

Visual Analytics: Project Report

A Visual Exploration of Manifold Learning for Images

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Abstract

The following work is a report on the development and implementation of a visual analytics system intended to aid the understanding of dimensionality reduction techniques. In creating an interactive interface to various embeddings of the well-known MNIST handwritten digit dataset we propose a system which allows users to manipulate the embedded representations using a web-based application. The system further allows its users to select the embedded images and to aggregate them using standard image processing algorithms to emphasize the technique's inner workings and visually aid the development of intuitions.

1 Motivation, Intended users and preliminary Research

1.1 Motivation

The creation of the system was motivated by the desire to create an aid to understanding dimensionality reduction and the manifold hypothesis, as these topics seem to be strangely ubiquitous in current development in the field of Computer Science.

Reducing the extrinsic dimensionality of data has many advantages, not only for processing efficiency, but also for visualization and algebraic manipulation of higher-dimensional manifolds. Images are a prime example of the discrepancy that can exist between the intrinsic and extrinsic complexity of data. Handwritten digits specifically lend themselves to a use as toy data. Especially, because as humans we can easily comprehend them, despite hundreds of degrees of freedom. The intention was to create a system, that would not only visualize the embeddings generated by various dimensionality reduction techniques as a common cartesian chart, but would further allow the user to select points in the embedded space, manipulate them and aggregate the instances they represent using image

processing techniques such as morphology. This last aspect was based on the expectation, that visualizing aggregations of the embedded instances, while knowing their position in the embedded space could yield insights on the inner workings of the embedding techniques employed, exposing characteristics such as linearity in the embedded space or the features represented by the degrees of freedom in the embedding.

The Manifold Hypothesis

In referring to the *Manifold Hypothesis* we intend the belief, that data recorded from the natural universe, despite a high dimensionality (think of the approx. 48000 *DOF* in a single sample of the 48KHz audio recording or 3 million *DOF* in a 1MP color image) lies on a lower-dimensional manifold. This belief has been extensively studied by papers such as (Fefferman et al., 2016) (which cites a plethora of other papers on the field) and though fascinating and interesting in its own right, it is the basis of many techniques used in Machine Learning and Data science as these fields tend to deal with highly dimensional data. Notable examples are the random sampling over a latent space used in generative models (Razavi et al., 2019) or generating plausible interpolations/deformations of instances, exploiting the euclidean nature of the latent space (Cosmo et al., 2020). While these are very interesting examples of advanced applications of the manifold hypothesis, the application proposed here intends to lay the groundwork to its understanding/intuition.

1.2 Goals

In an effort to create an accessible educational tool, one of the main goals was to build a powerful application that could run within the browser. As there would be image processing required for the various image aggregation techniques, the idea was

to incorporate an OpenCV build for *WebAssembly* to move any image processing to the frontend application. More on this in Section ??.

1.3 Target Audience

Being an educational tool at its core the application is geared towards anyone interested in deepening their understanding of dimensionality reduction or even comparing existing techniques with a specific use-case in mind. This includes Machine Learning Engineers/Data Scientists and students of the STEM fields.

Though the prototype of this application developed in the course of this project uses the well-known MNIST handwritten digit dataset as toy data to demonstrate the working principle with, the approach and large parts of the codebase could easily be adapted for custom image datasets and/or tailor-made dimensionality reduction techniques in a productive machine learning environment

1.4 Related Work and Preliminary Research

While searching for related work in the field of Visual Analytics, it immediately became apparent that dimensionality reduction is a very common tool for data visualization which given its expressive potential is unsurprising. Having a closer look at publications mentioning dimensionality reduction, a certain timeline emerges with respect to the role that it has played in scientific publications:

- 2000-2010: While Principal component analysis and Multi-dimensional scaling are methods that have been around since the last century, many publications in this period motivate/discover the techniques themselves and their potential for various applications. Many of these papers explore the mathematical properties of the lower dimensional embeddings. Examples include: The original paper presenting the Isomap embedding (Tenenbaum et al., 2000), or the Locally Linear embedding (lle) (Roweis and Saul, 2000). Contrary to this earlier focus on the techniques involved, towards the end of this decade, dimensionality reduction seems to have become pretty much standard practice for data visualization. Papers such as this survey (Zhang et al., 2010) suggest they are frequently used to visualize data in scientific publications.
- 2010-Present: With Big Data and Machine Learning becoming ever more relevant top-

ics, dimensionality reduction gained more traction not only in its capability to make data more comprehensible/intuitive to humans, but also as a means of counteracting the proverbial *curse of dimensionality*. Even more recently the focus seems to have once again shifted, as new models allow the enforcing of certain properties in the latent space, such as the preservation of semantics in *word2vec* (Mikolov et al., 2013) word embeddings. These machine learning based techniques, allow the transformation to be conditioned on desired properties, thereby extending the realm of possible applications.

While I couldn't find a work in the field of Visual Analytics that combines dimensionality reduction and image processing in the interactive way I envision, it is apparent that the underlying ideas are not new and that the techniques are still very relevant.

2 Implementation

2.1 Tech stack

In the following we will briefly address the technologies chosen to implement the prototype of the system proposed.

- Dataset We chose the well-known MNIST Handwritten digits dataset as toy data, as the images are small and the classification problem of handwritten digits is intuitive.
- Frontend As we decided to build the application to run in the browser, a powerful framework was required to enable the advanced features we envision. It was therefore decided that the advanced functionality of `ReactJS` would offset the additional effort involved in the initial setup.
- Charting Library: As a solution to creating charts `react-vis` was chosen. First published by Uber in 2016 and sadly deprecated in 2021, `react-vis` is a simple charting library, built for extensibility and interactivity.
- Backend: In an effort to prototype rapidly, there seemed to be no incentive to handle the dimensionality reduction in the browser, as far more powerful and versatile solutions exist for Python. We therefore decided to build a simple HTTP-server based on the `bottle` package to serve the data and files. The dimensionality

reduction techniques included were sourced from the `scikit-learn` library.

- **Image processing** To perform the image aggregation on the original instances we chose to use `OpenCV`. Initially it was our intention to perform all the processing in the browser, using a `WebAssembly` build of `OpenCV`. For practical reasons, it later became apparent that it would be much more efficient to simply refer to images by a common index (between frontend and backend) and let the frontend trigger the aggregation of instances in the backend as required.

2.2 Dimensionality Reduction Techniques

While we set out with the initial intention of incorporating approx. 5 different dimensionality reduction techniques, we limited ourselves to 3 in the prototype. We included

- Principal Component Analysis
- Locally linear embedding
- Isomap embedding

While it is desirable to incorporate and showcase as many different techniques as possible, it became apparent in the development process, that having too many different techniques wouldn't benefit the app as much as focussing on specific techniques and tailoring the application towards showcasing their properties as well as possible.

A property that wasn't sufficiently considered during planning, was whether the incorporated techniques have an inverse transformation or not. More on this in section 4

3 The Prototype

4 Insights

5 Demo

6 Conclusion

References

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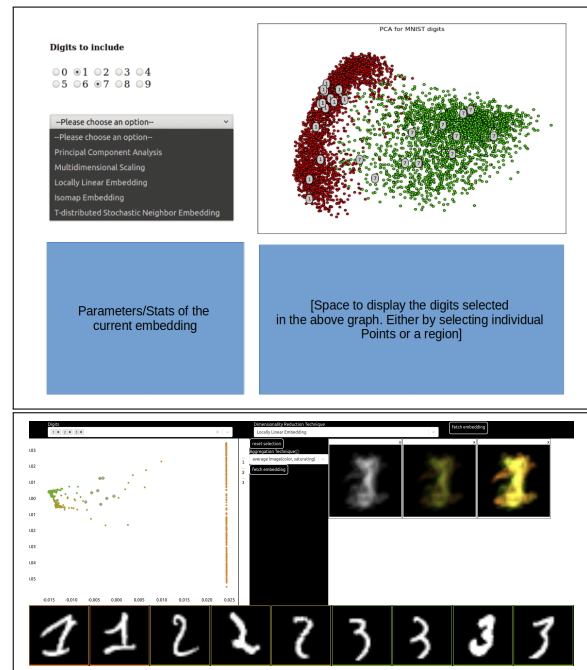


Figure 1: A picture of the proposed mockup vs. screenshot from the prototype of the application

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