Variational Autoencoders for Recommender Systems

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Motivation and Problem Definition

★ Recommender systems (RS):
  - Observe user interactions with items
  - Seek to predict unseen items users will like
  - Integral to the web - help users interact with content effectively

★ Collaborative Filtering (CF):
  - A family of RS algorithms
  - Predicts user preferences using similarity patterns across users and items

Prior Work on Collaborative Filtering

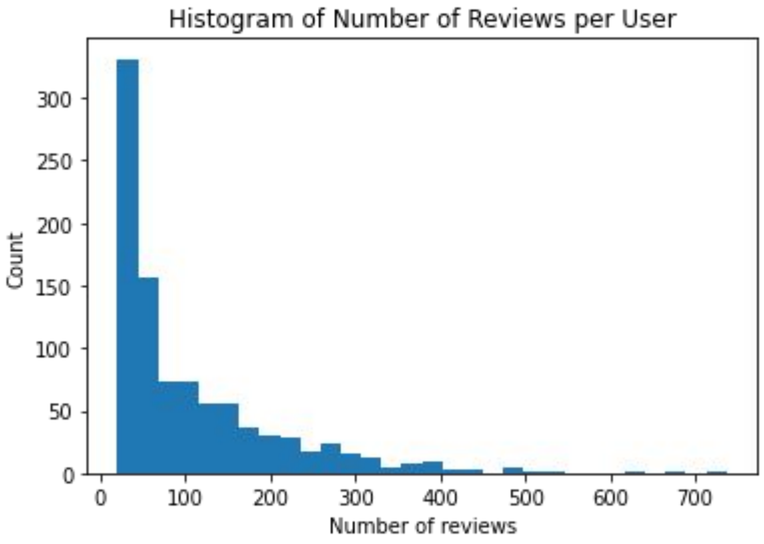
- ★ Neighbourhood methods: k-Nearest-Neighbors (kNN)
  - Filtering techniques: item-based, user-based (Sarwar et al., 2001; Resnick et al., 1994).
- ★ Latent-factor methods:
  - Matrix factorization (Luo et al., 2012)
  - Singular Value Decomposition (SVD) (Vozalis and Margaritis, 2007; Zhang et al., 2005)
  - **The extension of variational autoencoders to CF (VAE-CF)** (Liang et al., 2018)
    - Novel approach; no other prior work done for VAE applied to RS
- ★ Today: Movie recommendation using VAE-CF

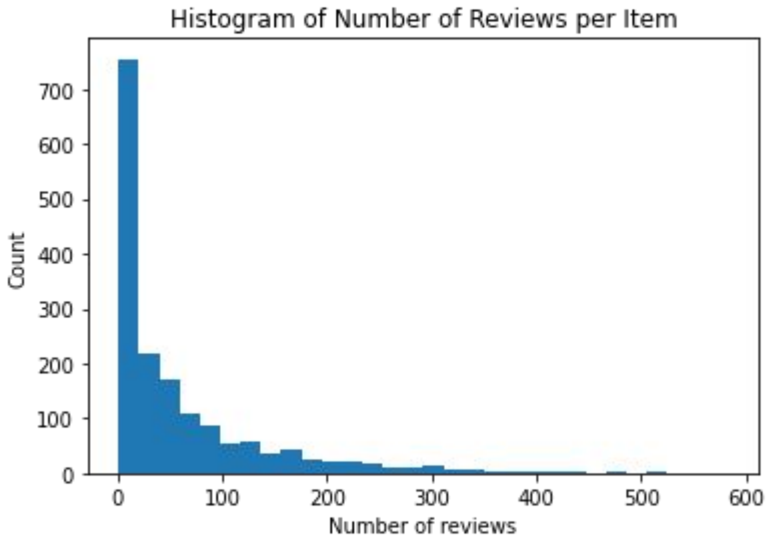
Dataset and Data Processing

- ★ MovieLens 100K dataset - Classic RS dataset
- ★ Describes people's preferences for movies in 1-5 star ratings at some time
  - ○ <userID, itemID, rating, timestamp> tuples
- ★ Since VAE-CF focuses on implicit feedback, change rating values to 1s
  - ○ Raw user behavior > numerical rating values
- ★ Split into 50% train, 20% validation, 30% test sets based on time of review
  - ○ Train on historic data
  - ○ Validate and test on future data

Exploratory Data Analysis

- ★ **100,000** reviews from **943** users and **1682** movies
- ★ Each user has rated **20+** movies, each item has **1+** ratings
- ★ There are **141** movies with only 1 rating
- ★ Item-based data is much more sparse than user-based data





Predictive Task, Baselines and Metrics

Predictive Task

Movie clicks predictions for users based on training data

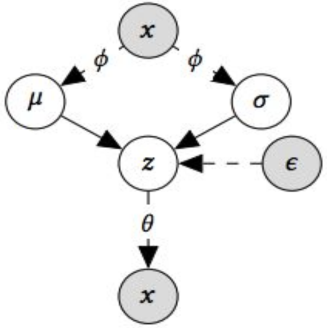
Baselines

★ User & item based Collaborative Filtering using kNN (da Costa et. al.,2018)
★ SVD

Metrics

★ Recall @ K
★ NDCG @ K (Normalized Discounted Cumulative Gain)

VAE-CF

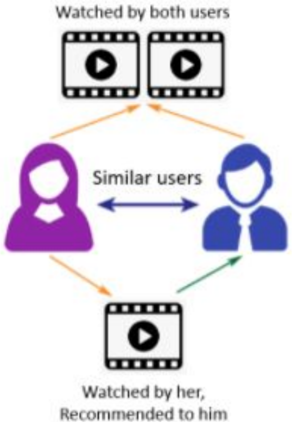


- ★ A probabilistic latent-variable model
- ★ VAE performs variational inference and generation:
  - ○ Inference (encoder): learns latent presentation
    - ■ Follows Gaussian prior $N(\mu_u, \mathrm{diag}\{\sigma^2_u\})$
    - ■ Uses **variational inference** to approximate the intractable posterior distribution for latent embedding given observations ($p(z|x)$)
  - ○ Generation (decoder): produce user click history
    - ■ $X_u \sim \mathrm{Mult}(N_u, \boldsymbol{\pi}(z_u))$

Model Comparison

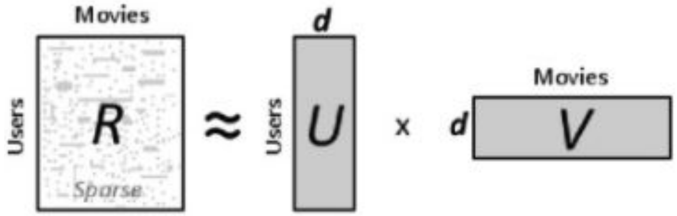
User-based KNN

✓ Introduce serendipity
✓ Easy implementation
× Cold-Start issue



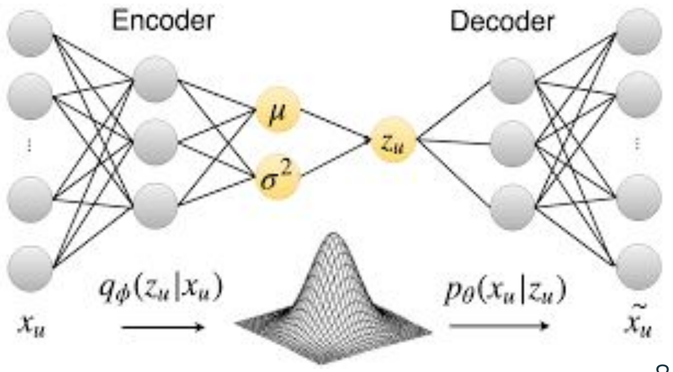
SVD

✓ Handle sparsity
× Uninterpretable latent representations
× Computationally expensive



VAE-CF

✓ Well suited for modelling implicit feedback data
✓ Handle Sparsity issues
× Computationally expensive



VAE-CF: Model Modifications

- VAE-CF was performed using a user-based approach in the original paper
- Item information could be used to augment user-based results
- Combination of predictions from both item-based and user-based VAE-CF model

Additional Hyperparameters:

- ❑ **Weight_u**
- ❑ **Weight_i**

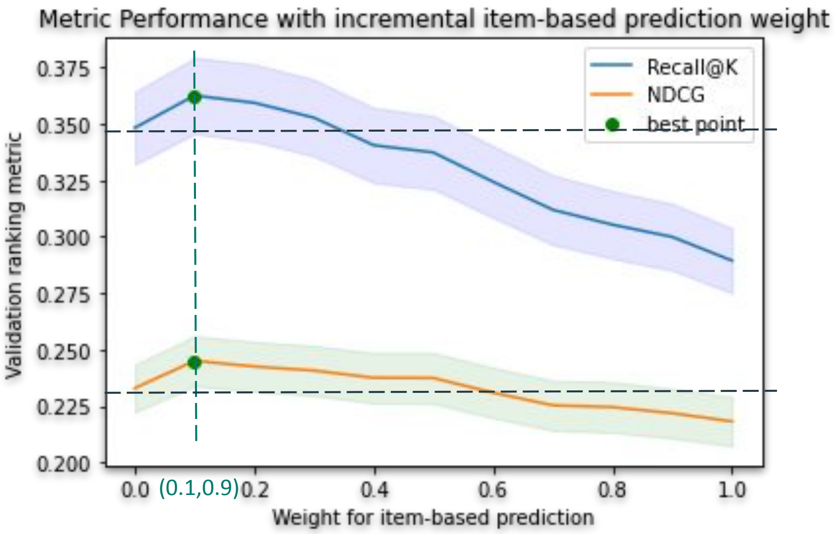
$$\textbf{Weight\_u} \bullet \begin{array}{cc} & I \\ U & \begin{pmatrix} \quad & \quad \\ \quad & \quad \end{pmatrix} \end{array} + \textbf{Weight\_i} \bullet \begin{array}{cc} & I \\ U & \begin{pmatrix} \quad & \quad \\ \quad & \quad \end{pmatrix} \end{array}$$

VAE-CF

- Model was trained by the user history click ({0,1}) data
- Hyperparameter tuning was performed using grid search
- Metrics used: Recall @ K, NDCG @ K

Hyperparameters:

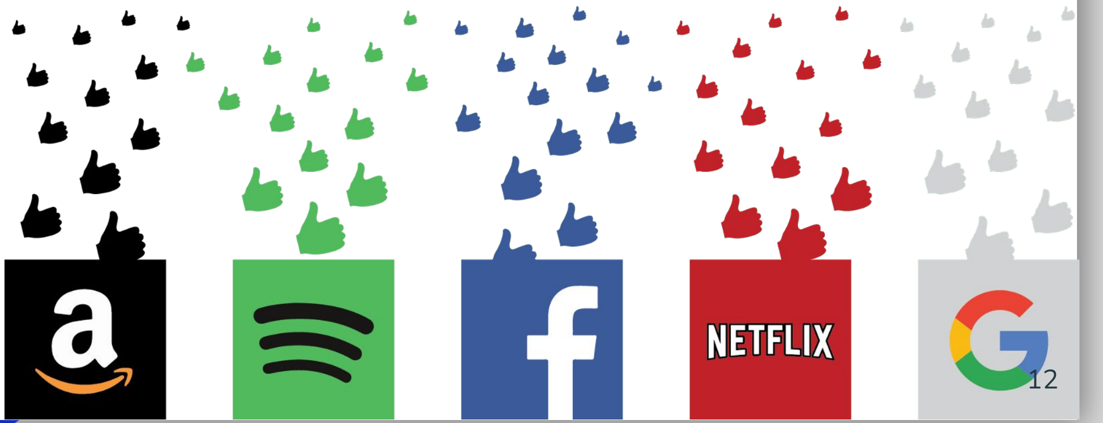
- ❑ Epoch
- ❑ Learning rate
- ❑ Lambda (regularization)
- ❑ Embedding latent dimension
- ❑ Corruption (1 - drop-out rate)
- ❑ Optimizer: RMSProp
- ❑ **Weight_u**
- ❑ **Weight_i**



Result

Method	Recall@50	NDCG@100
VAE-CF	0.31857	0.47528
VAE-CF Modified	**0.36250**	0.47637
User-based kNN	0.33932	**0.50341**
Item-based kNN	0.34181	0.50310
SVD	IPR	IPR

Thank you!



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