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A Joint Representation Learning and Feature Modeling Approach for One-class Recognition

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Outline

- What is One Class Classification(OCC)?
- Two Paradigms of OCC
  - Representation Learning
  - Feature Modelling
- Limitations of Existing Methods
- Proposed Method
- Results

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What is One Class Classification(OCC)

- An Extreme case in classification
- Knowledge of the classifier is limited to only a single class
- Given training samples from a class, the classifier is expected to reject samples from any outside class

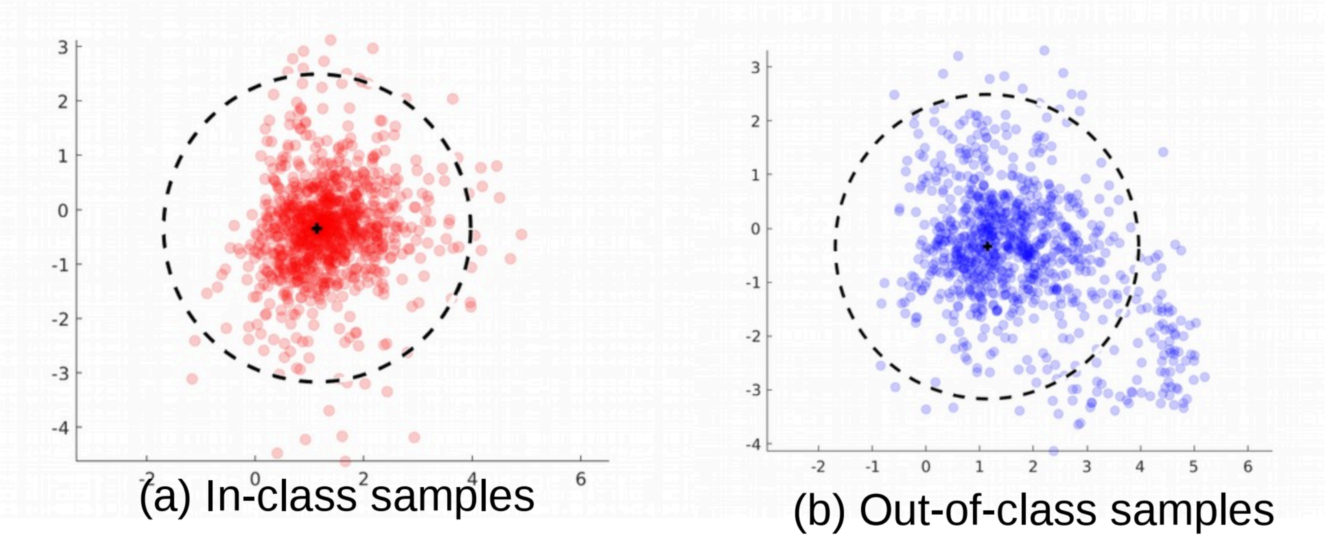
Two Paradigms of OCC

- Feature modelling
  - Use a one-class modeling method to identify the positive space in a given feature space.
  - Objects appearing outside the positive space are identified as out-of-class samples.
- Representation learning
  - An in-class representation learned during training.
  - During inference, test if the model is able to represent an input sample.

Limitations of Feature modelling

- Redundant space could be identified as a part of the positive space. Eg: redundant white-space in (a).

- Lack of guarantee that out-of-class samples will not get projected inside the identified decision boundary (b).



(a) In-class samples (b) Out-of-class samples

Two Paradigms of OCC

- Feature modelling
  - Use a one-class modeling method to identify the positive space in a given feature space.
  - Objects appearing outside the positive space are identified as out-of-class samples.
- Representation learning
  - An in-class representation learned during training.
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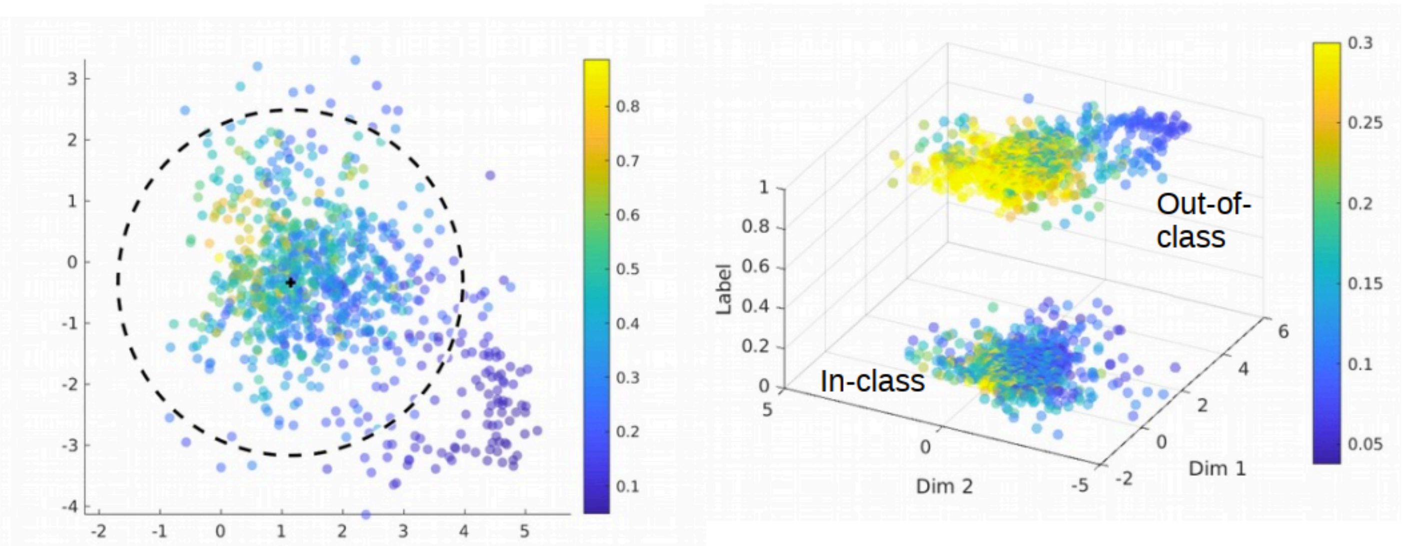
Limitations of Representation learning

- In-class samples are well represented.
- No guarantee that out of-class samples will not be represented well in the learned space.
- Specially when the representation is generic.



(c) Out-of-class samples (MSE)

(d) All samples (MSE)

Proposed Method

- Feature modelling fails only when out-of-class samples get projected inside the identified positive space.
- Provided that,
  - latent space is smooth
  - each latent code inside the positive space corresponds to an in-class sample

failed cases can be identified considering the reconstruction error.

	Inside + Space		Outside + Space	
	Low MSE	High MSE	Low MSE	High MSE
Feature Modeling	FP	FP	TN	TN
Representation Learning	FP	TN	FP	TN
Proposed	FP	TN	TN	TN

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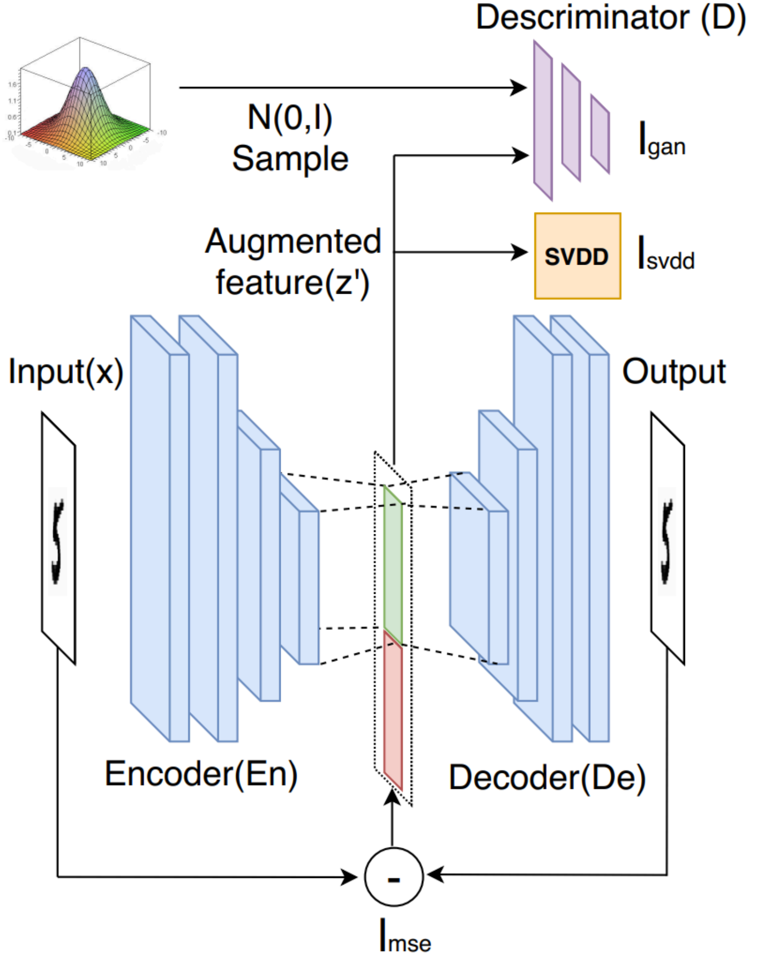
Proposed Method

- Autoencoder network that is trained on reconstruction loss
  $l_{mse} = \|x - \hat{x}\|^2$ where, $\hat{x} = De(En(x))$
- Extend the latent space by appending MSE to the latent feature
- Force extended latent features to follow a pre-determined distribution
  $l_{gan} = \mathbb{E}_{s \sim N(0,I) \in \mathbb{R}^{2k}}[logD(s)] + \mathbb{E}_{x \sim p_{z'}}[log(1 - D(z'))]$
- Fit a one-class classifier on extended feature space



Prevent out-of-class samples from entering positive space

Proposed Method

- Autoencoder network that is trained on reconstruction loss
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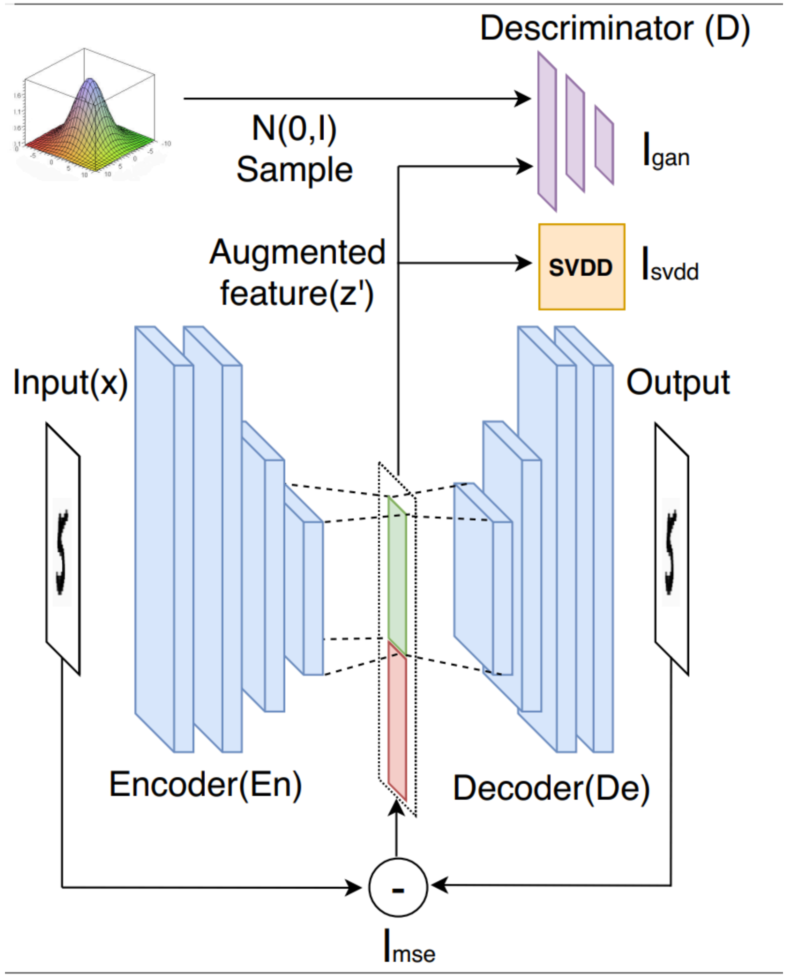
Reducing redundant positive space in the OCC



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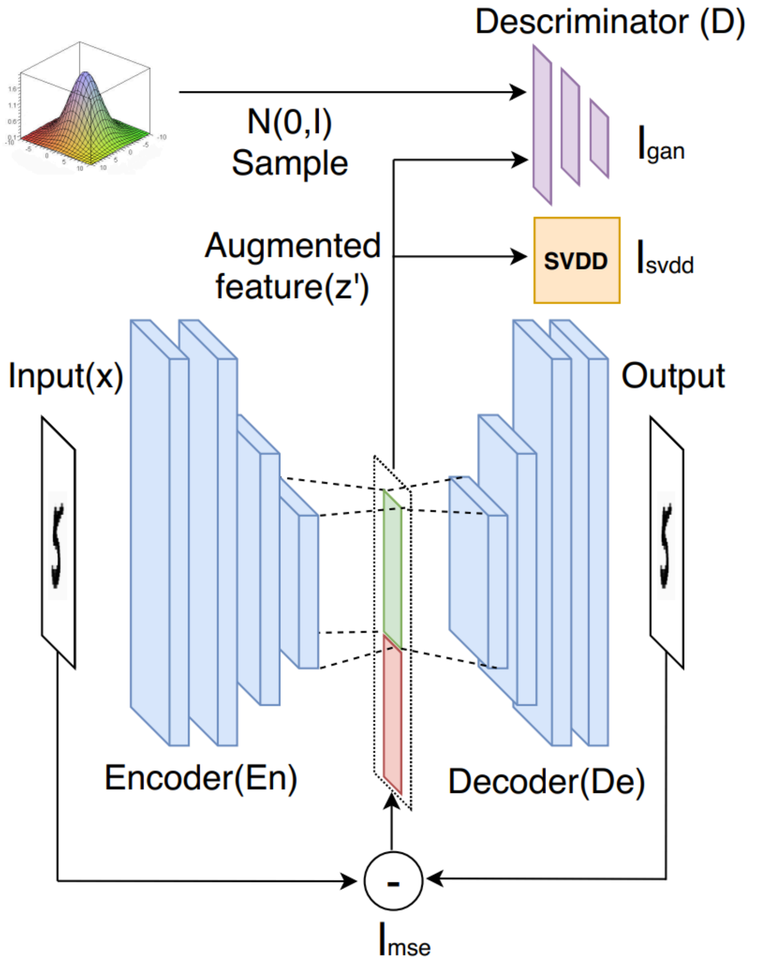
- Fit a one-class classifier on extended feature space



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Proposed Method

- Pre-determined distribution should be chosen to minimize white space volume in the positive half space
- In our work we chose SVDD as our choice of OCC
- We considered following criterion when selecting a distribution:
  - Distribution should be unimodal.
  - Distribution should be isotropic
  - Distribution should not have long tails.
- Gaussian distribution, student-t distribution and Cauchy distribution are good candidates
- We experimented using the Gaussian distribution

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Results

Average AUC on MNIST dataset

Class	OCSVM[10]		KDE[7]		IF[7]		DCAE[19]		ANOGAN[27] (IPIM17)		SDOCC[4] (ICML18)		DOCC[4] (ICML18)		AND*[6] (CVPR19)		OCGAN*[39] (CVPR19)		AE+SVDD		Ours	
0	98.6	*0.0*	97.1	*0.0*	98.0	*0.3*	97.6	*0.0*	96.6	*1.3*	97.8	*0.7*	98.0	*0.7*	99.3	*0.0*	**99.8**	*0.0*	96.8	*0.0*	99.6	*0.1*
1	99.5	*0.0*	98.9	*0.0*	97.3	*0.4*	98.3	*0.0*	99.2	*0.6*	99.6	*0.1*	99.7	*0.1*	**99.9**	*0.0*	**99.9**	*0.0*	99.3	*0.0*	98.8	*0.7*
2	82.5	*0.1*	79.0	*0.0*	88.6	*0.5*	85.4	*0.0*	85.0	*2.9*	89.5	*1.2*	91.7	*0.8*	95.9	*0.0*	94.2	*0.0*	83.4	*0.0*	**97.2**	*0.5*
3	88.1	*0.0*	86.2	*0.0*	89.9	*0.4*	86.7	*0.0*	88.7	*2.1*	90.3	*2.1*	91.9	*1.5*	**96.6**	*0.0*	96.3	*0.0*	86.8	*0.0*	95.5	*0.3*
4	94.9	*0.0*	87.9	*0.0*	92.7	*0.6*	86.5	*0.0*	89.4	*1.3*	93.8	*1.5*	94.9	*0.8*	95.6	*0.0*	**97.5**	*0.0*	92.4	*0.0*	95.7	*0.4*
5	77.1	*0.0*	73.8	*0.0*	85.5	*0.8*	78.2	*0.0*	88.3	*2.9*	85.8	*2.5*	88.5	*0.9*	96.4	*0.0*	**98.0**	*0.0*	75.8	*0.0*	96.3	*0.5*
6	96.5	*0.0*	87.6	*0.0*	95.6	*0.3*	94.6	*0.0*	94.7	*2.7*	98.0	*0.4*	98.3	*0.5*	**99.4**	*0.0*	99.1	*0.0*	93.1	*0.0*	98.8	*0.3*
7	93.7	*0.0*	91.4	*0.0*	92.0	*0.4*	92.3	*0.0*	93.5	*1.8*	92.7	*1.4*	94.6	*0.9*	98.0	*0.0*	**98.1**	*0.0*	92.6	*0.0*	95.7	*0.3*
8	88.9	*0.0*	79.2	*0.0*	89.9	*0.4*	86.5	*0.0*	84.9	*2.1*	92.9	*1.4*	93.9	*1.6*	95.3	*0.0*	93.9	*0.0*	88.9	*0.0*	**95.4**	*0.4*
9	93.1	*0.0*	88.2	*0.0*	93.5	*0.3*	90.4	*0.0*	92.4	*1.1*	94.9	*0.6*	96.5	*0.3*	**98.1**	*0.0*	**98.1**	*0.0*	93.7	*0.0*	97.7	*0.2*
Mean	91.3	*0.0*	86.9	*0.0*	92.3	*0.4*	89.7	*0.0*	91.3	*1.9*	93.5	*1.2*	94.8	*0.8*	**97.5**	*0.0*	**97.5**	*0.0*	90.2	*0.0*	97.1	*0.4*

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Results

Average AUC on CIFAR10 dataset

Class	OCSVM[10]		KDE[7]		IF[7]		DCAE[19]		ANOGAN[27] (IPIM17)		SDOCC[4] (ICML18)		DOCC[4] (ICML18)		AND*[6] (CVPR19)		OCGAN*[39] (CVPR19)		AE+SVDD		Ours	
Plane	61.6	*0.9*	61.2	*0.0*	60.1	*0.7*	59.1	*5.1*	67.1	*2.5*	61.7	*4.2*	61.7	*4.1*	73.5	*0.0*	**75.7**	*0.0*	55.2	*0.0*	66.4	*1.5*
Car	63.8	*0.6*	64.0	*0.0*	50.8	*0.6*	57.4	*2.9*	54.7	*3.4*	64.8	*1.4*	65.9	*2.1*	58.0	*0.0*	53.1	*0.0*	73.0	*0.0*	**78.5**	*0.6*
Bird	50.0	*0.5*	50.1	*0.0*	49.2	*0.4*	48.9	*2.4*	52.9	*3.0*	49.5	*1.4*	50.8	*0.8*	**69.0**	*0.0*	64.0	*0.0*	49.1	*0.0*	54.9	*0.6*
Cat	55.9	*1.3*	56.4	*0.0*	55.1	*0.4*	58.4	*1.2*	54.5	*1.9*	56.0	*1.1*	**59.1**	*1.4*	54.2	*0.0*	62.0	*0.0*	53.6	*0.0*	57.3	*0.6*
Deer	66.0	*0.7*	66.2	*0.0*	49.8	*0.4*	54.0	*1.3*	65.1	*3.2*	59.1	*1.1*	60.9	*1.1*	**76.1**	*0.0*	72.3	*0.0*	61.1	*0.0*	73.6	*0.1*
Dog	62.4	*0.8*	62.4	*0.0*	58.5	*0.4*	62.2	*1.8*	60.3	*2.6*	62.1	*2.4*	**65.7**	*2.5*	54.6	*0.0*	62.0	*0.0*	60.4	*0.0*	63.1	*0.4*
Frog	74.7	*0.3*	74.9	*0.0*	42.9	*0.6*	51.2	*5.2*	58.5	*1.4*	67.8	*2.4*	67.7	*2.6*	75.1	*0.0*	72.3	*0.0*	62.6	*0.0*	**80.8**	*0.1*
Horse	62.6	*0.6*	62.6	*0.0*	55.1	*0.7*	58.6	*2.9*	62.5	*0.8*	65.2	*1.0*	67.3	*0.9*	53.5	*0.0*	57.5	*0.0*	69.1	*0.0*	**72.0**	*1.1*
Ship	74.9	*0.4*	75.1	*0.0*	74.2	*0.6*	76.8	*1.4*	75.8	*4.1*	75.6	*1.7*	75.9	*1.2*	71.7	*0.0*	**82.0**	*0.0*	74.7	*0.0*	80.3	*0.6*
Truck	75.9	*0.3*	76.0	*0.0*	58.9	*0.7*	67.3	*3.0*	66.5	*2.8*	71.0	*1.1*	73.1	*1.2*	54.8	*0.0*	55.4	*0.0*	77.8	*0.0*	**79.9**	*1.0*
Mean	64.8	0.6	64.9	*0.0*	55.5	*0.6*	59.4	*2.7*	61.8	*2.6*	63.3	*1.8*	64.8	*1.8*	64.1	*0.0*	65.7	*0.0*	63.6	*0.0*	**70.7**	*0.7*

Results

Average AUC on GTSRB STOP SIGN dataset (Adversarial sample detection)

OCSVM [10]	67.5	*1.2*
KDE [7]	60.5	*1.7*
IF [7]	73.8	*0.9*
DCAE [19]	79.1	*3.0*
SDOCC [4]	77.8	*4.9*
DOCC [4]	80.3	*2.8*
Ours	**85.2**	*0.7*

Results

True positives

False Negatives

False Positives

Thank You!