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Central-diffused Instance Generation Method in Class Incremental Learning

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Background

- ✓ In a real environment, new classes of the emerging instances may appear at any time while instances keep arriving. For this circumstance, class incremental learning is proposed as a machine learning framework to handle the new class instances incrementally.
- ✓ In many real incremental scenarios, the distribution between new class instances and the existing ones is not well balanced. Therefore, how to solve the class imbalance learning effectively during the process of class incremental learning is a meaningful research.

Motivations

- ✓ Many techniques have been proposed to deal with class imbalance problem, but they are poor at dealing with the emerging class scenario.
- ✓ Some research focuses on discovering emerging new classes which can be defined as anomaly classes in data stream, but they cannot solving the class imbalance problem simultaneously.

Class Incremental Learning via CdIGM

✓ Framework of Class Incremental Learning(Algorithm 1)

The final goal of class incremental learning is to find a map $f: X \to Y$, so as to minimize the loss over S_K:

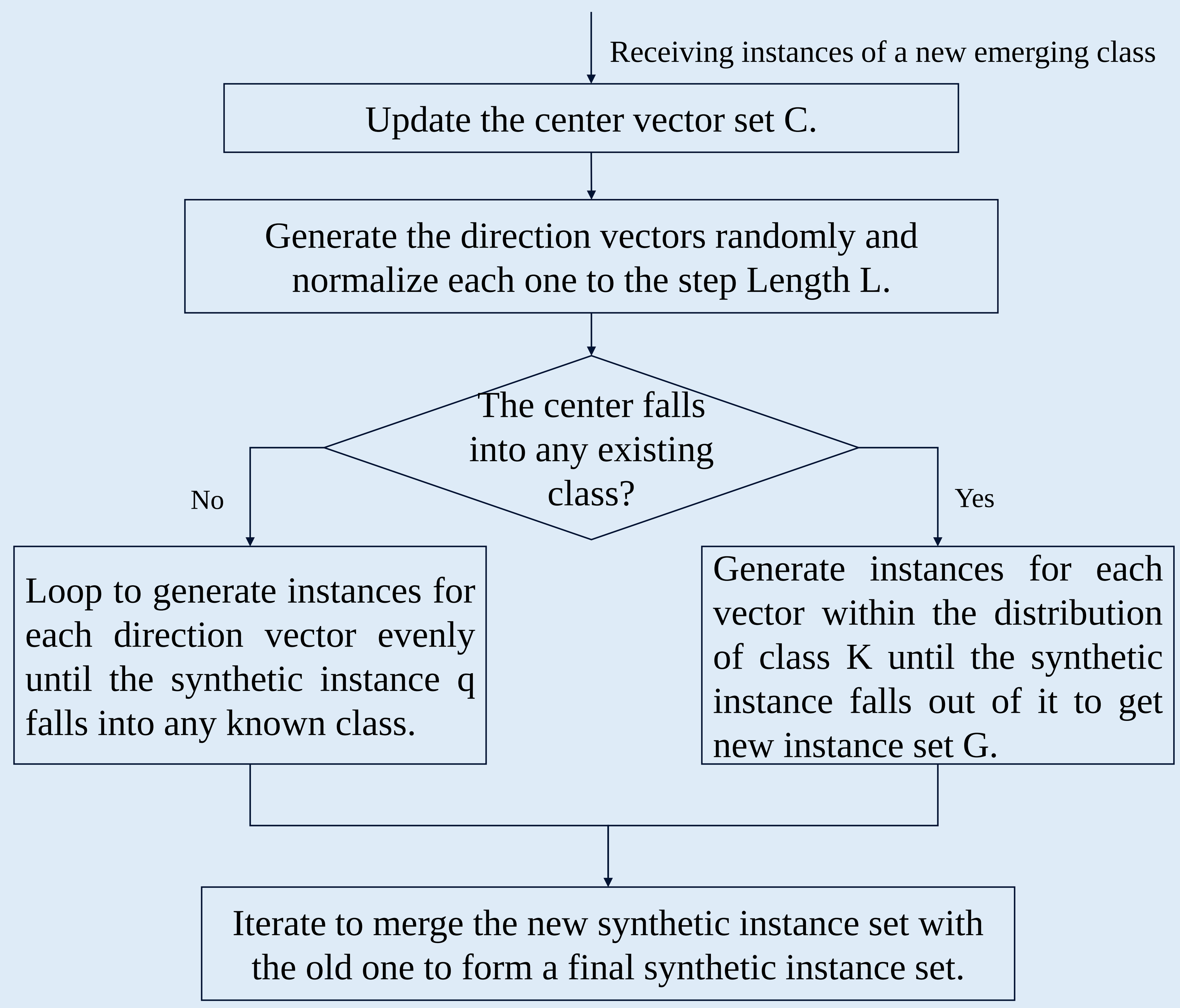
$$\sum_{j=1}^{K} I(f(x_i) \neq y_i), i \in \{1,2,\cdots,n_j\}$$

Algorithm 1. The Framework of Class Incremental Learning

Input: Sequence S_k; number set N; the number of the existing classes M.
Output: Weight W for prediction.

Receive supervised instances sets $\left\{\{(x_i,y_j)\}_{i=1}^{n_j}\right\}_{j=1}^{M}$ from sequence S_k;
$T \leftarrow \left\{\{(x_i,y_j)\}_{i=1}^{n_j}\right\}_{j=1}^{M}$;
$W \leftarrow$ Train multi-classification model for T;
Repeat:
    Receive a new instance set $\left\{\{(x_i,y_j)\}_{i=1}^{n_j}\right\}_{j=1}^{M}$ from sequence S_k;
    $S \leftarrow \left\{\{(x_i,y_{M+1})\}_{i=1}^{n_j}\right\}_{i=1}^{M}$;
    $T \leftarrow CdIGM(W,T)$;
    $M \leftarrow M+1$;
    $W \leftarrow Update(W,T)$;
Until $M = K$;

✓ Central-Diffused Instance Generation Method (CdIGM)



Experiments

Table 1. Overall Accuracy on Data Streams in Experiments.

Data	CdIGM	SMOTE	OPCIL	OB	SDCIL
ADS1	**94.23±0.084**	88.11±0.108	82.25±0.486	84.49±0.393	79.18±0.296
ADS2	**90.84±0.035**	83.89±0.075	76.26±0.349	80.34±0.486	72.67±0.834
ADS3	**86.64±0.079**	80.19±0.234	72.34±0.495	69.01±0.199	65.81±0.474
Glass	**91.33±0.934**	85.29±0.278	87.52±1.134	84.19±0.157	82.58±0.837
Iris	**93.24±0.259**	90.58±1.147	92.11±0.824	89.99±0.938	85.46±0.630
Segment	74.13±1.597	**78.43±0.392**	73.90±0.957	63.65±0.295	71.96±0.301
Svmguide2	**88.15±0.949**	84.36±0.395	80.65±0.284	74.99±0.851	80.03±0.047
Vehicle	**87.21±0.385**	82.11±0.884	78.45±0.955	80.34±0.751	76.03±0.937
Vowel	**79.31±0.753**	68.48±0.438	74.57±0.418	64.23±0.281	58.92±0.431
Minst	**65.45±0.413**	61.44±0.294	60.17±0.538	59.75±0.369	55.51±0.199

✓ The results show that CdIGM averagely achieves 4.01%, 4.49%, 8.81% and 9.76% performance improvement over SMOTE, OPCIL, OB and SDCIL, respectively. It is proved to possess the strength of class incremental learning and class imbalance learning with good accuracy and robustness.

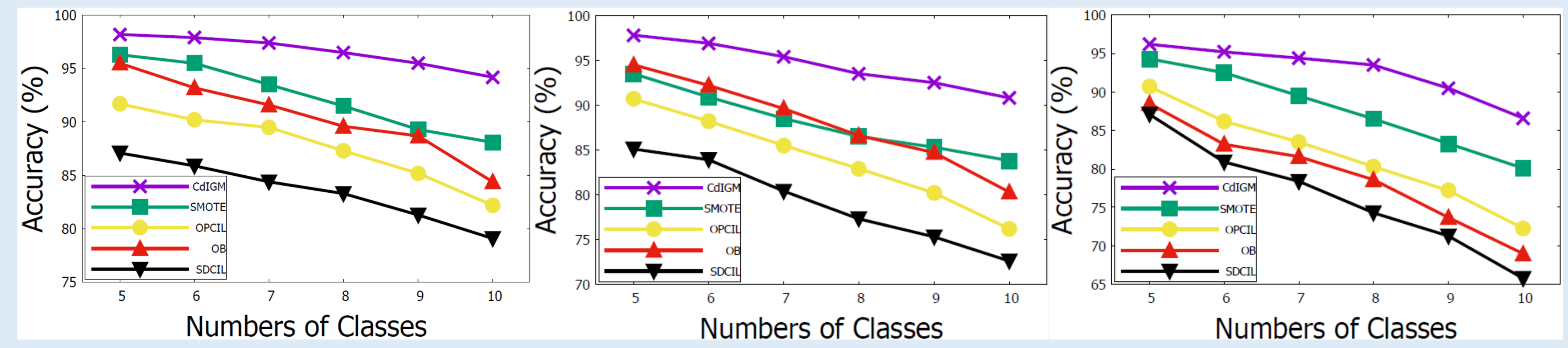


Fig. 1. Real-time Accuracy on Artificial Data Streams with Different Imbalance Rate