A Social Recommender System using Deep Architecture and Network Embedding

*Nisha C C, **Anuraj Mohan
*PG Scholar, **Assistant Professor, Department of Computer Science and Engineering
NSS College of Engineering Palakkad

Introduction

Recommender System (RS)

- Provide most relevant and accurate content to the users based on their preferences.

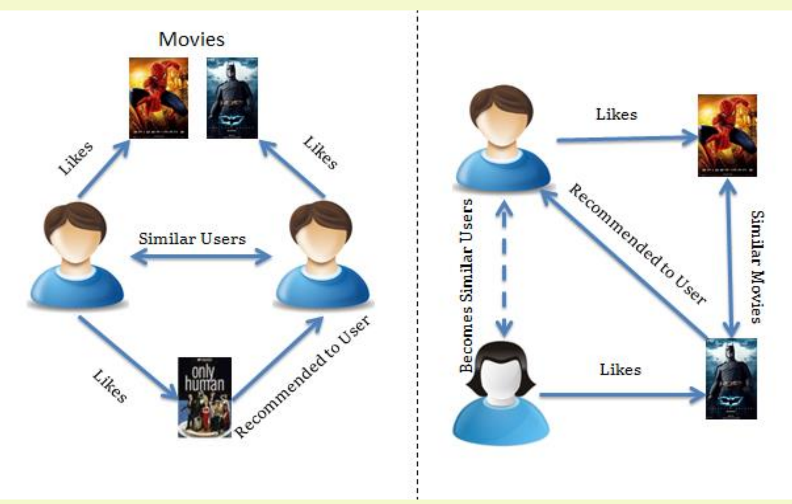


Fig. 1 Pictorial representation to demonstrate how RS provide items (movies) for users.

Different Paradigms for RS

1. Collaborative Filtering
2. Content Filtering
3. Demographic systems (DG)
4. Knowledge-based systems (KB)
5. Utility-based systems (UB)
6. Hybrid systems

Each of these approaches have its own strength and weakness

Directions to Improve Recommender Systems

- Use high performance prediction model
  - Deep learning architectures have proven state-of-the-art performance
- Increase the degree of personalization
  - Social information forms the additional user preference and is able to deal with the sparsity and cold-start problems of recommender systems.
- Network embedding techniques better captures implicit and reliable social information for RS

Problem Statement

Building a unified model for recommender system that integrates deep architecture with trust information is an open challenge. To address this challenge, an Autoencoder based Social Recommender system (AESR) is being proposed. It is a hybrid model that extends deep Autoencoder with semantic social information by learning a joint optimization function.

Autoencoder based Social Recommender System

Collaborative Filtering Autoencoder [1]

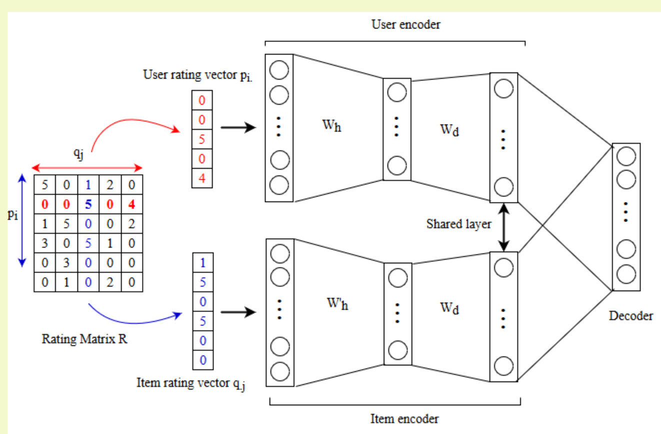


Fig. 2 Autoencoder with user encoder P, item encoder Q, and decoder $h(r_{ij};\theta)$

$$P = f\big(g(p_{i.}W_h + b_h)W_d + b_d\big)$$
$$Q = f\big(g(q_{.j}W'_h + b'_h)W_d + b_d\big)$$
$$h(r_{ij};\theta) = P^T Q$$

Objective Function

$$\underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{m}\sum_{j=1}^{n} ||r_{ij} - h(r_{ij};\theta)||^2 + L_R$$

$$L_R = \frac{\lambda}{2}\left(||W_h||^2 + ||b_h||^2 + ||W'_h||^2 + ||b'_h||^2 + ||W_d||^2 + ||b_b||^2\right)$$

The AESR Model

$$L = \underbrace{\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} ||r_{ij} - h(r_{ij};\theta)||^2 + L_R}_{\text{From Autoencoder}} + \underbrace{\frac{\gamma}{2}\sum_{i=1}^{m}\sum_{f\in S(i)} ||P_{i.} - P_{f.}||^2}_{\text{From social information}}$$

Generalization of AESR for Implicit Preference

$$L = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}||\hat{p}_{ij} - h(r_{ij};\theta)||^2 + L_R + \frac{\gamma}{2}L_S$$

- $\hat{p}_{ij}$: Preference indicator $\hat{p}_{ij} = \begin{matrix} 1 \; if \; r_{ij} > 0 \\ 0 \; if \; r_{ij} = 0 \end{matrix}$
- c_{ij}: Confidence level $c_{ij} = 1 + \beta r_{ij}$

Social Information Extraction

- Uses a graph construction procedure as given in Figure 3.
- Network embedding techniques are used to find similar nodes in the network as trustable links between the users

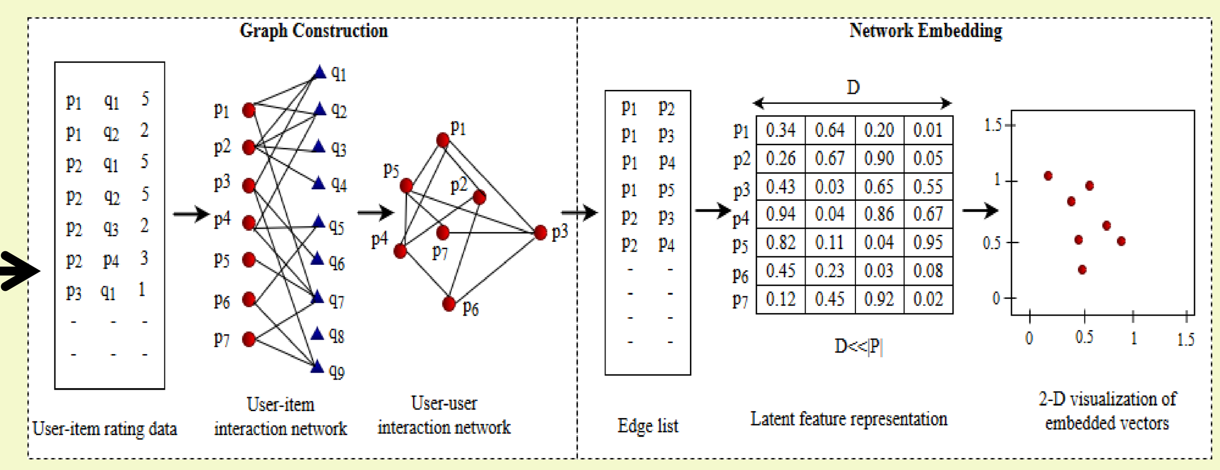


Fig. 3 Semantic social information extraction via network embedding

- Cosine similarity measure is used to find the similar nodes in the network.

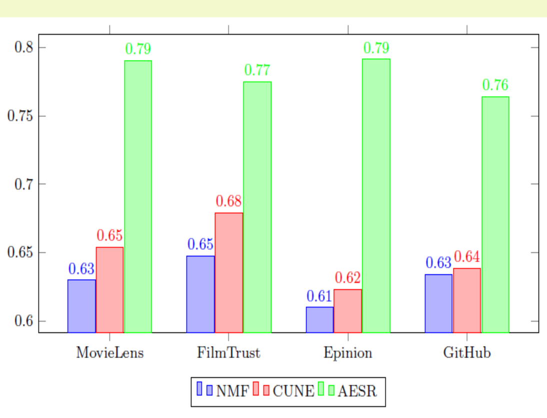
Experiments and Results

Comparison on Model Performance

1. Comparison with matrix factorization models

Data sets	Metric	NMF	CUNE	AESR
MovieLens	RMSE	0.9872	0.9156	**0.8022**
	MAE	0.8821	0.8203	**0.7216**
FilmTrust	RMSE	0.9842	0.9185	**0.7841**
	MAE	0.8983	0.8014	**0.7102**
Epinion	RMSE	1.5489	1.2435	**0.9203**
	MAE	1.1132	1.0138	**0.7614**
GitHub	RMSE	1.2615	0.9665	**0.8023**
	MAE	0.9578	0.8740	**0.7120**

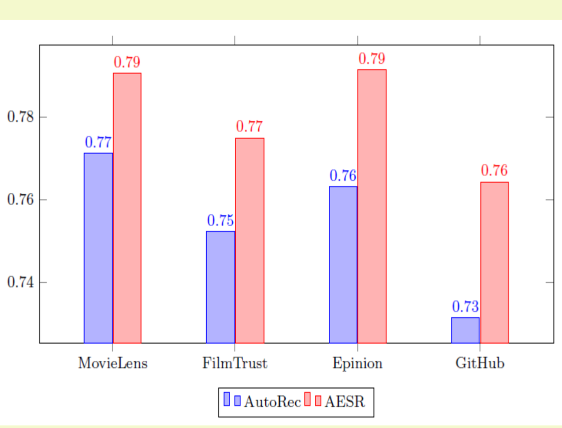
Values in bold case indicates better performance



2. Comparison with deep learning framework

Data sets	Metric	AutoRec	AESR
MovieLens	RMSE	0.8346	**0.8022**
	MAE	0.7719	**0.7216**
FilmTrust	RMSE	0.8647	**0.7841**
	MAE	0.7612	**0.7102**
Epinion	RMSE	0.9852	**0.9203**
	MAE	0.8366	**0.7614**
GitHub	RMSE	0.8731	**0.8023**
	MAE	0.7749	**0.712**

Values in bold case indicates better performance.

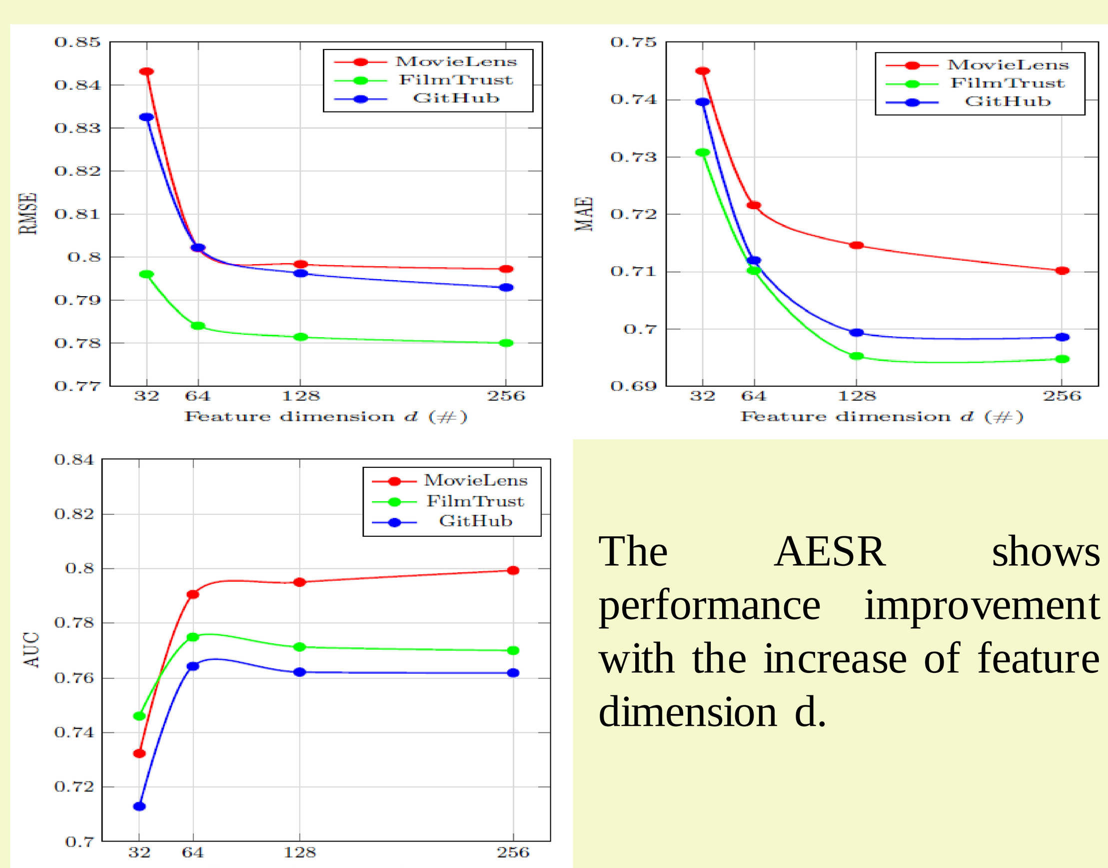


Inferences

- The ability of deep learning techniques to generate deep and latent features improves the prediction result.
- Since AESR is built on deep learning framework, it shows accurate predictions than the compared MF frameworks.
- Presence of social information improves the prediction quality and handles cold-start user problem.
- Among the four data sets, AESR shows drastic improvement for Epinion and GitHub which is sparse and larger than others.

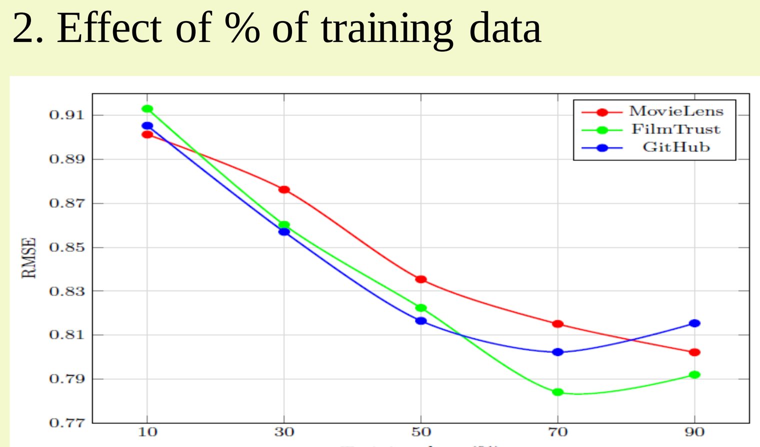
Effect of Hyperparameters

1. Effect of feature dimension



The AESR shows performance improvement with the increase of feature dimension d.

2. Effect of % of training data



Training the model with 70% of the data gives a good result for sparse data sets.

Effect of Social Information

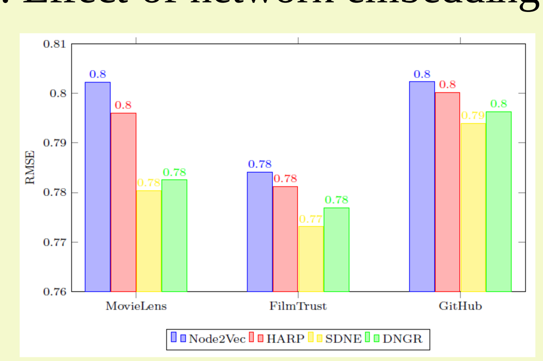
1. Effect of explicit and implicit social information

data set	Metric	Explicit links	Implicit links	Improv.
FilmTrust	RMSE	0.8031	**0.7614**	5.19%
	MAE	0.7326	**0.7102**	3.06%
	AUC	0.7134	**0.7749**	8.62%
Epinion	RMSE	0.9852	**0.9203**	6.59%
	MAE	0.7659	**0.7394**	3.46%
	AUC	0.7471	**0.7913**	5.92%

Values in bold case indicates better performance.

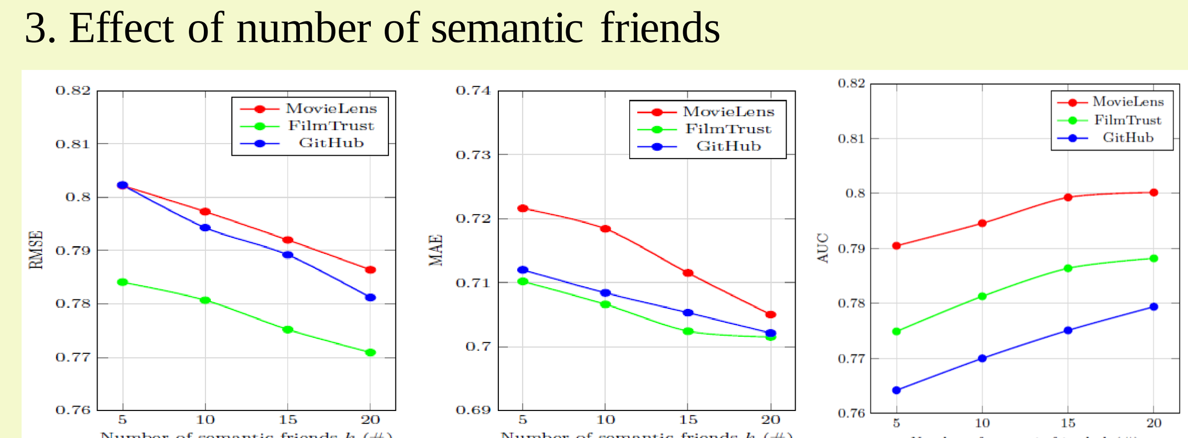
Implicit information better identify the user-user trust links than explicit data

2. Effect of network embedding techniques



Among different network embedding models, deep learning based models (e.g., SDNE and DNGR) show a good result for AESR.

3. Effect of number of semantic friends



- As the number of semantic users increases, the model accuracy also increases (tested up to top-20 friends).
- This indicates that the user's interests are always affected by their friends with whom they share common ideas.

Conclusions and Future works

- The AESR model incorporates semantic social information into the deep learning architecture, specifically Autoencoder, by learning a joint optimization function.
- One of the key ideas of the proposed model is to capture semantic social information through network embedding techniques.
- By learning the user preference and user ratings AESR is able to handle the sparsity and cold-start problems of recommender system.
- The model is extended to predict implicit user preference by modeling an objective function that supports implicit rating data.
- By modeling a joint optimization function the proposed AESR model outperforms the state-of-the-art methods.

Future Works

- Incorporate auxiliary information
- Leverage the effectiveness of different neural network models
- Explore the strength of network embedding techniques (both heterogeneous and dynamic)
- Generate predictions in dynamic environment

Reference

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Publication

1. Nisha C C, Anuraj Mohan (2019) A social recommender system using deep architecture and network embedding. In: Applied Intelligence, Springer, Vol. 49, Issue 5, pp 1937-1953