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UNTITLED

Master's thesis

Examiner:

1. INTRODUCTION

- A major challenge in modern data analysis is
- analysis of high dimensional data, examples
- dimensionality reduction
- curse of dimensionality
- linear and non linear
- problems with existing methods
- neural networks provide way for scalable learning of complex functions
- additionally enables parametric extension
- in this thesis...
- The structure of this thesis is as follows. Chapters /refch:vae and /refch:tsne cover the relevant background literature for the methods proposed in chapter /refch:methods, where chapter /refch:vae discusses the theory behind Variational Autoencoders and chapter /refch:tsne presents t-SNE, as well as its parametric extension. In chapter /refch:results several empirical results for the proposed method are presented, along with comparisons to other popular methods. The final chapters are reserved for discussion and conclusions.

2. VARIATIONAL AUTOENCODERS

3. T-DISTRIBUTED STOCHASTIC NEIGHBOR EMBEDDING

4. METHODS

5. RESULTS

5.1 Evaluation metrics

The quantitative evaluation of unsupervised, non-linear dimensionality reduction methods is a challenging problem.

To evaluate the efficacy of the method proposed in this work we employ three different quantitative metrics.

Namely, the trustworthiness score, continuity and for labeled data sets 1-NN classification accuracy will be used.

5.1.1 Trustworthiness

5.1.2 Continuity

5.1.3 1-NN classifier

5.2 Data sets

5.2.1 MNIST

One of the most widely used data sets in current machine learning, being the most used

5.2.2 SVHN

The Google *Street View House Numbers* data set bares a great resemblance to MNIST yet being a considerably harder data set to learn.

Typically supervised feature extraction has been used to preprocess the original images into feature vectors, such as in ... where convolutional neural networks are applied to ...

In this work we directly use the cropped and uncropped street view house numbers set.

5.2.3 Mass cytometry data

6. DISCUSSION

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