

Introduction to Data Shift & Concept Drift

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Outline

- **Chapter I: Introduction**
 - What is Data Shift?
 - Why Data Shift Happens?
 - Why Handle Data Shift?
 - What are the consequences of not properly addressing data shift?
 - How to approach data shift?
- **Chapter II: Data Shift**
 - Data Shift Types and Patterns
 - Data Shift Detection & Correction
 - Transfer and Active Learning
 - Evaluation and Discussion
 - Packages
- **Chapter III: Discussion and Q&A**

Introduction



Definition

What is Data Shift?

- In classic **Machine learning**, models are trained under the premise that the training and the real-world (i.e., both source and target) data are from the same distribution
- Such assumption may potentially result in predictive problems in **dynamic** industries and environments where the distribution of data changes over time
- The existence of such a difference between the dataset distributions is called as **dataset shift** in the machine learning community.
- In fact, most real-world applications should cope with some form of shift as the distribution of the data used to train a model differs from the distribution of the data that the model encounters after its **deployment**.

Why Data Shift Happens?

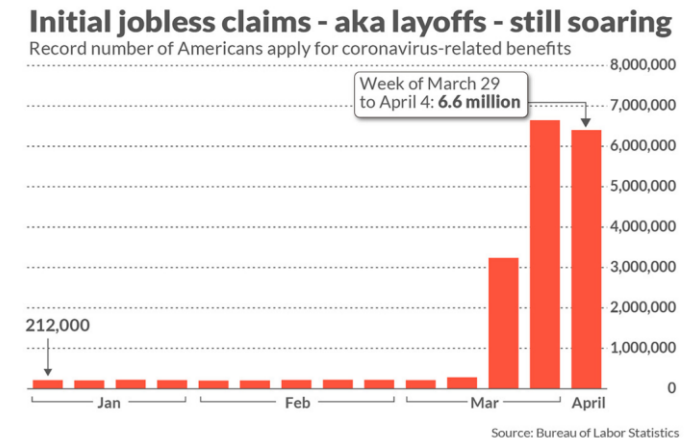
- **Reasons for experiences data shift could be:**
 - Political
 - Industrial (Solar & Clean Energy)
 - Financial (Shift from Fiat to Crypto...!)
 - Retail (supply and demand)
 - Pandemic, e.g., COVID 19 and SARS
 - War & Immigration
 - House Price (2007)
 - IT & Internet (e.g., Dot-com)
 - Security & Privacy (Cyber attack)
 - Environmental (Global warming, weather)
 - Natural (Bird Migrations)
 - Dynamic nature (Smart Houses)
 - Unexpected



Motivation

Why Handle Data Shift?

- We train a model to predict “Jobless Claims” in the US
- In practice, the model correctly predicts 200k claims for the fourth week of March 2020
- COVID 19 hits and unemployment claims skyrocket
- The model now predicts 800k claims; it’s higher than normal, but is it reliable? (In reality, it is over 6 millions...)
- After pandemic, the model parameters (e.g., layoffs, closures, mobility, data, etc.) may have dramatically changed
- The model trained on historical jobless claims data may underestimate the effect of the pandemic



Motivation

Why Handle Data Shift?

- **Pre-COVID:**
 - Trained a model to predict bankruptcy of an entity
 - Data:
 - 70% Non-bankrupted,
 - 20% Likely to Bankrupt,
 - 10% Will Bankrupt
 - The model had an accuracy of 80% (vs. 33% for a random classifier)
- **Post-COVID:**
 - After COVID, we observed:
 - 40% Non-bankrupted,
 - 60% bankrupted
 - Class distribution changed
 - The number of classes reduced
 - The model accuracy worsens although the problem is easier (a random classifier is now 50% accurate)



Motivation – Cont.

Why Handle Data Shift?

- **Consequences of not handling data shift could be loss of:**
 - Lives
 - Clients
 - Resources
 - Funds
 - Time
 - Trust
 - Reputation



Motivation – Cont.

Why Handle Data Shift?

- Consequences of not handling data shift in the finance world:

- Financial crimes:**

- Terrorist financing
- Money laundering
- Fraudulent transactions
- Scamming
- Slavery and human trafficking

- Client focused:**

- Inadequate financial plans
- Poor product recommendation
- Mortgage delinquency
- Credit and loan defaults
- Attrition & losing clients
- etc.

STOCK TAKE
African banks may wait until 2024 to return to pre-crisis revenues – Sérgio Pimenta, IFC

Special ATII Report: Crypto transactions and human trafficking – A non-traditional investigation perspective for traditional financial institutions

by Brian Monroe - 12/09/2020

Online Banking Shift Leads to 'Significant Uptick' in Fraud

Feedzai Financial Crime Report shows online banking fraud attacks rose 250% and ATO scams soared 650% in 2020

08/03/2021 - 19:19 | Written by Banking Exchange Staff | Comments: DISQUS_COMMENTS

Mortgage
Mortgage delinquencies are declining, but a rise is coming

Average debt per borrower rose to \$220,244

February 19, 2021, 1:45 pm By Tim Glaze

Share On

Woman loses \$340K in wire transfer scam – alleges 4 banks did little to stop it

How to approach data shift?

Reactive

- **React once something happened**
 - Transfer learning (reusing old models)
 - Adaptive learning (efficiently retraining)
 - Statistical correction
- **It is easier but more risky**



Proactive

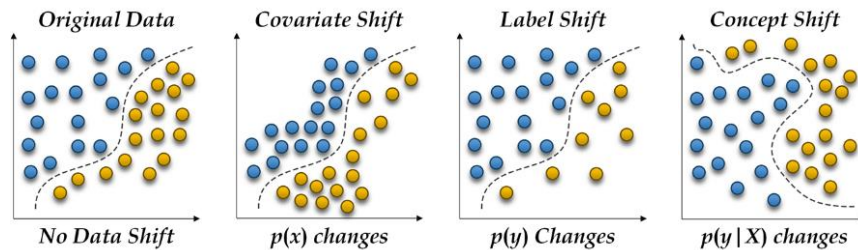
- **React before something happens**
 - Adding mitigation steps in ML pipelines
 - Using historical data to retrain the model (using COVID data for future pandemics)
 - Using synthetic datasets to estimate data shift e.g., adversarial training
 - It's not perfect. Must be an oracle.
- **It is harder but less risky**

Data Shift

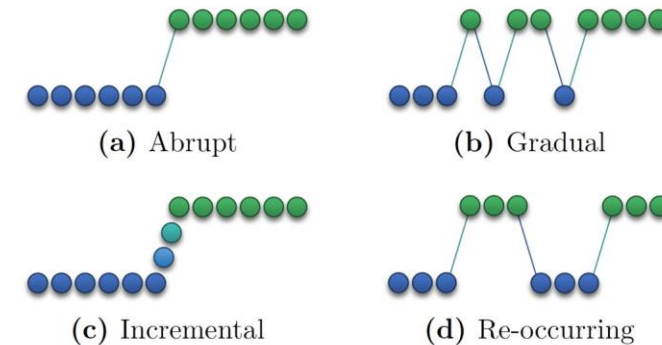


Data Shift

- **Common types of data shift:**
 - Covariate shift
 - Label shift
 - Concept shift



- **Data shift patterns:**
 - Abrupt
 - Gradual
 - Incremental
 - Re-occurring (or recurring)



Data Shift

Covariate Shift

Covariate Shift

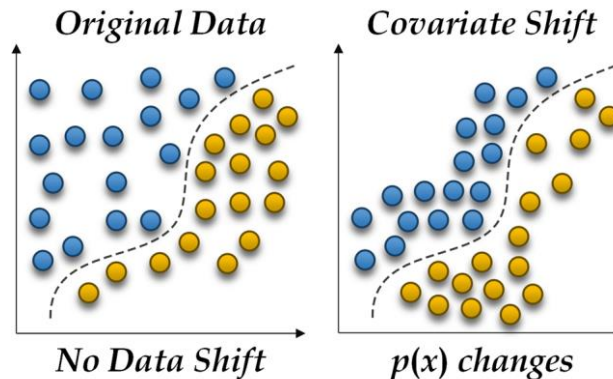
- Covariate shift happens when the conditional distribution $P_S(y|x)$ remains the same, i.e., that conditional distribution of the source and target domains are equal, but $P_S(x)$ changes. So, we have:

$$P_S(x)P_S(y|x) \neq P_T(x)P_T(y|x)$$

where

$$P_S(y|x) = P_T(y|x)$$

- Covariate shift appears in data due to lack of randomness, inadequate sampling, biased sampling, and non-stationary environment.



Data Shift

Label Shift

Label Shift

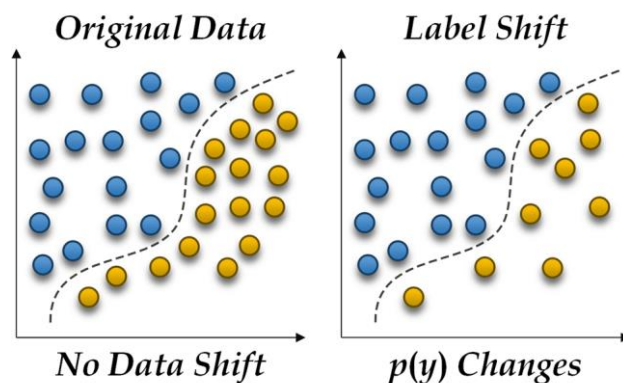
- Label shift is experienced when the conditional distribution $P_S(x|y)$ remains the same but $P_S(y)$ changes. So, we have:

$$P_S(y)P_S(x|y) \neq P_T(y)P_T(x|y)$$

where

$$P_S(x|y) = P_T(x|y)$$

- Having $P_S(y) \neq P_T(y)$ implies that label shift happens when some concepts are undersampled or oversampled in the target domain compared to the source domain.

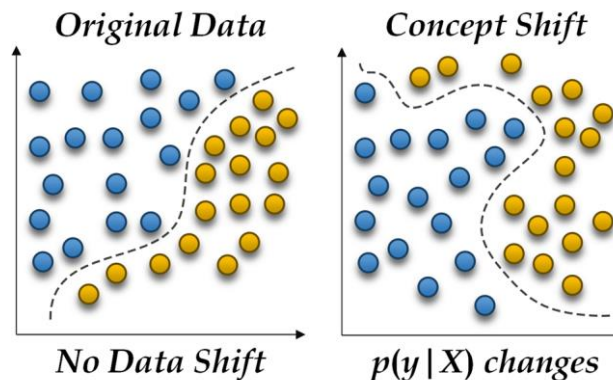


Data Shift

Concept Shift

Concept Shift

- In the case of concept shift, $P_S(y)$ and $P_T(y)$ follow the same distribution but $P_S(y|x)$ differs from $P_T(y|x)$.
- To address concept shift, we adapt our model globally or locally.
- Global adaptation is training our model from scratch using the target data whereas local adaptation works for learning algorithms that can be refitted for some part of their decision regions; for example consider decision trees where we may update some branches to reflect the change in the real world.
- Concept shift detectors compare the performance of a learner against both the source and target data; and if there is a significant difference they alarm for a drift.



Data Shift Detection



Covariate Shift Domain Classifier

Covariate Shift Detection

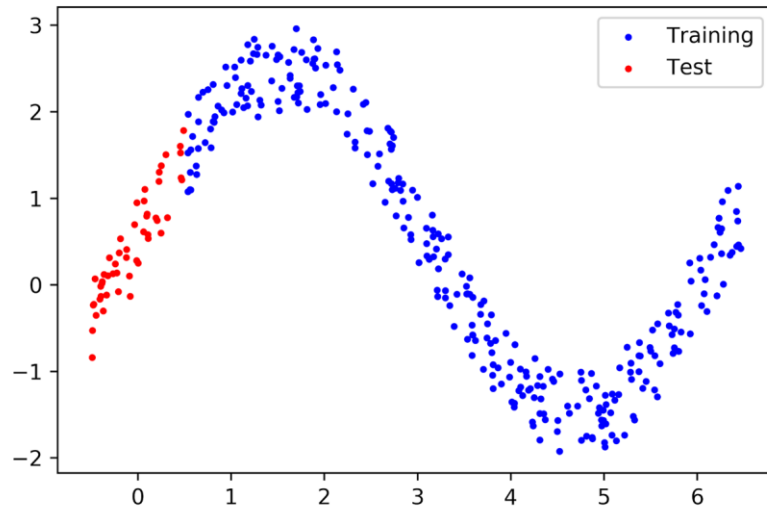
Domain Classifier

- Train a **domain classifier** to detect whether new data is from P_S or P_T
- That means we want to see if a data point is from source or target domain
- Domain classifier reduces dataset dimension to a **single dimension**, which specifically discriminate between source and target data
- The higher the error of the classifier \rightarrow the closer the distributions (i.e., unlikely to observe covariate shift)
- Applicable to high-dimensional data
- Can detect what feature(s) caused the shift using feature importance analysis
- Offline

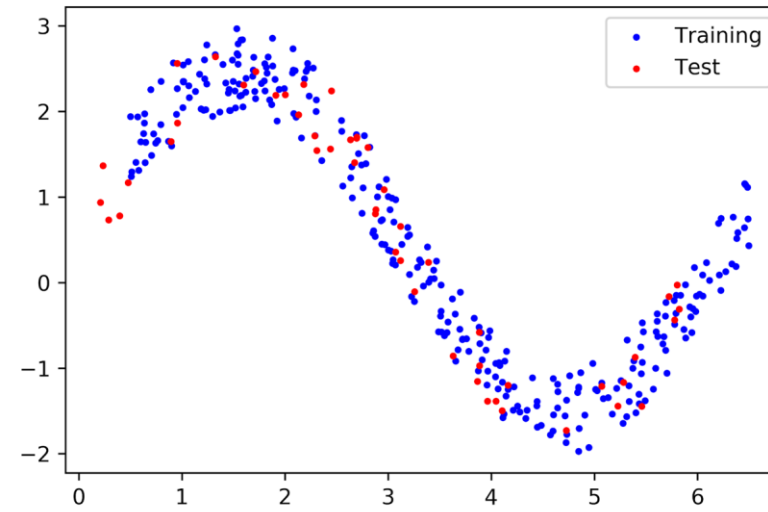
Covariate Shift – Cont.

Domain Classifier

- ROC-AUC score can be used to check if the performance of the classifier is statistically better than random chance (i.e., ROC-AUC score of 0.5)
- ROC-AUC score larger than 0.8 can be considered major shift
- Bi-nominal testing can be used as well



ROC-AUC = 0.91



ROC-AUC = 0.52

Covariate Shift & Domain Classifier – Cont.

Important considerations

Considerations

- Requires training a classifier
- Requires access to large samples from $x_i \sim P_T$ and may perform poorly with small samples
- Choosing a classifier to distinguish between two distributions at high level is equivalent to picking a measure between distributions distances
- The choice of the classifier may yield very different results
- To improve the shift detection confidence, one may consider using multiple classifiers and aggregate their predictions in some manner

Label Shift

Black Box Shift Detection

Label Shift Detection

- Detecting label shift is harder as we don't have access to labelled distribution
- Solution: Estimate it using a **pre-trained** classifier (Let's call it as *label classifier*)
- The label classifier must have an invertible confusion matrix
 - This condition is easily satisfied if the classifier is well-trained
- **Black Box Shift Detection:** Given a pre-trained label classifier $f(x)$ with invertible confusion matrix, detecting that the source distribution P_S is different from the target distribution P_T only requires detecting that $P_S(f(x)) \neq P_T(f(x))$

Data shift Correction



Sample Re-weighting

Sample Re-weighting

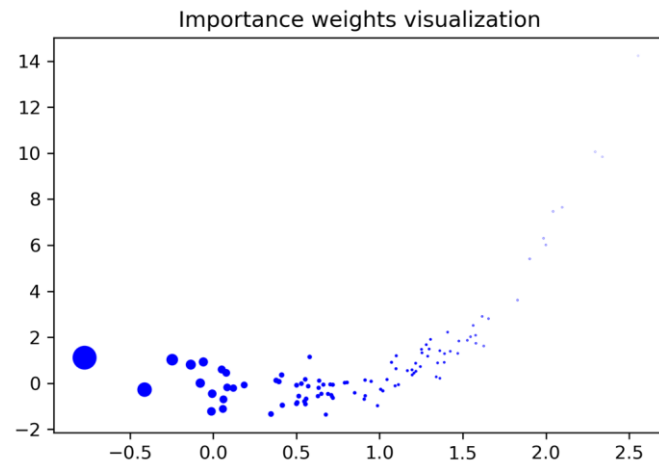
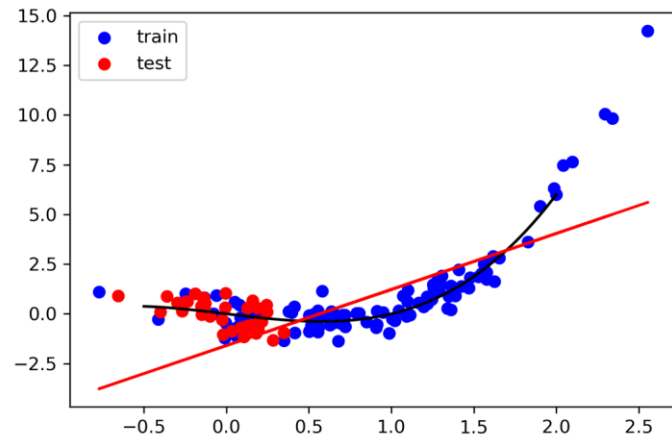
- Idea: Re-weight each data point by the ratios of the probabilities:

$$\beta_i \equiv \frac{P_T(x)}{P_S(x)}$$

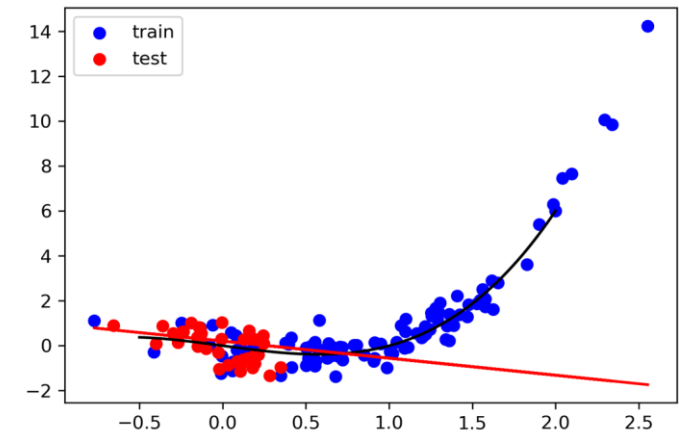
- In order to calculate β_i , we need to estimate the distribution ratios
- One of the ways to estimate β is to train a classifier to distinguish between the training and test sets
- If the training and test data is drawn from the same distribution, the classifier would not be able to distinguish between them (equal likelihood that a sample is drawn from either one of the distributions)
- We hope that the classifier can find a useful re-weighting factor
- **NOTE:** The classifier may fail to detect a dataset shift (false negative)

$$\beta = \frac{p(z = -1|x)}{p(z = 1|x)}$$

Sample Re-weighting Example



Re-weighting



Label Shift Correction

Label Shift Correction

- Idea: Re-weight each class using the ratio below:

$$\beta_i \equiv \frac{P_T(y)}{P_S(y)}$$

- **Challenge:** *How to estimate $y_i \sim P_T(y)$?*
- To estimate target label distribution, we use *confusion matrix* $C_{k \times k}$ of a classifier that is trained on the source data
- Since we don't have access to the labels in the target data, we average model predictions on the test data to create $\mu(\hat{y})$ whose i th element is the fraction of total prediction on the test set where the classifier predicted label i
- **Assuming that the confusion matrix is invertible** we can estimate β by solving the following linear system:

$$C_{k \times k} \equiv \mu(\hat{y})$$

Concept Shift Correction

Advanced

Transfer Learning & Active Learning



What if we could not correct a model?

- **Transfer learning - Reusing an existing model**
 - Same domain, different tasks
 - Target data has more/less classes (CIFAR-10 vs CIFAR-100)
 - Completely different tasks (trained for question-answering, used in sentiment analysis)
 - Different domains, same task
 - Training on grayscale images and testing on colored images
- **Active learning - Learning interactively with fewer training labels**
 - Not enough data from the target domain
 - Significant difference between the source and target distributions (no overlap)
 - We have the option to collect new samples: how can we do it more efficiently and effectively?

Transfer Learning

Transfer Learning

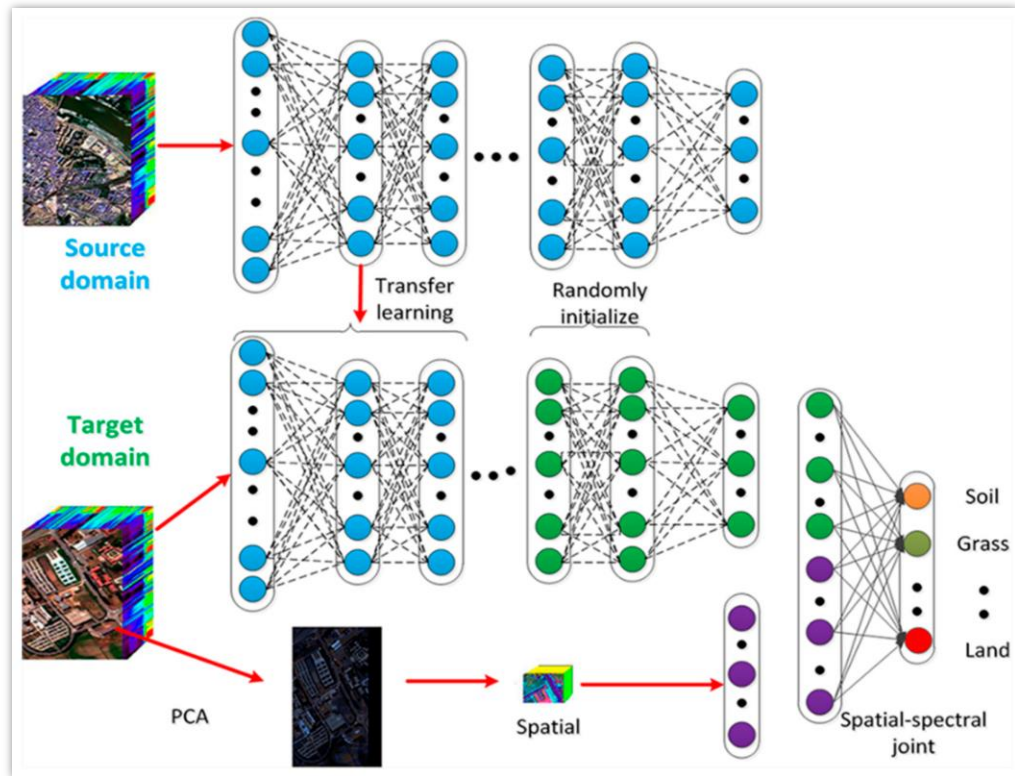
- Idea:
 - Layers in a neural network can be considered as feature representations
 - A common transfer paradigm is to **maintain the weights** in the earlier layers of network trained on some source task, and adapt only the weights in the last layer for a target task
 - Earlier layers may learn about abstract features such as edges and corners, which are common among different domains and tasks

Transfer Learning – Cont.

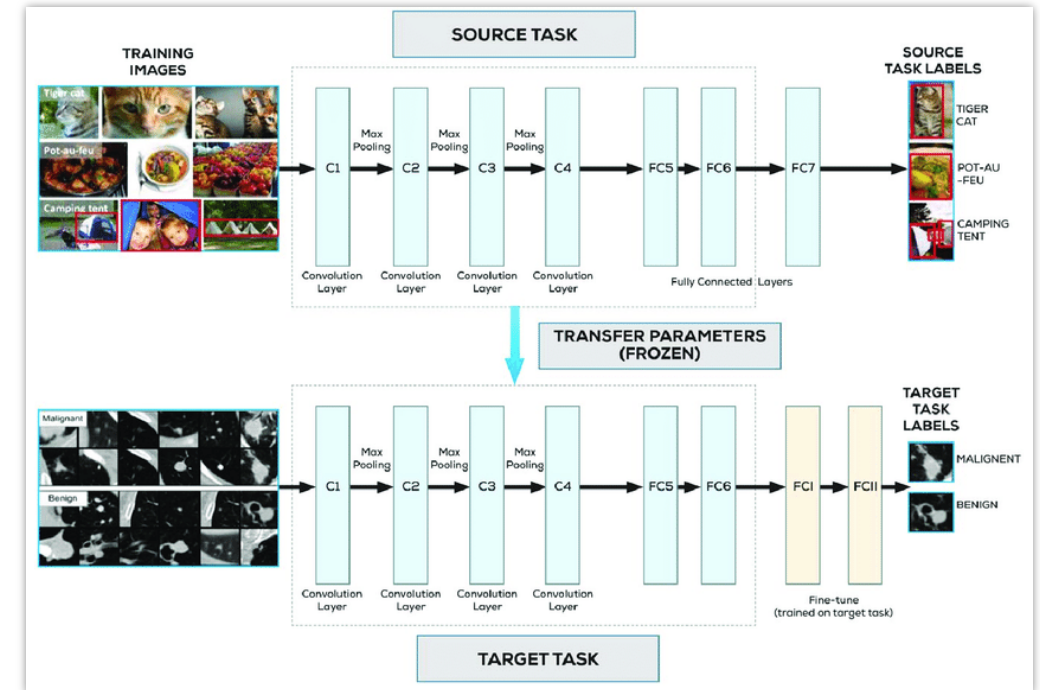


Different domains, same task

Transfer Learning – Cont.



<https://www.mdpi.com/2076-3417/9/7/1379/htm>

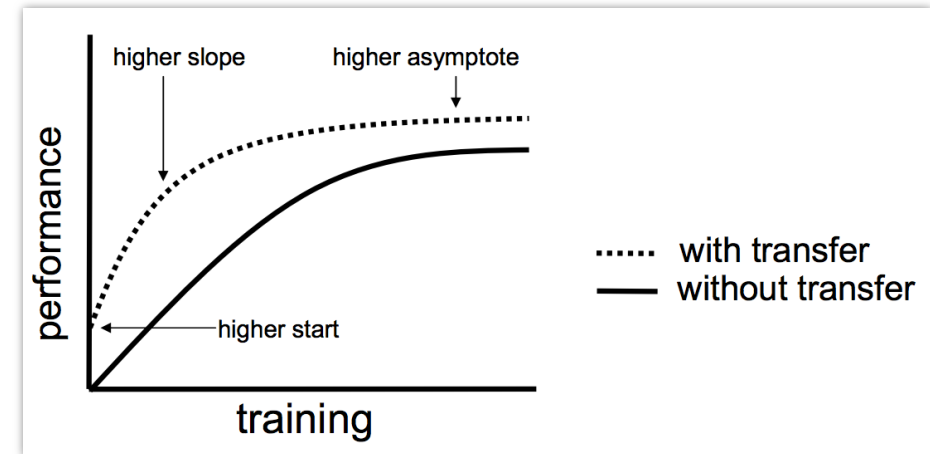


<https://pubmed.ncbi.nlm.nih.gov/30383900/>

Same domain (colored images), different tasks

Transfer Learning – Cont. Benefits

- Use the knowledge gained by a machine learning model from one task and apply it to a different task
- Possibility of reusing the same model
- The model training may have a higher start
- The training rate would improve
- The overall model performance may increase



Active Learning

- The model prioritize the labeling of new data such that training the model on the new data would have the maximum impact on model performance
- Interactively query the user to label new data points
- Can significantly reduce the number of new labeled data points required
- Query selection strategies
 - **Uncertainty Sampling**
 - Classification uncertainty: Being less confident about the model predictions - probabilities are not significantly different
 - Classification entropy: Uncertainty is proportional to the average number of guesses one must make to find the correct class

Active Learning – Cont.

Types

- **Pool-based active learning**
 - The model has access to a large pool of unlabeled data points
 - Query or rank the most informative samples
- **Stream-based active learning**
 - Stream of unlabeled samples
 - Decide to query the user for labeling of the streamed sample or not

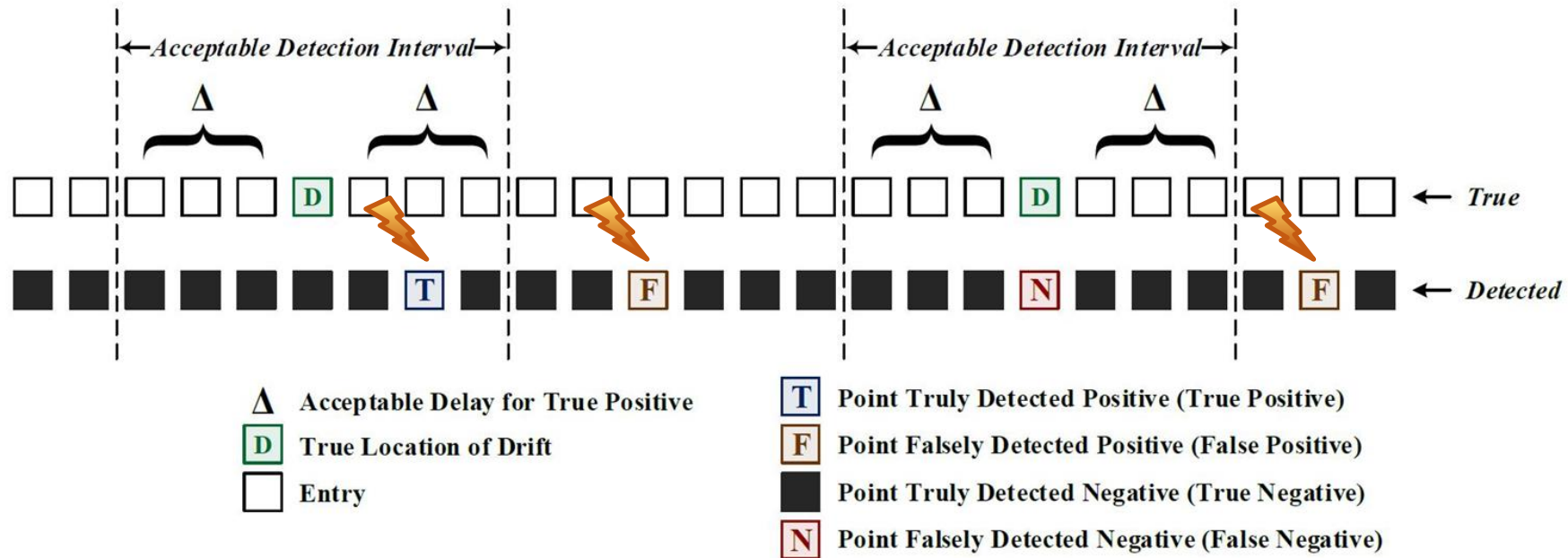
Discussion



Evaluation Measures

- What shift detector is preferred?
 - ***Highest true positive, lowest false positive*** and the ***lowest false negative***
 - The resources will be kept busy if the drift detector incorrectly alarms for concept drift repeatedly.
 - The error-rate of classification typically increases as does the false negative number.
- **The delay of detection:**
 - Shorter detection delay results in losing less data for learning, it means more instances from the new distribution can be used for learning.
- **How about the model accuracy or loss:**
 - It confirms whether using drift detection methods are beneficial or not!

Evaluation Measures



Discussion

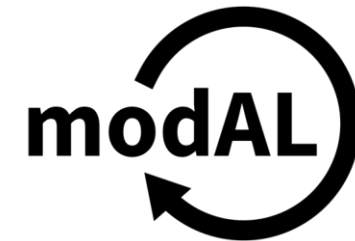
- Always keep track of your data and your model performance
- If your model accuracy dropped (significantly), something is off... most likely due to some shift in data
- The significant level varies from my domain to another
- If you are not detecting a shift, there could still be a shift in your data
- Domain knowledge helps a lot
- Different types of data shift can co-occur
- Model repository for recurring concepts – Potentially for transfer learning
 - Some models trained in 2008 could be potentially used in 2020
- Track influencers



Packages



TORNADO





Q&A