Revisiting Neighbourhood-Based Recommenders for Temporal Scenarios

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Preliminaries

- Classical nearest neighbourhood-based approach
  - Rating aggregation from the *k* most similar users:

$$\hat{r}_{ui} = \frac{\sum_{v \in N_i(u)} r_{vi} w_{uv}}{\sum_{v \in N_i(u)} |w_{uv}|}$$

  - A similarity function is used to weight the rating and to select the closest users
  - Different rating normalisations can be applied

Main idea

- How can we incorporate time in kNN recommenders?
- Several options in the literature:
  - Contextual filtering: pre and post [Baltrunas & Amatriain 2009] [Adomavicius & Tuzhilin 2015]
  - Adaptive heuristics: using a function to penalise older preferences
    - For rating prediction [Ding & Li 2005]
    - For similarity computation [Hermann 2010]
  - Selecting *k* dynamically [Lathia et al 2009]

Proposal

- Reformulate the kNN problem so the temporal dimension can be exploited intuitively
  - Each neighbour provides a list of suggestions for each user
  - These suggestions are later combined considering rank aggregation techniques from Information Retrieval
  - The temporal aspect can be considered at different stages
- This approach provides an intuitive rationale about what is being recommended and why

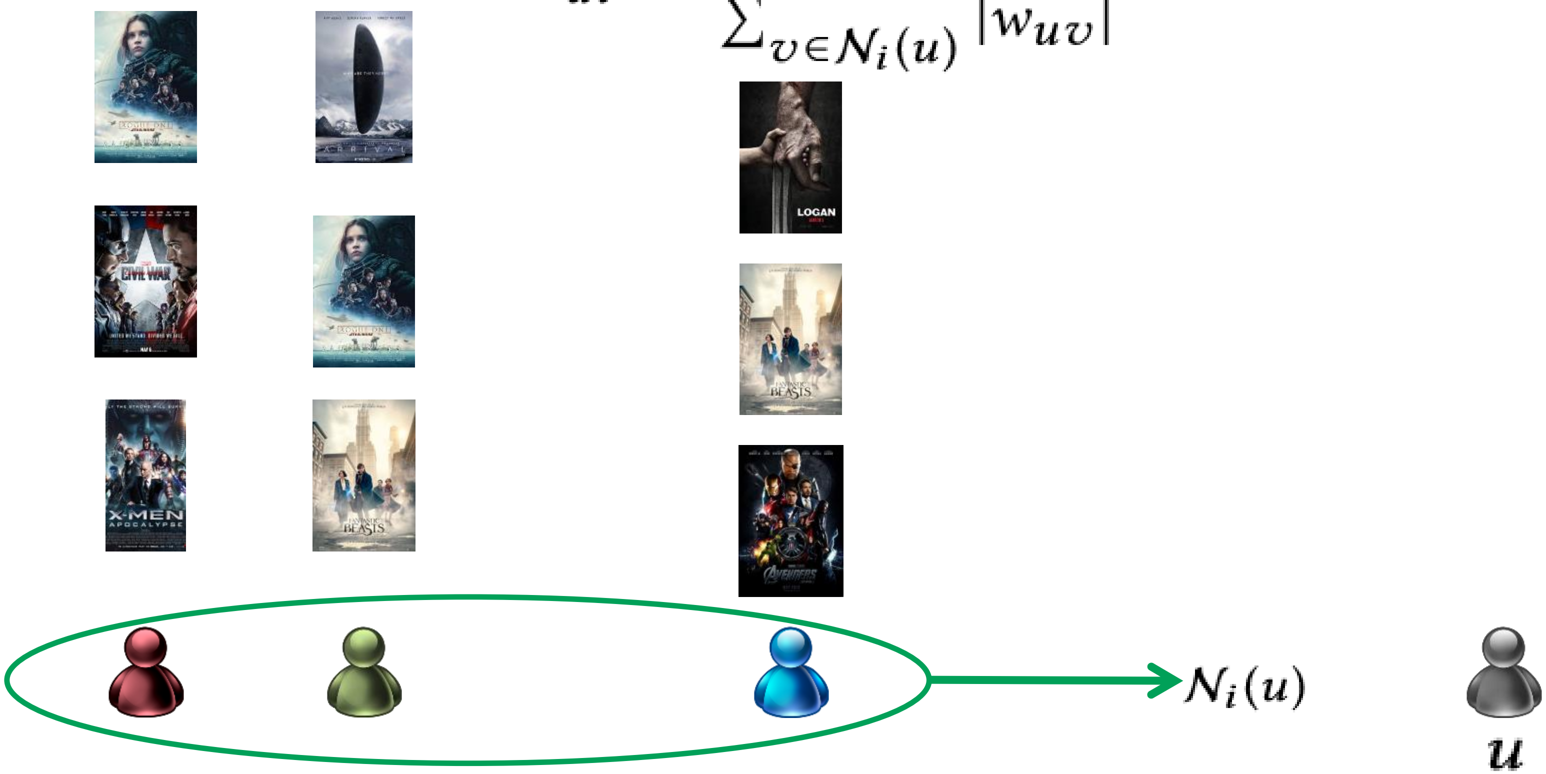
Background: Rank aggregation

- Each algorithm (*judge*, e.g., a search engine in IR) generates a document ranking
- A final ranking has to be returned
- The process is usually divided in
  - Normalisation: scores or ranks from each judge to a document are normalised in a common scale
  - Combination: a fused score is computed for every document

kNN as rank aggregation

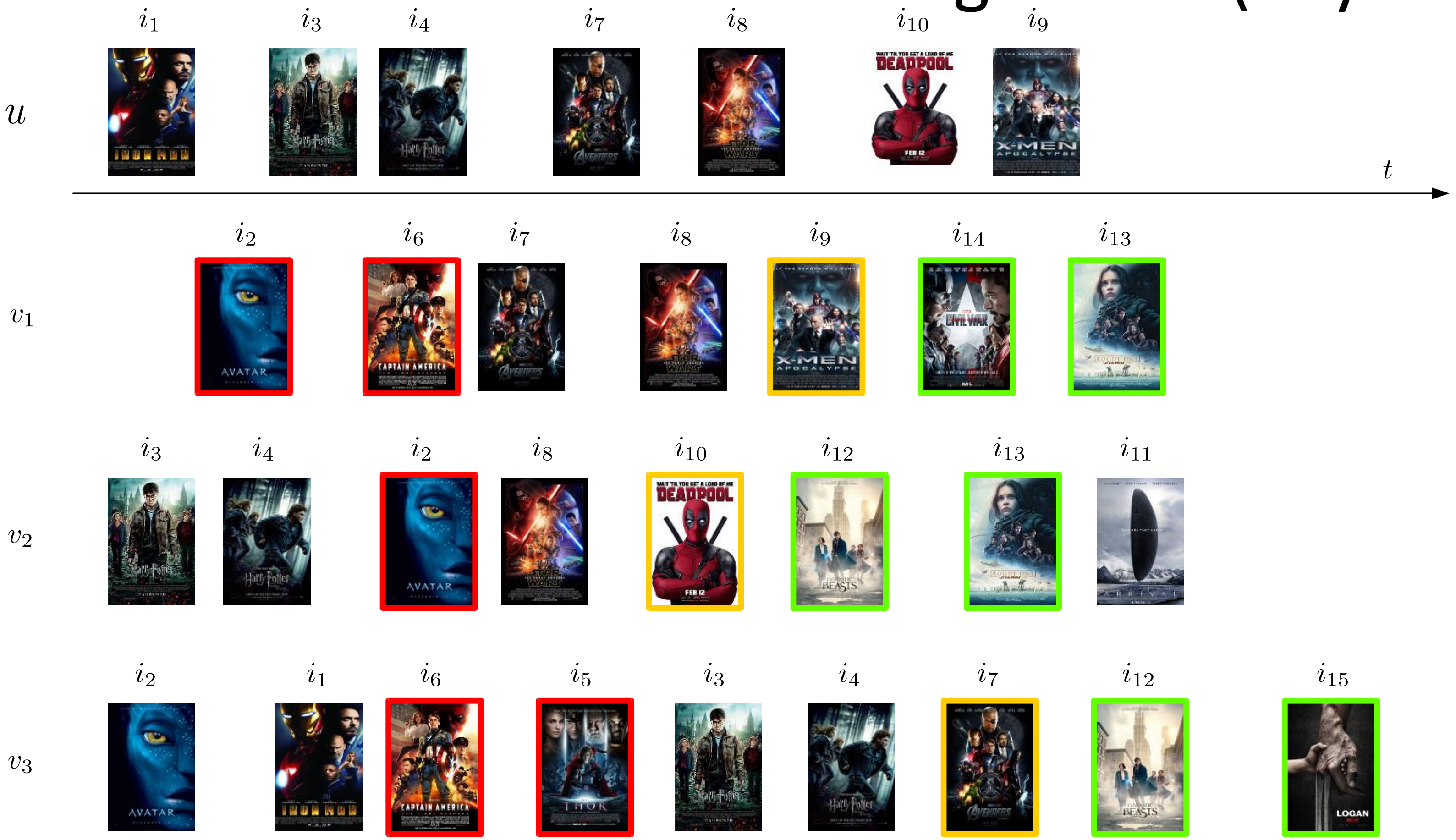
- The kNN problem can be seen as "ask each neighbour to provide a list of candidate items"

$$\hat{r}_{ui} = \frac{\sum_{v \in N_i(u)} r_{vi} w_{uv}}{\sum_{v \in N_i(u)} |w_{uv}|}$$



Incorporating time in kNN

- Each neighbour will only provide items **around** the last item interacted with the target user (in yellow)



Incorporating time in kNN

- Each neighbour will only provide items **around** the last item interacted with the target user
  - Most recent *m* items <u>after</u> the interaction: Forward (F)
  - Most recent *m* items <u>before</u> the interaction: Backward (B)
  - A combination: Backward-Forward (BF)

- Time is considered twice:
  - Involving the target user (last common interaction)
  - Exploiting how the neighbour interacted with the items (temporal order)

Experiments

- Dataset: Epinions (from [He & McAuley 2016]), very sparse (0.004%), unbiased sample

- Evaluation methodologies (temporal split)
  - **CC**: same timestamp for everyone (more realistic), 80% of data as training
  - Fix: last 2 actions of each user (with at least 4 actions) are included in the test split

Experiments

- Baselines
  - ItemPop
  - KNN: kNN for ranking (no normalisation) using Jaccard coefficient
  - TD: exponential time decay weight
  - FMC: factorised Markov chains
  - FPMC: factorised personalised Markov chains
  - Fossil: factorised sequential prediction with item similarity models
- The first 3 baselines were implemented in RankSys
- We use the implementation provided by the authors for the rest

Results: CC split – Baselines

- KNN is one of the best baselines
- TD does not improve unless many items are considered
- Fossil is the best performing one among the sequential-based baselines

Method	Precision@5	nDCG@5	Recall@5	nDCG@10	Precision@50	Recall@50	cvg	Δ wrt KNN	Δ wrt Fossil
ItemPop	1.81E-04	8.89E-04	2.25E-03	1.21E-03	**3.80E-04**	**4.69E-02**	100.00%	-144.08%	-36.88%
KNN	2.29E-04	2.17E-03	2.17E-03	2.94E-03	4.59E-05	4.34E-03	100.00%	–	43.92%
TD	2.29E-04	2.17E-03	2.17E-03	2.17E-03	6.88E-05	6.51E-03	100.00%	0.00%	43.92%
FMC	0.00E+00	0.00E+00	0.00E+00	4.49E-04	2.69E-05	1.22E-03	85.21%	NA	NA
FPMC	0.00E+00	0.00E+00	0.00E+00	0.00E+00	2.69E-05	1.22E-03	85.21%	NA	NA
Fossil	2.69E-04	1.22E-03	2.43E-03	1.22E-03	2.69E-05	2.43E-03	85.21%	-78.31%	–
BFuCF	2.29E-04	2.17E-03	2.17E-03	2.17E-03	6.88E-05	4.49E-03	100.00%	0.00%	43.92%
BFwCF	**4.59E-04**	**3.10E-03**	**4.34E-03**	**3.10E-03**	9.17E-05	6.66E-03	100.00%	30.10%	60.80%

Results: CC split – Backward-Forward

- BF performs better than F or B alone (not shown)
- BF coverage is the same as KNN (same similarity)
- Better performance than KNN in all metrics
- In this split, BFwCF (where each neighbour is weighted by the similarity) outperforms BFuCF

Method	Precision@5	nDCG@5	Recall@5	nDCG@10	Precision@50	Recall@50	cvg	Δ wrt KNN	Δ wrt Fossil
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Conclusions

- A new formulation for neighbourhood-based recommenders is presented
  - Bitbucket repo: PabloSanchezP/bfrecommendation
- This formulation allows to integrate the temporal information in different parts of the algorithm
- Large performance improvements are obtained with respect to classical kNN methods and sequential-based baselines
  - These results depend on the splitting strategy
  - Results are more positive for the more realistic strategy (CC)

Future work

- Explore more aggregation (normalisation and combination) functions
- Analyse effect in other datasets
- Compare against other baselines (SVD++, BPR, …)
- Study sensitivity to the number *m* of items each neighbour includes in the ranking
- Explore sequence-aware similarity metrics
  - The temporal dimension could be also considered when selecting the neigbours
  - We are working on applying Longest Common Subsequence to recommendation [Bellogín & Sánchez 2017]

Thank you

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References

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- [Hermann 2010] Time-based recommendations for lecture materials. EMHT
- [Lathia et al 2009] Temporal collaborative filtering with adaptive neighbourhoods. SIGIR

Results: Fix split – Baselines

- KNN is one of the best baselines
- TD does not improve the performance
- ItemPop is the best one when several items are considered
- Fossil is **not** the best performing one among the sequential-based baselines

Method	Precision@5	nDCG@5	Recall@5	nDCG@10	Precision@50	Recall@50	cvg	Δ wrt KNN	Δ wrt Fossil
ItemPop	3.32E-04	1.28E-03	1.74E-03	2.12E-03	**4.06E-04**	**2.19E-02**	100.00%	-200.02%	-5.48%
KNN	**1.05E-03**	3.84E-03	**5.56E-03**	**4.94E-03**	3.83E-04	2.05E-02	97.20%	–	64.84%
TD	3.15E-04	1.09E-03	1.99E-03	1.62E-03	2.97E-04	1.68E-02	97.20%	-252.10%	-23.79%
FMC	4.34E-04	1.39E-03	2.42E-03	2.27E-03	2.91E-04	1.57E-02	100.00%	-176.32%	2.85%
FPMC	4.08E-04	1.08E-03	1.93E-03	1.67E-03	2.20E-04	1.10E-02	100.00%	-255.14%	-24.86%
Fossil	3.32E-04	1.35E-03	1.64E-03	2.28E-03	2.60E-04	1.38E-02	100.00%	-184.43%	–
BFuCF	**1.05E-03**	**3.89E-03**	**5.56E-03**	4.75E-03	3.62E-04	1.96E-02	97.20%	1.39%	65.33%
BFwCF	9.46E-04	3.48E-03	4.96E-03	4.65E-03	3.55E-04	1.91E-02	97.20%	-10.50%	61.15%

Results: Fix split – Backward-Forward

- BF performs better than F or B alone (not shown)
- BF coverage is the same as KNN (same similarity)
- Better performance than KNN in most metrics for BFuCF
- In this split, BFuCF outperforms BFwCF (the opposite of what we observed in CC)

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BFwCF	9.46E-04	3.48E-03	4.96E-03	4.65E-03	3.55E-04	1.91E-02	97.20%	-10.50%	61.15%