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Adversarial and Implicit Modality Imputation with Applications to Depression Early Detection

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Motivation

1. Real-world data suffer from modality-missing issue.
In the early stage of depression, patients may just take some tests and thus only some modalities are available for disease prediction. Even for patients having complete modalities, their multi-modal data may be stored in different hospitals and cannot be fully-accessible because of the privacy and security issues. This issue may affect the performance of SOTA multi-modal model.

2. Existing imputation algorithms may not satisfy.
Some data imputation methods proposed single-value imputation, matrix completion methods, grouping and merging strategies, etc. Recently, deep learning-based methods adapted Generative Adversarial Network(GAN) and autoencoder(AE) to learn the real data distribution. However, without any feedback mechanisms, imputed modalities achieved by the above methods are unchanged and may lead to catastrophic error propagation.

Our Contribution

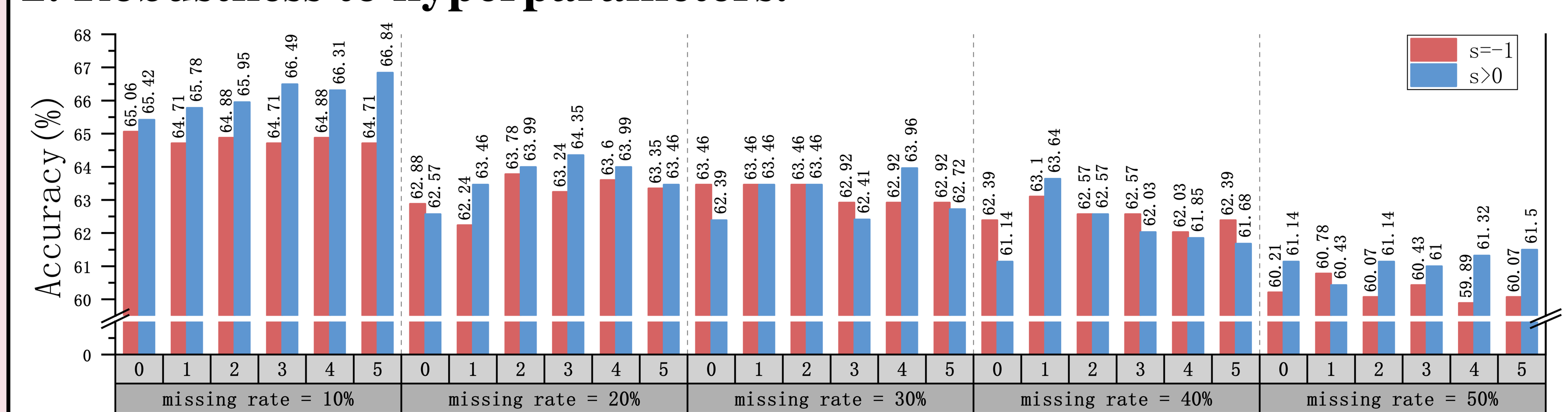
- Proposed a novel multi-modal data imputation method **AIMI** and apply it to real-world depression early detection task when modalities are randomly missing.
- Demonstrated the superiority and robustness when imputing modalities with feedback loops, via an adversarial network with an implicit imputation mechanism.

Results

1. Comparisons on robust multi-modal depression diagnosis.

Dataset	$\text{UKB}_{Complete}$				$\text{UKB}_{Balanced}$				UKB_{All}
α ($\times$100%)	0	10	30	50	0	10	30	50	76
FeatCon	87.95	81.44	77.85	74.69	62.21	61.67	60.07	58.28	58.85
Fusion_{mean}	92.83	88.54	87.80	87.15	61.67	62.21	61.32	57.04	59.86
Fusion_{att}	90.30	89.77	88.78	82.64	62.21	61.85	60.96	55.79	59.63
DCCA	92.22	89.94	88.73	79.03	66.67	65.78	62.57	60.07	60.05
LMNN	75.70	73.08	73.16	69.75	62.92	64.17	62.38	59.89	58.12
CPM-Net	**95.83**	93.03	89.12	84.24	58.47	60.07	57.93	51.87	61.27
AIMI_{mean}	**95.83**	95.63	93.79	93.49	66.13	65.24	62.92	61.14	61.69
AIMI_{att}	95.49	**95.83**	**95.60**	**94.78**	**68.27**	**66.84**	**63.96**	**61.50**	**61.73**

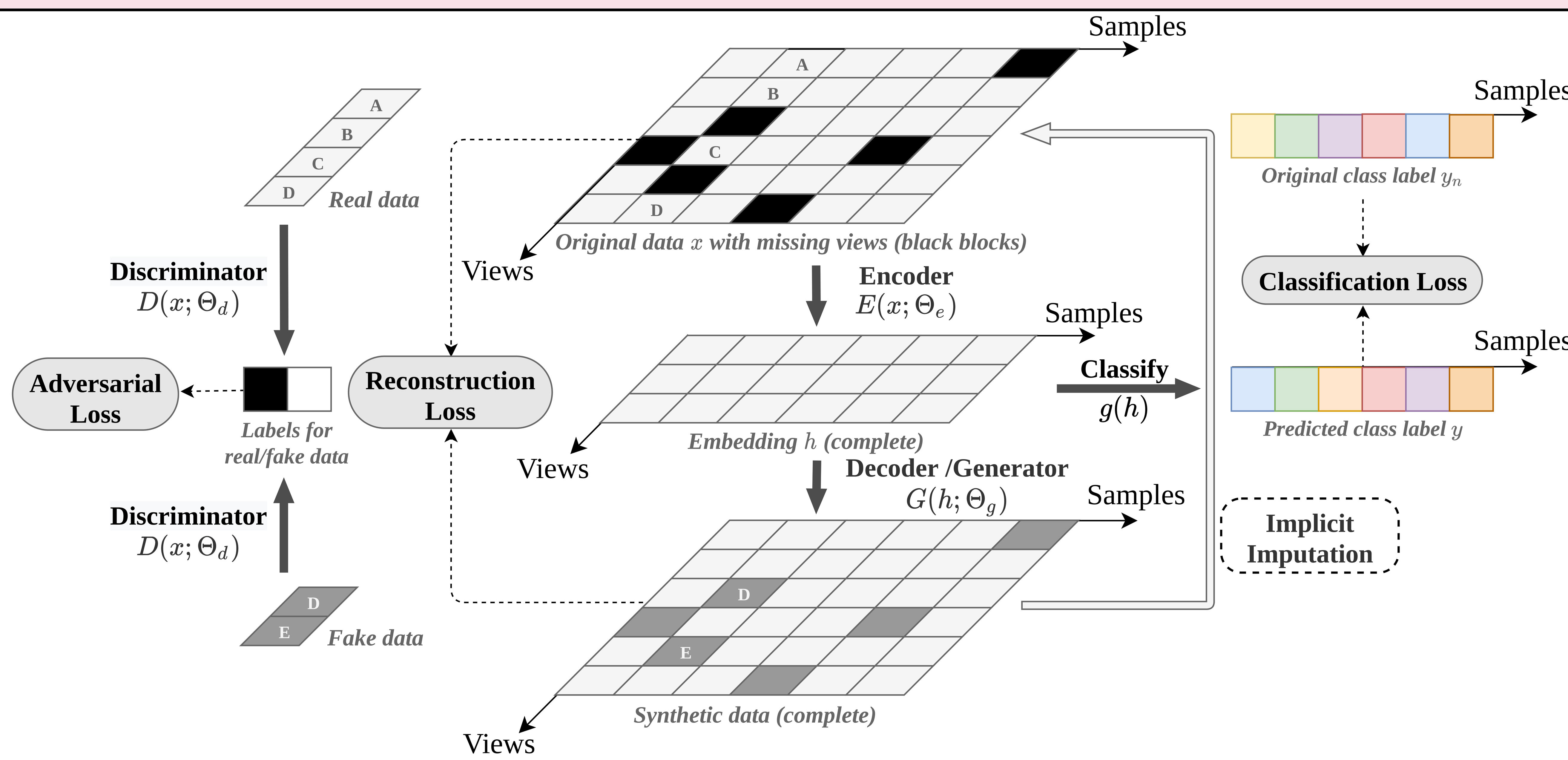
2. Robustness to hyperparameters.



3. Advantages on modality imputation and representation.

	Clustering Accuracy (ACC)					RMSE
α ($\times$100%)	10	20	30	40	50	50
DAE	57.70	57.11	56.32	54.58	54.26	0.5944
LRMC	56.68	58.29	57.58	55.97	55.79	0.3961
AIMI_{mean}	**60.61**	53.48	57.04	56.86	53.30	0.1027
AIMI_{att}	59.44	**58.82**	**58.69**	**58.46**	**56.68**	**0.0947**

Networks and Training Process



1. Learning multi-modal representations via auto-encoding.

- ***Auto-encoding***: Encoder projects samples with arbitrary modality-missing patterns into a common latent space and connects to a classifier, while Decoder reconstructs complete multi-view data from the latent codes.
- ***CPM-Net***: We adopt CPM-Net as the classifier to enhance the clustering structure of the latent codes.

2. Adversarial and implicit modality imputation (AIMI).

- ***Adversarial learning***: Cheating a Discriminator that checks whether a modality is observed or generated to improve the performance of Decoder in auto-encoding architecture.
- ***Implicit imputation with a feedback loop:*** For the t-th inner iteration, we will take the imputed modalities obtained in the previous iteration as the input of the encoders and update them by the auto-encoding architecture.

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Paper, code, and data are available: https://github.com/rucnyz/AIMI