Deep Transfer Learning

Logistics & Intro to Deep Transfer Learning

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William & Mary

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About this Course

- Deep Learning
  - Convolutional Neural Network (CNN)
  - Recurrent Neural Network (RNN) & its variations (GRU, LSTM)
  - Graph Neural Networks (GNN)
  - Attention & Transformers
- Transfer Learning using Deep Learning
  - Unsupervised Domain Adaptation
  - Domain Generalization
- Coursework is aimed at graduate students. We will use multivariate calculus, probability, and linear algebra.

About this Course

- First Half
  - We will cover the basic techniques in deep learning (i.e. transformers, GNN) in lectures
- Second Half
  - We will read papers
  - Students will present the papers during class (signup sheet to “adopt" papers to present will be available soon!)

About this Course

- Course website
  - https://lindagaw.github.io/courses/CSCI680/CSCI680.html Main source of information is the course webpage; check regularly!
- Announcements & Grades
  - Class announcements will be sent to you via email via Blackboard
  - Your grades for your assignments will be posted on Blackboard
- Discussion
  - General discussions are held on Piazza
  - Your grade does not depend on your participation on Piazza. It's just a good way to ask questions, and to discuss with your instructors and your peers. We will only allow questions that are related to the course materials/assignments/exams.

Office Hours

- Instructor: T/R: 11:00-12:30, McGlothlin-Street Hall, 004
- Office hours may change (temporarily) throughout the semester.
- Pay attention to the emails sent to you, as well as the course website's announcement section

Course Information

- For the first half of the class
  - Recommended readings and videos will be given for each lecture
  - There are lots of freely available, high-quality deep learning resources.
- For the second half of the class
  - We will read papers on unsupervised domain adaptation (UDA) and domain generalization (DG)
  - The list of the papers will be provided to you

Requirements & Marking

- (25%) Homework
  - Combination of pen & paper derivations and programming exercises
- (25%) Course Project
  - Will require you to apply DG/UDA to a challenging problem and to write a short report analyzing the results
  - Due on the last day of class
  - More details TBA
- (15%) Paper Presentation
- (10%) Attendance
- (25%) Final Exam

On Assignments

- Collaboration on the assignments is not allowed. Each student is responsible for his/her own work. Discussion of assignments should be limited to clarification of the handout itself, and should not involve any sharing of pseudocode or code or simulation results. Violation of this policy is grounds for a semester grade of F.
- The schedule of assignments will be posted on the course webpage.

Deep Transfer Learning

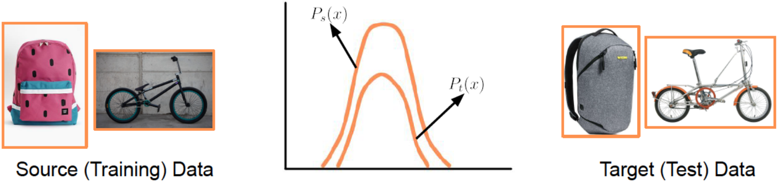
- Assignments should be handed in by the deadline; a late penalty of 10% per day will be assessed thereafter (up to 3 day(s), then submission is blocked).
- Extensions will be granted only in special situations, and you will need to complete an absence declaration form and notify us to request special consideration, or otherwise have a written request approved by the course instructors at least one week before the due date.

Deep Transfer Learning

- Unsupervised Domain Adaptation
  - Goal is to adapt a model trained on one domain (the source domain) to perform well on a different domain (the target domain), without having access to labeled data in the target domain.
- Domain Generalization
  - focuses on training a model on multiple source domains with the aim of generalizing well to unseen target domains.
  - Unlike UDA, in domain generalization, there is no access to any data (labeled or unlabeled) from the target domain during training.

Why UDA & DG?

Standard visual recognition task:

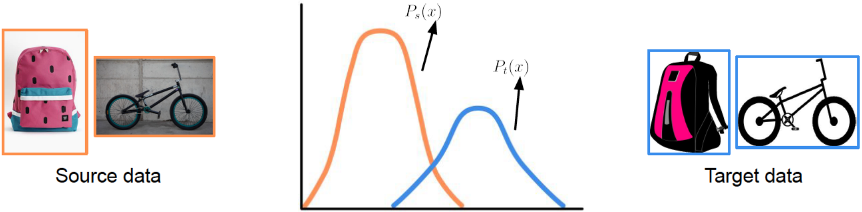


Hypothesis: source and target data are from same distribution.

Goal: learn a model f with source data that can perform well on target data.

Why UDA & DG?

Real-world visual recognition task:



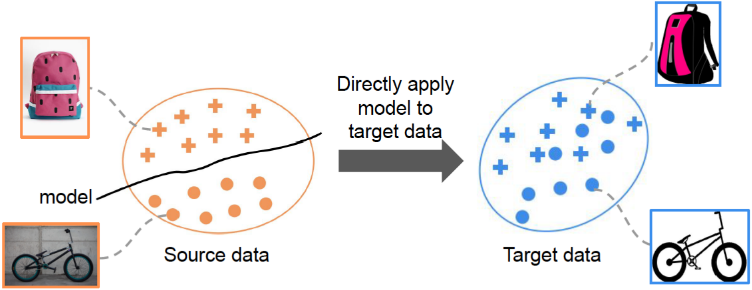
Hypothesis: source and target data are from same distribution.

Actual situation: source and target data are from different distributions.

Goal: learn a model f with source data that can perform well on target data.

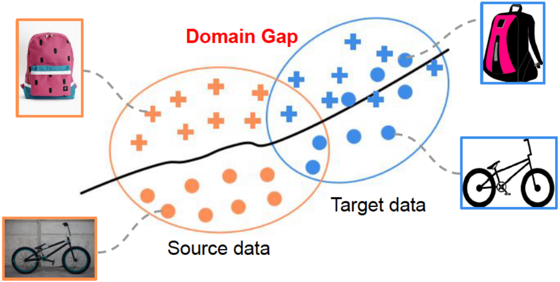
Why UDA & DG?

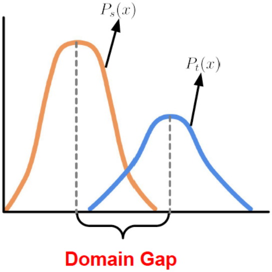
Real-world visual recognition task:



Why UDA & DG: Domain Gap

- Due to **domain gap**, the model trained on source data would perform unsatisfactorily on target data in real-world visual recognition tasks.
- **Domain gap** would significantly decrease the performance of the model in real-world visual recognition tasks.



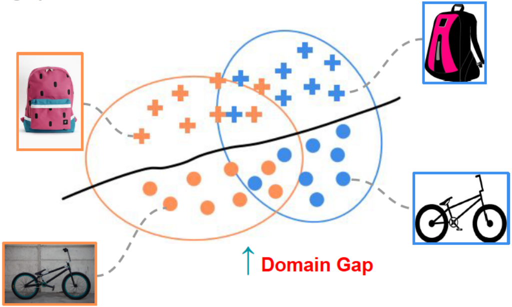


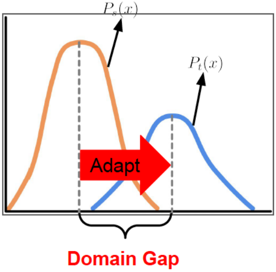
Potential Reasons for Domain Gap

- Out-of-distribution scenarios due to varied types of distribution shifts (e.g.,covariate shift, concept shift, temporal shift)
- Different data collection ways (e.g., images of the same object from different cameras)
- Different illumination, pose, color, and background (e.g., person re-identification)
- Different image styles (e.g., real images vs. simulation images)
- Different culture behind the images

UDA (& DG)

Domain Adaptation is the ability to apply an algorithm trained in one or more "source domains" to a different (but related) "target domain" via reducing the domain gap.

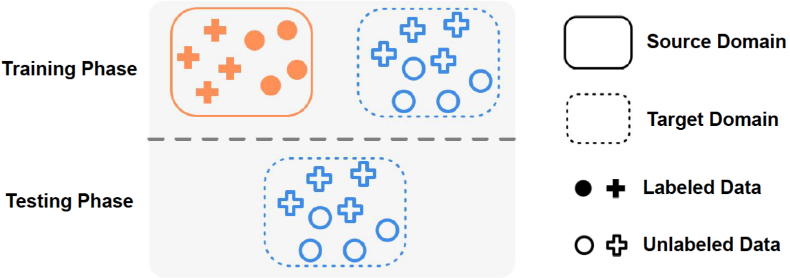




Available Domain Adaptations

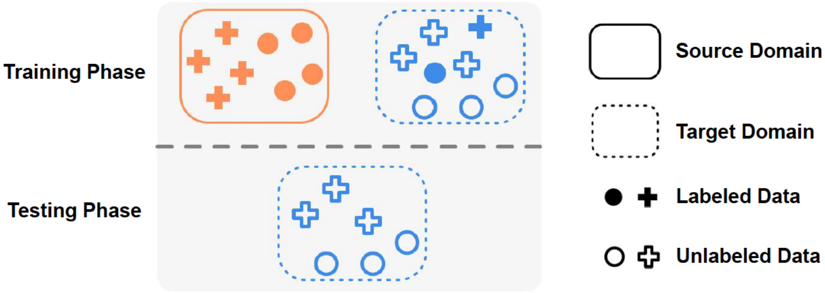
- Unsupervised Domain Adaptation (UDA)
- Semi-Supervised Domain Adaptation (SSDA)
- Supervised Domain Adaptation (SDA)
- Partial Domain Adaptation (PDA)
- Open-Set Domain Adaptation (OSDA)
- Universal Domain Adaptation (UniDA)

Unsupervised Domain Adaptation

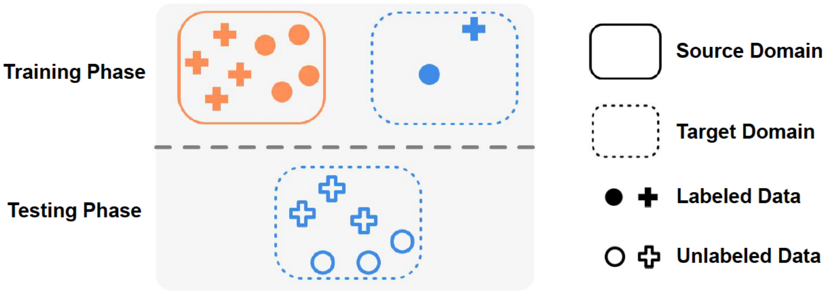


Yaroslav, Ganin et al. (2015). "Unsupervised domain adaptation by backpropagation." In: ICML.

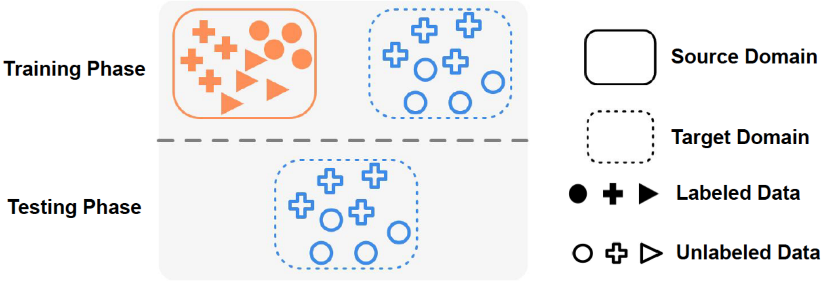
Semi-Supervised Domain Adaptation



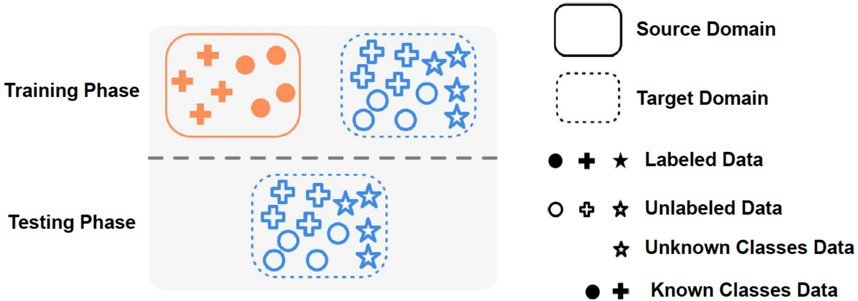
Supervised Domain Adaptation



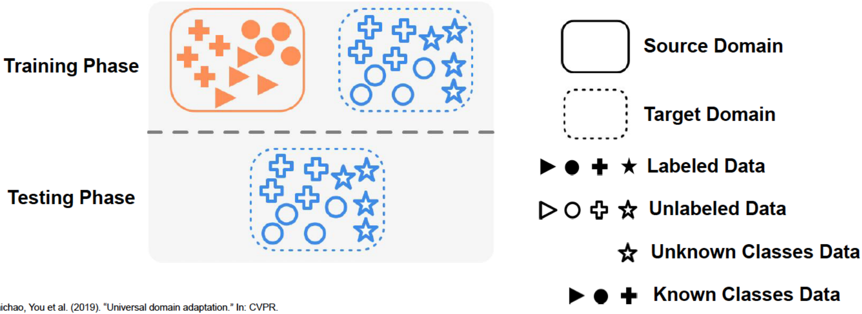
Partial Domain Adaptation



Open-Set Domain Adaptation



Universal Domain Adaptation



Kaichao, You et al. (2019). "Universal domain adaptation." In: CVPR.

Domain Adaptation

ImageNet **CiFAR100**

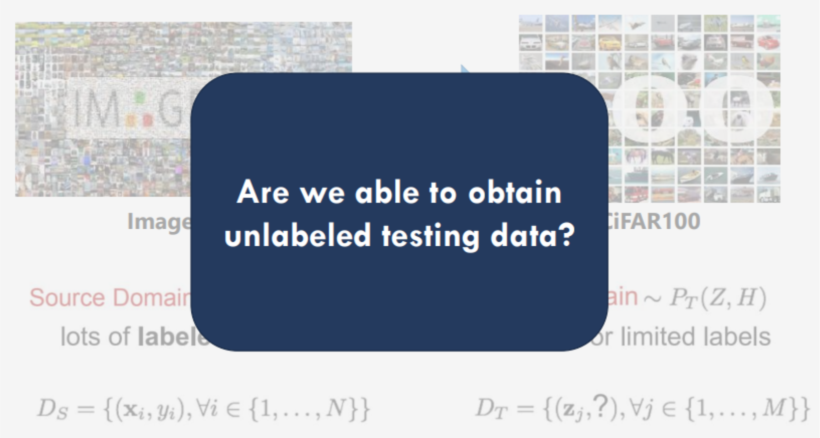
Source Domain $\sim P_S(X, Y)$ $\neq$ Target Domain $\sim P_T(Z, H)$

lots of **labeled** data — unlabeled or limited labels

$$D_S = \{(\mathbf{x}_i, y_i), \forall i \in \{1, \ldots, N\}\}$$

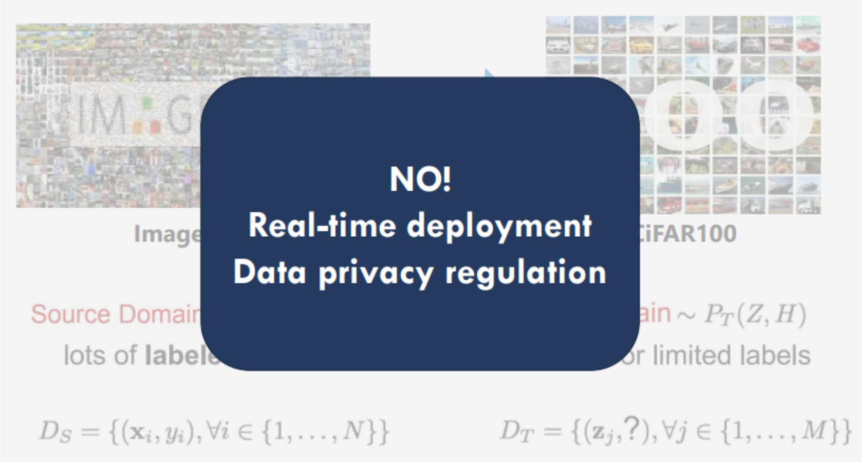
$$D_T = \{(\mathbf{z}_j, ?), \forall j \in \{1, \ldots, M\}\}$$

Domain Adaptation



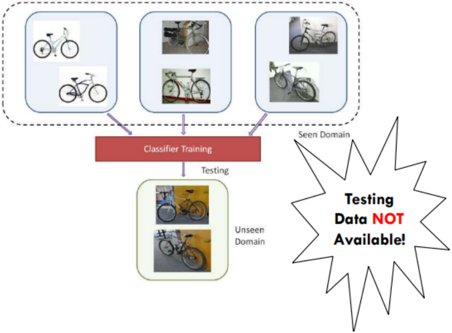
Are we able to obtain unlabeled testing data?

Domain Adaptation



Domain Generalization

Domain Generalization (DG): Build a system for previously unseen datasets, given one or multiple training datasets.



- Data augmentation and generation
- Distribution alignment
- Meta-learning
- Contrastive Learning
- Adversarial Training
- ...

The Big Picture