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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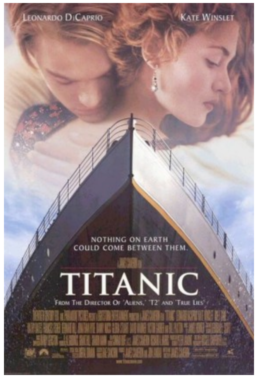
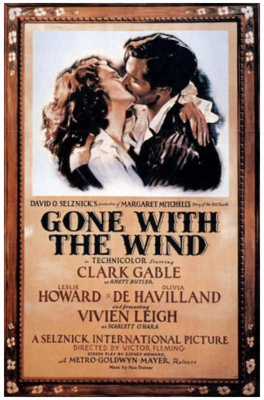
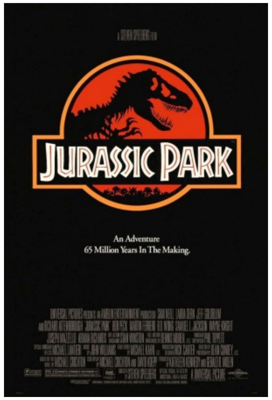
- Good to identify items of potential interest to the users
- …but too trivial to produce interesting recommendations
- E.g., the *non-personalized model* [Cremonesi et al.] recommends a fixed list of popular items to all the users







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Welcome Stranger
Predicted rating: 4.9/5

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Titanic
Predicted rating: 4.9/5

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Our strategy

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

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

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  3. Recommendations are performed by using both the predicted rating and the DPI

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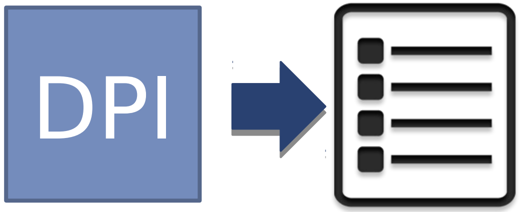

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- Novel recommendation approach (*Popularity-Based SVD*++, PBSVD++)
- Evaluation on 3 real-world datasets
  - Our proposal outperforms the state-of-the-art recommendation approach (SDV++)

Our approach

Domain Popularity Index (DPI)

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- DPI(i,U) represents the frequency of evaluation of the item w.r.t. the others

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- 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:

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

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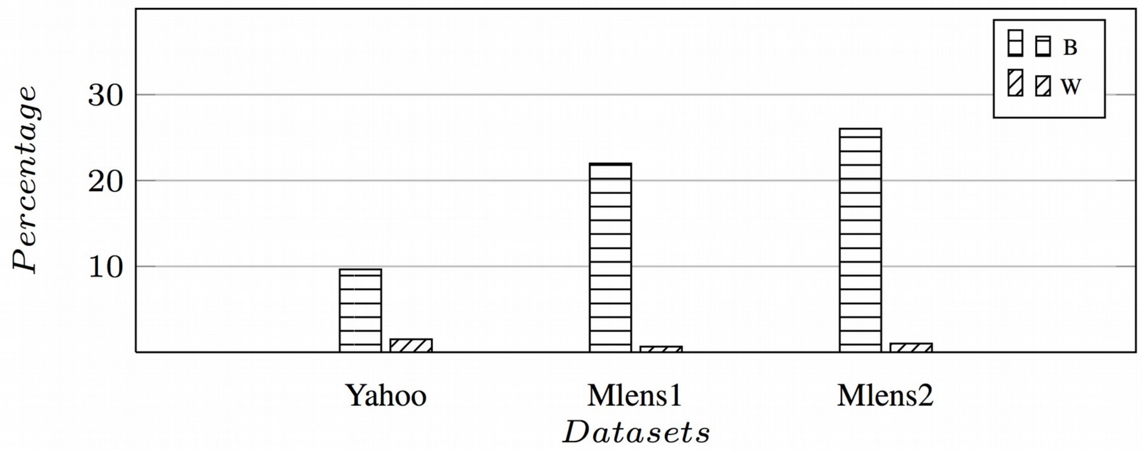
  - *F1@n* (harmonic mean of Precision and Recall when *n* recommendations are generated)
  - We will present the difference of the F1 obtained by SVD++ and PBSVD++ (*F1-variation@n*)

Experiments
Results overview



(a) General performance

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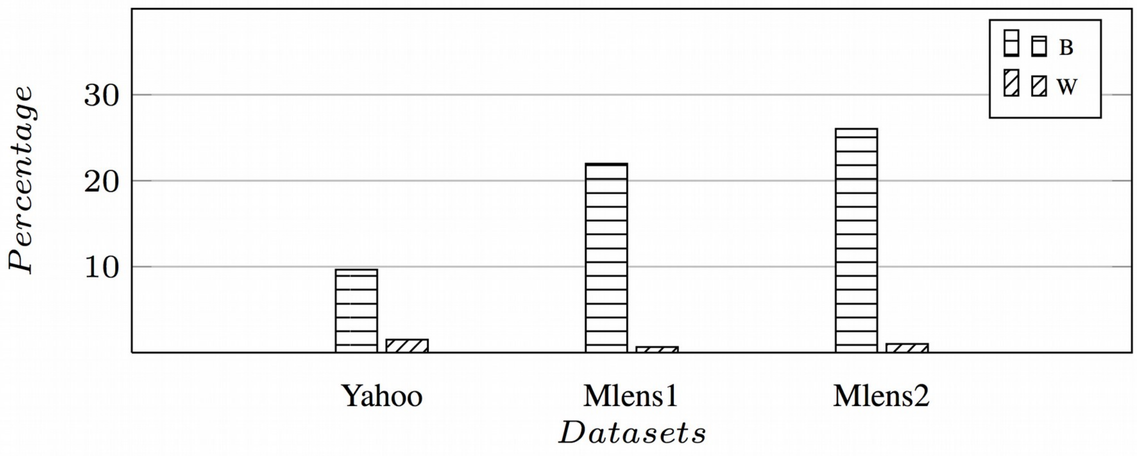

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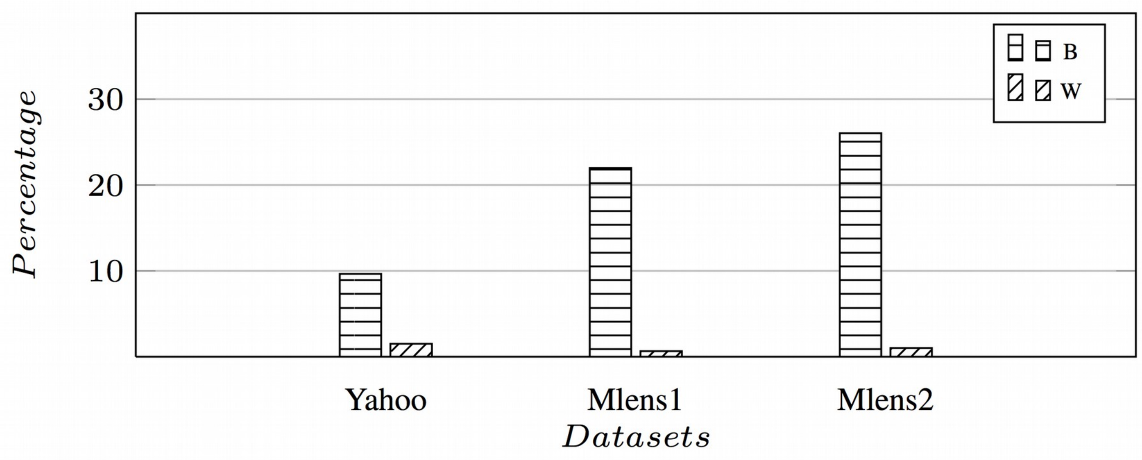

(a) General performance

- 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

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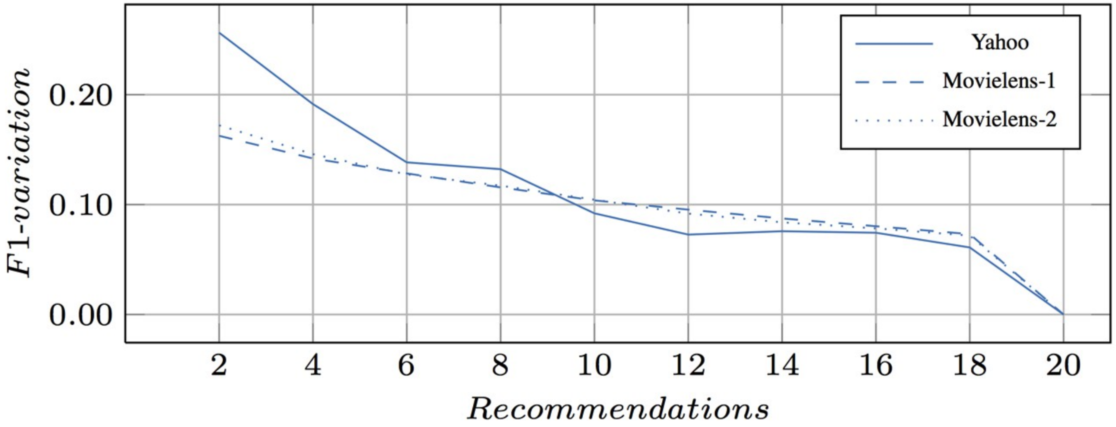
Improvement w.r.t. SDV++



(b) F1-Measure@n

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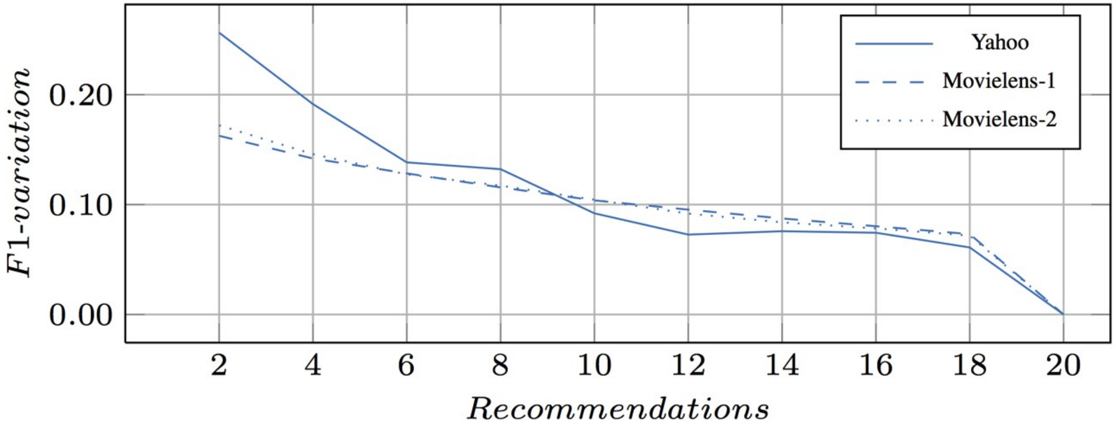

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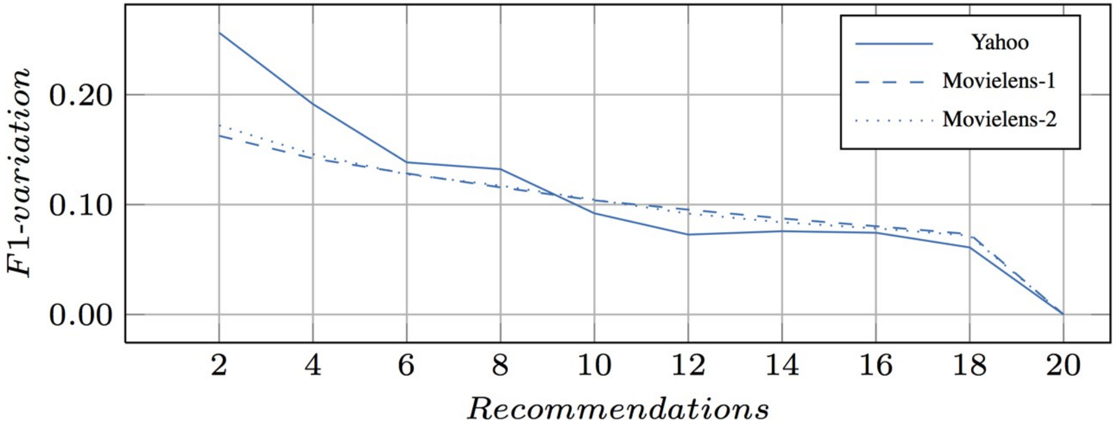

(b) F1-Measure@n

- 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

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- We proposed an algorithm (PBSVD++) that
  1. employs the state of the art in recommendation (SVD++)
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- Experimental results show the capability of our approach to outperform SDV++

Future work

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

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- Introduction of other popularity metrics
  - Geographic
  - Demographic
  - …

Bibliography

[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.*