RecNet: A Deep Learning Based Collaborative Filtering Recommender System

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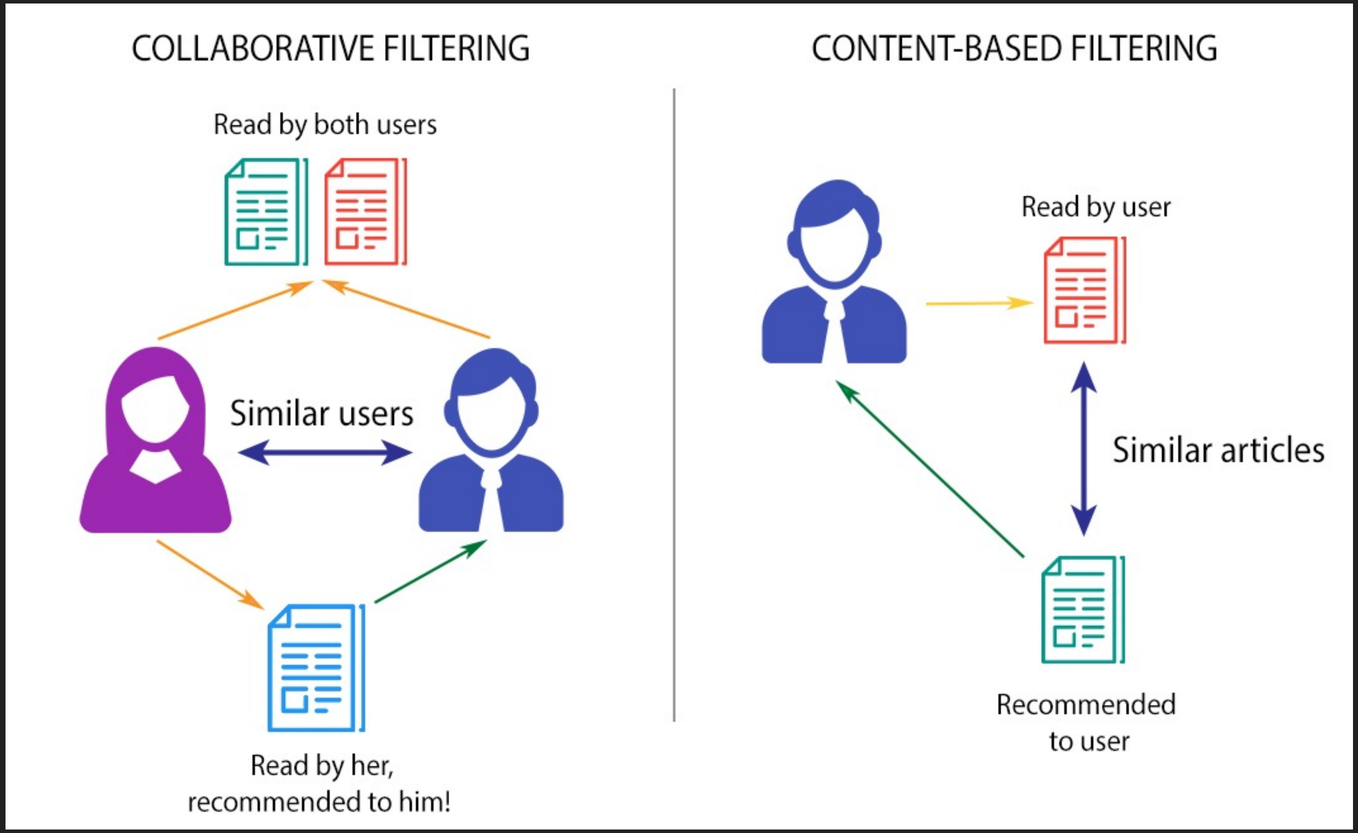
Introduction

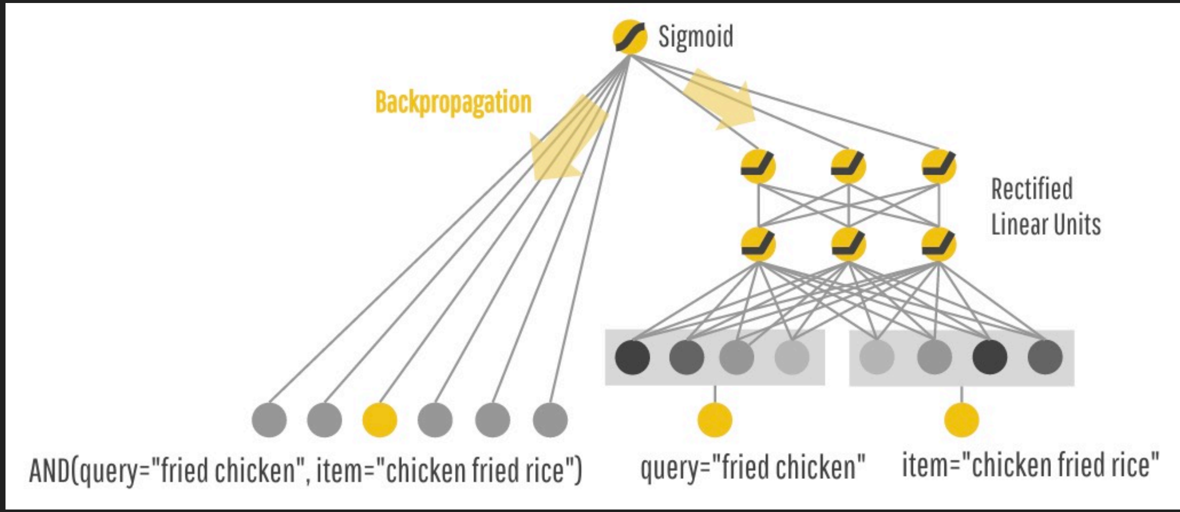
- Increasing amount of online data leads to an Information Overload
- Recommender Systems is a filtering tool which recommends items of interest
- Traditional Approaches
- Deep Learning methods have improved performance of traditional methods
- RecNet illustrates the improvements Deep Learning can make in Collaborative Filtering



Related Work

- Developed for the Google Play mobile app store
- Combines memorization benefits of a wide linear network with the generalizability of a Deep Neural Network
- Various authors have made modifications to this model

Wide and Deep Learning

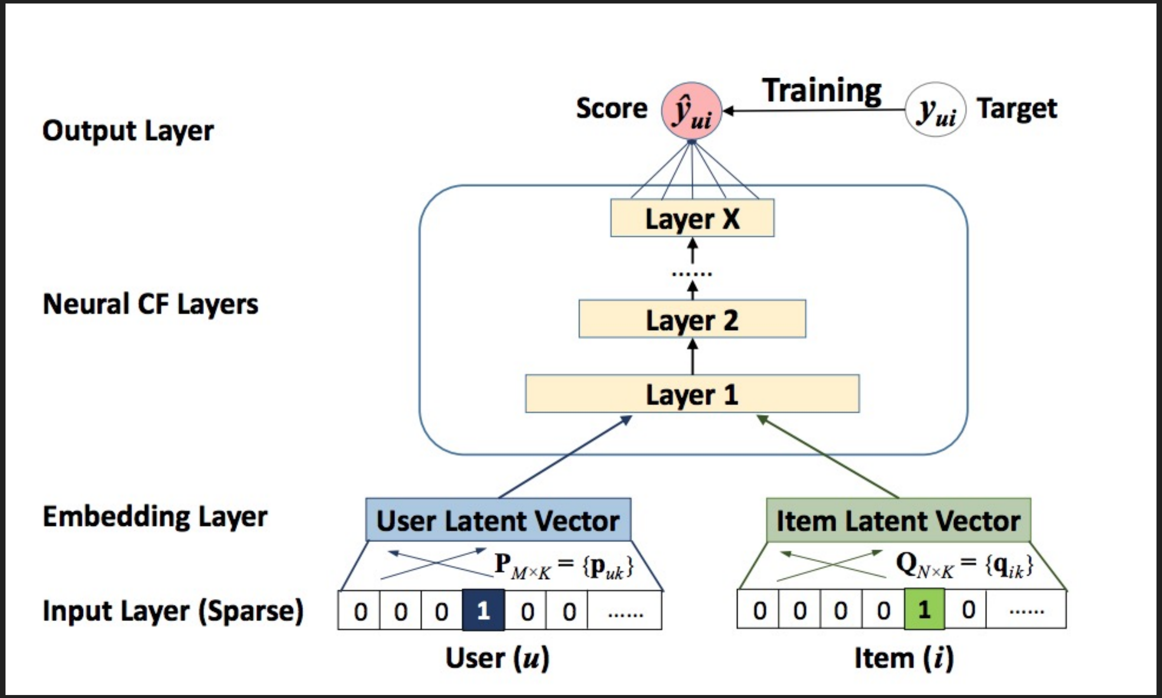


Cheng *et al.* [2016]

Related Work

- He *et al.* [2017] proposed a general framework
- User and item representations are projected into dense embeddings
- These embeddings are used in a Multi-Layer Perceptron to predict ratings

Neural Collaborative Filtering



He *et al.* [2017]

Data

	userId	movieId	rating
0	0	0	4.0
1	0	2	4.0
2	0	5	4.0
3	0	43	5.0
4	0	46	5.0

- MovieLens Dataset is the most popular in Recommender System Research [Zhand *et al.* 2019]
- MovieLens100K contains 100 000 ratings given to 9742 movies by 610 users.
- Each entry contains the User ID, Movie ID and the rating between 0.5 and 5

Collaborative Filtering

- Traditional CF utilizes user-item matrix, here we use user-movie matrix
- Columns represent users, Rows represent movies, Cells represent ratings
- Objective of CF Recommender System is to predict ratings and recommend items with highest predicted ratings

	u_1	u_2	u_3	$\dots$	u_i
m_1	4		3	2	
m_2		1			5
m_3			2		4
$\dots$	3			1	
m_j		2	5		r_{ij}

Collaborative Filtering

- Quantify User Similarity – Cosine Similarity

$$cos(u_1, u_2) = \frac{u_1 \bullet u_2}{||u_1|| \cdot ||u_2||}$$

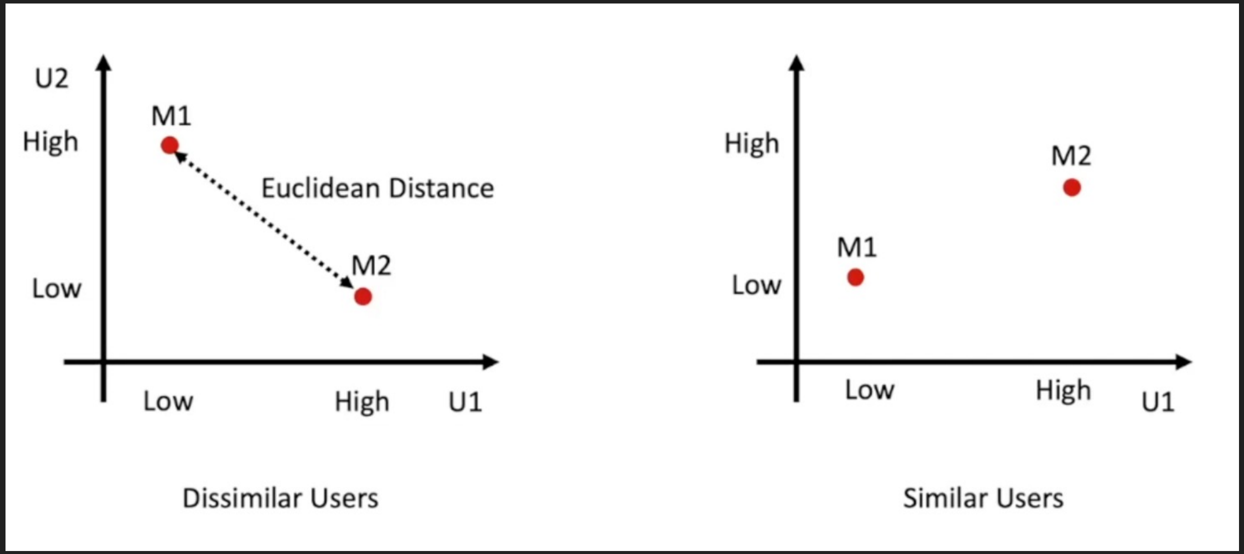
- Centered Cosine same as Pearson Correlation Coefficient , accounts for bias

$$cos(u_1, u_2) = \frac{(u_1 - \bar{u_1}) \bullet (u_2 - \bar{u_2})}{||(u_1 - \bar{u_1}))|| \cdot ||(u_2 - \bar{u_2})||}$$

- Make predictions using weighted sum of k most similar users

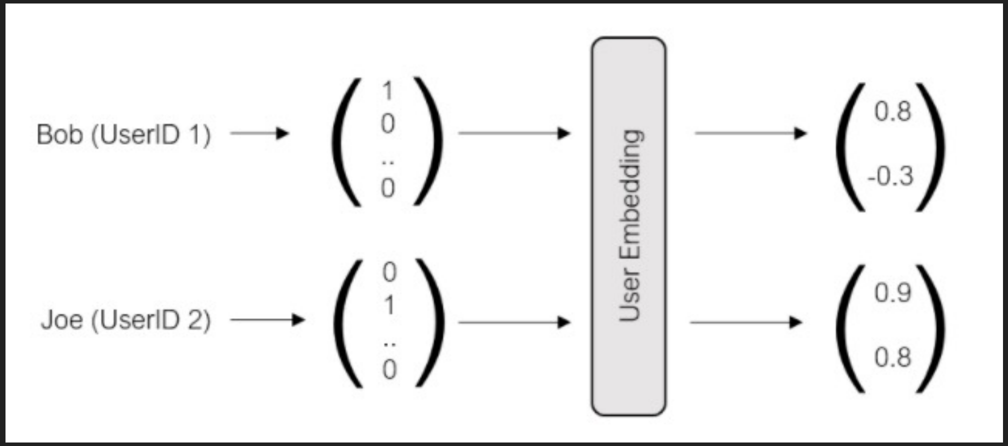
$$r_{aj} = (\sum_{i=0}^{k} r_{ij} \cdot S_i)/(\sum_{i=0}^{k} S_i)$$

User Vectors in 2 dimensions

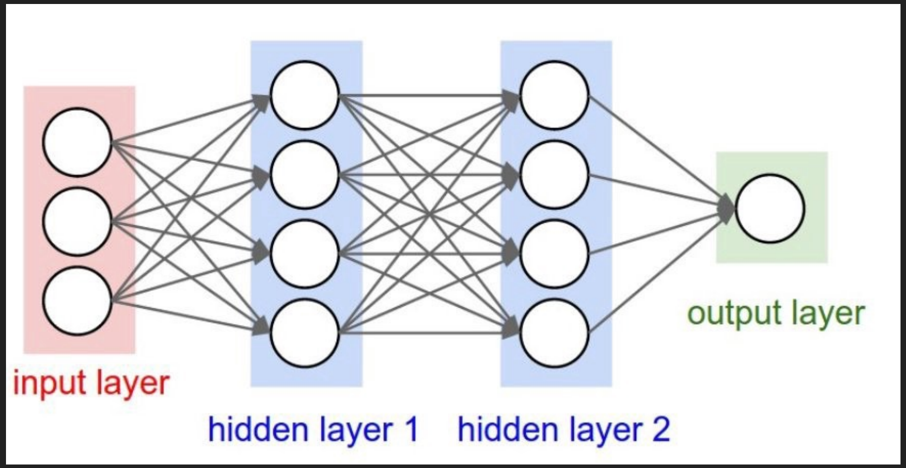


Neural Collaborative Filtering

- Embeddings



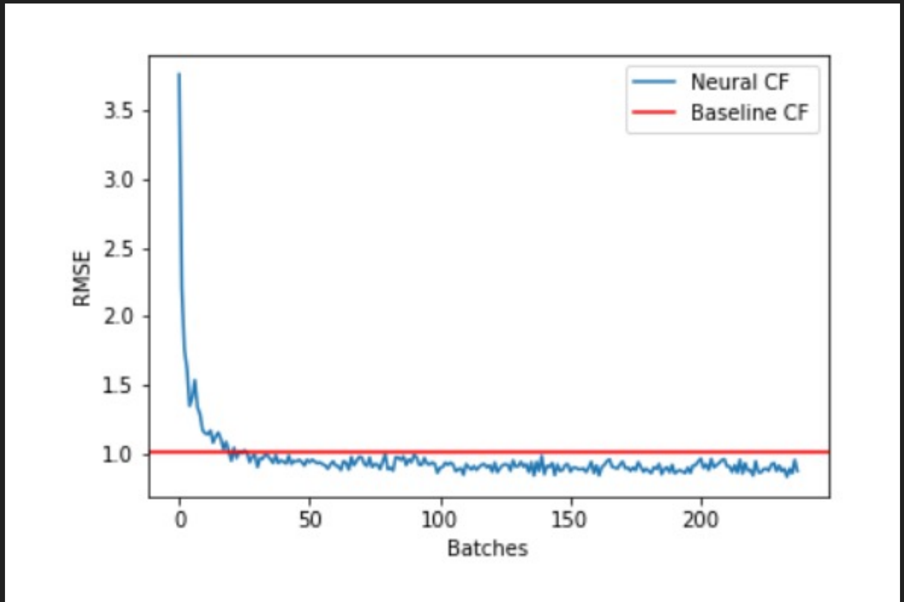
- Multi-layer Perceptron



Neural Collaborative Filtering

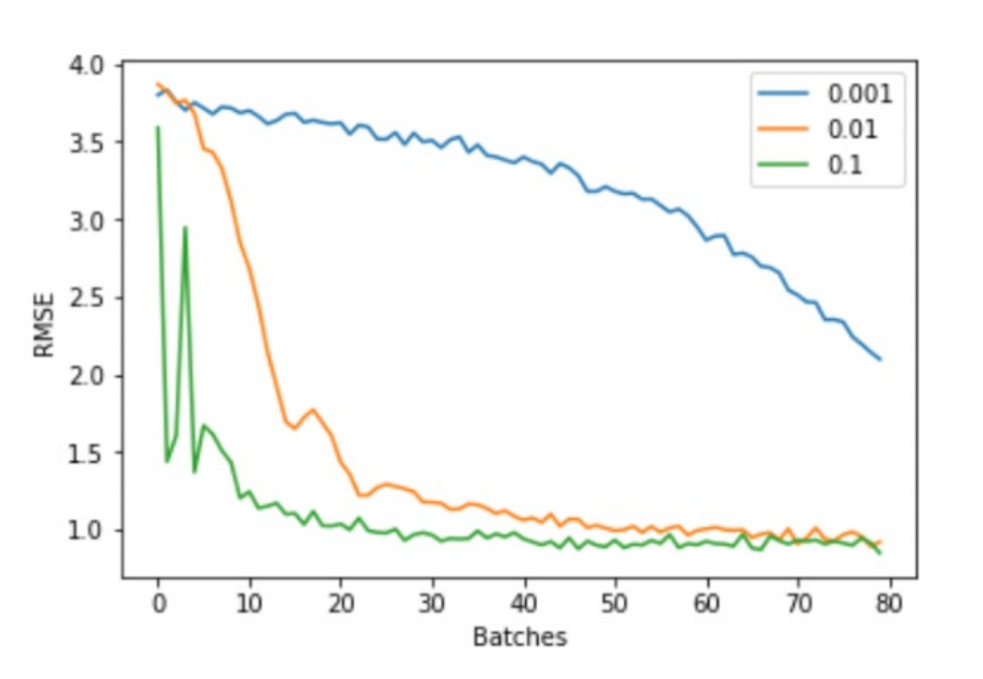
- Initial Neural Collaborative Filtering
  - 32 Neurons for embeddings
  - MLP 2 hidden layers of 32 neurons each
  - 1 output neuron for predicted rating
- Traditional User-to-user Collaborative Filtering used as the baseline
- Evaluation Metric: Root Mean Squared Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(r_i - \hat{r_i}^2)}{N}}$$

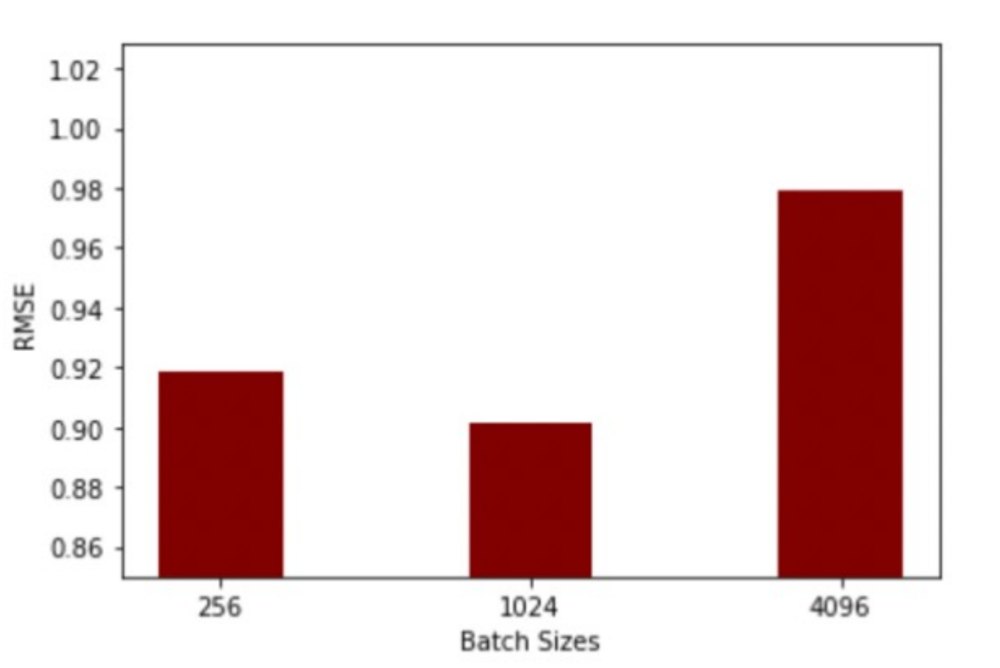


Improved Learning

Learning Rate

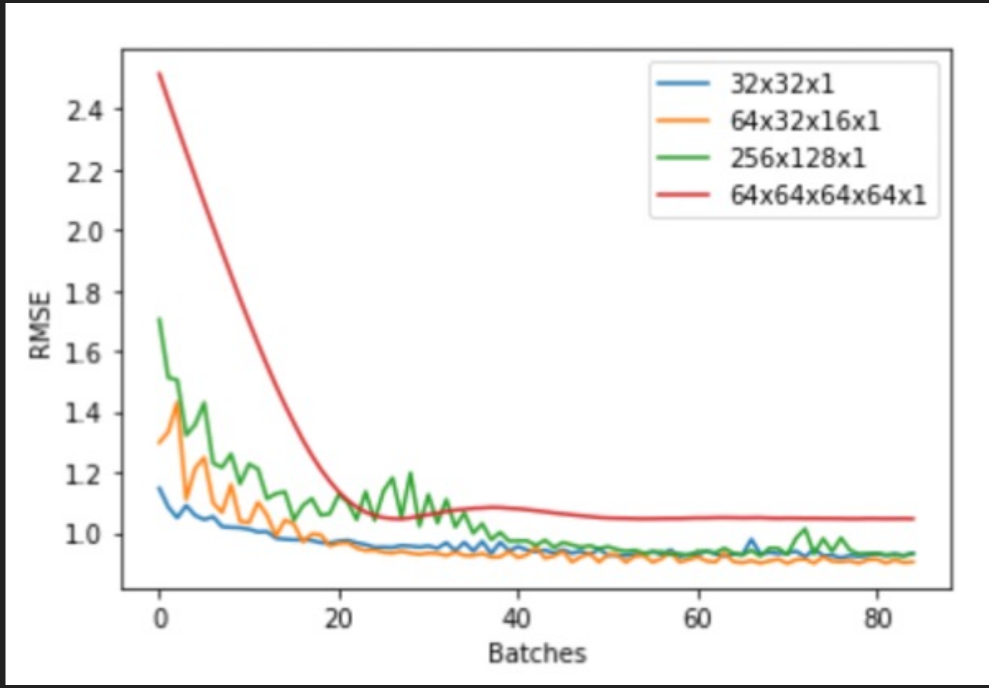


Batch Size

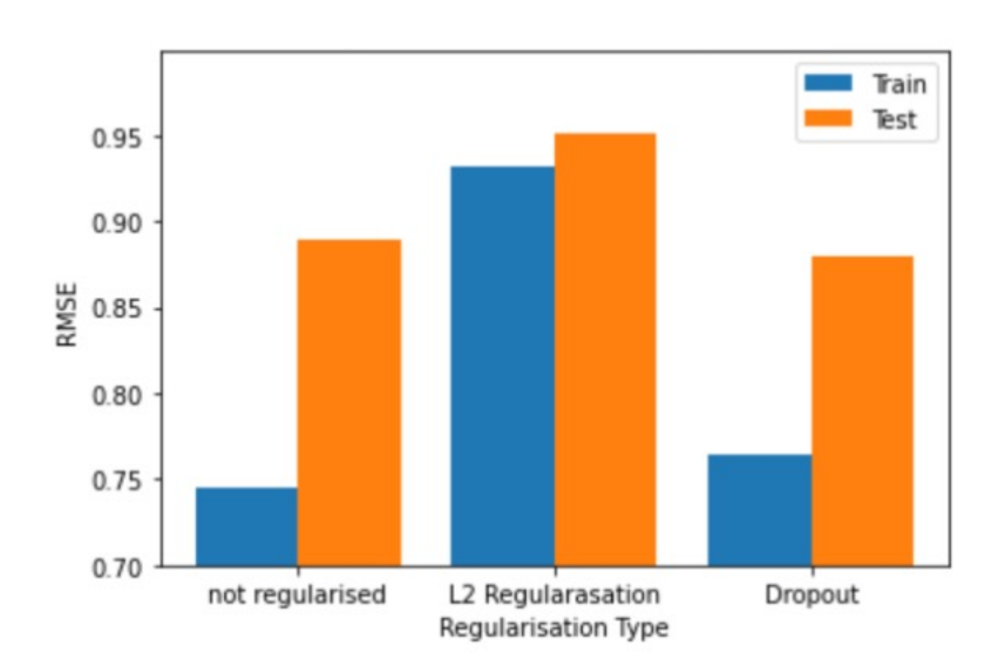


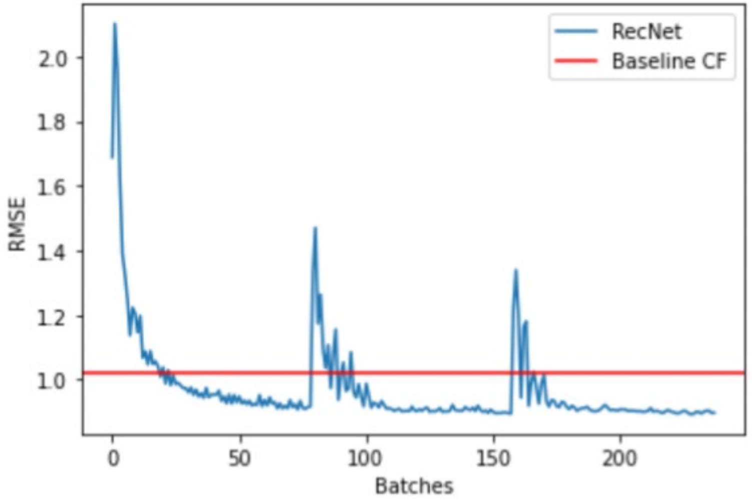
Improved Learning

Model Architectures



Regularisation





Model	Train RMSE	Test RMSE
Baseline CF	-	1.0204
Initial NCF	0.8008	0.9396
Final NCF (RecNet)	0.7674	0.8976

RecNet Performance

- 64 neurons for embeddings
- 3 Hidden layers of 64, 32, 16 neurons respectively
- 1 Output Layer

Thank you