

Recommender System



User's review Amazon products

<https://github.com/antoniosh97/Recommender-System-2023>



Recommender System - Our Team

“A” Team



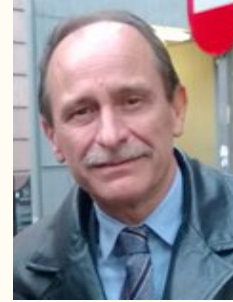
Antonio



Brenda



Evaristo



Joan



Recommender System – 1. Motivation

The ultimate goal of a recommender systems is to **unlock the maximum potential of customer purchases**, making them a crucial component of a successful personalized marketing strategy.



Improve user experience: help users to discover new products and services based on their own interests.



User **loyalty**: encourage customers to return.



User engagement: encourage users to **engage with the content** based on the recommendation of the products or services.



More direct and **personalized marketing campaigns**



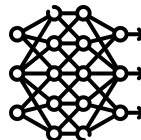
Recommender System - 2. Goals



Baseline

Propose **two simple approaches** to give a recommendation: **most popular products (1)** and **random products (2)**.

Define and develop the initial ETL and data preparation for modelling.



Deep learning models

Develop two different **deep learning approaches for the recommender system**: **Factorization machines (FM)** and **Neural matrix Factorization model (NeuMF)**.

Perform ablation experiments to give an intuition on hyperparameter tuning.



Business sense of a recommender system

Understand the **performance** of the different models based on a **business perspective**.

Conclude the project with **next steps** to perform in the future.

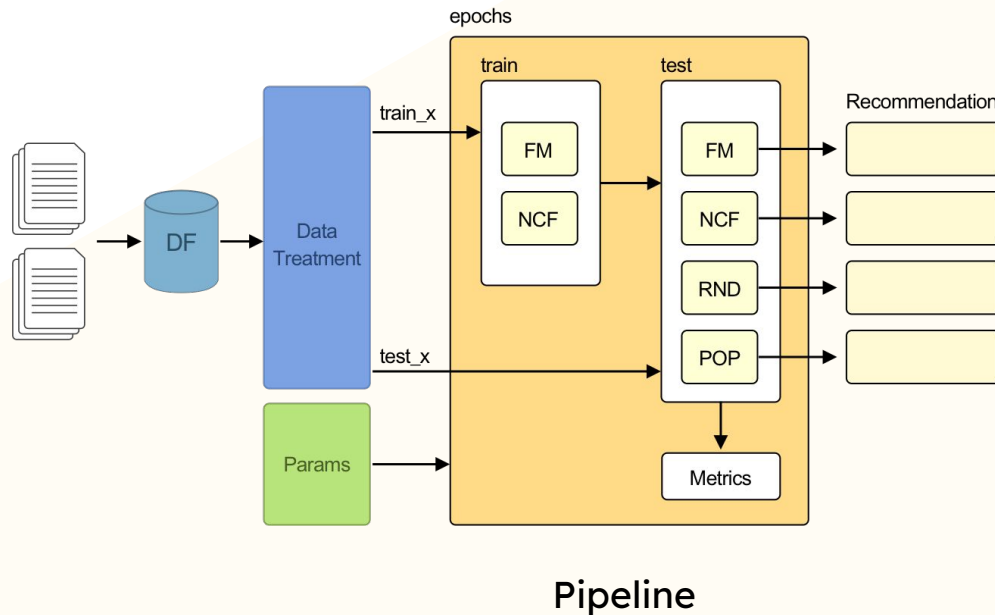


Recommender System - 3. Proposal



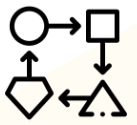
Strategy

1. Models: FM, RND, POP, NCF
2. Different Datasets:
Amazon and MovieLens
3. Data transformation and
Sampling strategy
4. Training and Test
5. Metrics: HR, NDGC, Coverage
6. Histograms and Graphics:
Plot and Tensorboard
7. Tuning parameters
8. Custom parametrization

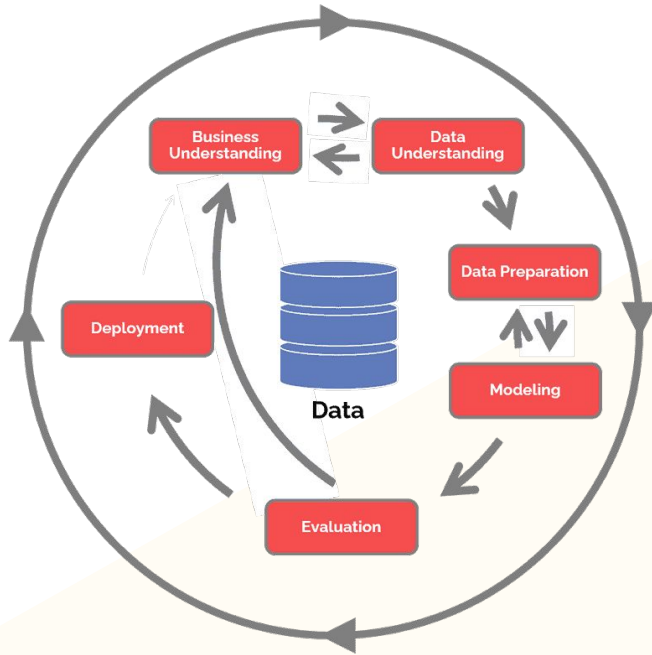




Recommender System - 3. Proposal



Methodology



CRISP-DM
Cross Industry Standard
Process for Data Mining

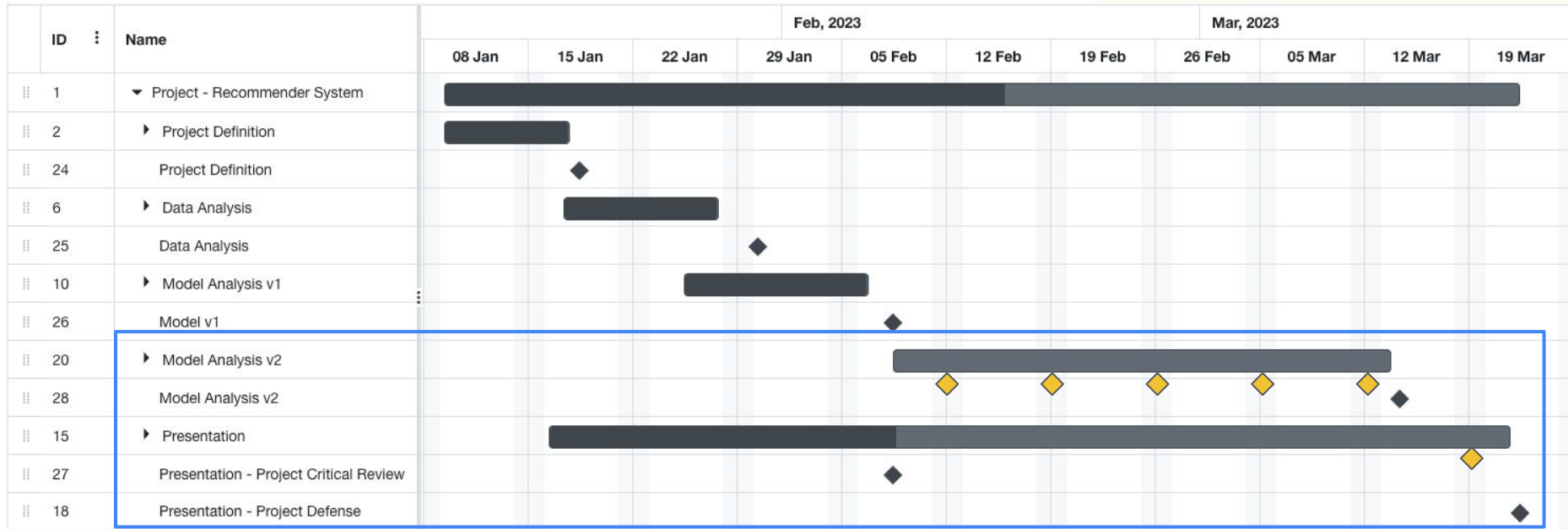
1. Business understanding
2. Data understanding
3. Data preparation
4. Modeling
5. Evaluation
6. Deployment

Waterfall



Recommender System - 3. Proposal

Project Plan and Milestones





Recommender System - 4. Implementation



Datasets

Amazon: Original

Total Reviews
233.1 million

Subset: Musical Instruments

Reviews
1,512,530

Products
112,222

Users
903,330

MovieLens-100k

Reviews
100.000

Movies
1,682

Users
943

Structure: User, Item, Review(1-5), Timestamp

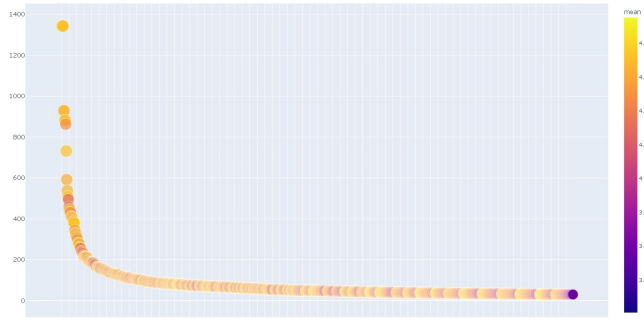


Recommender System - 4. Implementation

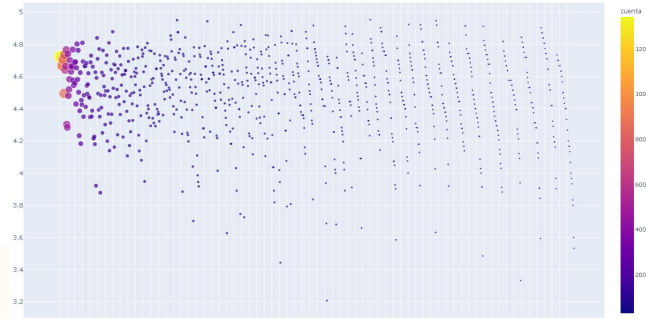


Datasets

Amazon

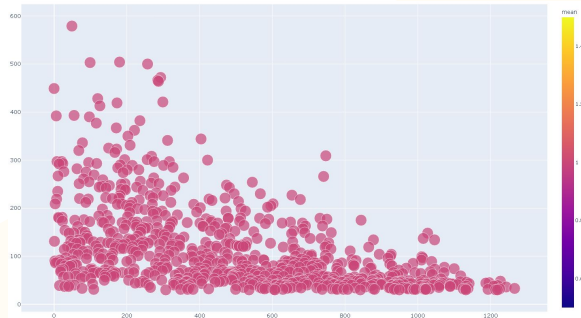


1 . Reviews for Items: >29, 952 of 137364

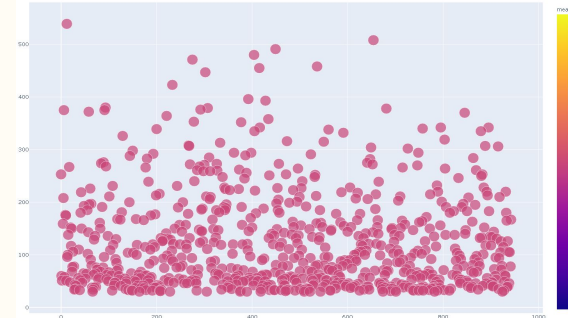


2 . Reviews 1-5: >29, 952 of 137364

MovieLens



3 . Reviews for Items: >29, 806 of 94443



4 . Reviews by User: >29, 732 of 94443



Recommender System - 4. Implementation



Datasets

Data: Transformation and cleaning

- Format data types
- Remove duplicates
- Reduce reviews by user and item

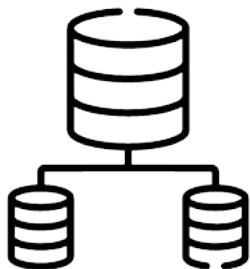
	Amazon		MovieLens
Users	4.275	14.138	943
Items	2.080	6.178	1.682
Reviews	52.023	137.364	100.000
RxUxI	8x8	6x6	20 reviews



Recommender System - 4. Implementation



Sampling



Training

Implicit feedback (1-5 -> 1)

Negative Sampling (k=4-6)

Test

TLOO Time Leave One Out (x=1)
RLOO Random Leave One Out (x=1)

Full Ranking

(add neg all items/user)



Recommender System - 4. Implementation



Models



Random

Popularity

FM - Factorization Machine

NCF - Neural Collaborative Filtering



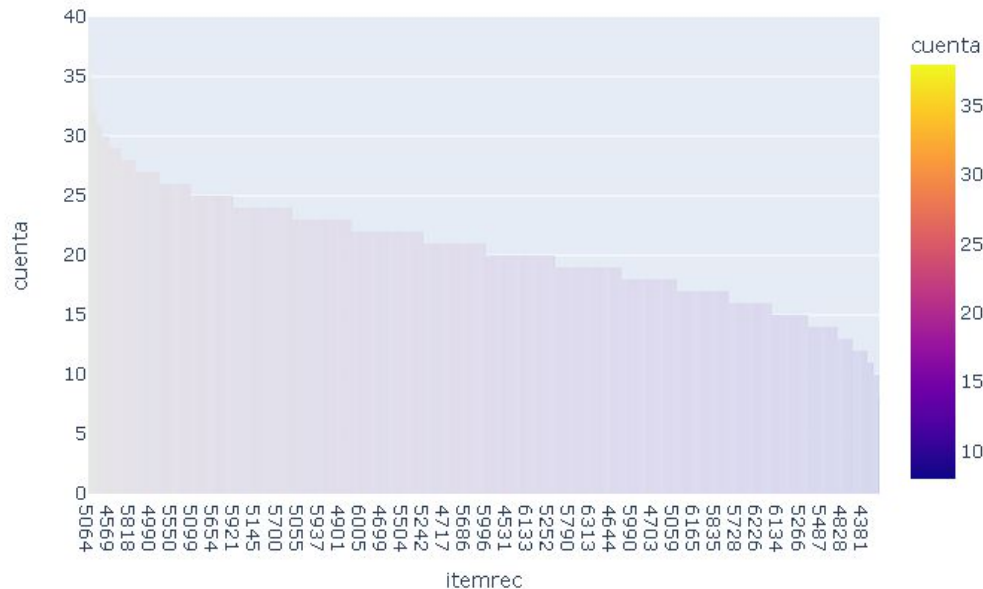
Recommender System - 4. Implementation



Models

Random

EPOCH:15 - Recommended items - number of different items=2080
Items also in popularity list=10 - model=Random



- Recommend items of the top@k list randomly
- Has a coverage of 100% of the products set

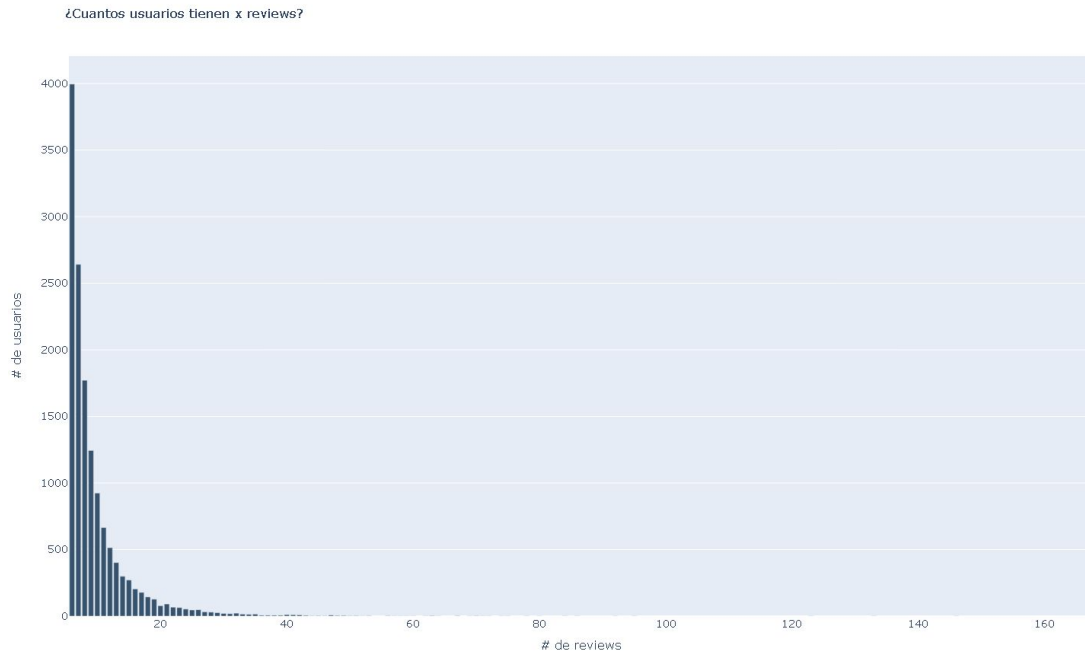


Recommender System - 4. Implementation



Models

Popularity



- Most simple statistic method
- Select the first top@K items with more ratings
- Solves the cold start problem with new users but always recommends the same set of products



Recommender System - 4. Implementation



Models

FM - Factorization Machine

Feature vector x															Target y							
$x^{(1)}$	1	0	0	...	1	0	0	0	...	0.3	0.3	0.3	0	...	13	0	0	0	0	...	5	$y^{(1)}$
$x^{(2)}$	1	0	0	...	0	1	0	0	...	0.3	0.3	0.3	0	...	14	1	0	0	0	...	3	$y^{(2)}$
$x^{(3)}$	1	0	0	...	0	0	1	0	...	0.3	0.3	0.3	0	...	16	0	1	0	0	...	1	$y^{(3)}$
$x^{(4)}$	0	1	0	...	0	0	1	0	...	0	0	0.5	0.5	...	5	0	0	0	0	...	4	$y^{(4)}$
$x^{(5)}$	0	1	0	...	0	0	0	1	...	0	0	0.5	0.5	...	8	0	0	1	0	...	5	$y^{(5)}$
$x^{(6)}$	0	0	1	...	1	0	0	0	...	0.5	0	0.5	0	...	9	0	0	0	0	...	1	$y^{(6)}$
$x^{(7)}$	0	0	1	...	0	0	1	0	...	0.5	0	0.5	0	...	12	1	0	0	0	...	5	$y^{(6)}$
	A	B	C	...	TI	NH	SW	ST	...	TI	NH	SW	ST	...	Time	TI	NH	SW	ST	...		
	User				Movie					Other Movies rated					Time	Last Movie rated						

Implement Factorization Machine to perform a ranking prediction task of top@k

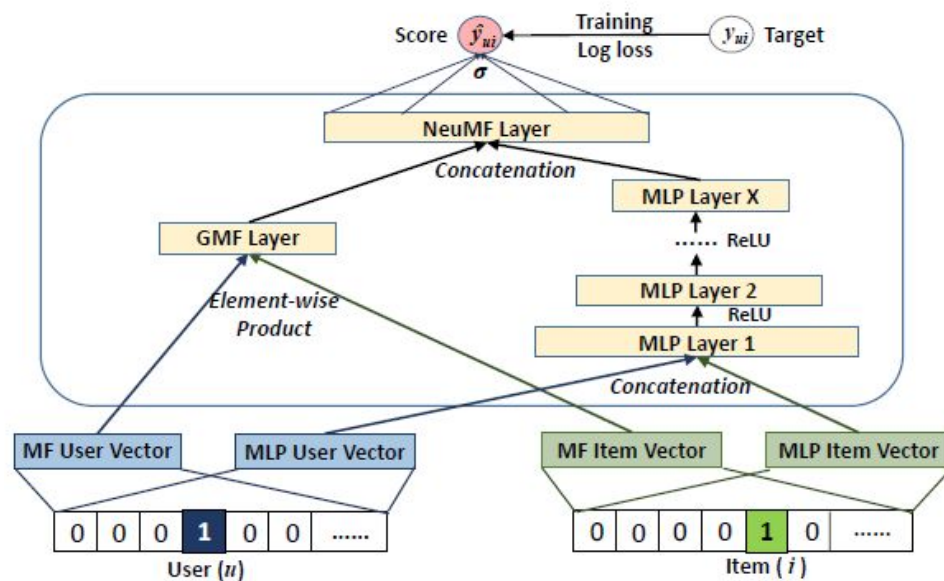


Recommender System - 4. Implementation



Models

NeuMF



- We implemented NeuMF Neural Matrix Factorization model that combines MF with Neural MLP
- Changed the original last MLP layer activation function SIGMOID followed by BCELoss to use only a [BCEwithLogitsLoss](#) function in train



Recommender System - 4. Implementation



Metrics



Hit Ratio $HR@topk$.

How often is the GT item present in the recommendation list



NDCG Normalized Discounted Cumulative Gain.

Measures ranking quality



Coverage compares the set of total recommended items with the total items in train dataset



Recommender System - 4. Implementation



Computational
resources

- GIT repository ([recommender system project AIDL2023](#))
- Colab notebooks
- CPU (local)
- Tensorboard
- Miniconda environment
- Process average time: 2h



Recommender System – 5. Results. Ablation studies

Illustrative for NeuMF
and TLOO

	<i>K negative sampling</i>	<i>Learning rate</i>	<i>Hidden size</i>	<i>Metrics</i>
Exp 1	5	1 e-3	32	HR: 0.05 NDCG:0.02 COVERAGE: 68.2
Exp 2	6	1 e-4	64	HR: 0.07 NDCG:0.04 COVERAGE: 16.2
Exp 3	6	1 e-4	32	HR: 0.06 NDCG:0.03 COVERAGE: 16.3
...

To determine the best hyperparameters, a grid is created with different configurations. The performance is measured in every iteration and the final model is chosen from the best of these experiments.



Recommender System – 5. Results. Final configuration

	<i>K negative sampling</i>	<i>Learning rate</i>	<i>Hidden size</i>	<i>Metrics</i>
Best exp NeuMF	5	1 e-4	64	HR: 0.07 NDCG:0.04 COVERAGE: 35.8
Best exp FM	5	1 e-3	64	HR: 0.06 NDCG:0.03 COVERAGE: 49.6
Random	-	-	-	HR: 0.004 NDCG:0.002 COVERAGE: 100

NeuFM model has the best metrics in terms of HR and NDCG. With the deep learning approach we have an x10 improvement from the random recommendation.



Recommender System – 6. Conclusions



Hypothesis accomplished
Key points in REC
Compliance in business



Add context
Bias in dataset and models
Control and insertion of bias
Docker & Flask

Next steps



Transparency
Limits
Privacy

Ethical

Project Conclusions

Recommender System



Thank you! Questions?

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