



POPULARITY DOES NOT ALWAYS MEAN TRIVIALITY

HOW THE INTRODUCTION OF POPULARITY CRITERIA CAN
IMPROVE A RECOMMENDER SYSTEM PERFORMANCE

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Recommender Systems

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- Aim: suggest items that might be interesting for a user

Recommender Systems

3

- Aim: suggest items that might be interesting for a user
- Analyze the items a user previously evaluated or considered

Recommender Systems

4

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Popularity in Recommender Systems

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- Items' popularity is an aspect widely studied in this context

Popularity in Recommender Systems

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- Items' popularity is an aspect widely studied in this context
- Good to identify items of potential interest to the users

Popularity in Recommender Systems

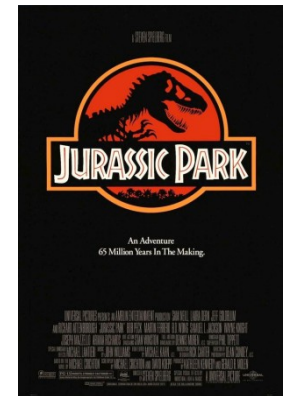
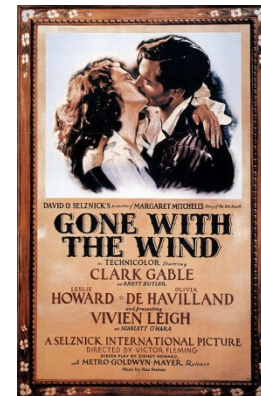
7

- Items' popularity is an aspect widely studied in this context
- Good to identify items of potential interest to the users
- ...but too trivial to produce interesting recommendations

Popularity in Recommender Systems

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- Items' popularity is an aspect widely studied in this context
- Good to identify items of potential interest to the users
- ...but too trivial to produce interesting recommendations
- E.g., the *non-personalized model* [Cremonesi et al.] recommends a fixed list of popular items to all the users



Intuition

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- Popularity can give us useful information

Intuition

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 - **Not** in the filtering/prediction process
 - **But** in the decision making process

Intuition

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Intuition

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 - **Use** a state-of-the-art approach of recommendation
 - **Re-rank** its results by considering the item popularity

Intuition

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1

Welcome Stranger

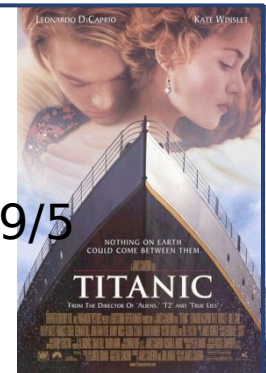
Predicted rating: 4.9/5



2

Titanic

Predicted rating: 4.9/5



Intuition

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Titanic

Predicted rating: 4.9/5



2

Welcome Stranger

Predicted rating: 4.9/5



Our strategy

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□ Novel recommendation approach

1. Build the predictions with the state of the art in recommender systems (SVD++)

$$\begin{array}{c} X \\ \left(\begin{array}{cccc} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & \\ \vdots & \vdots & \ddots & \\ x_{m1} & & & x_{mn} \end{array} \right) \\ m \times n \end{array} = \begin{array}{c} U \\ \left(\begin{array}{ccc} u_{11} & \dots & u_{1r} \\ \vdots & \ddots & \\ u_{m1} & & u_{mr} \end{array} \right) \\ m \times r \end{array} \begin{array}{c} S \\ \left(\begin{array}{ccc} s_{11} & 0 & \dots \\ 0 & \ddots & \\ \vdots & & s_{rr} \end{array} \right) \\ r \times r \end{array} \begin{array}{c} V^T \\ \left(\begin{array}{ccc} v_{11} & \dots & v_{1n} \\ \vdots & \ddots & \\ v_{r1} & & v_{rn} \end{array} \right) \\ r \times n \end{array}$$

Our strategy

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1. Build the predictions with the state of the art in recommender systems (SVD++)
2. Calculate the frequency of evaluation of an item (*Domain Popularity Index, DPI*)

$$\begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & \\ \vdots & \vdots & \ddots & \\ x_{m1} & & & x_{mn} \end{pmatrix} \begin{matrix} X \\ m \times n \end{matrix} = \begin{pmatrix} u_{11} & \dots & u_{1r} \\ \vdots & \ddots & \\ u_{m1} & & u_{mr} \end{pmatrix} \begin{matrix} U \\ m \times r \end{matrix} \begin{pmatrix} s_{11} & 0 & \dots \\ 0 & \ddots & \\ \vdots & & s_{rr} \end{pmatrix} \begin{matrix} S \\ r \times r \end{matrix} \begin{pmatrix} v_{11} & \dots & v_{1n} \\ \vdots & \ddots & \\ v_{r1} & & v_{rn} \end{pmatrix} \begin{matrix} V^T \\ r \times n \end{matrix} + \text{DPI}$$

Our strategy

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□ Novel recommendation approach

1. Build the predictions with the state of the art in recommender systems (SVD++)
2. Calculate the frequency of evaluation of an item (*Domain Popularity Index, DPI*)
3. Recommendations are performed by using both the predicted rating and the DPI

$$\begin{pmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & \\ \vdots & \vdots & \ddots & \\ x_{m1} & & & x_{mn} \end{pmatrix}_{m \times n}^X = \begin{pmatrix} u_{11} & \dots & u_{1r} \\ \vdots & \ddots & \\ u_{m1} & & u_{mr} \end{pmatrix}_{m \times r}^U \begin{pmatrix} s_{11} & 0 & \dots \\ 0 & \ddots & \\ \vdots & & s_{rr} \end{pmatrix}_{r \times r}^S \begin{pmatrix} v_{11} & \dots & v_{1n} \\ \vdots & \ddots & \\ v_{r1} & & v_{rn} \end{pmatrix}_{r \times n}^{V^T} + \text{DPI} \Rightarrow \text{Recommendations}$$

Scientific contributions

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Scientific contributions

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- Novel recommendation approach (*Popularity-Based SVD++*, PBSVD++)

Scientific contributions

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- The employment of the popularity as a form of post-processing is novel
- Novel recommendation approach (*Popularity-Based SVD++*, PBSVD++)
- Evaluation on 3 real-world datasets
 - Our proposal outperforms the state-of-the-art recommendation approach (SDV++)

Our approach

Domain Popularity Index (DPI)

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$$DPI(i, U) = \frac{np_{i,U}}{\sum_{\forall j \in I} np_{j,U}}$$

Domain Popularity Index (DPI)

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Domain Popularity Index (DPI)

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- $np_{i,U}$ is the number of positive preferences expressed by all users U for an item i
- $DPI(i,U)$ represents the frequency of evaluation of the item w.r.t. the others

$$DPI(i,U) = \frac{np_{i,U}}{\sum_{\forall j \in I} np_{j,U}}$$

PBSVD++ Algorithm

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- Let $rating_{i,u}$ be a SVD++ prediction and R_u the list of recommended items

PBSVD++ Algorithm

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- Let $rating_{i,u}$ be a SVD++ prediction and R_u the list of recommended items
- We normalize it in a $[0,1]$ range:

$$STD(i, u) = \frac{rating_{i,u}}{\sum_{\forall j \in R_u} rating_{j,u}}$$

PBSVD++ Algorithm

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- Let $rating_{i,u}$ be a SVD++ prediction and R_u the list of recommended items
- We normalize it in a $[0,1]$ range:

$$STD(i, u) = \frac{rating_{i,u}}{\sum_{\forall j \in R_u} rating_{j,u}}$$

- The final rating will be:

$$\rho_{i,u} = STD(i, u) + \frac{DPI(i, U)}{\sum_{\forall j \in R_u} DPI(j, U)}$$

Experiments

Experiments

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- We validated our proposal with two experiments:

Experiments

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 1. Percentage of times we out-/under-performed SVD++

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Experiments

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Experiments

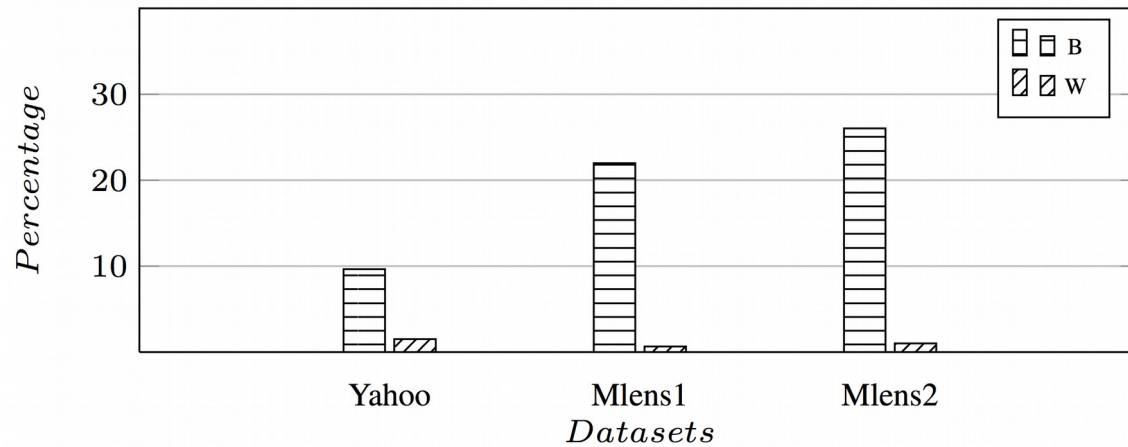
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- Measure
 - $F1@n$ (harmonic mean of Precision and Recall when n recommendations are generated)
 - We will present the difference of the F1 obtained by SVD++ and PBSVD++ ($F1\text{-variation}@n$)

Experiments

Results overview

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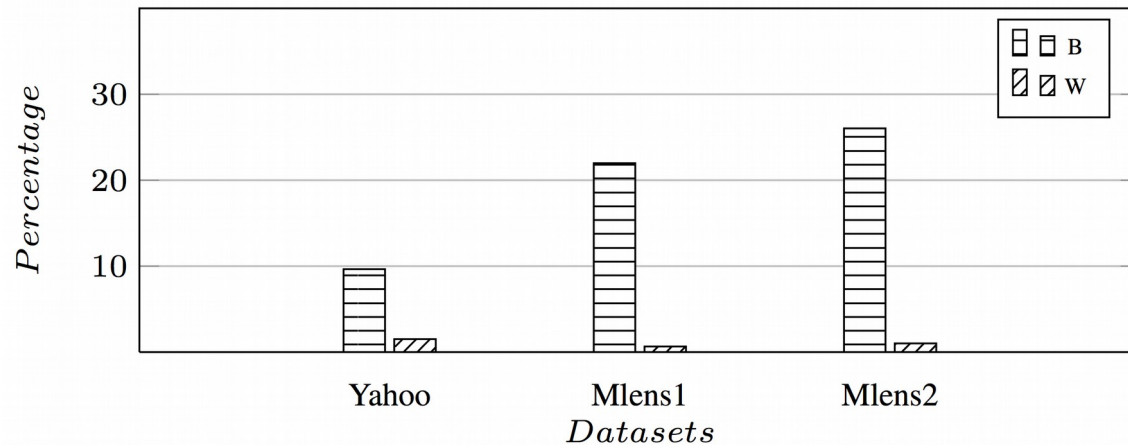


(a) General performance

Experiments

Results overview

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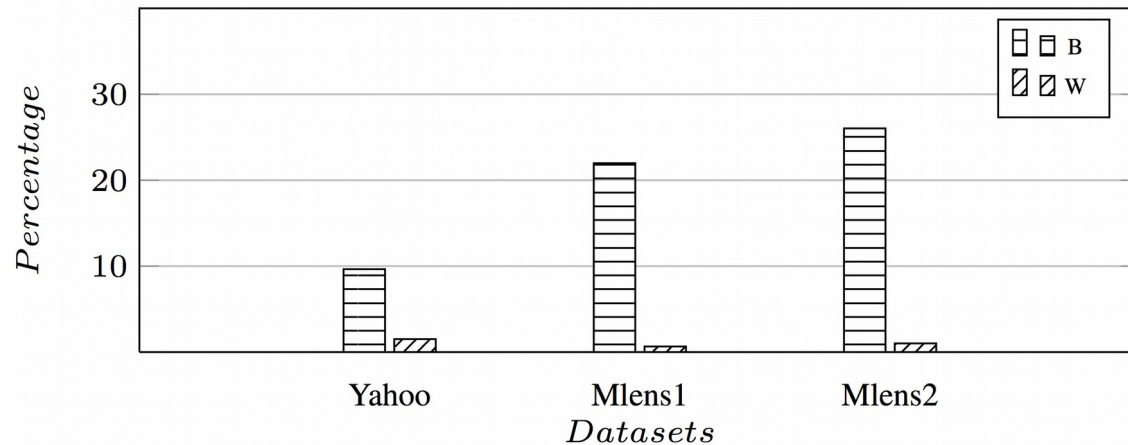
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- With all the three datasets, between 10 and 30% of the times our approach outperforms the state-of-the-art

Experiments

Results overview

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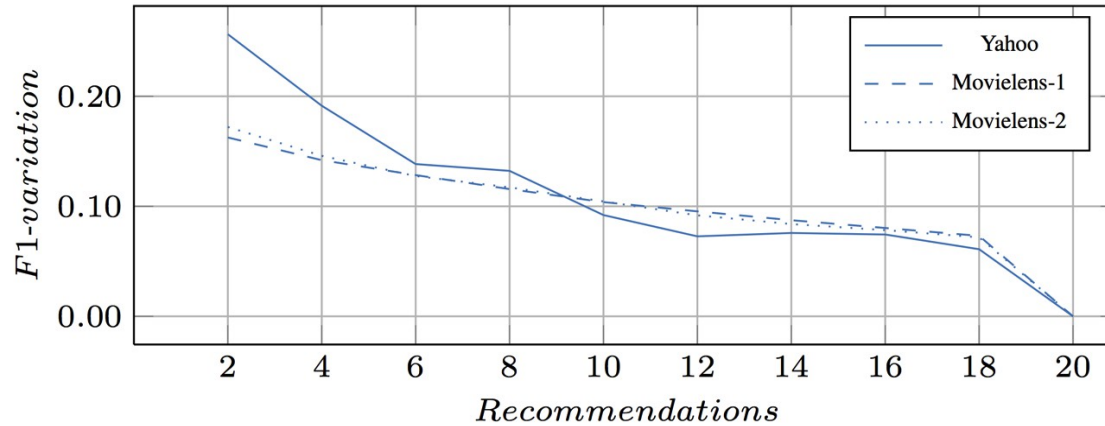
(a) General performance

- With all the three datasets, between 10 and 30% of the times our approach outperforms the state-of-the-art
- The additional information we employ for the re-ranking leads to significant improvements

Experiments

Improvement w.r.t. SDV++

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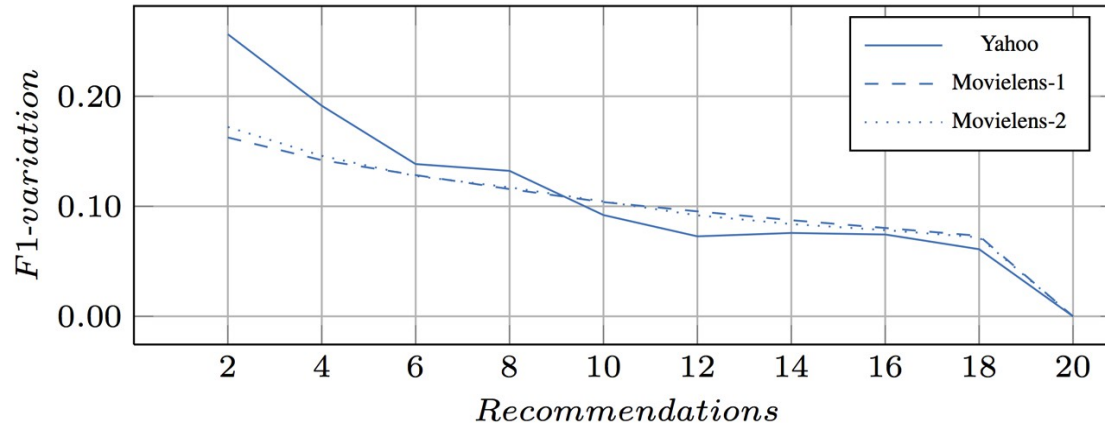


(b) F1-Measure@n

Experiments

Improvement w.r.t. SDV++

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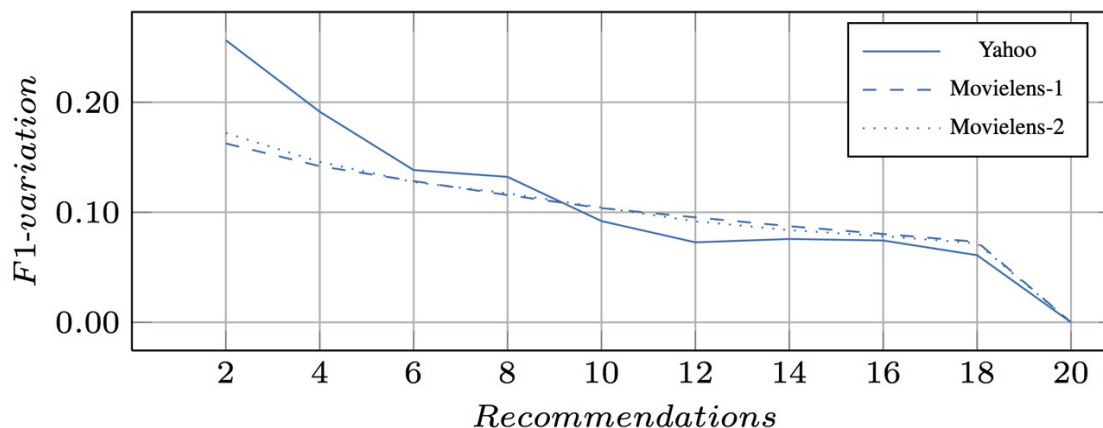
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- In all the three datasets there is a strong improvement (almost 30% for Yahoo and 2 recommended items)

Experiments

Improvement w.r.t. SDV++

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(b) F1-Measure@n

- In all the three datasets there is a strong improvement (almost 30% for Yahoo and 2 recommended items)
- No improvement with the maximum number of recommendations (i.e., 20)
 - No matter how you re-rank them, the recommended items are the same

Conclusions and future work

Conclusions

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- We proposed an algorithm (PBSVD++) that
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Conclusions

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- The popularity has proven to be a useful source of information in recommendation process
 - But do not lead to accurate suggestions
- We proposed an algorithm (PBSVD++) that
 1. employs the state of the art in recommendation (SVD++)
 2. integrates a popularity index to modify the rating and re-rank the results
- Experimental results show the capability of our approach to outperform SDV++

Future work

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- When an item belongs to more domains (e.g., movies with multiple genres) evaluate the popularity in each domain

Future work

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- When an item belongs to more domains (e.g., movies with multiple genres) evaluate the popularity in each domain
- Introduction of other popularity metrics
 - Geographic
 - Demographic
 - ...

Bibliography

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[Cremonesi et al.] Cremonesi, Y. Koren, and R. Turrin, “Performance of recommender algorithms on top-n recommendation tasks,” in *Proceedings of the 2010 ACM Conference on Recommender Systems*.