Fashion-MNIST Classification based on Manifold Learning

CSIC 5011 Final Project

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Overview

Data Description

- The Fashion-MNIST dataset contains
  - 60,000 training images and 10,000 test images
  - size 28-by-28 in grayscale
  - labels for 10 distinct types
- Select 10,000 images for our project

Samples in the Fashion-MNIST Dataset

Goal

1. Apply several manifold learning methods to find the lower-dimensional embedding of the high-dimensional Fashion-MNIST dataset
2. Conduct the classification for the types of the fashion based on the embedding results
3. Estimate the intrinsic dimension of the dataset by using residual variance

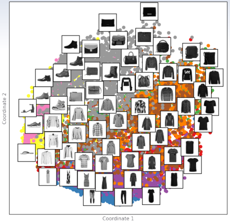
Manifold Learning

- Find the manifold on which the high dimensional dataset resides and the corresponding embedding
- Reconstruct the low dimensional manifold
- Dimensioanlity reduction and data visualization

Methods

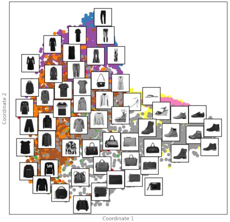
- Principal Component Analysis (PCA)
- Multidimensional Scaling (MDS)
- Isometric Maps method (ISOMAP)
- Locally Linear Embedding (LLE)
- Modified Locally Linear Embedding (MLLE)
- Hessian Locally Linear Embedding (Hessian LLE)
- Laplacian Eigenmaps
- Local Tangent Space Alignment (LTSA)
- Diffusion Maps
- t-Distributed Stochastic Neighbor Embedding (t-SNE)

Embedding

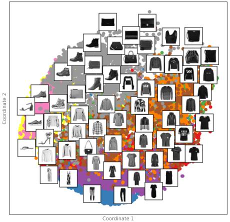


PCA

MDS

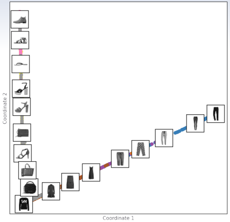


ISOMAP

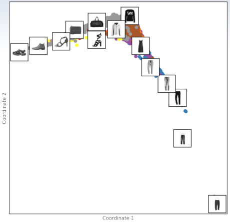


t-SNE

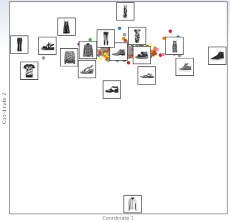
Embedding



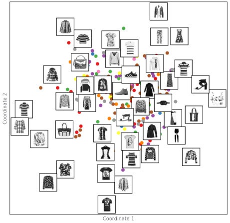
LLE



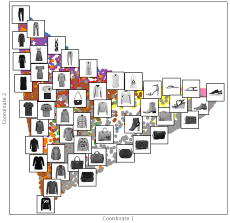
MLLE



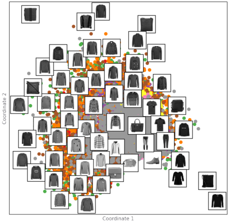
LTSA



Hessian LLE



Laplacian Eigenmaps



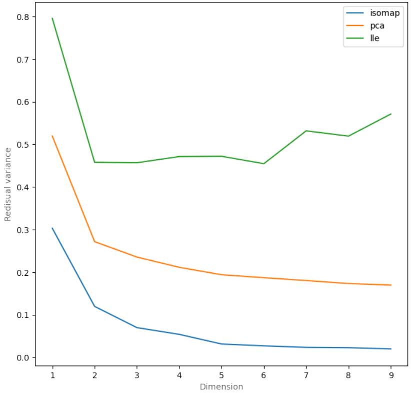
Diffusion Maps

Classification

Methods for embedding	Accuracy via Random Forest	Accuracy via SVM
PCA	49.5%	54.5%
MDS	53.4%	57.3%
ISOMAP	56.8%	59.7%
LLE	67.4%	50.2%
MLLE	64.3%	61.6%
Hessian LLE	10.3%	10.3%
Laplacian Eigenmaps	55.4%	58.0%
LTSA	10.9%	10.6%
Diffusion Maps	14.1%	16.4%
t-SNE	59.2%	56.1%
None	84.7%	84.5%

Table: Classification Accuracy

Residual Variance vs. Intrinsic dimension



Residual Variance

- Residual variance R_v:

$$R_v = 1 - R^2,$$

  where R is the linear correlation for all the data points of original graph distances and embedded euclidean distances.

- The intrinsic dimension of the data can be estimated from the figures about the residual variances for different embedding dimensions. Here the approximation of intrinsic dimension is 2.

Conclusion

1. Perform different manifold learning methods to embed the high dimensional Fashion-MNIST dataset into two dimensional space and visualize it
2. Classify the types of the fashion by using different combinations of embedding methods and classifiers, where LLE + Random Forest obtains the highest accuracy
3. Calculate the residual variances for different embedding dimensions to estimate intrinsic dimension of the dataset

References

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Thank you.