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Insight

EVALUATING RECOMMENDER SYSTEMS

RELATIVE PERFORMANCE OF COLLABORATIVE FILTERING RECOMMENDER SYSTEMS

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21-09-2016

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RECOMMENDER SYSTEMS

Enable **content discovery**
by learning the user preferences and
exploiting the wisdom of the crowd.

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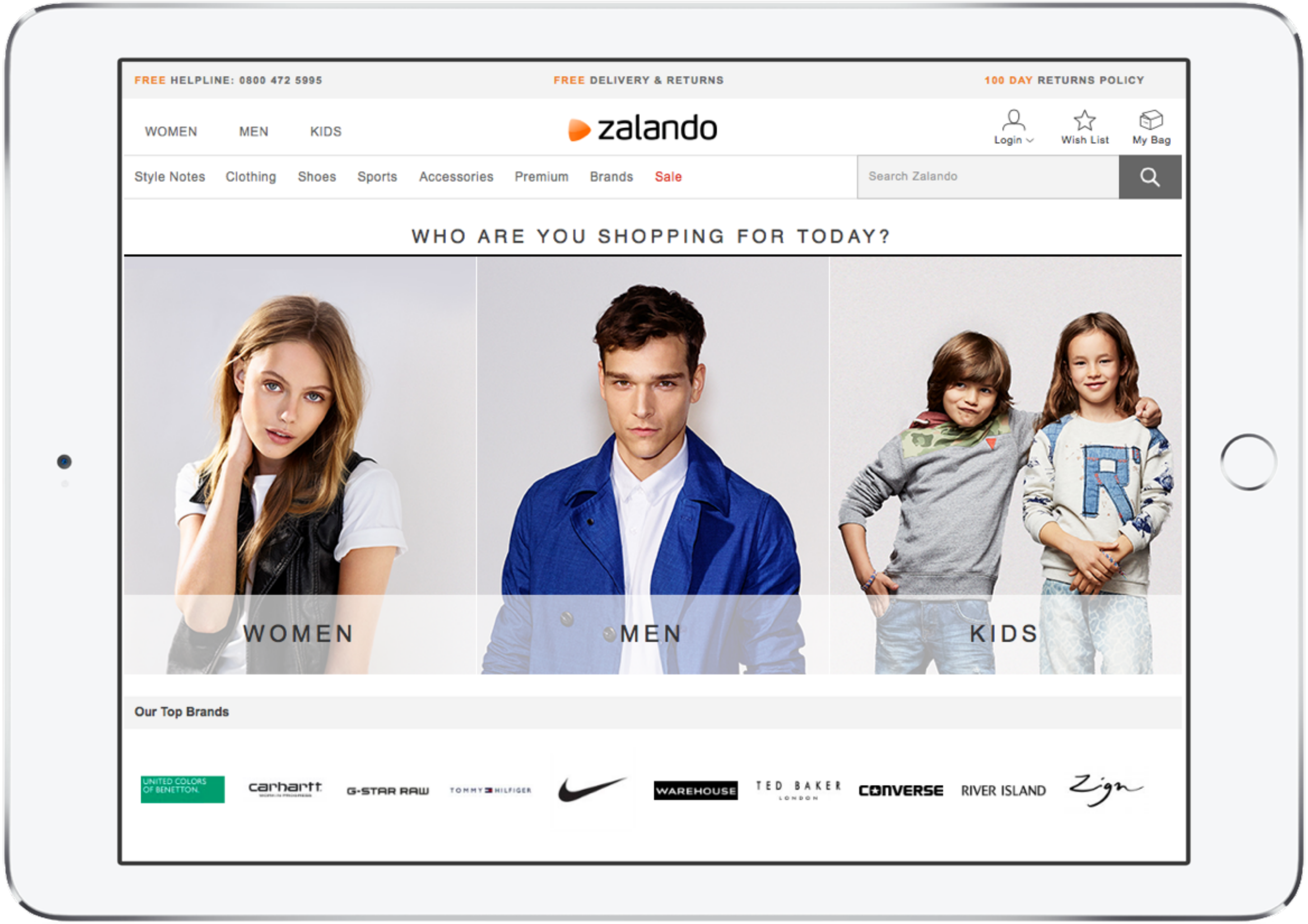
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RECOMMENDER SYSTEMS IN ZALANDO

RECOMMENDER SYSTEMS IN ZALANDO

https://www.zalando.co.uk/women-street-style/
https://www.zalando.co.uk/men-street-style/

A BIAS ANALYSIS

EXPERIMENT DESIGN

THE DATA

- FACEBOOK DATASET
- MOVIELENS - HETREC
- LASTFM - HETREC

- TRAINING DATA
- TESTING DATA
- 10 FOLD CROSSVALIDATION

THE MODELS

- UKNN
- IKNN
- WMF

- ACCURACY OPTIMISATION

EVALUATION

- ACCURACY
- BEYOND ACCURACY
- SIGNIFICANCE

THE DATASETS

Dataset	# users	# items	# ratings	Mean (std. dev.) ratings per user	Mean (std. dev.) ratings per item	Sparsity
FB	1,428	5,846	64,612	45 (49)	11 (26)	0.9923
LastFM	1,864	6,945	82,037	44 (7)	12 (32)	0.9937
ML	2,040	7,459	374,352	183 (187)	50 (110)	0.9754

Table 1: Summary statistics for the datasets after pre-processing.

FACEBOOK DATASET	MUSIC / BANDS
LASTFM - HETREC	MUSIC / BANDS
MOVIELENS - HETREC	MOVIES

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THE ALGORITHMS

USER BASED COLLABORATIVE FILTERING (UKNN)

- Find similar users
- word of mouth
- The neighbours paradigm
- Scales with number of users

ITEM-BASED COLLABORATIVE FILTERING (IKNN)

- Find similar items
- Scalable
- Widely used

MATRIX FACTORISATION (WEIGHTED)

- Latent Factors
- Really good accuracy
- Scalable
- Parallel computing
- Very accurate

EVALUATION METRICS

PRECISION

RECALL

F-1

DIVERSITY

POPULARITY

CATALOG COVERAGE

PER USER ITEM COVERAGE

UNIQUENESS

EVALUATION METRICS

- **PRECISION**: Out of the items recommended, how many are good recommendations?
- **RECALL**: How many of the items the user likes are being recommended?
- **F-1**: Mixes the properties of Precision and Recall into a single metric

- **DIVERSITY**: How different are the items in the list of the recommendations?
- **POPULARITY:** How popular are the items recommended
- **(PER USER) ITEM COVERAGE:** Proportion of items that are *candidates* for recommendations
- **CATALOG COVERAGE:** The proportion of items of the catalog that ever get recommended
- **UNIQUENESS:** How many items in two recommendation lists are different from each other?

RESULTS

	Algorithm	Pop	CCov (%)	UICov (%)	DIV	PRC	RCL	F-1
FB	Most Popular	0.500	0.684	98.957*	0.706*	0.066	0.089	0.076
	UKNN (**60**)	0.310	5.132	16.049	0.711	0.136	0.181	0.156*
	IKNN (**300**)	0.251*	27.386	40.478	0.672*	0.132	0.182	0.153*
	WMF (**20,20**)	0.254*	7.030	98.957*	0.747	0.155	0.202	0.176
LastFM	Most Popular	0.507	0.374	98.675*	0.654	0.068	0.073	0.070
	UKNN (**50**)	0.286	7.790	9.709	0.730	0.167	0.183	0.175*
	IKNN (**300**)	0.239	30.194	38.815	0.714	0.180	0.201	0.190^{+}
	WMF (**20,50**)	0.234	5.37	98.675*	0.788	0.180	0.196	0.188^{*+}
ML	Most Popular	0.282	0.724	99.464*	0.490	0.221	0.082	0.120
	UKNN (**140**)	0.104	1.823	46.130	0.519	0.294	0.110	0.160*
	IKNN (**300**)	0.095	3.365	50.611	0.527	0.284	0.106	0.154*
	WMF (**25,40**)	0.079	8.861	99.464*	0.603	0.344	0.133	0.191

Table 2: Comparison of the performance of the recommendation algorithms. Bold numbers indicate optimal algorithm parameter values (neighbourhood size for UKNN and IKNN, number of factors and number of iterations for WMF). Pairs of non statistically significant results are annotated with the symbols * or $^{+}$.

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RESULTS - POPULARITY BIAS

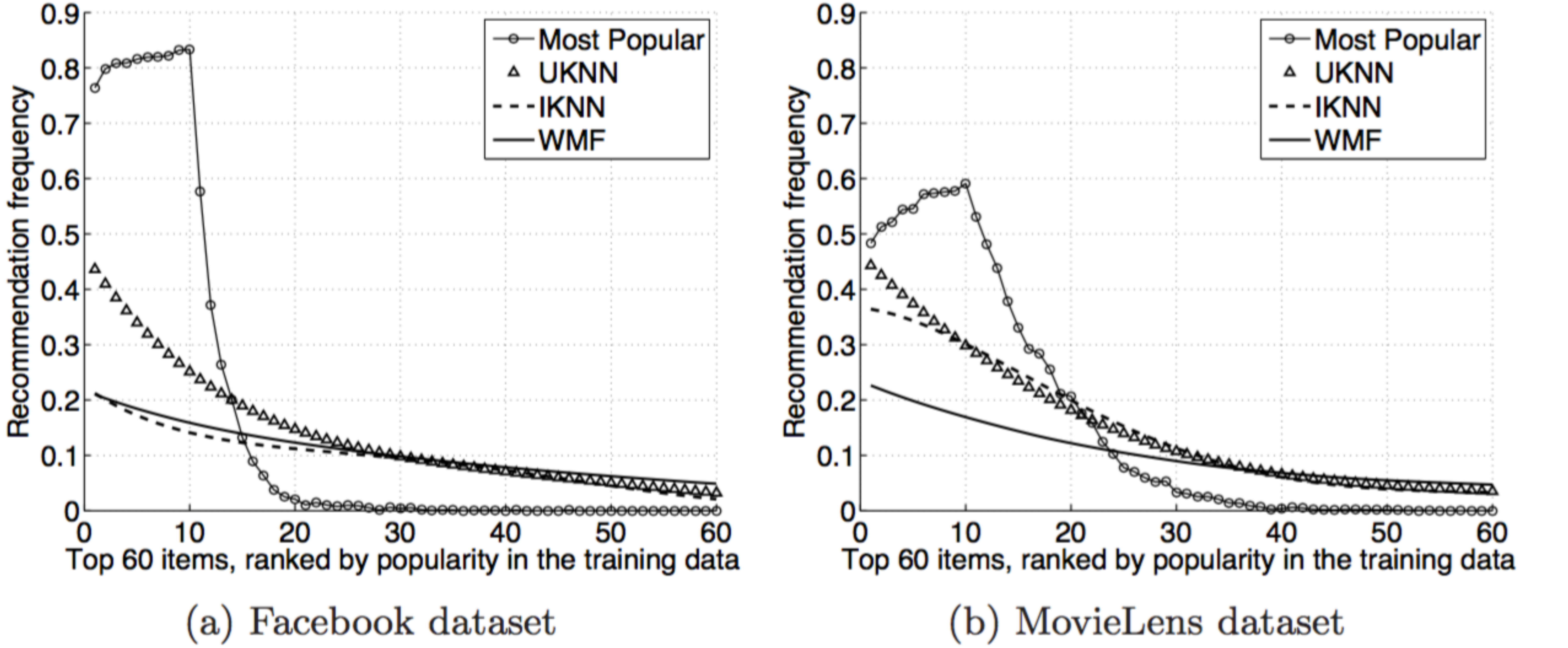


Figure 1: Recommendation frequency of the 60 most popular items. For clarity, *UKNN*, *IKNN* and *WMF* are approximated by a 5-degree polynomial function.

RESULTS - OTHER PROPERTIES

- **Accuracy**: WMF performs best in terms of F-1 for the Facebook and MovieLens datasets, while the accuracy of the UKNN and IKNN algorithms are similar.

- **Per-user item coverage**
  - WMF algorithm considers almost every item as a candidate (UICov > 98%).
  - The UKNN algorithm (by definition) only items which are in the user's neighbourhood can be considered as recommendation candidates. IKNN was seen to outperform UKNN in all datasets in terms of

- **Coverage**: the IKNN algorithm, performs significantly better than the other algorithms, covering up to 30% of the item catalog - Up to 6 times more items than the UKNN and WMF algorithms.

- **Diversity:** the WMF algorithm performs better, with a performance around 9% higher on average than the best neighbourhood-based approach

RESULTS - CONSISTENCY

- Important to evaluate in different datasets.
- MovieLens dataset, (3 times more dense than the Facebook and LastFM datasets), the catalog coverage of the IKNN algorithm is ~ 10 times smaller than for the LastFM and Facebook datasets.

ARE UKNN AND IKNN REALLY THAT DIFFERENT?

EXPERIMENT DESIGN

THE DATA

MOVIELENS - 100K

MOVIELENS - 1M

TRAINING DATA

TESTING DATA

10 ITEMS TEST SET

THE MODELS

UKNN

IKNN

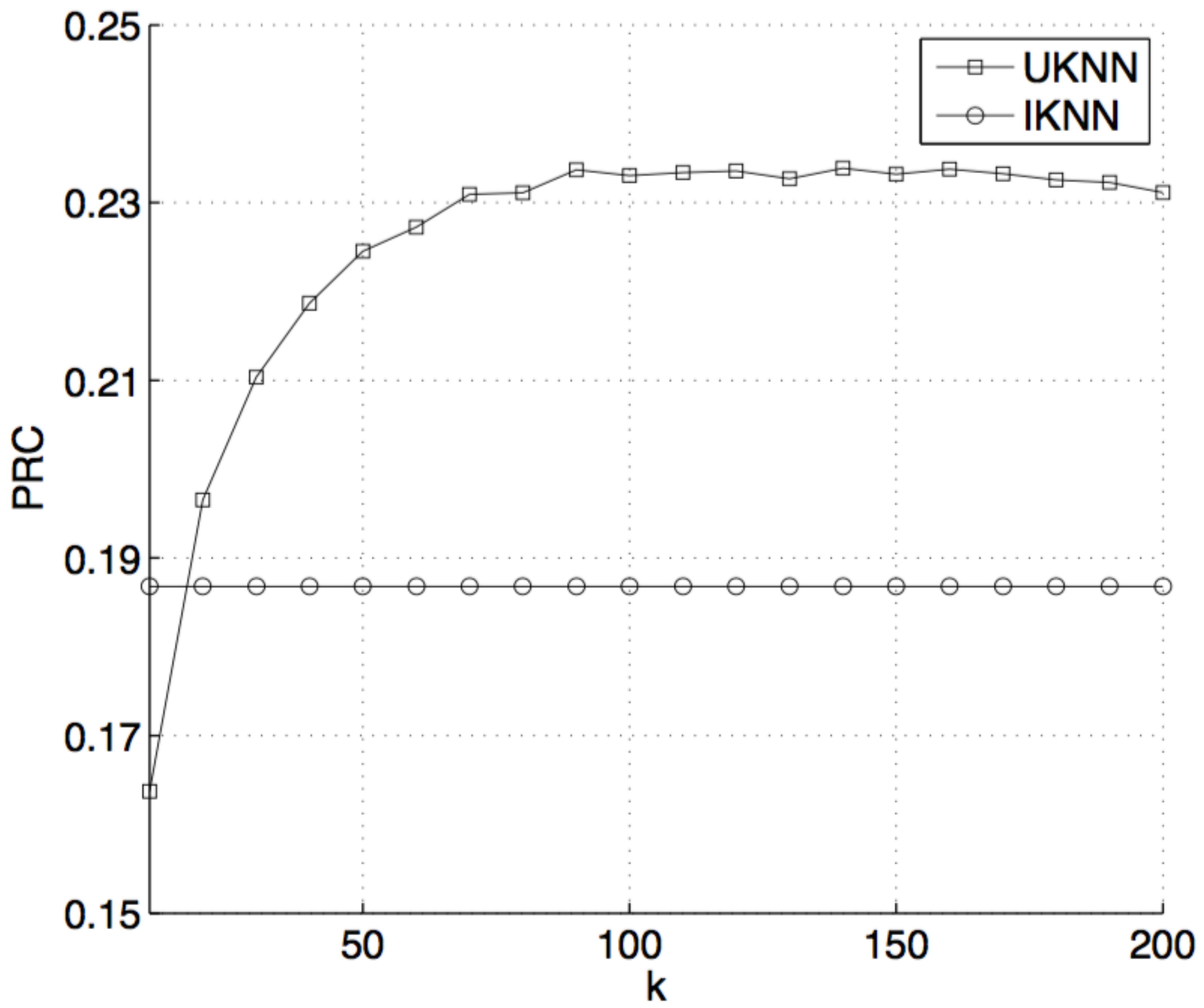
UKNN [20, 200]

IKNN FIXED

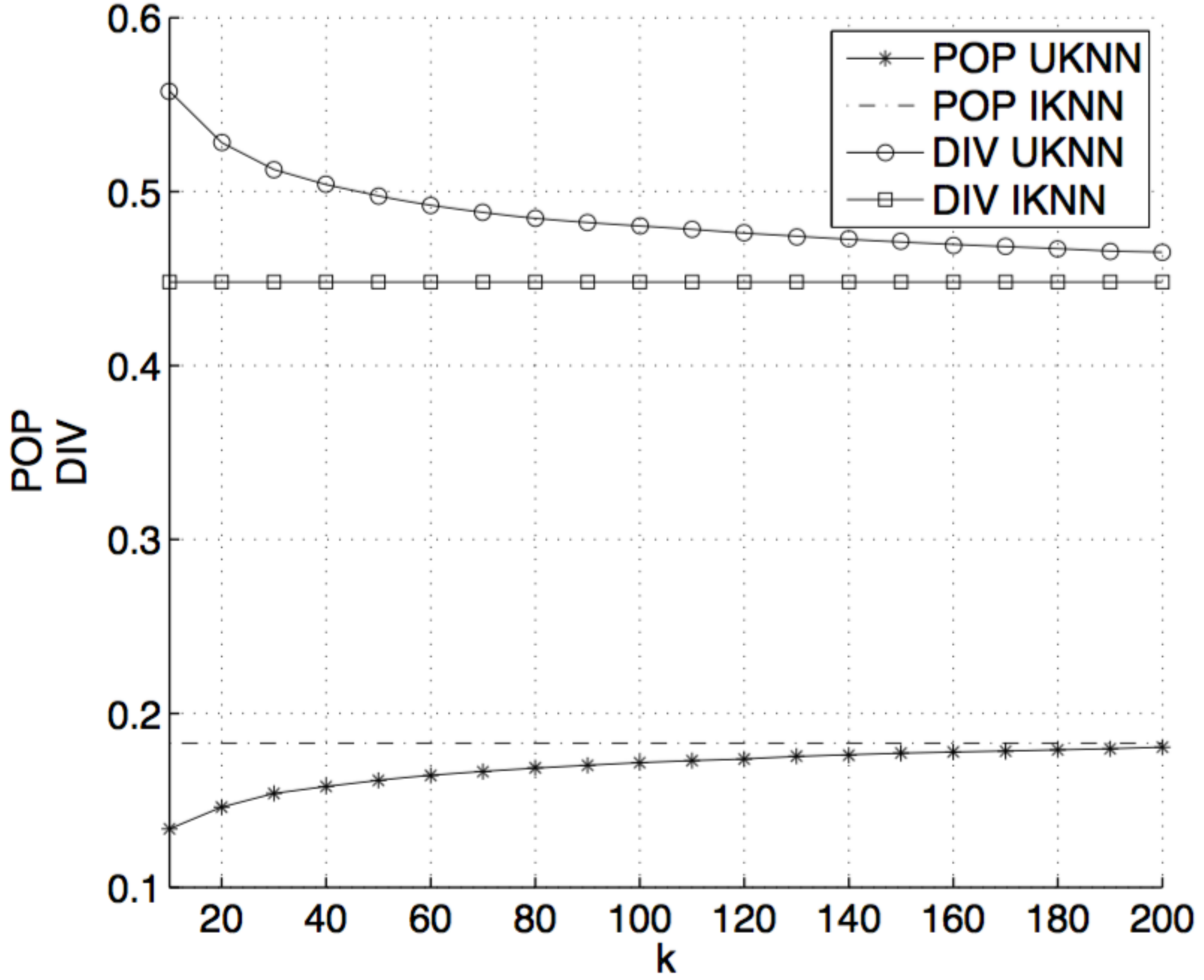
EVALUATION

ACCURACY

BEYOND ACCURACY

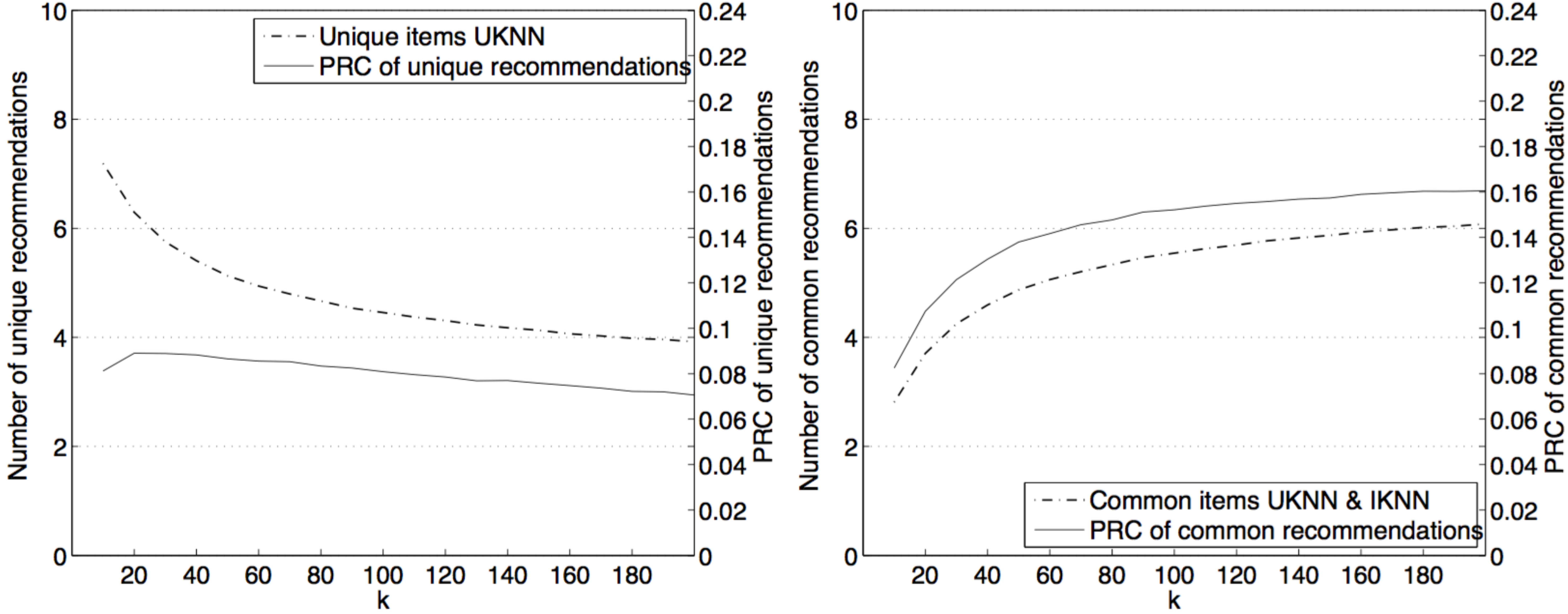


(a) Precision vs. neighbourhood size.



(b) POP and DIV vs. neighbourhood size.

A COMPARATIVE ANALYSIS



(c) Number and precision of unique *UKNN* recommendations vs. neighbourhood size.

(d) Number and precision of common recommended items vs. neighbourhood size.

Smaller neighbourhood sizes (for UKNN) lead to more unique, less popular, and more diverse recommendations.

SUMMARY

CONCLUSIONS

- User-based (UKNN) and item-based (UKNN) collaborative filtering algorithms have a high inverse correlation between popularity and diversity.
- Smaller neighbourhood sizes (for UKNN) lead to more unique, less popular, and more diverse recommendations.
- Recommend a common set of items at large neighbourhood sizes.

- Matrix factorisation approach (WMF) leads to more accurate and diverse recommendations, while being less biased toward popularity.
- item-based collaborative filtering (IKNN) has significantly better catalog coverage.

LESSONS LEARNED

- One size fits all is not true, **never, ever!**
- Use many metrics, even if you don't optimise for them
  - **They help understanding what is the model doing**
- Use various datasets (if you want to publish a paper) - **Do results generalise?**
- Understand what is the best proxy or dataset for your evaluation goal.

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