer learning for autonomous driving with systematic accident simulation. In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 5986-5993). IEEE.

Transfer learning in ChatGPT



Why, when, and where

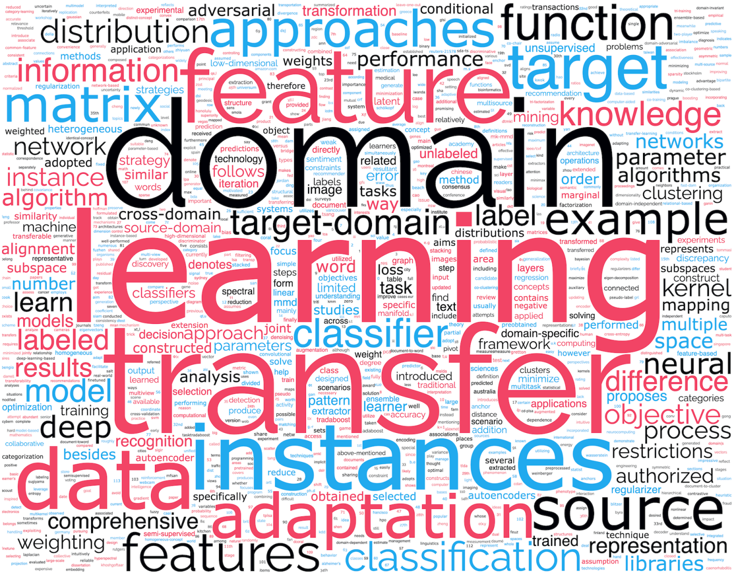
- **Why:** Improve the performance on the target dataset of limited (or zero) sample size
- **When:** There is some similarity between the target and source to transfer
- **Where:** Various applications in many areas
  - Computer vision
  - Healthcare
  - Natural Language Processing
  - Finance
  - Autonomous Driving
  - ......

See Pan and Yang (2009); Weiss et al. (2016); Zhuang et al. (2020) for more comprehensive surveys of transfer learning.

[1] Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10), 1345-1359.
[2] Weiss, K., Khoshgoftaar, T. M., & Wang, D. (2016). A survey of transfer learning. Journal of Big data, 3, 1-40.
[3] Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., ... & He, Q. (2020). A comprehensive survey on transfer learning. Proceedings of the IEEE, 109(1), 43-76.

§1.2: Concepts

Terminologies do not matter



The word cloud is generated based on ``Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., ... & He, Q. (2020). A comprehensive survey on transfer learning. Proceedings of the IEEE, 109(1), 43-76."

Concepts: domain and task

Most definitions are quoted from Redko et al. (2019, 2020).

- **Domain:** We may call $(\mathcal{S}^{(0)}, \mathbb{P}^{(0)})$ as the **target domain** and $(\mathcal{S}^{(1)}, \mathbb{P}^{(1)})$ as the **source domain**, where $\mathbb{P}^{(0)}$ and $\mathbb{P}^{(1)}$ are the distributions defined on corresponding spaces $\mathcal{S}^{(0)}$ and $\mathcal{S}^{(1)}$. [1]
- **Task:** There is a learning **task** associated with each domain, which can be classification, clustering, regression, on $\mathcal{S}^{(k)}$. For supervised learning problems, $\mathcal{S}^{(k)}$ consists a feature space $\mathcal{X}$ and an output space $\mathcal{Y}$. The task usually is to learn a predictor from $\mathcal{X}$ to $\mathcal{Y}$. We can denote the task for target and source as $t^{(0)}$ and $t^{(1)}$
- **Transfer learning:** How to improve the performance on target domain for $t^{(0)}$ by the knowledge of the source domain for $t^{(1)}$.

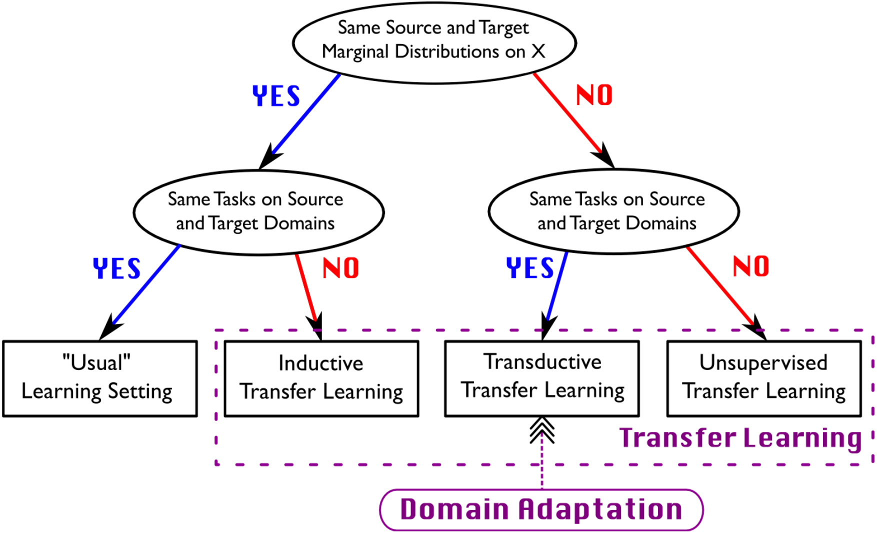
[1] There can be more than one sources.

[1] Redko, I., Morvant, E., Habrard, A., Sebban, M., & Bennani, Y. (2019). Advances in domain adaptation theory. Elsevier.
[2] Redko, I., Morvant, E., Habrard, A., Sebban, M., & Bennani, Y. (2020). A survey on domain adaptation theory: learning bounds and theoretical guarantees. arXiv preprint arXiv:2004.11829.

Categories of TL by goals

- **Transfer learning:** Using the information from the **source domain** to improve the performance on **target domain**.
- **Multi-task learning:** Each domain is called a **task** and we want to simultaneously learn well on **all domains** by borrowing information from each other.

Categories of TL by tasks

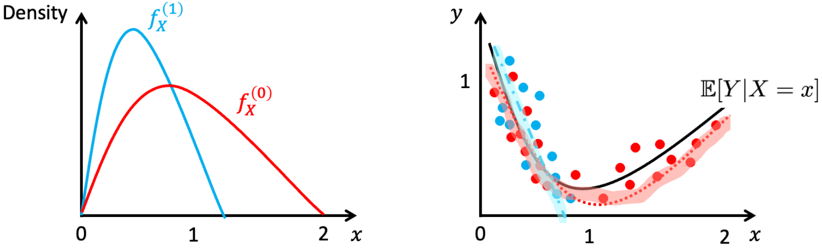


Picture source: Redko, I., Morvant, E., Habrard, A., Sebban, M., & Bennani, Y. (2020). A survey on domain adaptation theory: learning bounds and theoretical guarantees. arXiv preprint arXiv:2004.11829.

Categories of TL by shift types

Consider the supervised learning setting, and we have the same feature space $\mathcal{X}$ and output space $\mathcal{Y}$ for target and source [2]. $\mathbb{P}^{(k)}$ is the joint distribution of (X, Y) on target $(k = 0)$ or source $(k = 1)$ domains.

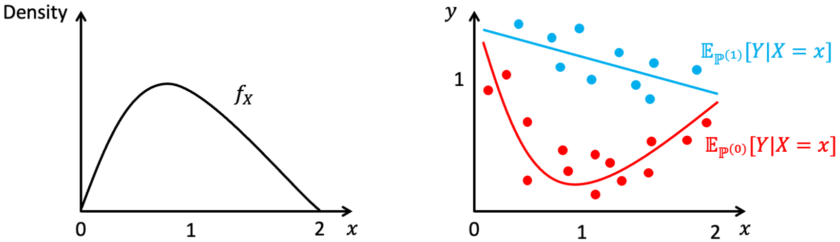
- **Covariate shift:** $\mathbb{P}^{(0)}_X \neq \mathbb{P}^{(1)}_X$, $\mathbb{P}^{(0)}_{Y|X} = \mathbb{P}^{(1)}_{Y|X}$ (in the sense of $\mathbb{P}^{(0)}_X$-a.e.)
- **Posterior drift:** $\mathbb{P}^{(0)}_X = \mathbb{P}^{(1)}_X$, $\mathbb{P}^{(0)}_{Y|X} \neq \mathbb{P}^{(1)}_{Y|X}$
- **Concept drift:** $\mathbb{P}^{(0)}_X \neq \mathbb{P}^{(1)}_X$, $\mathbb{P}^{(0)}_{Y|X} \neq \mathbb{P}^{(1)}_{Y|X}$



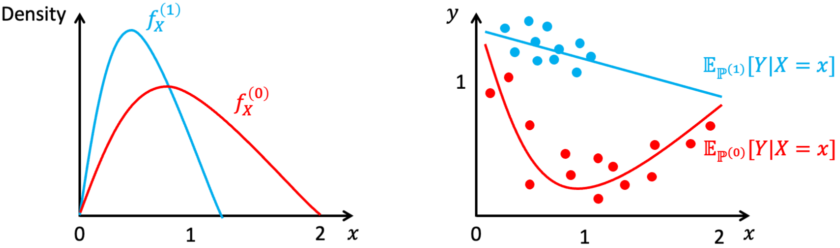
``Covariate shift"

[2] We will also discuss distribution shift where the space $\mathcal{X} \times \mathcal{Y}$ can be different for target and source, in Lecture 3.

Categories of TL by shift types



``Posterior drift"



``Concept drift"

§1.3: Overview of the short course

Overview of the short course

A (Selective) Introduction to the Statistical Foundations of Transfer Learning

Lecture 2: Generic Analysis of Domain Adaptation by Divergence Notions

- No target data
- Few target data + many source data
- Posterior drift
- Hardness results
- Other similarity notions beyond divergence

Lecture 3: Covariate Shift

- Adaptivity to covariate shift for free?
- The reweighting method
- Approaches of density ratio estimation
- Other methods

Lecture 4: Posterior Drift and Biased Regularization

- Biased regularization
- Extension to high-dimensional regressions
- Other applications of biased regularization
- Statistical inference
- Unsupervised multi-task learning
- Representation learning

Next time!

Lecture 5: Selected Topics (coming in future)

- Adversarial contamination and outlier tasks
- Federated learning
- Differential privacy
- ……

References I

Akhauri, S., Zheng, L. Y., and Lin, M. C. (2020). Enhanced transfer learning for autonomous driving with systematic accident simulation. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 5986--5993. IEEE.

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Pan, S. J. and Yang, Q. (2009). A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345--1359.

Redko, I., Morvant, E., Habrard, A., Sebban, M., and Bennani, Y. (2019). *Advances in domain adaptation theory*. Elsevier.

Redko, I., Morvant, E., Habrard, A., Sebban, M., and Bennani, Y. (2020). A survey on domain adaptation theory: learning bounds and theoretical guarantees. *arXiv preprint arXiv:2004.11829*.

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References II

Weiss, K., Khoshgoftaar, T. M., and Wang, D. (2016). A survey of transfer learning. *Journal of Big data*, 3(1):1--40.

Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., and He, Q. (2020). A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1):43--76.