

5.10 Imbalanced Learning for Functional State Assessment

Imbalanced Learning for Functional State Assessment

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Abstract. This paper presents results of several imbalanced learning techniques applied to operator functional state assessment where the data is highly imbalanced, i.e., some function states (majority classes) have much more training samples than other states (minority classes). Conventional machine learning techniques usually tend to classify all data samples into majority classes and perform poorly for minority classes. In this study, we implemented five imbalanced learning techniques, including random under-sampling, random over-sampling, synthetic minority over-sampling technique (SMOTE), borderline-SMOTE and adaptive synthetic sampling (ADASYN) to solve this problem. Experimental results on a benchmark driving test dataset show that accuracies for minority classes could be improved dramatically with a cost of slight performance degradations for majority classes.

1.0 INTRODUCTION

An Operator Functional State (OFS) refers to a multidimensional pattern of the human psychophysiological condition that mediates performance in relation to physiological and psychological costs [1]. Accurate OFS assessment for human operators plays critical roles in automated aviation systems because it can ensure mission success and improve mission performances [2].

Researchers proposed various modeling tools to assess OFS. In Ref. [3], a stepwise discriminate analysis (SWDA) method and artificial neural networks (ANN) were proposed to perform OFS assessment. As a nonlinear model, the ANN is considered more advantageous in complex task situations, especially if multiple features are used. In Ref. [2], committee machines proved useful in improving the assessment accuracy. Errors of individual committee members can be canceled if the errors are independent. Therefore, improvement can be achieved if individual members have low biases and are less correlation i.e., they are diversified [4]. In addition to the traditional "bagging" technique, which generates multiple versions of prediction based on the bootstrap technique to produce the final prediction [5], performing a feature selection

procedure before training can further reduce correlations among committee members [2].

To successfully perform OFS assessment, however, researchers often face the challenge of modeling imbalanced datasets where datasets are not balanced, i.e., some OFS states have much more data samples than others do. In the machine learning community, those OFSs having more data samples than others are named 'majority' classes while those having less samples are called 'minority' classes. Traditional classifiers tend to classify all data samples into majority classes, resulting in poor performances for minority classes [6], which is not acceptable for OFS assessment.

Many imbalanced learning techniques have been proposed to balance performances among majority and minority classes. Those techniques could be divided into four categories [6]: sampling methods, cost-sensitive methods, kernel-based methods, and active learning methods. Sampling methods aim to reduce the imbalance by removing (under-sampling) samples from majority classes or generating (over-sampling) more training samples for minority classes [7]. Cost-sensitive methods improve classification performance by using different cost matrices to compensate for

imbalanced classes [8]. Kernel based methods, such as the support vector machine (SVM), are based on the principles of statistical learning and Vapnik-Chervonenkis (VC) dimensions [9]. Active learning is a type of iterative supervised learning technique, which is used in situations where unlabeled data is abundant. Active learning is often integrated into kernel-based learning methods by selecting the closest instance to the current hyper plane from the unseen training data and adding it to the training set to retrain the model [10].

We have developed an OFS assessment strategy based on a committee machine for a closed-loop adaptive task manage system, where the OFS assessment was treated as a regression problem [2]. In this paper, we redesigned a similar model for the same task; however, we treated the OFS assessment as a classification problem. Because the data sets are highly imbalanced, traditional classifiers failed to classify minority states. We implemented several imbalanced techniques to improve classification performances for those minority OFS states.

The remainder of the paper is organized as follows: Section 2 describes several imbalanced learning techniques implemented in this paper. Section 3 presents the architecture of a committee classifier. Section 4 illustrates our experimental design, including implementation of the imbalanced learning techniques and the design of a committee classifier. Section 5 shows our achieved experimental results. Section 6 provides discussions for the results and Section 7 concludes the paper.

2.0 IMBALANCED LEARNING TECHNIQUES

There exist many imbalanced learning techniques in the literature as described in the excellent review paper [6]. In our study, we implemented five of them as described below.

- Random under-sampling
- Random over-sampling
- Synthetic minority over-sampling technique (SMOTE)
- Borderline-SMOTE
- Adaptive synthetic sampling (ADASYN)

All the methods have been detailed in the Ref. [6], including their implementations, performances and limitations. The overall goal of those methods is to make data samples balanced among classes by dropping some data samples from majority classes and adding samples to minority classes, and to keep roughly the equal number of data samples for all classes.

2.1 Random under-sampling

Random under-sampling was only applied to majority classes. The method randomly selects a number of majority data samples to keep. This method may loss information in the majority classes.

2.2 Random over-sampling

The random over-sampling method was only utilized to minority classes. In contrary to the random under-sampling technique, this method randomly selects data samples from minority classes and duplicates them till the data set is roughly balanced. This method may lead to overfitting because data samples are repeatedly used.

2.3 SMOTE

To overcome the overfitting defect of the random over-sampling method, SMOTE generates or synthesizes new samples for minority classes. To create a new synthetic sample for a given data point (seed) from minority classes, it first randomly selects one of its K -nearest minority neighbors (K is specified by researchers arbitrarily). Then, a random point that is on the line between the seed and the selected neighbor will be synthesized as a new data sample. SMOTE may lead to the problem of over generalization [12]. The following methods, Borderline-SMOTE and ADASYN, are developed to overcome this limitation.

2.4 Borderline-SMOTE

Borderline-SMOTE and SMOTE differ in the ways they select seeds. SMOTE may select any minority sample as a seed while Borderline-SMOTE only considers those who are from minority classes and are on the borderline between minority and majority classes. A minority class sample is considered as on the borderline if majority of its M nearest samples belong to majority classes (M is specified by researchers arbitrarily).

2.5 ADASYN

The difference between ADASYN and SMOTE is the amount of new data samples to be synthesized for each seed. SMOTE generates the same number of data samples for each seed while ADASYN synthesizes data samples according to the distribution of seeds. Considering K nearest neighbors of a seed, the more belonging to majority classes, the more new samples will be synthesized for the seed.

3.0 COMMITTEE MACHINE

A committee machine is an ensemble of multiple estimators (committee members), which could be any learning method for classification or regression. The output of a committee machine is fusion of the outputs from all of its members. A theoretic interpretation for the principle of committee machine is that the errors from individual committee members can be canceled to some extent if they are uncorrelated.

Research results show that the performance improvement can be affected by two factors: accuracies of individual committee members and correlations among them [4]. For the first factor, selection of an appropriate individual model is essential, because a better performance will usually be achieved if each of the individual members performs well. For the second factor, several techniques like bagging, boosting, averaging or voting, mixture of experts have proved effective [4]. In this paper, we use the following techniques to build the committee machine.

- Use the bootstrapping technique to generate multiple 'copies' of the training data.
- Apply an advanced feature selection algorithm, Piecewise Linear Orthogonal Floating Search (PLOFS) [11], to diversify the committee members such that their performances are not highly correlated.
- Train a Multi-Layer Perceptron (MLP) by the standard Back Propagation (BP) algorithm as a base classification model
- Delete the committee members having high biases (accuracy < 50%).
- Utilize the majority vote scheme to fuse decisions from committee members. For example, if majority of the 15 total committee members predict class 1, the final output of the committee is class 1.

The system diagram of the committee machine is shown in Figure. 1.

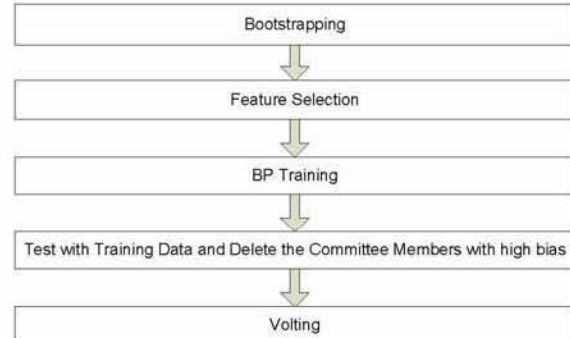


Figure 1: Diagram of the Committee Machine

4.0 EXPERIMENT DESIGN

4.1 The driving test dataset

We utilized a driving test dataset to validate our proposed method for OFS assessment. The dataset was collected by participants performing a driving test over the course of two hours. The collected information includes description of the driving task, system dynamics related information, performance measures, physiological signals (128-channel EEG, ECG,

respiration, etc.), and eye tracking. The workload was also analyzed according to the driving conditions (city-driving, stopped, highway passing, etc.), and seven OFSSs, which indicate seven workload levels, were defined.

Six subjects participated in the driving test and data was recorded in a separate file for each participant, resulting in six individual datasets. Each dataset has seven operator functional states (workload) that are considered as seven classes by our committee classifier. In the dataset, the number of data samples in each class is not balanced. Four classes (minority class) have much less data samples than other three majority classes do. Table 1 and Figure 2 show data distributions for all classes.

Data distributions are similar for all subjects. Class 2 has the largest number of samples (about 35% of the whole data). Class 3 and 4 have the second largest number of samples (about 20%). Therefore, around 75% of samples belong to those three classes. Class 7 has the smallest number of samples accounting for less than 1% of the whole data, and subjects 2, 4 and 6 even have no data for class 7. Class 6 is the second smallest class having about 3% of the whole data samples. Both class 1 and 5 account for 5% of the data samples.

4.2 Imbalanced learning techniques

To implement the five imbalanced techniques, we first compute a desired percentage of data samples per class as,

$$N_d = 100 / \text{no. of classes} * 100\% \\ = 100/7 * 100\% = 14.29\%$$

We then calculate a high threshold (T_H) and a low threshold (T_L) for the number of data samples in each class as,

$$T_H = N_d * (1 + 0.1) \\ = 14.29\% * 1.1 = 15.71\% \\ T_L = N_d * (1 - 0.1) \\ = 14.29\% * 0.9 = 12.86\%$$

Table 1: Data Distribution among Classes

Class	Data set 1 (%)	Data set 2 (%)	Data set 3 (%)	Data set 4 (%)	Data set 5 (%)	Data set 6 (%)
1	6.17	8.70	6.29	5.59	3.52	3.86
2	38.34	39.24	33.83	39.66	32.65	39.87
3	19.96	21.42	24.56	32.94	26.39	20.16
4	23.55	19.40	21.07	16.43	31.24	27.05
5	8.03	8.25	11.30	3.03	2.99	6.10
6	3.89	2.98	2.67	2.35	2.99	2.96
7	0.06	0.00	0.28	0.00	0.22	0.00

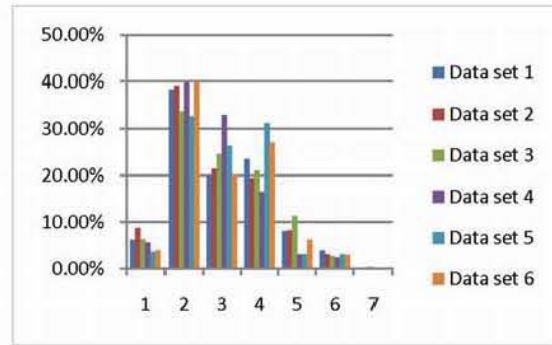


Figure 2: Data Distribution among Classes

Classes having data samples more than T_H are considered as majority classes while classes with data samples less than T_L are considered as minority classes and others are treated as medium classes.

As such, there are seven classes and N_d , T_L and T_H are 14.29%, 12.86% and 15.71%, respectively. Referring to Table 1, it is clear that classes 2, 3 and 4 are majority classes. Class 1, 5, 6 and 7 are minority classes and there is no medium class in our datasets. In order to achieve a balanced dataset, the data portions in both majority and minority classes are made roughly the same as N_d . We apply the random under-sampling technique to the majority classes and four over-sampling methods to the minority classes, resulting in four balanced datasets as shown in Figure 3. For each participant, the balanced dataset shares the majority classes' data samples but has different data samples from minority classes, depending upon which oversampling method is used.

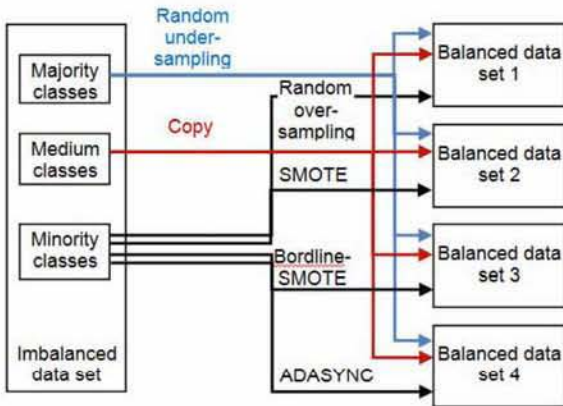


Figure 3: Generation of Balanced Datasets

4.3 Committee classifier

The committee classifier consists of a bootstrap procedure, a feature selection process and a majority voting scheme (see Figure. 4). A MLP trained by the BP algorithm was implemented as the base classification model. Basic procedures performed by the committee classifier are as follows:

1. Randomly divide a subject's dataset into two parts with equal number of data points, one for training and another for testing.
2. Generate M bootstrapped datasets for the training dataset.
3. Apply one of the imbalanced learning techniques to the bootstrapped datasets. A balanced dataset is then obtained for each of the M datasets.
4. Select a set of most effective features for each of the balanced datasets using the PLOFS algorithm. Selected features for different datasets maybe different.
5. Train a MLP classifier for each of the datasets using the features selected for that dataset.
6. Apply the trained MLP to the training and testing datasets.
7. Generate the final classification result by majority voting. MLPs having training

accuracies greater than 50% are used only. Repeat the above procedures by exchanging the role of training and testing datasets.

8. Repeat the above steps for each of the imbalanced learning techniques described in Section 3.

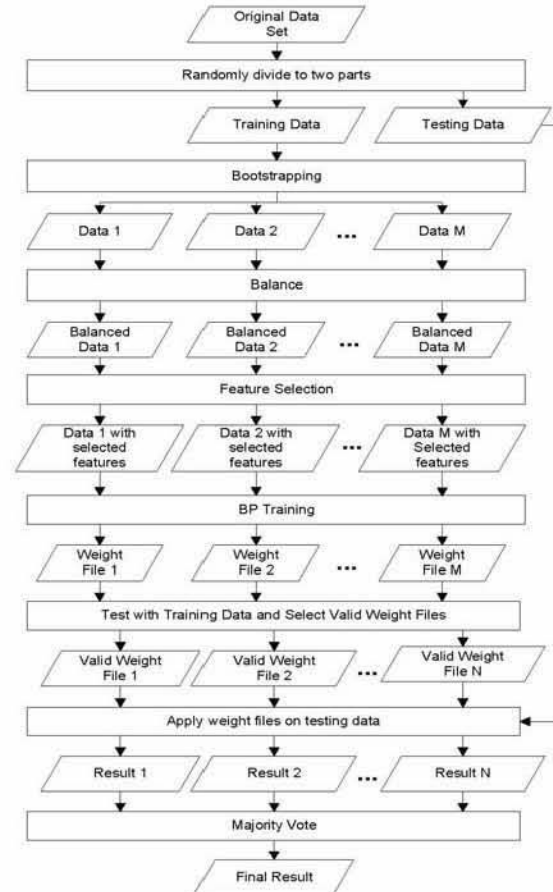


Figure 4: Design of the Committee Classifier

5.0 RESULTS

We trained a committee classifier for each of the six participants (datasets) and results are shown in Tables 2 - 7 and Figs. 5 - 10.

In the Tables, the 'Untreated' column illustrates results achieved on the original data sets. Other four columns present accuracies (in percentage) for each class achieved by applying the four imbalanced learning techniques to the minority classes. The last row shows the average (overall)

accuracies achieved by each of the techniques.

6.0 DISCUSSION

It is observed that the classification accuracies are highly imbalanced if no imbalanced learning technique is used. For instances, the minority class 7 always has 0% accuracy for all subjects but good performances are usually achieved for majority classes 2, 3 and 4. Classification accuracies have been balanced among minority and majority classes by applying the four imbalanced learning techniques to minority classes. Accuracies often have been significantly improved for minority classes while those for majority classes have been decreased slightly. As a result, the overall performance has been slightly degraded. Note that different sampling algorithms appear to perform similarly, indicating the robustness of the imbalanced learning techniques.

Table 3: Results for Dataset 2

Class	Un treated	Over Sample	Smote	Border	AdaSyn
1	96.23%	96.92%	98.97%	99.32%	99.32%
2	99.92%	98.25%	99.16%	98.56%	98.33%
3	88.46%	75.10%	73.44%	84.98%	79.00%
4	67.43%	57.91%	46.08%	61.14%	63.75%
5	10.47%	55.60%	74.01%	23.10%	24.19%
6	58%	96%	90%	81%	89%
Over all	82.21%	81.76%	80.99%	81.70%	81.17%

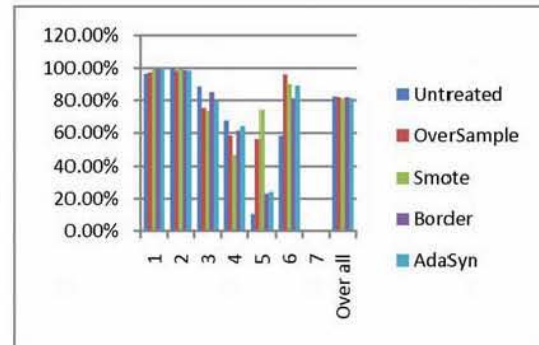


Figure 6: Results for Dataset 2

Table 2: Results for Dataset 1

Class	Un treated	Over sample	Smote	Border	Ada Syn
1	94.27%	97.40%	98.44%	96.35%	97.40%
2	99.75%	98.58%	99.08%	98.49%	98.99%
3	90.82%	85.67%	74.24%	77.78%	82.13%
4	70.53%	57.30%	42.84%	66.85%	59.07%
5	2.80%	38.40%	71.20%	15.60%	26.80%
6	57.02%	89.26%	82.64%	66.12%	73.55%
7	0%	100%	100%	100%	100%
Over all	81.23%	81.01%	77.96%	78.86%	79.34%

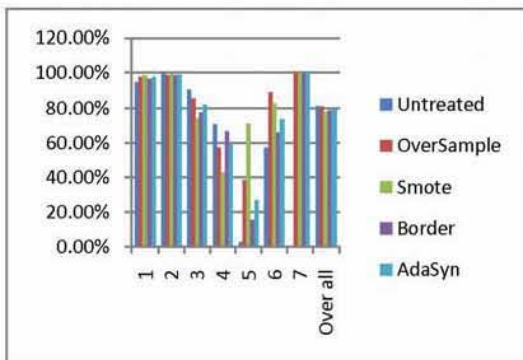


Figure 5: Results for Dataset 1

Table 4: Results for Dataset 3

Class	Un treated	Over Sample	Smote	Border	AdaSyn
1	89.83%	93.22%	94.92%	95.48%	94.35%
2	100%	96.74%	96.11%	96.74%	96.64%
3	78.00%	65.70%	61.51%	67.15%	65.56%
4	47.05%	45.19%	36.26%	46.21%	47.05%
5	45.91%	52.52%	68.24%	52.52%	51.89%
6	70.67%	85.33%	78.67%	78.67%	77.33%
7	0%	100%	87.50%	87.50%	87.50%
Over all	75.62%	72.74%	71.29%	73.24%	72.81%

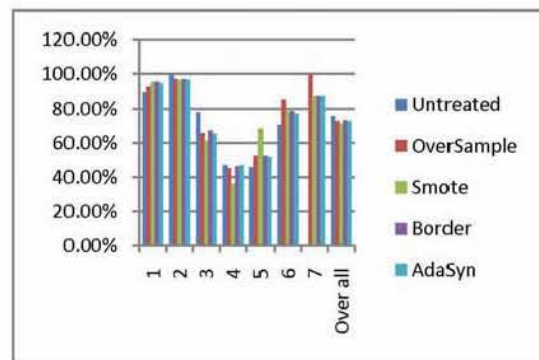


Figure 7: Results for Dataset 3

Table 4: Results for Dataset 4

Class	Un treated	Over Sample	Smote	Border	AdaSyn
1	60.49%	88.29%	89.76%	85.85%	89.76%
2	96.97%	93.87%	93.67%	95.94%	95.53%
3	90.39%	72.74%	66.36%	77.13%	75.64%
4	67.11%	70.27%	70.43%	72.43%	71.26%
5	34.23%	63.96%	61.26%	51.35%	53.15%
6	44.19%	96.51%	96.51%	87.21%	95.35%
Over all	84.72%	81.88%	79.72%	83.76%	83.38%

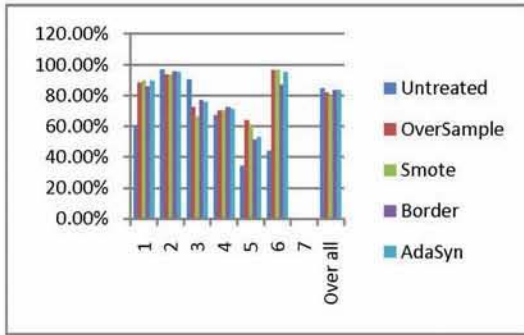


Figure 7: Results for Dataset 4

Table 6: Results for Dataset 6

Class	Un treated	Over Sample	Smote	Border	AdaSyn
1	92.86%	97.32%	99.11%	98.21%	95.54%
2	97.23%	93.78%	93.00%	93.78%	94.90%
3	89.23%	75.04%	71.62%	85.30%	74.36%
4	68.28%	59.24%	49.30%	64.20%	60.13%
5	3.95%	43.50%	55.37%	10.73%	27.68%
6	29.07%	87.21%	83.72%	60.47%	82.56%
Over all	79.91%	77.53%	74.53%	78.19%	76.91%

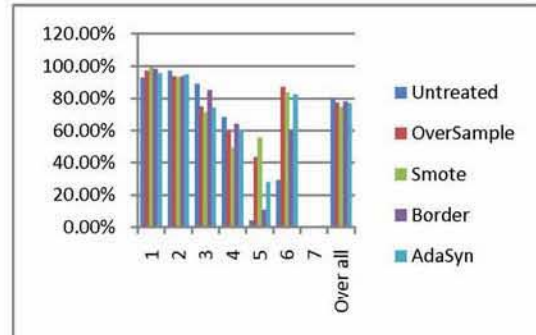


Figure 9: Results for Dataset 6

Table 5: Results for Dataset 5

Class	Un treated	Over Sample	Smote	Border	AdaSyn
1	55.36%	95.54%	98.21%	95.54%	96.43%
2	96.63%	97.88%	97.69%	98.07%	97.50%
3	82.96%	75.92%	73.78%	78.31%	77.83%
4	59.62%	26.99%	30.21%	35.65%	34.14%
5	53.68%	61.05%	77.89%	62.11%	73.68%
6	84.21%	94.74%	94.74%	97.89%	96.84%
7	0%	100%	71.43%	85.71%	71.43%
Over all	78.14%	68.67%	69.58%	72.16%	71.69%

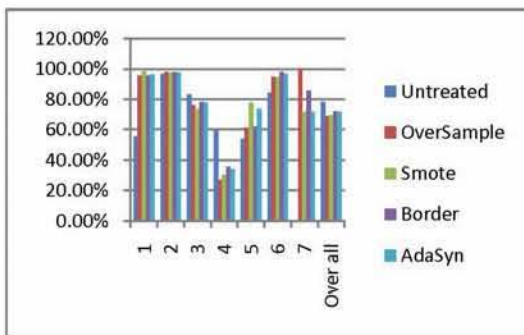


Figure 8: Results for Dataset 5

7.0 CONCLUSIONS

We have implemented five different imbalanced techniques for OFS assessment and validated our methods on driving test benchmark datasets. Experimental results consistently show that classification accuracies for minority classes in the tested datasets are improved dramatically with a cost of slight performance degradations for majority classes, indicating that imbalanced learning techniques could be very useful for OFS assessment.

In a practical setting, an OFS assessment model will be trained offline. We can utilize the imbalanced learning techniques to improve recognition accuracies of the assessment model for minority OFSs without severely decreasing assessment effectiveness for majority OFSs. Once the model is trained, it will then be able to recognize all possible OFSs relatively accurately on the fly. This is critical because some minority OFSs may be highly correlated to aviation safety.

Our future work includes further testing the applicability of more imbalanced learning techniques to the OFS assessment task, validating those methods on more subjects' datasets and integrating the most effective scheme into a real time OFS assessment system.

8.0 ACKNOWLEDGEMENT

This project was funded by the NASA (Contract No: NNX10CB27C). We thank Dr. Alan T. Pope, our COTR, for his comments and suggestions as we performed this research. We also thank Dr. Kara Latorella for her comments and feedback during various discussions over the course of this project

9.0 REFERENCES

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October 14, 2010

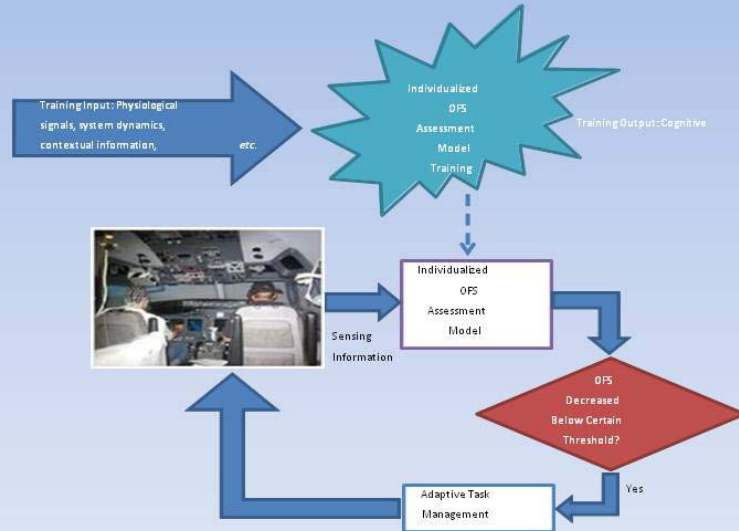
1

Outline

- Introduction
- Imbalanced Learning Techniques
- Experiment Design
- Results & Discussion
- Conclusion

2

Operator Functional State (OFS)



3

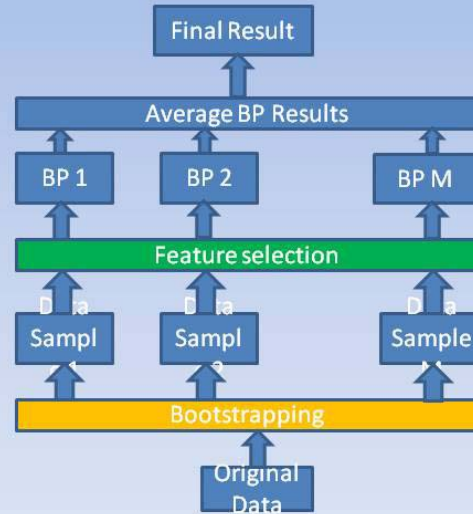
Related Work

- a stepwise discriminate analysis (SWDA) method and artificial neural networks (ANN) were proposed to perform OFS assessment [3];
- committee machine proves to be useful in improving the assessment accuracy [2];
 - Bootstrap (Bagging)
 - Feature Selection

4

Recent Work

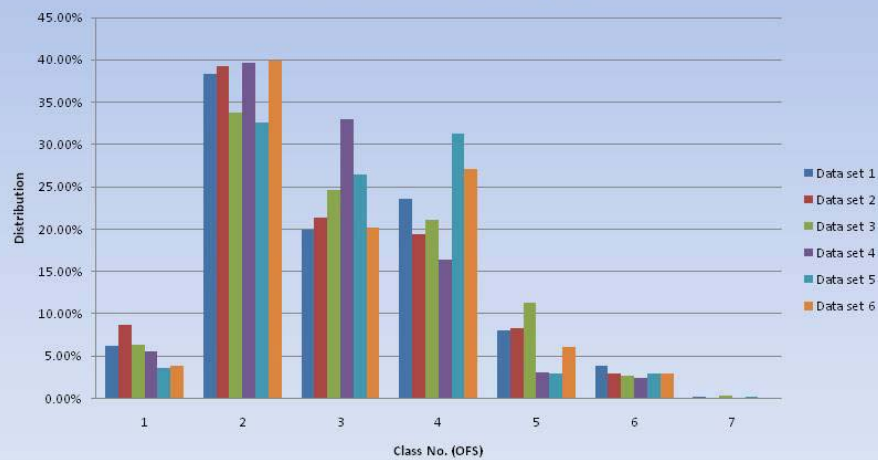
- Data Description
- Committee Machine
- Regression



5

Data Description

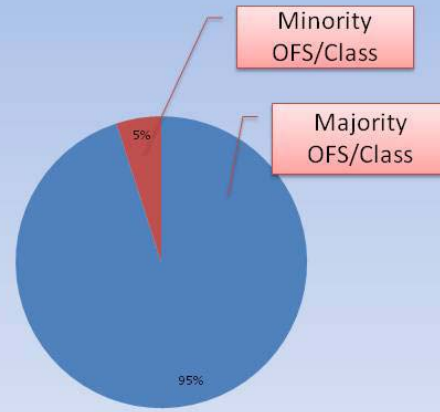
Distribution of data samples



6

Challenge

- Imbalanced data set
- Problem
- Techniques [6]
 - Sampling methods
 - Cost-sensitive methods
 - Kernel-based methods
 - Active learning methods



Distribution of 2-class data set

7

Our Goal

- Classification based on Committee Machine
- Imbalanced Learning Techniques

8

Outline

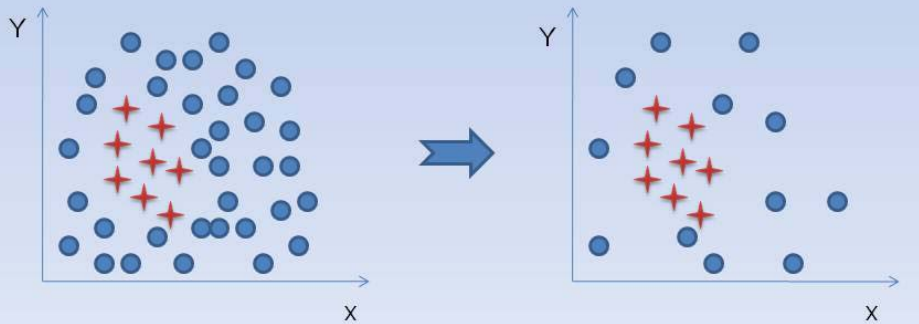
- Introduction
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Sampling methods

- Random under-sampling [6]
- Random over-sampling
- Synthetic minority over-sampling (SMOTE)
- Borderling-SMOTE
- Adaptive synthetic sampling (ADASYN)

Random Under-sampling

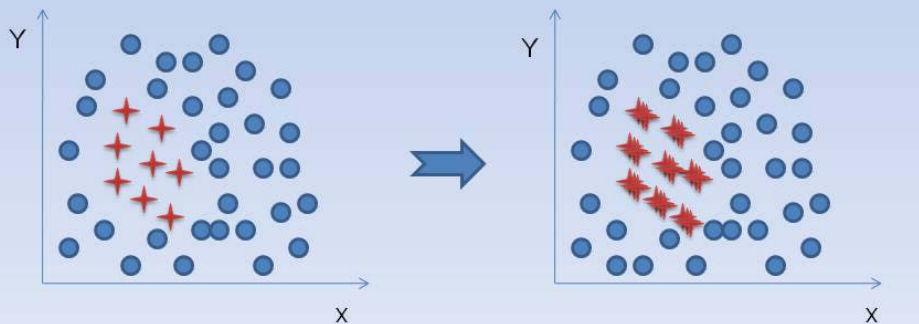
- Randomly select a number of majority data samples and remove them.
- May loss important information.



11

Random Over-sampling

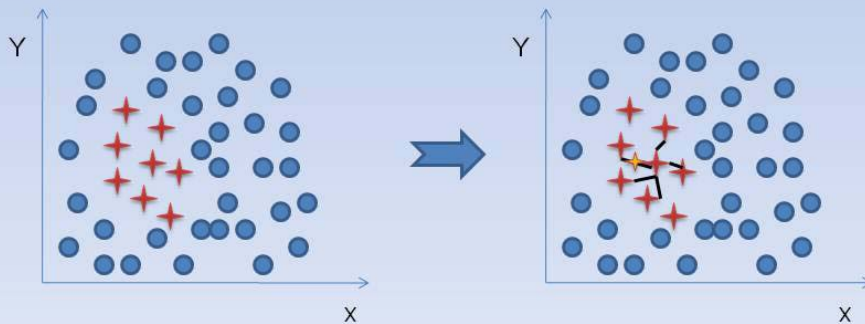
- Randomly select minority data samples and duplicate them to training data set.
- May lead to over-fitting.



12

Synthetic Minority Over-sampling Technique (SMOTE)

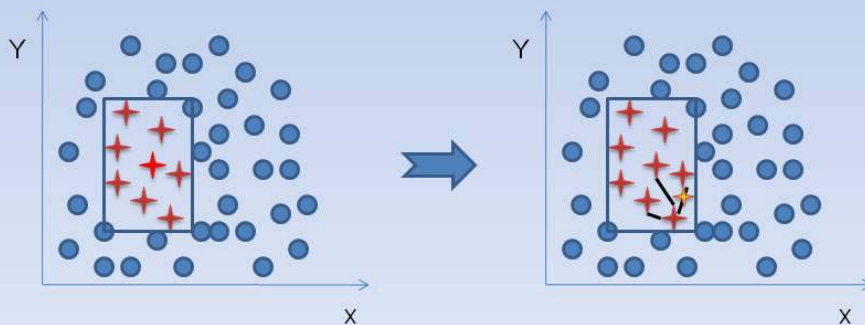
- Synthesize a random point on the line between the seed and the neighbor
- May lead to overgeneralization



13

Borderline-SMOTE

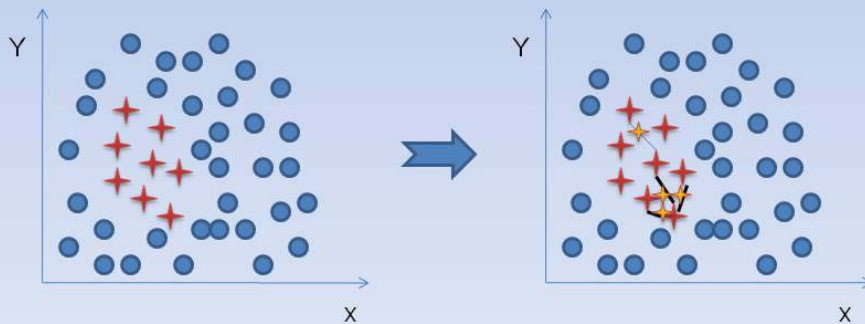
- Borderline-SMOTE and SMOTE differ in how they select seeds. Borderline-SMOTE only selects seeds on the borderline.



14

Adaptive Synthetic Sampling (ADASYN)

- ADASYN and SMOTE defer in the amount of new samples that need to be synthesized. The more neighbors belong to majority OFSs, the more samples need to be synthesized.



15

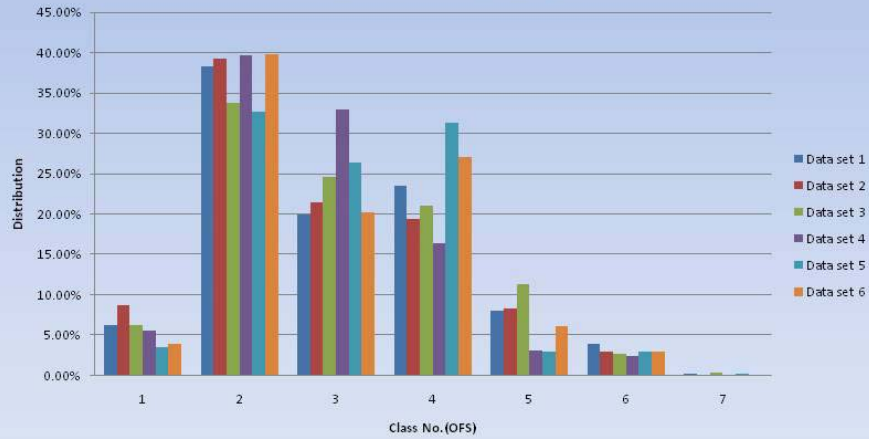
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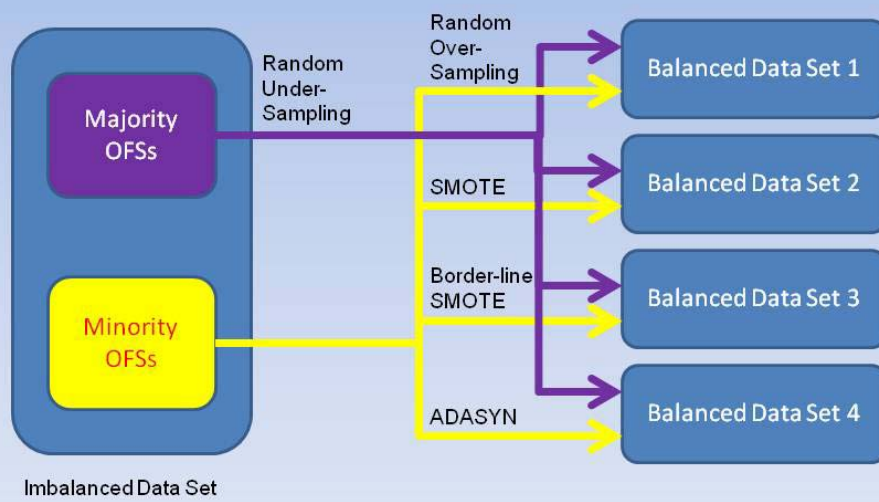
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Data Description

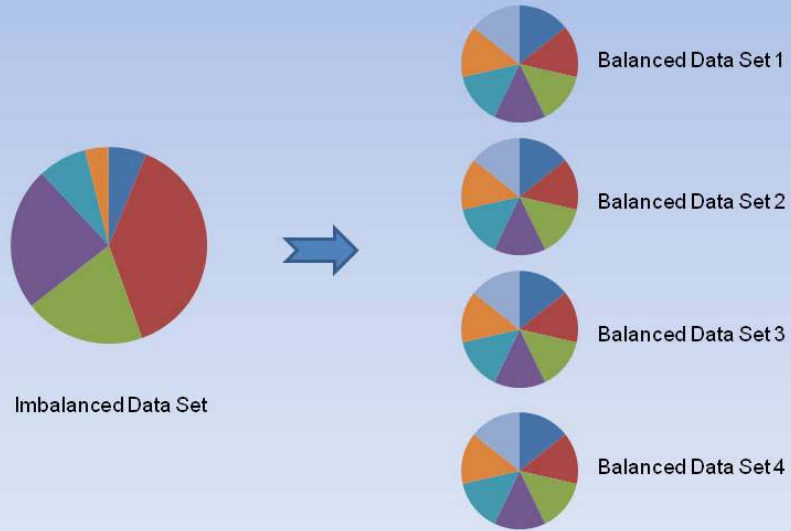
Distribution of data samples



Achieve balanced data set

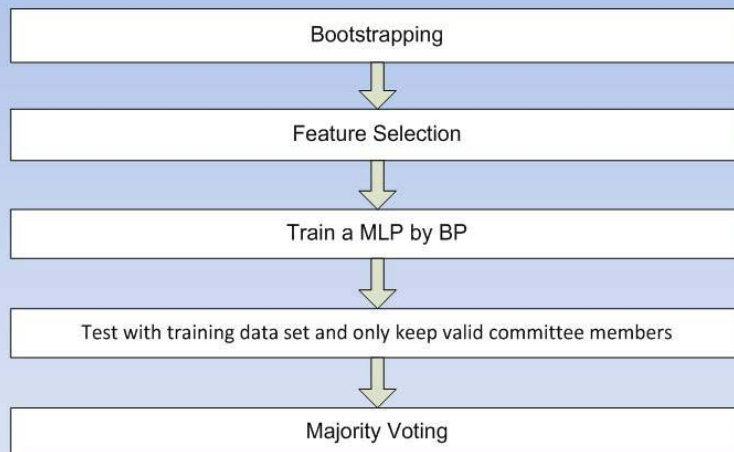


Achieve balanced data set



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Committee Machine

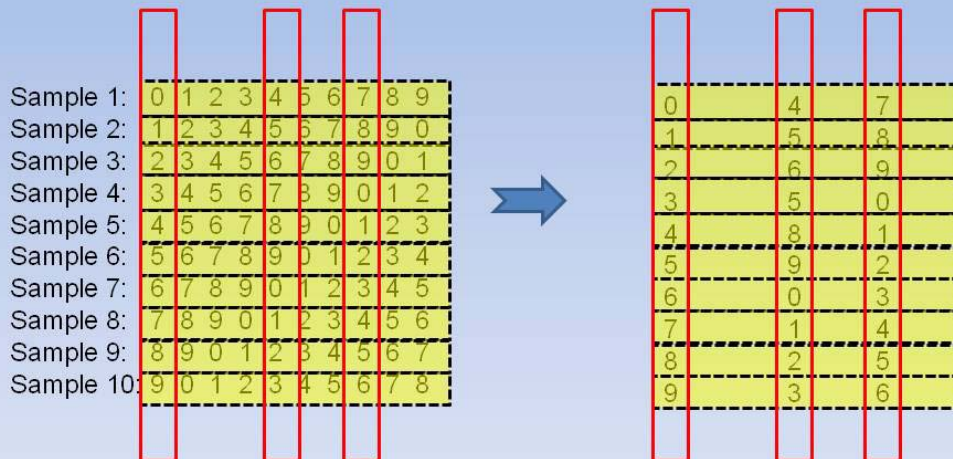


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Bootstrapping

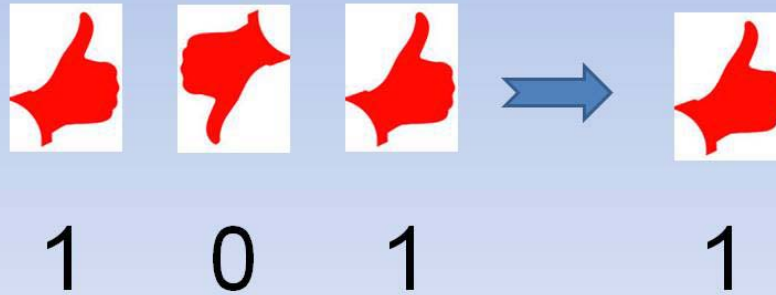


Feature Selection



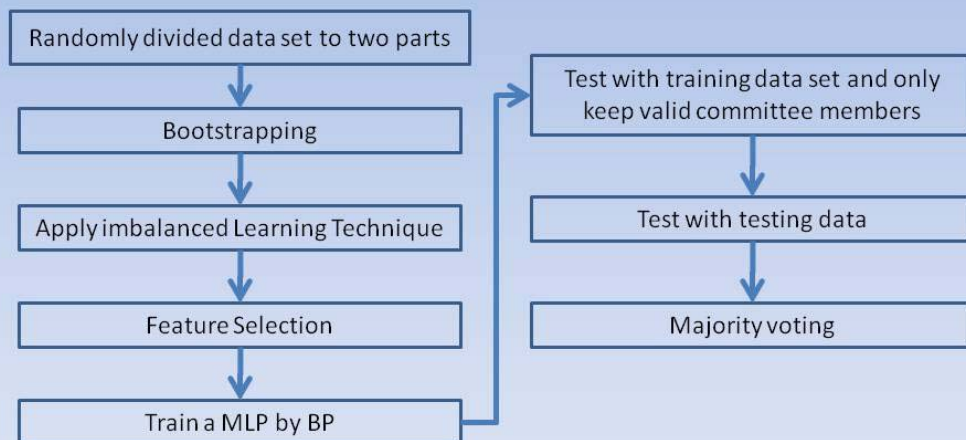
Piecewise Linear Orthogonal Floating Search (PLOFS)

Majority Voting



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Framework of the OFS Assessment Strategy



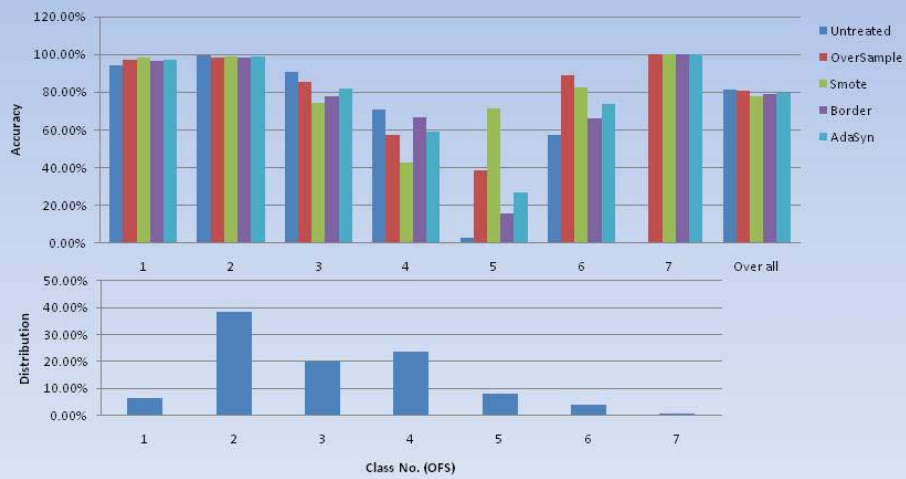
24

Outline

- Introduction
- Imbalanced Learning Techniques
- Experiment Design
- Results & Discussion
- Conclusion

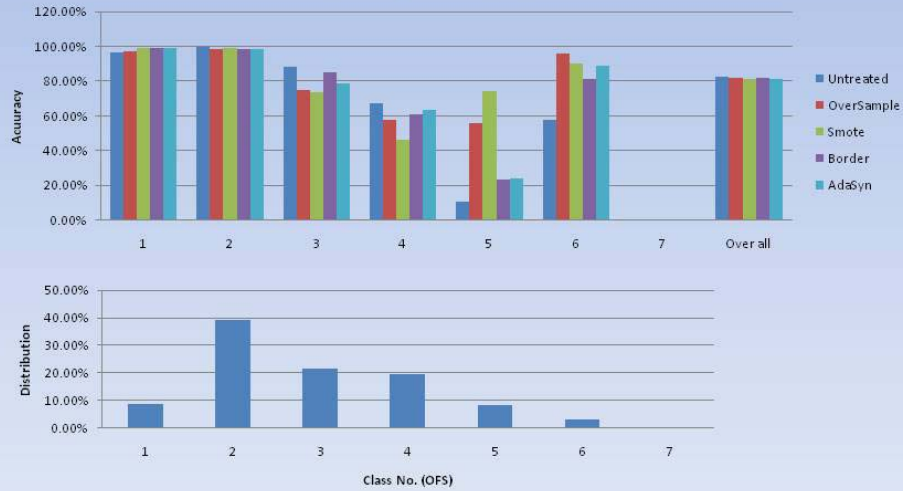
Result for Data Set 1

Accuracy of Classification



Result for data set 2

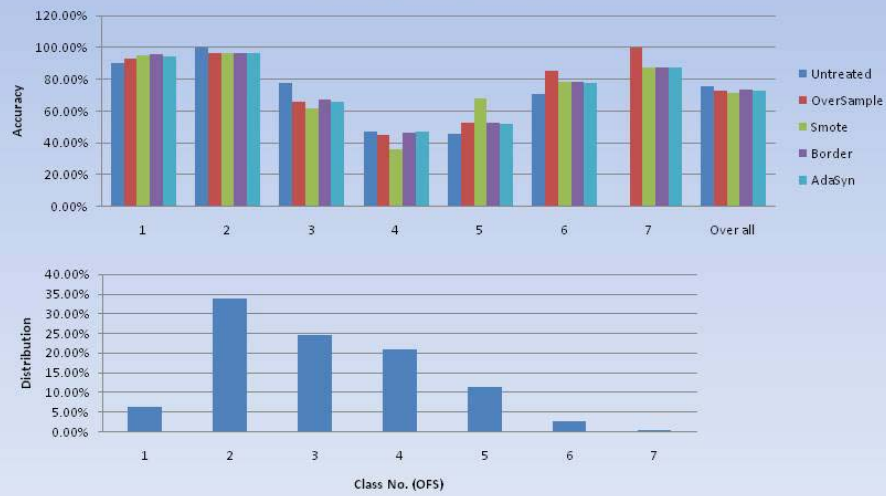
Accuracy of Classification



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Result for data set 3

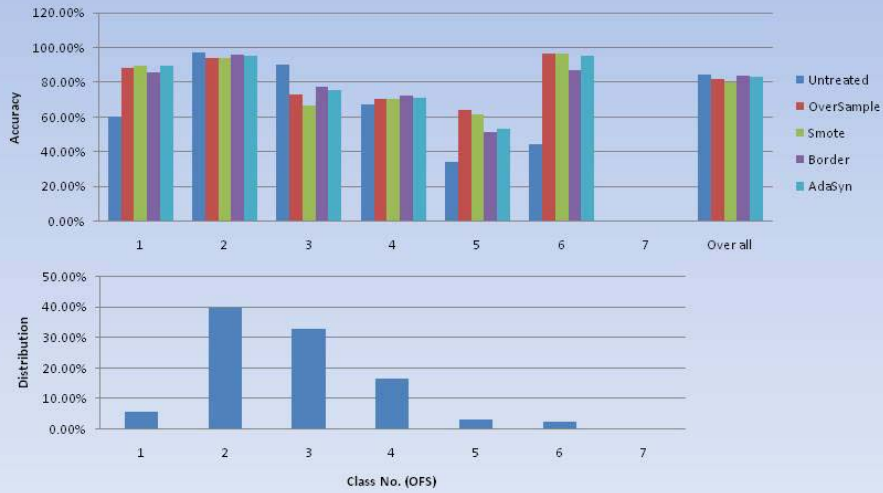
Accuracy of Classification



28

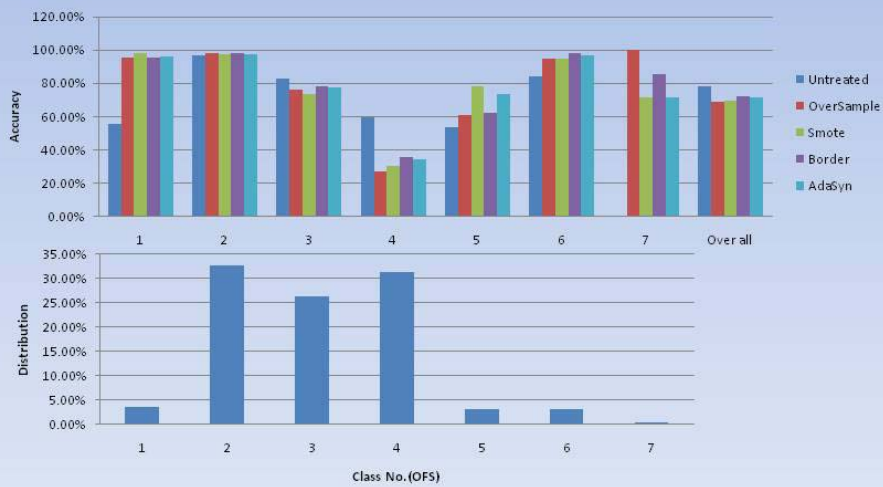
Result for data set 4

Accuracy of Classification

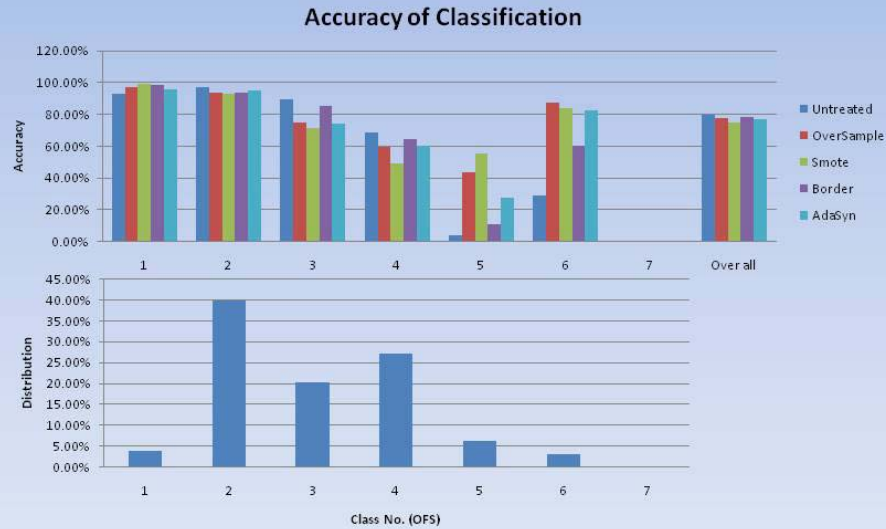


Result for data set 5

Accuracy of Classification



Result for data set 6



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- Introduction
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Conclusions

- By using imbalanced learning techniques, classification accuracies for minority OFSs are improved dramatically with a cost of slight performance degradations for majority OFSs
- Different sampling algorithms appear to perform similarly
- Future work
 - Test more imbalanced techniques
 - Validate those techniques on more subjects' datasets

Acknowledgement

- This project was funded by the NASA (Contract No: NNX10CB27C). We thank Dr. Alan T. Pope, our COTR, for his comments and suggestions as we performed this research. We also thank Dr. Kara Latorella for her comments and feedback during various discussions over the course of this project.

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• Thank you
• Q & A