Alike and Unlike: Resolving Class Imbalance Problem in Financial Credit Risk Assessment

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Content

- Background and Motivation
- Method - ADAAR
- Experiment
- Conclusion and Future Work

Background

➢Credit Payment

- Promise to pay the bill before the due day
- Examples: Credit Card, Ant Credit Pay, PayPal Credit Pay

➢Credit Risk Assessment

- Low-risk: repay the bill in-time
- High-risk: default, fraud, …

花呗 ANT CREDIT PAY

➢Importance

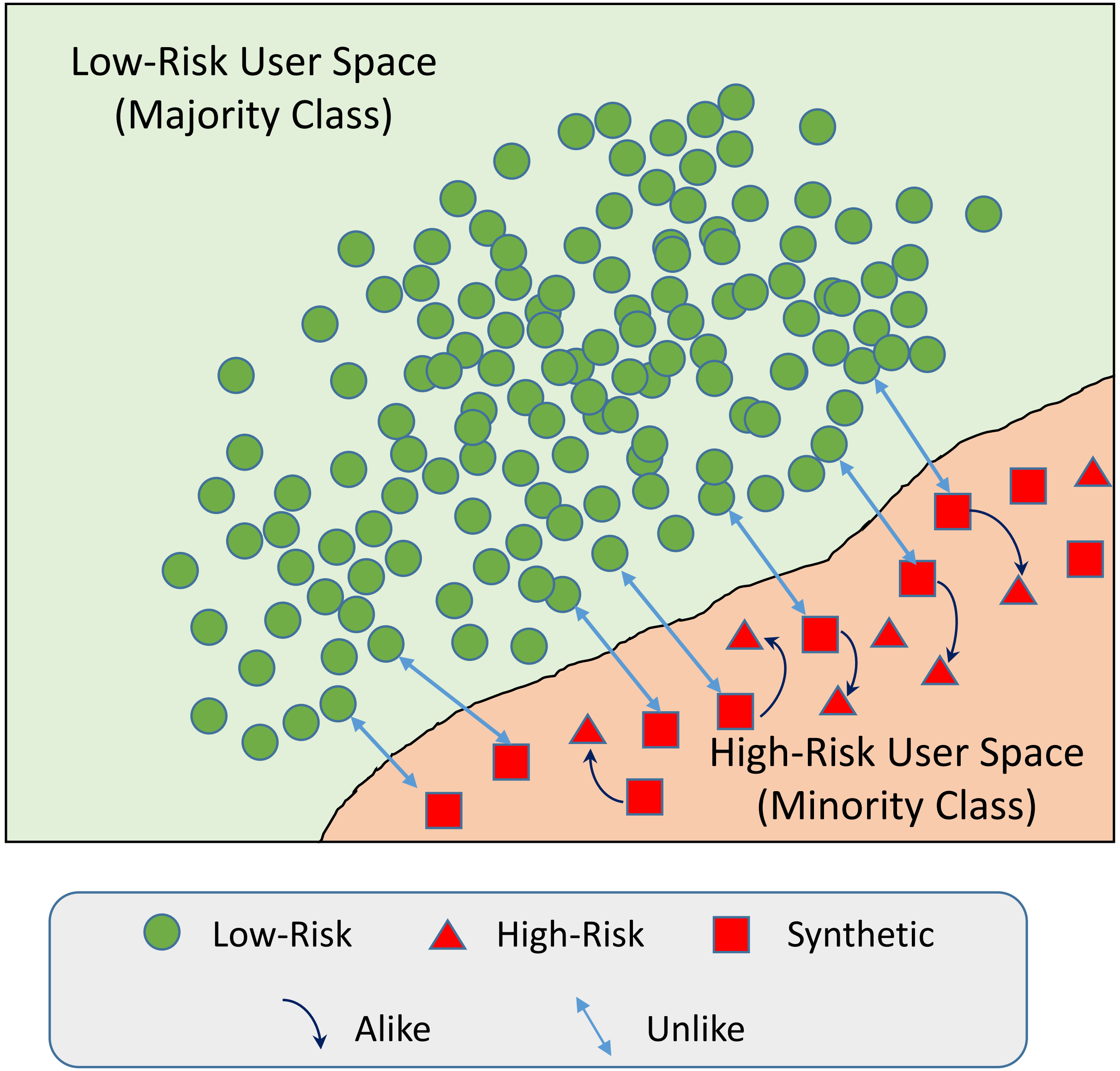
- High-risk payments account for **0.68%** of retail revenue in the U.S. but the fraud cost reached as high as **$32 billion**.[1]

PayPal CREDIT

[1] Annual report by LexisNexis. From http://www.lexisnexis.com/risk/downloads/assets/true-cost-fraud-2014.pdf

Motivation

- Credit risk assessment is a class-imbalanced problem.
  - Majority class - Low-risk users(>99%)
  - Minority class - High-risk users(<1%)
- Solution:
  - Data augmentation for the minority class.
- Objective:
  - **Alike** the minority class
  - **Unlike** the majority class



Method

➢ Adversarial **D**ata **A**ugmentation method with **A**uxiliary discriminato**R** (ADAAR)

➢ **Alike** the minority class

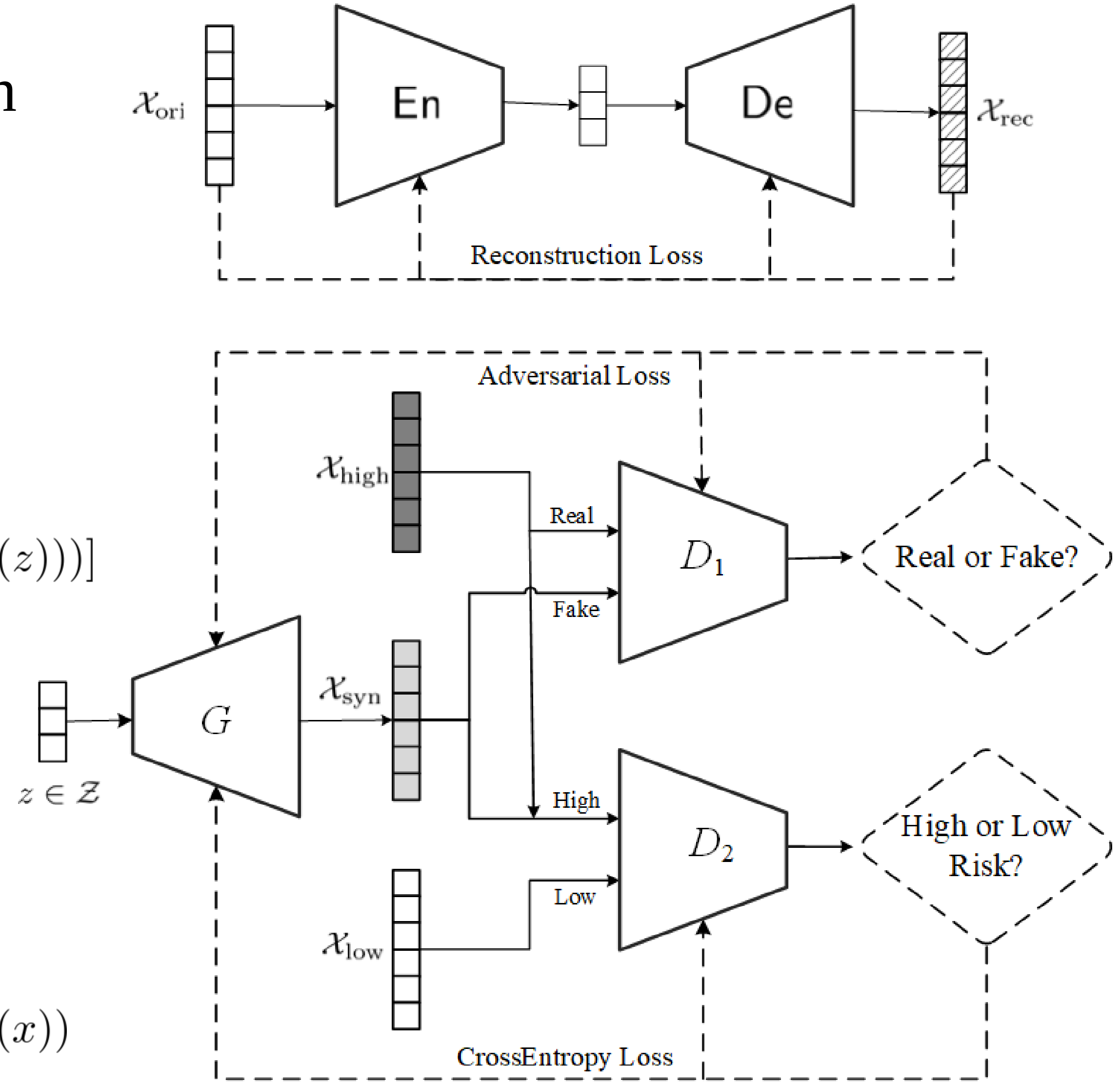
- D_1 identifies real samples from fake samples
- Adversarial loss for D_1 and G

$$\min_{D_1}\max_{G}\mathcal{L}_{adv} = -\sum_{x\in\mathcal{X}_{\text{high}}}\log(D_1(x)) - \sum_{z\in\mathcal{Z}}[1-\log(D_1(G(z)))]$$

➢ **Unlike** the majority class

- D_2 discriminates low or high risk users
- Cross-entropy loss for G and D_2

$$\min_{D_2,G}\mathcal{L}_{ce} = -\sum_{x\in\mathcal{X}_{\text{high}}\cup\mathcal{X}_{\text{syn}}}\log(D_2(x)) - \sum_{x\in\mathcal{X}_{\text{low}}}\log(1-D_2(x))$$



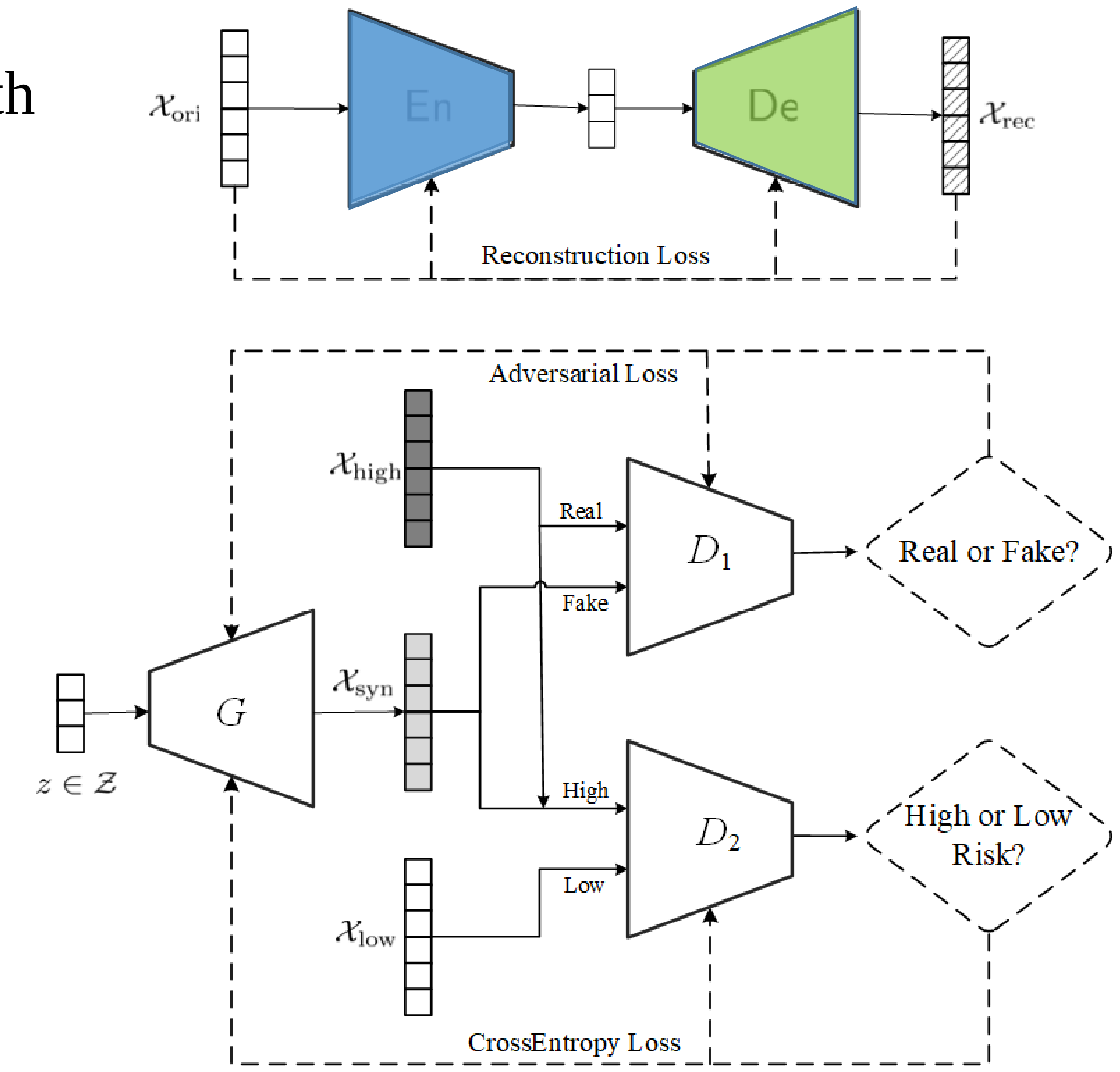
Method

➢ **A**dversarial **D**ata **A**ugmentation method with **A**uxiliary discriminato**R** (ADAAR)

- To obtain better initialization:
  - AutoEncoder with reconstruction loss

$$\mathcal{L}_{AE} = \sum_{x \in \mathcal{X}_{\text{ori}}} \|x - \hat{x}\|_2^2$$

  - D_1 and D_2 are initialized with encoder
  - G is initialized with decoder



Data

➢User

- Time Range：

  M7 (2018/07/01 ~ 2018/07/31)

  M9 (2018/09/01 ~ 2018/09/30)

  M11 (2018/11/01 ~ 2018/11/30)

- Train/Test： M7/M9, M9/M11

Dataset	#Users	#Major	#Minor	Rate
M7	334,695	330,785	3,910	1.18%
M9	404,491	400,778	3,713	0.93%
M11	524,935	520,369	4,566	0.88%

➢Feature

- User profile, credit information, purchasing behaviors, and asset information, etc.
- Dimension： 908

➢Compared with state-of-the-art BAGAN[ICML'18 Workshop]

- AUC improvement 0.4%~1.82%
- $R@P_{0.1}$ improvement 1.8%~3.8%

	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

Conclusion and Future work

➢Conclusion

- We design an adversarial training framework to generate synthetic samples alike the real high-risk samples.
- We propose an auxiliary discriminator to assess the risk to make synthetic samples unlike the low-risk samples.

➢Future Work

- Cost-sensitive imbalanced learning methods
- Extensions to other structures like graph data

Thanks for listening!

If you have any question, feel free to contact us at

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