

Movie Recommendation System using Stacked Autoencoders CS 677 Data Science with Python

Paritosh Shirodkar paritosh@bu.edu

The Dataset

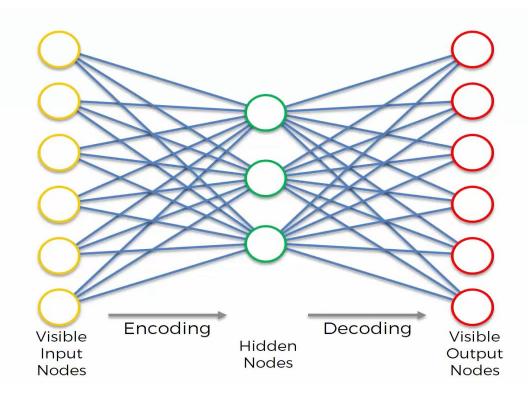
- I have used the MovieLens dataset for this project
- The dataset consists of 100000 instances
- The training set consists of 80000 instances
- The test set consists of 20000 instances
- The training set consists of the UserID, MovieID, Rating and Timestamp
- Additionally the data has information about popular genres, IMDb link, occupation, age and gender of the users who gave the ratings.
- Overall, there are 943 users, 1682 movies and 100000 ratings

Source: https://grouplens.org/datasets/movielens/

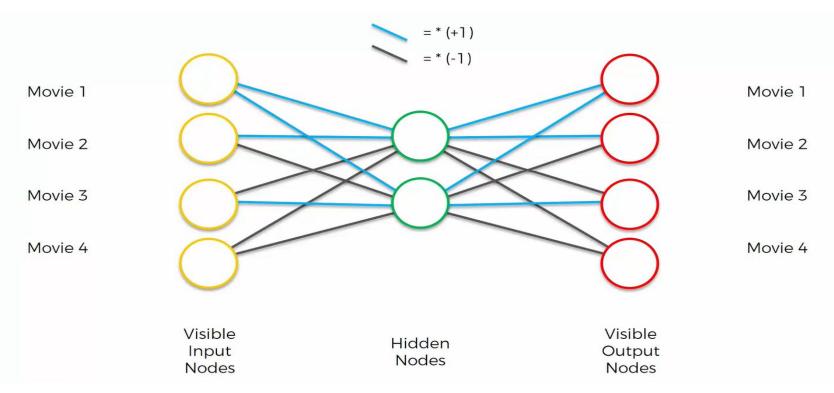
What are Autoencoders?

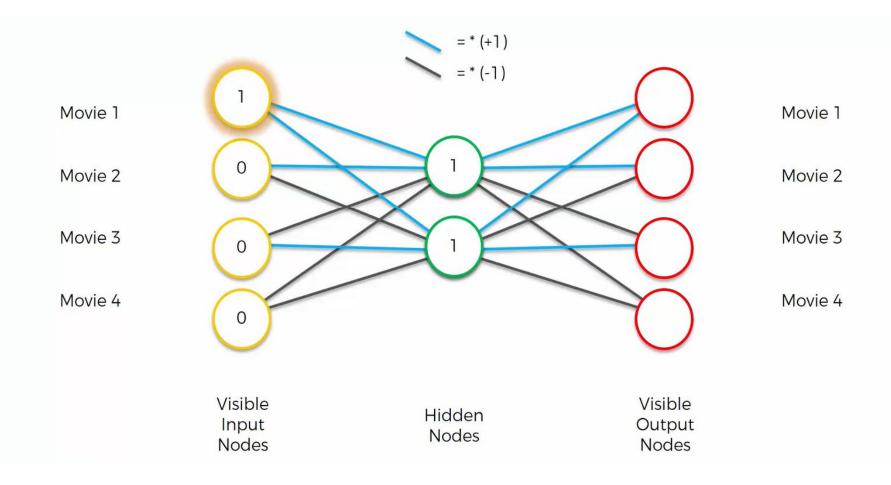
- It is a directed type of Neural Network
- It comes under the umbrella of unsupervised learning
- The philosophy behind Autoencoders is that it takes some inputs encodes them using the hidden neurons and then decodes them in an attempt to recreate the input
- Then the output is compared to the input and the error is computed
- Based on this error the weights of the network are adjusted to minimize the error

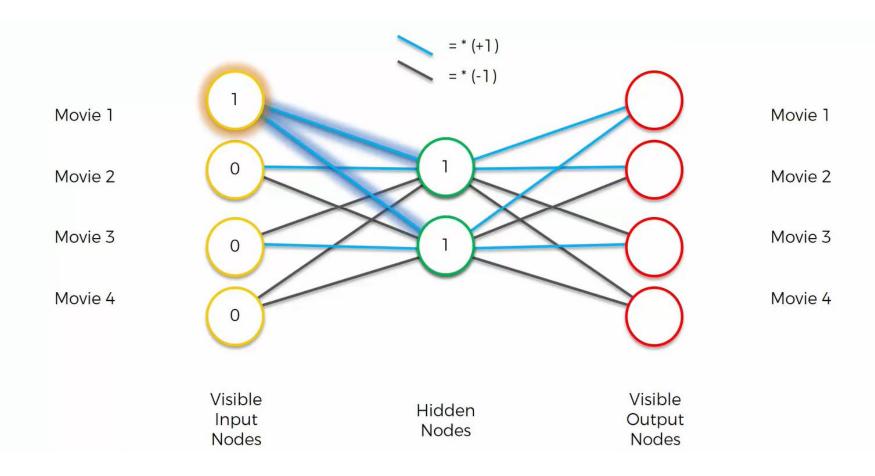
Architecture of Autoencoders

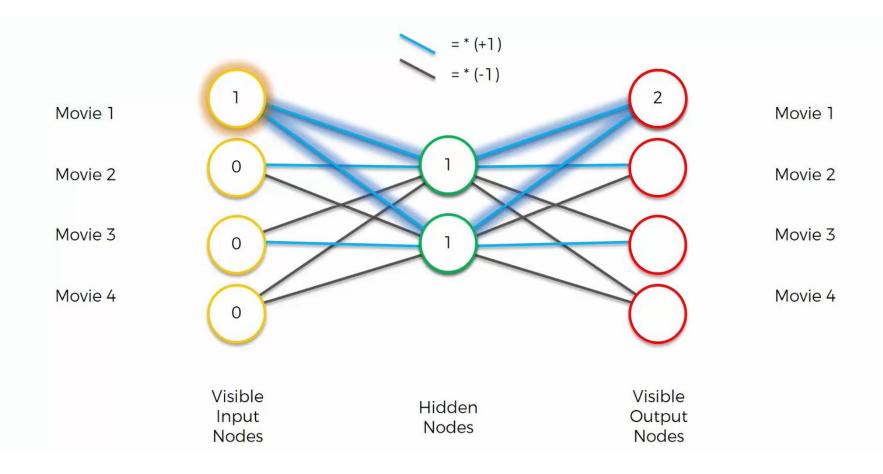


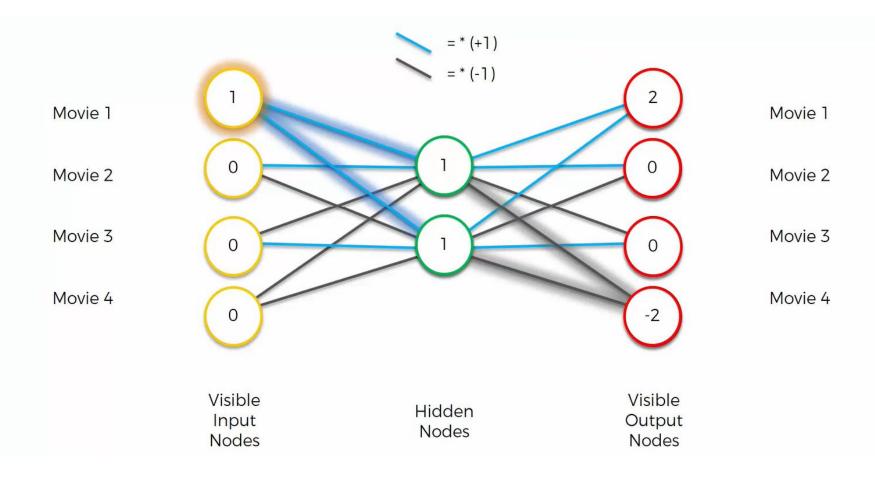
The working on an intuitive level

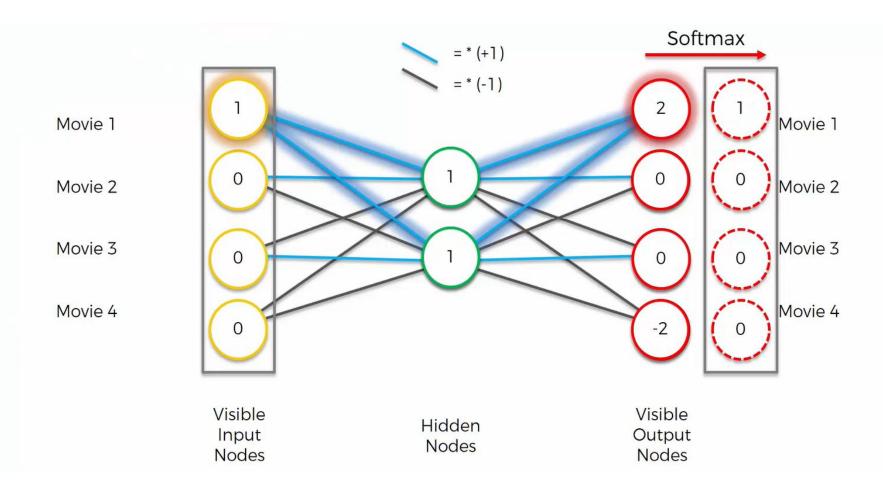


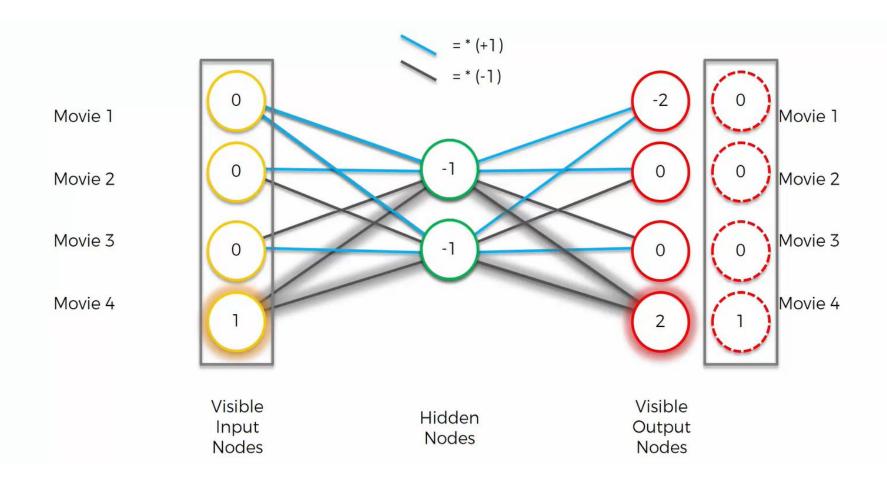






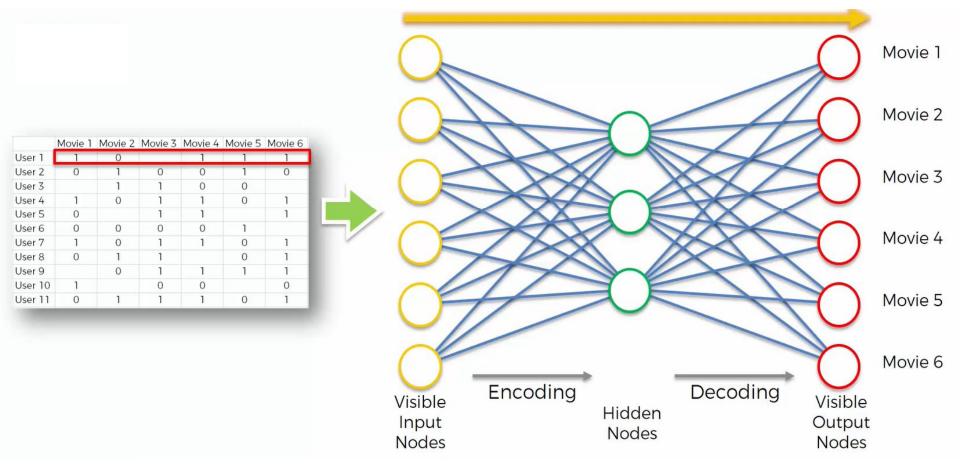


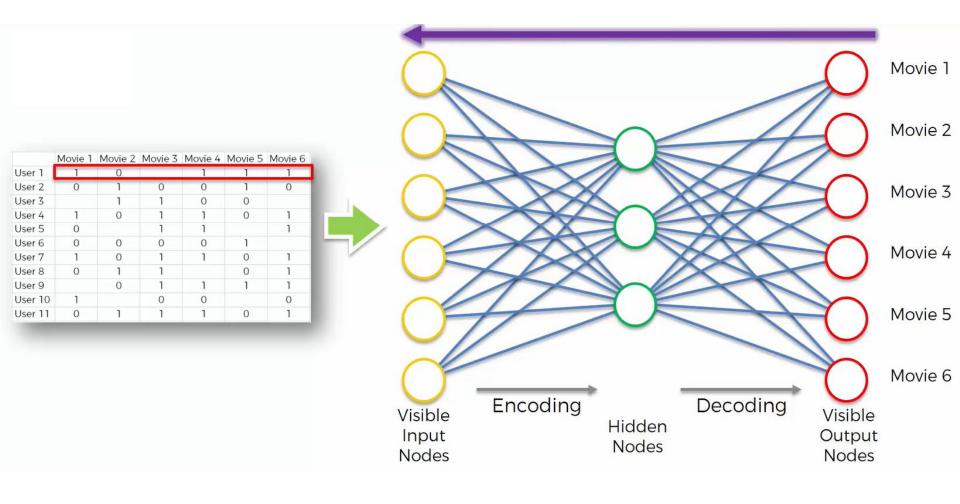




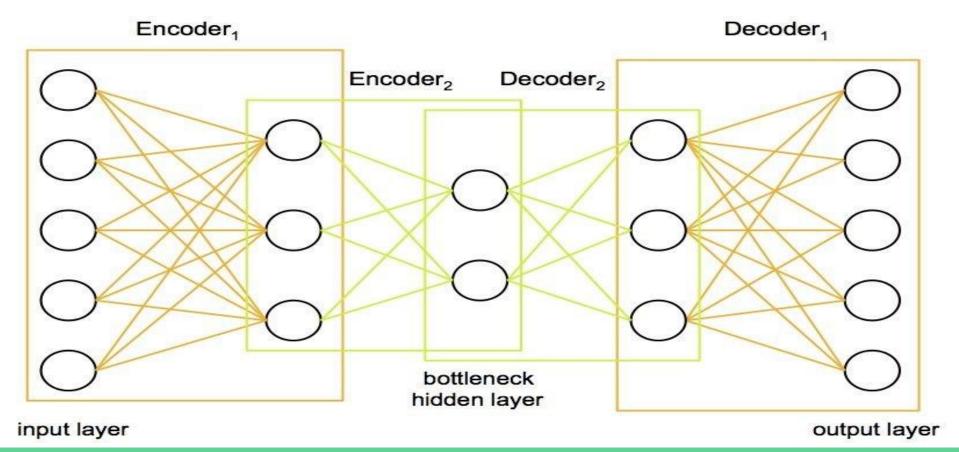
Why Stacked Autoencoders?

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6
User 1	1	0		1	1	1
User 2	0	1	0	0	1	0
User 3		1	1	0	0	
User 4	1	0	1	1	0	1
User 5	0		1	1		1
User 6	0	0	0	0	1	
User 7	1	0	1	1	0	1
User 8	0	1	1		0	1
User 9		0	1	1	1	1
User 10	1		0	0		0
User 11	0	1	1	1	0	1





Architecture of Stacked Autoencoders



Challenges

- Rapid training of the neural network
- Choosing the optimal parameters for the neural networks
- Making predictions with the least possible test loss

Solutions

- Using the RMSprop Optimizer
- Developing the neural network using the PyTorch Framework
- Selecting the learning rate to be 0.01 and number of training epochs to be
 200

$$egin{aligned} v_{dw} &= eta \cdot v_{dw} + (1-eta) \cdot dw \ & v_{db} &= eta \cdot v_{dw} + (1-eta) \cdot db \end{aligned}$$

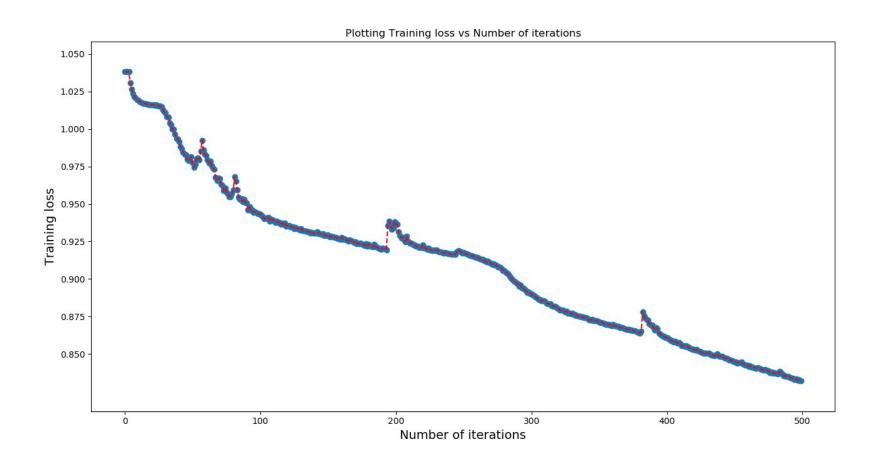
$$W = W - lpha \cdot v_{dw}$$

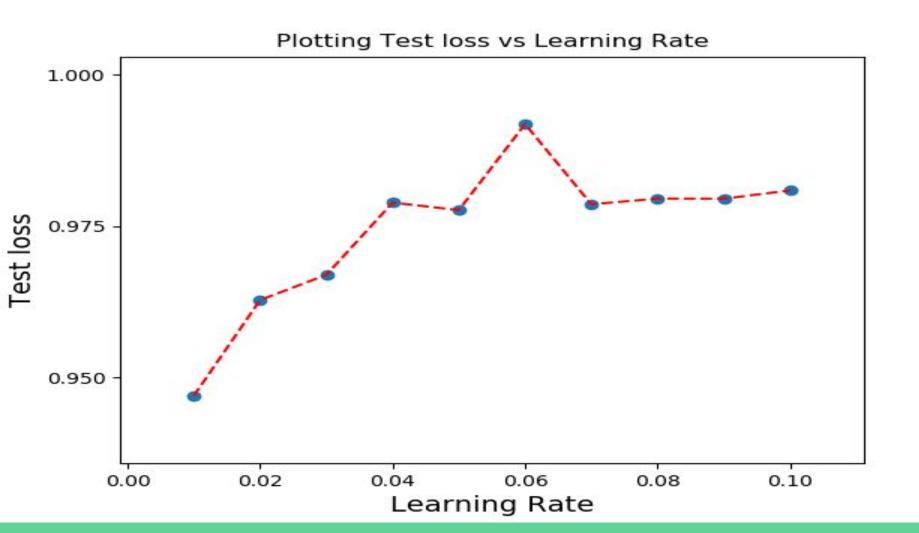
$$b = b - \alpha \cdot v_{db}$$

Gradient descent with momenttum

$$egin{aligned} v_{dw} &= eta \cdot v_{dw} + (1-eta) \cdot dw^2 \ v_{db} &= eta \cdot v_{dw} + (1-eta) \cdot db^2 \ W &= W - lpha \cdot rac{dw}{\sqrt{v_{dw}} + \epsilon} \ b &= b - lpha \cdot rac{db}{\sqrt{v_{db}} + \epsilon} \end{aligned}$$

RMSprop optimizer





Conclusion

So the model that I have developed is able to predict the movie ratings for users, where the predicted rating would be different from the actual rating only by one star.

Future Improvements

- Movie lens also has a dataset with 1 million rating
- It would be interesting to fine tune my model to be used with that dataset and see how well it performs

References

- https://probablydance.com/2016/04/30/neural-networks-are-impressively-good-at-compression/
- https://www.superdatascience.com/deep-learning/
- https://towardsdatascience.com/a-look-at-gradient-descent-and-rmsprop-optimizers-f77d483ef08b