Context Incorporation Techniques for Social Recommender Systems

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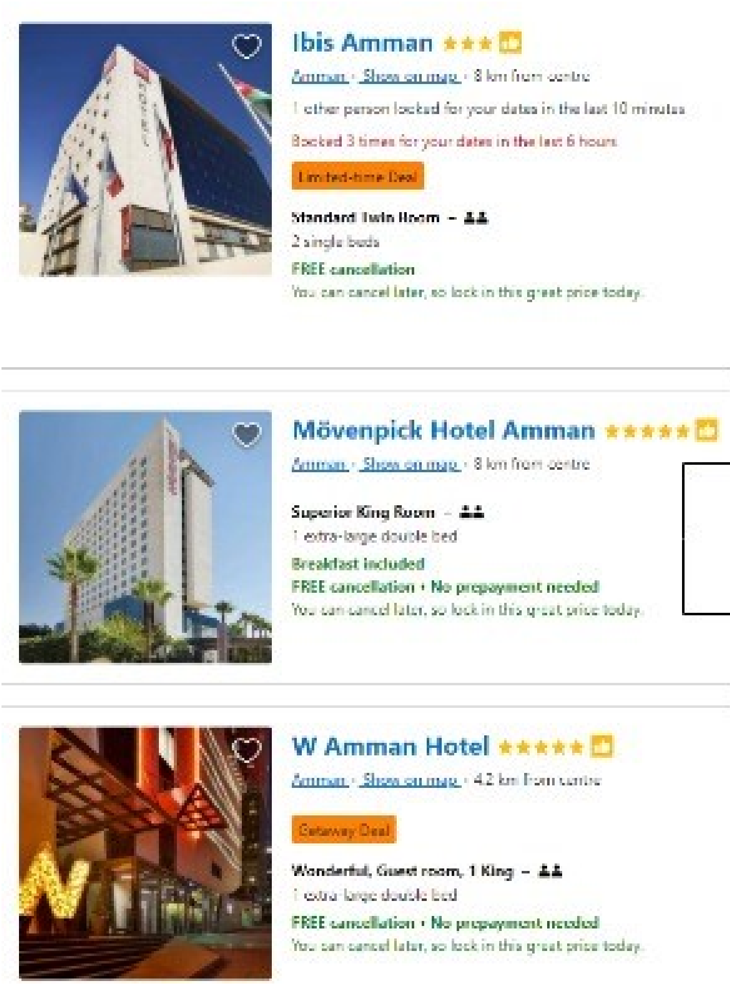
Agenda

- ➢ *Traditional Recommender Systems*
- ➢ *Context-Aware Recommender Systems*: Background and Motivations
- ➢ *Context Incorporation Algorithms*
  - Filtering Approaches
- ➢ US-NCF: A prefiltering approach for a DL-based context incorporation
- ➢ US-NCF hybridization with social recommender systems
- ➢ Deployment
  - Baselines
  - Testing setup
- ➢ Results and Discussion
  - BigDL: Engineered atop Apache Spark
- ➢ Concluding remarks

Recommender Systems

- ***Recommender systems(RSs)*** provide recommendations to users on items of interest.
- RSs work by calculating top ranking list of items recommended for users.
- A deep analysis of historical user-item interaction
  - Explicit: ratings (a.k.a. explicit feedback) or
  - Implicit: the time a user spends viewing a page of a specific item online.
- Collaborative Filtering (CF) remains the most predominant conventional RS.

Explicit Feedback



U/I	I1	I2
U2	☆ ☆☆	☆
U3	☆ ☆ ☆ ☆	☆☆

User X Item → Rating

Are additional attributes helpful!

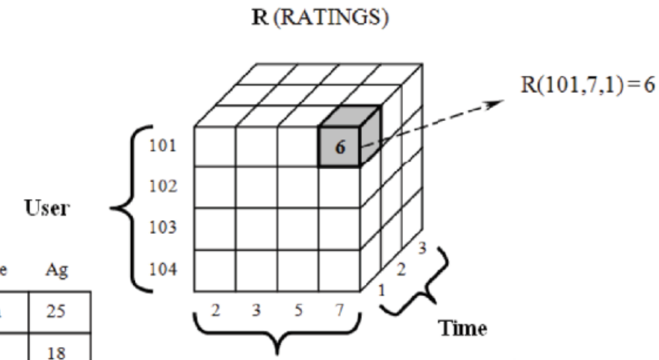
- Conventional RSs are not aware of the contextual information that may be served as additional information with the input data.
- Additional contextual information has a utility in improving the overall recommendation precision.

Context

- Any associated information that is useful for characterizing the situation of an object.

Context-aware interactions

- Contextual interaction is multidimensional
- Users X Items X Context → ratings



User

Id	Name	Ag
10	John	25
10	Bob	18
10	Alice	27
10	Mary	21

Item

Id	Name	Cost
2	AB17	250.0
3	AB23	299.9
5	XY70	150.0
7	ZZ55	115.5

Time

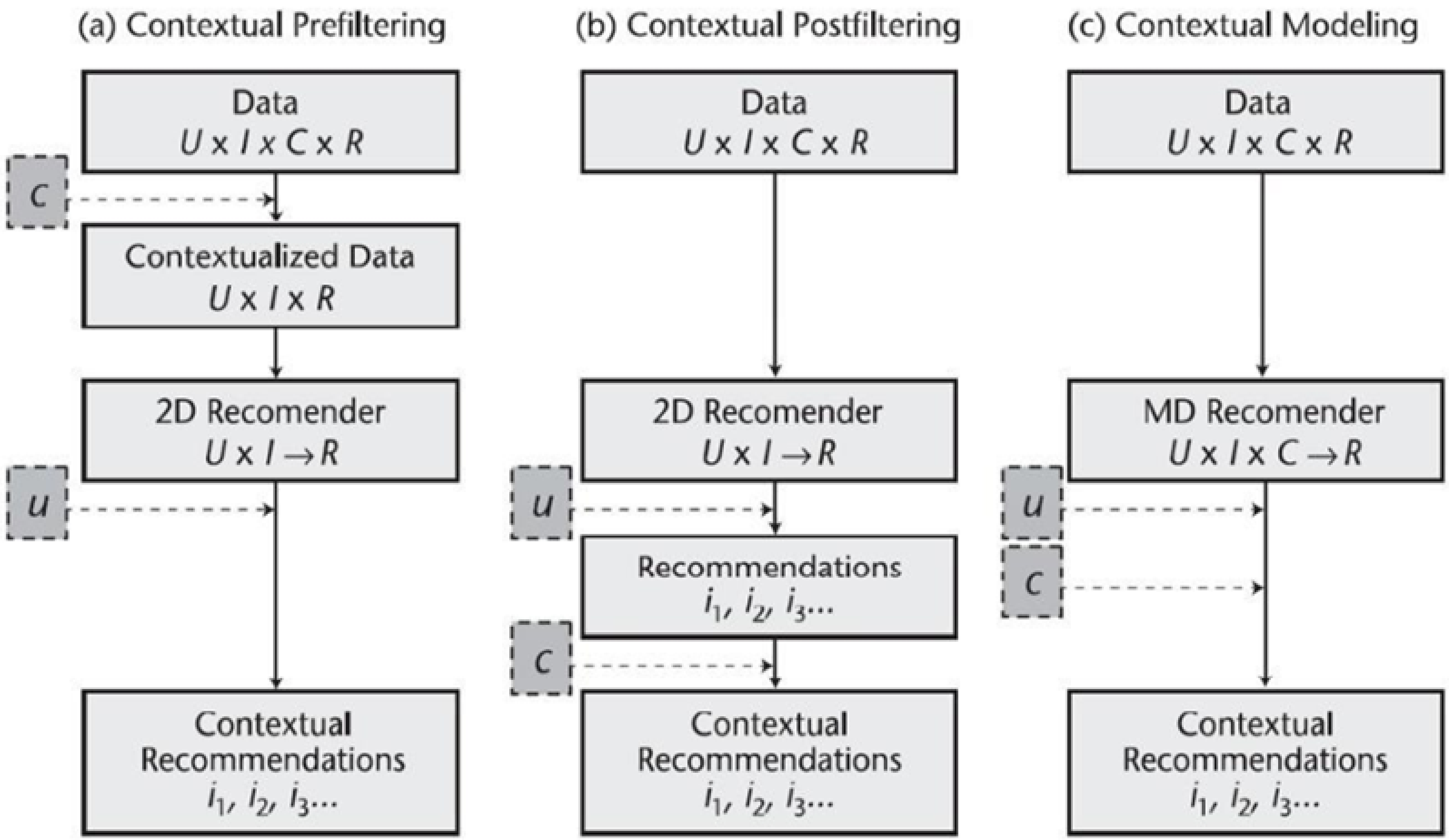
Id	Name
1	Weekday
2	Weekend
3	Holiday

User	+	Item	+	context	=	rating
Laila		Song1		weekend		★★★★☆
Laila		Song1		weekday		☆

<u>Image source:</u> Adomavicius, Gediminas, and Alexander Tuzhilin. "Context-aware recommender systems." *Recommender systems handbook*. Springer, Boston, MA, 2011. 217-253.

Incorporating Context Information into Recommender Systems

- Three approaches:



Item Splitting

- A dimensionality reduction: transforming a 3-dimensional rating interactions into a 2-dimensional counterpart.

User	Item	Context	rating
User1	Item1	weekend	5
User2	Item1	weekday	3

Item Split

User	new Item	rating
User1	Item11	5
User2	Item12	3

User Splitting

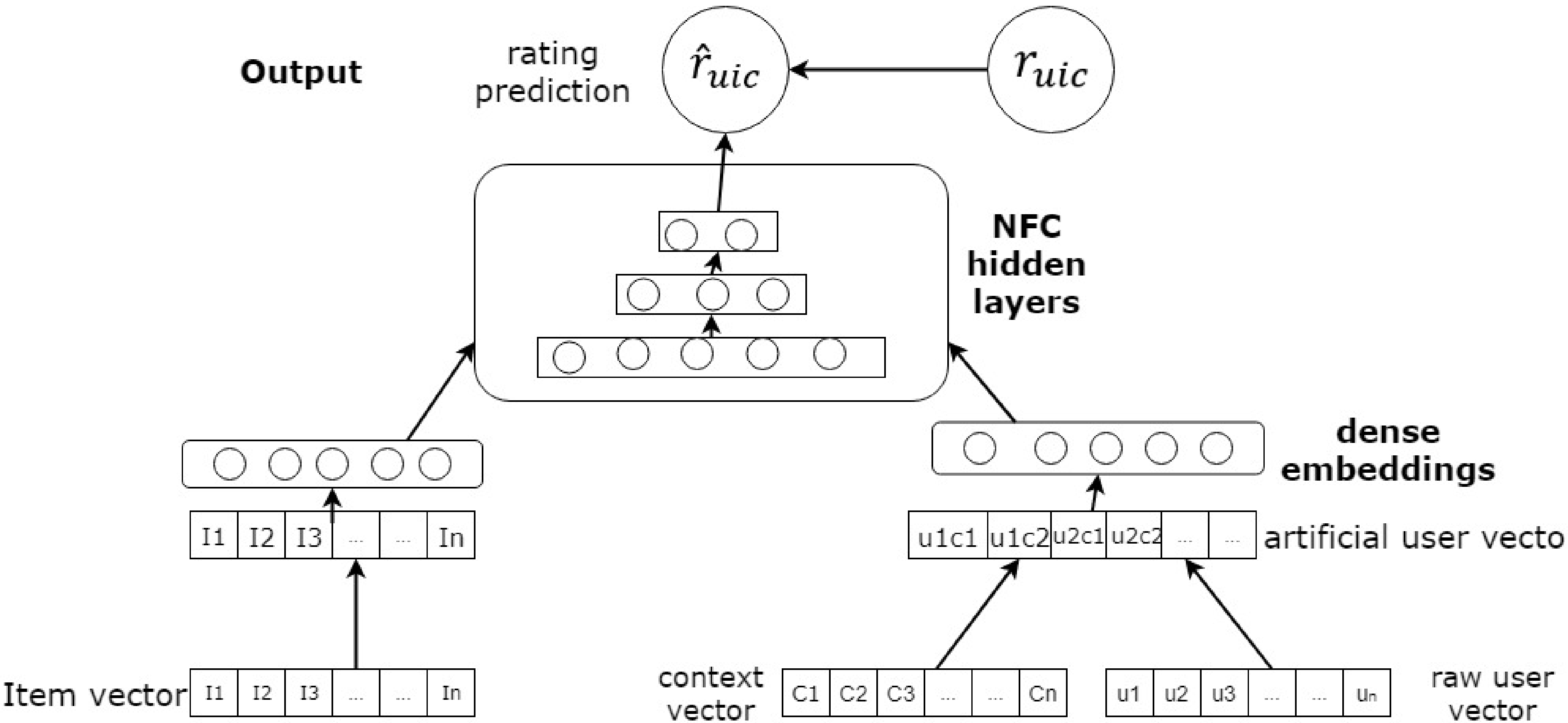
- Same users show statistically significant feedback differences depending on various contextual conditions.

User	Item	Context	rating
User1	Item1	weekend	5
User1	Item1	weekday	3

User Split

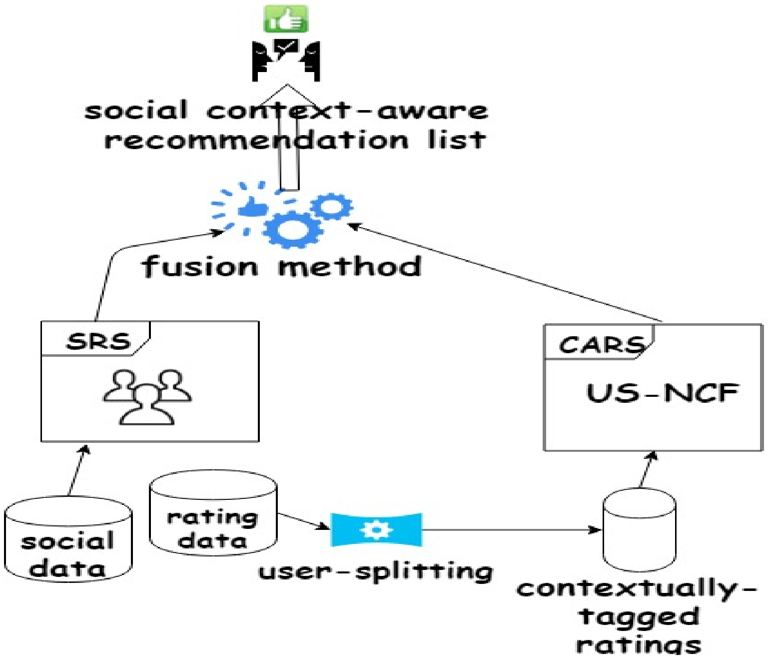
User	new Item	rating
User11	Item1	5
User12	Item1	3

US-NCF: context incorporation for DL-based RSs



Using US-NCF with Online Social Networks

- Our context-aware recommender system can be used for supporting the operation of context-aware social recommender systems.

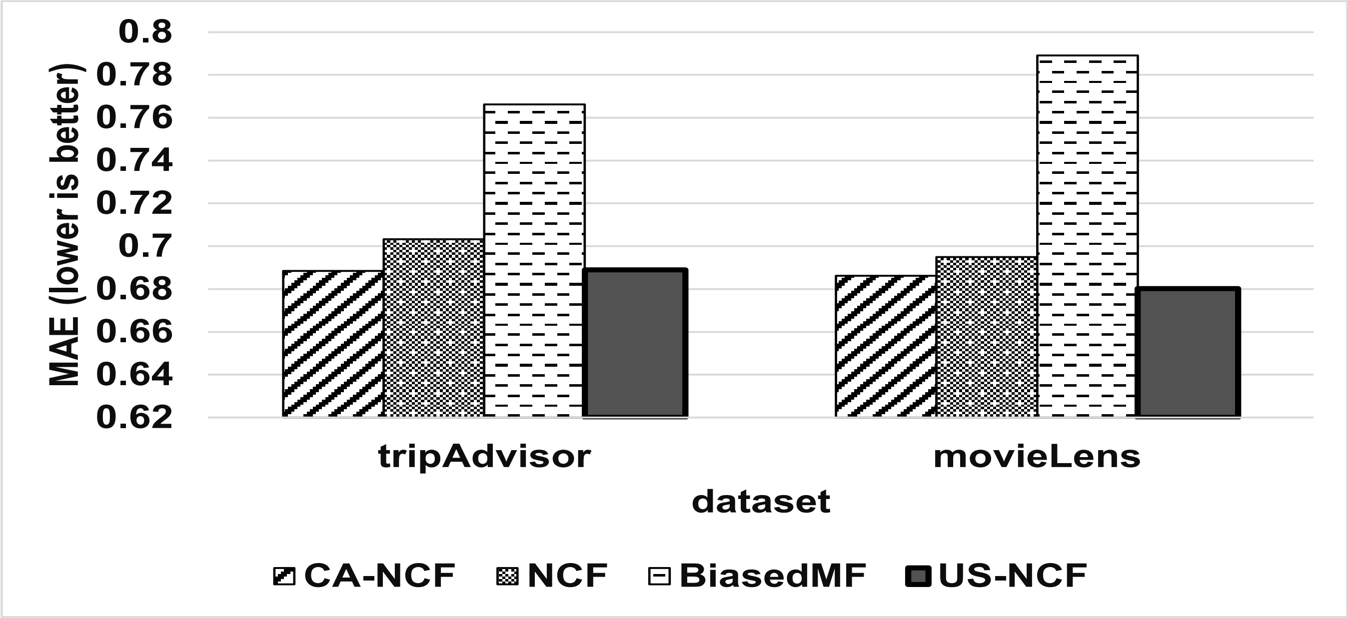


$$\hat{r}_{uics} = p\,(v_i = r_c)\,.\,\hat{r}_{uic} + (1 - p\,(v_i = r_c)\,)\,.\,\hat{r}_{uis}$$

Experimental setup

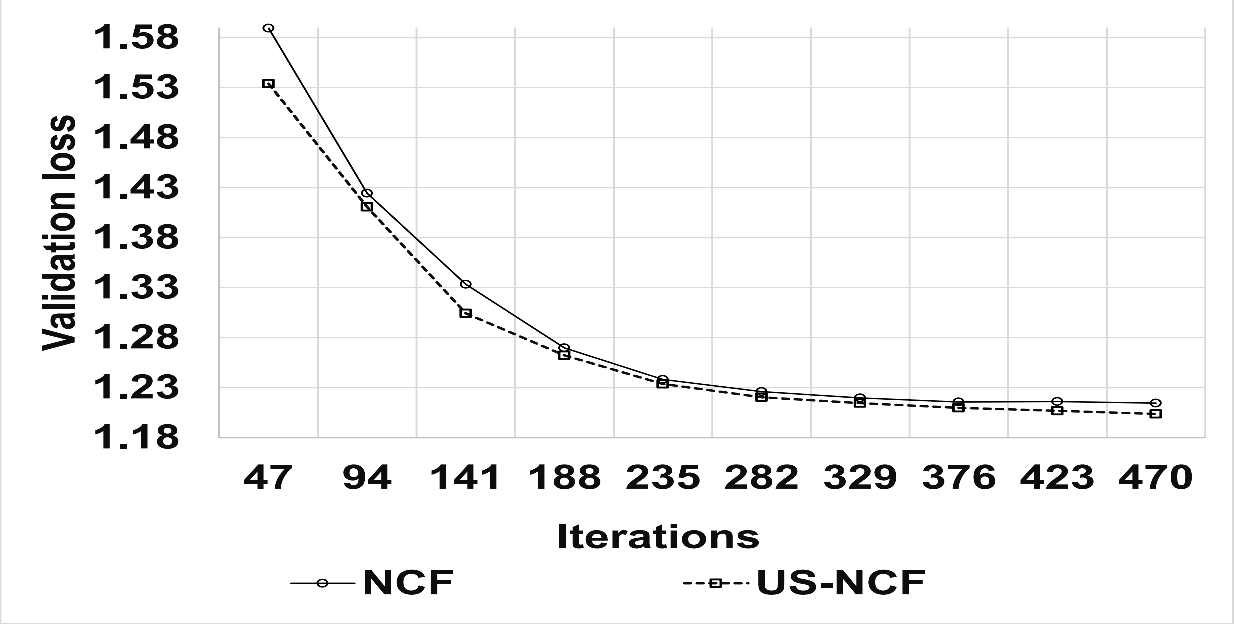
- Evaluation metrics
  - average Mean Absolute Error (MAE) and validation loss
  - For ranking (i.e., top-N), we adopt an accuracy measure known as precision-in-top-N. We specifically have adopted ‘top-one-accuracy’ (a.k.a. P@1)
- Testbed
  - Cluster: our prototype over BigDL [9] , which is coined over Apache Spark [10]. Therefore, taking advantage of the distributed running of the training models
  - Datasets:
    - two explicit feedback rating datasets
      - Movie rating dataset, Movielens 1M
      - trip planning website TripAdvisor

MAE of US-NCF Vs. baselines for all datasets



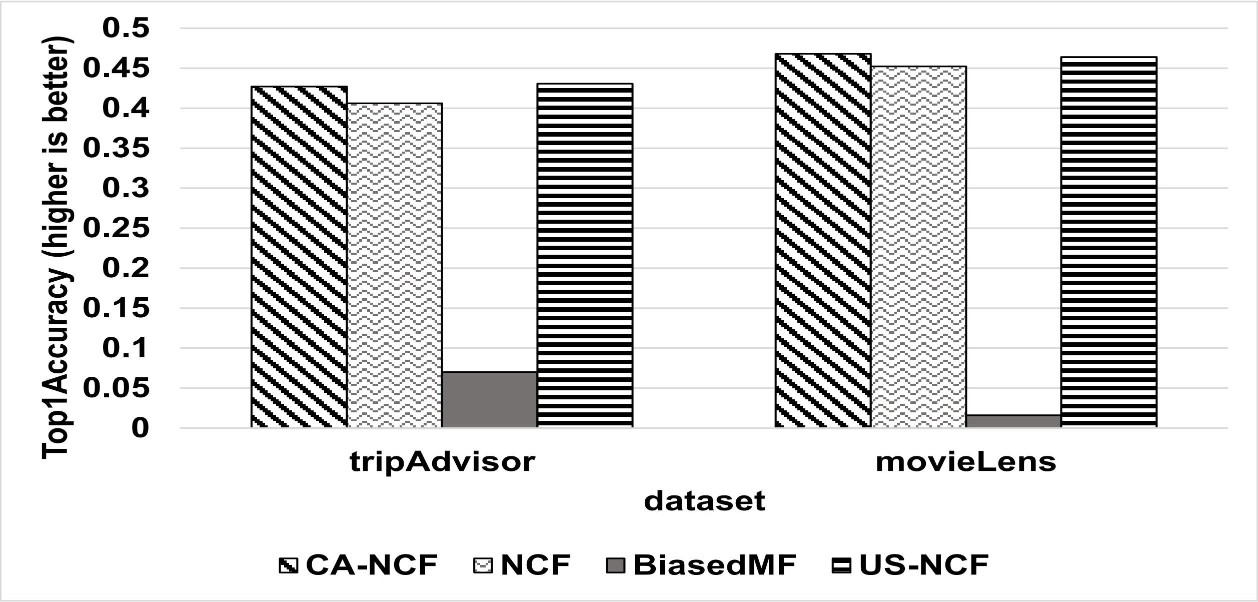
- our model US-NCF significantly surpasses several baselines. On average, a gain that equals 1.8% was obtained compared to plain NCF, slightly better that that obtained when applying the state of art CA-NCF.
- A higher gain is obtained when comparing US-NCF with conventional context-free model, specifically BiasedMF, where we obtain, on average, a gain that equals roughly 13.3%.

Validation loss of US-NCF Vs. NCF against ‘number of iterations’ on MovieLens 1M dataset.



- , averaged from 100 running sessions. On average, we got roughly 1.2% loss gain because of applying US-NCF instead of the stock version NCF.

Top1Accuracy US-NCF against baselines on all datasets



- US-NCF compares favorably to the baselines. We roughly obtain 4% and 90% when comparing US-NCF to the context-free plain NCF and BiasedMF, respectively. This signifies the importance of incorporating contexts in RSs. Also, it suggests that even context-free deep-learning based RSs perform better than traditional counterparts. The novel method US-NCF performs similarly when comparing it with the item-based state-of-art context-aware RS (CA-NCF).

Concluding remarks

- Incorporating context information into social recommender systems is important for generating more personalized recommendations.
- US-NCF is favorable over CA-NCF for social recommender systems. It is designed to model user's contexts, whereas CA-NCF was designed to model item's context.
- For SRSs, it is the relationships between the users that is the center of the analysis, not between items.
- The state-of-art method CA-NCF incorporates contexts with items of the plain NCF, thus recovering an item-based NCF, whereas the novel method US-NCF incorporates context into users, thus recovering a user-based version of NCF.
- A future work would include testing other pre-filtering approaches such as User-Item-Splitting, which combines the benefits of user-splitting and item-splitting.

Q&A and Contacts

Thanks for your attention!

Question's time...

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