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DISTRIBUTION SHIFT

A Study on Their Effects on Statistical Models and
Strategies for Mitigation

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Introduction

Models:

- Logistic Regression
- Random Forest
- Gradient Boosting
- XGBoost

Roadmap:

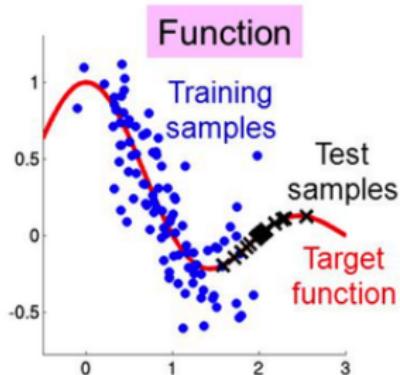
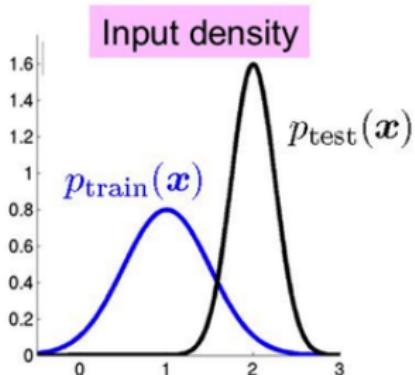
- Creation of synthetic data and data affected by shift
- Evaluation of model performance on the data
- Identification of improvement strategies (R.A.W.)

Dataset shift

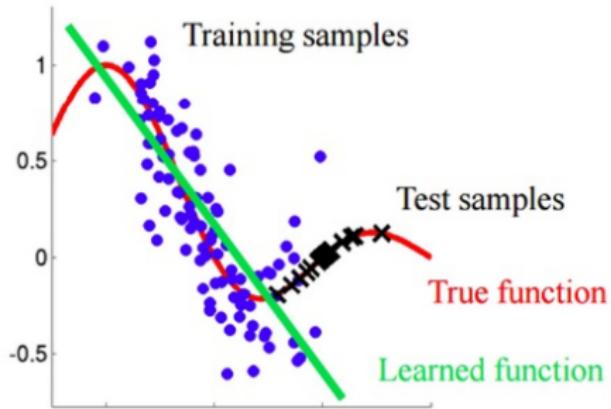
- **Dataset shift** is a common problem in machine learning.
- It occurs when the distribution of the training data differs from the distribution of the test data.
- The two most common and well-studied causes of Dataset shift are:
 - Sample selection bias
 - Non stationary environments

Covariate shift

$$P_{\text{tra}}(Y | X) = P_{\text{tst}}(Y | X) \quad \text{but} \quad P_{\text{tra}}(X) \neq P_{\text{tst}}(X)$$



Inaccurate Model



Changes in the features distribution can significantly impact the model's *effectiveness*.

Example

Consider a model designed to distinguish between images of cats and dogs:

Training set:



Test set:



Model will not accurately distinguish between cats and dogs because the feature distribution will differ.

Data Generation

Training Dataset: Features

The dataset consists of $n = 10^4$ observations with 3 features and 1 binary target variable.

Features:

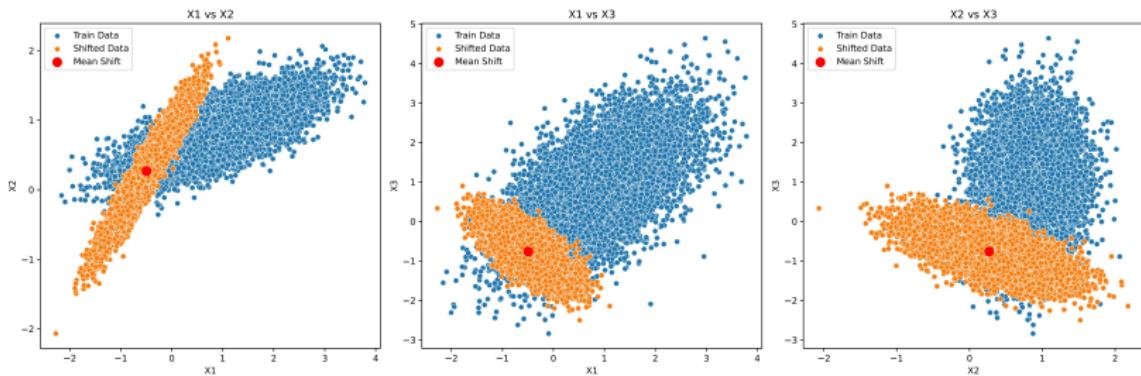
- $X_{\text{train}} = (X_{\text{train}1}, X_{\text{train}2}, X_{\text{train}3}) \sim \mathcal{N}(\boldsymbol{\mu}_{\text{train}}, \boldsymbol{\Sigma}_{\text{train}})$
- $\mu_{\text{train}i} \sim \mathcal{U}_{[0,1]}$ for $i = 1, 2, 3$
- $[\boldsymbol{\Sigma}_{\text{train}}]_{i,j} \sim \mathcal{U}_{[-1,1]}$ for $i, j = 1, 2, 3$

Note: The $\boldsymbol{\Sigma}$ randomly generated has been transformed to a symmetric and positive semidefinite matrix by computing $\boldsymbol{\Sigma}\boldsymbol{\Sigma}^T$.

Testing Dataset

Same dataset structure as the train set, but:

- $X_{\text{shift}} = (X_{\text{shift}1}, X_{\text{shift}2}, X_{\text{shift}3}) \sim \mathcal{N}(\mu_{\text{shift}}, \Sigma_{\text{shift}})$
- $\mu_{\text{shift}} = Q_{0.05}(X_{\text{train}})$
- $[\Sigma_{\text{shift}}]_{i,j} \sim \mathcal{U}_{[-0.5, 0.5]}$ for $i, j = 1, 2, 3$



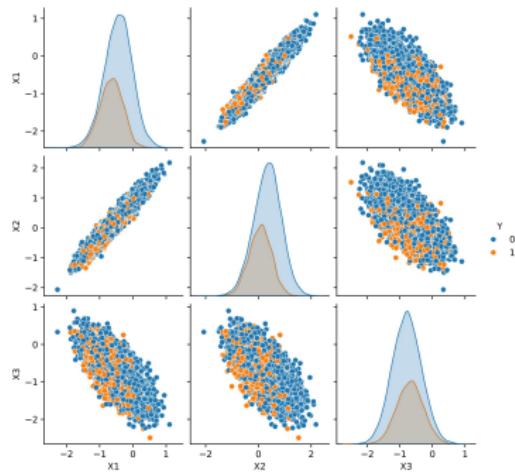
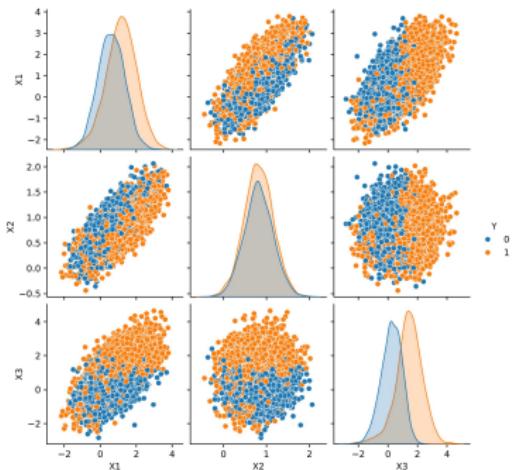
Target Variable

Building the **target variable** $Y \in \{0, 1\}$:

$$z = \beta_0 + \sum_{i=1}^3 \beta_i x_i + \sum_{i=1}^3 \beta_{ii} x_i^2 + \sum_{i=1}^2 \sum_{j=i+1}^3 \beta_{ij} x_i x_j, \quad \beta. \sim \mathcal{U}_{[-1,1]}$$

$$Y \sim \text{Be}(p), \quad p = \frac{1}{1 + e^{-z}}$$

Label Distributions



Note: IR from 1.19 to 2.36

Testing Mixture

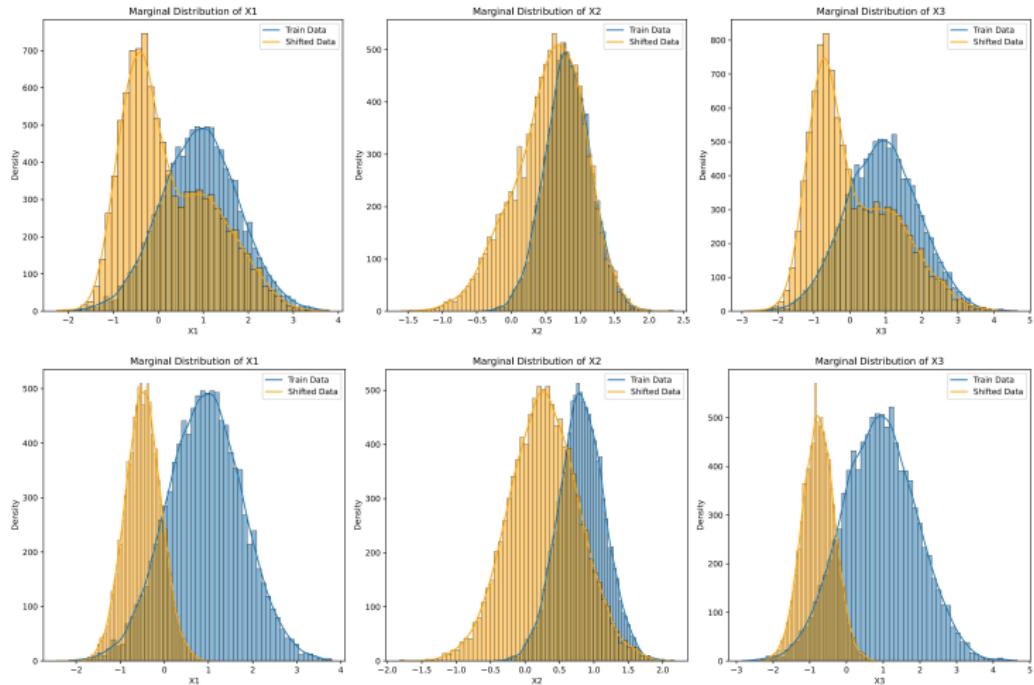
Series of datasets using **statistical mixtures** of the training features distribution and the fully shifted distribution.

$$X_\alpha \sim \alpha \cdot \mathcal{N}(\boldsymbol{\mu}_{\text{shift}}, \boldsymbol{\Sigma}_{\text{shift}}) + (1 - \alpha) \cdot \mathcal{N}(\boldsymbol{\mu}_{\text{train}}, \boldsymbol{\Sigma}_{\text{train}})$$

$$\alpha \in \{0.0, 0.1, \dots, 1.0\}$$

Y_α generated as before

Note: $X_{0.0}$ and X_{train} come from the same distribution, but the former are used as fresh new data.



Top: $\alpha = 0.5$. Bottom: $\alpha = 1.0$.

Performance Degradation

Performance Degradation

We evaluated four distinct statistic models:

- **Random Forest:** An ensemble method combining multiple decision trees, where final prediction is determined by majority voting
- **Gradient Boosting:** Sequential ensemble approach that iteratively improves predictions by combining weak learners (in our case decision trees)
- **XGBoost:** Advanced implementation of gradient boosting with enhanced regularization and computational efficiency
- **Logistic Regression:** [baseline] Classic linear classifier used as a reference model

Fine Tuning and Performance Metric

Performance Metric

We used the **Area Under the Receiver Operating Characteristic Curve (ROC-AUC)** as the performance metric for our models.

Fine Tuning

We performed a **hyperparameter tuning** using the **Grid Search** method with 5-fold cross-validation.

Random Forest

Params	Value
n_estimators	125
max_depth	5
min_samples_split	5
min_samples_leaf	1
bootstrap	True

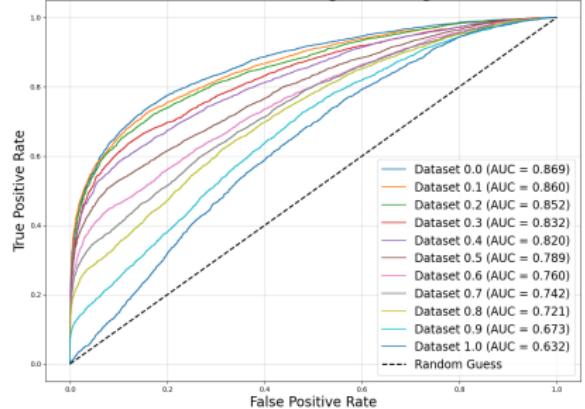
Gradient Boosting

Params	Values
n_estimators	500
max_depth	3
learning_rate	0.005
subsample	0.4

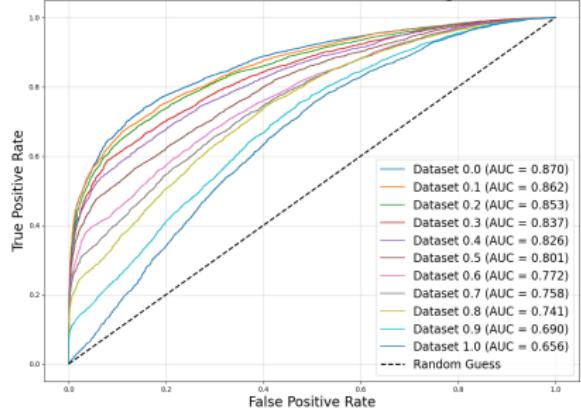
XGBoost

Params	Values
n_estimators	100
max_depth	6
learning_rate	0.1
subsample	0.7
gamma	5

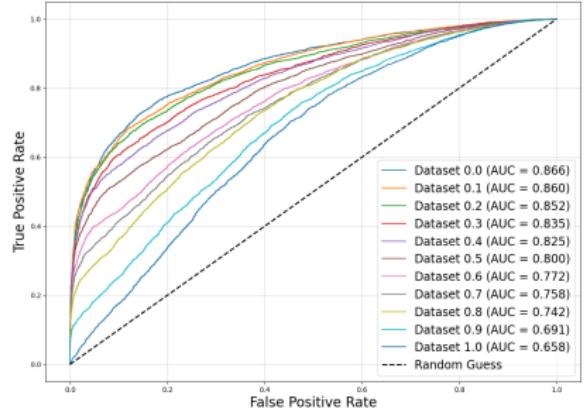
ROC Curves for LogisticRegression



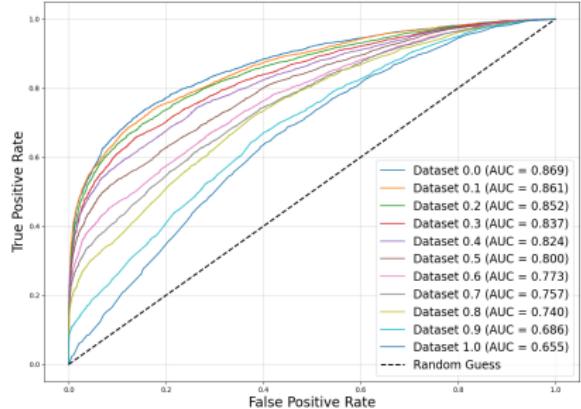
ROC Curves for GradientBoostingClassifier



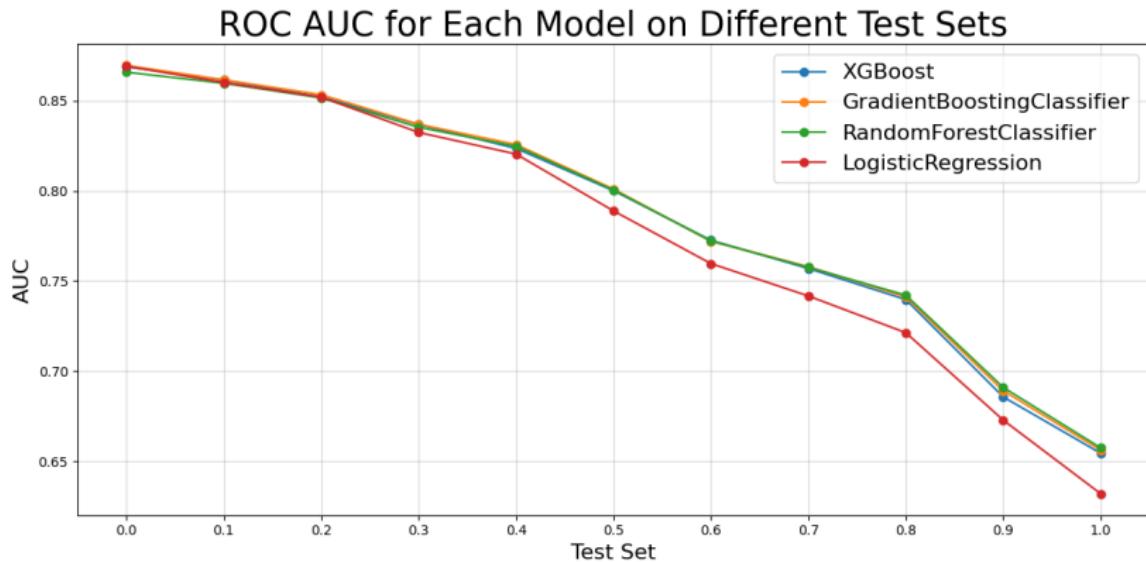
ROC Curves for RandomForestClassifier



ROC Curves for XGBoost



Performance Comparison



The figure illustrates how model performance (AUC) decreases as α increases, reflecting greater covariate shift.

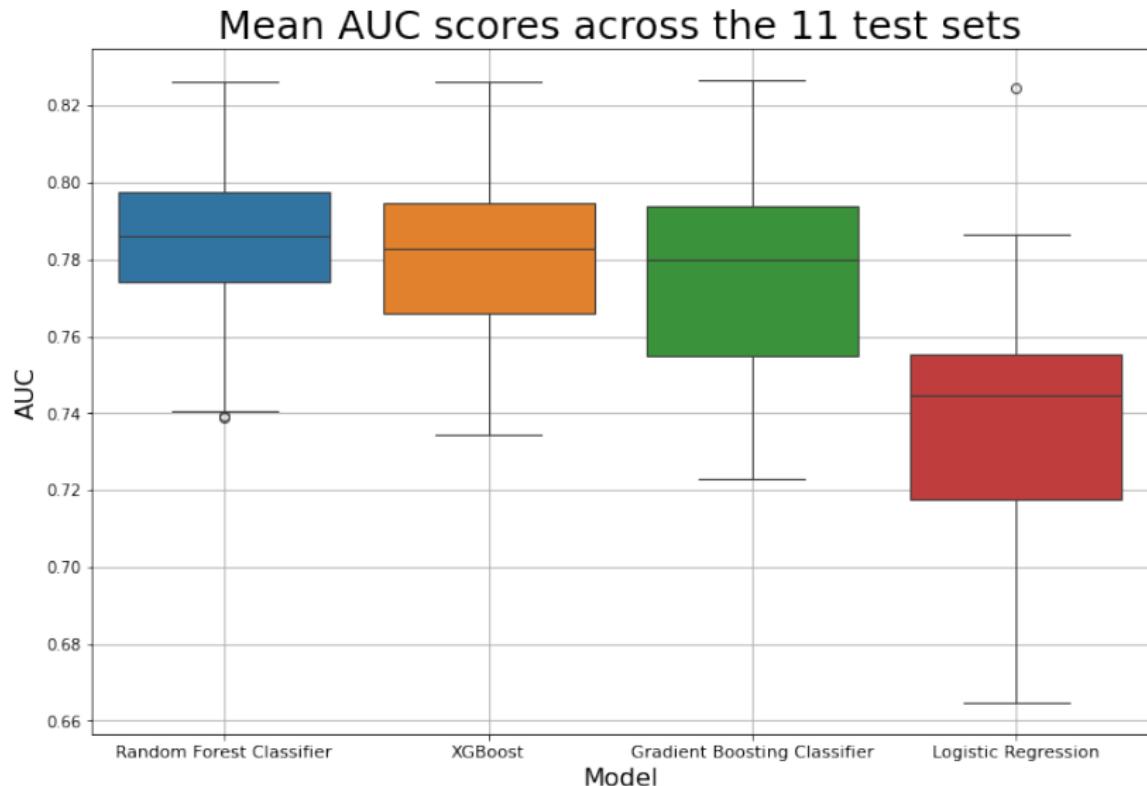
Ensemble models demonstrate higher robustness compared to the Logistic Regression baseline.

Statistical Performance Comparison

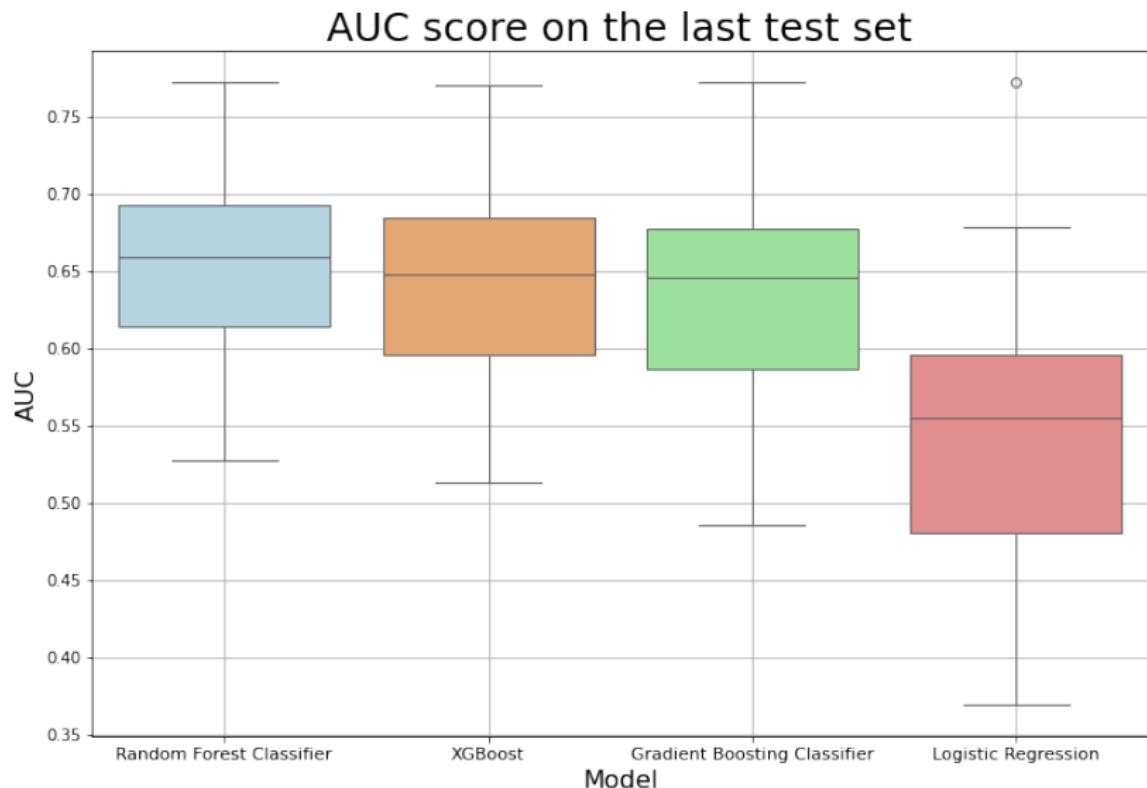
To give statistical support to our study we repeated this experiment $N = 50$ times. Keeping always the same training set (in order to not train the models several times), for each repetition we:

1. defined a new shifted distribution $\mathcal{N}(\boldsymbol{\mu}_{\text{shift}}, \boldsymbol{\Sigma}_{\text{shift}})$
2. created 11 **testing** datasets \mathcal{D}_α with $\alpha \in \{0.0, 0.1, \dots, 1.0\}$, where α represents the mixing probability as before
3. computed the ROC-AUC score for each model on each testing dataset

Statistical Performance Comparison



Statistical Performance Comparison



Performance Enhancement

1. No Prior Shift Knowledge Needed

- Simplifies implementation by eliminating the need for shift estimation.
- Adaptable to various datasets without additional shift information.

2. Built-in Regularization

- Prevents overfitting by introducing controlled noise.
- Enhances model generalization on unseen data.

- Random
- Augmentation
- Walk

Input: $Data_{train}$, $Size$, N , ε .

$Data\% \leftarrow$ random subset of $N\%$ of $Data_{train}$

For x_i in $Data\%$

$x'_i \leftarrow \begin{cases} X_i + \varepsilon & \text{with probability 0.5} \\ X_i - \varepsilon & \text{with probability 0.5} \end{cases}$

$y'_i \leftarrow y_i$

End For

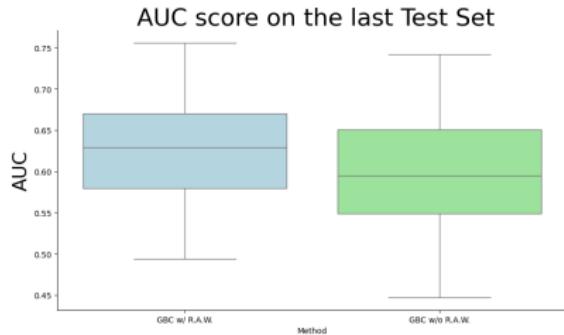
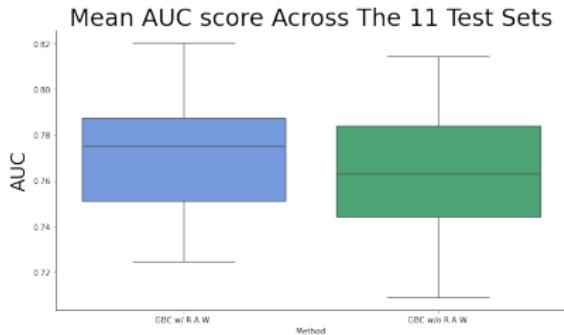
$Data_{aug} \leftarrow Data_{train} \cup Data\%$

$Data_{final} \leftarrow$ Downsample($Data_{aug}$, $Size$)

Return $Data_{final}$

Classify With Gradient Boosting Using R.A.W.

1. Apply the R.A.W. pre-processing method to the training data to address covariate shift.
2. Train a Gradient Boosting Classifier on the augmented dataset.
3. Evaluate the model's performance on shifted test sets.



A Statistical Analysis Of The Results

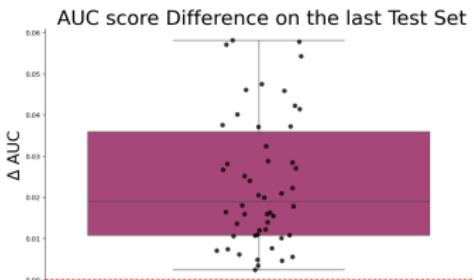
- H_0 :

$$\Delta_{AUC} = AUC_{R.A.W.} - AUC_{base} = 0$$

- H_1 :

$$\Delta_{AUC} = AUC_{R.A.W.} - AUC_{base} \neq 0$$

- **Test:** Student's t-Test on 50 independent Δ_{AUC} .



	Δ_{AUC}	t-stat	p-value	95 % CI
$\Delta_{\overline{AUC}}^*$	0.0083	8.75	1.39×10^{-11}	[0.006, 0.010]
$\Delta_{AUC_{last}}^{**}$	0.0235	10.59	2.86×10^{-14}	[0.019, 0.028]

* Mean AUC score difference across all 11 shifted test sets.

** AUC score difference on the most shifted test set.

Conclusion

How can we address the initial questions posed?

- Covariate shift was explored via synthetic data and repeated simulations.
- Performance degradation highlights the need for "fine-tuned" robust models.
- Every tuned model performed equally across each shift, with the exception of the Logistic Regression.
- **Future work:** Since augmentation showed mitigation potential, we are think about how to further improve the R.A.W. algorithm.

Thank You!