Table 2: Performance of compared methods on M7/M9 and M9/M11.

	Dataset	M7/M9		M9/M11	
	Method	AUC	R@P$_{0.1}$	AUC	R@P$_{0.1}$
Baselines	NS	0.8698 ± 0.0029	0.3626 ± 0.0223	0.8366 ± 0.0041	0.2399 ± 0.0099
	ROS	0.8742 ± 0.0031	0.3909 ± 0.0275	0.8468 ± 0.0076	0.2478 ± 0.0253
	SMOTE	0.8717 ± 0.0079	0.3606 ± 0.0404	0.8410 ± 0.0059	0.1933 ± 0.0226
	ADASYN	0.8751 ± 0.0019	0.3582 ± 0.0252	0.8389 ± 0.0071	0.2072 ± 0.0170
	BAGAN	0.8740 ± 0.0012	0.3991 ± 0.0104	0.8410 ± 0.0046	0.2523 ± 0.0081
	GLGAN	0.8737 ± 0.0016	0.3849 ± 0.0128	0.8341 ± 0.0043	0.2455 ± 0.0109
Ours	ADAAR	**0.8780 ± 0.0009**	**0.4170 ± 0.0065**	**0.8592 ± 0.0008**	**0.2910 ± 0.0063**
Ablation Test	ADAAR w/o *AE*	0.8736 ± 0.0021	0.3871 ± 0.0126	0.8322 ± 0.0026	0.2384 ± 0.0138
	ADAAR w/o D_1	0.8748 ± 0.0019	0.3946 ± 0.0097	0.8380 ± 0.0049	0.2644 ± 0.0328
	ADAAR w/o D_2	0.8757 ± 0.0015	0.3928 ± 0.0059	0.8549 ± 0.0076	0.2689 ± 0.0253

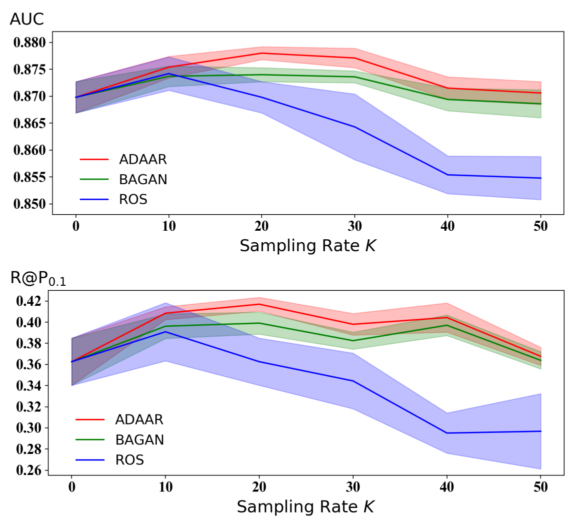

Figure 2: AUC and R@P$_{0.1}$ on M7/M9 with different oversampling rate K.

augmentation framework to solve the class imbalance problem in financial credit risk assessment.

Financial credit risk assessment recently are achieved by machine learning [9, 14] or graph mining methods [15]. Both the two technical routes suffer from the class imbalance problem and most of the approaches adopt the random oversampling method to resolve. Different from that, we solve the problem by a novel adversarial data augmentation framework.

5 CONCLUSION

In this paper, we study the class imbalance problem of financial credit risk assessment and propose ADAAR, an adversarial data augmentation framework. The synthetic samples output by ADAAR resembles real high-risk users since we design an autoencoder to learn the user space and the generator has to fool the discriminator which identifies fake samples. Meanwhile, synthetic samples could be distinguished from low-risk users because we have an auxiliary discriminator to assess the risk. Experimental results demonstrate that ADAAR outperforms other data augmentation methods on three real-world datasets.

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