Representation Disentanglement for Multi-task Learning with application to Fetal Ultrasound

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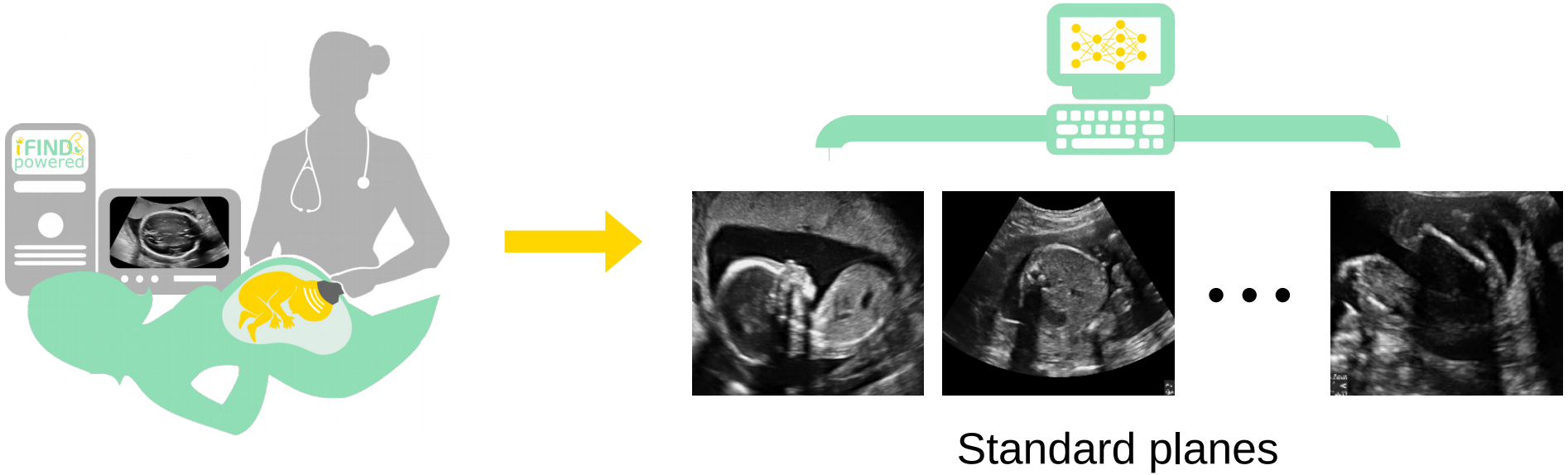
Introduction



Standard planes

- Important for abnormality detection in early pregnancy

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Introduction

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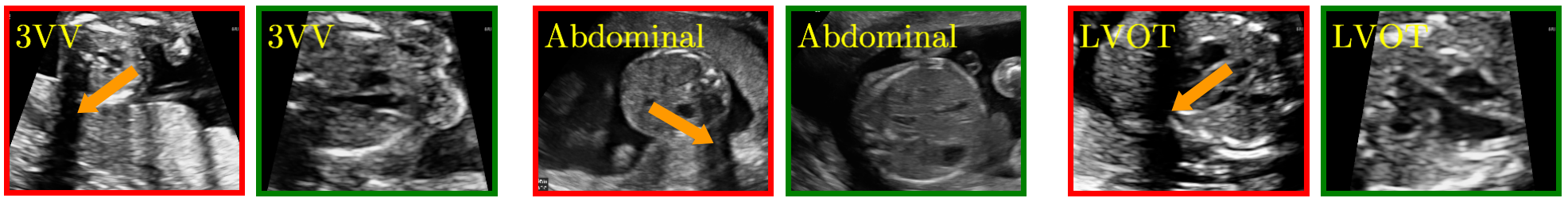
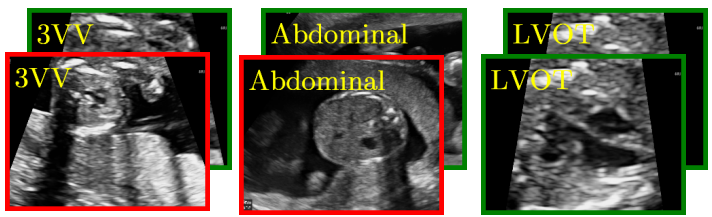


- CNNs learn *anatomical features* and *shadow features* simultaneously.

Introduction

Seen entangled properties (anatomy and artifacts)



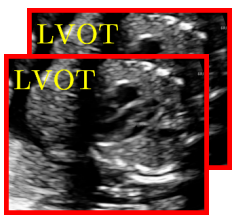
Train

CNNs

Classification

Test

Unseen entangled properties



- CNNs exhibits weak generalizability
- Our goal is to disentangle *anatomical features* from *shadow features*

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Motivation

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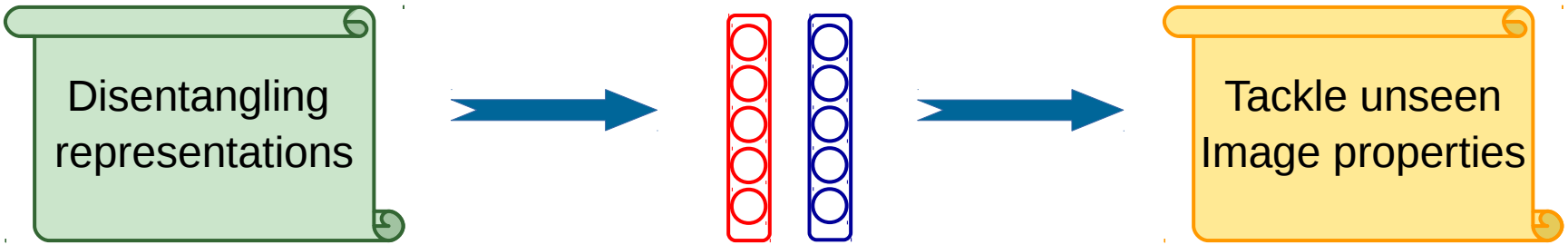
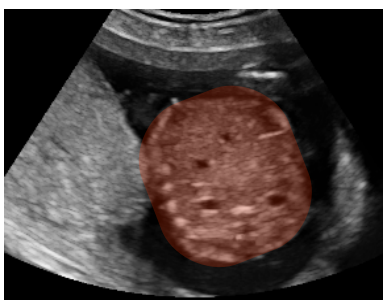
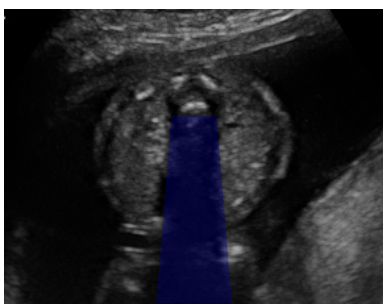


Generalized features

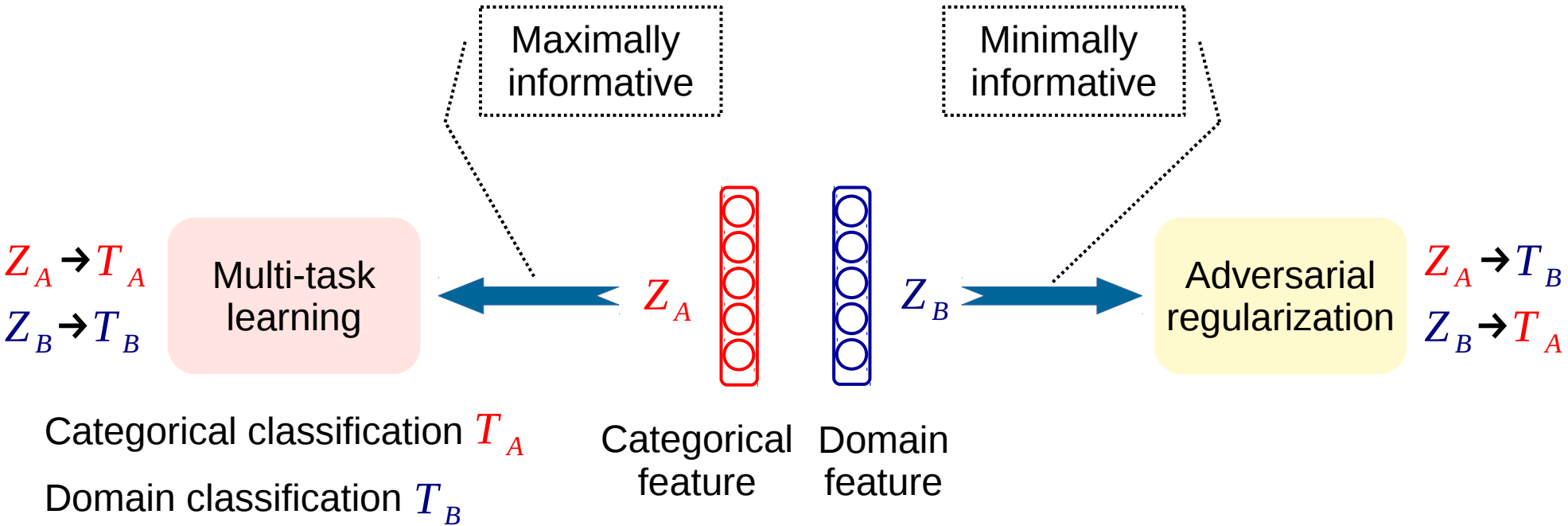


Anatomical feature



Shadow feature

Method


Maximally informative
Minimally informative
$Z_A \rightarrow T_A$
$Z_B \rightarrow T_B$
Multi-task learning
Z_A
Z_B
Adversarial regularization
$Z_A \rightarrow T_B$
$Z_B \rightarrow T_A$
Categorical classification T_A
Domain classification T_B
Categorical feature
Domain feature

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Method

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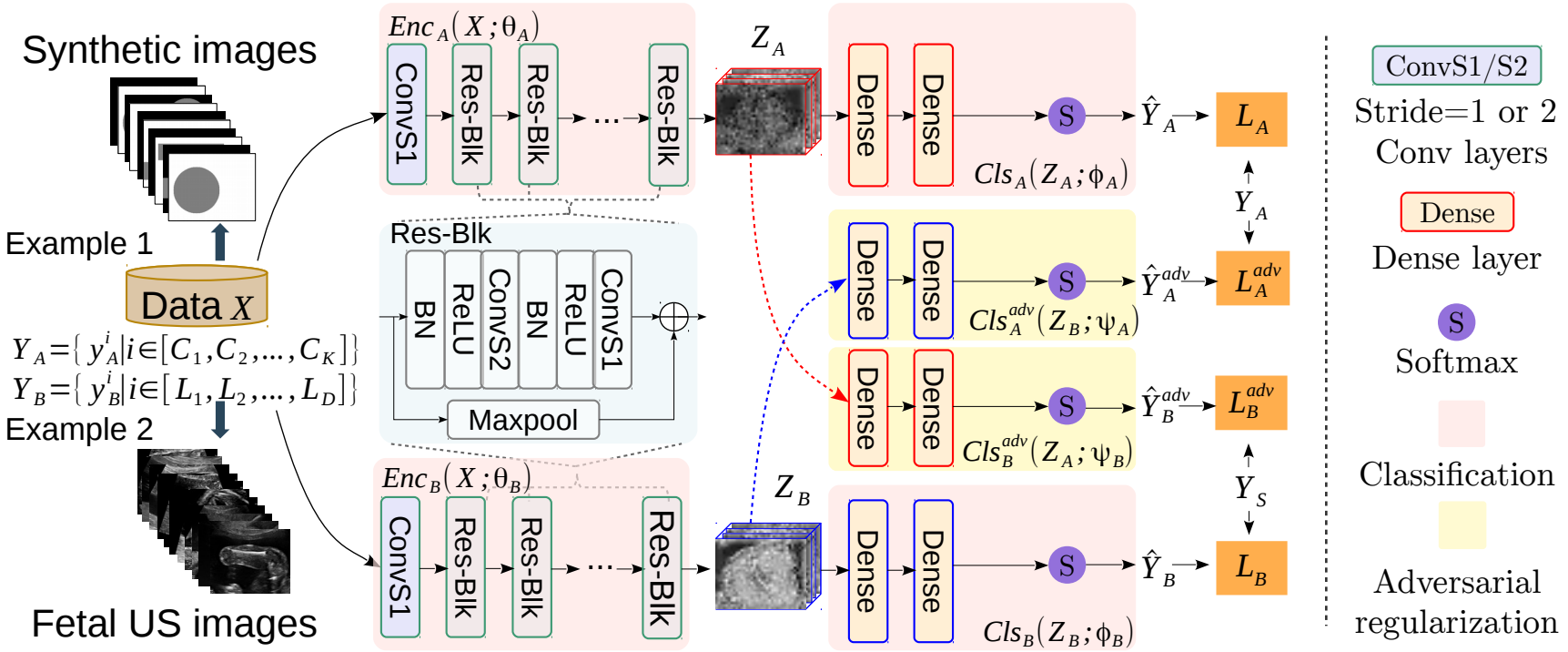

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Method

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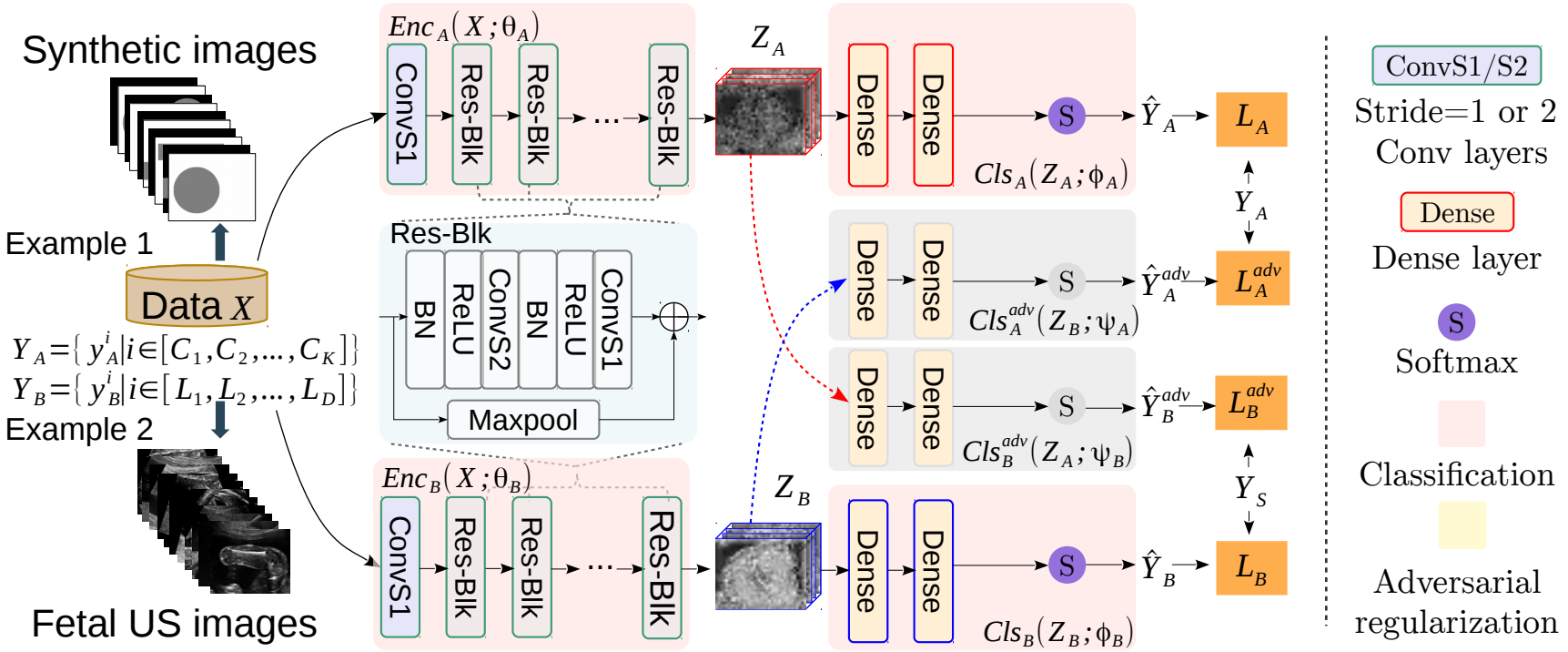

Training objective $$min_{\{\theta_A,\theta_B,\phi_A,\phi_B\}}\{L_A+L_B-\lambda*(L_A^{adv}+L_B^{adv})\},\lambda>0$$

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Method

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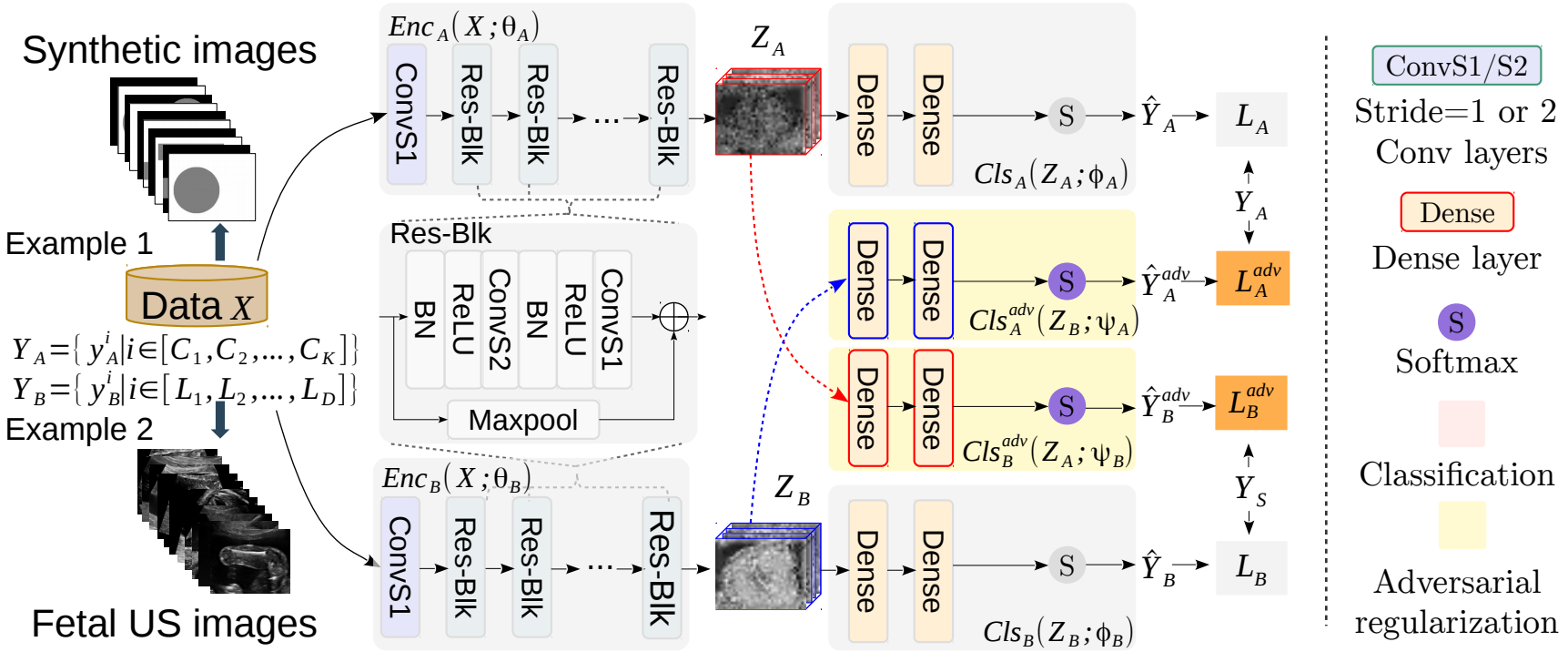

Training objective $min_{\{\psi_A,\psi_B\}}\{L_A^{adv}+L_B^{adv}\}$

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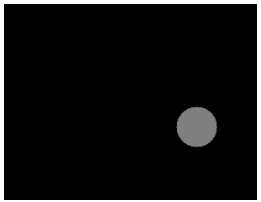
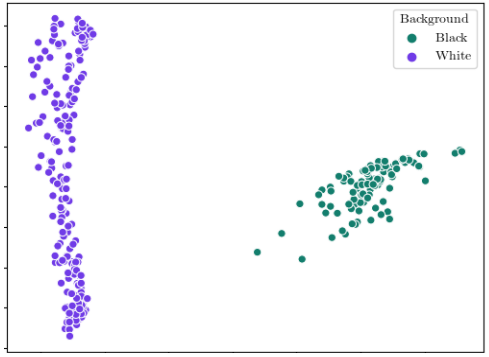
Evaluation–synthetic data

Train/Test_seen

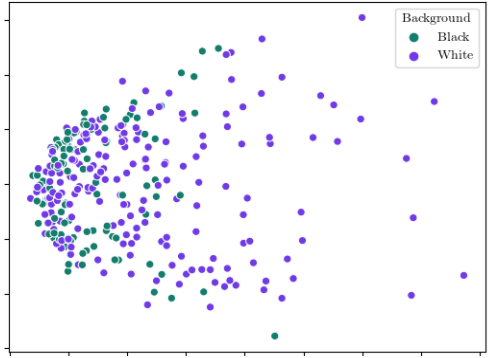


Unseen test

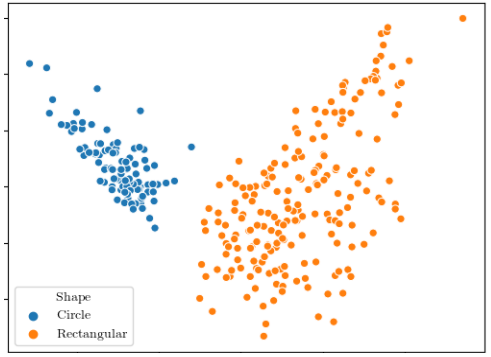
- Background classification T_A
  Background feature Z_A
- Shape classification T_B
  Shape feature Z_B



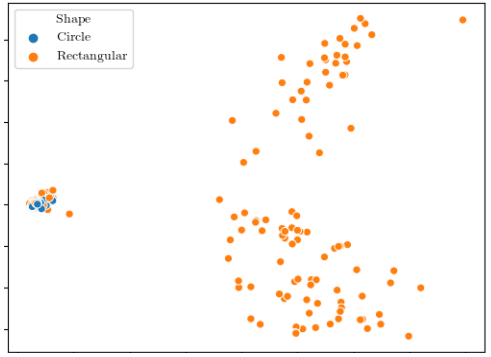
(a) $Z_A \rightarrow T_A$ 100%



(b) $Z_B \rightarrow T_A$ 59.67%



(c) $Z_B \rightarrow T_B$ 99.67%



(d) $Z_A \rightarrow T_B$ 62%

- Our model achieves 99% accuracy on unseen test data (baseline is 10%)

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Evaluation–fetal US data

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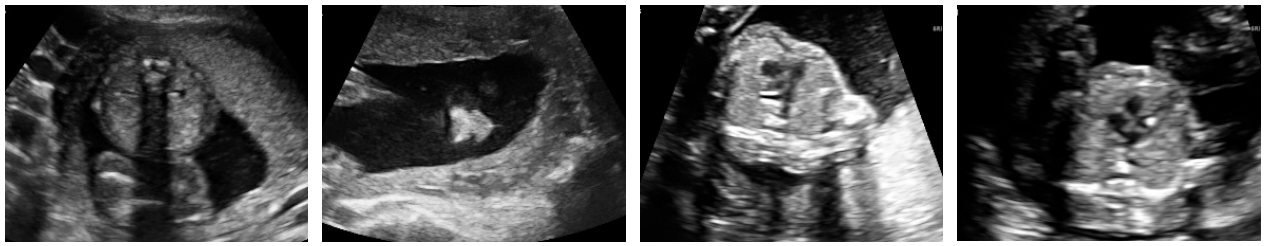
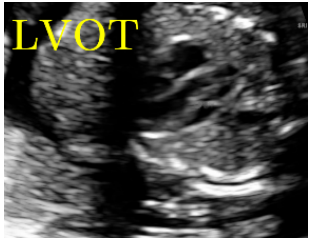
Train/
Test_seen



Unseen test for shadow artifacts classification



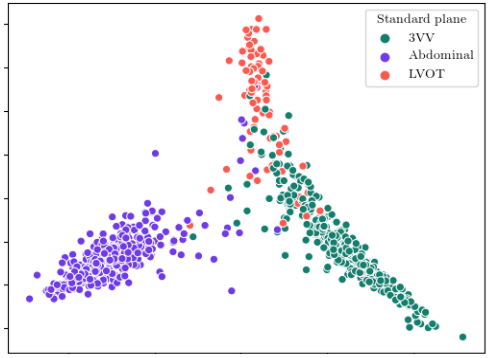
Unseen test for
anatomical classification

- Anatomical classification task T_A / feature Z_A
- Shadow artifacts classification task T_B / feature Z_B

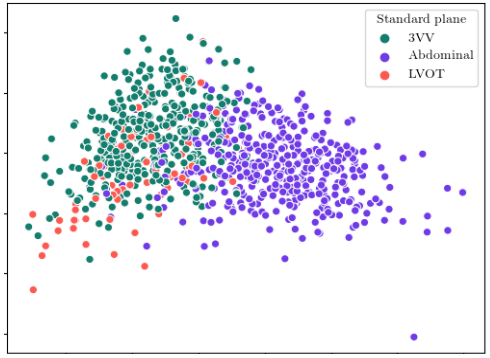
Evaluation–fetal US data

- Classification accuracy of different methods for various tasks.

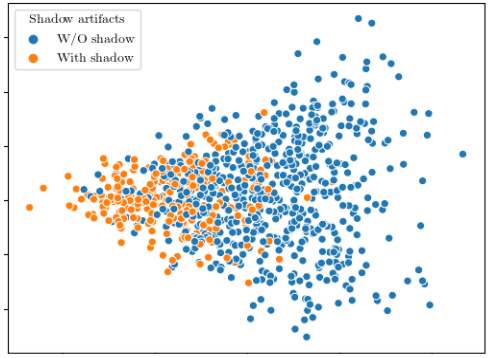
Methods			Std plane only	Artifacts only	Proposed$_{W/O_adv}$	Proposed	Proposed$_{irr_task}$
Test_seen		T_A	78.36	--	81.25	**94.44**	64.35
		T_B	--	78.7	78.74	**79.05**	72.57
Unseen test	LVOT(W_S)	T_A	34.93	--	37.56	**73.68**	--
	Artifacts(OTHS)	T_B	--	69.26	69.50	69.50	--



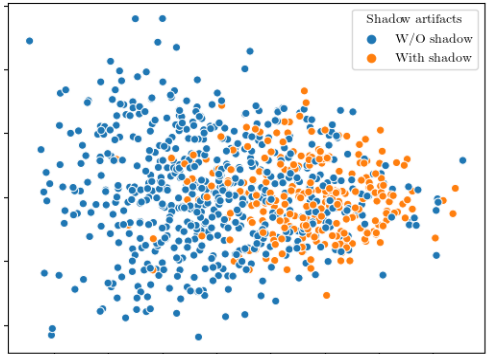
(a) $Z_A \rightarrow T_A$



(b) $Z_B \rightarrow T_A$



(c) $Z_B \rightarrow T_B$



(d) $Z_A \rightarrow T_B$

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Discussion

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We require Less data collection compare with data augmentation

Disentanglement occurs in last layers because of adversarial training

Disentanglement is able to provide benefits for model generalization

Thank you!

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