Movie Recommendations Using Low-dimensional Codes

Christopher Curro, David Katz, Harrizon Zhao
The Cooper Union
Electrical Engineering

***Abstract*—We present a movie recommendation system that finds a weighted set of nearest neighbors to an arbitrary desired movie based on user specified interests in a latent space learned by an autoencoder. We learn a low-dimensional representation to make recommendations in from a much larger feature space consisting of approximately one thousand tags and their relevancies to about ten thousand movies.**

I. Introduction

Movie recommendation is complex task that generally involves high dimensional feature spaces; a common approach today is the collaborative filtering approach [1]–[3]. The collaborative filtering approach is powerful because successfully reduces a complex high-dimensional feature space into a rich low-dimensional latent space. We aim to present an alternative approach to generating a rich low-dimensional latent space capable of producing high quality movie recommendations based on nearest neighbor approach where the queried sample is determined by user input. We work with the dataset created by Vig et al. [4]. This dataset provides a approximately ten thousand movies each with relevance weightings for approximately one thousand tags.

A. Autoencoders

An autoencoder is particular type of neural network. A neural network is a computational graph where nodes can be defined in the form:

$$\mathbf{y} = f\left(W\mathbf{x} + \mathbf{b}\right) \tag{1}$$

Where $\mathbf{x}$ is an input vector, W and b are parameters that define a linear relationship, and $f(\cdot)$ is an activation function. The activation function is generally a non-linear function so each node in the graph can perform a non-linear mapping from $\mathbf{x}$ to $\mathbf{y}$.

Nodes can be connected successively to one another in a feed-forward fashion to create increasingly complex representations of the input data. Nodes in these networks are generally referred to as layers, and can be represented diagrammatically as in Figure 1.

Figure 1 in particular shows an autoencoder. Unlike an ordinary neural network the network contains a bottleneck in the middle. It is this bottleneck that creates the rich dimensionality reduction power of an autoencoder. This bottleneck essentially splits the network into two stages: the encoder stage and the decoder stage. We interpret the autoencoder as having two stages because we optimize the learned parameters of the autoencoder to minimize the reconstruction error at the output of the decoder. By following this objective and applying other constraints, such as a sparsity constraints, rich coding schemes can be achieved at the bottleneck.

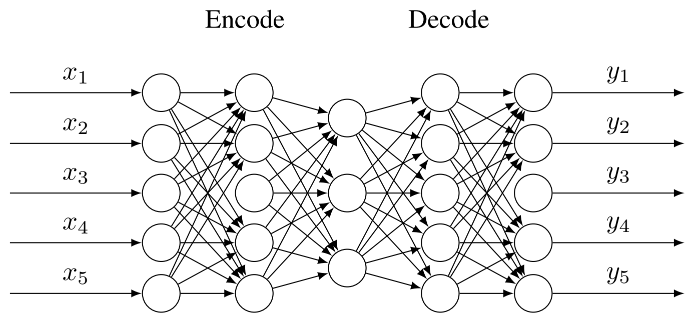

Fig. 1: A simple autoencoder with a two layer encoder/decoder pair. This autoencoder would code a five dimensional space into a three dimensional space. Each neuron represents a weighted sum passed through an activation function.

B. Nearest Neighbors Recomendations

II. System Description

A. Autoencoder

B. Recomendations

III. Results

IV. Conclusion

References

[1] M. D. Ekstrand, J. T. Riedl, and J. A. Konstan, "Collaborative filtering recommender systems," *Foundations and Trends in Human-Computer Interaction*, vol. 4, no. 2, pp. 81–173, 2011.
[2] N. Good, J. B. Schafer, J. A. Konstan, A. Borchers, B. Sarwar, J. Herlocker, and J. Riedl, "Combining collaborative filtering with personal agents for better recommendations," in *AAAI/IAAI*, 1999, pp. 439–446.
[3] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, no. 8, pp. 30–37, 2009.
[4] J. Vig, S. Sen, and J. Riedl, "The tag genome: Encoding community knowledge to support novel interaction," *ACM Transactions on Interactive Intelligent Systems (TiiS)*, vol. 2, 2012. [Online]. Available: http://www.grouplens.org/system/files/tag_genome.pdf