A Hands-on Introduction to Transfer Learning

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Agenda

- Module 1: Theory of Transfer Learning
- Module 2: Applications of TL: Images
- Module 3: Applications of TL: Text
- Module 4: Application of TL: Audio
- Module 5: Advanced Application of TL

Module 1: Theory of Transfer Learning

What, when and How to transfer

Module 1: Detailed Agenda

- What is transfer learning?
- When to use transfer learning?
- Formal definition of transfer learning.
  - Mathematical Formulation
  - Formally, when to use transfer learning
  - Types of Transfer learning
- How to Do transfer learning in various scenarios
- Challenges of Transfer learning
- Presentation Time : 20 minutes

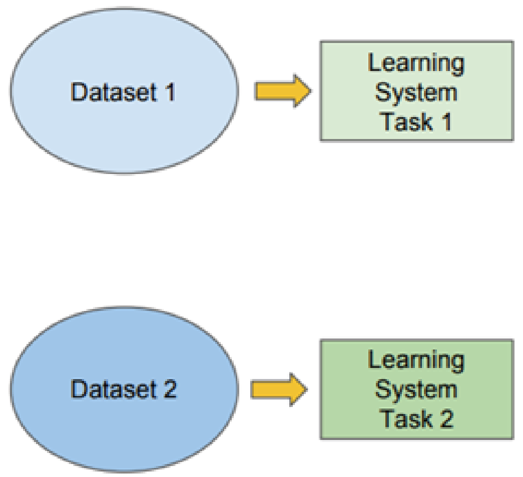
Transfer Learning

- To learn a new task, we humans need not always start afresh but rather apply previous learned knowledge. Any new concept is not learned in isolation, but considering connections to what is already known, which makes the skill of building analogies one of the cores of human intelligence
- Can Machines learn in the same way?
- "Transfer Learning" (TL) allows a machine learning model to port the knowledge acquired during training of one task to a new task.

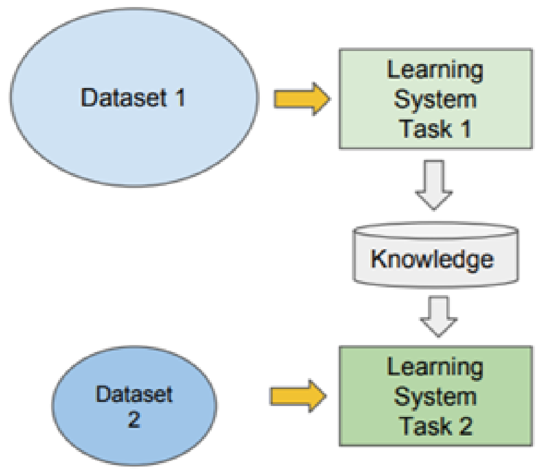
How TL is different from traditional ML

Traditional ML **vs** **Transfer Learning**

- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks



- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



When to use TL

- TL is a mostly used to obtain well-performing machine learning model in settings where high-quality labelled data is scarce. Sometimes, training data is expensive or difficult to collect.
- Even we have access to large dataset, but we have scarcity of resources like time or compute
- Privacy Preserving ML: Train ML models without exposing private data in its original form.
- Multimodal Deep Learning: Data has multiple modalities (audio, video, text, structured) and we need to use all forms of data to build a model.

Formal Definition of Transfer Learning

- Notations
  - $\mathcal{D}$ *–Domain*
  - $\mathcal{X}$ *–n dimensional Feature Space*
  - $\mathcal{Y}$ *– Target Space (discrete or continuous)*
  - $\mathcal{T}$ *– Task*
  - $f(.) \sim P(Y|X)$ *- Predictive Function , where* $Y \in \mathcal{Y}$ *and* $X \in \mathcal{X}$ –

  - **Domain** $\boldsymbol{\mathcal{D}} = (\boldsymbol{\mathcal{X}}, \boldsymbol{P}(\boldsymbol{\mathcal{X}}))$ ***, where*** $\boldsymbol{P}(\boldsymbol{\mathcal{X}})$ ***represents probability distribution over*** $\boldsymbol{\mathcal{X}}$

  - **Task** $\boldsymbol{\mathcal{T}} = (\boldsymbol{\mathcal{Y}}, \boldsymbol{f}(.))$

Example to Demonstrate the Notations

- Consider the food review sentiment analysis problem
  - *$\mathcal{D}$ – Food Reviews*
  - *$\mathcal{X}$ –Tf-idf representation of the review text or some dense representation of the review text as fixed size vectors*
  - *$\mathcal{Y}$ – Discrete – Positive or Negative*
  - *$\mathcal{T}$ – Classification*
  - *$f(.)$ - Predictive Binary classification model which takes a text representation from $\mathcal{X}$ and outputs a probability for the positive review.*

Transfer Learning

- Given a source domain $\boldsymbol{\mathcal{D}_S}$ with a corresponding source task $\boldsymbol{\mathcal{T}_S}$
- A target domain $\boldsymbol{\mathcal{D}_T}$ with a corresponding task $\boldsymbol{\mathcal{T}_T}$
- Transfer learning is the process of improving the target predictive function $\boldsymbol{f_T}$ by using the related information from $\boldsymbol{\mathcal{D}_S}$ and $\boldsymbol{\mathcal{T}_S}$, where $\boldsymbol{\mathcal{D}_S \neq \mathcal{D}_T}$ or $\boldsymbol{\mathcal{T}_S \neq \mathcal{T}_T}$.

How Domains and Tasks Vary

- $\boldsymbol{\mathcal{D}_S} \neq \boldsymbol{\mathcal{D}_T}$, where $\boldsymbol{\mathcal{D}_S} = \left(\mathcal{X}_S, P(\mathcal{X}_S)\right)$ and $\boldsymbol{\mathcal{D}_T} = \left(\mathcal{X}_T, P(\mathcal{X}_T)\right)$
  - Either $\mathcal{X}_S \neq \mathcal{X}_T$,Feature spaces are different
  - Or $P(\mathcal{X}_S) \neq P(\mathcal{X}_T)$, Feature space same but the distribution of features is different
- $\boldsymbol{\mathcal{T}_S} \neq \boldsymbol{\mathcal{T}_T}$, where $\boldsymbol{\mathcal{T}_S} = (\mathcal{Y}_S, f_S(.))$ and $\boldsymbol{\mathcal{T}_T} = (\mathcal{Y}_T, f_T(.))$
  - Either $\mathcal{Y}_S \neq \mathcal{Y}_T$, label spaces are different
  - or $f_S(.) \neq f_T(.)$ i.e., conditional probability distributions between the source and target domains are different
  - or $P(\mathcal{Y}_S) \neq P(\mathcal{Y}_T)$ i.e., different target data distribution like imbalance in classes

Scenarios When to use TL (Formal terms Source & Target Domains)

- **Unsupervised Transfer:** No labelled data in either source or target domain, but domains are similar with *unsupervised task* in the target domain.
- **Inductive Transfer:** Same source and target domains, but tasks are different. Use the knowledge from the source model to improve the target task model.
- **Transductive Transfer**: Similarities between the source and target tasks, but the corresponding domains are different. Source domain has a lot of labeled data, while the target domain has none.

Measuring Domain Closeness

- Domain/Task relatedness can be determined by simple reasoning, such as images from different viewing angles or different lighting conditions. Examples:
    1. In medical field, images captured from different devices
    2. In case of handwriting one domain of data may be handwriting on smart board whereas the other is handwriting on smart phone or tablet
    3. Food Reviews vs Hotel Reviews vs Movie Reviews.
- Formally:
    - Data for both domains are similar if they can be generated from a fixed probability distribution using a set of transformations.
    - Two tasks to be similar if they use the same features to make a decision.

Mathematically Measuring Closeness of Domains

- Maximum mean discrepancy (MMD) is an index to measure the discrepancy of two distributions in terms of distances between *mean embeddings* of features.
- Given $P(\mathcal{X}_S) \neq P(\mathcal{X}_T)$ and a ***nonlinear mapping function*** $\emptyset$: $\mathcal{X} \rightarrow \mathcal{H}$ ($\mathcal{H}$ is reproducing Kernel Hilbert space (RKHS)),

$$\text{MMD} = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(x_i^S) - \frac{1}{n_t} \sum_{i=1}^{n_t} \phi\left(x_i^T\right) \right\|_{\mathcal{H}}^2$$

Here, $\mathcal{H}$ is a space of real valued functions defined on $\mathcal{X}$.
A function $K: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ $(\mathrm{K(x,y)} = \phi(\mathrm{x})^{\mathrm{T}}\phi(\mathrm{y}))$ is called a kernel. ϕ is called the feature map. K is called reproducing kernel if it satisfies the following properties:

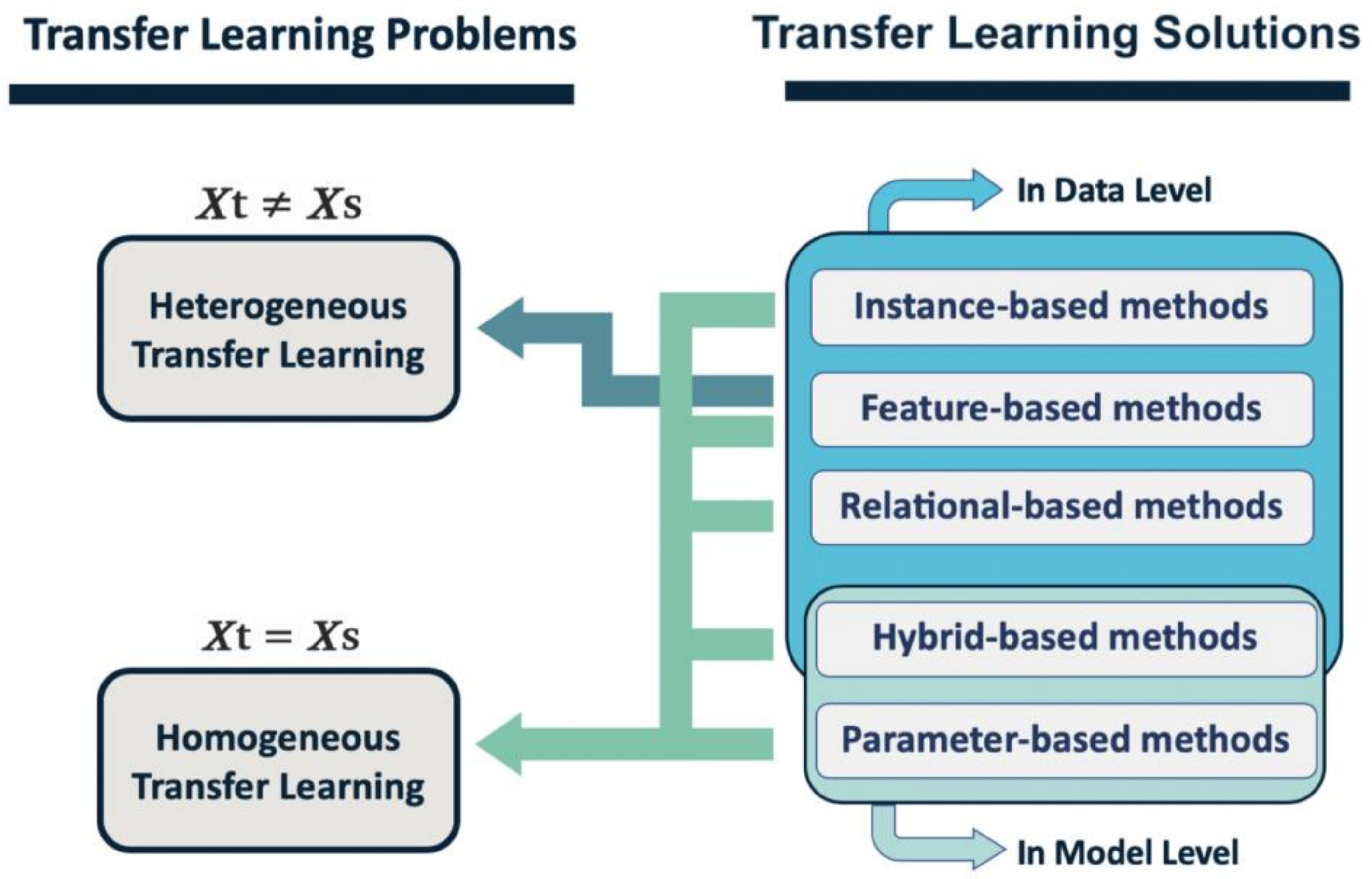
- $\forall x \in \mathcal{X}, \;\; k(\cdot, x) \in \mathcal{H}$,
- $\forall x \in \mathcal{X}, \forall f \in \mathcal{H}, \;\; \langle f, k(\cdot, x)\rangle_{\mathcal{H}} = f(x)$ (the reproducing property).

Reference (RHKS): https://www.gatsby.ucl.ac.uk/~gretton/coursefiles/RKHS_Notes1.pdf

Types of TL

- Homogeneous Transfer:
  - $\boldsymbol{\mathcal{X}_S} = \boldsymbol{\mathcal{X}_T}$ But $P(\mathcal{X}_S) \neq P(\mathcal{X}_T)$
  - $\mathcal{Y}_S = \mathcal{Y}_T$ But $P(\mathcal{Y}_S) \neq P(\mathcal{Y}_T)$
- Heterogeneous Transfer
  - $\boldsymbol{\mathcal{X}_S} \neq \boldsymbol{\mathcal{X}_T}$ And / OR
  - $\mathcal{Y}_S \neq \mathcal{Y}_T, \mathcal{Y}_S$ and or $\mathcal{Y}_S$ can be Ø (unsupervised)

How to Transfer



Source: https://medium.com/georgian-impact-blog/transfer-learning-part-1-ed0c174ad6e7

Instance Based Transfer

- To make a source domain trained model perform better, certain instances from the source domain can be reused along with target data to improve results.
  - AdaBoosting type approaches can be used to improve target model. Transfer AdaBoost learning framework TrAdaBoost, extends AdaBoost for transfer learning. It allows users to utilize a small amount of newly labeled data to leverage the old data to construct a high-quality classification model for the new data.
- This is extended to multi source transfer.

References:

- Dai W, Yang Q, Xue GR, Yu Y (2007) Boosting for transfer learning. In: Proceedings of the 24th international conference on machine learning. p. 193–200.
- Yao Y, Doretto G. Boosting for transfer learning with multiple sources. In: Proceedings of the IEEE computer society conference on computer vision and pattern recognition. 2010. p. 1855–62.

Feature Based Approach

- Applicable to both homogeneous and heterogeneous problems. There are 2 types:
- **Symmetric**: discovers underlying meaningful structures between the domains to find a common latent feature space Figure (a)
- **Asymmetric**: Transforms the features of the source to more closely match the target domain Figure (b)

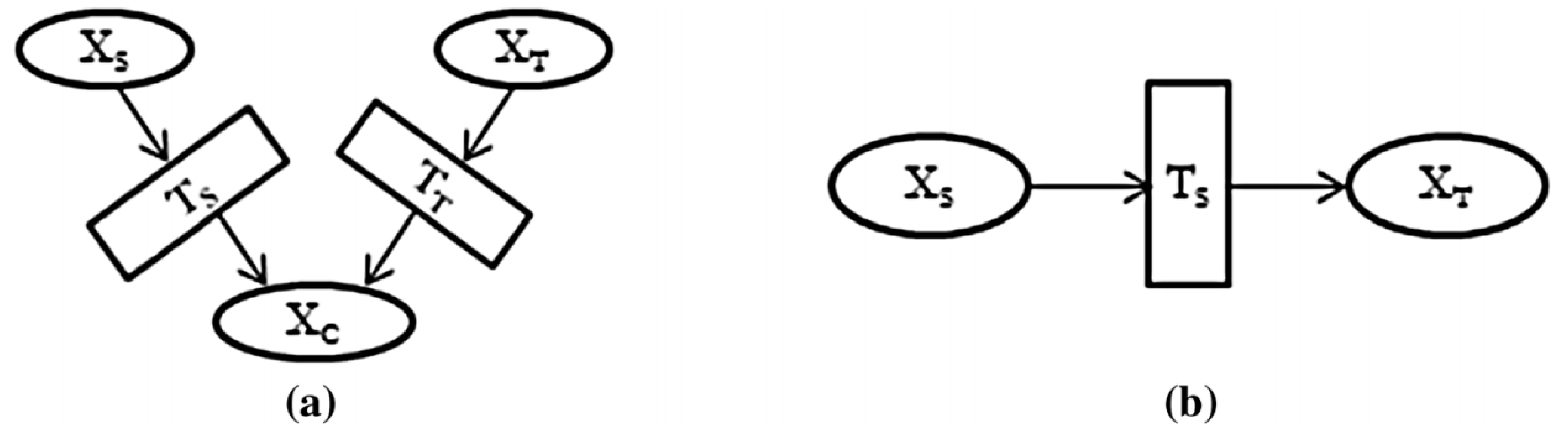


Fig. 1 **a** The symmetric transformation mapping (T_S and T_T) of the source (X_S) and target (X_T) domains into a common latent feature space. **b** The asymmetric transformation (T_T) of the source domain (X_S) to the target domain (X_T)

Parameter Based

A parametric model is learned in the source domain and transferred knowledge is encoded into parameters

- Multi-Source Parameter Transfer: If we have limited labelled target data and multiple labeled source domains, we can train separate classifiers for the source domains and optimally combine the re-weighted learners like ensemble learners to form an improved target learner.
- Single-Source Transfer: NN are parametric models, we can transfer the parameters learned in source domain to train a classifier in target domain.

Relation Based Transfer

- Relational-knowledge transfer attempts to handle non-i.i.d data.
    - where each data point has a relationship with other data points; for instance, social network data utilizes relational-knowledge-transfer techniques.
- Reference: GLoMo: Unsupervisedly Learned Relational Graphs as Transferable Representations
    - Instead of transferring features, we transfer the graphs output by a network. The graphs are multiplied by task-specific features (e.g. embeddings or hidden states) to produce structure-aware features

Transfer Learning Strategies in Deep Learning(DL)

- Domain Adaptation: (Parameter or Asymmetric Feature based)
- Domain Confusion: (Symmetric Feature based)
- Extreme Variants of TL: Multi-Task Learning, Zero-short and Few Short (Symmetric feature Based)

Challenges

- Learning without Forgetting
- Negative Transfer

Module 2: Application of TL For Image Source and Target Domains

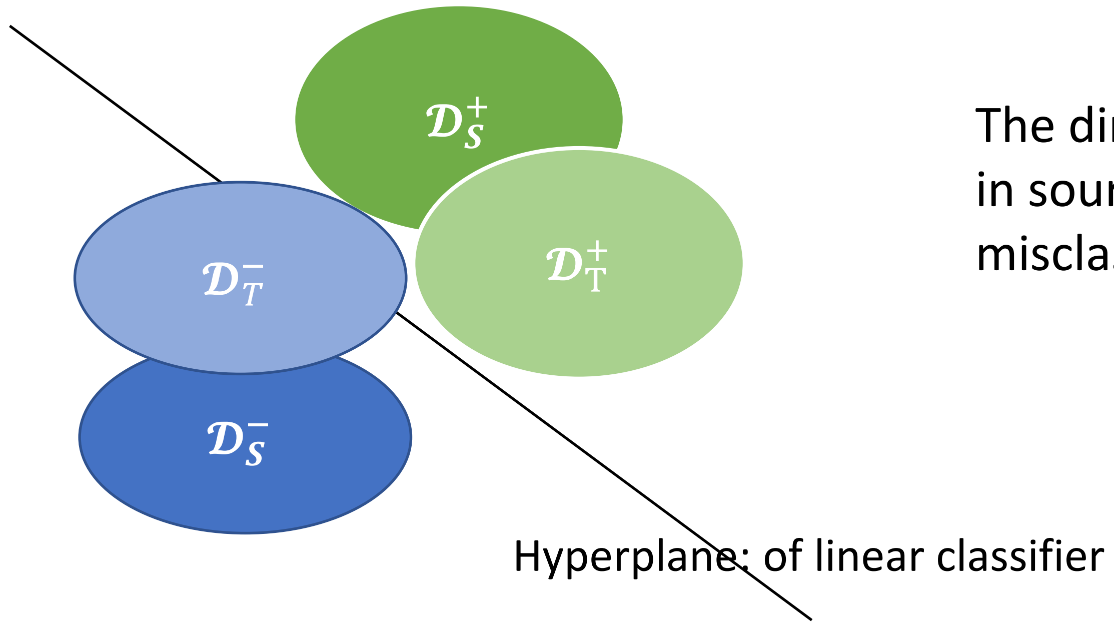
Module 2: Detailed Agenda

We will cover deep transfer technique: Unsupervised Domain Adaptation: there are no labelled observations in the target domain, but lots of training data in source domain.

- Asymmetric Feature Based:
  - Joint Distribution Adaptation: MNIST (source) -> USPS (Target w/o labels)
- Symmetric Feature Based Approach:
  - Adversarial Domain Adaptation: MNIST (source) -> USPS (Target w/o labels)

Case of No Labelled data in target domain Only: Feature based Transfer

- No Labelled data in target domain, enough labelled data in source domain. However, source and target domains have the same label spaces



The direct use of trained discriminative hyperplane in source domain will lead to the extensive misclassification in target domain.

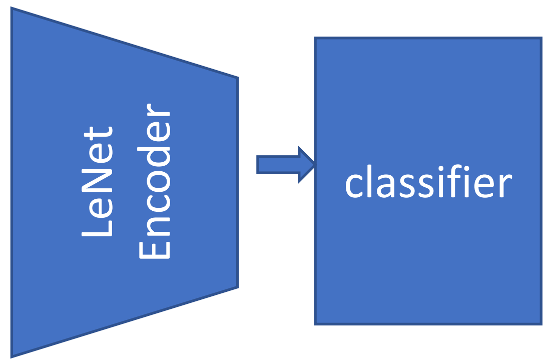
Joint Distribution Adaptation (JDA)

- First Introduced : Transfer Feature Learning with JDA(1CCV 2013) Cited by 1386
- Later Work: Deep Transfer Network with JDA by T Han · 2018 · Cited by 277
- USPS dataset consists of 7,291 training images and 2,007 test images of size 16 × 16. MNIST dataset has a training set of 60,000 examples and a test set of 10,000 examples of size 28 × 28.

https://openaccess.thecvf.com/content_iccv_2013/papers/Long_Transfer_Feature_Learning_2013_ICCV_paper.pdf

Approach

- Domains: Source = MNIST , Target = USPS (w/o labels)
- Train Model on Source and Adapt to the target later
- Model:



- Train Full model with cross-entropy loss on source
- Joint Training on target and source with same cross-entropy loss on Source data batch and JDA loss on target. JDA loss requires class labels, we will use labels predicted by model and compute JDA loss for target data.
- Encoder adapts to both domains and tries to perform better in both domains.

JDA Loss

- JDA : $\min D(P_s(\phi(X_S)), P_T(\phi(X_T)))$, D is the function to evaluate the domain discrepancy.
- JDA = MDA + CDA
- MDA = Marginal Distribution Adaptation : contributes to improving transfer performance – can be approximated by MMD Metric
- CDA = Conditional Distribution Adaptation: aims to match the discrimination structures between labeled source data and unlabeled target data.
    - Can be approximated by computing class wise MMD, where class labels in target are obtained using pseudo-labels predicted by source trained model

Notebook JDA

- https://github.com/tamoghnaG/ODSC22-west-A-Hands-on-Introduction-to-Transfer-Learning/blob/main/Notebook_01_JDA.ipynb

Adversarial Discriminative Domain Adaptation (ADDA)

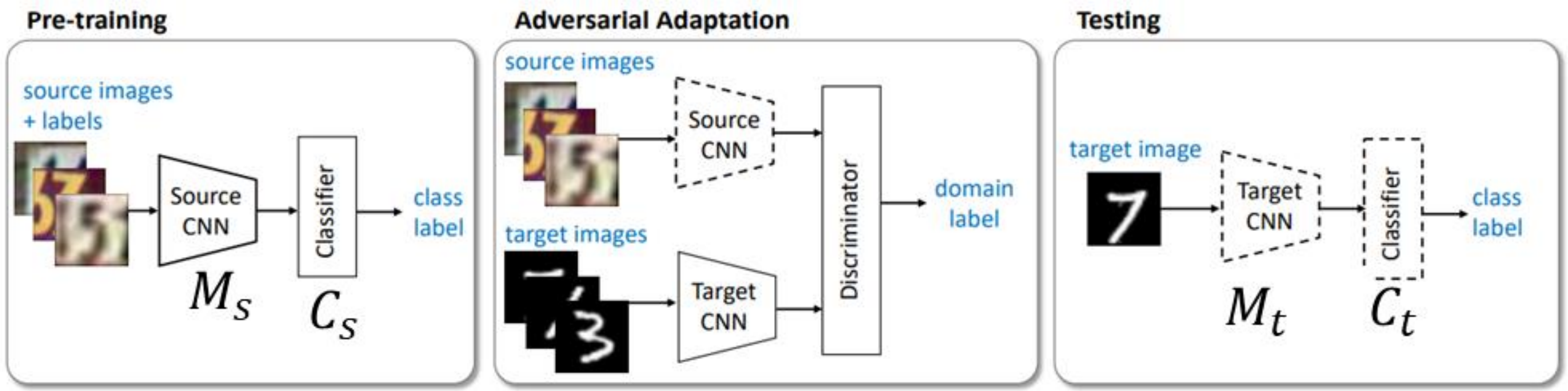


Figure 3: An overview of our proposed Adversarial Discriminative Domain Adaptation (ADDA) approach. We first pre-train a source encoder CNN using labeled source image examples. Next, we perform adversarial adaptation by learning a target encoder CNN such that a discriminator that sees encoded source and target examples cannot reliably predict their domain label. During testing, target images are mapped with the target encoder to the shared feature space and classified by the source classifier. Dashed lines indicate fixed network parameters.

AADA: Approach

- Let M_s, M_t represent the source and target encoders respectively
- Let C_s, C_t represent the source and target classifiers
- Pretraining: Train CNN based Classifier for source domain i.e., M_s, C_s
- Regularize the learning of M_s, M_t, to minimize distance between empirical source, target mapping distributions: $M_s(X_s)$ and $M_t(X_t)$.
- Learn to adapt source model for use in the target domain in an adversarial setting as follows:
  - Generators: M_s is considered real and M_t the fake generated encodings
  - Domain discriminator, D, which classifies whether an encoded image is drawn from the source or the target domain.
  - Train Target encoder to fool the discriminator.
  - **No need to learn a separate target classifier** and instead setting, $C = C_s = C_t$.

Notebook : ADDA

- https://github.com/tamoghnaG/ODSC22-west-A-Hands-on-Introduction-to-Transfer-Learning/blob/main/Notebook_02_ADDA.ipynb
- Pytorch Implementation of the paper:

  https://github.com/corenel/pytorch-adda

Module 3: Transfer Learning in Text

Module 3: Detailed Agenda

- Unsupervised Transfer: Unsupervised Text Representation or word embedding. Examples:
  - SkipGram with hands-on code
- Feature based asymmetric Transfer: Sentiment Analysis: Target domain has less labelled data, source has labelled data.
  - SA learned on Amazonreviews (product reviews) works on small movie review dataset with fine-tuning final layers of source classifier (Hands-on)
- Feature based Symmetric Transfer: Sentiment Analysis: Target domain has No labelled data source has labelled data.
  - SDAE : Domain Adaptation for Large-Scale Sentiment Classification (by X Glorot ICML 2011 · Cited by 2024)
  - BERT Pre-Trained with MLM on both datasets to get sentence embedding. Train classifier on product review and apply directly on movie review w/o further finetuning

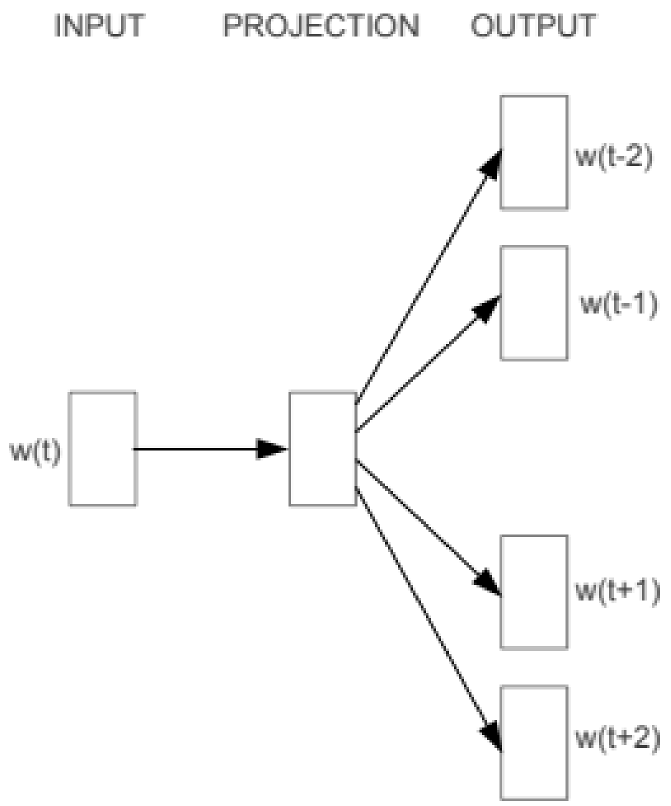
Text Pre-processing Steps

- Each Document Is Processed As Follows:
  - Tokenize document to Words
  - Lowercasing Words
- Build Vocab: Keep Words Appearing > MIN_WORD_COUNT

Skip-Gram Model: Unsupervised Word Embedding

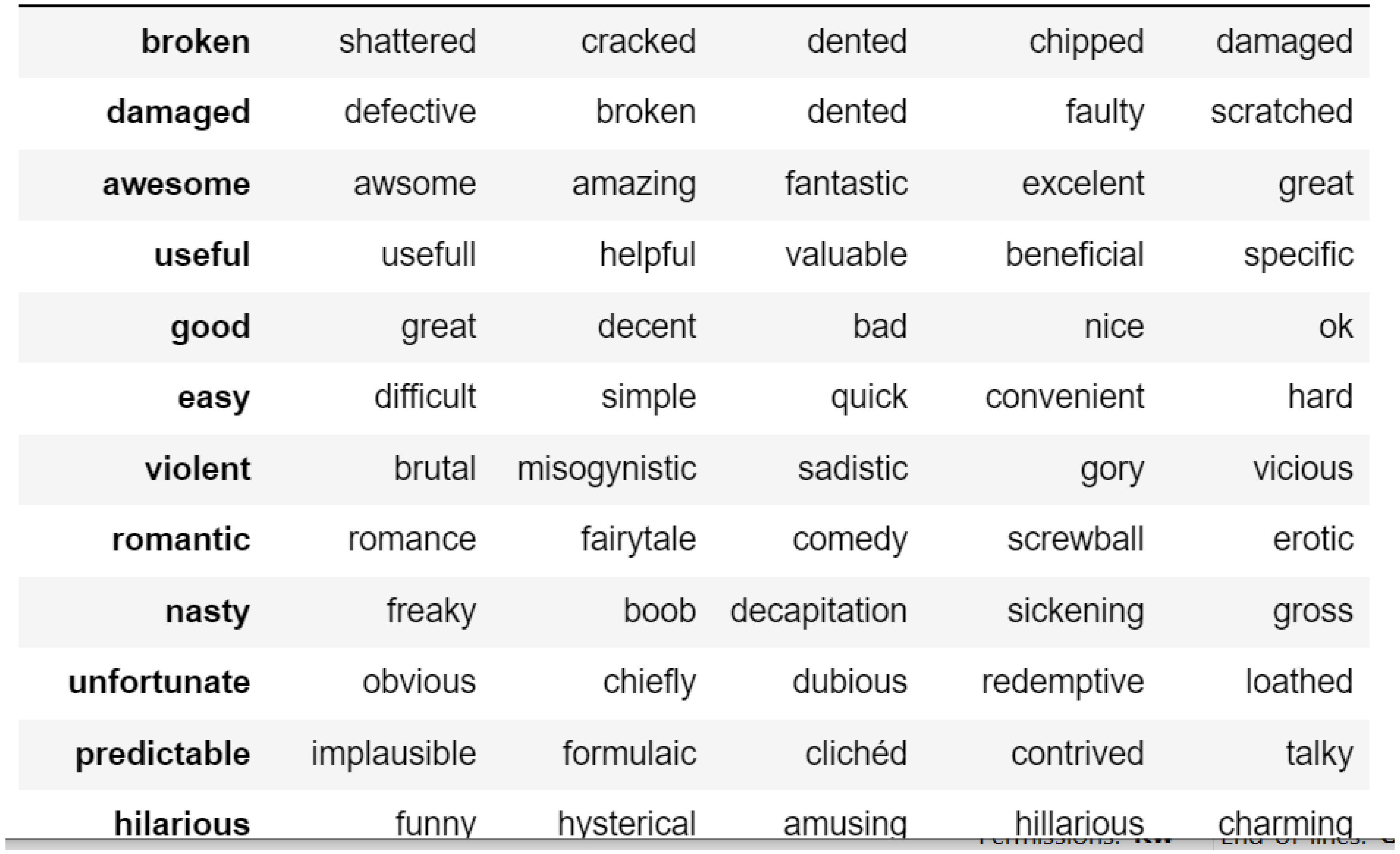
Window Size	Text	Skip-grams
2	[The **wide** road shimmered] in the hot sun.	wide, the wide, road wide, shimmered
	The [wide road **shimmered** in the] hot sun.	shimmered, wide shimmered, road shimmered, in shimmered, the
	The wide road shimmered in [the hot **sun**].	sun, the sun, hot
3	[The **wide** road shimmered in] the hot sun.	wide, the wide, road wide, shimmered wide, in
	[The wide road **shimmered** in the hot] sun.	shimmered, the shimmered, wide shimmered, road shimmered, in shimmered, the shimmered, hot
	The wide road shimmered [in the hot **sun**].	sun, in sun, the sun, hot

Source: https://www.tensorflow.org/tutorials/text/word2vec



Skip-gram

Learned SkipGram Embeddings

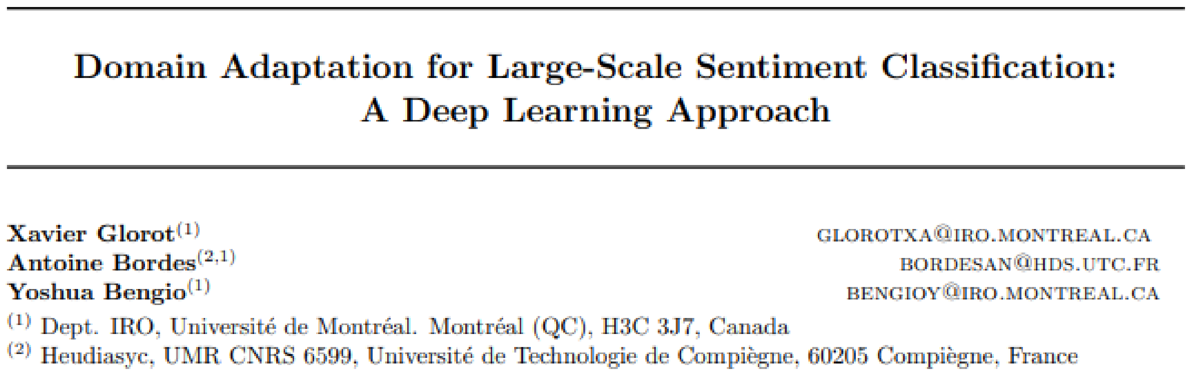


broken	shattered	cracked	dented	chipped	damaged
damaged	defective	broken	dented	faulty	scratched
awesome	awsome	amazing	fantastic	excelent	great
useful	usefull	helpful	valuable	beneficial	specific
good	great	decent	bad	nice	ok
easy	difficult	simple	quick	convenient	hard
violent	brutal	misogynistic	sadistic	gory	vicious
romantic	romance	fairytale	comedy	screwball	erotic
nasty	freaky	boob	decapitation	sickening	gross
unfortunate	obvious	chiefly	dubious	redemptive	loathed
predictable	implausible	formulaic	clichéd	contrived	talky
hilarious	funny	hysterical	amusing	hillarious	charming

Asymmetric Transfer

- 1D CNN based SA learned on Amazonreviews (product reviews) works on small movie review dataset with fine-tuning final layers of source classifier and document embedding layer (Hands-on)
- Notebook Link: https://github.com/tamoghnaG/ODSC22-west-A-Hands-on-Introduction-to-Transfer-Learning/blob/main/Notebook_SA_03.ipynb

Symmetric Transfer


Domain Adaptation for Large-Scale Sentiment Classification: A Deep Learning Approach

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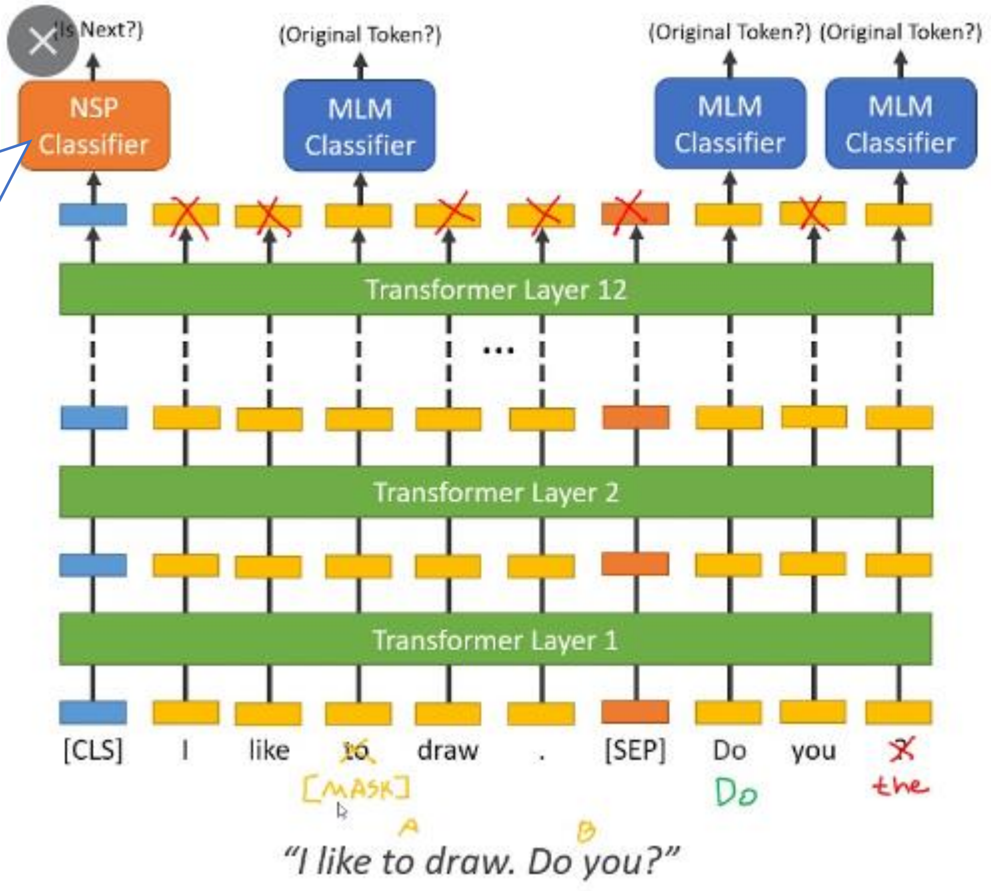
Use Stacked denoising autoencoder (SDA) to resolve the marginal distribution differences between a labeled source domain and an unlabeled target domain.

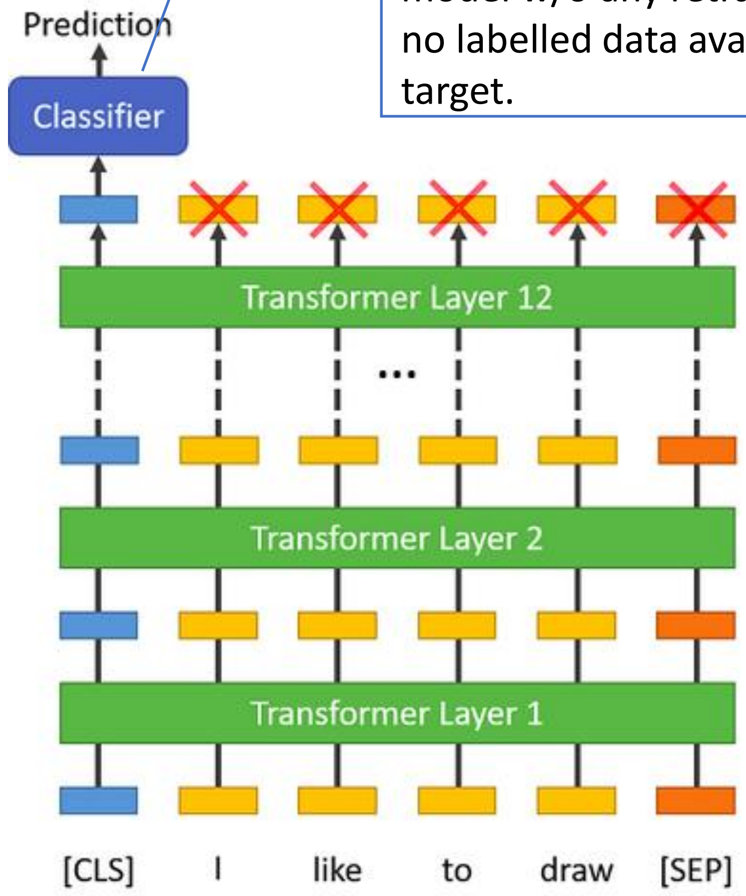
- train SDA with unlabeled data from the source and target domains to transforms the input space to discover the common invariant latent feature space.
- train a classifier using the transformed latent features with the labeled source data

Symmetric Transfer: BERT based pretraining to create doc-embedding

Pretrain with NSP,MLM on both source and target docs to get generic document embedding common for both domains.

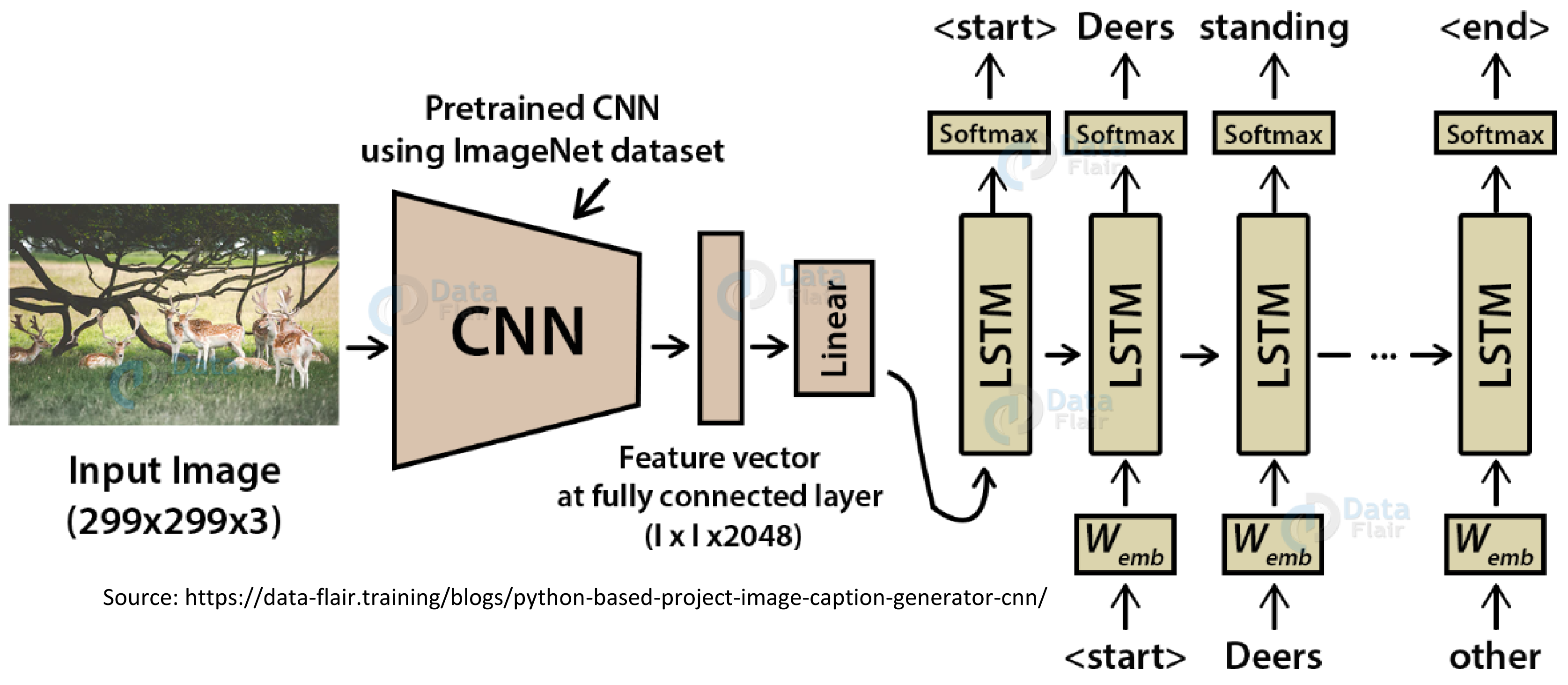


Source: https://www.youtube.com/watch?v=Fs8Zb4T-_CE



Sentiment Classifier trained on the document embeddings of source model, also performs well for target model w/o any retraining as no labelled data available in target.

Image Captioning: Symmetric Transfer



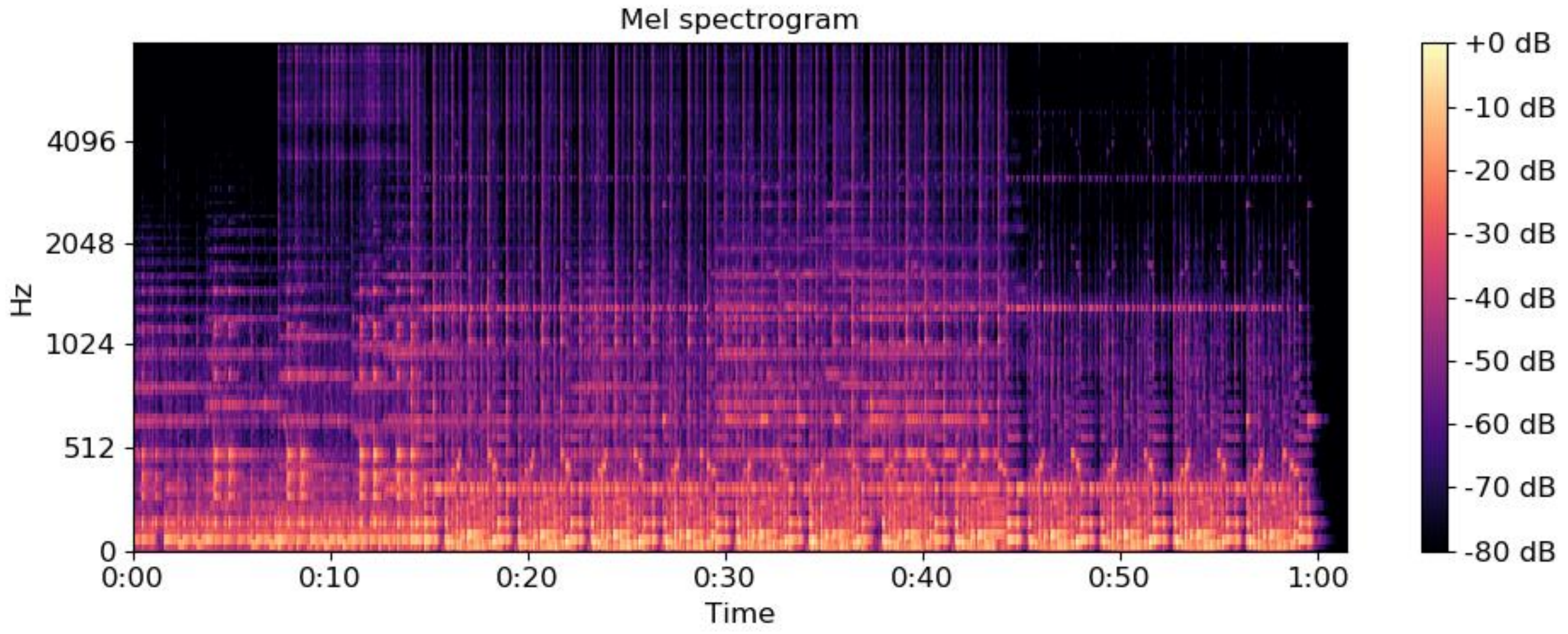
Source: https://data-flair.training/blogs/python-based-project-image-caption-generator-cnn/

LINK TO CODE
https://github.com/tamoghnaG/hands-on-transfer-learning-with-python/tree/master/notebooks/Ch11%20-%20Automated%20Image%20Caption%20Generator

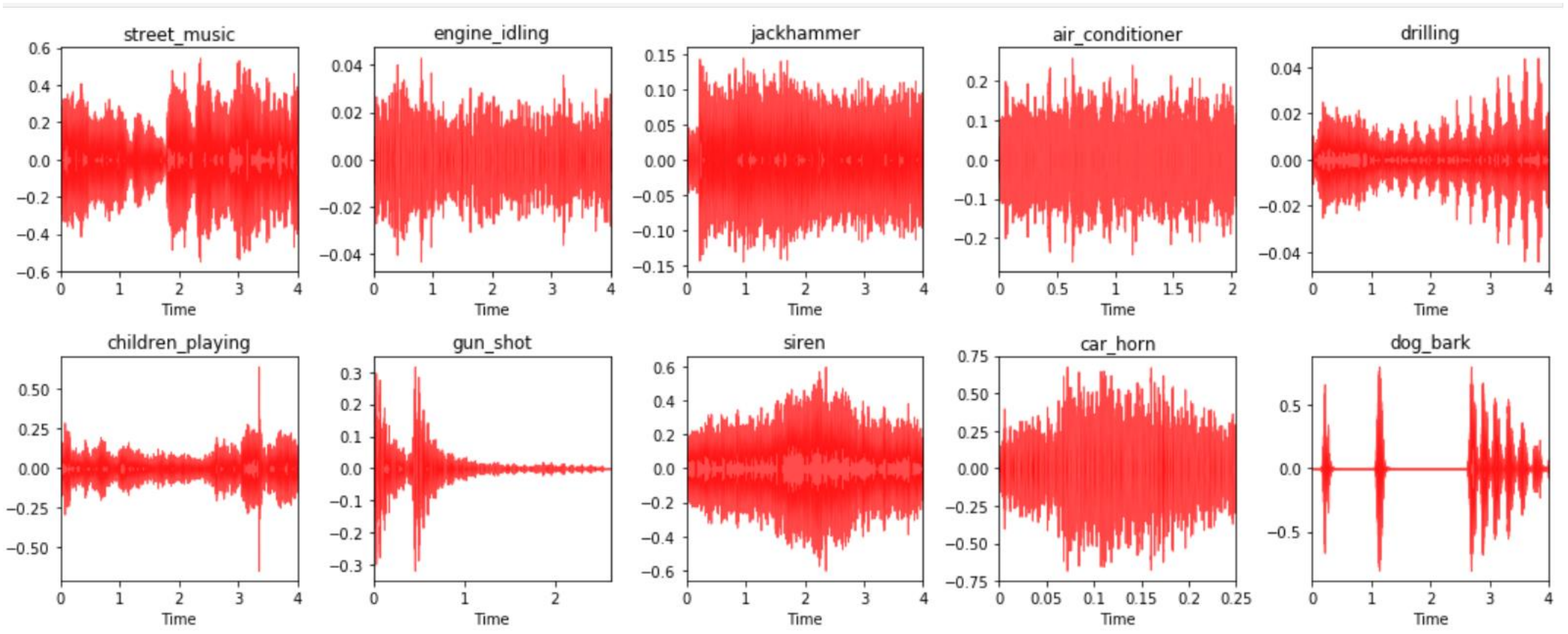
Module 4: Transfer Learning For Audio Event Detection

Audio Event Classification

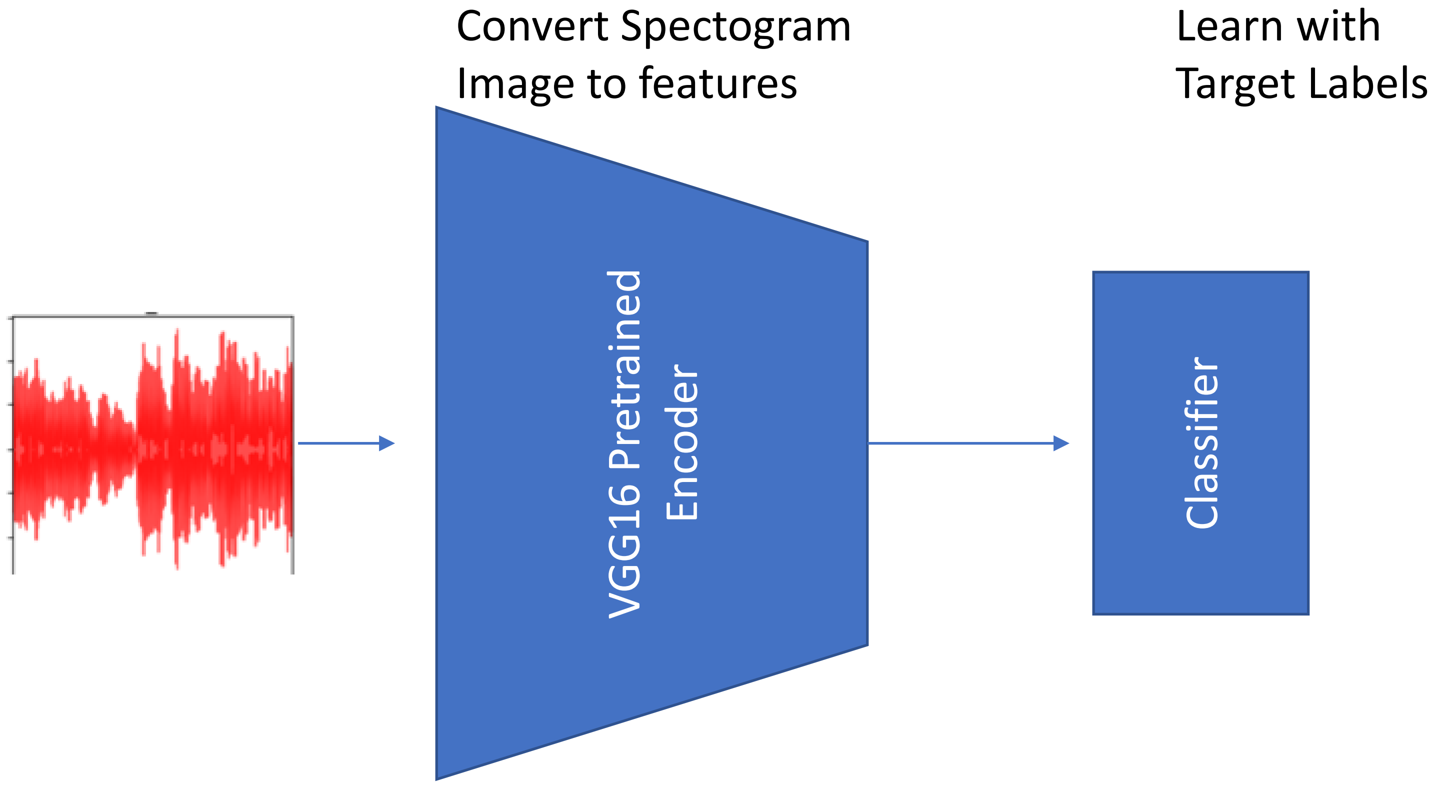
- The UrbanSound dataset consists of 8732 labelled short (less than 4 s) sound excerpts of urban sounds from 10 different classes



Types of Audio Events



Model



LINK to Code:
https://github.com/dipanjanS/hands-on-transfer-learning-with-python/tree/master/notebooks/Ch08%20-%20Audio%20Identification%20and%20Categorization

Module 5: Advanced Applications of Transfer Learning

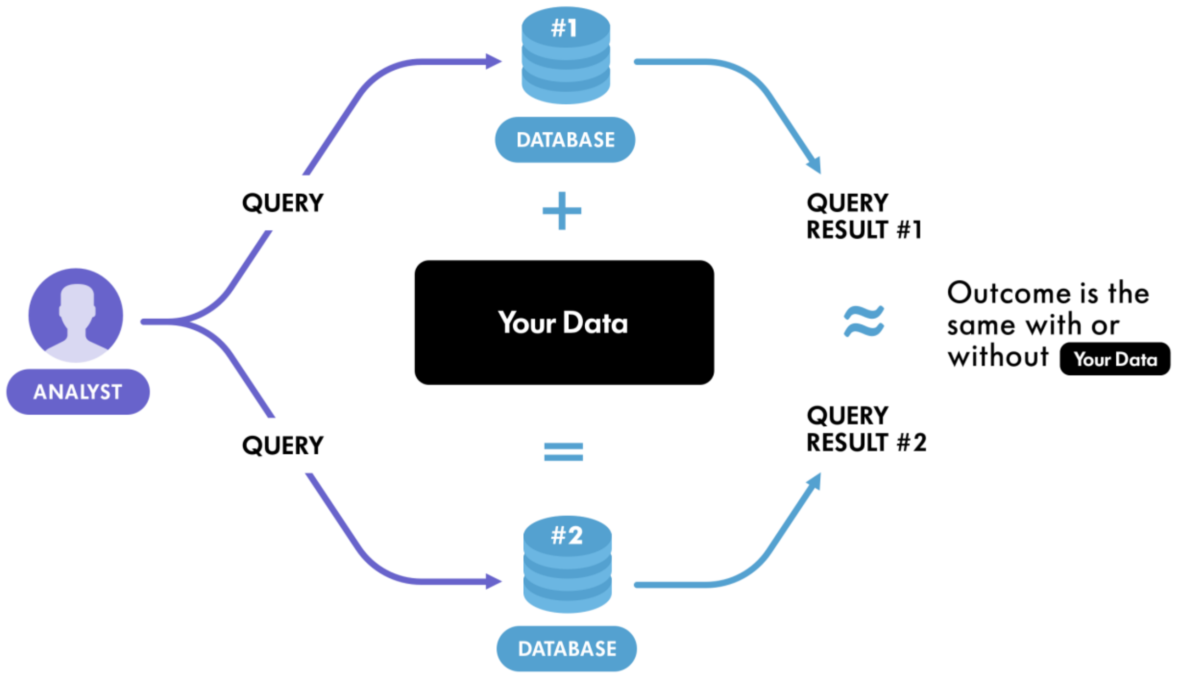
Advanced Application of Transfer learning

- *Multimodal Deep Learning*: Learn features over multiple modalities (audio, video, text, structured)
- *Privacy Preserving ML*: Train ML models without exposing private data in its original form.

Privacy Preserving ML

- The goal of privacy-preserving machine learning is to bridge the gap between privacy while receiving the benefits of machine learning.
- Differential Privacy (DP) provides a formal framework for training machine learning models with individual example level privacy.
- Differentially Private Stochastic Gradient Descent (DP-SGD) has emerged as a popular private training algorithm.
  - the computational cost of training large-scale models with DP-SGD is substantially higher than non-private training
- Reference: https://arxiv.org/abs/2205.02973

Differential Privacy



A simple Scenario
Query1: Sum of all for a col M

Query2: Sum of all for a col M

Query1-Query2 = Your Data
(Privacy Leaked)

Simple Mitigation Strategy:
1. Local: Adding noise before appending to the database.
2. Global: Adding noise before extracting the information

https://www.section.io/engineering-education/understanding-differential-privacy/

Differential Privacy in ML

- We only need loss value to compute gradient
  - So, we can query out private database to return the loss for a data batch. No, need to have direct access to data.
- However, large gradients norms may indicate sensitive data in the selected batch and we may have a privacy breach.

Overview of DP-SGD

For each example in a minibatch:

1. compute the gradient
2. clip to a pre-selected norm
3. add Gaussian noise before averaging over the minibatch
4. Average over batch and compute SGD step

In practice, DP training can be very expensive or even ineffective for very large models. Not only does the cost of calculating the per-example gradient increase with parameter count, but the norm of the noise added also increases.

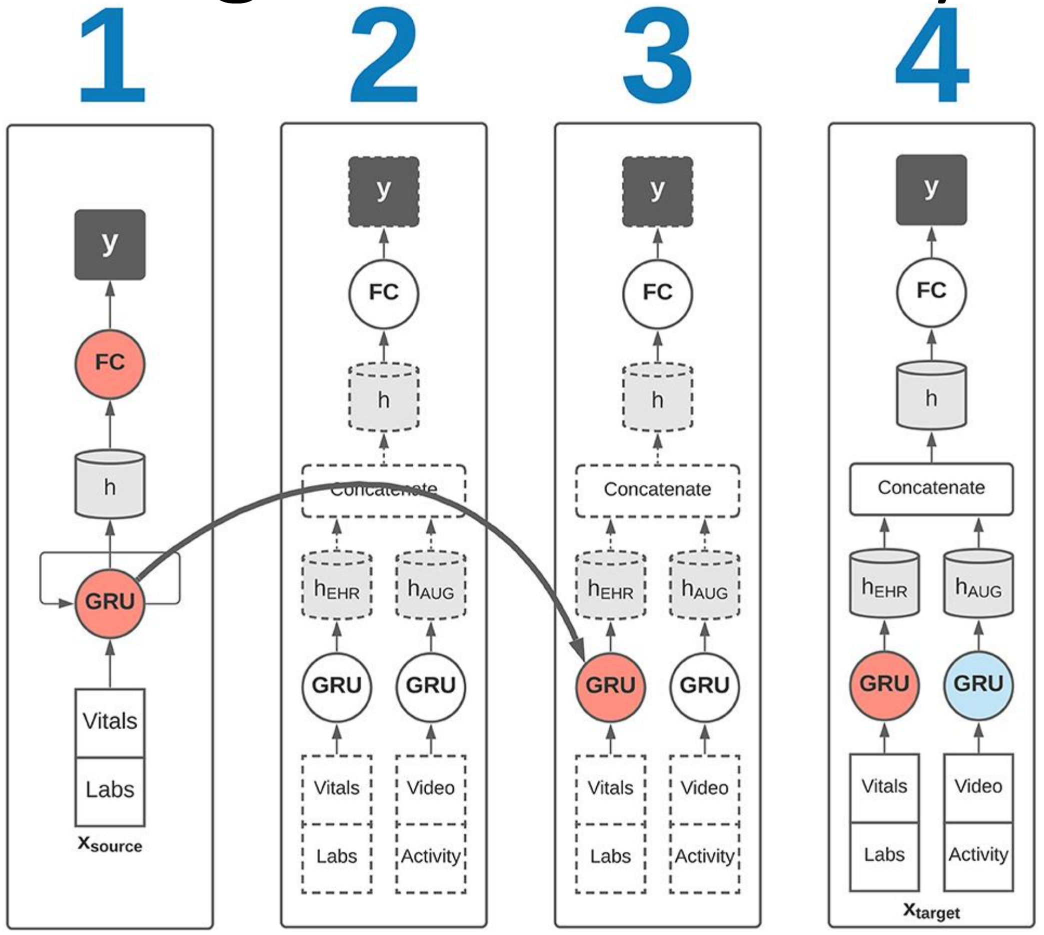
Transfer Learning For PPML

- Have access to a large public or non-sensitive dataset of the same modality as the private data.
- The model is first pre-trained using the large public or non-sensitive dataset in the traditional non-private way.
- Then at finetuning time do we resort to DP-SGD updates to ensure privacy guarantees for the fine-tuned model.
- Some Recommendations For Implementation:
    1. Increase pretraining data and model size.
    2. Use very large batch sizes in combination with optimizers that can work well with large batch sizes (e.g. LAMB)
    3. Initialize the last layer to zero (or very small) when doing finetuning with DP.

Multi-Modal Learning

- Data has different modalities
    - Example: A social media post (video + Text Comments + description)
    - Example: Sensors - Patient Acuity Assessment in the Intelligent ICU (vital sensors data + patient Video + Audio)

Transfer Learning: Patient Acuity



Train single GRU source model using EHR data from large traditional ICU cohort.

Initialize final Intelligent ICU model with parallel GRUs.

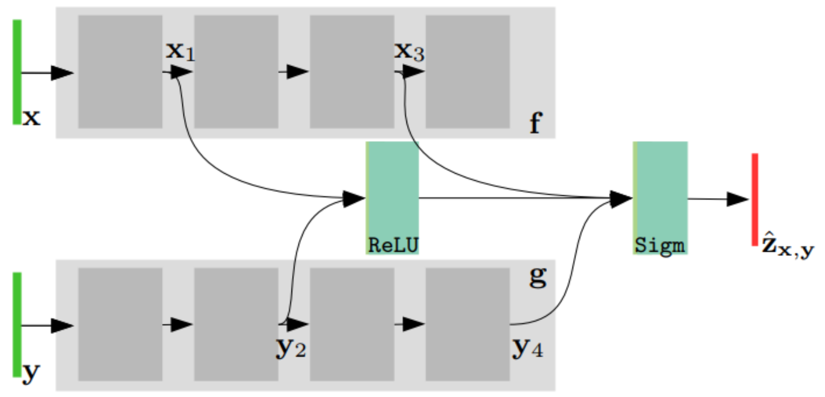
Transfer GRU weights from trained source model to EHR portion of Intelligent ICU model.

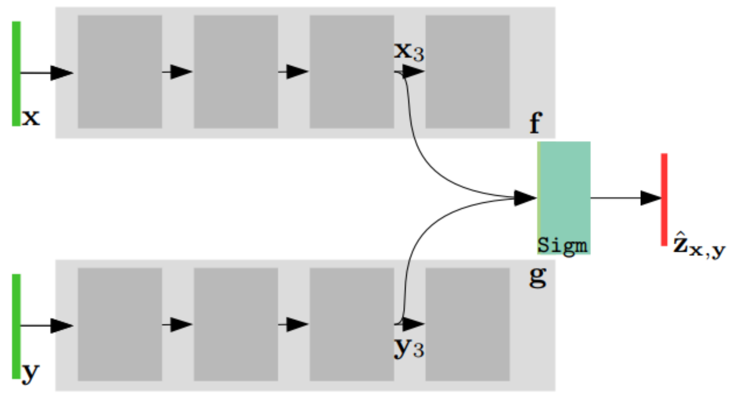
Train/fine-tune Intelligent ICU model using all available target data.

https://www.frontiersin.org/files/Articles/640685/fdgth-03-640685-HTML/image_m/fdgth-03-640685-g003.jp

Typical Approach: Multimodal Transfer

- Use pre-trained networks to extract features from each modality and then either concatenate them or project them to a common space.
- Which Layer Of Feature Extractor to use? Brute-Force?





MFAS: Multimodal Fusion Architecture Search

- Exhaustively exploring all possible architectures is intractable.
- A surrogate function is trained during progressive exploration of the search space, and it is used to reduce the amount of neural networks that have to be trained and evaluated by predicting performance of unseen architectures
- Reference: https://arxiv.org/abs/1903.06496 by JM Pérez-Rúa · 2019 · Cited by 117

Conclusion

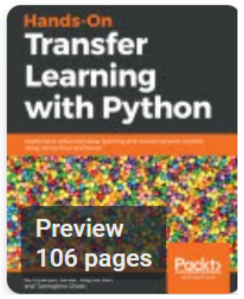
- We learned about various types of transfer learning
- Deep Transfer Learning: Domain Adaptation & Domain Confusion
- Advanced Transfer Learning Applications
- More on Transfer Learning

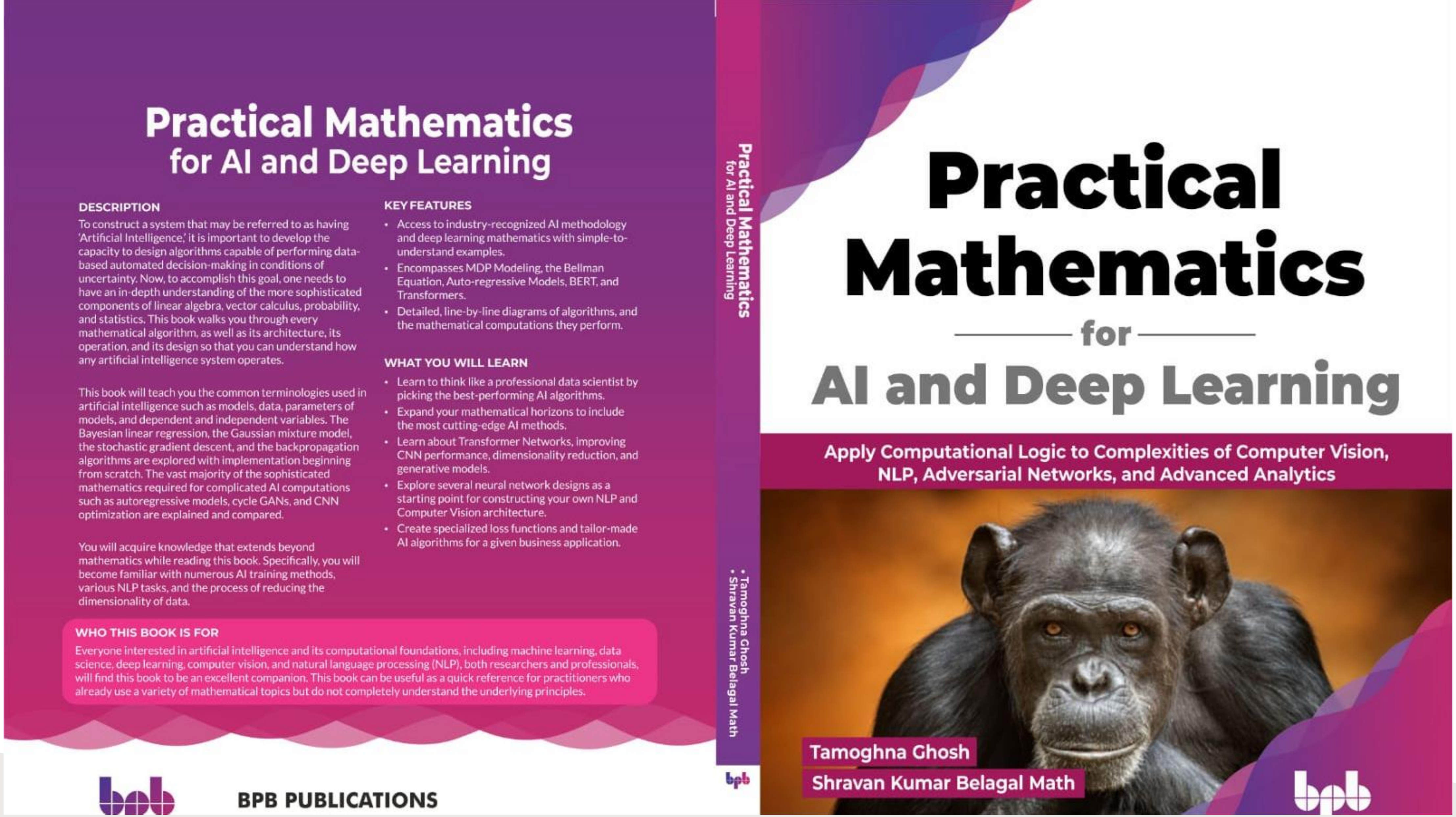
https://www.amazon.in/Hands-Transfer-Learning-Python-TensorFlow/dp/1788831306

Hands-On Transfer Learning with Python

Implement Advanced Deep Learning and Neural Network Models Using TensorFlow and Keras

By Dipanjan Sarkar, Raghav Bali, Tamoghna Ghosh · 2018





Practical Mathematics for AI and Deep Learning

DESCRIPTION

To construct a system that may be referred to as having 'Artificial Intelligence,' it is important to develop the capacity to design algorithms capable of performing data-based automated decision-making in conditions of uncertainty. Now, to accomplish this goal, one needs to have an in-depth understanding of the more sophisticated components of linear algebra, vector calculus, probability, and statistics. This book walks you through every mathematical algorithm, as well as its architecture, its operation, and its design so that you can understand how any artificial intelligence system operates.

This book will teach you the common terminologies used in artificial intelligence such as models, data, parameters of models, and dependent and independent variables. The Bayesian linear regression, the Gaussian mixture model, the stochastic gradient descent, and the backpropagation algorithms are explored with implementation beginning from scratch. The vast majority of the sophisticated mathematics required for complicated AI computations such as autoregressive models, cycle GANs, and CNN optimization are explained and compared.

You will acquire knowledge that extends beyond mathematics while reading this book. Specifically, you will become familiar with numerous AI training methods, various NLP tasks, and the process of reducing the dimensionality of data.

KEY FEATURES

- Access to industry-recognized AI methodology and deep learning mathematics with simple-to-understand examples.
- Encompasses MDP Modeling, the Bellman Equation, Auto-regressive Models, BERT, and Transformers.
- Detailed, line-by-line diagrams of algorithms, and the mathematical computations they perform.

WHAT YOU WILL LEARN

- Learn to think like a professional data scientist by picking the best-performing AI algorithms.
- Expand your mathematical horizons to include the most cutting-edge AI methods.
- Learn about Transformer Networks, improving CNN performance, dimensionality reduction, and generative models.
- Explore several neural network designs as a starting point for constructing your own NLP and Computer Vision architecture.
- Create specialized loss functions and tailor-made AI algorithms for a given business application.

WHO THIS BOOK IS FOR

Everyone interested in artificial intelligence and its computational foundations, including machine learning, data science, deep learning, computer vision, and natural language processing (NLP), both researchers and professionals, will find this book to be an excellent companion. This book can be useful as a quick reference for practitioners who already use a variety of mathematical topics but do not completely understand the underlying principles.

BPB PUBLICATIONS

Practical Mathematics for AI and Deep Learning

• Tamoghna Ghosh • Shravan Kumar Belagal Math

Practical Mathematics for AI and Deep Learning

Apply Computational Logic to Complexities of Computer Vision, NLP, Adversarial Networks, and Advanced Analytics

Tamoghna Ghosh

Shravan Kumar Belagal Math

Coming Soon ...

Thankyou

BACKUP

Multi Model Knowledge Transfer (MMKT)

- Learning Categories from Few Examples
  - A lot of annotated data on a source problem and the need to solve a different target problem with few labeled samples, where source and target present a distribution mismatch
  - Example: We want to learn the target object class *okapi* from few examples, having already a model for the source categories *horse, zebra, melon and apple.*
    - The okapi looks like horse / zebra. Thus, in the learning process we would like to transfer information from these two categories.

okapi

How to Transfer Parameters

- Train Binary Classifiers on each of the source classes (One-vs-Rest)
- A Linear classifier will look like the following:
  - $f(\boldsymbol{x}) = \boldsymbol{w}^T \phi(\boldsymbol{x}) + b$
  - Here $\phi(\boldsymbol{x})$ is a feature mapping, that maps the samples into a high, possible infinite dimensional space, where the dot product is expressed with a functional form $K(\boldsymbol{x}, \boldsymbol{x}') = \phi(\boldsymbol{x})^T \phi(\boldsymbol{x}')$ - the kernel function
- Given **J** source classifiers for each source: $f_j(\boldsymbol{x}) = \hat{\boldsymbol{w}}_{\boldsymbol{j}}^T \phi(\boldsymbol{x}) + b$
- The target classifier parameters $\boldsymbol{w}$ can be defined as a weighed combination of the source parameters : $\boldsymbol{w} = \sum_j \beta_j \hat{\boldsymbol{w}}_{\boldsymbol{j}}$
- From few target labels we can learn the β_js.

Finding the domain weights β_j

- The transfer learning problem boils down to finding the weights β_j such that we can find the target classifier weights as $\boldsymbol{w} = \sum_j \beta_j \hat{\boldsymbol{w}}_{\boldsymbol{j}}$
- This can be formulated as an LS-SVM (least square support vector machine) type optimization problem.
- In LS-SVM, due to the use of equality constraints in the formulation of optimization problem, a set of *linear equations* must be solved instead of a quadratic programming problem in classical SVM

Adaptive LS-SVM Formulation for finding weights β_j from limited (N) target labelled data

$$\min_{w,b} \frac{1}{2}\left\| w - \sum_{j=1}^{J} \beta_j \hat{w}_j \right\|^2 + \frac{C}{2}\sum_{i=1}^{N} \zeta_i \xi_i^2$$
$$\text{s.t.} \quad y_i = w^\top \phi(x_i) + b + \xi_i, \ \forall i = 1, \ldots, N,$$

parameter ζi can be used to balance the contribution of positive and negative samples

$$\zeta_i = \begin{cases} \frac{N}{2N^+} \text{ if } y_i = +1 \\ \frac{N}{2N^-} \text{ if } y_i = -1 \ . \end{cases} \qquad (9)$$

Here N^+ and N^- represent the number of positive and negative examples respectively.