DISCRIMINATIVE AUTOENCODER

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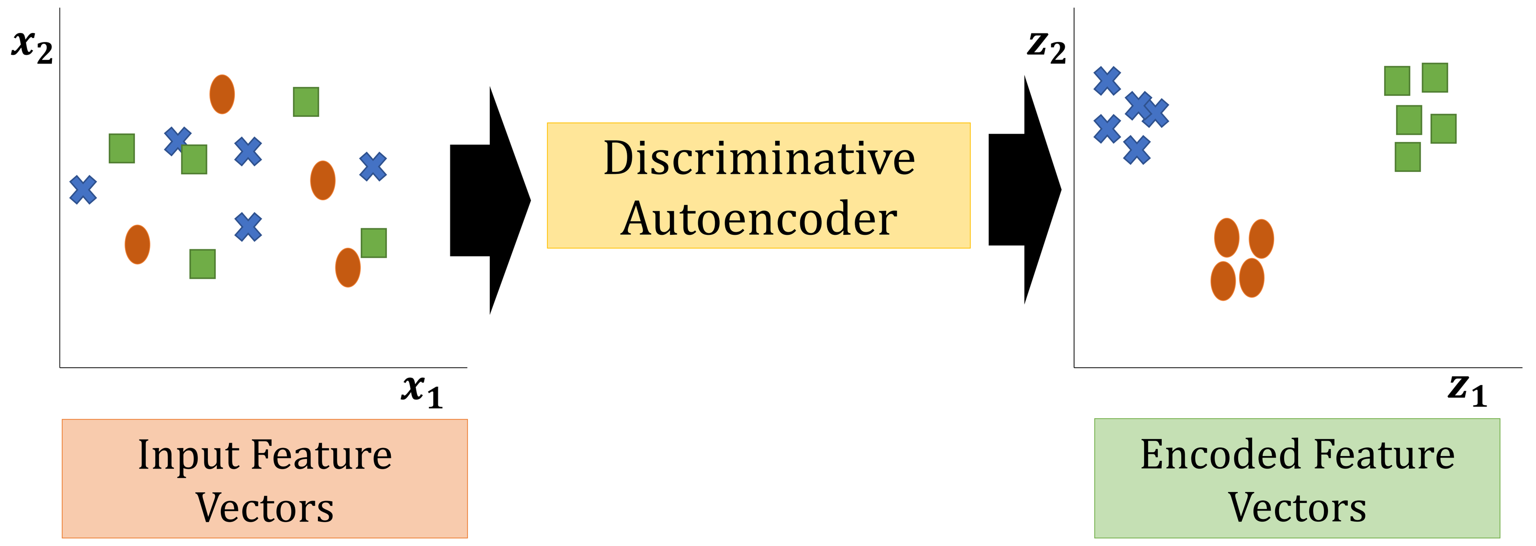
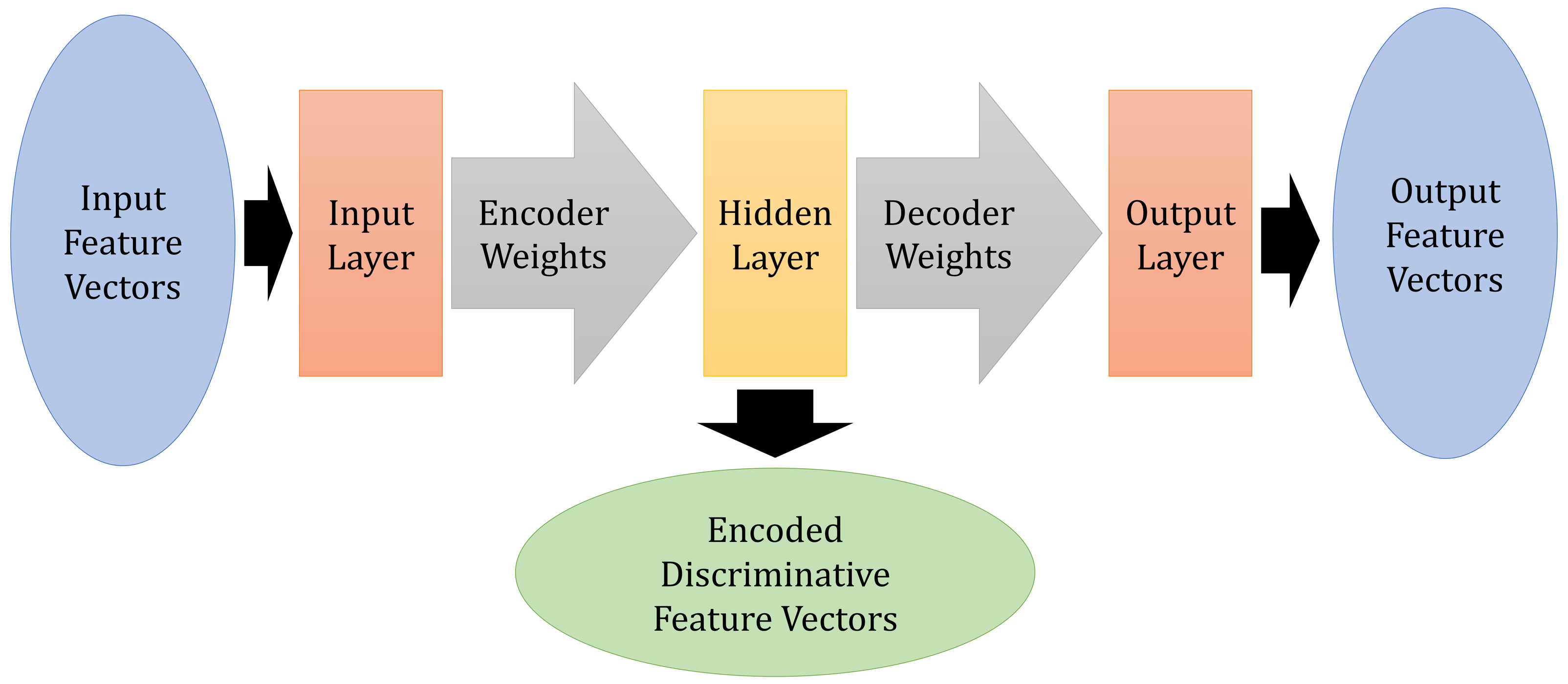
1. Introduction



- Discriminative AE: encoder map with discriminative features
- Cross dataset experiments: Training with dataset A testing with similar dataset B
- Useful in problems with weakly labelled data (e.g. in medical imaging)

2. Design Goal



3. Design Considerations

- Use of class labels: supervised method
- Encoder map: need to be discriminative
- Decoder output: same as input to the autoencoder
- Fast approach to find encoder and decoder weights

4. AE Objective Function

- Input feature vectors $\boldsymbol{X}$; Encoded feature vectors $\boldsymbol{Z}$
- Encoder weight $\boldsymbol{W}$; Decoder weight $\boldsymbol{W'}$
- Activation function $\boldsymbol{\phi}$
- AE objective function:

$$J = \|X - W'Z\|_F^2 = \|X - W'\phi(WX)\|_F^2$$

5. Discriminative AE

- Addition of regularization terms
- $\boldsymbol{Z_i}$: encoded feature vectors of class i with cluster centre $\boldsymbol{\bar{Z}_i}$
- First regularization term: minimizes the radius of a cluster in the encoded feature space: $J_1 = \lambda_1 \sum_{i=1}^{C} \|Z_i - \bar{Z}_i\|_F^2$
- Second regularization term: maximizes the inter-cluster distances between the clusters corresponding to different classes: $J_2 = -\lambda_2 \sum_{i=1}^{C} \sum_{j \neq i} \left\|\bar{Z}_i - \bar{Z}_j\right\|_F^2$
- Objective function of DAE:

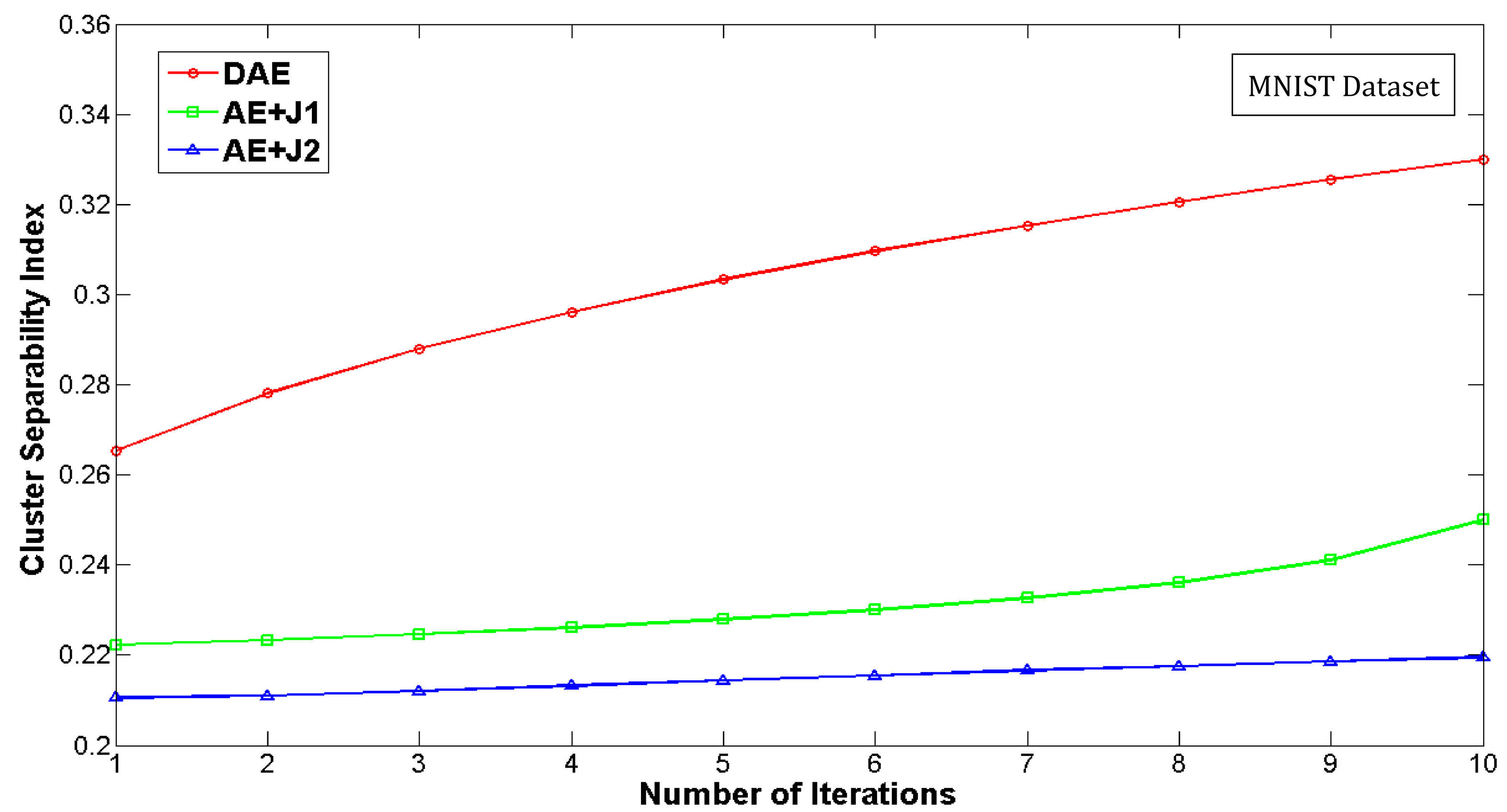
$$J_{DAE} = \|X - W'Z\|_F^2 + \lambda_1 \sum_{i=1}^{C} \|Z_i - \bar{Z}_i\|_F^2 - \lambda_2 \sum_{i=1}^{C} \sum_{j \neq i} \left\|\bar{Z}_i - \bar{Z}_j\right\|_F^2$$

6. Minimization of the Objective Function

- ADMM for minimization of J_{DAE} by dividing into sub-problems:
- P1: $\underbrace{argmin}_{W'} \|X - W'Z\|_F^2$
- P2: $\underbrace{argmin}_{Z_i} \|X - W'Z\|_F^2 + \lambda_1 \sum_{i=1}^{C} \|Z_i - \bar{Z}_i\|_F^2 - \lambda_2 \sum_{i=1}^{C} \sum_{j \neq i} \left\|\bar{Z}_i - \bar{Z}_j\right\|_F^2$
- P3: $\underbrace{argmin}_{W} \|Z - \phi(WX)\|_F^2$

7. Experiments

- Datasets: MNIST, variants of MNIST, USPS, CIFAR – 10, SVHN
- Parameters λ_1 and λ_2: tuned using 5-fold cross-validations
- Competing approaches: SSA [1], DBN [2], LC2 [3], SE [4]
- Cluster separability index: better clusters in the encoded feature space
- Improvement with iterations during training

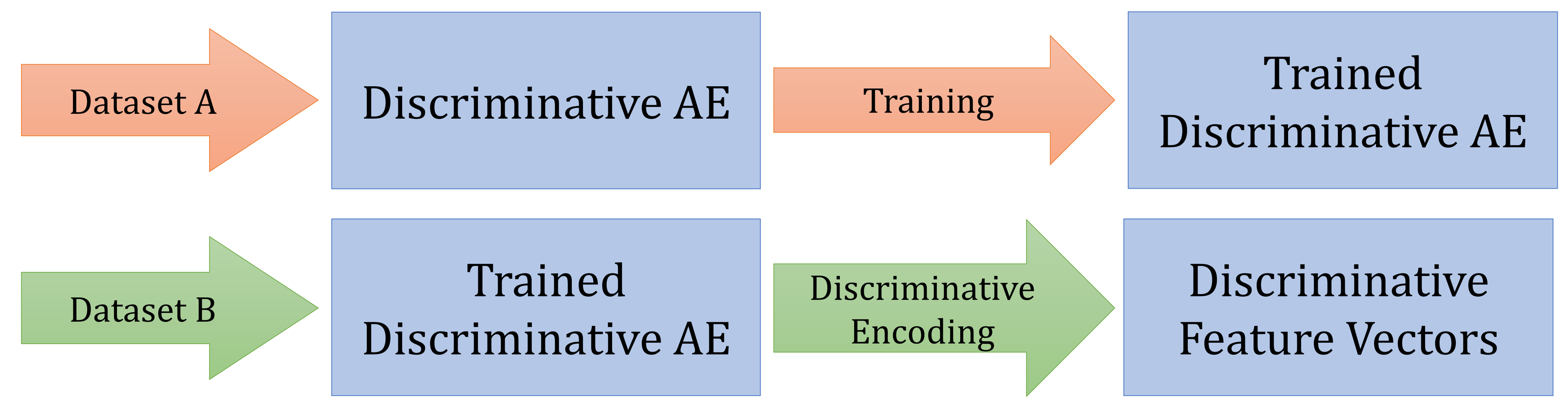


8. Classification Results

- Classification by random forest using encoded features

Dataset	SSA	DBN	LC2	SE	Proposed
MNIST	96.82	96.7	94.6	95.68	**97.12**
MNIST-R	86.86	85.2	85.68	83.44	**88.54**
MNIST-RB	52.71	**56.2**	54.43	49.82	51.9
USPS	95.12	94.82	91.34	87.24	**95.44**
CIFAR – 10	31.48	28.72	27.06	22.82	**32.28**
SVHN	27.21	30.8	30.64	26.27	**33.1**

9. Cross-Dataset Experiments



- Breast cancer datasets: training using MITOS-ATYPIA [5] and test on MITOS [6] and AMIDA [7]
- Feature extraction using [8], encoding using different methods, classification using random forest

Dataset	SSA	DBN	LC2	SE	Proposed
MITOS	59.2	67.8	61.3	67.2	**75.3**
AMIDA	51.4	61.2	60.7	59.5	**66.2**

10. Conclusions

- Discriminative features using autoencoder
- Fast due to use of ADMM for minimization of J_{DAE}
- Useful for cross-dataset experiments
- Outperforms state-of-the-art competitors

References

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