Novel Approaches to Mitigate Abnormal Instances in Imbalanced Datasets

for Improved Classification Performance

Surani Matharaarachchi

PhD Candidate, Department of Statistics, University of Manitoba

Data Scientist, Government of Manitoba

matharas@myumanitoba.ca

Joint work with Dr. Saman Muthukumarana, and Dr. Mike Domaratzki

University of Manitoba

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Outline

- Introduction
- Existing methods
- Challenges
- Novel approaches for imbalanced data
- Simulation & Application Results
- Conclusion

Introduction: Class Imbalance

- Occurs when the number of instances in different classes is significantly disproportionate.
- Examples:
  - Spam Detection
  - Fraud Detection
  - Medical Diagnosis
  - Churn Prediction
- Issue:
  - Leads to biased models
  - Decreases predictive accuracy

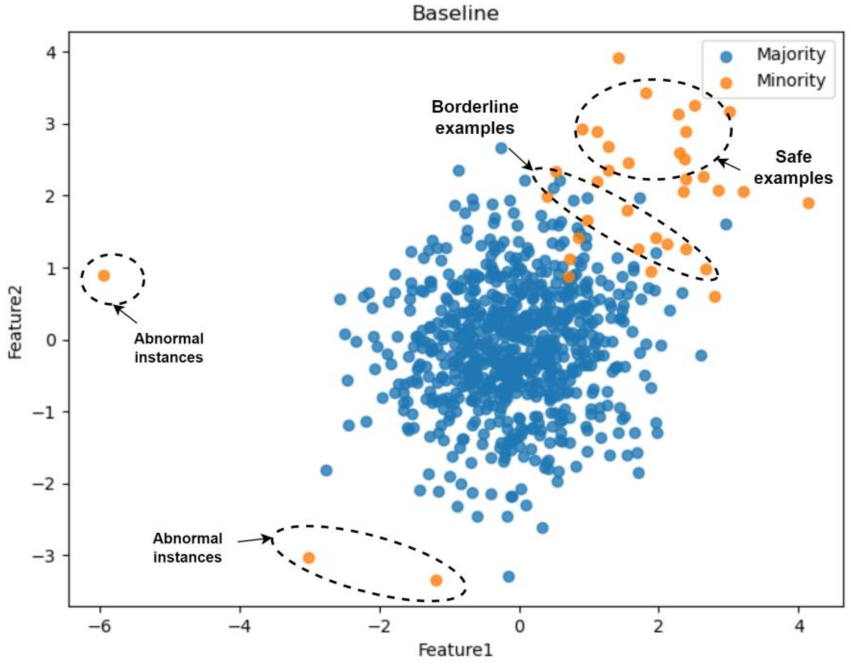


Figure: Class imbalance with outliers in the minority class

Synthetic Minority Oversampling Technique (SMOTE)

- Balancing the Dataset:
  - Strategy:
    - Create new samples for the minority class to help balance the dataset.
  - Technique:
    - Interpolate between randomly chosen minority class samples and their nearest neighbors.
    - $p_{new} = p_0 + \alpha(p_3 - p_0)$

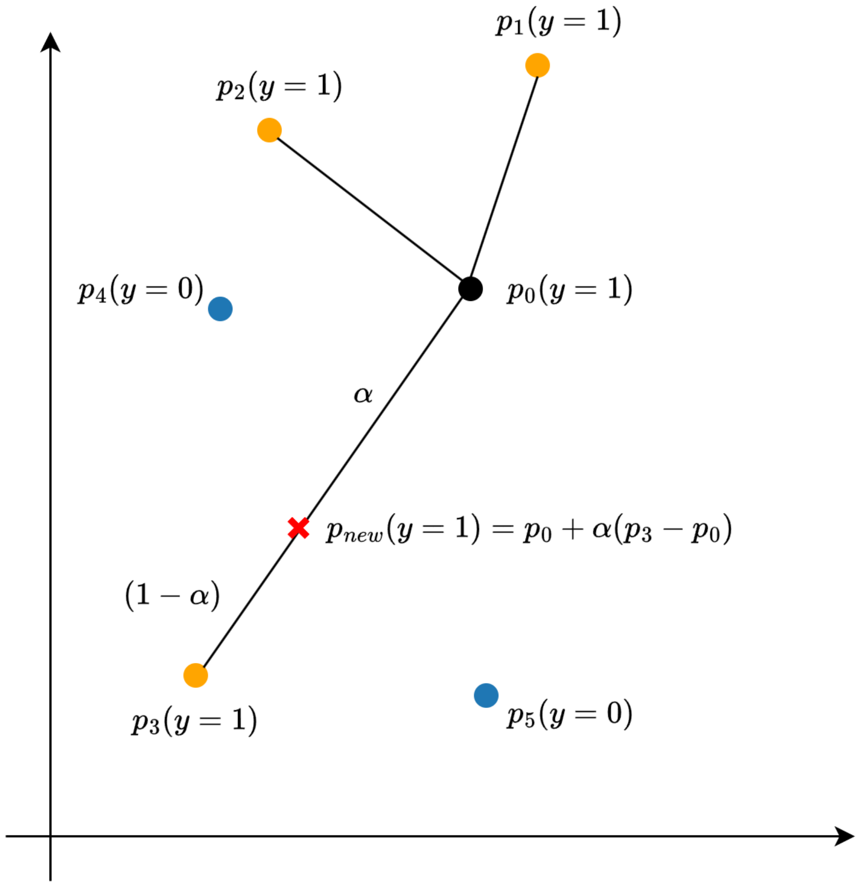


Figure: SMOTE data generation

Challenges of SMOTE

- SMOTE is challenged by outliers within the minority class.

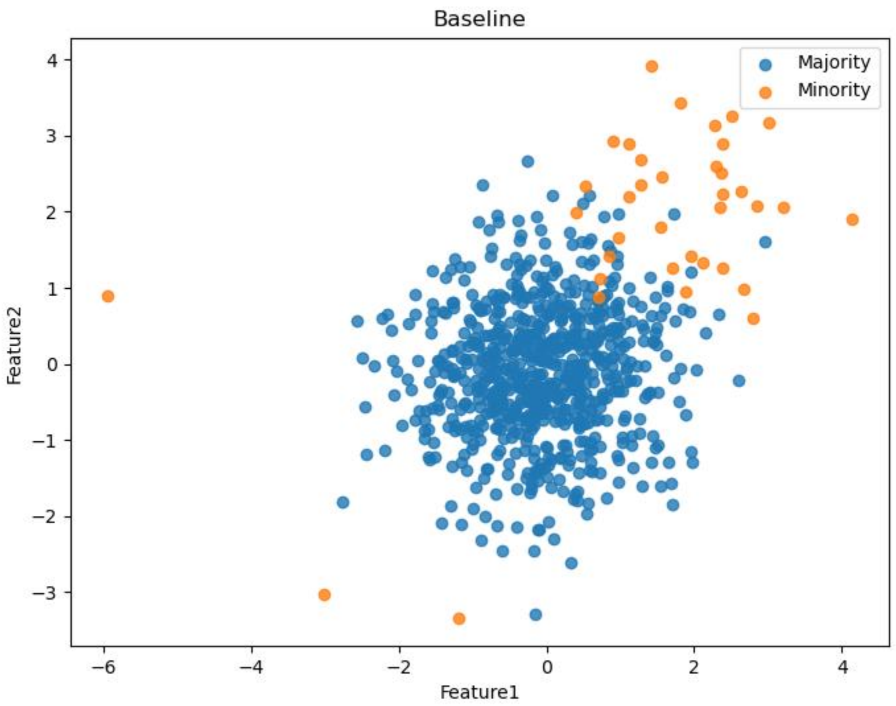


Figure: Original Data

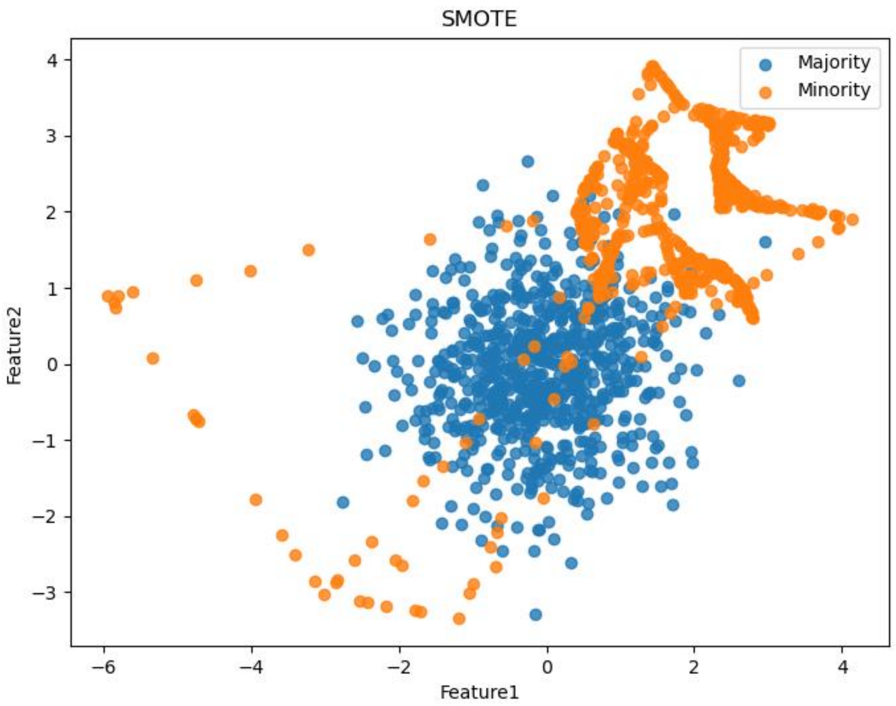


Figure: Re-sampled data with SMOTE

Novel Methods

- Technique:
  - Use a weighted average of neighbouring instances.
  - $p_{new} = \frac{\sum_{j=1}^{k}(w_j \times p_j)}{\sum_{j=1}^{k} w_j}, j = 1, \ldots, k$
  - Improve robustness against outliers and noisy data.
  - Learn from a more extensive set of nearest neighbours
- Challenge:
  - Selecting suitable weights to enhance resilience to outliers and noisy data.

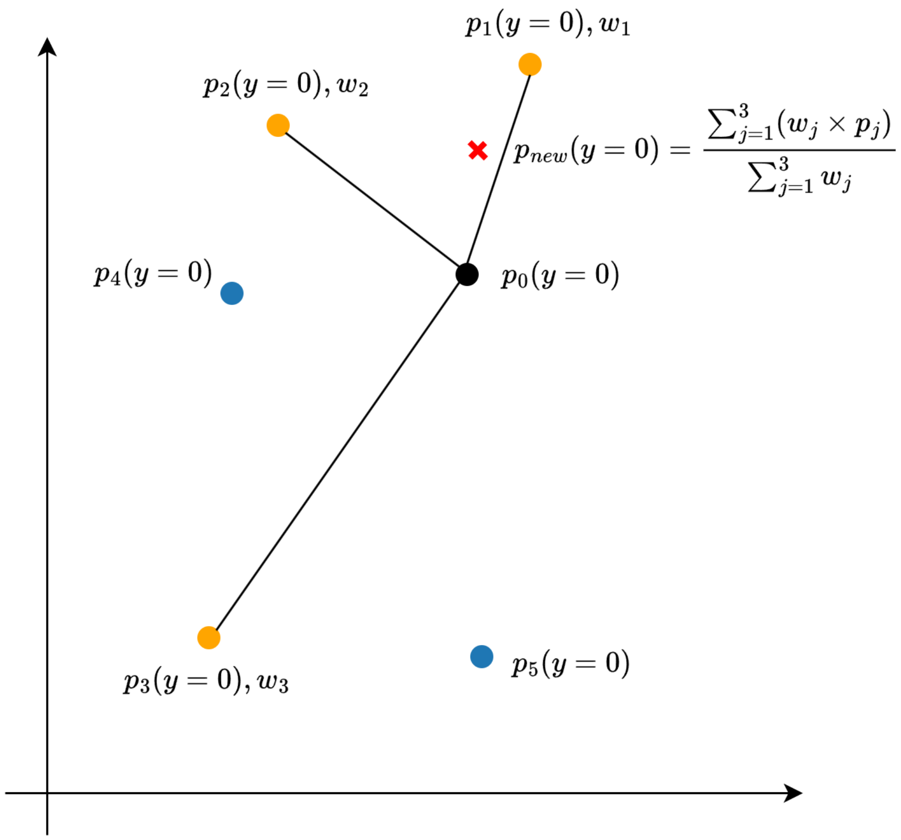


Figure: Proposed method data generation

Developing new SMOTE extensions

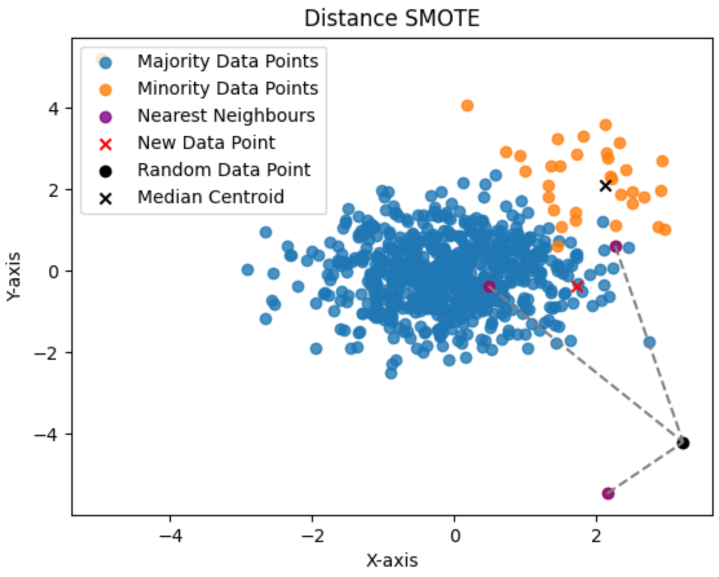
- Solution:
  - **Use inverse distance to the median centroid of the minority class**.
  - Higher weights for closer instances in feature space.

1. Distance extSMOTE
2. Dirichlet extSMOTE
   I. Uniform Random Vector
   II. Uniform Vector
   III. Inverse Distance
3. FCRP SMOTE - SMOTE with Finite Chinese Restaurant Process Idea
4. BGMM SMOTE - SMOTE with Bayesian Gaussian Mixture Model
   I. with Dirichlet prior
   II. with Dirichlet Process prior

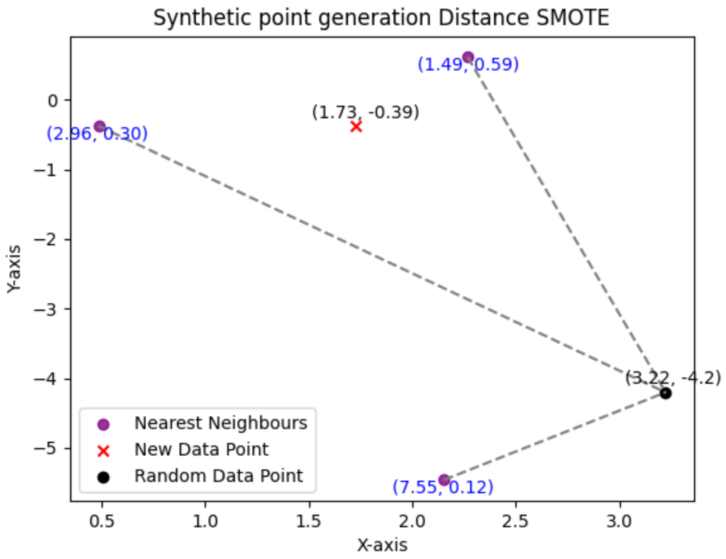
Distance extSMOTE

- $d_j \in \mathbb{R}$ is the Euclidean distance between the median centroid of the minority class and the nearest neighbours
- $w_j = d_{j,norm}^{-1}$ = Normalized inverse distance

An example of creating a sample - Distance extSMOTE



(a). This scenario occurs when an outlier is chosen as a neighbouring point.

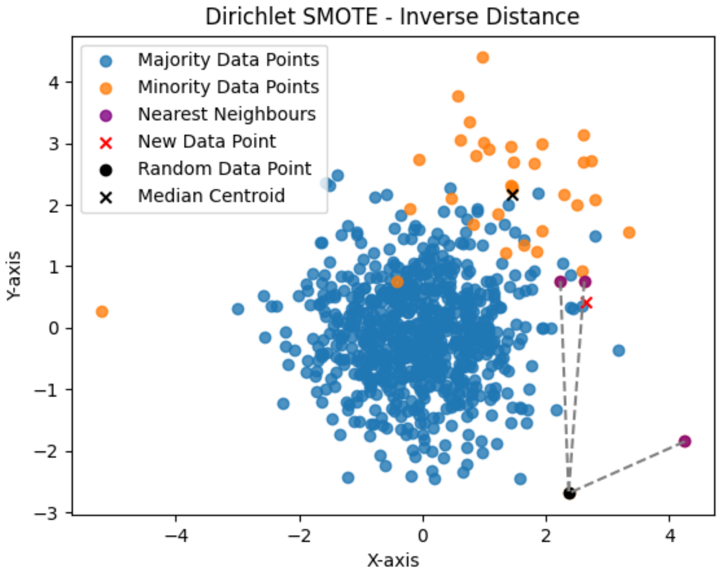


(b). The values within parentheses indicate (d_j, w_j).

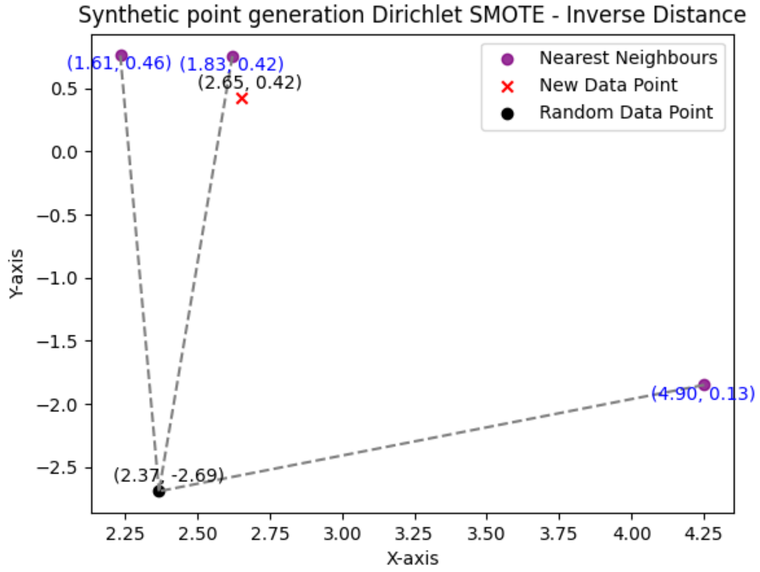
Dirichlet extSMOTE (Inverse Distance)

- $w_j = Dir(\alpha)_j$
- $\alpha = m.\boldsymbol{D}^{-1}, \boldsymbol{D} = [d_1, \dots, d_k], \boldsymbol{D}^{-1} = [\frac{1}{d_1}, \dots, \frac{1}{d_k}]$

An example of creating a sample - Dirichlet extSMOTE

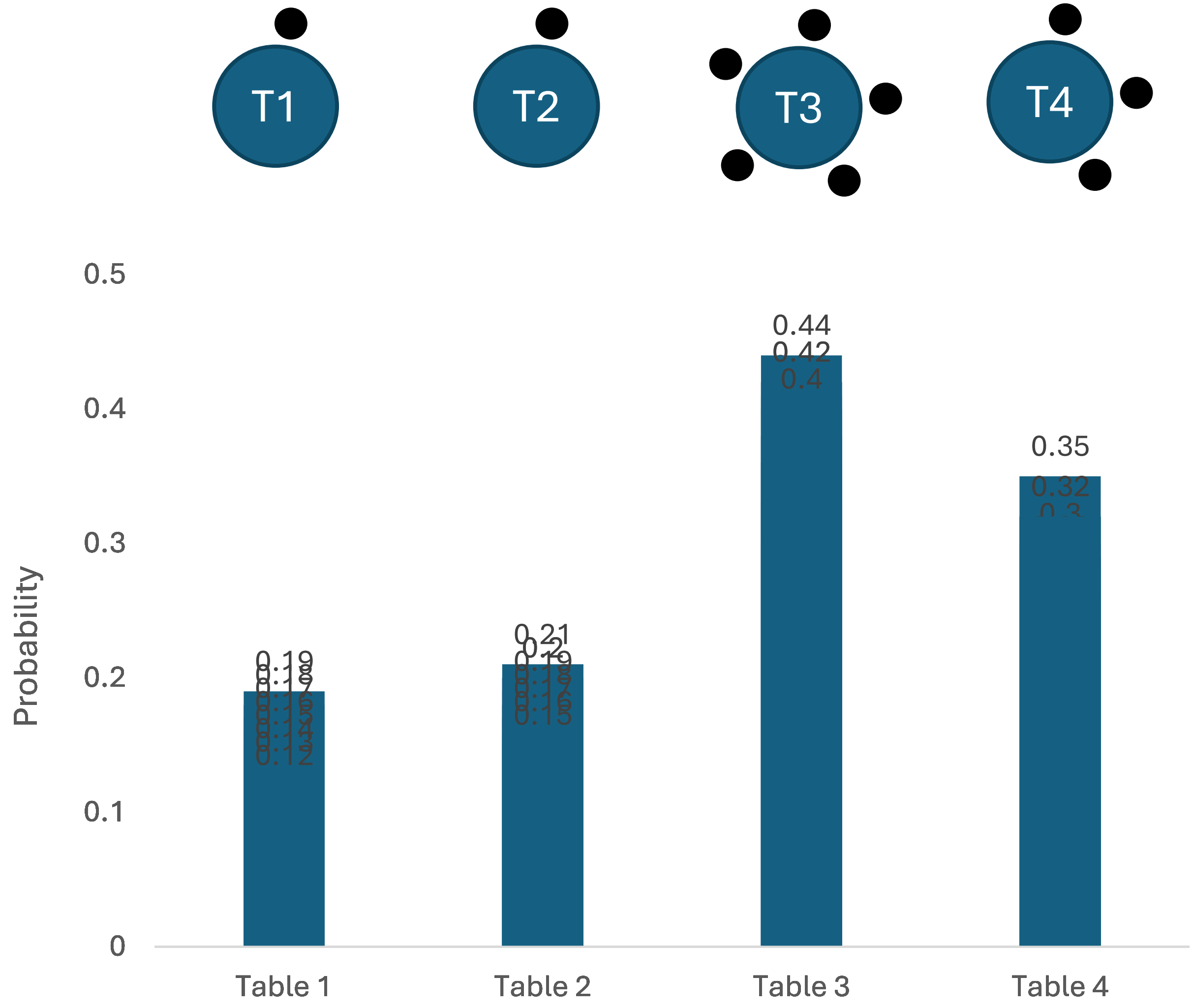


(a). This scenario occurs when an outlier is chosen as a neighbouring point.



(b). The values within parentheses indicate (d_j, w_j).

FCRP SMOTE

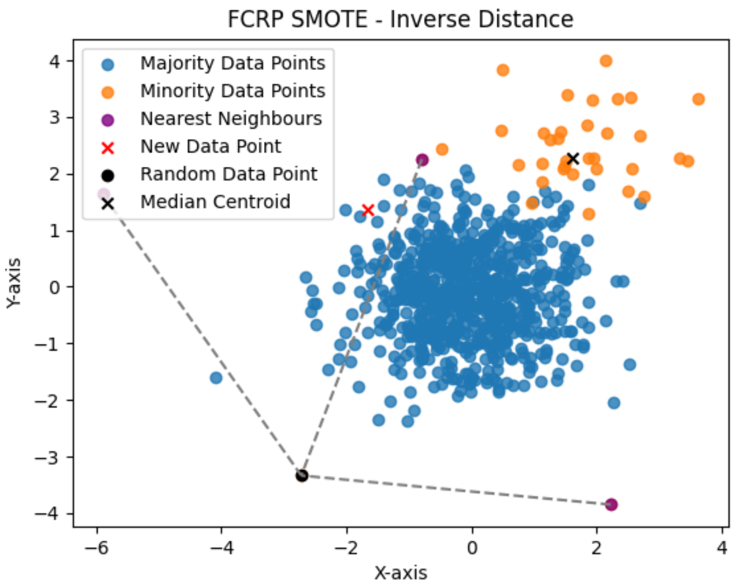


Showcasing the weight selection of FCRP SMOTE using Finite Chinese Restaurant Process with scaling parameter $\alpha = 0.1$

FCRP SMOTE

- Initial preferences $= d_{norm}^{-1}$
- w_j = Final allocation probabilities

An example of creating a sample – FCRP SMOTE



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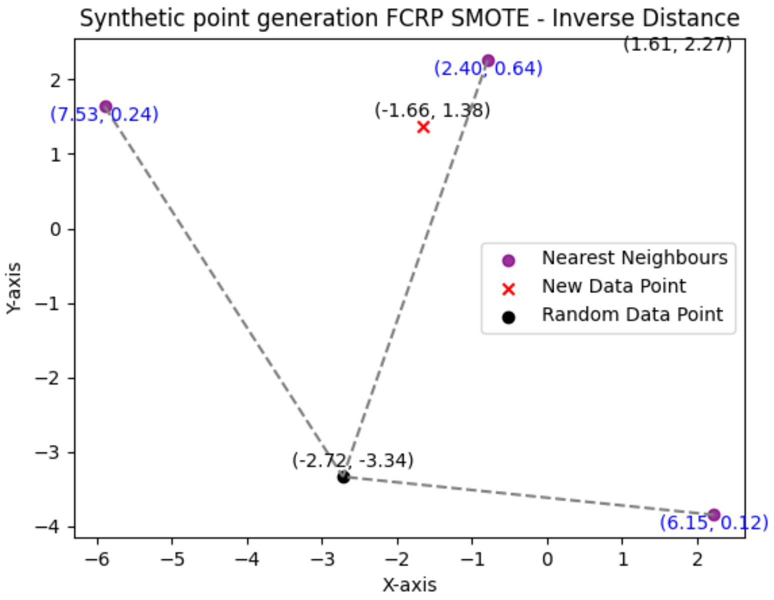


(b). The values within parentheses indicate (d_j, w_j).

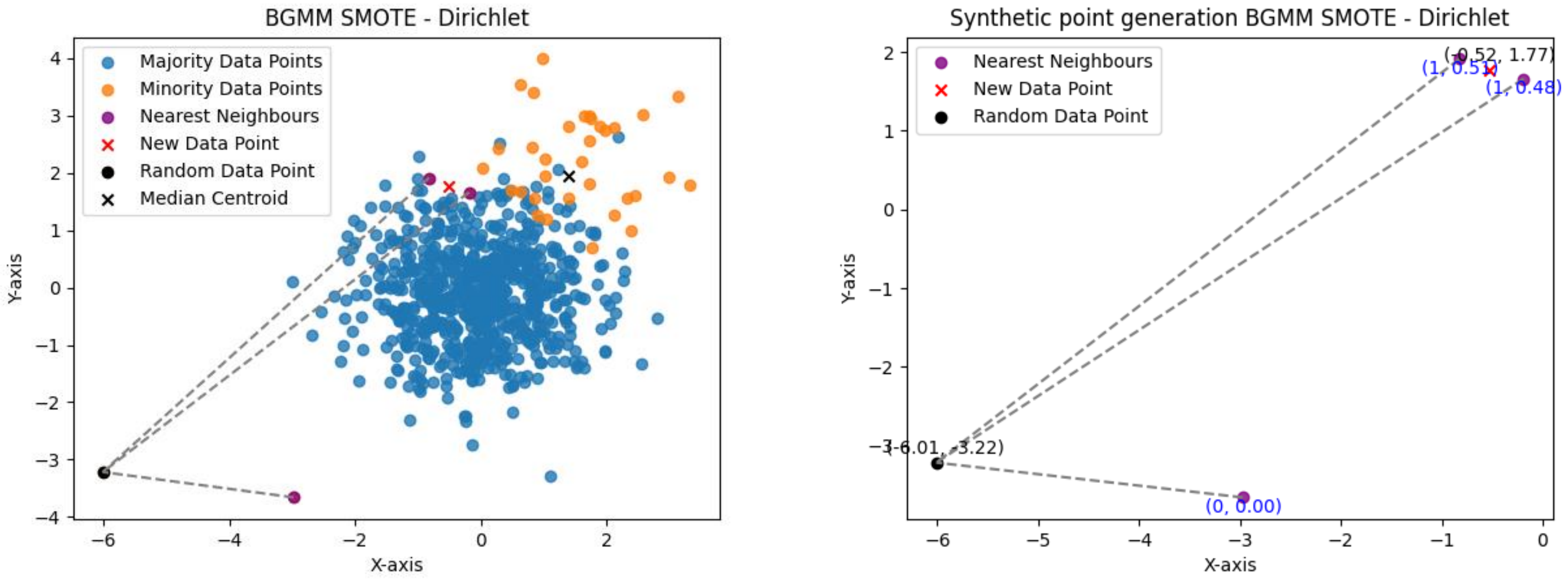
BGMM SMOTE

- A probabilistic model used for clustering
- Cluster Assignment
    1. Expectation Maximization:
        - Expectation (E-step): For each data point, the model calculates the probability of the point belonging to each cluster
        - Maximization (M-step): Update the parameters of the model by maximizing the expected log-likelihood
    2. Cluster Assignment: Probabilistically assigns data points to clusters based on the calculated probabilities.
    3. Soft Assignments: This does not definitively allocate a point to a single cluster.

BGMM SMOTE

- C_j = Cluster assignment of the J^{th} nearest neighbour
- w_j = Normalized cluster probability of the cluster which the median centroid belongs

An example of creating a sample – BGMM SMOTE



(a). This scenario occurs when an outlier is chosen as a neighbouring point.

(b). The values within parentheses indicate (d_j, w_j).

Simulation Results

- $\boldsymbol{X}_{minority-outliers} \sim \mathcal{N}(\mu_1, \Sigma_1)$
- $\boldsymbol{X}_{majority} \sim \mathcal{N}(\mu_2, \Sigma_2)$
- $\boldsymbol{X}_{outliers} \sim Uniform(-10,10)$

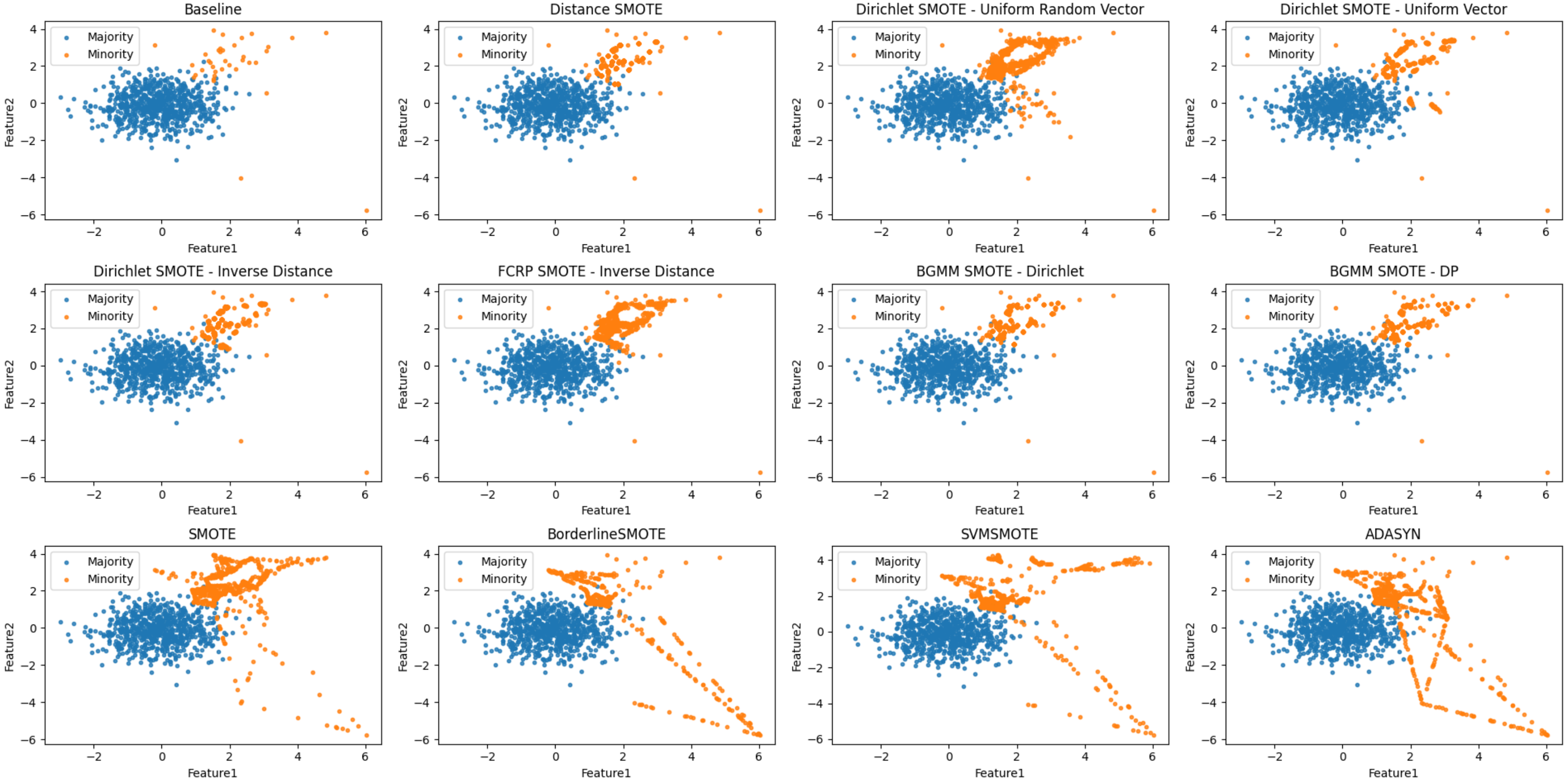


Figure: Comparison of resampled data

Simulation Results

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$= \frac{TP}{TP + \frac{1}{2}(FP + FN)}$$

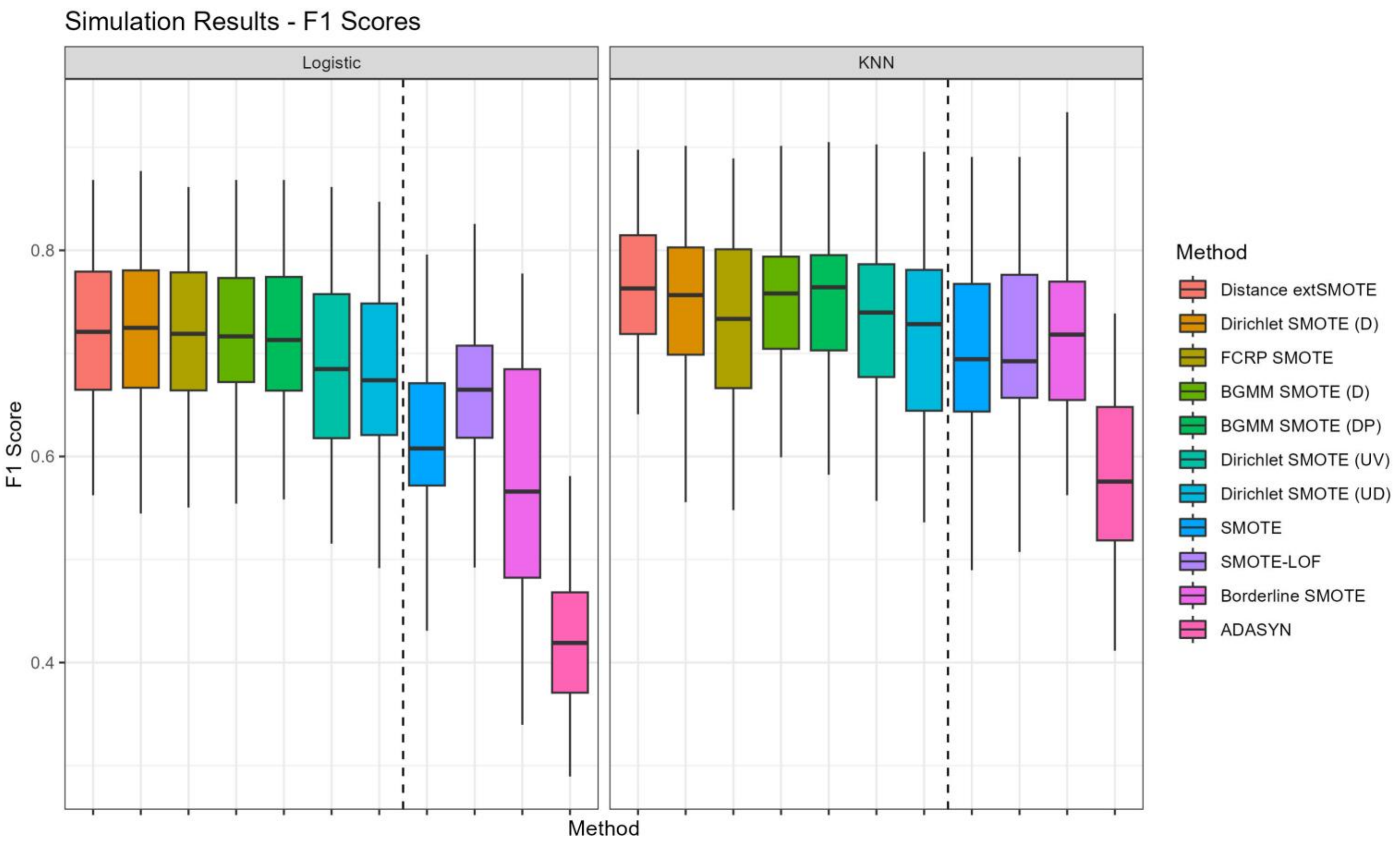


Figure: F1 Scores for 100 simulated datasets with 5-fold cross-validation.

Application Results

- Used 11 imbalanced datasets from the UCI repository

	Name	Target	Ratio	#S	#F
1	mammographic_masses	malignant	2.2:1	961	5
2	Breast_cancer	malignant	2.7:1	569	30
3	Diabetes	Diagnosis: yes	2.9:1	768	8
4	Ecoli	imU	8.6:1	336	7
5	Spectrometer	>=44	11:1	531	93
6	Isolet	A, B	12:1	7797	617
7	Car_eval_34	Good, v good	12:1	1728	21
8	Us_crime	>0.65	12:1	1994	100
9	Thyroid_sick	Sick	15:1	3772	52
10	Oil	Minority	22:1	937	49
11	Abalone19	Age 19	130.5:1	4177	8

Application Results

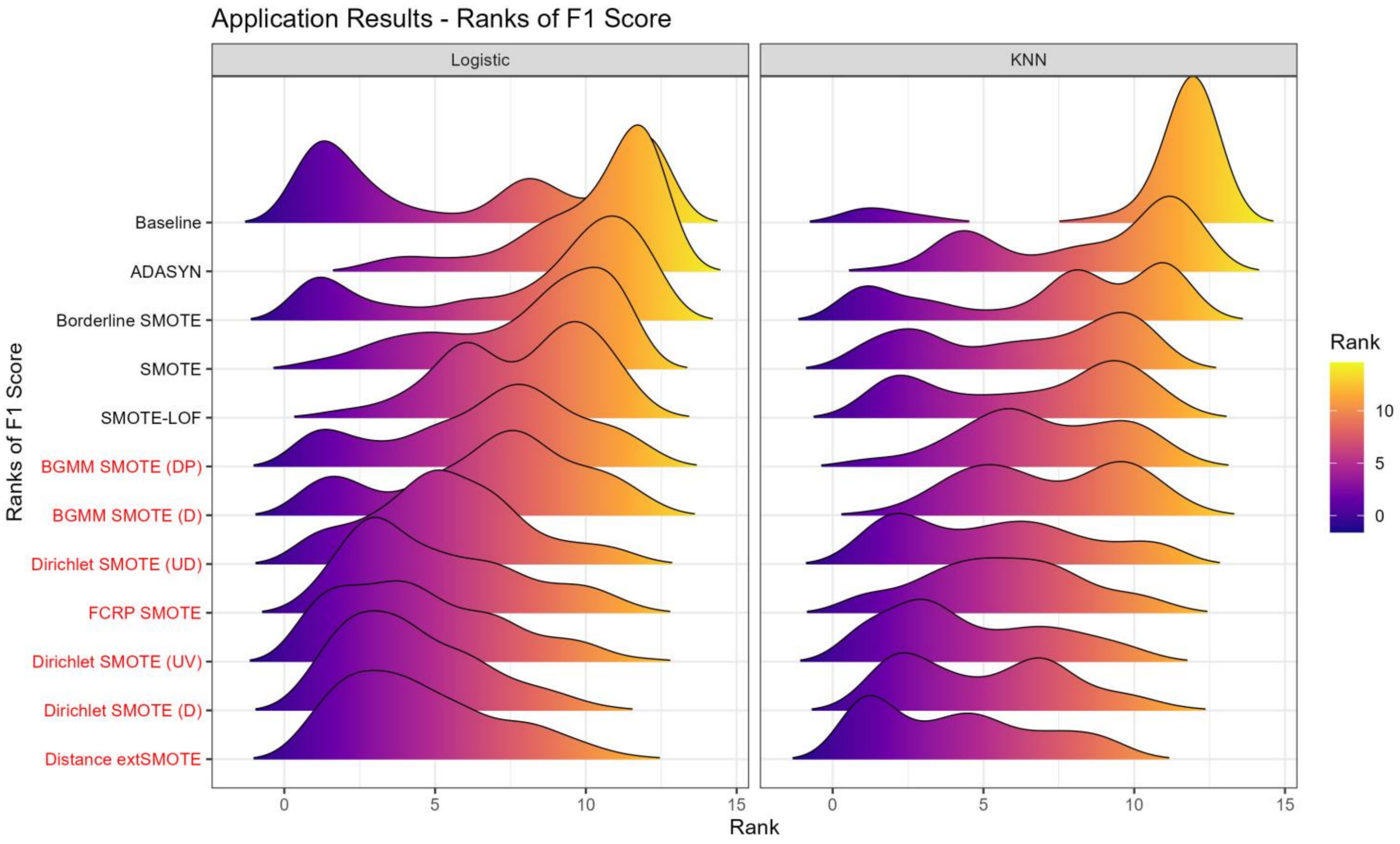


Figure: F1 Score Ranks for the datasets with 30 x 5-fold cross-validation.

Conclusion

- Class imbalance is a significant problem in classification.
- Novel methods are advancing imbalanced classification within machine learning.
- Effectively incorporate measures to minimize outlier effects.
- Creating more **accurate and reliable predictive models.**
- Across diverse domains, including fraud detection, medical diagnosis, and churn prediction, where imbalanced datasets with outliers are prevalent.
- The manuscript related to this work is in review.

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Surani Matharaarachchi, UoM

Thank You!

matharas@myumanitoba.ca