Learning Under Different Training and Testing Distributions

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GitHub: Lab work and presentation

Follows the steps:

- Go to link `https://github.com/sagihaider/IADS_SC_2018`
- Look at right hand side in green color: Clone or download. Click it and Download Zip
- When downloading is finished. Copy the Zip file and take to the location you want such any folder and paste it. Extract it.
- If you have **Anaconda3** installed. Go to terminal or command prompt and type "jupyter notebook"

Outline

Notation

- A set of features or covariates X.
- A set of target or class variables Y.
- A joint distribution P(Y,X) or $P(Y \cap X)$ (i.e. Probability of Y and X).
- $(X \rightarrow Y)$: Y is determined by values of X (e.g. credit card fraud detection) Predictive models (e.g. Logistic Regression, SVM, and Neural Networks.)
- $(Y \rightarrow X)$: Y determines the values of X (e.g. medical diagnosis) Generative models (e.g. GMM, HMM, and Naive Bayes).
- The joint distribution P(Y,X) can be written as
  1. $P(Y|X)P(X)$ in $X \rightarrow Y$ problems.
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- Imbalanced dataset
- Overlapping dataset
- Density: Lack of data
- Noise in data
- Dataset Shift

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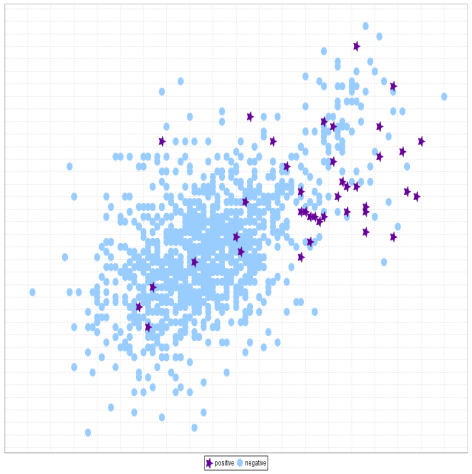

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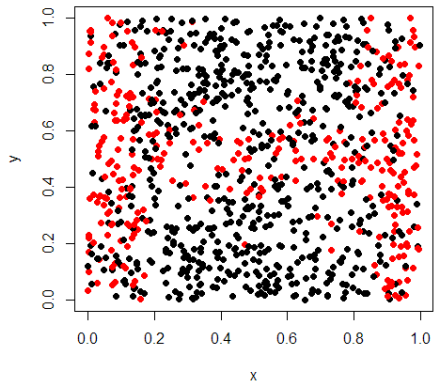

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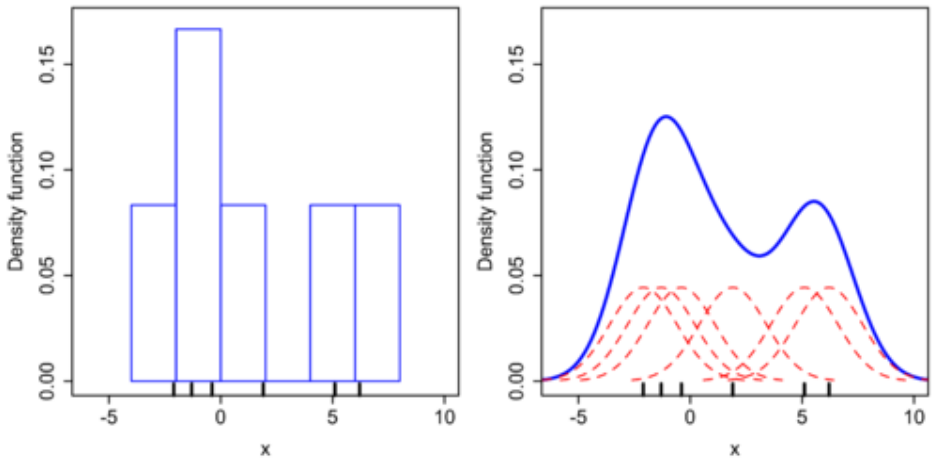

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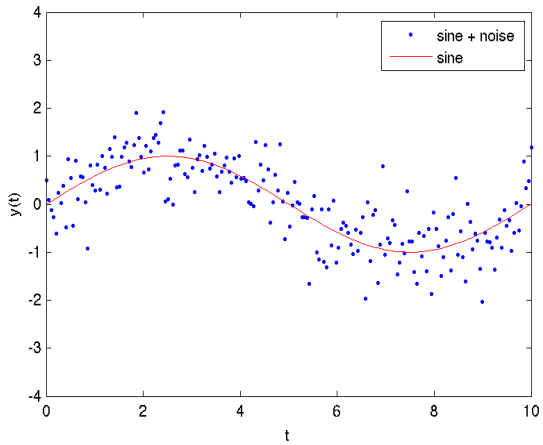

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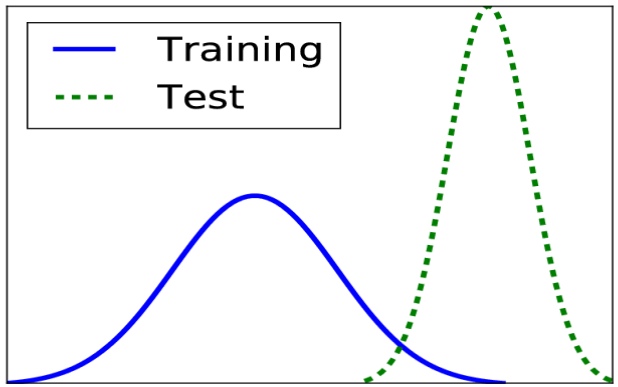

Motivation

- In learning theory independent and identically distributed (i.i.d) assumption (i.e. each random variable has the same probability distribution as the others and all are mutually independent).
- In practice train and test inputs have different distributions.
- The difference in distribution arises from operating in non-stationary environments in real-world application such as finance, healthcare, brain signals, much more...
- Learning in such non-stationary environment is difficult and we need an think before operating.

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Shifts in Data

Outline

Dataset Shift

- "cases where the joint distribution of inputs and outputs differs between training and test stage"[1]
  1. "concept shift/drift" G. Widmer et al., 1996, 1998
  2. "changes of classification" K. Wang et al., 2003
  3. "changing environments" R. Alaiz-Rodrıguez et al., 2008
  4. "fracture point" N.V. Chawla et al., 2009
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Dataset Shift: General Example

- Speech recognition system
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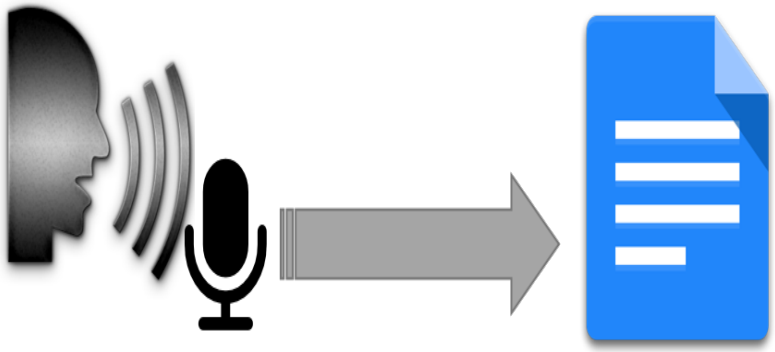

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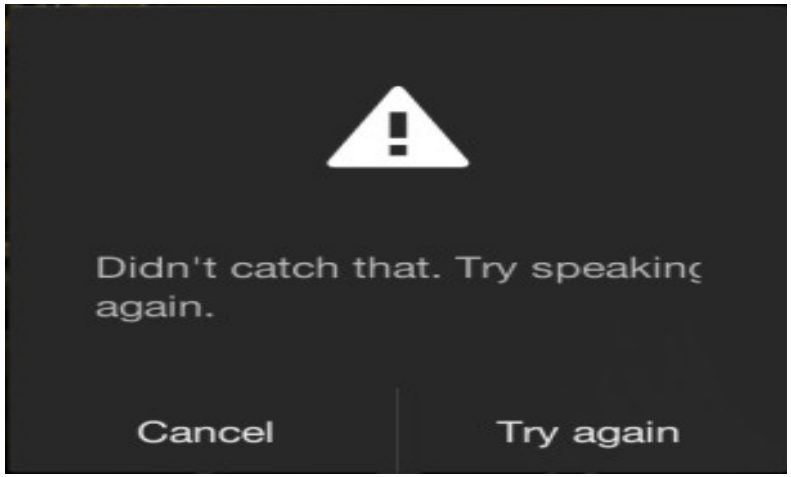
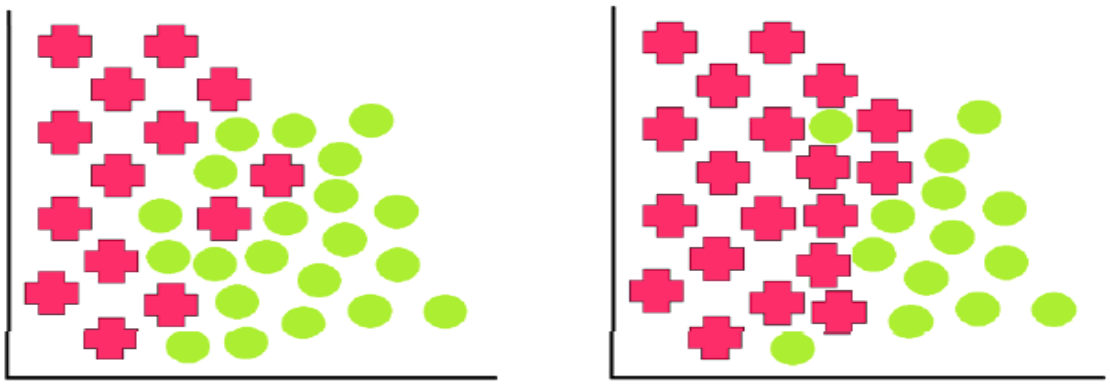


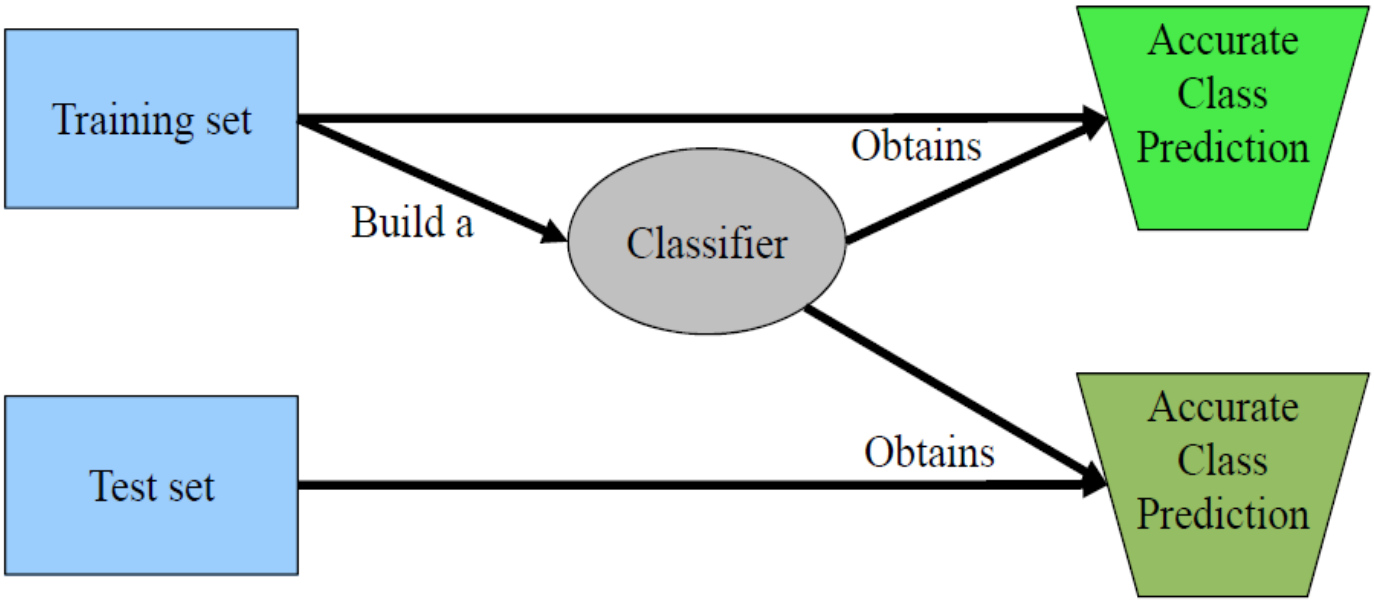
Dataset Shift...cont

- **Dataset shift** appears when training and test joint distributions are different. That is, when $P_{tr}(X, Y) \neq P_{ts}(X, Y)$



Dataset Shift...cont

- Basic assumption for classification in operating under stationary environment



Dataset Shift...cont

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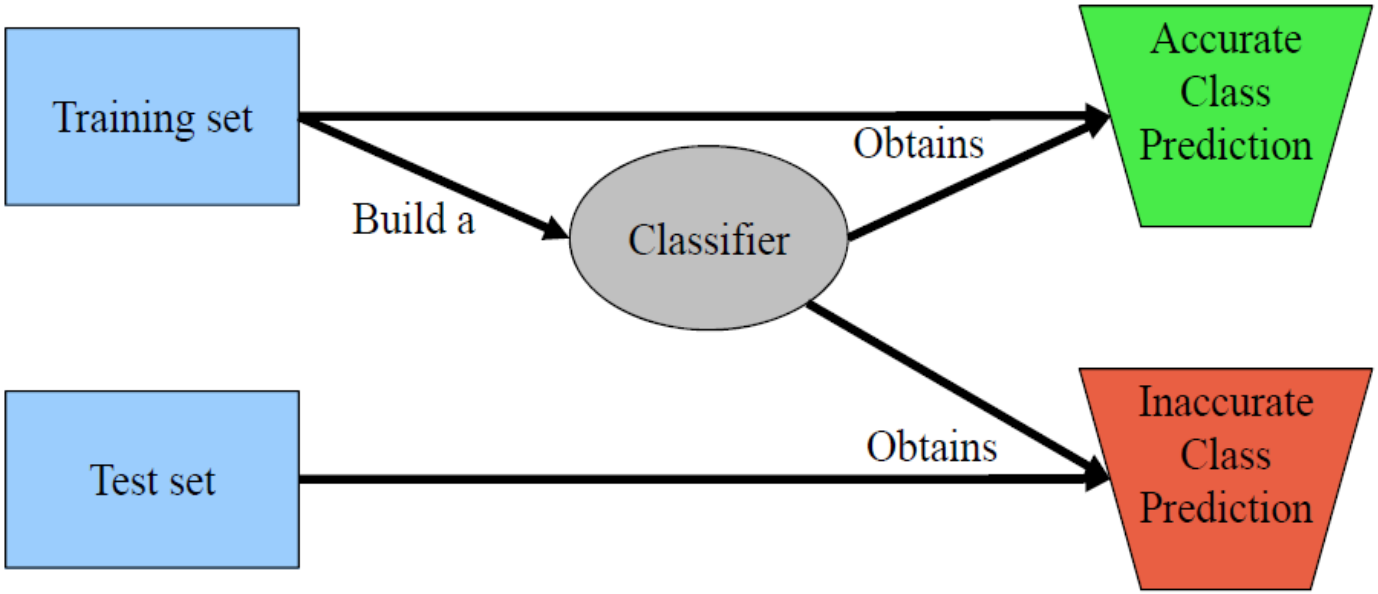

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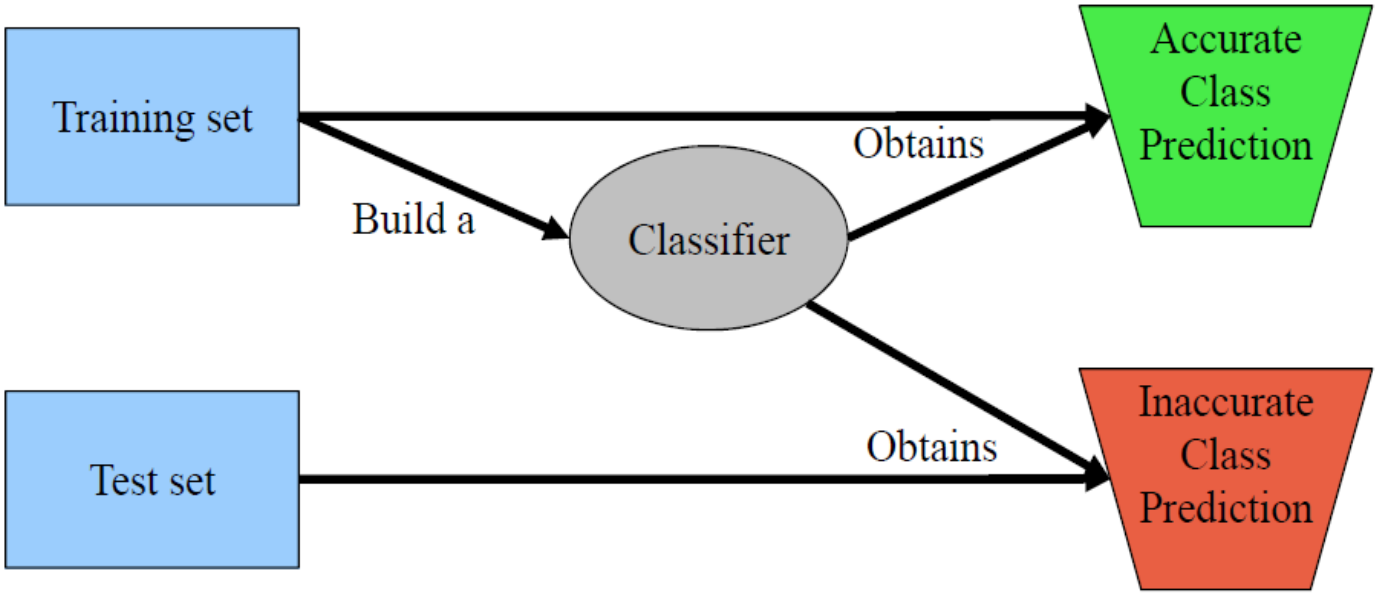

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The problem of Dataset Shift

- **If** the classifier has an overfitting problem: **then** possible actions
  - Change the parameters of the algorithm
  - Use a more general learning method
- **If** there is a change in the data distribution between training and test sets: **then** possible actions [2]
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Dataset Shift: A literature review

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- Covariate shift appears only in X $\rightarrow$ Y problems [4], and is defined as the case where

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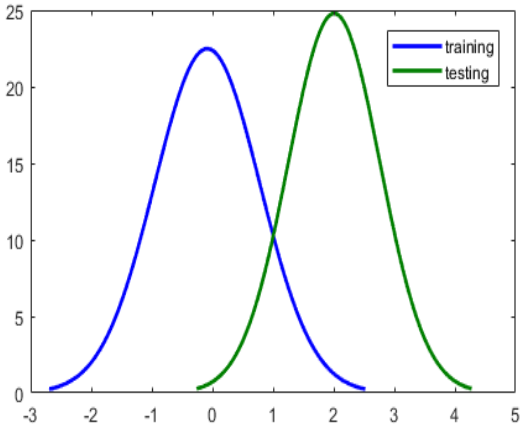

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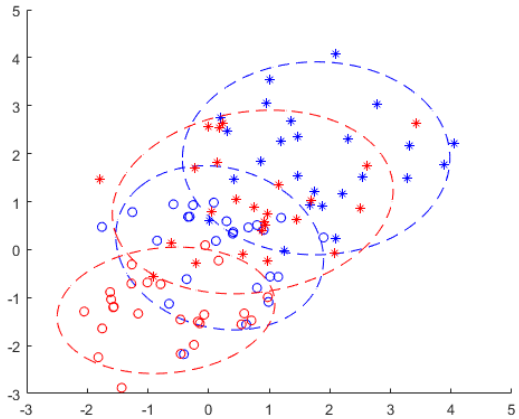

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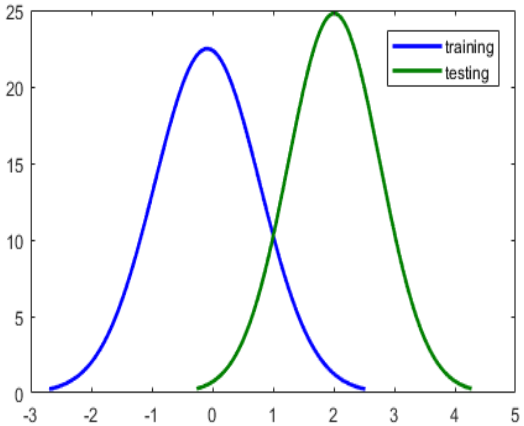

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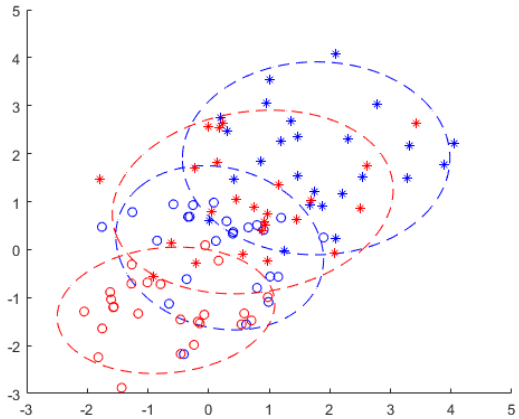

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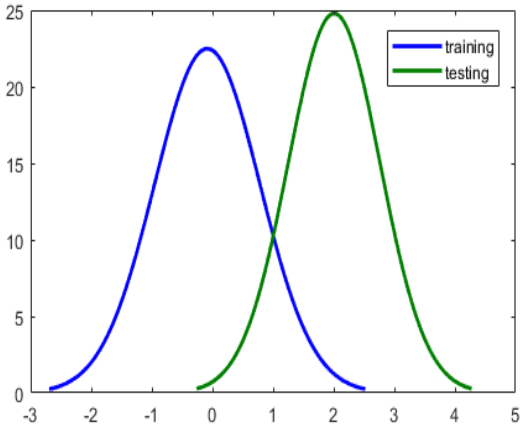

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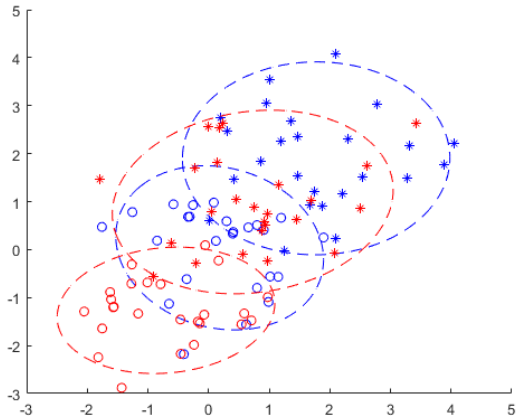

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- Covariate shift is probably the most studies type of shift, but there appears to be some confusion in the literature about the exact definition of the term. There are also some equivalent names, such as "population drift", "changes in the data distributions", "differing training and test distributions".

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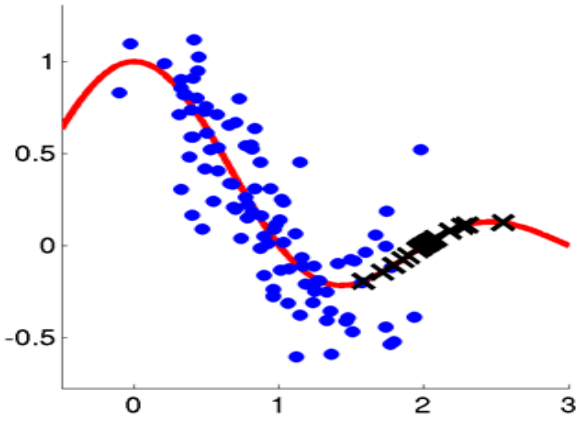
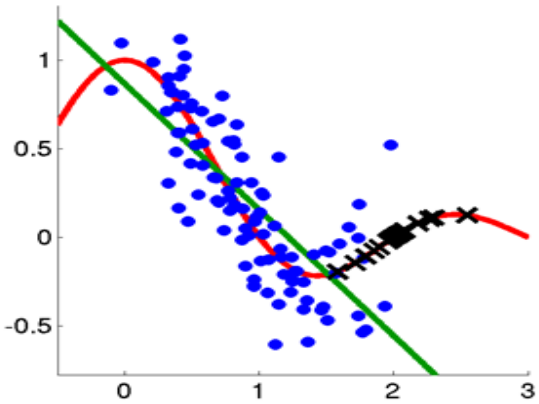
Covariate Shift: An Example

- A regression example [6]



Training



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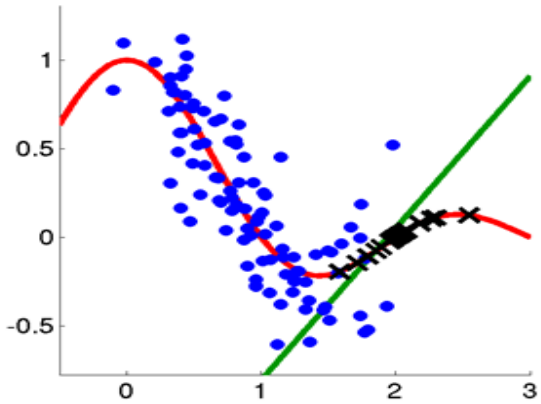

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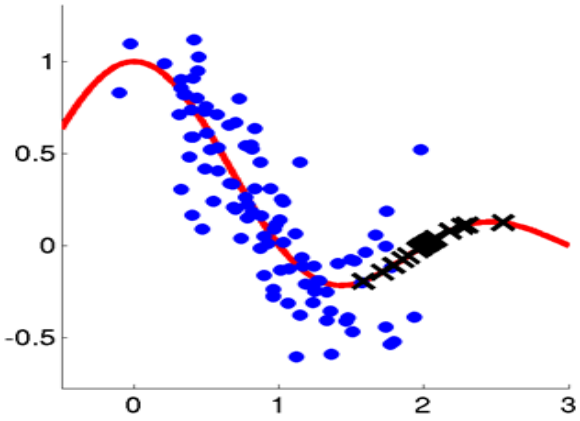

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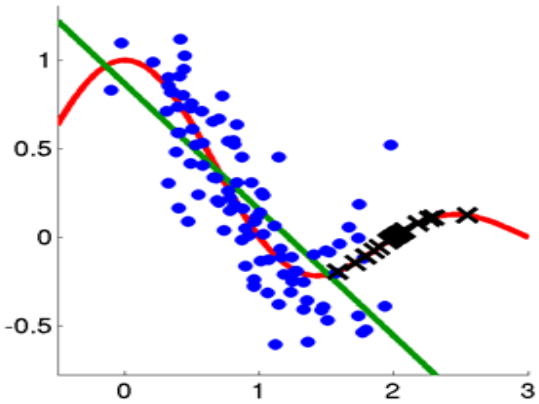

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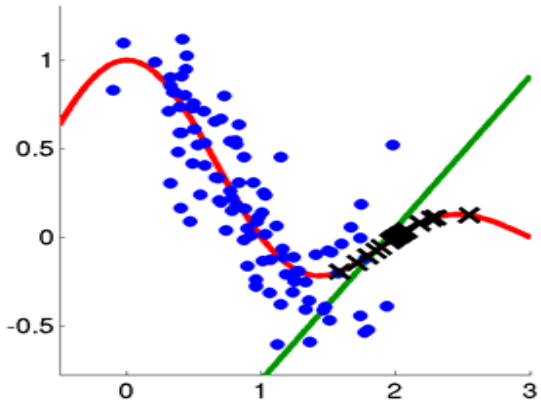

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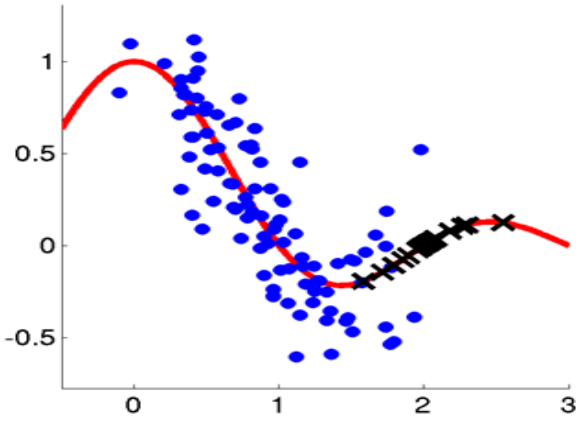

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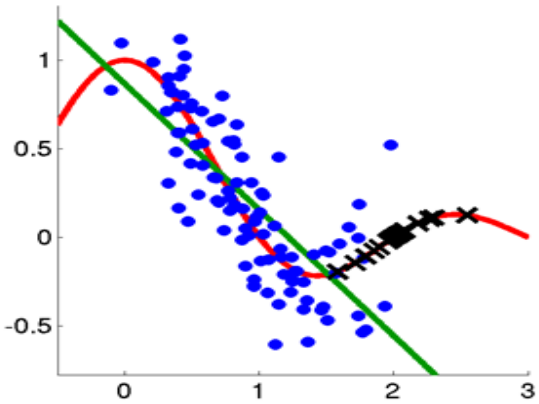

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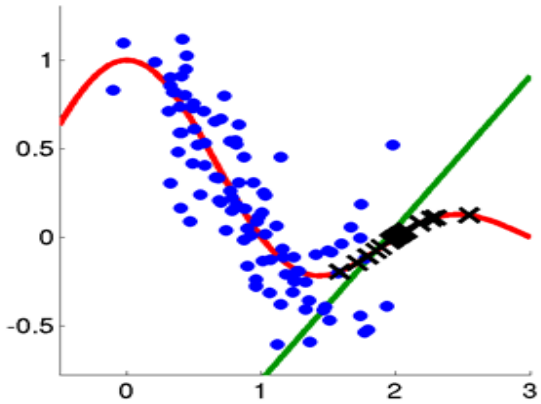

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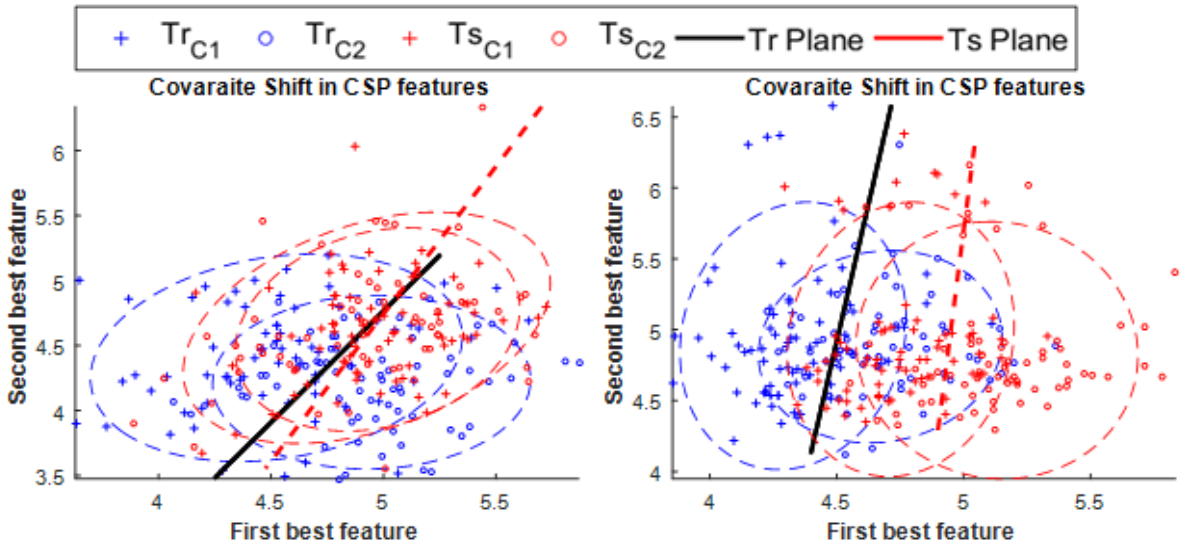

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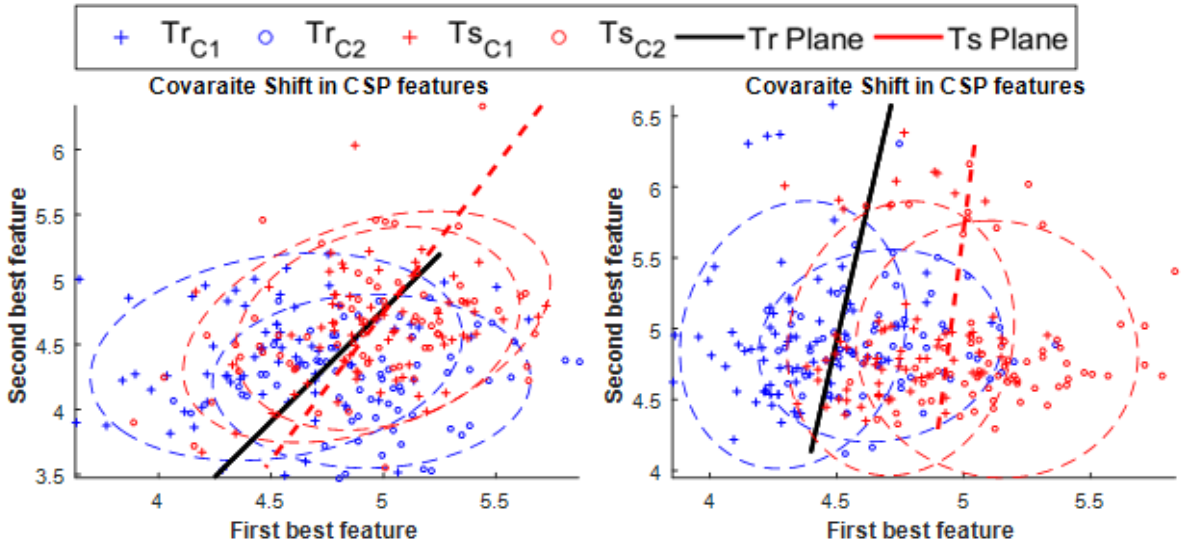

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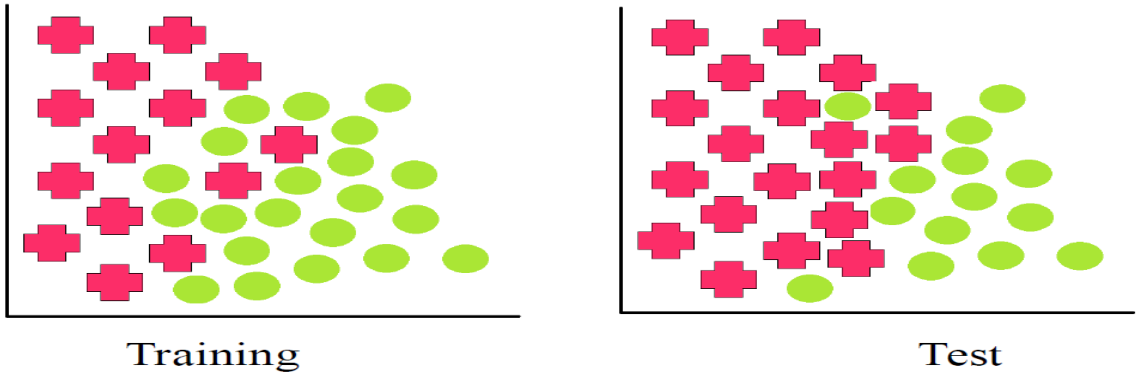

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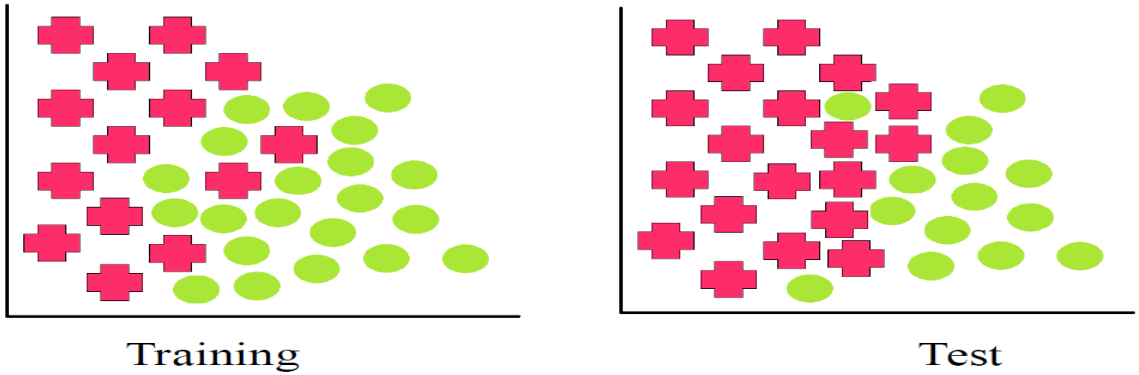

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Now consider that in the test data $P_{ts}(x_0 \mid y = 0)$ and $P_{ts}(x_0 \mid y = 1)$ remains unchanged, but the class prior probabilities vary, taking the values $P_{ts}(y = 0) = 0.70$ and $P_{ts}(y = 1) = 0.30$. This example is illustrated in the figure below

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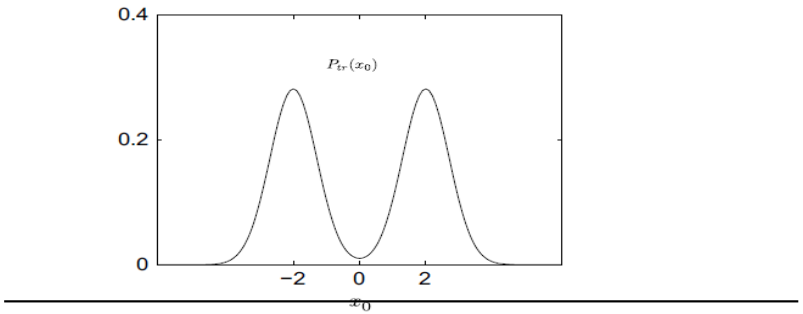

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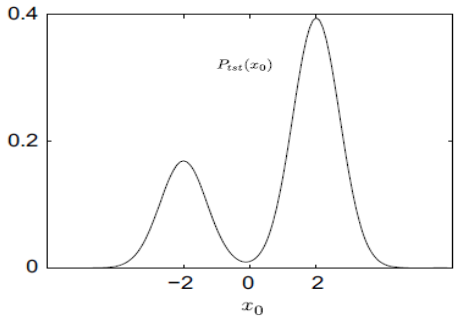

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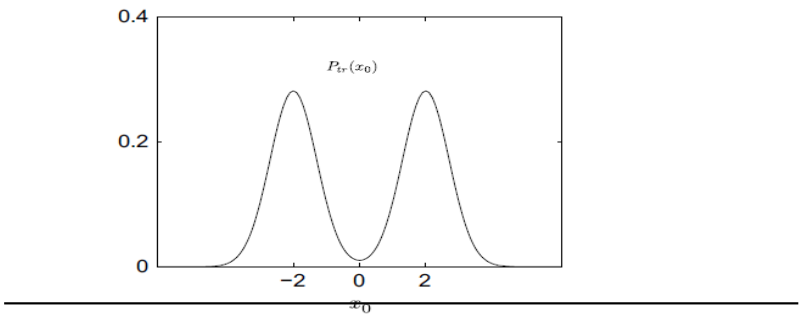

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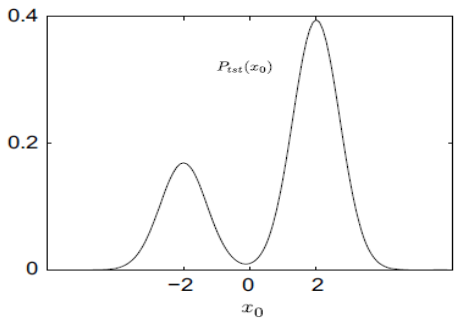

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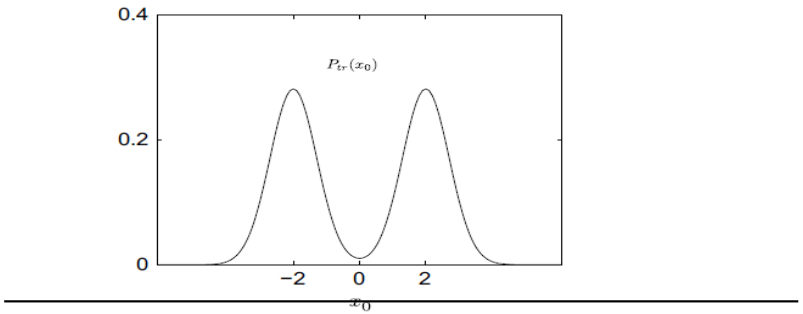

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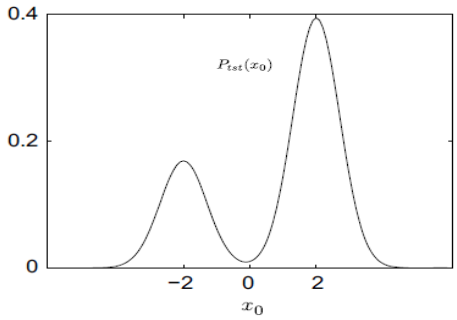

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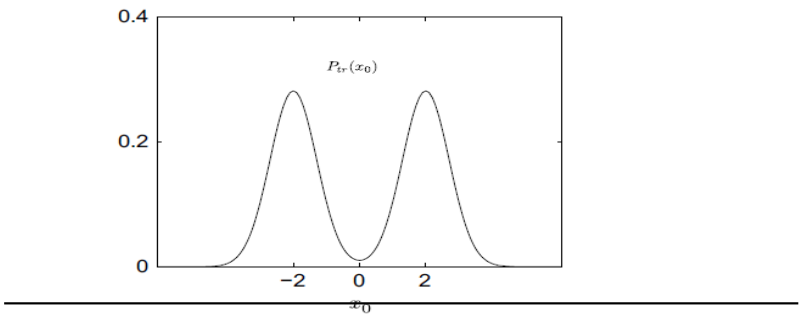

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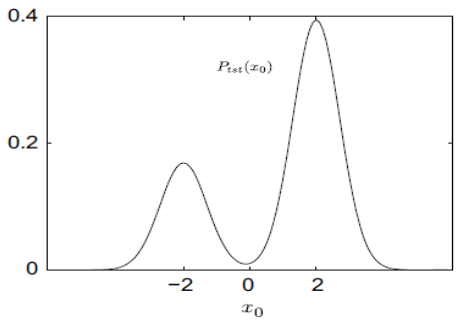

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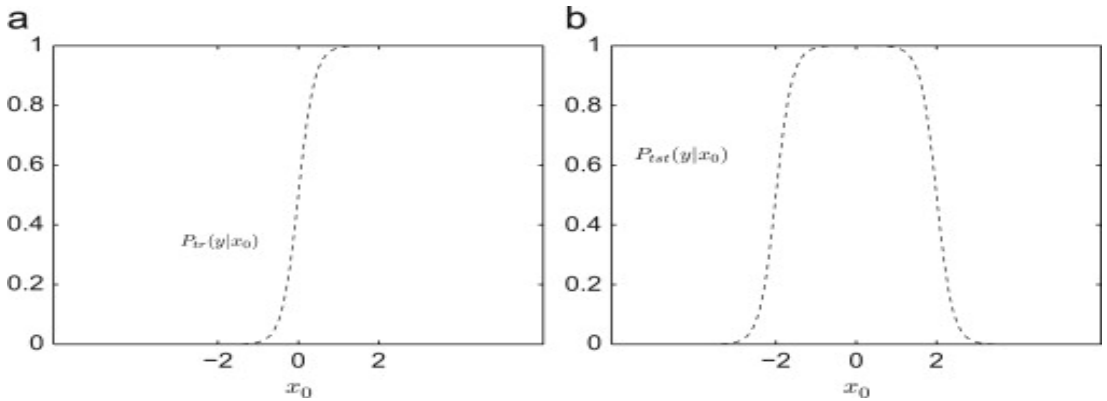

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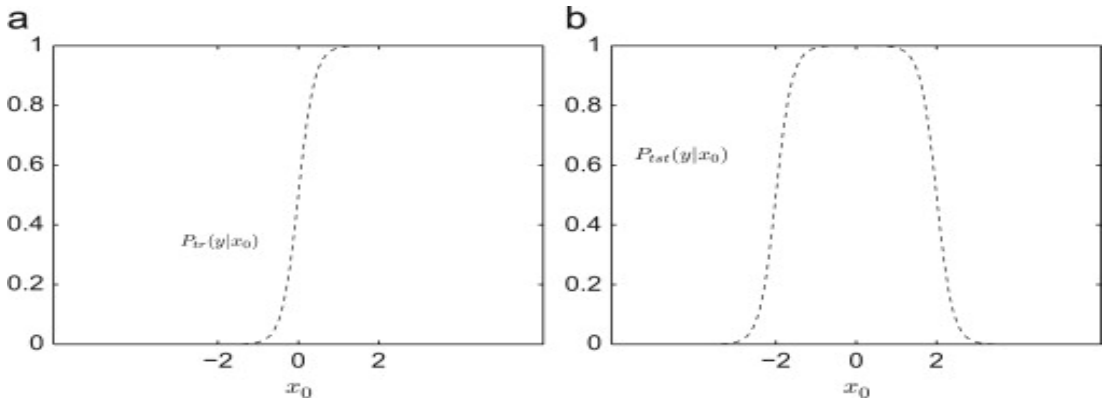

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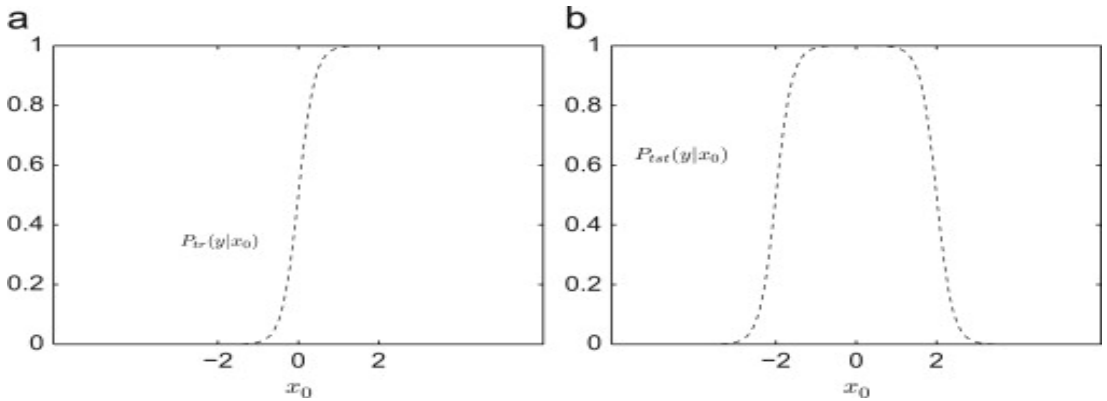

Outline

Causes of Dataset Shift

1. The main two causes of dataset are Sample **Selection Bias** and **Non-stationary environments**.
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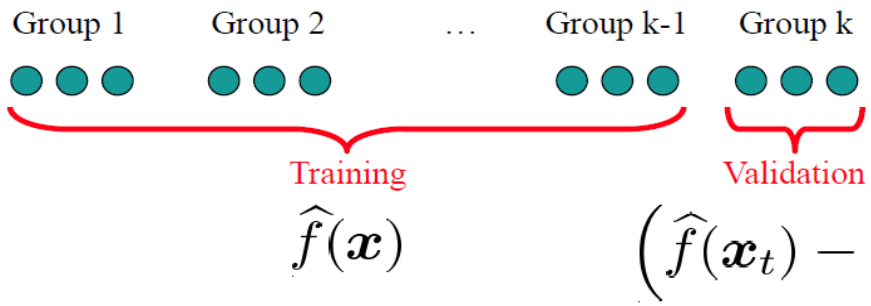
Correcting: Dataset shift generated by Sample Selection Bias

1. Divide the training samples into k groups.
2. Train a learning machine with $k-1$ groups.
3. Validate the trained machine using the rest.
4. Repeat this for all the combination and output the mean validation error.



5. This method is cross-validation (CV) and is almost unbiased without covariate shift.
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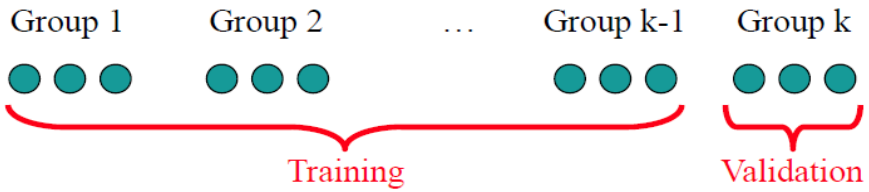

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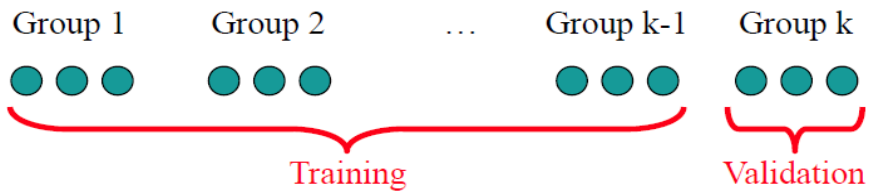

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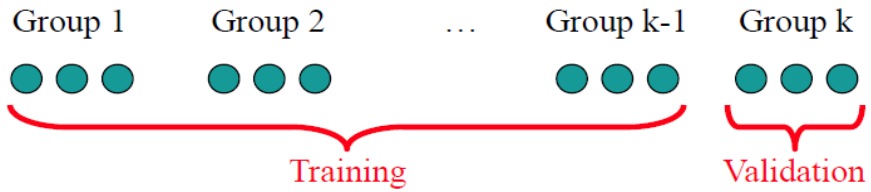

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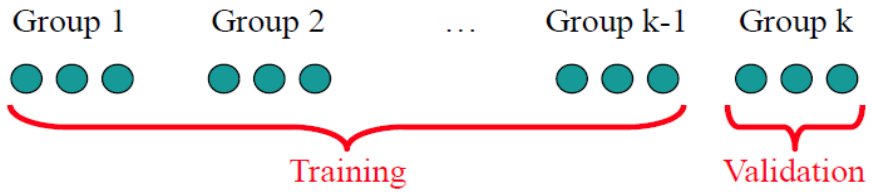

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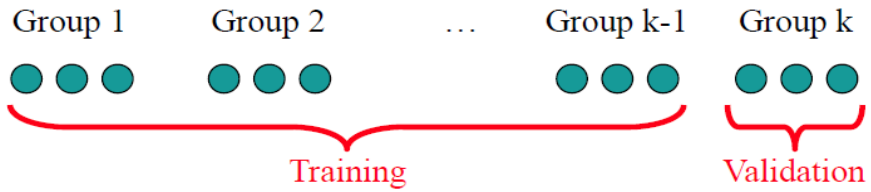

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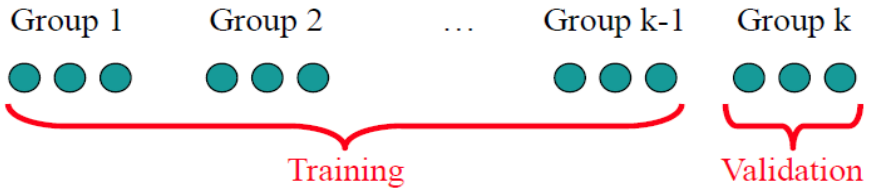

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Non-stationary environments

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Learning in Dataset Shift

Learning in Non-stationary environments

Ditzler, G et al., (2015). Learning in Nonstationary Environments : A Survey. *IEEE Computational Intelligence Magazine*, 10(4), 12–25.

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Passive Approaches

1. Does not uses a shift detection method to detect changes.
2. Perform a continuous adaptation of the model parameters every time new data arrive.
3. Advantage: Maintain an up-to-date model at all times.
4. Advantage: Avoiding the potential pitfall associated with the active approaches, that is, failing to detect a change or falsely detecting a non-existent change (false alarm).
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Passive Approaches Methods

1. **Single Classifier**:
   - Provide lower computational cost.
   - Decision trees are the most common classifier for data stream mining.
   - Very Fast Decision Tree (VFDT) and Online Information Network (ONI) are very popular approaches based on sliding window method.
   - Recently, Extreme Learning Machine (ELM) based on neural networks gaining popularity for learning non-stationary data.
2. **Ensemble Classifier**:
   - More accurate than single classifier due to reduction in the variance of the error.
   - Flexible to incorporate new data, simply by adding new members to ensemble.
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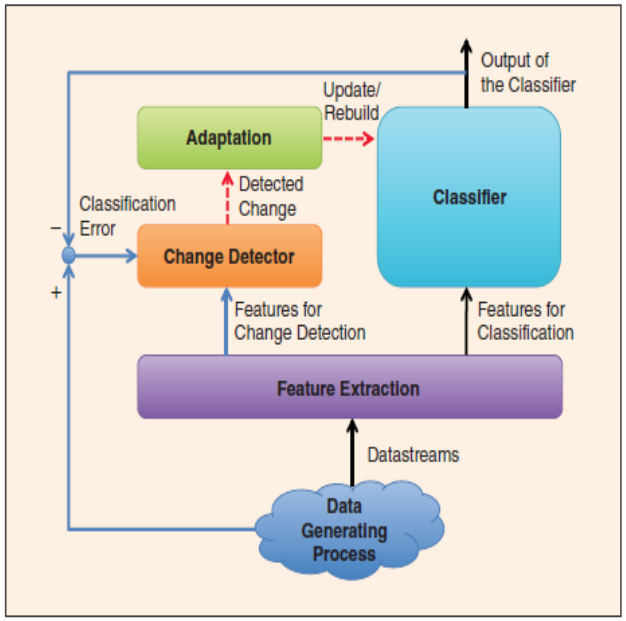

It is based on change detection mechanism that triggers, whenever advisable, an adaptation mechanism aiming at reacting to the detected change by updating or building new classifier.

Active Approaches Methods

1. **Change/Shift Detection**:
   - Hypothesis Test, Change-point methods, Sequential hypothesis test, and Change-detection test.
   - Popular methods: EWMA, CUSUM, JIT, ICI, DDM and many more.
2. **Adaptation**:
   - Supervised adaptation, unsupervised adaptation, semi-supervised adaptation, and transduction.
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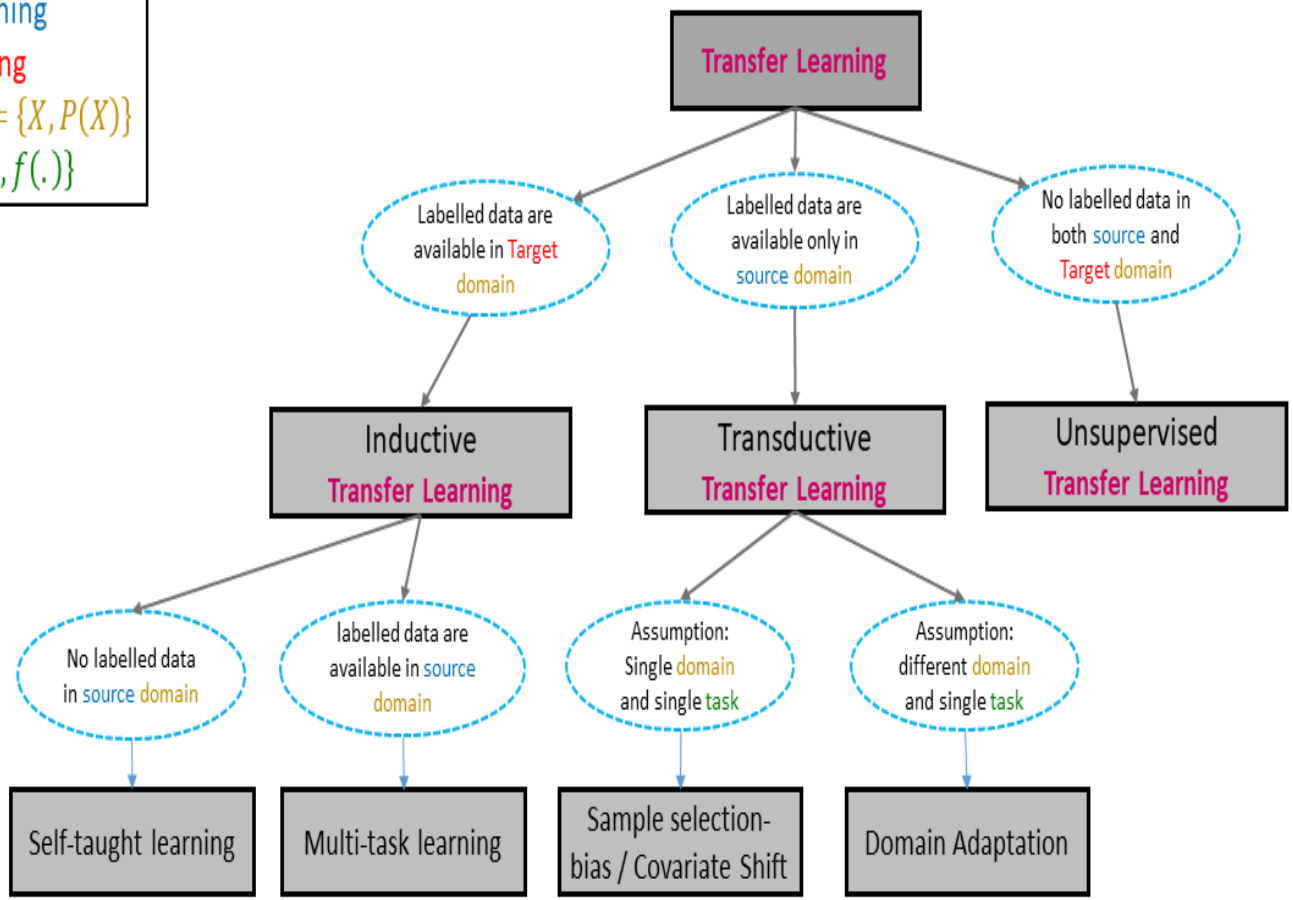
Other Learning Approaches

Source: Training
Target: Testing
Domain: $D = \{X, P(X)\}$
Task: $T = \{Y, f(.)\}$



Domain Adaptation

- Learning from a source (training) data distribution a well performing model on a different (but related) target (testing) data distribution.
- Example, one of the tasks of the **common spam filtering problem** consists in adapting a model from one user (the source distribution) to a new one who receives significantly different emails (the target distribution).
- Note that, when more than one source distribution is available the problem is referred to as **multi-source domain adaptation.**
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Multi-task Learning (MLT)

- MTL is sub-field of learning in which multiple learning tasks are solved at the same time, while utilizing commonalities and differences across tasks.
- It aims to improve the performance of multiple classification tasks by learning them jointly
- Example:
  1. Spam-filtering, which can be treated as distinct but related classification tasks across different users.
  2. To make this more concrete, consider that different people have different distributions of features which distinguish spam emails from legitimate ones, for example an Persian speaker may find that all emails in French are spam, not so for French speakers.
  3. Yet there is a definite commonality in this classification task across users, for example one common feature might be text related to money transfer.
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Covariate Shift Adaptation

- Covariate shift appears only in X $\rightarrow$ Y problems, and is defined as the case where

$$P_{tr}(Y \mid X) = P_{ts}(Y \mid X)$$

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$$P_{tr}(X) \neq P_{ts}(X)$$

- Under covariate shift, the ratio $\frac{P_{tr}(X,Y)}{P_{ts}(X,Y)}$ can be re-written as follows:

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