# Quantifying The Dimensionality Of Image Manifold For Classification

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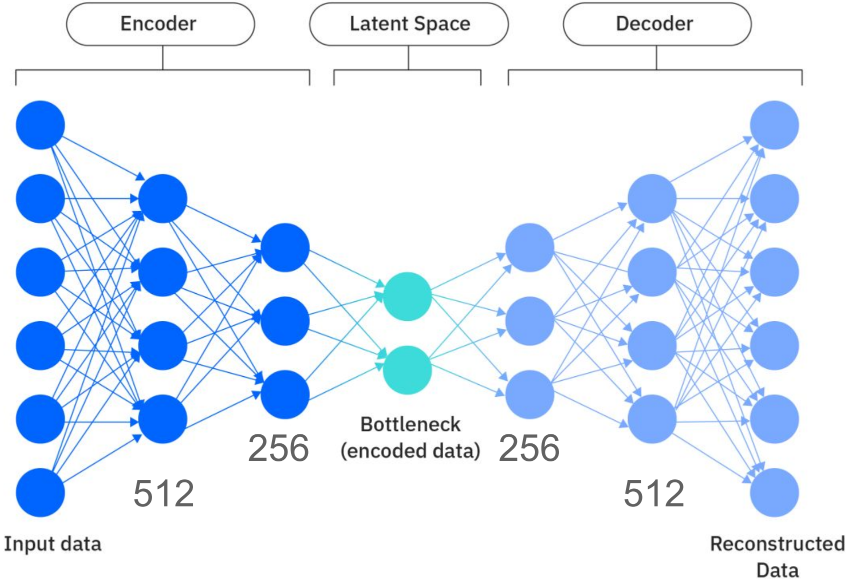
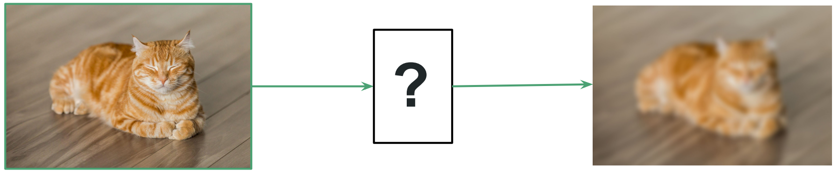
# Introduction

## Why quantify dimensionality of a dataset?

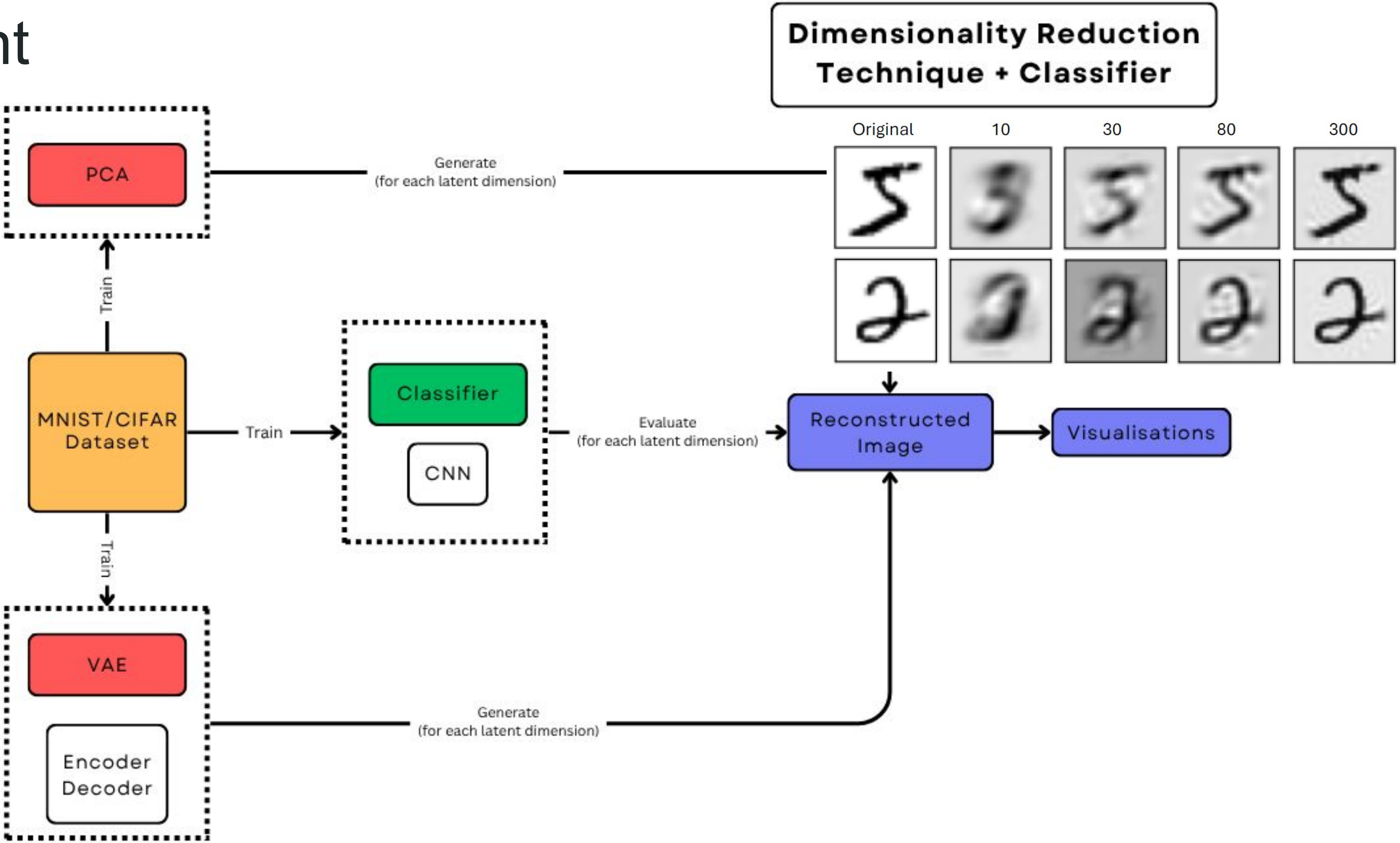
- *Manifold Hypothesis: A low dimensional manifold can approximate the dataset embedded in a high dimensional space (Causin & Marta, 2025).*

- *Dimensionality of input affects representations of networks trained on it (Huh et al, 2024).*



# Experiment Pipeline



# Results

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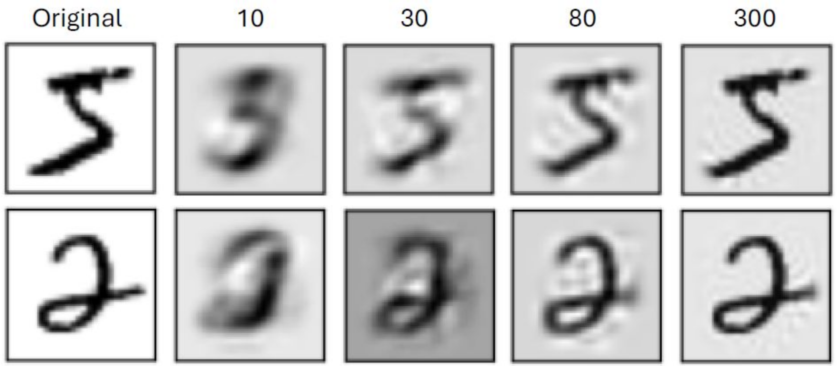
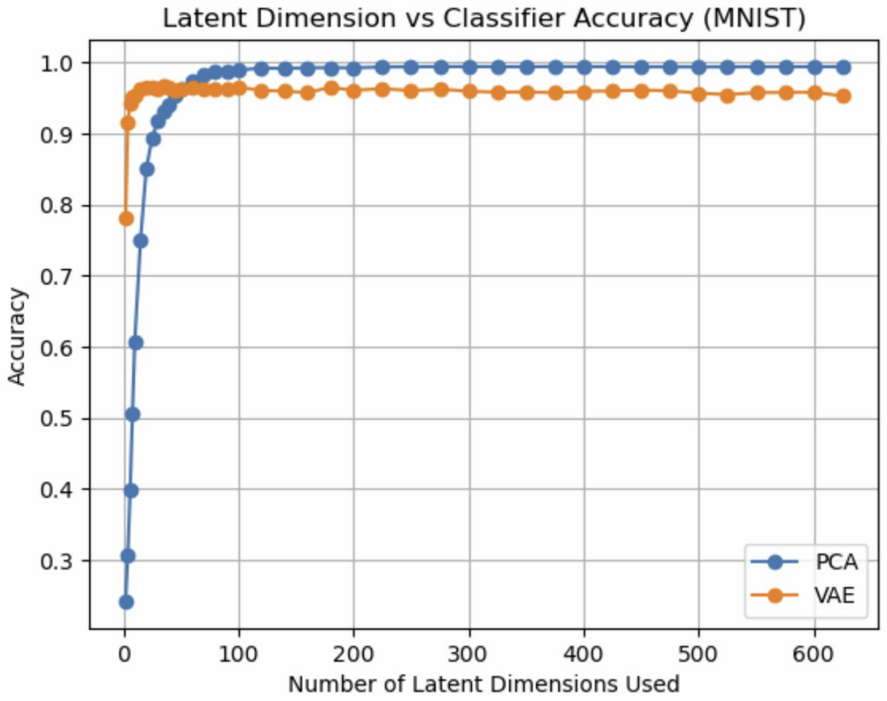
# PCA vs VAE

Example reconstructed images

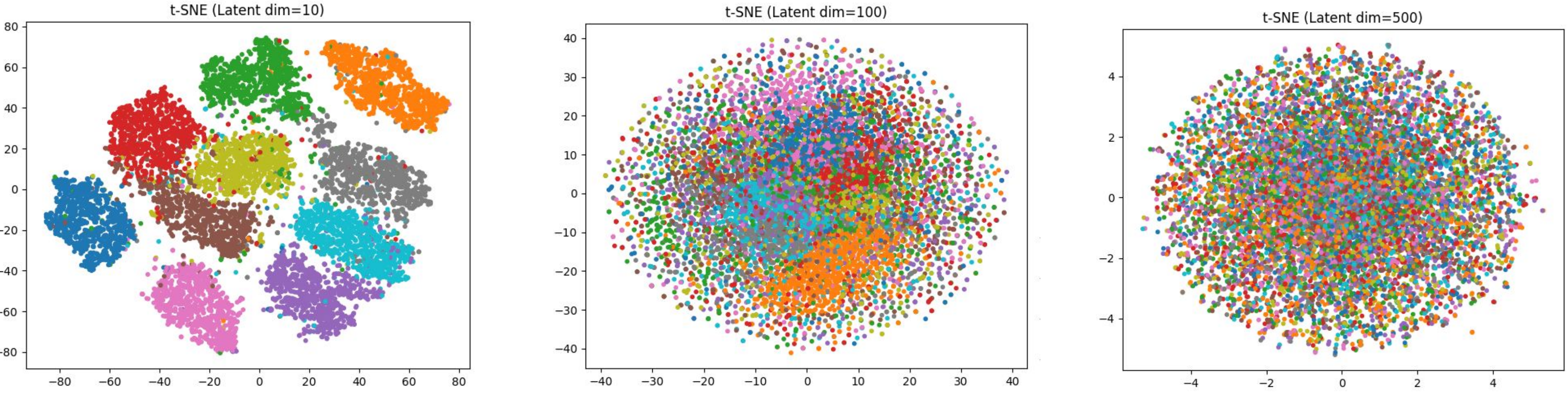



- Test accuracy rises with latent size, then plateaus.
- VAE rises much earlier than PCA (nonlinear technique is more powerful)
- PCA has higher accuracy at the plateau

# Effect of Latent Dimension on Latent Space Structure (MNIST)

## t-SNE




- t-SNE shows clear clusters at low latent dims.
- Clusters blur at high dims, showing less structure.
- Tradeoff: small latent spaces compress well; large ones better reconstruct but low dimensionality visualization shows less clusters

# β-VAE

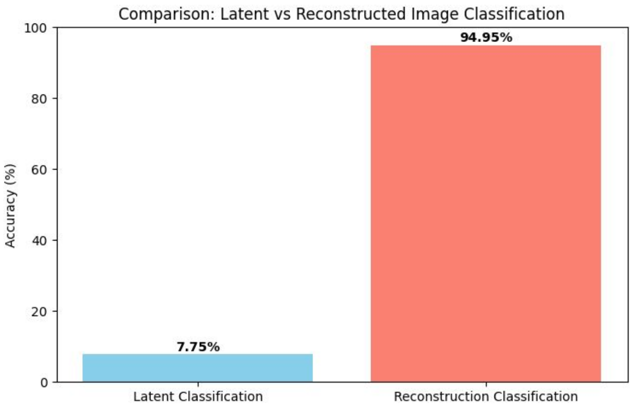
We manipulated Loss function parameters to understand how it affects classification of the reconstructed images and of the bottleneck features

Loss Function = BCE + *beta* * KLD + *alpha* * CE

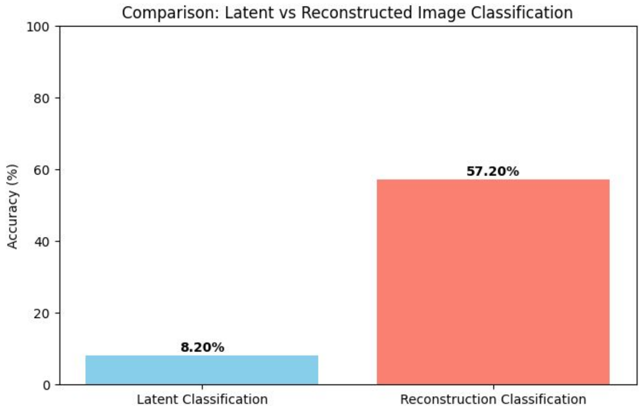
Reconstruction

Bottleneck distribution regularization (Gaussian)

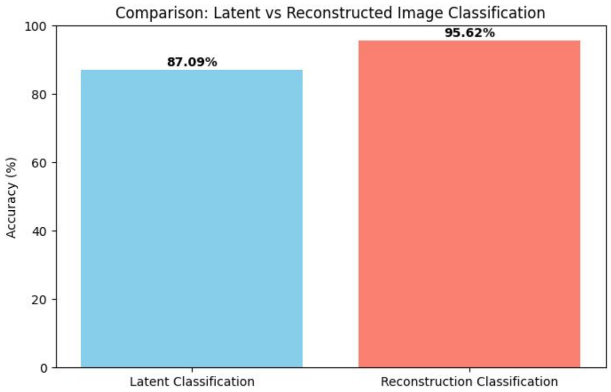
Classifiability of the bottleneck




alpha=0, beta=1




alpha=0, beta=10.0




alpha=1, beta=1

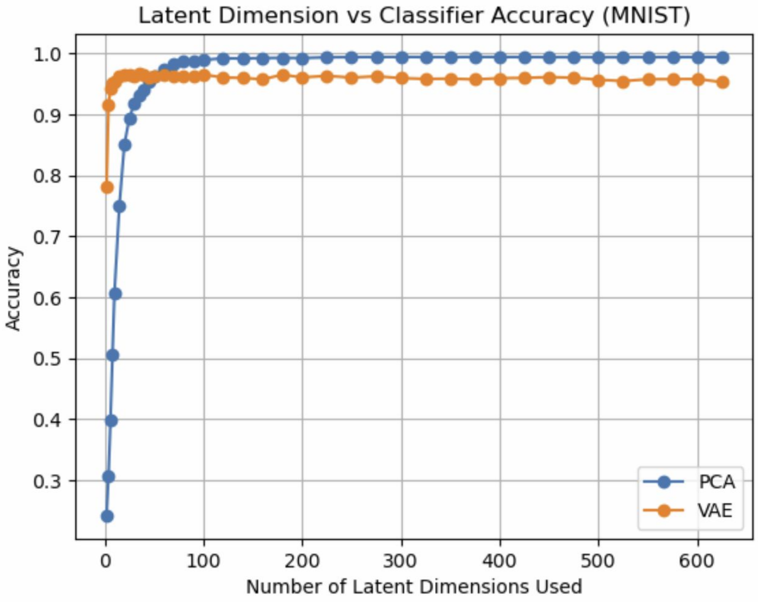
Bottleneck features are not linearly classifiable

Increasing beta collapses representations in the bottleneck and harms classification accuracy

Including bottleneck classification in the loss increases its classifiability

# Conclusion

- VAE can represent images with fewer latent dimensions than PCA, preserving classification accuracy for low dimensional latent space
- PCA does better than VAE at higher dimensions
- Better understanding of manifold dimensionality by comparing VAE and PCA



# In the next episode…

- We’re closer to quantifying latent dimensionality but not entirely
- Why is VAE’s accuracy lower than PCA at higher dimensions? Can it potentially change with different VAE modifications?
- How do these results change with more complex datasets?

# Thank you to our colleagues, TAs and NMA!

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# Appendix

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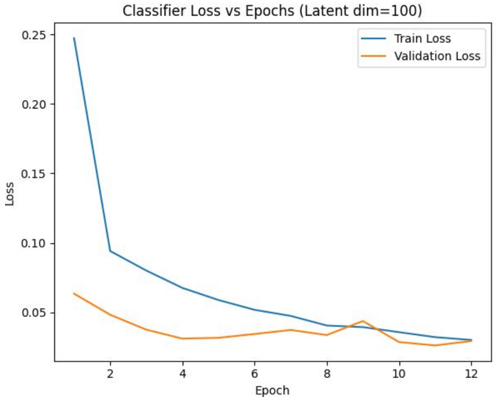
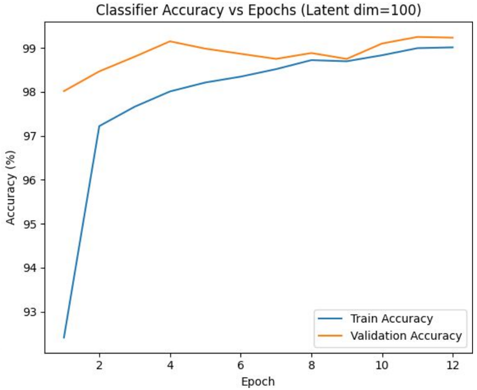
# Training

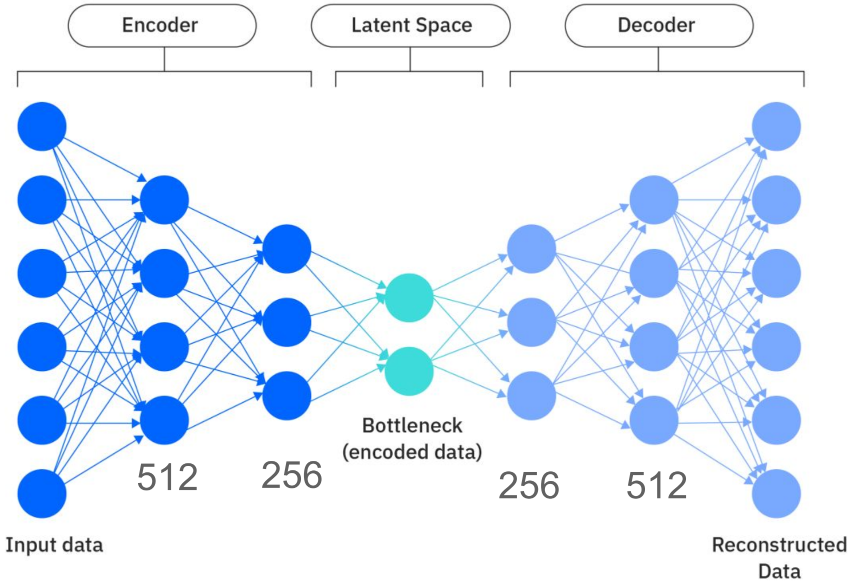
No overfitting:



# VAE architecture

BatchNorm1d, ReLU



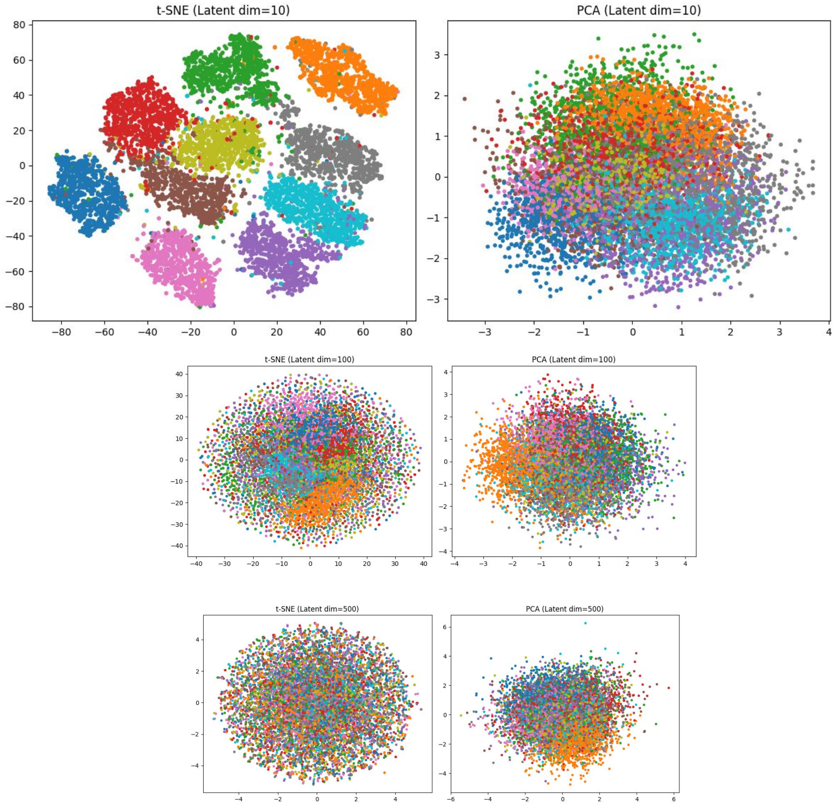
# Classifier

```
nn.Conv2d(1, 32, kernel_size=3, padding=1),
nn.BatchNorm2d(32),.ReLU(), nn.MaxPool2d(2, 2),

nn.Conv2d(32, 64, kernel_size=3, padding=1),
nn.BatchNorm2d(64), .ReLU(), .MaxPool2d(2, 2),

nn.Flatten(),
nn.Linear(64 * 7 * 7, 128),
nn.ReLU(),
nn.Dropout(0.25),
nn.Linear(128, 10)
```

# t-SNE | PCA


t-SNE (Latent dim=10)
PCA (Latent dim=10)
t-SNE (Latent dim=100)
PCA (Latent dim=100)
t-SNE (Latent dim=500)
PCA (Latent dim=500)