Hybrid models with Alternating Least Squares(ALS)

Research: Louvain's algorithm-alternating least square algorithm(LA-ALS)

- date: 17 August 2020
- authors: Lakshmikanth Paleti; P. Radha Krishna; J. V. R. Murthy
- aim: to address cold start problem
- scenario: social media
- samples: trained with 70,000, tested with 30,000
- environment: Apache Spark 2.3.0, Python 3.6.5, on a 4 GB RAM, Ubuntu 16.04 LTS System

Paleti, L., Radha Krishna, P. and Murthy, J.V.R. (2021) "Approaching the cold-start problem using community detection based alternating least square factorization in recommendation systems," *Evolutionary intelligence*, 14(2), pp. 835–849. Available at: https://doi.org/10.1007/s12065-020-00464-y.

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- General block diagram of LA-ALS methodology:

Dataset →	Louvain's algorithm →	Ratings matrix →	Building ALS →	Recommendations
Movie dataset, Facebook dataset	create user communitie s	user-item matrices	address data sparsity problem	top K movie items

- parameters:
  - final recommendations: 10
  - max iterations: 100
- performance metrics
  - Mean absolute error (MAE)
  - Root mean square error (RMSE)
  - Prediction coverage

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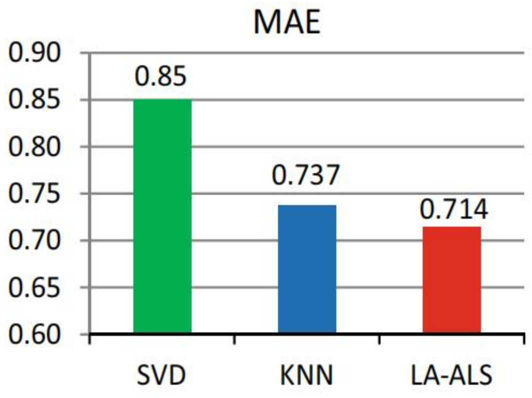
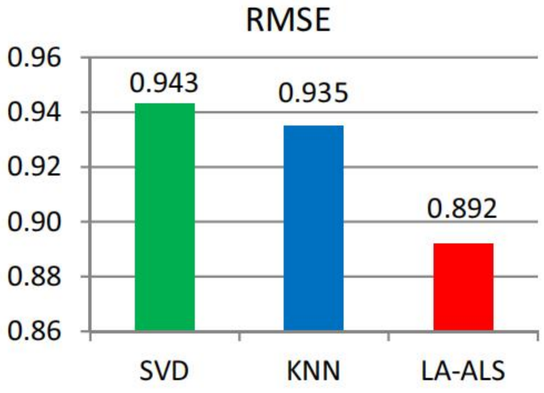
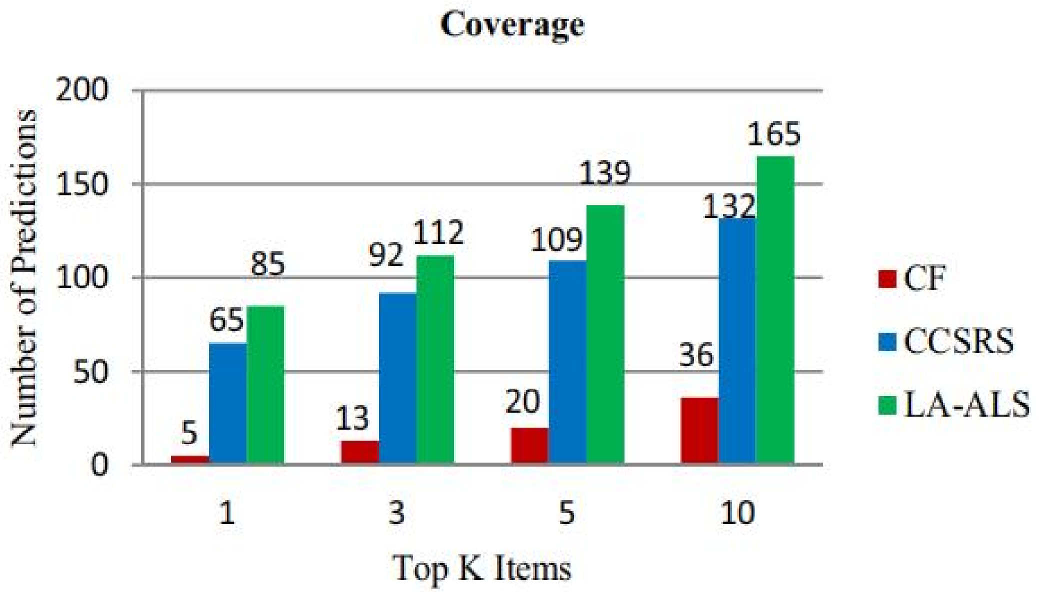
- compared with KNN and SVD -> MAE, RMSE

Method	RMSE	MAE
SVD [32]	0.943	0.850
KNN [18]	0.935	0.737
LA-ALS	0.892	0.714





- compared with CF, CCSRS and LA-ALS -> Prediction coverage

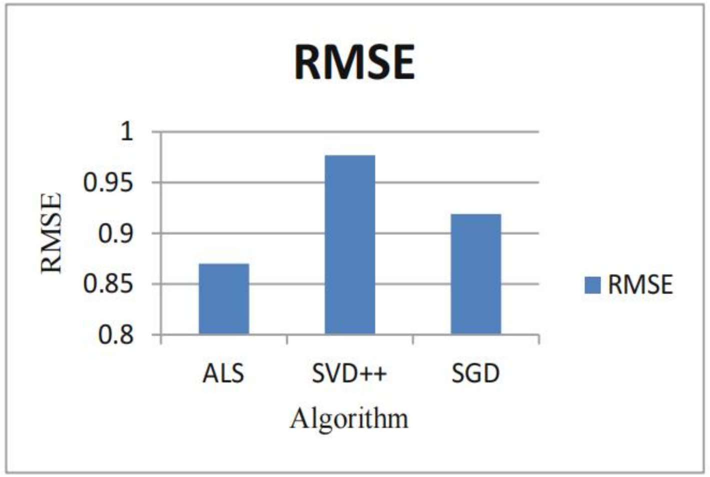


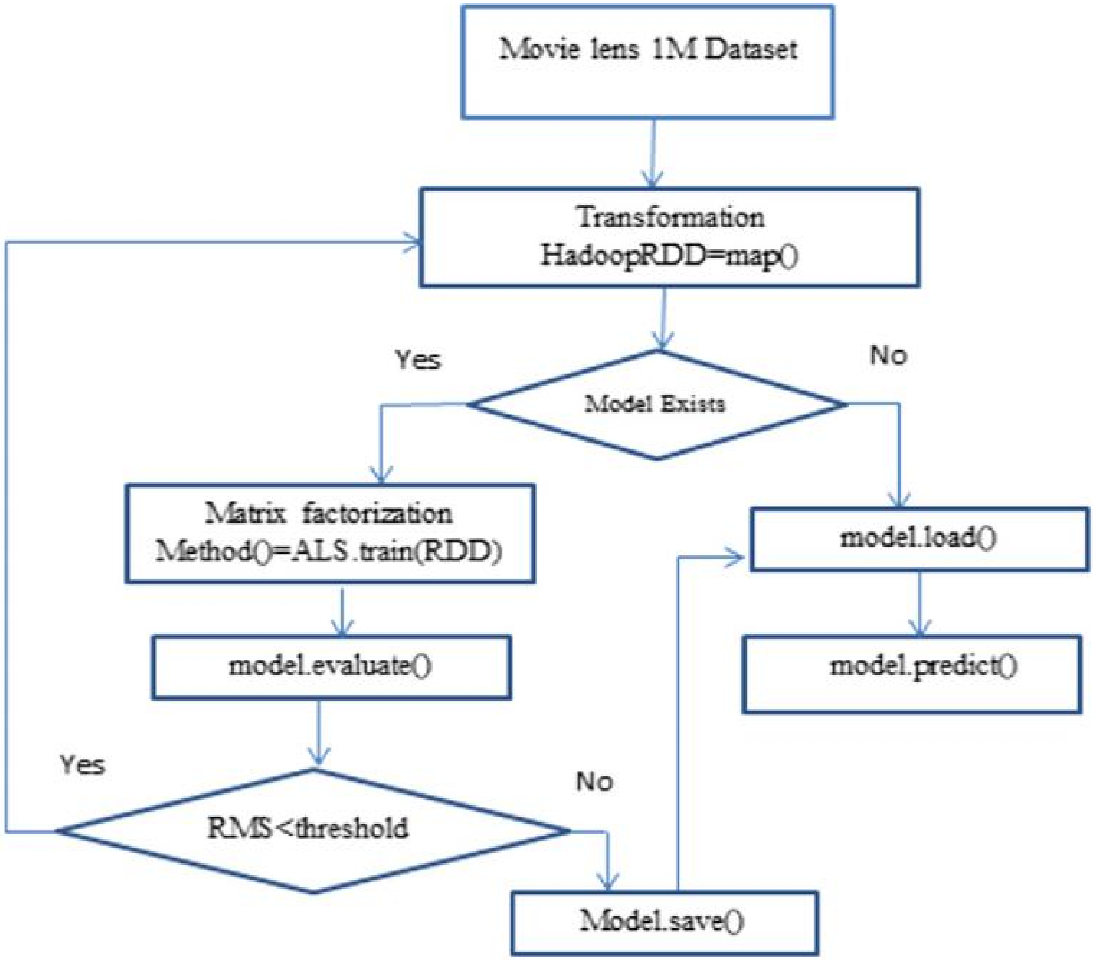
Hybrid models with Alternating Least Squares(ALS)

Research: Using Alternating Least Squares(ALS) on Apache Spark

- initial paremeters: Lambda -> 0.01, iteration -> 5
- performance metrics
  - Root mean square error (RMSE)
- compared with SGD(Stochastic Gradient Descent) and SVD (Singular Value Decomposition)

Algorithm	RMSE
ALS	0.870
SVD++	0.977
SGD	0.919





method workflow

Hybrid models with Alternating Least Squares(ALS)

Research: Using Alternating Least Squares(ALS) on Apache Spark

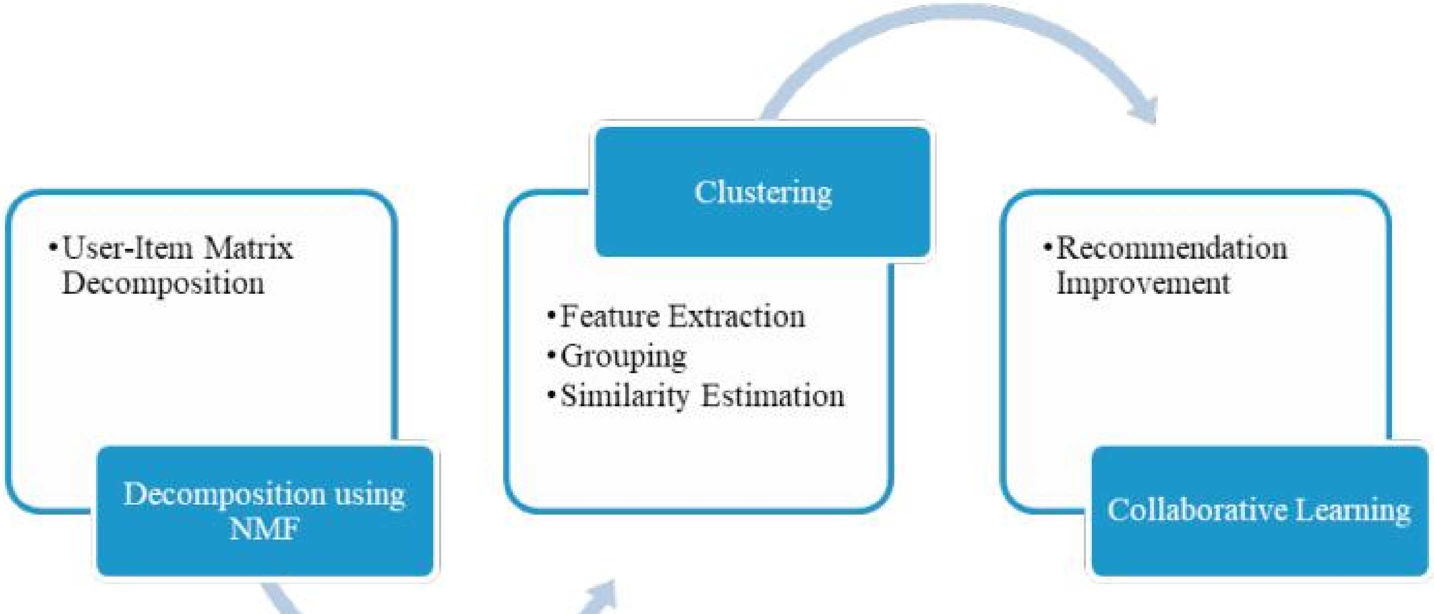
- date: 2021
- authors: Subasish Gosh; Nazmun Nahar; Mohammad Abdul Wahab; Munmun Biswas; Mohammad Shahadat Hossain; Karl Andersson
- aim: develop a RS with ALS to solve the overfitting issue in sparse data
- scenario: interactive e-commerce sites
- samples: 71567 users, 10681 movies, 10000054 ratings
- environment: Apache Spark 2.4.5, Apache Hadoop 3.2.1 and Aapche HBase.

Gosh, S. *et al.* (2021) "Recommendation system for E-commerce using alternating least squares (ALS) on Apache spark," in *Advances in Intelligent Systems and Computing*. Cham: Springer International Publishing, pp. 880–893.

Non-Negative Matrix Factorization

Research: Content Streaming Platform using Non-Negative Matrix Factorization Clustering

- date: 2023
- authors: Nikita Jain Nahar; L. K. Vishwamitra; Deepak Sukheja
- aim: introduces a joint method employing non-negative matrix factorization clustering (NNMFC)
- methodology:



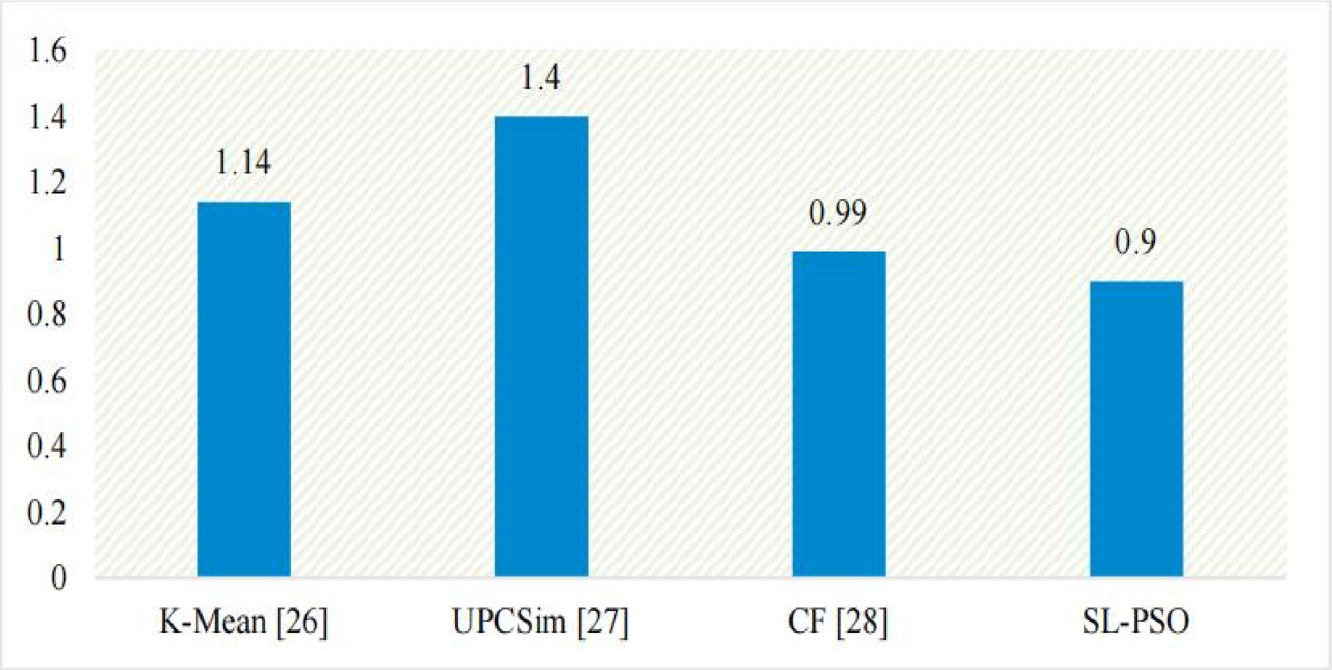
Nahar, N.J., Vishwamitra, L.K. and Sukheja, D. (2023) "Collaborative learning based recommendation system for content streaming platform using non-negative matrix factorization clustering," *Procedia computer science*, 230, pp. 427–435. Available at: https://doi.org/10.1016/j.procs.2023.12.098.

Non-Negative Matrix Factorization

Research: Content Streaming Platform using Non-Negative Matrix Factorization Clustering

- samples: 25 million movie ratings, 162,000 users, 62,000 movies
- environment: Python, Keras framework backed by TensorFlow, a GPU via Google Colab
- parameters: window size -> 10, learning rate -> 0.001, learning epochs -> 100
- performance metrics:
  - Root Mean Squared Error (RMSE).
- Comparative Performance Evaluation:

Methods	RMSE
K-Mean	1.14
UPCSim	1.4
CF	0.99
SL-PSO	0.9



Non-Negative Matrix Factorization

Research: non-negative matrix factorization for recommender systems based on dynamic bias (NMFRS-DB)

- date: 2019
- authors: Wei Song, Xuesong Li
- aim: decrease training cost, improve NMF-based RS
- methodology:
  - extends standard NMF by introducing two additional bias matrices
  - uses Dirichlet, Beta, and Binomial distributions to model uncertainty.
- datasets: MovieLens 100K, MovieLens 1M, Jester Dataset 2, 80% for training, 20% for testing

Song, W. and Li, X. (2019) “A non-negative matrix factorization for recommender systems based on dynamic bias,” in *Modeling Decisions for Artificial Intelligence*. Cham: Springer International Publishing, pp. 151–163.

Non-Negative Matrix Factorization

Research: non-negative matrix factorization for recommender systems based on dynamic bias (NMFRS-DB)

- performance metrics: Mean Absolute Error (MAE)； F1-measure
- Comparison of MAE results:

Dataset	LFM-RS	BPM-RS	NMFRS-DB
MovieLens 100 K	0.691	0.764	0.662
MovieLens 1 M	0.683	0.723	0.665
Jester Dataset 2	0.801	0.842	0.778

- Comparison results of F1-measure:

Table 5. Comparison results of F1-measure

Dataset	Algorithm	Number of recommendations			
		10	30	50	70
MovieLens 100 K	LFM-RS	0.018	0.044	0.063	0.074
	BPM-RS	0.021	0.062	0.068	0.070
	NMFRS-DB	0.073	0.088	0.091	0.094
MovieLens 1 M	LFM-RS	0.011	0.034	0.043	0.047
	BPM-RS	0.068	0.079	0.086	0.091
	NMFRS-DB	0.082	0.089	0.096	0.100
Jester Dataset 2	LFM-RS	0.083	0.103	0.102	0.095
	BPM-RS	0.088	0.104	0.100	0.097
	NMFRS-DB	0.095	0.110	0.110	0.110

Wide & deep

Research: Wide & deep generative adversarial networks(W & DGAN)

- date: 2023
- authors: Jianhong Li, Jianhua Li, Chengjun Wang, Xin Zhao
- aim: addressing the limitations of GAN-based recommendation systems
  - Incomplete User Preference Learning
  - Loss Function Limitation
- how to solve:
  - Uses Wide & Deep Learning in the generator to enhance user preference modeling.
  - Combines Cross-Entropy loss (G) and Wasserstein loss (D) to model the global data distribution.

Li, Jianhong *et al*. (2023) "Wide & deep generative adversarial networks for recommendation system," *Intelligent data analysis*, 27(1), pp. 121–136. Available at: https://doi.org/10.3233/ida-216400.

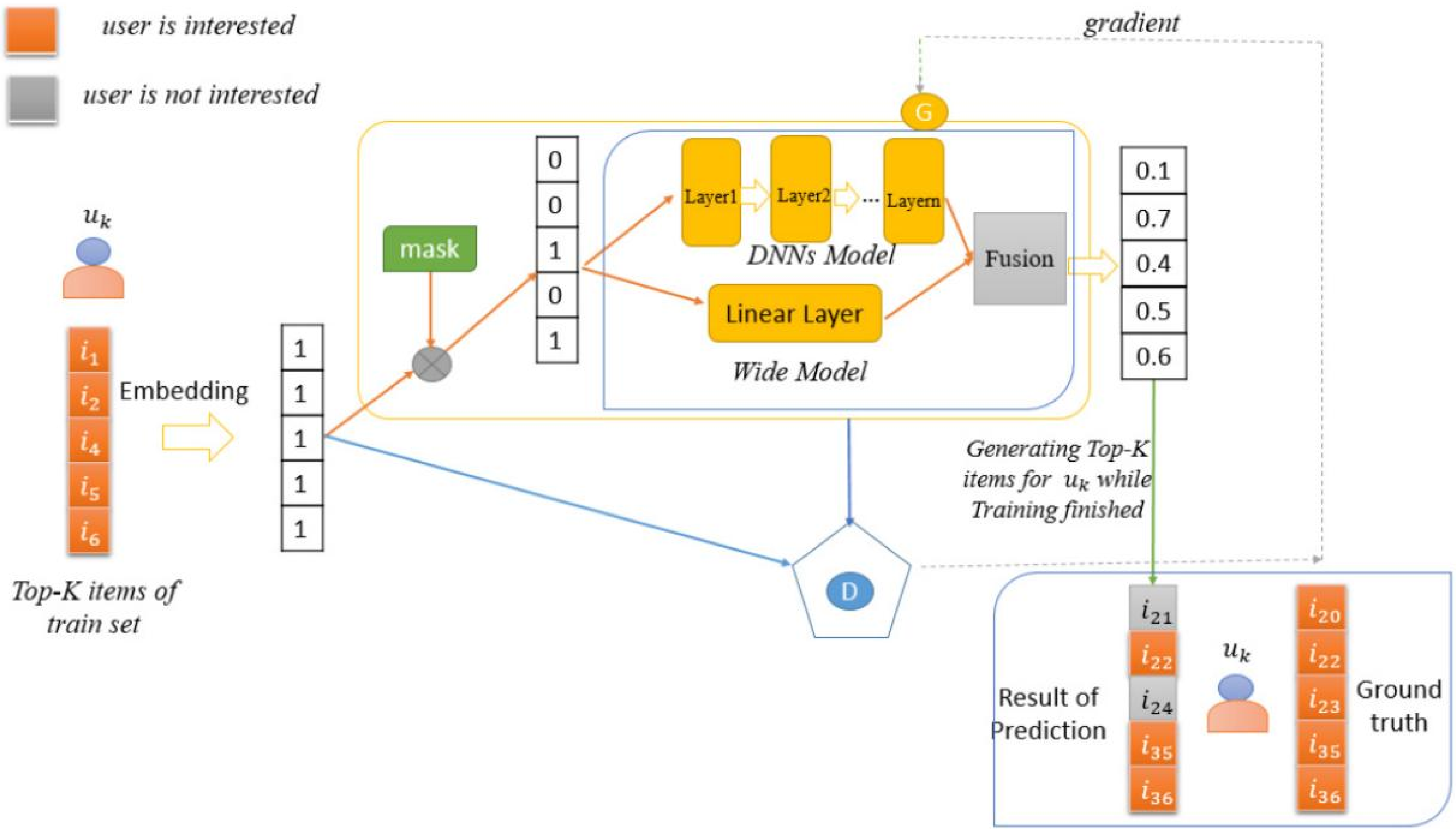


Fig. 2. W&DGAN framework.

Wide & deep

Research: Wide & deep generative adversarial networks(W & DGAN)

- datasets: 80% for training, 20% for testing

Statistics of the experimental datasets

	Ciao	MovieLens 100K	MovieLens 1M
Users	996	943	6,040
Items	1,927	1,682	3,883
Records	18,648	100,000	1,000,209
Sparsity	98.72%	93.7%	95.8%

- environment: TensorFlow-1.13, NVIDIA Tesla P100 GPU with 16 GB of memory, OS -> Ubuntu 16.04.5LTS server and 128GB memory
- Metrics: Recall, Normalized Discounted Cumulative Gain (NDCG), Mean Reciprocal Rank (MRR), Precision

Experimental performance of W&DGAN and baselines on the Ciao dataset

	Precision@5	Precision@20	Recall@5	Recall@20	NDCG@5	NDCG@20	MRR@5	MRR@20
ItemPop	0.031	0.024	0.040	0.127	0.047	0.065	0.056	0.067
BPR	0.036	0.025	0.040	0.141	0.052	0.066	0.066	0.078
FISM	0.062	0.040	0.072	0.178	0.079	0.109	0.127	0.147
CDAE	0.061	0.042	0.075	0.185	0.081	0.108	0.127	0.151
GraphGAN	0.026	0.017	0.1041	0.100	0.041	0.058	0.057	0.068
IRGAN	0.035	0.023	0.042	0.111	0.046	0.066	0.082	0.088
CAAE	0.067	0.042	0.079	0.187	0.086	0.120	0.144	0.164
CFGAN	0.072	**0.045**	0.081	0.194	0.092	0.124	0.154	0.167
W&DGAN	**0.073**	**0.045**	**0.084**	**0.198**	**0.094**	**0.127**	**0.161**	**0.186**

Experimental performance of W&DGAN and baselines on the MovieLens 100K dataset

	Precision@5	Precision@20	Recall@5	Recall@20	NDCG@5	NDCG@20	MRR@5	MRR@20
ItemPop	0.181	0.138	0.102	0.251	0.163	0.195	0.254	0.292
BPR	0.348	0.236	0.116	0.287	0.370	0.380	0.556	0.574
FISM	0.426	0.285	0.140	0.353	0.462	0.429	0.674	0.685
CDAE	0.433	0.287	0.144	0.353	0.465	0.425	0.664	0.674
GraphGAN	0.212	0.151	0.102	0.260	0.183	0.249	0.282	0.312
IRGAN	0.312	0.221	0.107	0.275	0.342	0.368	0.536	0.523
CAAE	0.435	0.289	0.151	0.348	0.475	0.432	**0.686**	**0.697**
PLASTIC	0.312	–	–	–	0.331	–	–	–
CFGAN	0.444	0.294	0.152	0.360	0.476	0.433	0.683	0.693
W&DGAN	**0.451**	**0.298**	**0.158**	**0.362**	**0.484**	**0.442**	**0.686**	**0.697**

Experimental performance of W&DGAN and baselines on the MovieLens 1M dataset

	Precision@5	Precision@20	Recall@5	Recall@20	NDCG@5	NDCG@20	MRR@5	MRR@20
ItemPop	0.157	0.121	0.076	0.197	0.154	0.181	0.252	0.297
BPR	0.341	0.252	0.077	0.208	0.349	0.362	0.537	0.556
FISM	0.420	0.302	0.107	0.270	0.443	0.399	0.637	0.651
CDAE	0.419	0.307	0.108	0.272	0.439	0.401	0.629	0.644
GraphGAN	0.178	0.194	0.070	0.179	0.205	0.184	0281	0.316
IRGAN	0.263	0.214	0.072	0.166	0.264	0.246	0.301	0.338
CFGAN	0.432	0.309	0.108	0.272	0.455	0.406	0.647	0.660
FG-ACAE	–	–	–	–	0.458	–	–	–
CollaGAN	0.428	–	–	–	0.417	–	–	–
W&DGAN	**0.437**	**0.314**	**0.110**	**0.275**	**0.461**	**0.412**	**0.652**	**0.666**

Experimental performance of W&DGAN in NDCG@10 on the MovieLens 100K dataset

	MovieLens 100K NDCG@10
BMF	0.408
NMF	0.234
GAT	0.256
MCRec	0.262
NGCF	0.418
DGRBR	0.327
SEMI-FL-MV-DSSM	0.317
FED-MVMF	0.280
W&DGAN	**0.453**