Multifaceted Collaborative Filtering Model

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Dr. Ravi Kiran Sarvadevabhatla

Team Name: Team Houdini (33)

Mentor: Nikhil Gogate

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Problem Statement

- To use collaborative filtering techniques to apply on Movie dataset that recommends the movies for users based on the reviews and past data.
- Implement baseline CF models
  - Neighborhood model
  - SVD++ model
- Improve them using technique that integrates the two models.

What are Recommender Systems ?

- Information filtering system that seeks to predict the "rating" or "preference" a user would give to an item.
- Two main types of Recommender Systems:
  - Content based
  - Collaborative Filtering
    - Neighborhood Model
    - SVD++(Latent Factor Model)
- Used in variety of areas:
  - Video and music recommenders (Netflix, YouTube, Spotify)
  - Product recommenders (Amazon, Myntra)

Motivation

- Enhancing user satisfaction and loyalty by matching consumers with appropriate products.
- Netflix Prize - Open competition for best CF algorithm to predict user rating for films.
- "We need to go win a million dollars"

Dataset

- MovieLens 100k data.
- Collected by the GroupLens Research Project at the University of Minnesota.
- 100,000 ratings (1-5) from 943 users on 1682 movies.
- Each user has rated at least 20 movies.

```
u_data.head()
```

	user_id	movie_id	rating	timestamp
0	196	242	3	881250949
1	186	302	3	891717742
2	22	377	1	878887116
3	244	51	2	880606923
4	166	346	1	886397596

Fig1 : Dataset entries

Dataset - EDA

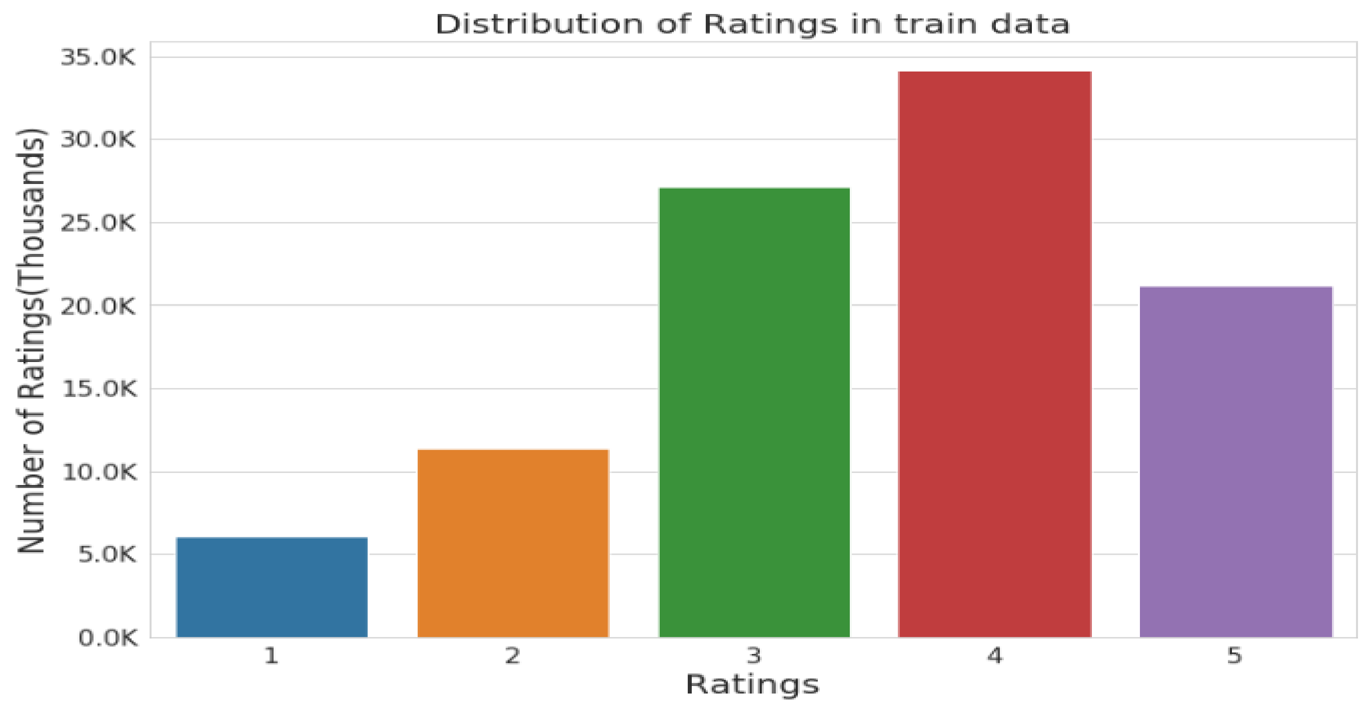


Fig2 : Rating Distribution v/s Number of Ratings

Dataset - EDA

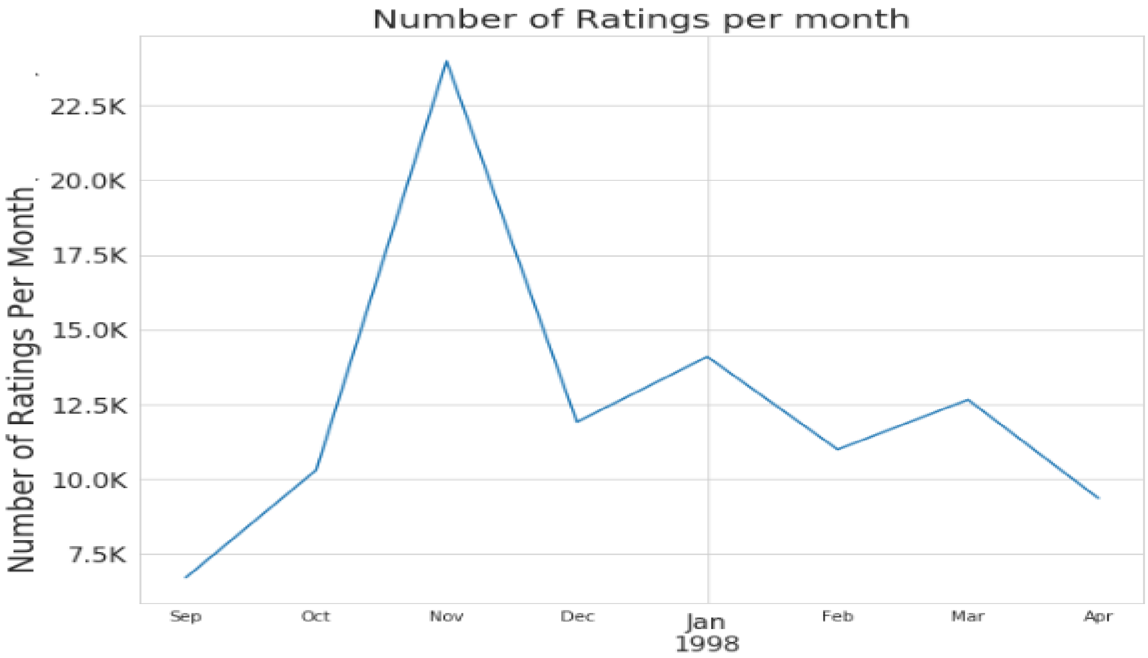


Fig3 : Rating Distribution

Dataset - EDA

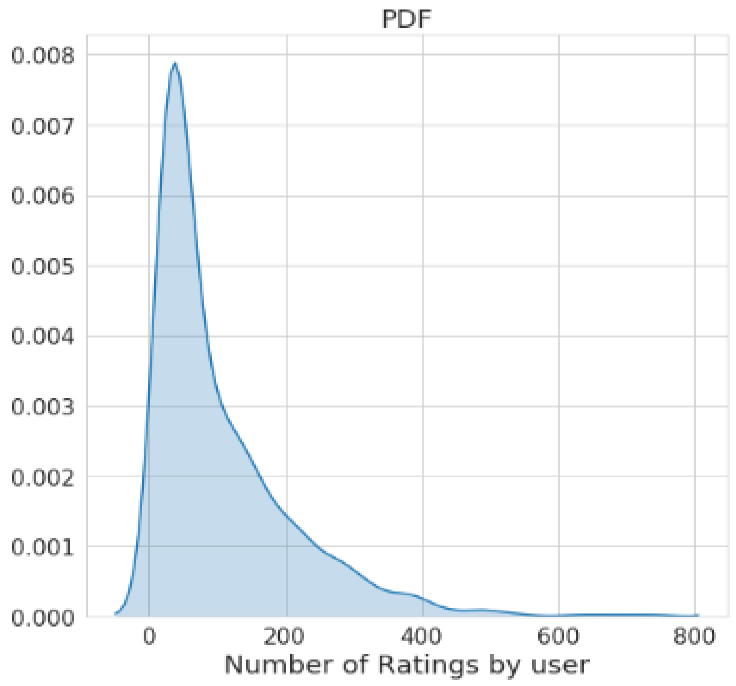


Fig4 : PDF of Number of Ratings by user

- PDF graph shows that almost all of the users give very few ratings. There are very few users who's ratings count is high.

Dataset - EDA

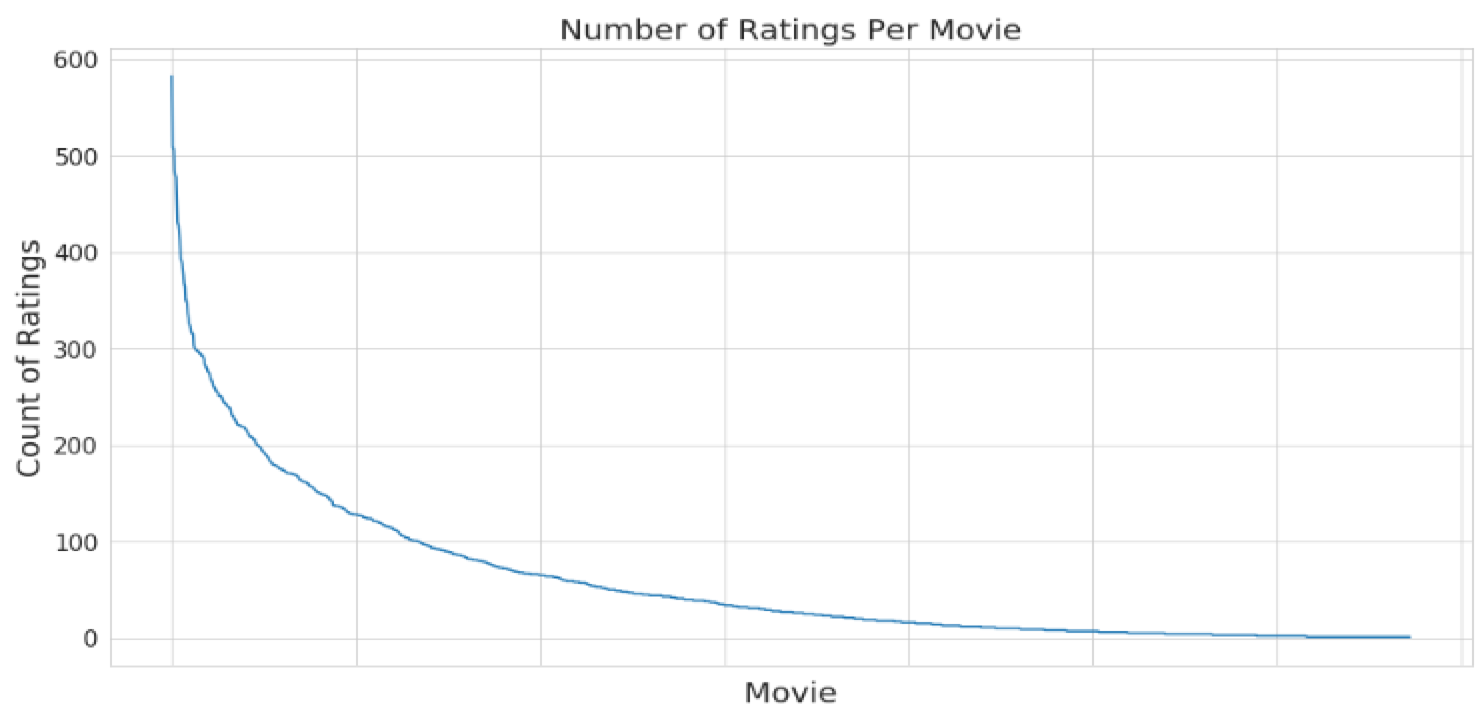


Fig5 : Number of Ratings per Movie

- Some movies are very popular and rated by many users vs other movies.

Dataset - EDA

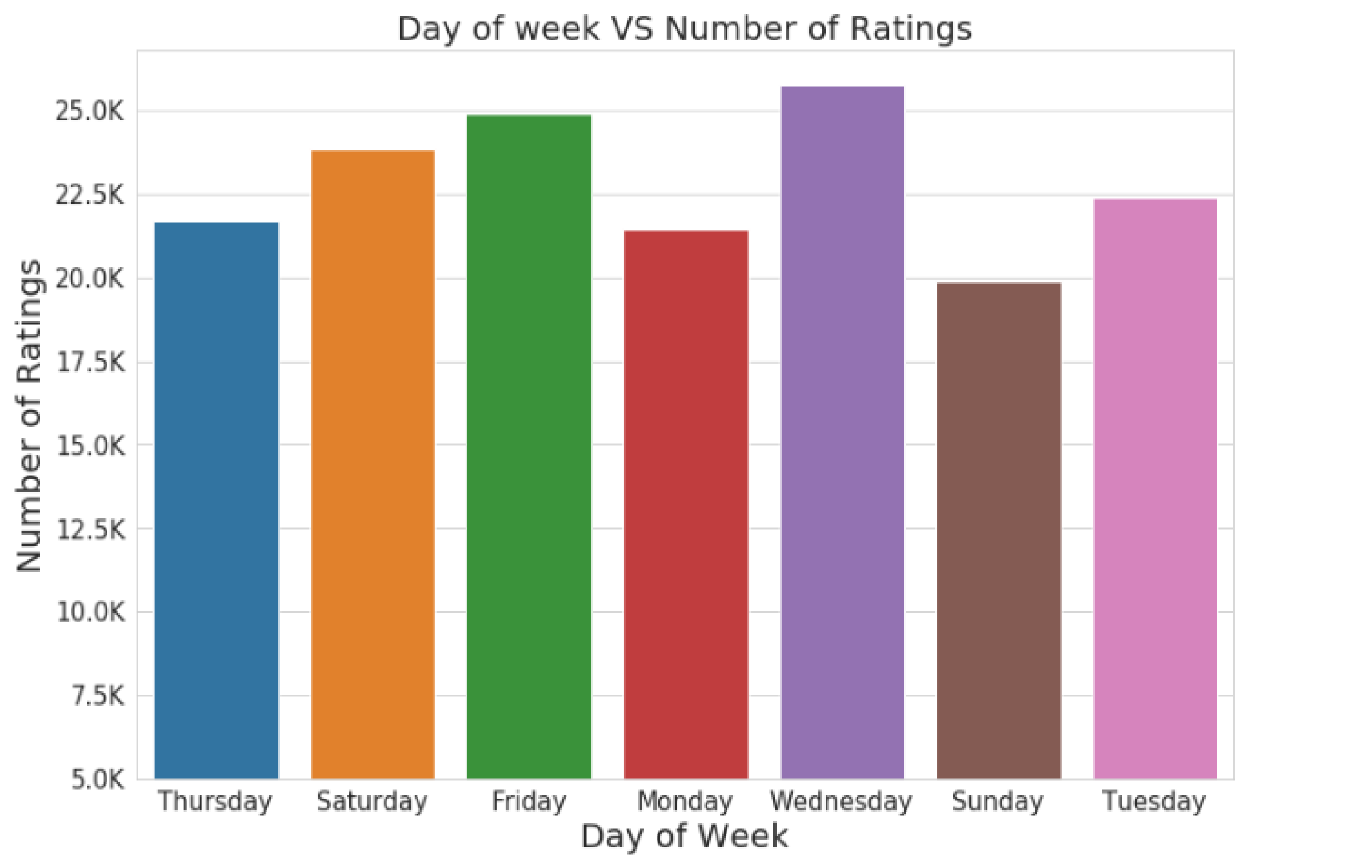


Fig6 : Day of Week v/s Number of Ratings

Baseline estimate

- Baseline estimate for predicting rating for movie i by user u (b_{ui})

$$b_{ui} = \mu + b_u + b_i$$

  - User bias (b_u)
  - Item bias (b_i)
  - Rating by user u for item i (r_{ui}).
- Implicit feedback (N(u)) contains all items for which implicit preference was provided by user u.)

SVD and SVD++ model

- **Matrix factorization** is a class of collaborative filtering algorithms.
- A popular approach to latent factor models is induced by an SVD-like lower rank decomposition of the ratings matrix.
- Each user u is associated with a user-factors vector $p_u \in R_f$, and each item i with an item-factors vector $q_i \in R_f$.
- Prediction is done by the rule: $\hat{r}_{ui} = b_{ui} + p_u^T q_i$
- This is the SVD model. An improvement to this model is Asymmetric SVD which uses implicit feedback.
- As we do not really have much independent implicit feedback for the our ml-100k dataset, so we turn towards an improved model.

SVD and SVD++ model

SVD++ model :

$$\hat{r}_{ui} = b_{ui} + q_i^T \left(p_u + |\mathrm{N}(u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{N}(u)} y_j \right)$$

- Its results are more accurate than all previously published methods on the Netflix data and other similar movie datasets which struggles with the same implicit feedback limitation.

Neighborhood model

- User oriented CF system.
- Estimate unknown ratings based on recorded ratings of like minded users.
- Improved Neighborhood model as described by the equation :

$$\hat{r}_{ui} = b_{ui} + \sum_{j \in \mathrm{R}(u)} (r_{uj} - b_{uj}) w_{ij}$$

Neighborhood model

- We can use implicit feedback, which provide an alternative way to learn user preferences. To this end, we add another set of weights, and rewrite the previous equation :

$$\hat{r}_{ui} = b_{ui} + \sum_{j \in \mathrm{R}(u)} (r_{uj} - b_{uj}) w_{ij} + \sum_{j \in \mathrm{N}(u)} c_{ij}$$

- Final Model :

$$\hat{r}_{ui} = \mu + b_u + b_i + |\mathrm{R}(u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{R}(u)} (r_{uj} - b_{uj}) w_{ij} + |\mathrm{N}(u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{N}(u)} c_{ij}$$

Integrated model

- A combined model which will sum the predictions of previously defined neighborhood and SVD++ model.

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T \left(p_u + |\mathrm{N}(u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{N}(u)} y_j \right)$$
$$+ |\mathrm{R}^k(i;u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{R}^k(i;u)} (r_{uj} - b_{uj}) w_{ij} + |\mathrm{N}^k(i;u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{N}^k(i;u)} c_{ij}$$

Integrated model

- Backprop for Integrated model :

  - $b_u \leftarrow b_u + \gamma_1 \cdot (e_{ui} - \lambda_6 \cdot b_u)$
  - $b_i \leftarrow b_i + \gamma_1 \cdot (e_{ui} - \lambda_6 \cdot b_i)$
  - $q_i \leftarrow q_i + \gamma_2 \cdot (e_{ui} \cdot (p_u + |\mathrm{N}(u)|^{-\frac{1}{2}} \sum_{j \in \mathrm{N}(u)} y_j) - \lambda_7 \cdot q_i)$
  - $p_u \leftarrow p_u + \gamma_2 \cdot (e_{ui} \cdot q_i - \lambda_7 \cdot p_u)$
  - $\forall j \in \mathrm{N}(u)$:
    $y_j \leftarrow y_j + \gamma_2 \cdot (e_{ui} \cdot |\mathrm{N}(u)|^{-\frac{1}{2}} \cdot q_i - \lambda_7 \cdot y_j)$
  - $\forall j \in \mathrm{R}^k(i;u)$:
    $w_{ij} \leftarrow w_{ij} + \gamma_3 \cdot \left(|\mathrm{R}^k(i;u)|^{-\frac{1}{2}} \cdot e_{ui} \cdot (r_{uj} - b_{uj}) - \lambda_8 \cdot w_{ij}\right)$
  - $\forall j \in \mathrm{N}^k(i;u)$:
    $c_{ij} \leftarrow c_{ij} + \gamma_3 \cdot \left(|\mathrm{N}^k(i;u)|^{-\frac{1}{2}} \cdot e_{ui} - \lambda_8 \cdot c_{ij}\right)$

Implementation Insights

- We've implemented all three models mentioned
  - Neighborhood Model
  - SVD++ Model
  - Integrated Model
- Datasets was around 99% sparse, so we used Sparse Matrix (CSR format) instead of Dense Matrix.
- One assumption made was that every user who have watched the movie has rated it.
- Number of Latent factors for user and item used were 2**0** and Epoch count was **30**

Implementation Insights

- Parameters used :
- Meta parameters: $\gamma 1 = \gamma 2 = 0.007$, $\gamma 3 = 0.001$, $\lambda 6 = 0.005$, $\lambda 7 = \lambda 8 = 0.015$.
  - We decrease step sizes (the γ's) by a factor of 0.9 after each iteration.
  - All results are measured for Epochs of 30.
  - Epoch time for running the models on Kaggle were :
    - Neighborhood Model : 1.312 mins
    - SVD++ model : 2.45 mins
    - Integrated model : 4.54 mins

Implementation Insights

Initialization of Parameters

```
def train(train_sparse,test, n_epochs = 30, n_factors = 20) :

    matrix = train_sparse.tocsc()
    user_num = matrix.shape[0]
    item_num = matrix.shape[1]

    #global mean
    global_mean = np.sum(matrix.data) / matrix.size
    #user bias
    bu = np.zeros(user_num, np.double)
    #item bias
    bi = np.zeros(item_num, np.double)
    #user factor
    p = np.zeros((user_num, n_factors), np.double) + .1
    #item factor
    q = np.zeros((item_num, n_factors), np.double) + .1
    #item preference facotor
    y = np.zeros((item_num, n_factors), np.double) + .1
    #weights for neihbourhood
    w = np.zeros((item_num,item_num))
    #implicit feedback
    c = np.zeros((item_num,item_num))
    n_lr = 0.001
    lr = 0.007
    reg = 0.001
    n_reg = 0.015

    reg7 = 0.005
```

Implementation Insights

Forward Prop

```
for u,i,r in all_ratings(matrix):
    Nu = get_user(matrix,u)[0]
    I_Nu = len(Nu)
    sqrt_N_u = np.sqrt(I_Nu)
    y_u = np.sum(y[Nu], axis=0)
    u_impl_prf = y_u / sqrt_N_u
    c_ij = np.sum(c[i,Nu] , axis = 0)
    w_ij = np.dot((get_user(matrix,u)[1] - global_mean - bu[u] - bi[Nu]) ,w[i][Nu])
    c_w =  (c_ij + w_ij )/sqrt_N_u
    rp = global_mean + bu[u] + bi[i] + np.dot(q[i], p[u] + u_impl_prf) + c_w
```

Implementation Insights

Backward Prop

```
        #sgd
        bu[u] += lr * (e_ui - reg7 * bu[u])
        bi[i] += lr * (e_ui - reg7 * bi[i])
        p[u] += lr * (e_ui * q[i] - reg * p[u])
        q[i] += lr * (e_ui * (p[u] + u_impl_prf) - reg * q[i])
        for j in Nu:
            y[j] += lr * (e_ui * q[j] / sqrt_N_u - reg * y[j])
        for j in Nu :
            w[i,j] += n_lr * (e_ui/ sqrt_N_u * (r - global_mean - bu[u] - bi[j]) - n_reg * w[i,j])
        for j in Nu :
            c[i,j] += n_lr * ((e_ui / sqrt_N_u) - n_reg * c[i,j])
    n_lr *= 0.9
    lr *= 0.9
```

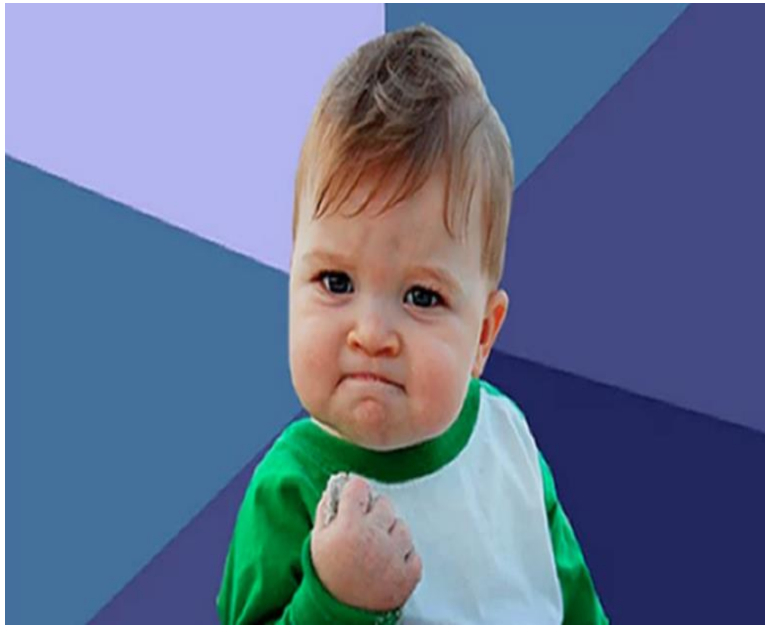
Results

```
 processing epoch 28
Time For Epoch :: 0:03:02.497476
Err =  0.9283700156796918
Time For Error :: 0:00:06.288783
 processing epoch 29
Time For Epoch :: 0:03:02.442041
Err =  0.928305834760709
Time For Error :: 0:00:06.636619
0.928305834760709
```

RMSE Error (Integrated Model)

Neighborhood Model	SVD++	Integrated Model
1.7757	0.941	0.9283

Error in RMSE (root mean square error)



Limitations

- Insufficient hardware support to run large dataset (Netflix dataset), even in CSR format.
- Better sources needed for implicit feedback.
- Data sparsity
- Scalability
- Cold Start is genuine problem for Recommender Models. It's relevant for both new users and new movies which the model encounters.
- For our model :
  - If the { User , Movie } pair is new to the model, we predict the global mean of all the movies.

Thank You.