

Catch-Up TV Recommendations: Show Old Favourites and Find New Ones

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TV Content Discovery

- Motivation: Web + social Web + IPTV + connected TV = overwhelming choice
 - Video on demand
 - Broadcast TV
 - Catch-up TV
 - YouTube, Facebook, Twitter, ...
- How do users discover relevant content?
 - Search – content they know and are looking for
 - Discovery – content they do not know yet but may like
 - Personalisation and recommendations
- Industry project with Australian national broadcaster



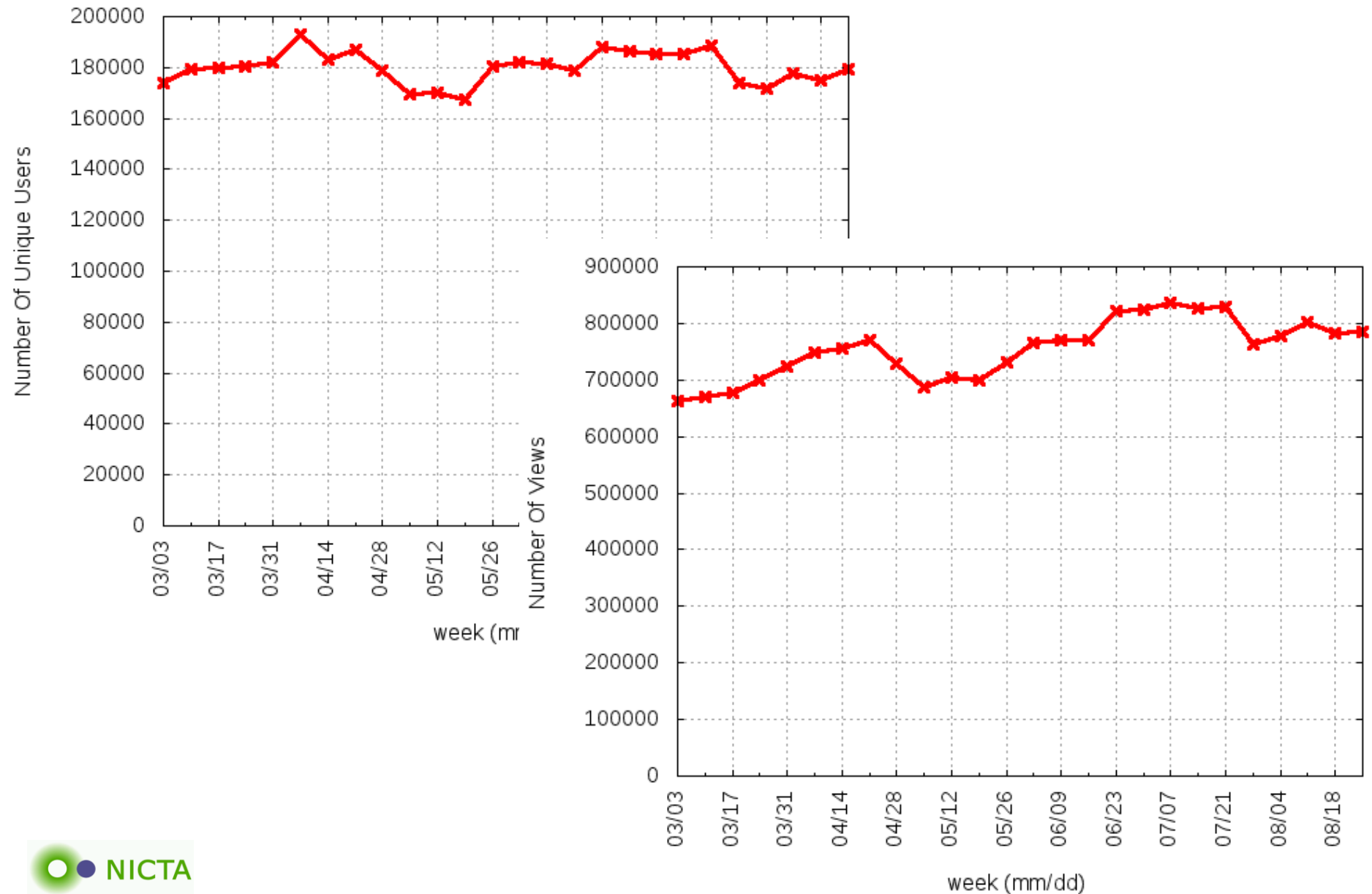
Catch-Up TV Content Discovery

- Dynamicity over time
 - Items appear and retire regularly
 - New item cold start problem
- Unreliable user data
 - Small fraction through catch-up TV
 - Imprecise consumption logs
 - Composite: multiple users sharing a device
 - Cross-device: one user with multiple devices
- This work
 - Exploratory study into user viewing behaviour
 - Recommendations of catch-up TV programs

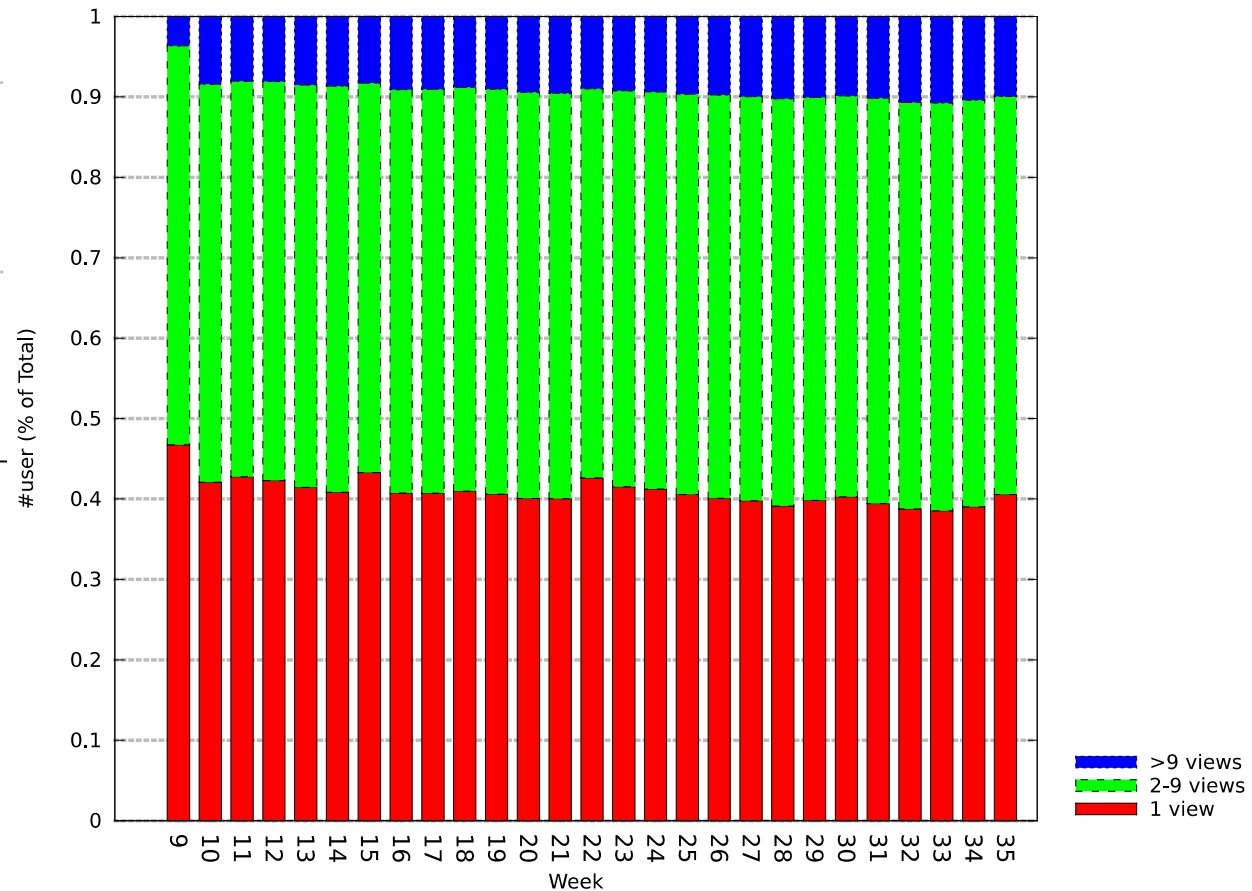
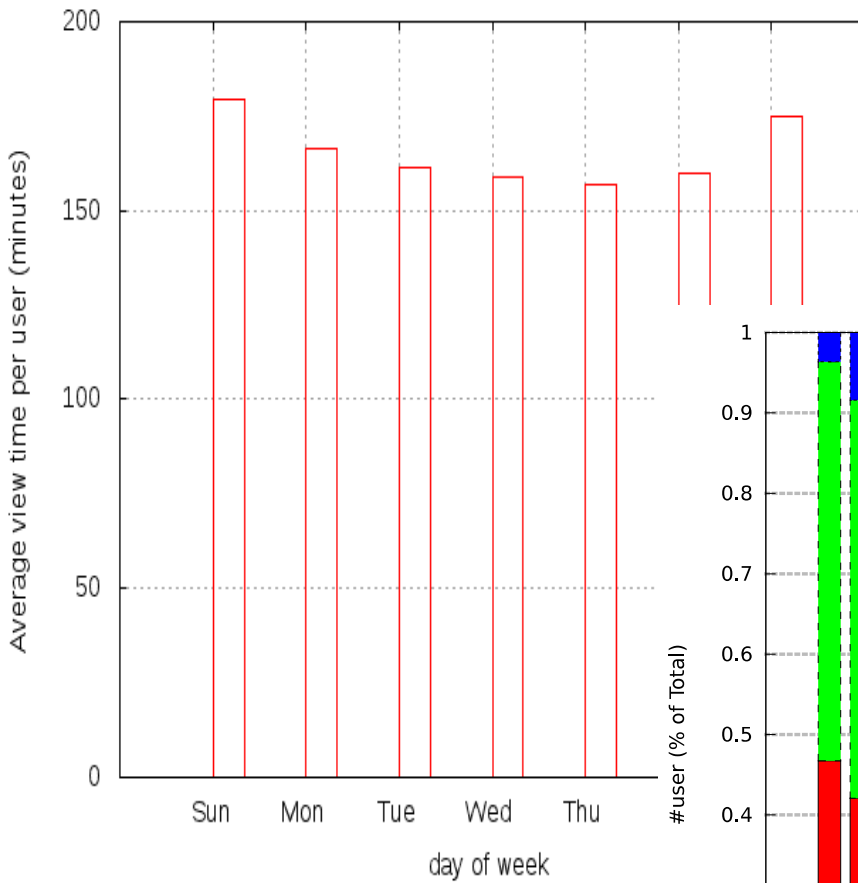
Dataset

- Past logs
 - 184 days of Australia wide viewing logs
 - 19.8M views [play clicks only]
 - 2.02M unique users
 - 9.1K unique programs viewed
 - Dates (no timestamps)
 - Limited program information
 - Title
 - Publication/retirement date
 - Category
 - Art, children (6-15), comedy, documentaries, drama, education, lifestyle, news, panel, preschool (<6), children reruns, shop, sport.
 - User information
 - Browser cookie id

Overall Characterisation



User Characterisation

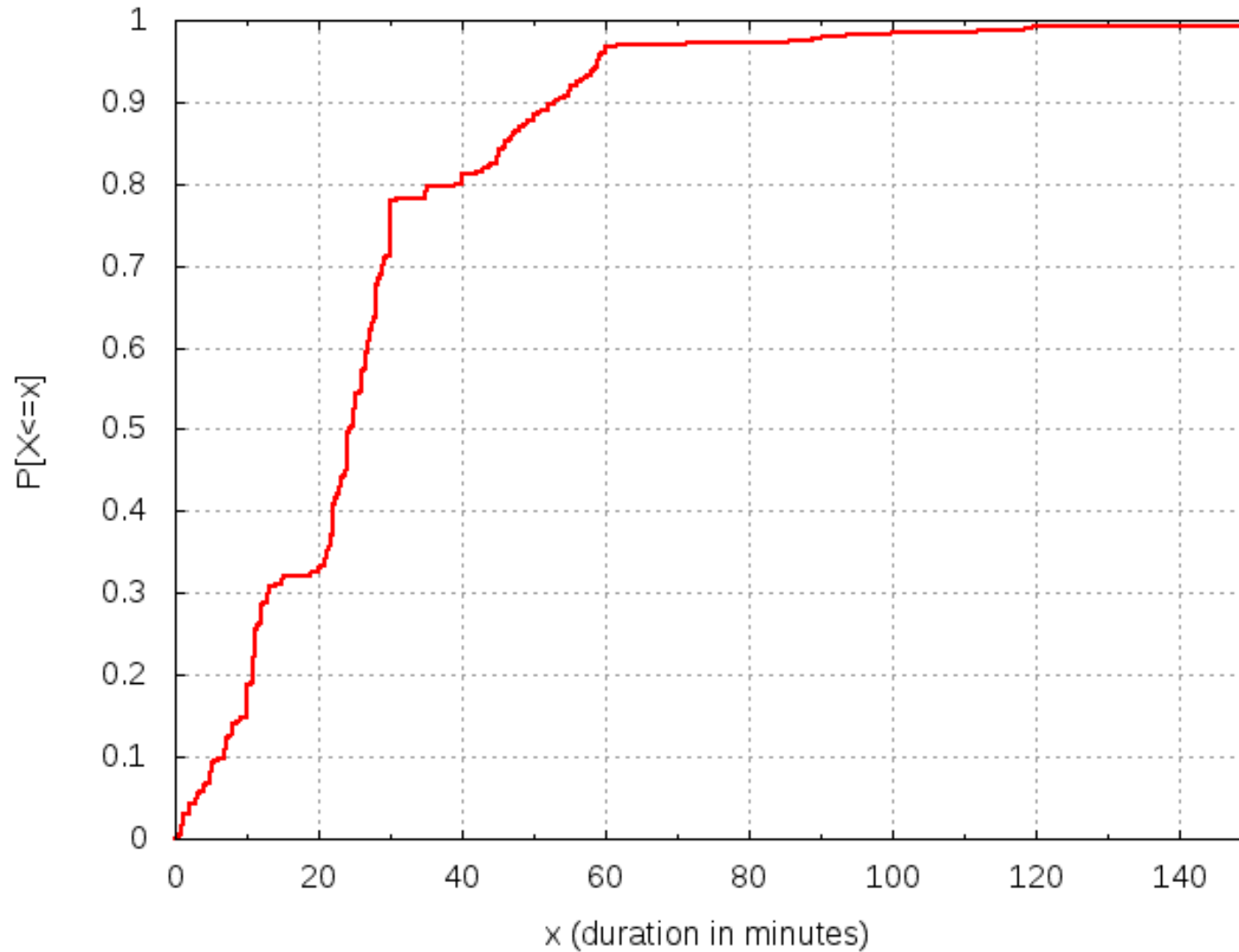


User Clustering

- With respect to frequency of categories
 - Distance based clustering
 - Optimised for cohesion and separation
- Identified clusters
 - Some have a small number of dominant categories
 - c8, c5, c1
 - Others are less pronounced

num	1st category		2nd category		3rd category		4th category		size	week
	category	score	category	score	category	score	category	score		
c1	drama	0.734							27,740	1
c2	docu	0.489	lifestyle	0.128	comedy	0.105			8,175	4
c3	lifestyle	0.500	docu	0.113	drama	0.107	comedy	0.106	8,462	2
c4	children	0.514	drama	0.158	preschool	0.137			9,332	3
c5	preschool	0.868							16,755	1
c6	panel	0.253	drama	0.169	comedy	0.155	lifestyle	0.108	14,698	9
c7	comedy	0.540	drama	0.139					11,485	1
c8	children	0.920							13,514	1

Content Characterisation



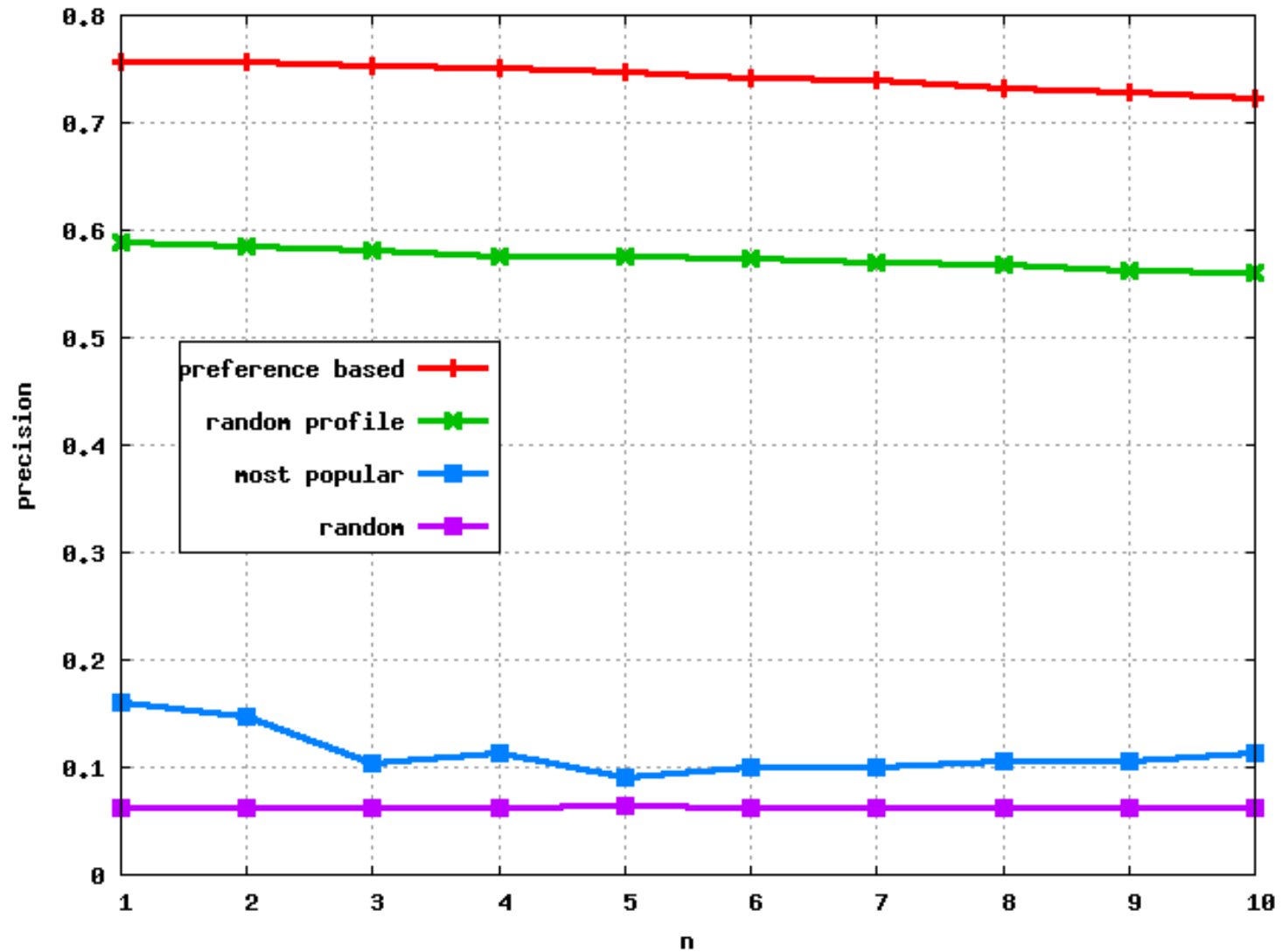
Content Characterisation

- Vast majority of programs are linked
 - Series, shows, news, sport, ...
 - We refer to these as *series* and *episodes*
- Recommend series rather than individual episodes
- $\text{score}(\text{user } u, \text{series } s) =$
 $\frac{\text{number episodes of } s \text{ that } u \text{ watched}}{\text{number episodes of } s \text{ available since } u \text{ joined}}$
- $\text{subscription}(\text{user } u, \text{series } s) = 1$ iff
 $\text{score}(u,s) > \alpha$ && number of watched episodes $> \beta$
- Two recommendation use cases
 - **Subscribed**: recommend series a user regularly watches
 - **New**: recommend series a user does not watch but may like

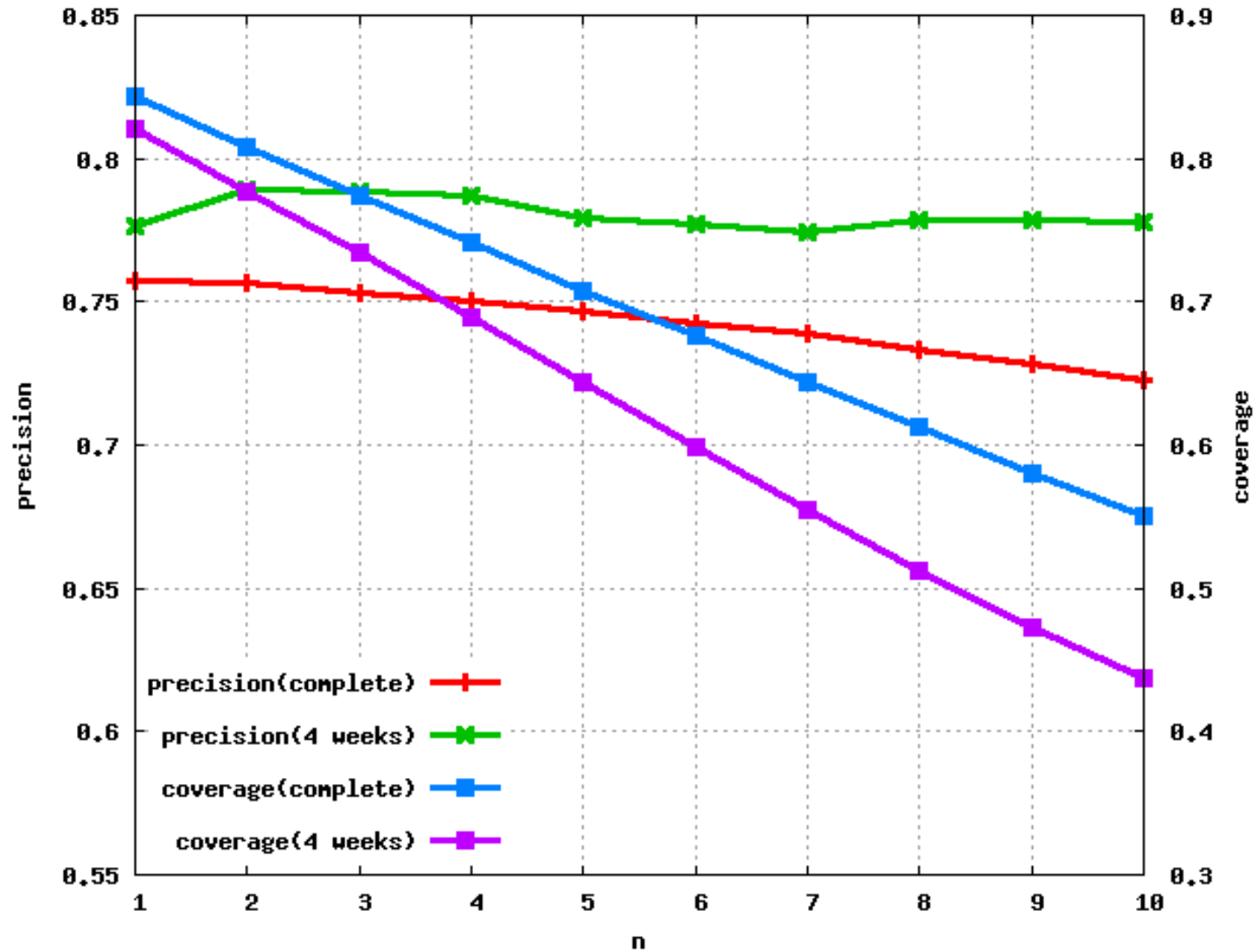
Subscribed Series Recommendations

- Rule-based recommender: if $\text{subscription}(u,s)=1$ && exists episode of s not watched by u then recommend s
 - According to $\text{score}(u,s)$
 - Randomly selected amongst s s.t. $\text{subscription}(u,s)=1$
- Non personalised recommendations
 - Most popular across the entire community
 - Randomly selected
- Methodology
 - Training / test split: first 136 days / 3 immediately following days
 - Ground truth: s watched by u during the test period
 - Metric: precision

Subscribed Series Recommendations



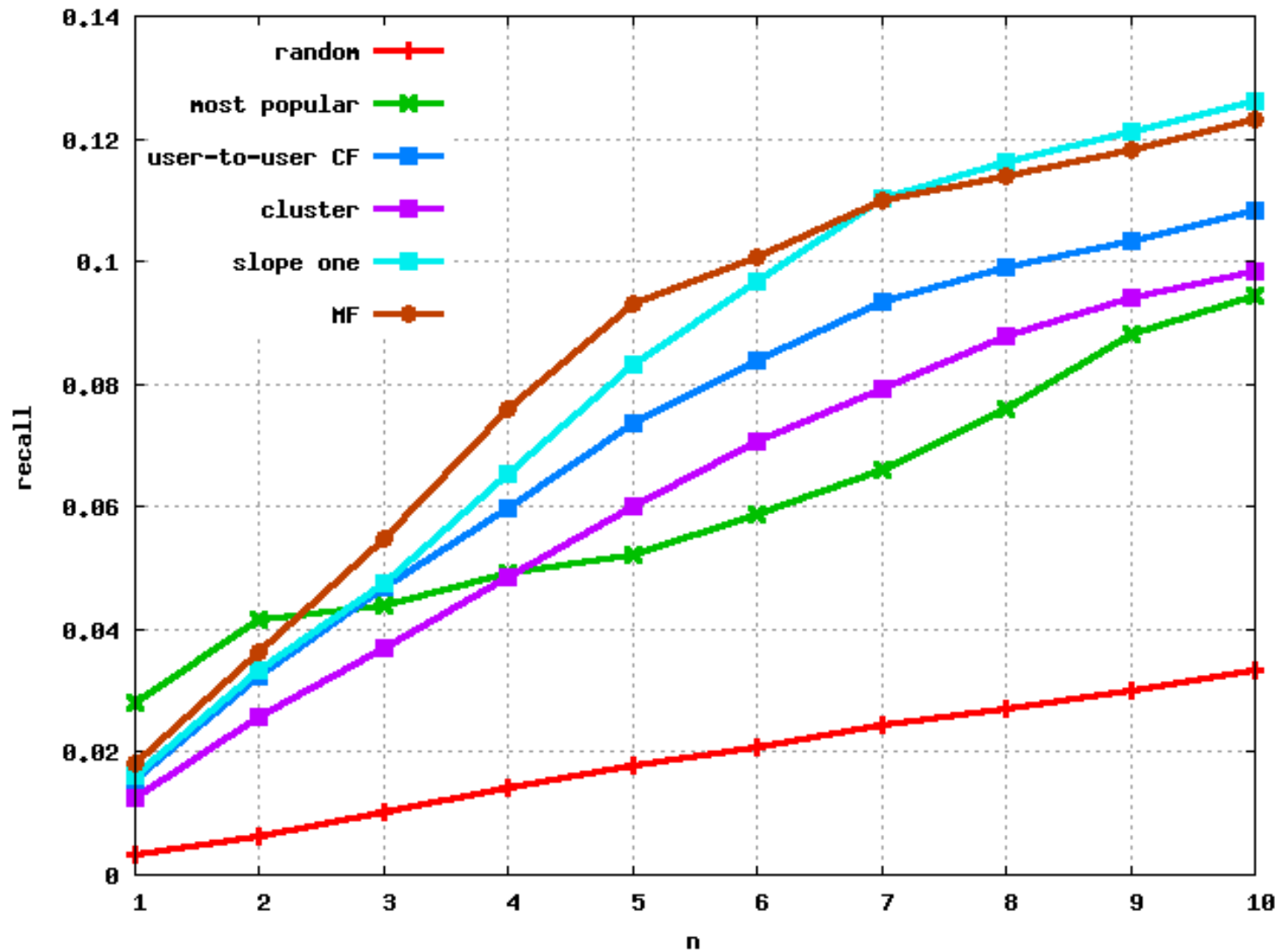
Subscribed Series Recommendations



New Series Recommendations

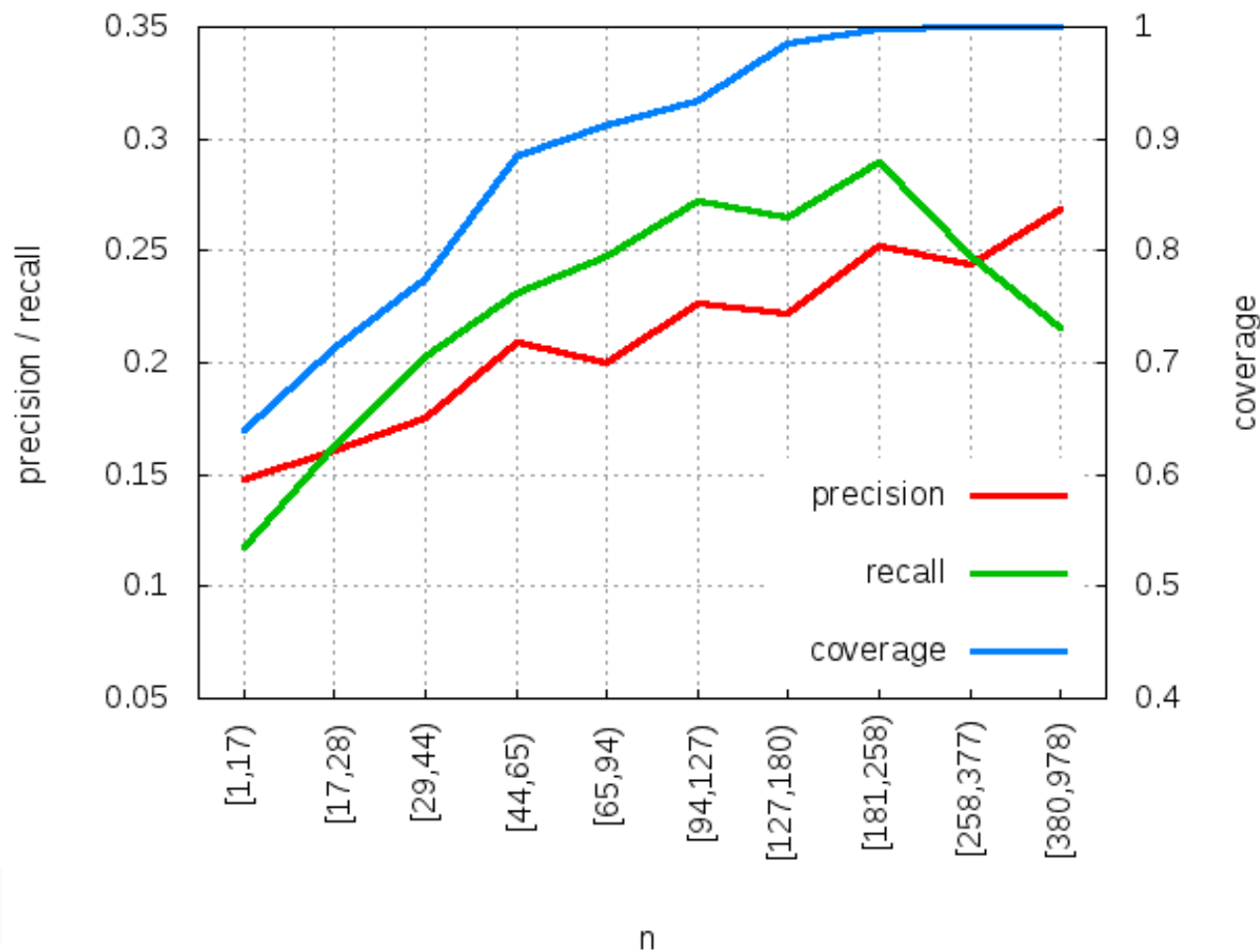
- Existing model- and memory-based algorithms
 - User-to-user collaborative filtering
 - Cluster-based recommendations
 - Slope-one recommender
 - Matrix factorisation
- Non personalised recommendations
 - Most popular across the entire community
 - Randomly selected
- Methodology
 - Training / test split: first 136 days / remaining days
 - Ground truth: u subscribed to s during the test period
 - Metric: recall

New Series Recommendations



Hybrid Recommendations

- Mix the *outputs* of the two recommenders
 - 5 from subscribed and 5 from new recommender



Summary

- Catch-up TV recommender using real-life 6 months logs
- Two use cases evaluated
 - Subscribed: recommendations for already watched content
 - 75% accuracy with simple rule based recommender
 - Short term profile more accurate but loses coverage
 - New: serendipitous recommendations for unfamiliar content
 - 12% accuracy with state-of-the-art MF
 - New use case is inherently harder
- Future work
 - Identify composite and cross-device profiles
 - Recommendations for groups of viewers
 - Pilot trial and live user study

Thank You!



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