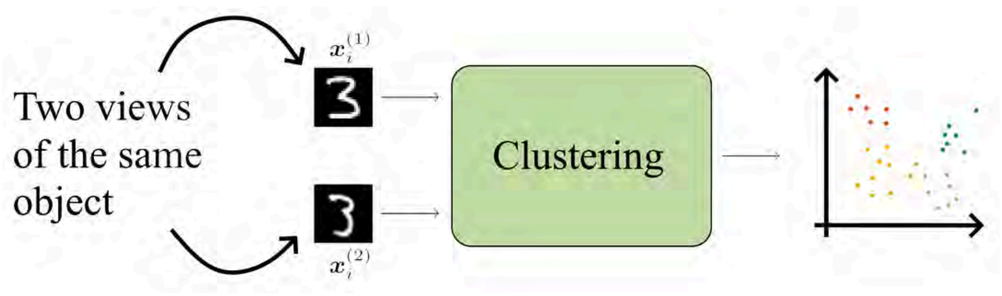
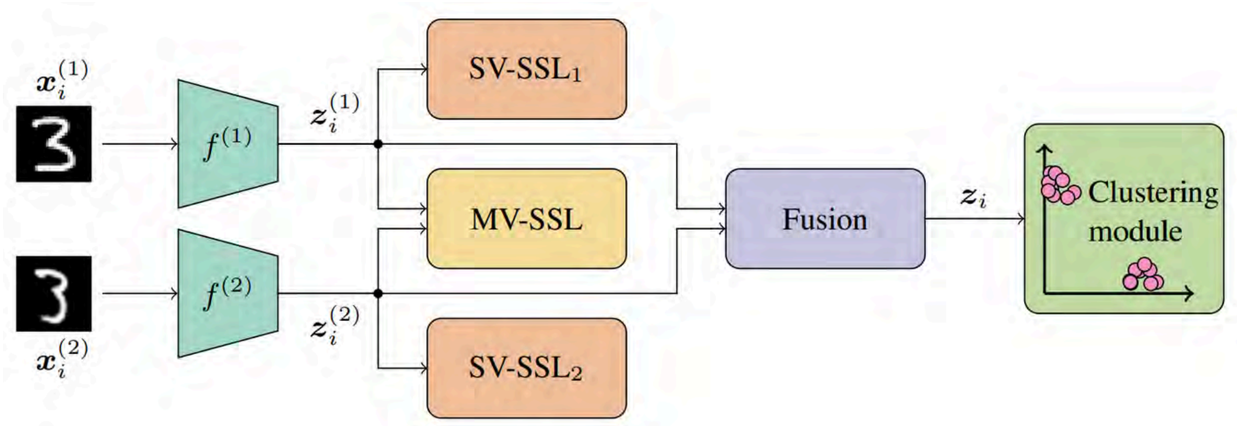
Exploring the Current State of the Art in Deep Multi-View-Clustering

Michael Oster & Alexander Sturm supervised by Lukas Miklautz & Sebastian Tschiatschek

Introduction and contributions

- Multi-View-Clustering (MVC) generalizes the clustering setting to multi-view data
- E.g. images of same object taken from different angles
- Recently Trosten et al. invented a new approach to MVC called AECoDDC, which uses:
  - reconstruction loss as single-view self-supervised-learning objective (SV-SSL)
  - contrastive loss as the multi-view self-supervised-learning objective (MV-SSL)
  - Deep Divergence-based (DDC) clustering loss for the *Clustering module*





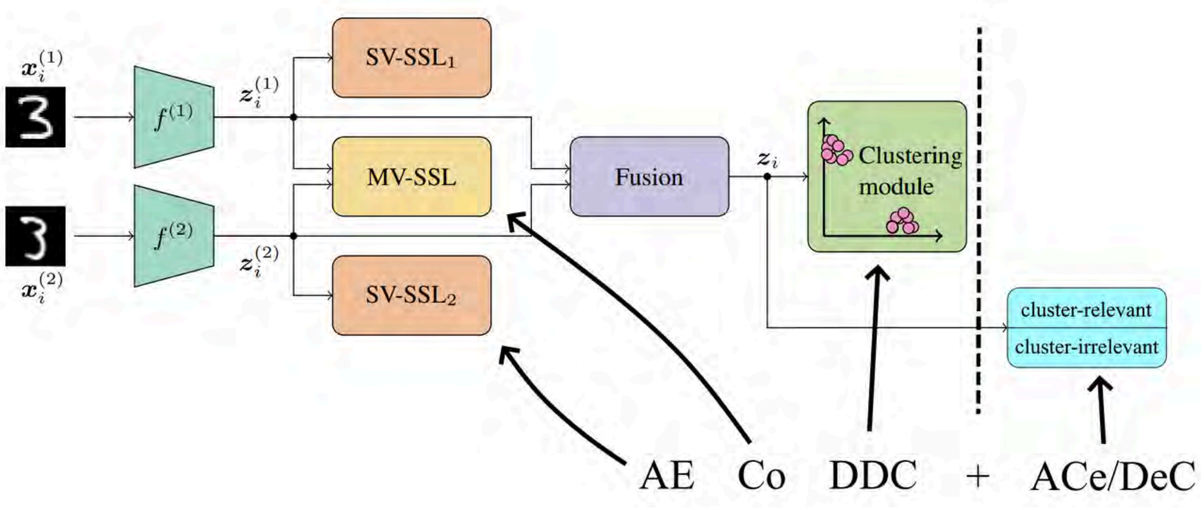
Framework by Trosten et al.

Contributions of our project:

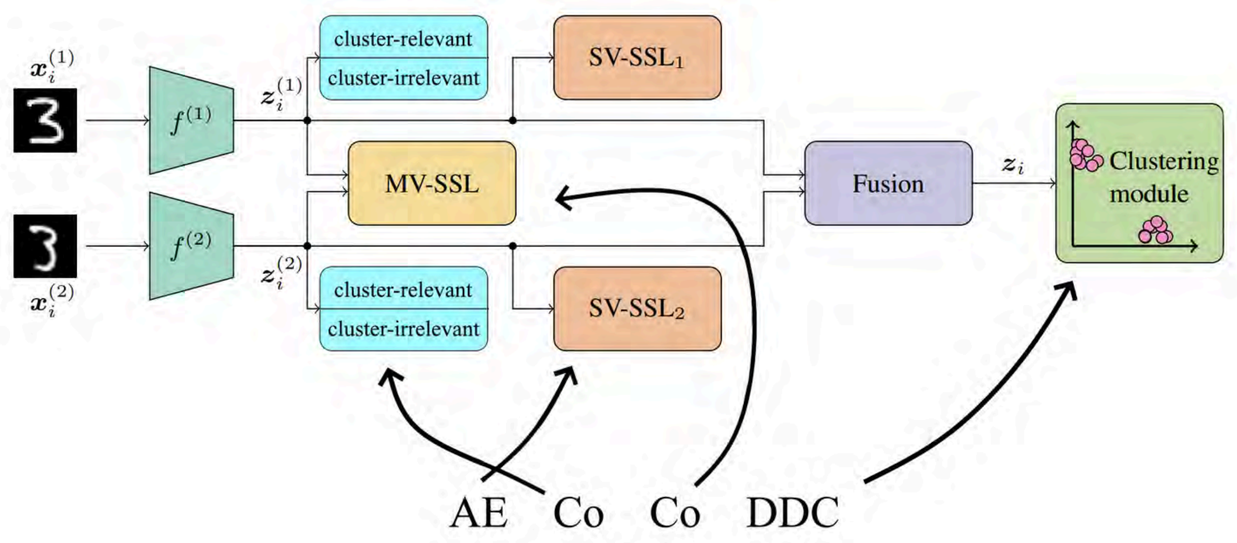
- developed new architectures building upon AECoDDC
- investigated how methods using contrastive alignment suffer from noise
- looked at the benefits of splitting the latent space into cluster-relevant and -irrelevant information
- conducted extensive latent space exploration

Architectures

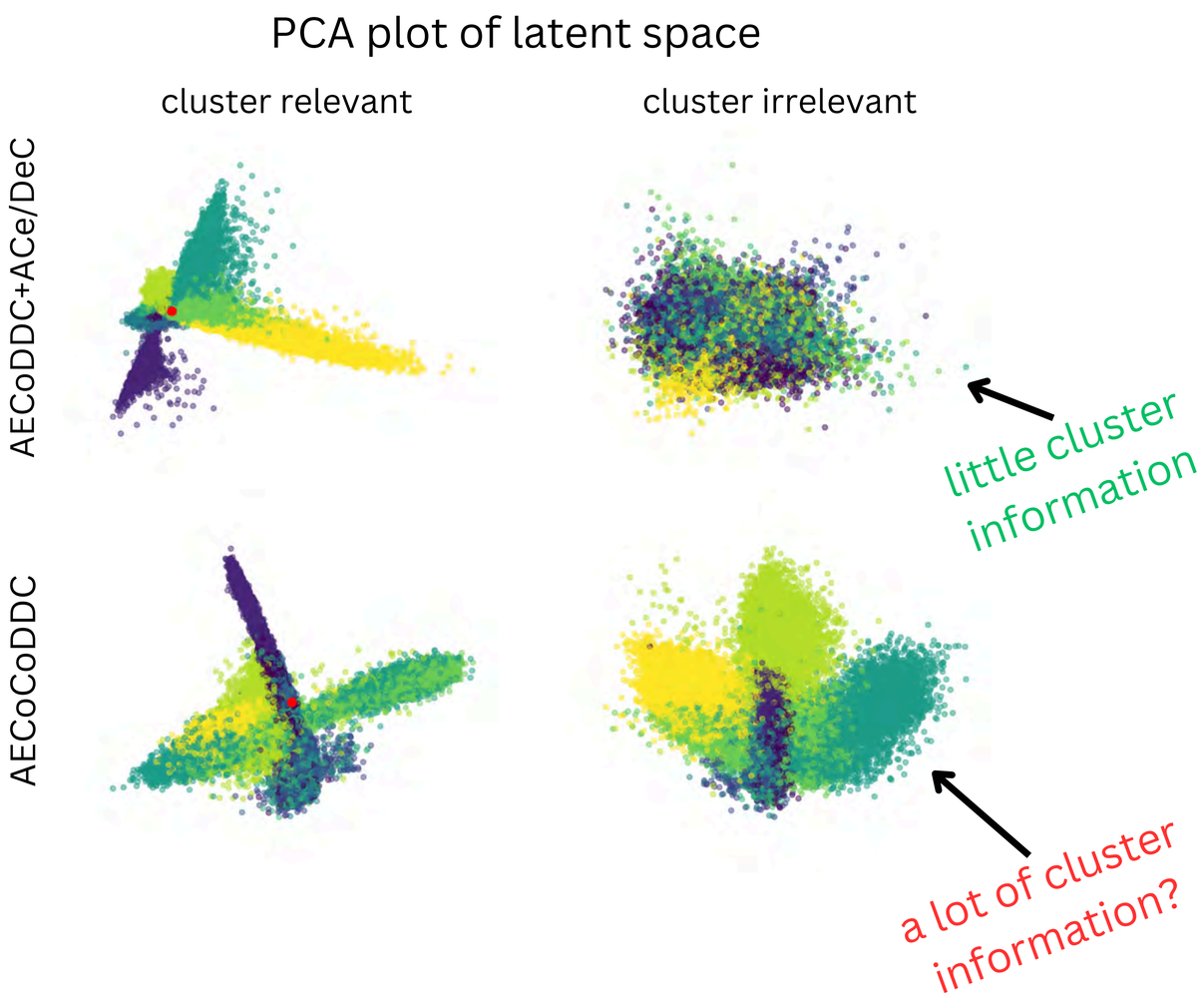
- Introduce ACe/DeC module after training to split into cluster-relevant and -irrelevant
- Same behaviour as AECoDDC

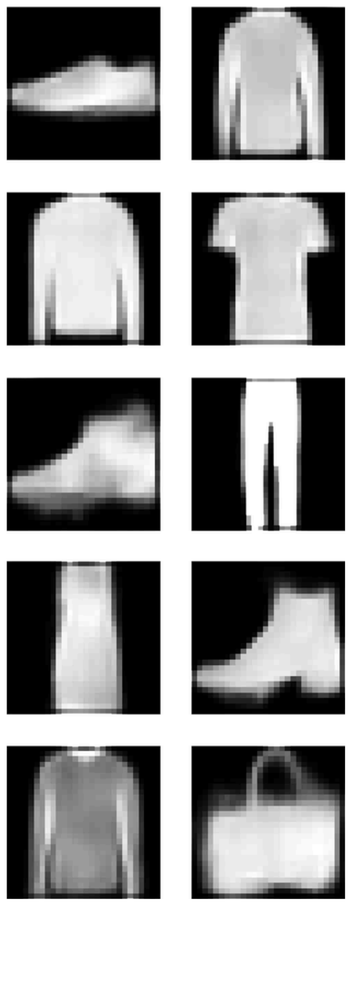


- Include ACe/DeC module within original architecture
- New Compression loss term while training leads to different bevaviour



Results for “Noisy Fashion” MVC dataset





Architecture	ACC	NMI
AECoDDC (prior best)	0.8 (0.02)	0.77 (0.01)
AECoCoDDC	**0.86** (0.02)	**0.81** (0.01)

Conclusion:

- Contrastive learning benefits from ground truth label information embedded in the views
- AECoDDC+ACe/DeC is able to split into cluster-relevant and -irrelevant
- The model finds human interpretable centroids
- Performance improvement on “Noisy Fashion” does not generalize to more complex datasets

References:

- Daniel J. Trosten et al.: “On the Effects of Self-supervision and Contrastive Alignment in Deep Multi-view Clustering”
- Lukas Miklautz et al.: “Details (Don’t) Matter: Isolating Cluster Information in Deep Embedded Spaces”