Factored MDPs for Detecting Topics of User Sessions

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DIPF
Educational Research and Educational Information

Traditional Item-to-Item

- A user views the following item:

- Task: Recommend an item that is likely to be clicked
- But: What's the reason for viewing that item?

Session-to-Item

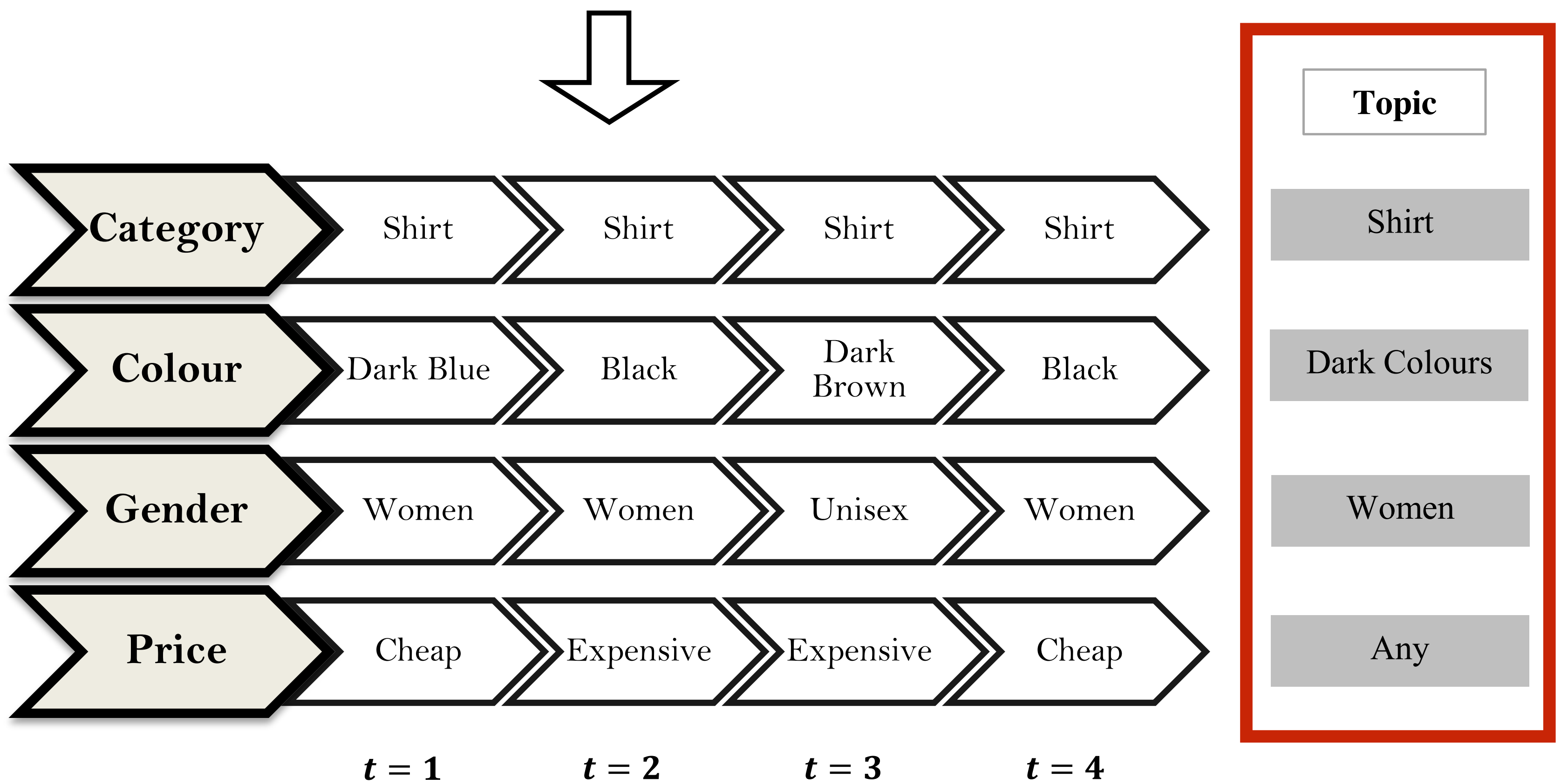
- A user views the following **sequence** of items:

- What is the user's goal of the session?
- Take a content-based approach!

Attribute View

	$t=1$	$t=2$	$t=3$	$t=4$
Category	Shirt	Shirt	Shirt	Shirt
Colour	Dark Blue	Black	Dark Brown	Black
Gender	Women	Women	Unisex	Women
Price	Cheap	Expensive	Expensive	Cheap

Attribute View



Markov Decision Processes

- 4-tuple $\langle S, A, R, P \rangle$
- Set of states S (last k viewed items/user clicks)
- Set of actions A (items)
- Reward function $R : S \times A \rightarrow \mathbb{R}$ (positive for clicks on recommended items)
- Transition probabilities $P : S \times A \times S \rightarrow [0, 1]$

Factored MDPs

- States decompose into **state variables**

$$S = X_1 \times X_2 \times \ldots \times X_n$$

colour brand price

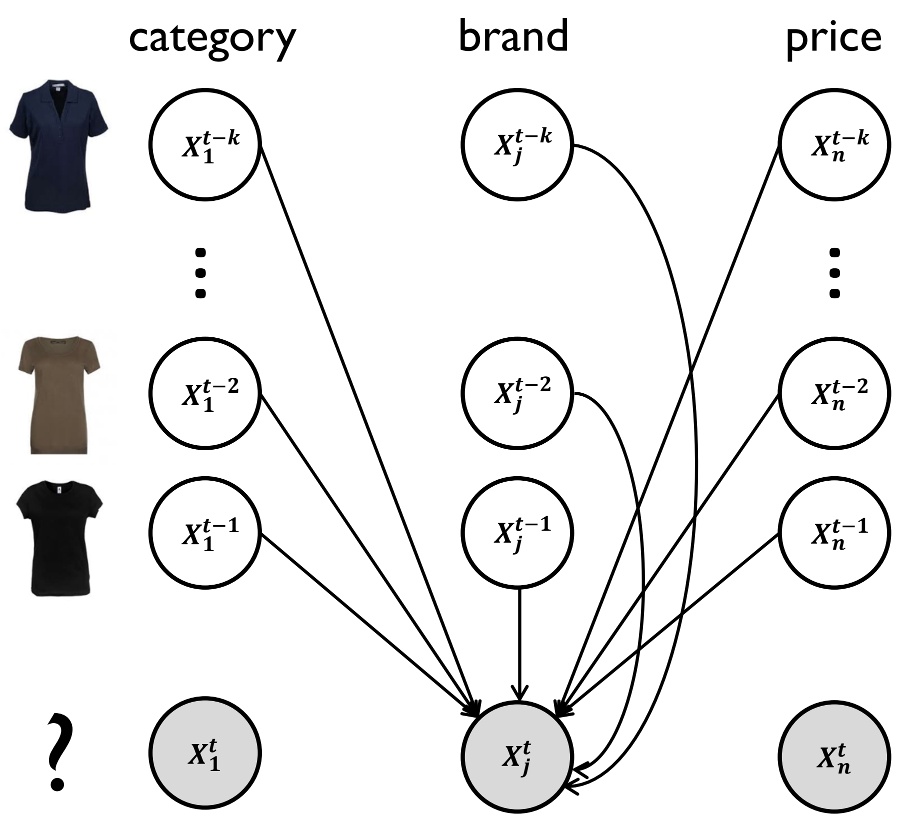
- Factorisation of probability distribution

$$P(S'|S,a) = \prod_{j=1}^{n} P(X'_j|parent(X'_j),a)$$

value of attribute j given all attributes of previous items

Attribute Independence

complete model infeasible



$$\mathcal{O}(d^n)$$

Attribute Independence

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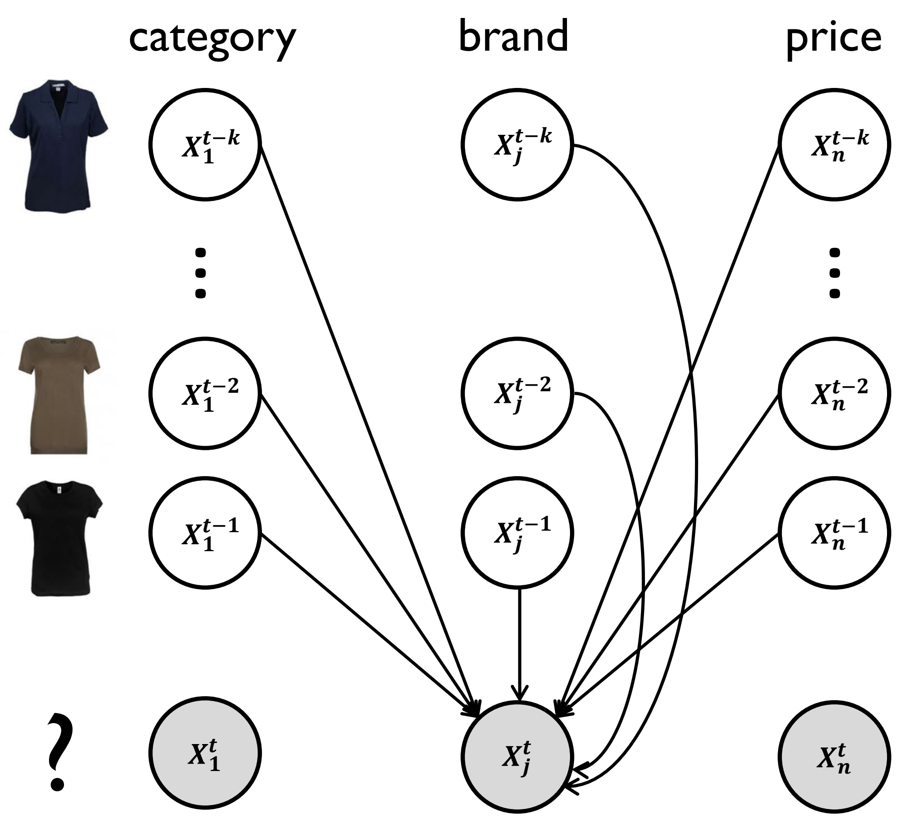
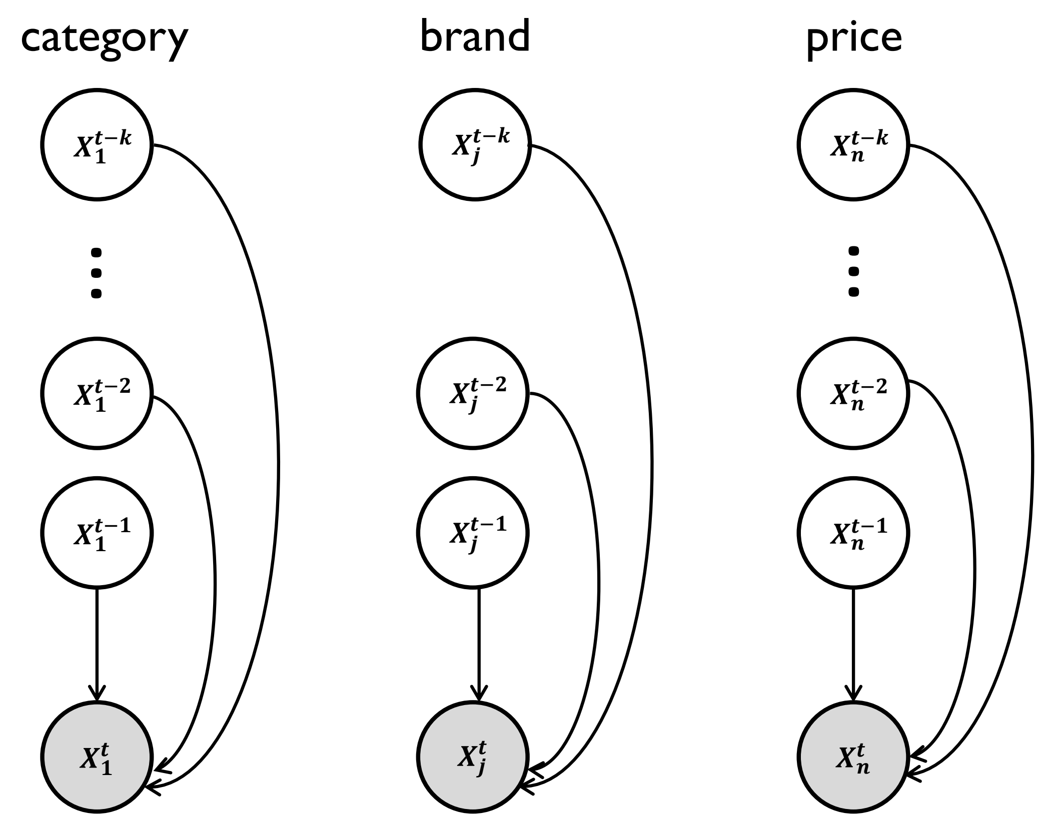


$$\mathcal{O}(d^n)$$

exploit independence



$$\mathcal{O}(dn)$$

(see theorem in the paper)

Exact and Approximate fMDPs

- Exact $P(x'|s,x)$ estimated by Maximum Likelihood
- Approximate (Shani et al., JMLR 2005)
  approximate $P(x|s,x) \approx \alpha P(x|s)$ and $P(x|s,x') \approx \beta P(x|s)$
- Optimisation by value iteration

$$Q(s_t, x_t) = R(s_t, x_t) + \gamma \sum_{s'_t} P(s'_t|s_t, x_t) V^*(s'_t)$$

value of recommending attribute realisation x_t when in state s_t

Topic Detection

- Use min-max normalisation of $Q(s_j, x_j)$ values

$$q(\mathcal{X}_j = x_j | s_j) = \frac{Q(s_j, x_j) - \min_{x'_j}[Q(s_j, x'_j)]}{\max_{x'_j}[Q(s_j, x'_j)] - \min_{x'_j}[Q(s_j, x'_j)]}$$

- Thresholding important!

colour	price
q(black|s) = 0.8	q(expensive|s) = 0.8
q(blue|s) = 0.7	q(cheap|s) = 0.8
q(green|s) = 0.4	q(sale|s) = 0.7
q(red|s) = 0.2	

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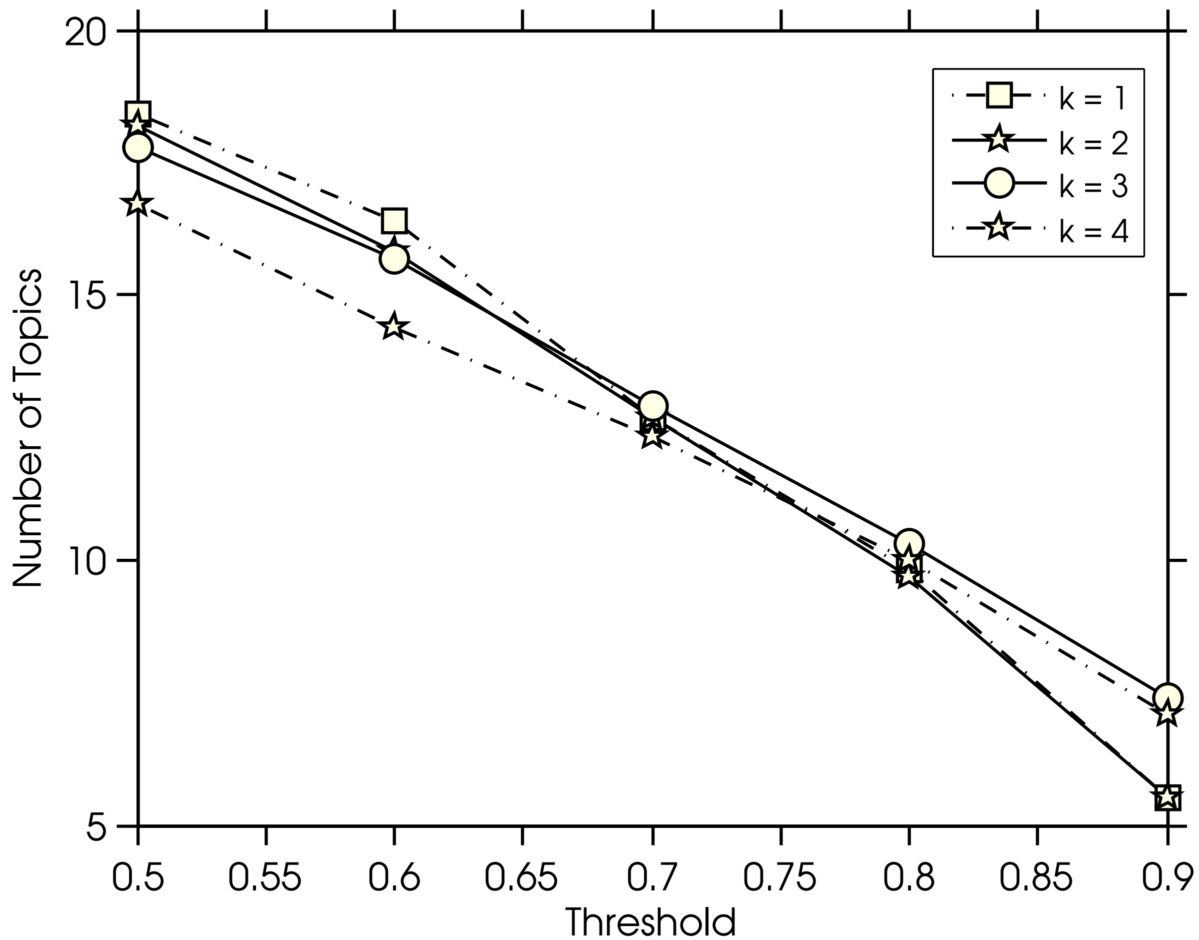
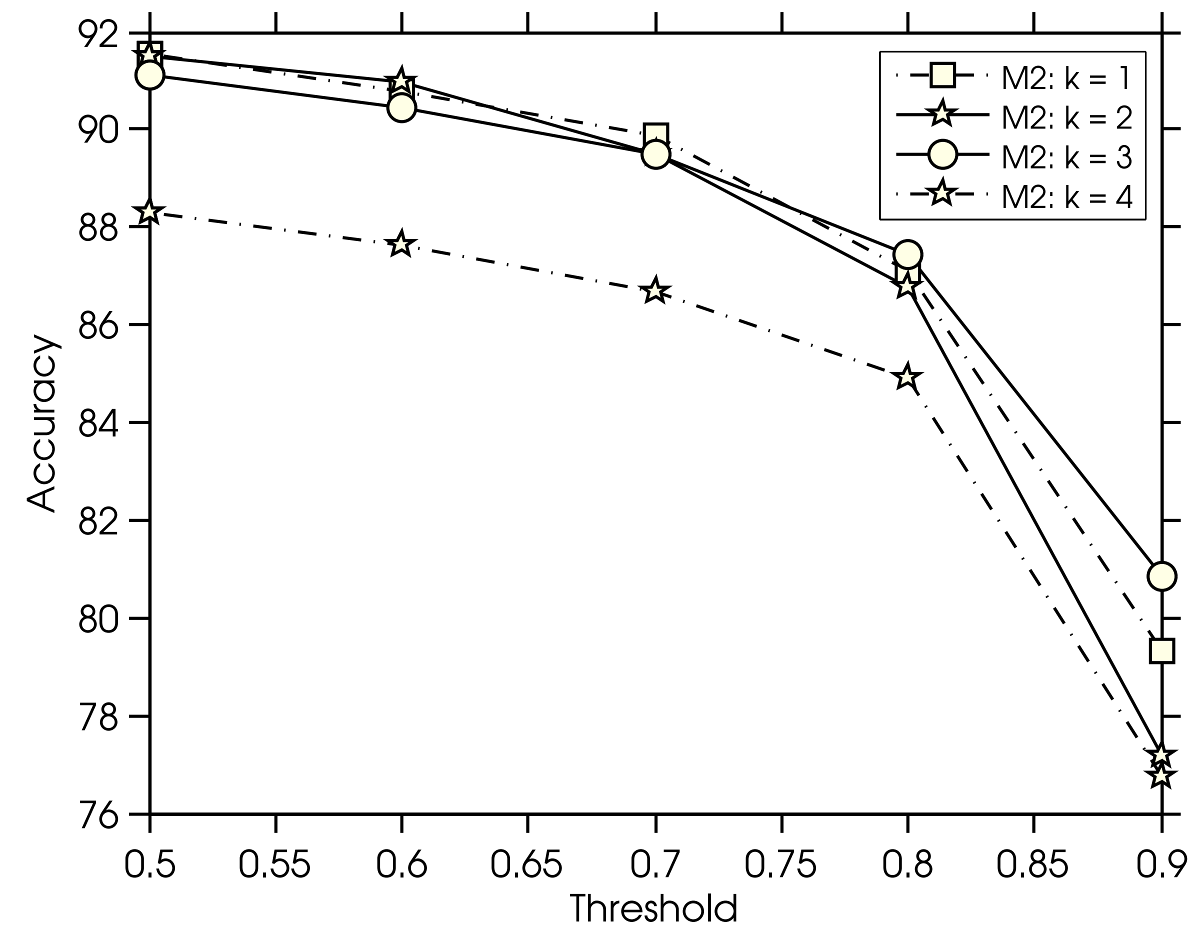
topic = {black, blue, expensive, cheap, sale}

Empirical Evaluation

- Transaction data from Zalando
- About 1.7 million user sessions
- > 24 million clicks
- Attributes: category, colour, gender, price
- User parameters optimised by model selection

Impact of Threshold





- Size of topics decreases wrt threshold
- Topic accuracy decreases wrt threshold

Accuracies (Small-Scale)

	k	joint	colour	gender	category	price
Markov Process	4	33.69	49.78	92.24	78.52	63.96
	3	37.70	52.98	92.31	79.50	65.06
	2	37.65	52.15	92.22	79.68	64.24
	1	28.06	44.31	91.85	79.01	56.28
MDP (exact)	4	67.53	85.61	95.00	90.70	78.68
	3	69.56	93.94	95.21	93.36	72.01
	2	40.62	45.96	95.30	94.90	78.39
	1	16.47	28.37	95.31	95.28	46.55
MDP (approx)	4	75.33	81.92	94.65	90.05	92.38
	3	89.52	92.95	94.83	92.81	94.48
	2	93.69	95.12	94.97	94.45	95.00
	1	94.14	95.25	94.98	94.82	94.97
LDA	-	1.65	11.76	85.89	52.8	21.14

longer chains better but data too sparse

estimation of α and β better for shorter chains

Accuracies (Large-Scale)

	k	joint	colour	gender	category	price
Markov Process	4	39,56	53,50	89,70	77,93	71,25
	3	39,53	52,83	89,70	78,09	71,04
	2	38,37	50,78	89,57	77,94	71,09
	1	30,82	42,37	89,15	77,29	70,02
MDP (approx)	4	88,3	91,09	92,61	90,88	92,19
	3	91,13	92,73	92,45	92,04	92,56
	2	91,48	92,82	92,46	92,37	92,49
	1	91,53	92,85	92,4	92,39	92,55
LDA	-	2.84	12.31	81.18	51.22	41.71

more data diminish effect of shorter chains

Topic-driven Recommendations

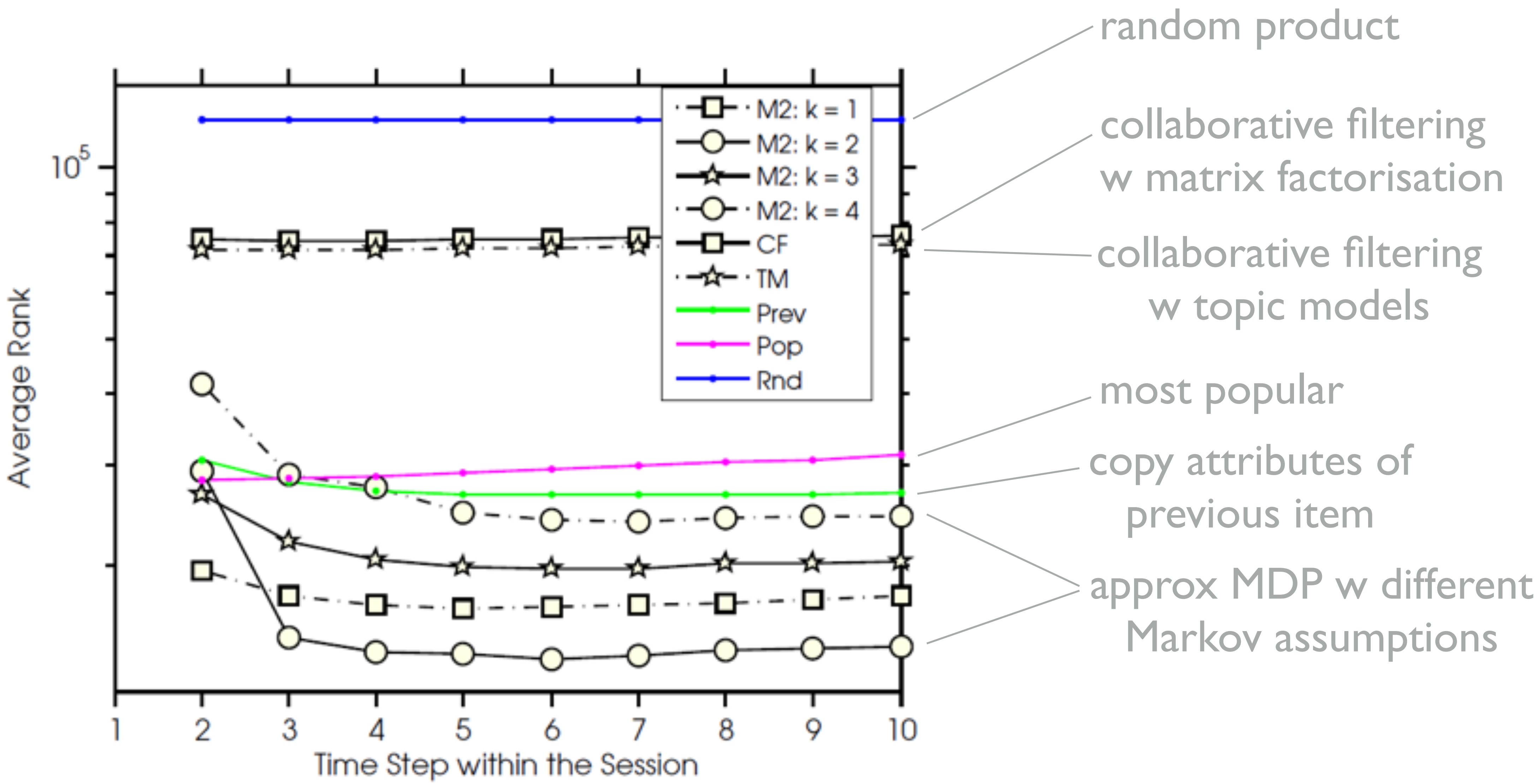
- Turn Q-values into probabilities (softmax)

$$\Pr(\mathcal{X}_j = x_j | s_j) = \frac{\exp\{Q(s_j, x_j)\}}{\sum_{x'_i} \exp\{Q(s_j, x'_i j\}}$$

- Rank items i according to sum of log-probabilities (exploiting independence)

$$score(i; s) = \prod_{j=1}^{n} P(\mathcal{X}_j = x_j | s_j) \propto \sum_{j=1}^{n} \log P(\mathcal{X}_j = x_j | s_j)$$

Topic-driven Recommendations



- Topic-driven recommendation outperforms traditional CF/MF approaches

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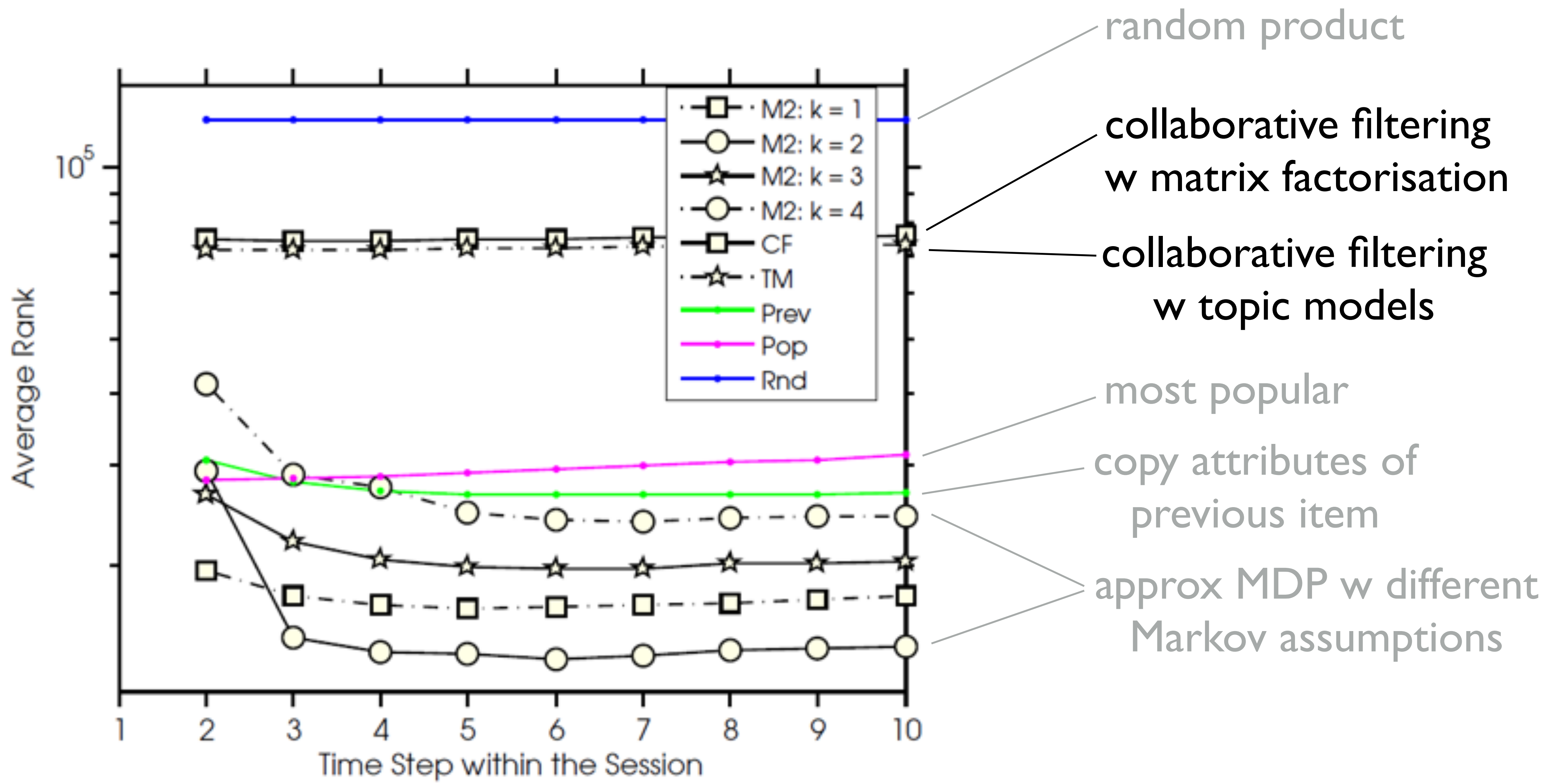

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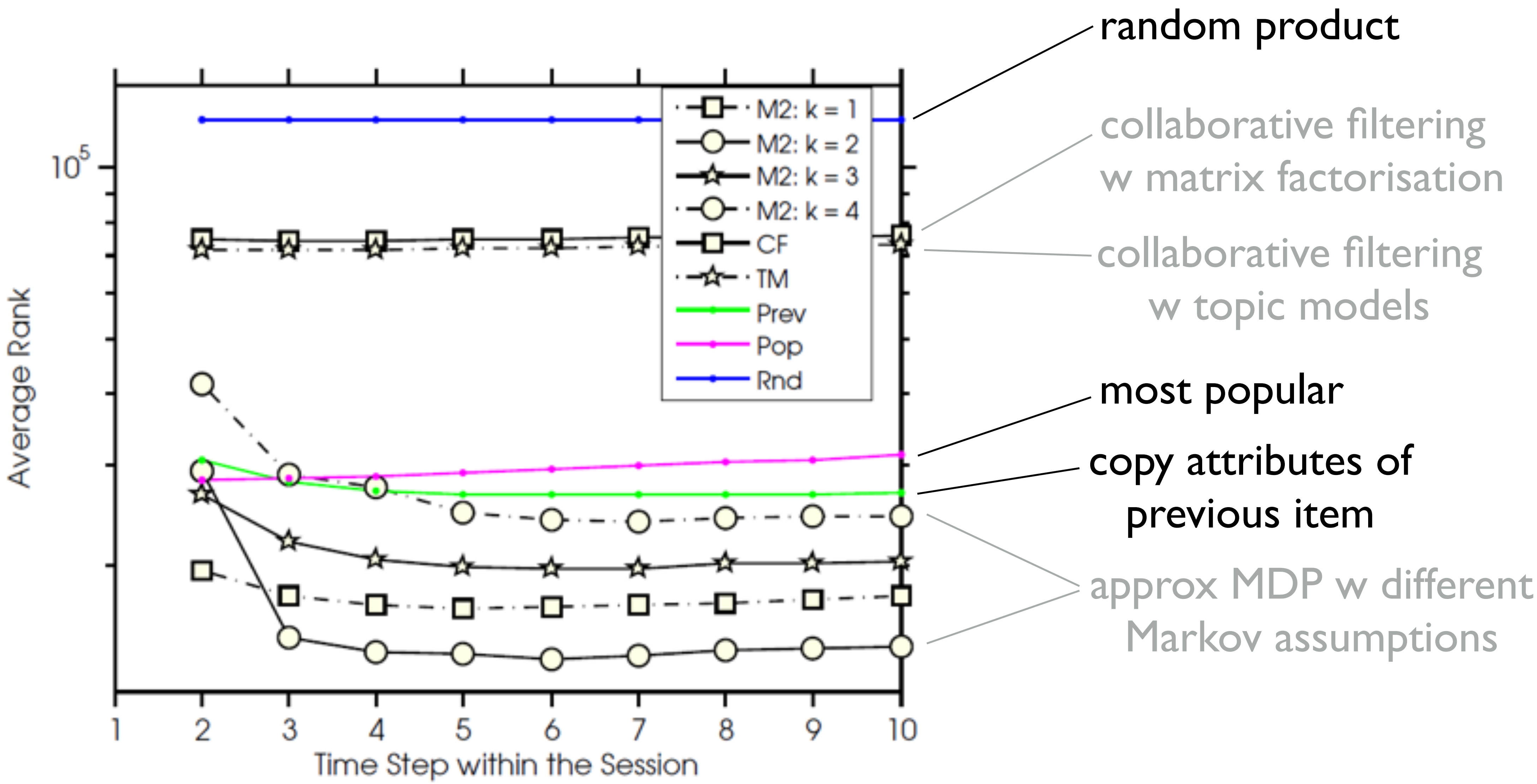

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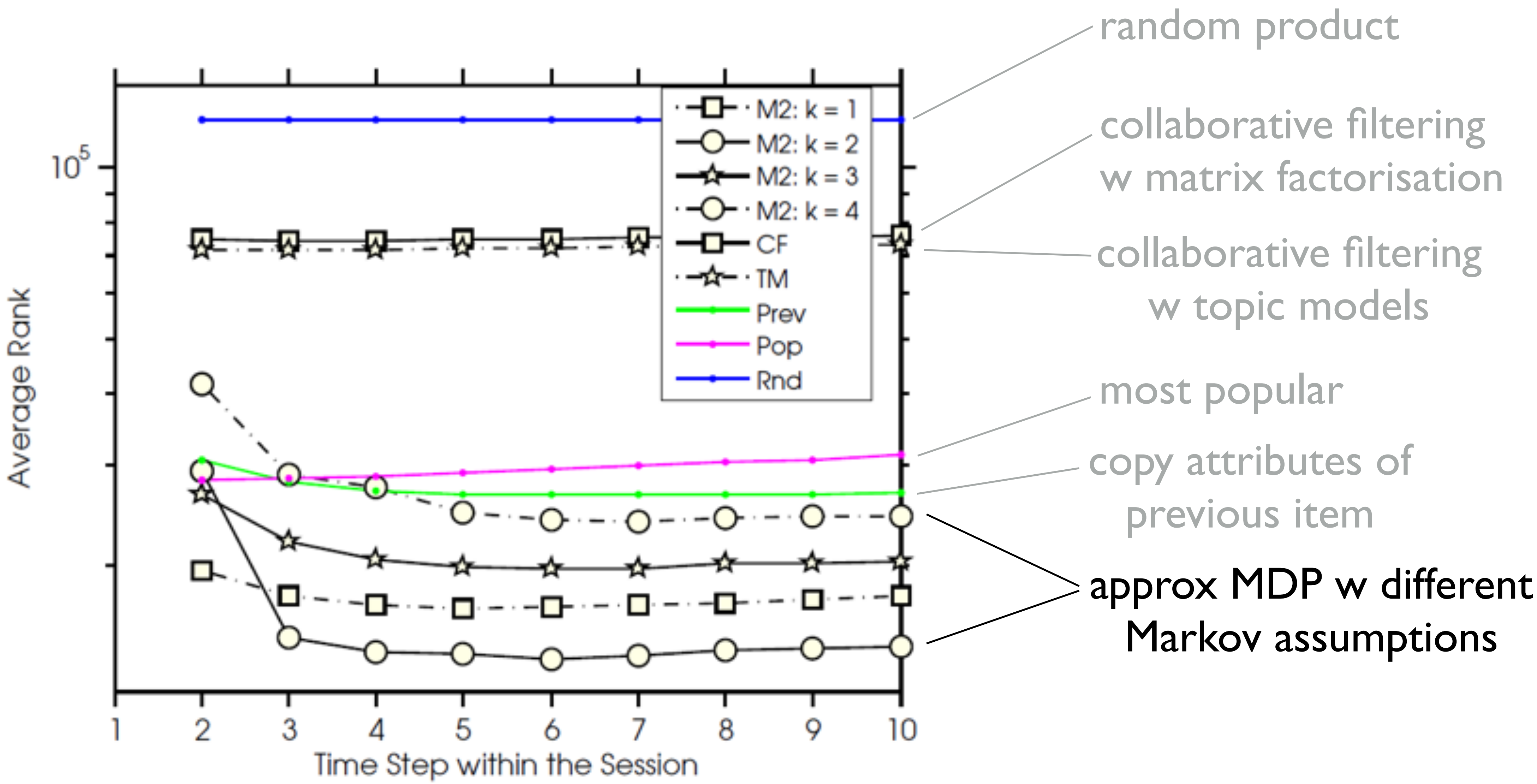

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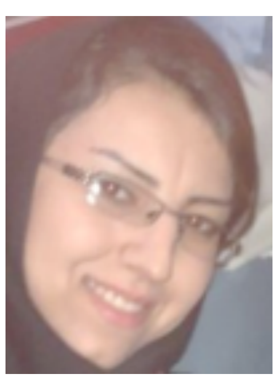
Conclusion

- Topic detection for user sessions
    - Sessions-based approach = short-term interests
    - Exploit sequential nature of the data (MDP)
    - Content-based (factorise over attributes)
- Empirically outperform traditional CF/MF recommenders and straw men



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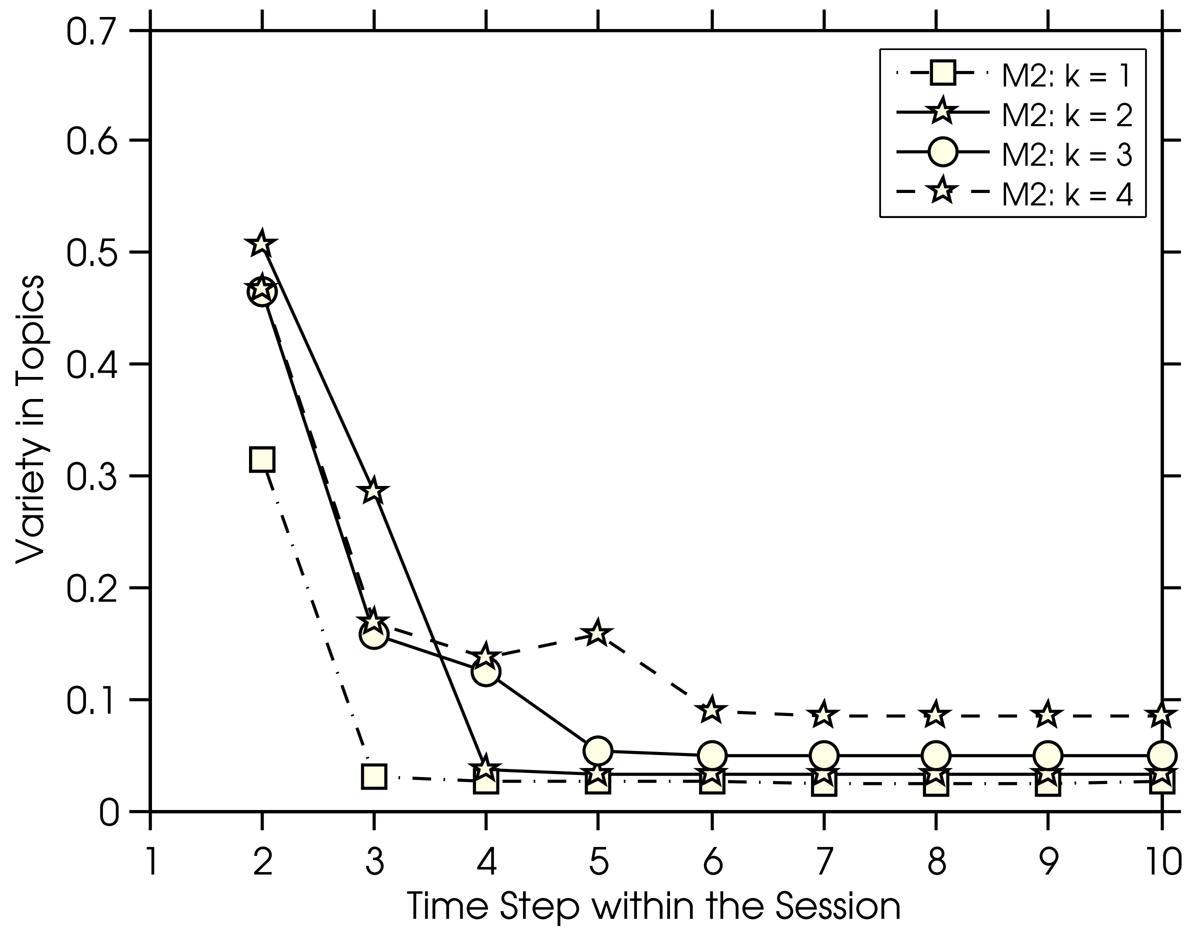
Variance of Topics



- Uncertainty decreases in length of session
- Markov assumption influences convergence