Estimating attention flow in online video networks

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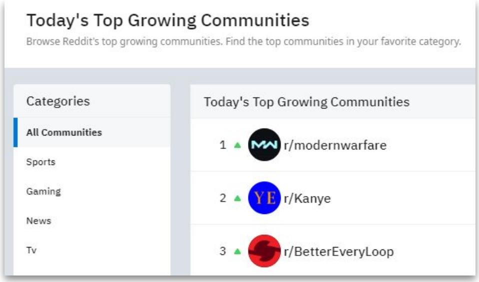
Recommender systems are ubiquitous in online platforms



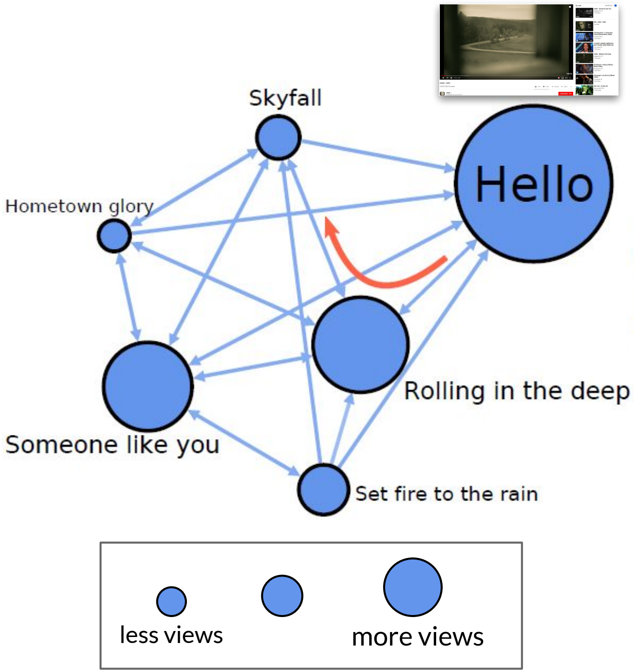
The evolution of YouTube recommender systems

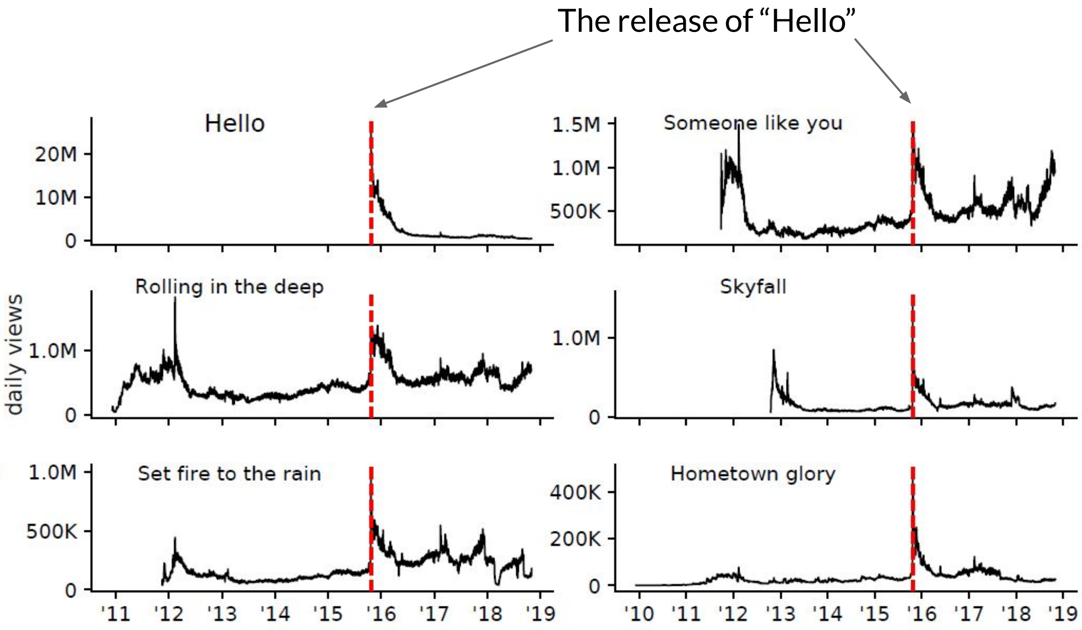
Method	Papers
Collaborative Filtering	[Davidson et al. *RecSys* ’10] [Bendersky et al. *KDD* ’14]
Deep Learning	[Covington et al. *RecSys* ’16] [Beutel et al. *WSDM* ’18]
Reinforcement Learning	[Chen et al. *WSDM* ’19] [Ie et al. *IJCAI* ’19]
Unbiased recommendation	[Zhao et al. *RecSys* ’19] [Yi et al. *RecSys* ’19]

Effects of recommender systems:
what does the network look like? how does it affect video popularity?

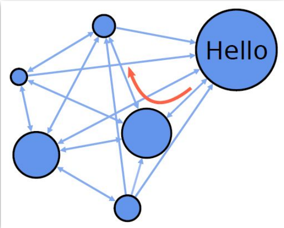
The “Hello” effect

The release of “Hello” excited other videos from Adele.





Talk outline



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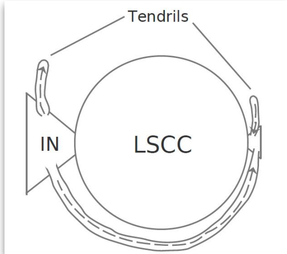

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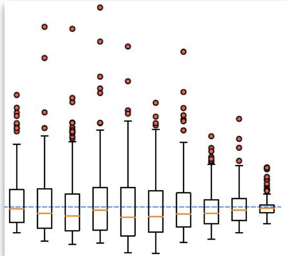
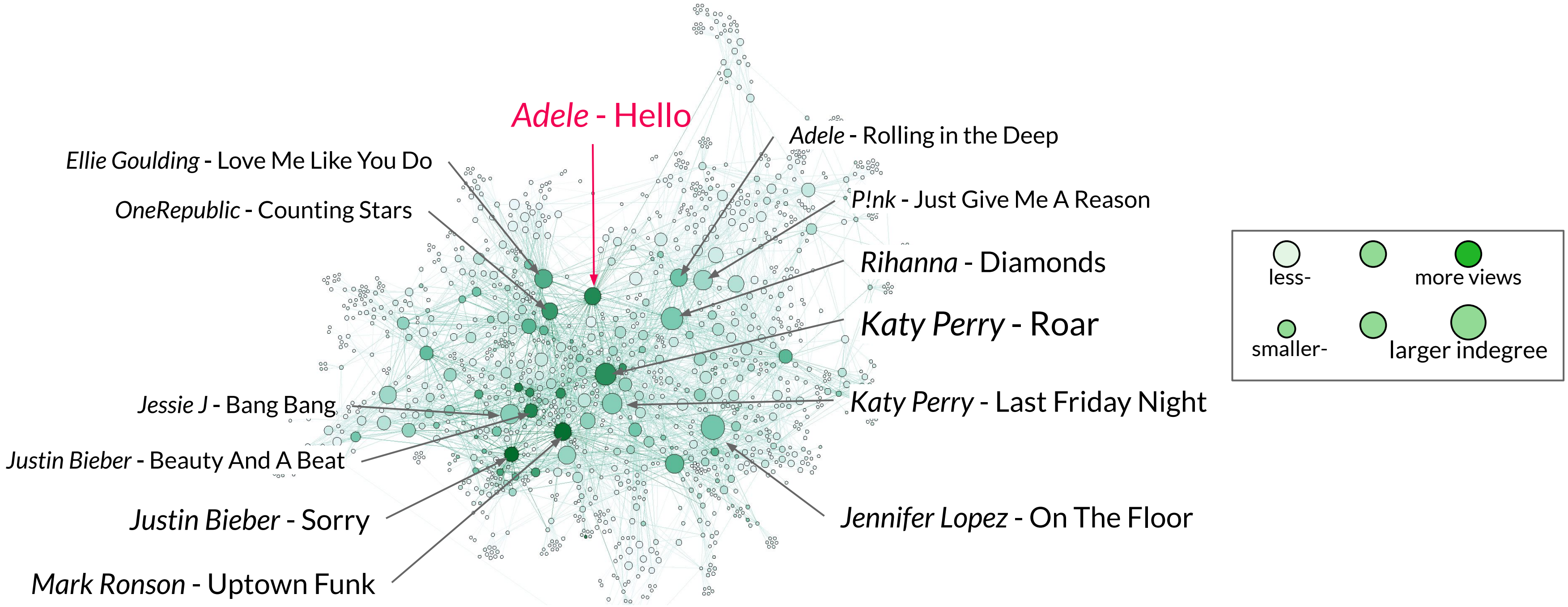


3. How to model video popularity under recommender systems?

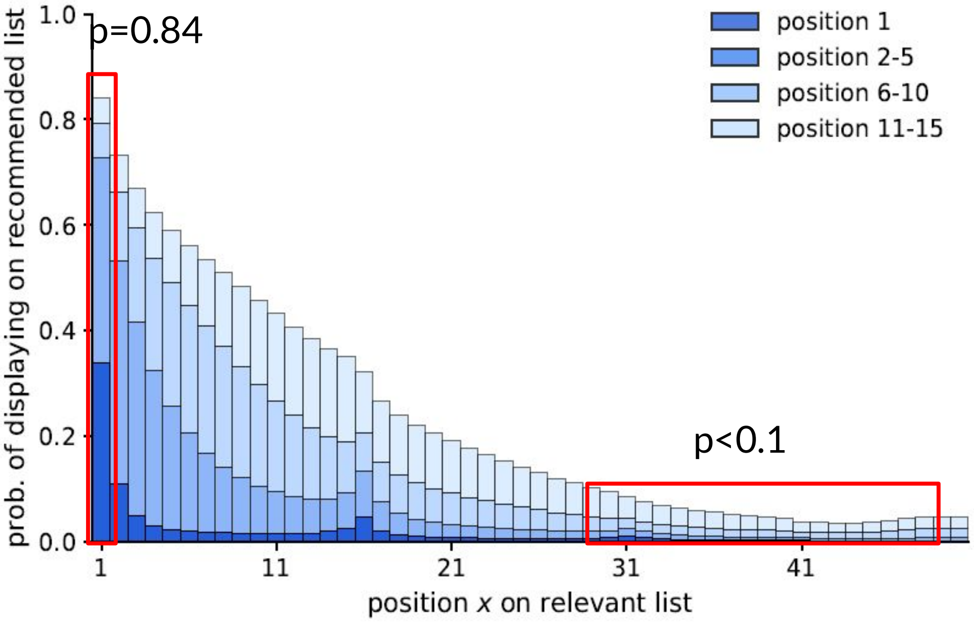
VEVO music graph dataset

- 60,740 music videos from 4,435 VEVO artists who are active in major English-speaking countries.
- 337K~394K directed links in 63 daily snapshots.
- Links consist of *non-personalized* feed from YouTube API.

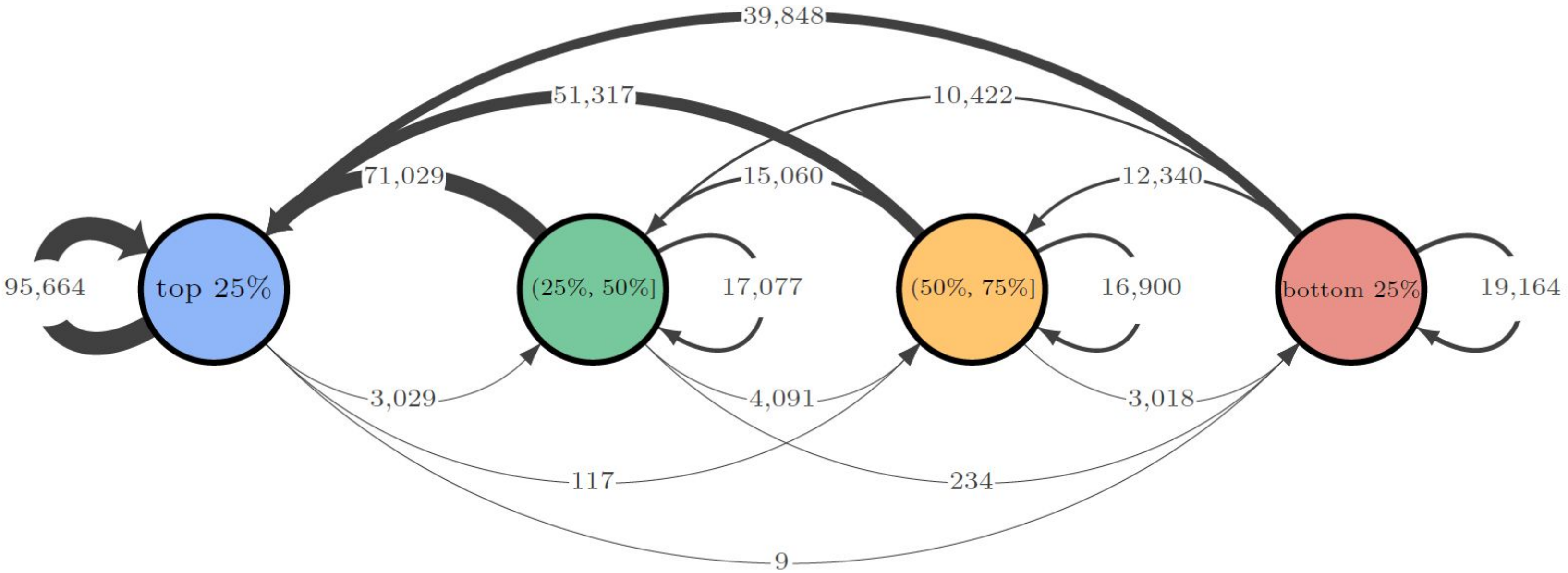


Relations for recommendations on YouTube webpage and API

Rank higher in API → more likely to display on video webpage, with higher rank.



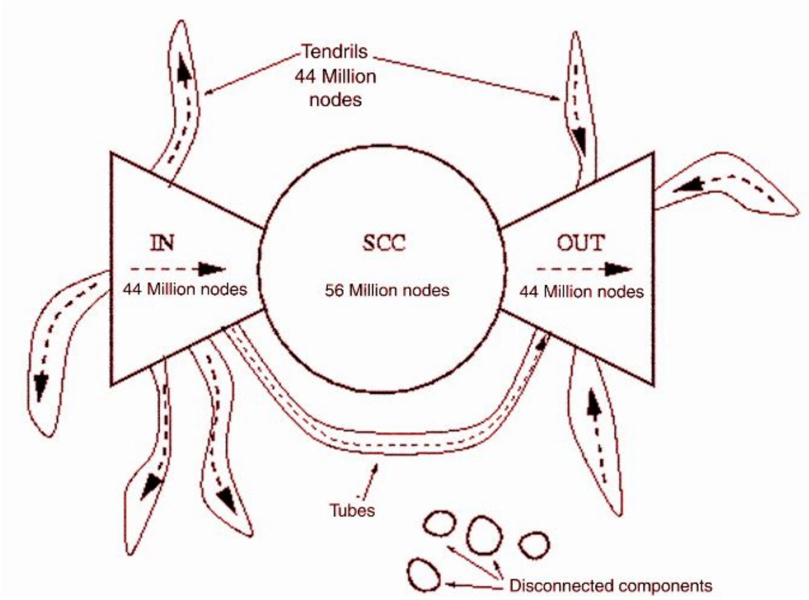
Videos disproportionately point to more popular videos



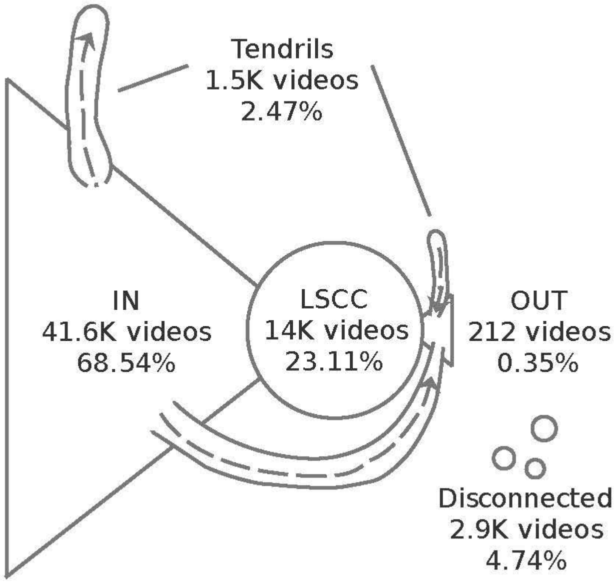
The bow-tie structure

- LSCC: largest strongly connected component.
- IN: nodes can reach LSCC, but not reachable from the nodes in LSCC.
- OUT: nodes that can be reached by LSCC but not pointing back to LSCC.

Web graph 1997



VEVO network

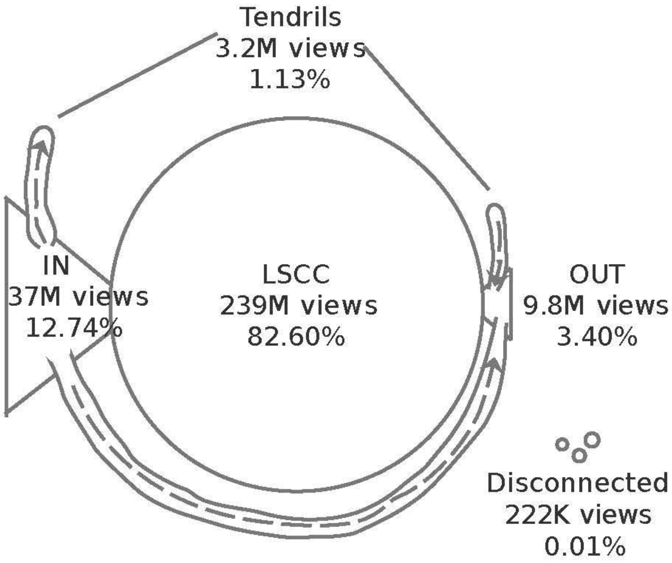


Graph structure in the Web. Broder et al. *WWW '00*

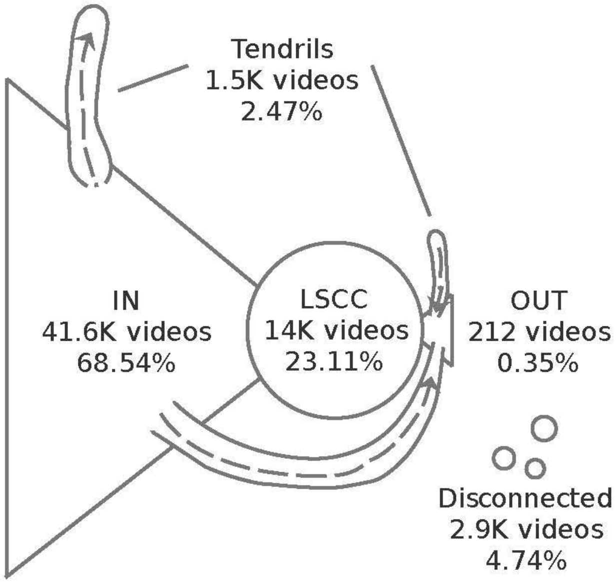
The attention bow-tie of Vevo network

- Attention flow in one direction: IN → LSCC → OUT.
- LSCC (23.1% of the videos) occupies most of the attention (82.6% of the views).
- IN component shrinks (68% → 12%).

attention bow-tie



structure bow-tie



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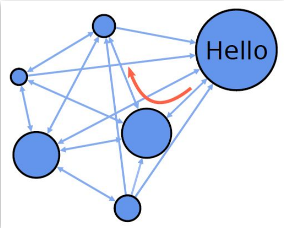

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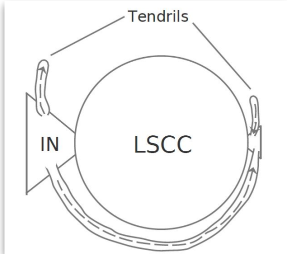

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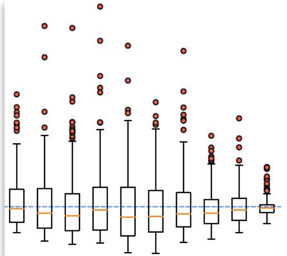
(b) Microscopic profilings

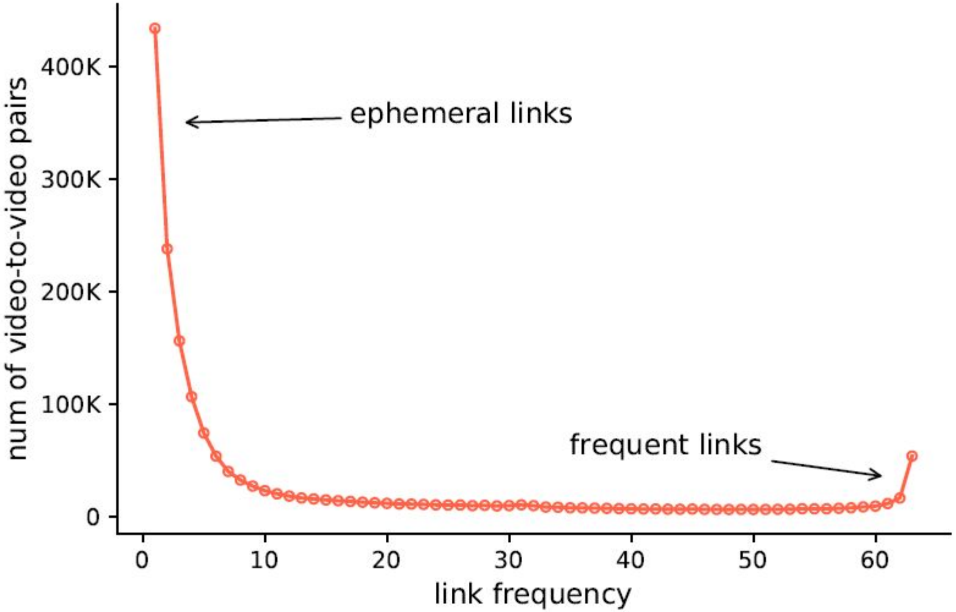
(c) Temporal patterns



3. How to model video popularity under recommender systems?

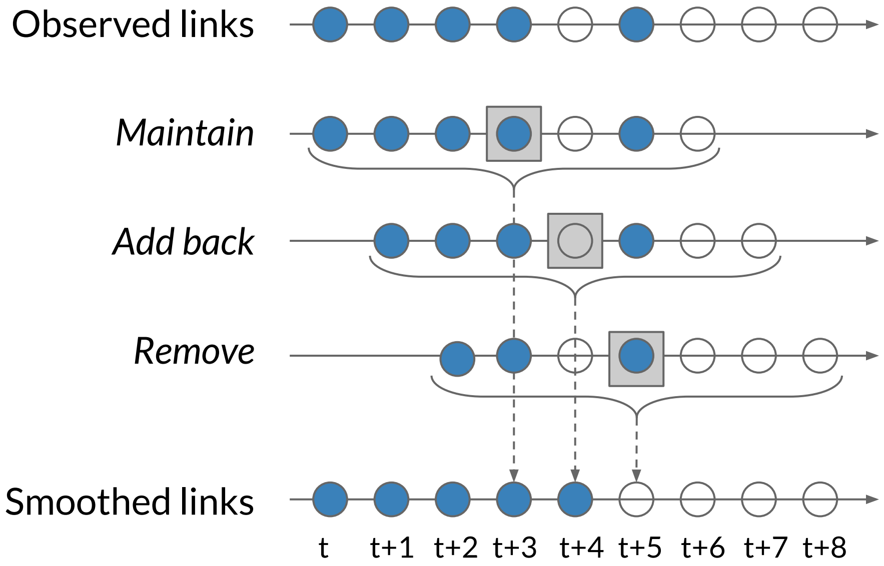
Temporal evolution of Vevo network

434K (25%) links only appear once, 54K (3.1%) links appear in every snapshot.



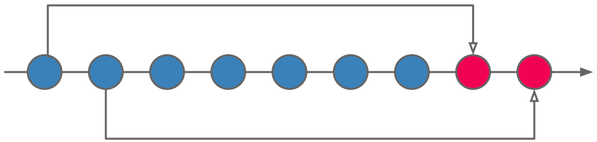
Building a persistent network

- 2 popularity filters: (a) avg. daily views >= 100; (b) >= 1% compared to target videos.
- A link is maintained/added if it appears in a majority (>=4) of surrounding 7 days windows.
- Persistent network: 52,758 directed links; 28,657 source videos → 13,710 target videos.

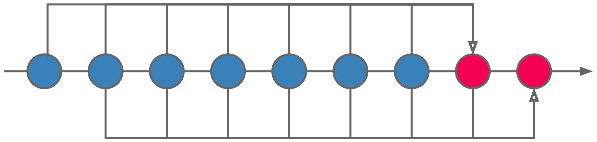


Baselines:

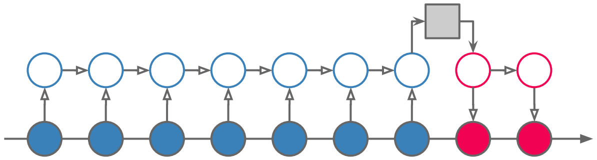
- Seasonality -> Seasonal Naive model (SN)

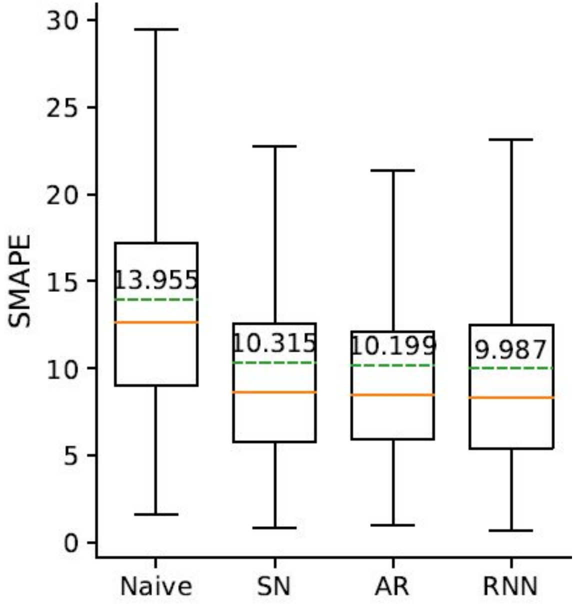


- Autocorrelation -> AutoRegressive model (AR)



- RNN with LSTM units





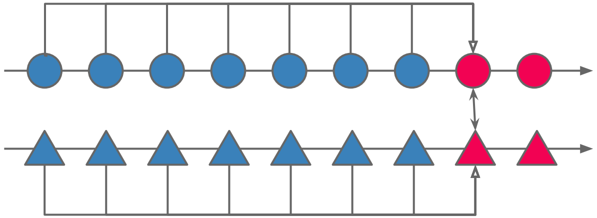
ARNet model and results

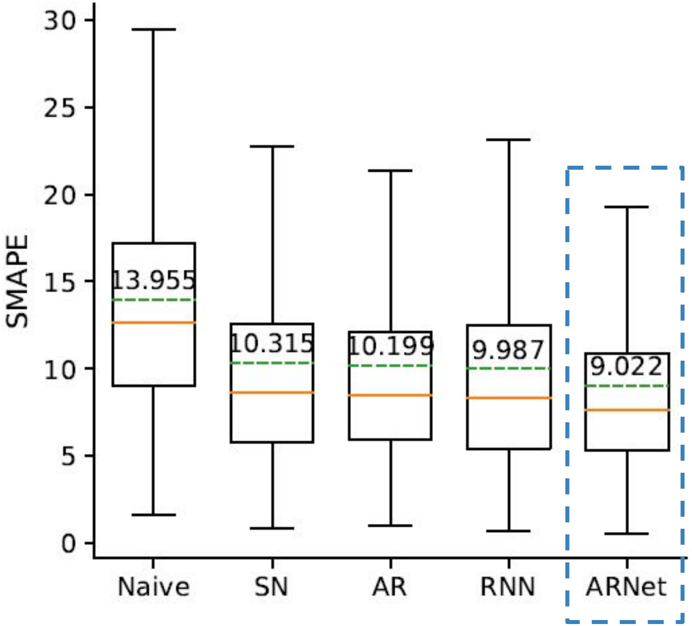
Baselines:

- Seasonality -> Seasonal Naive model (SN)
- Autocorrelation -> AutoRegressive model (AR)
- RNN with LSTM units

Proposed model:
AutoRegressive + Network (ARNet)

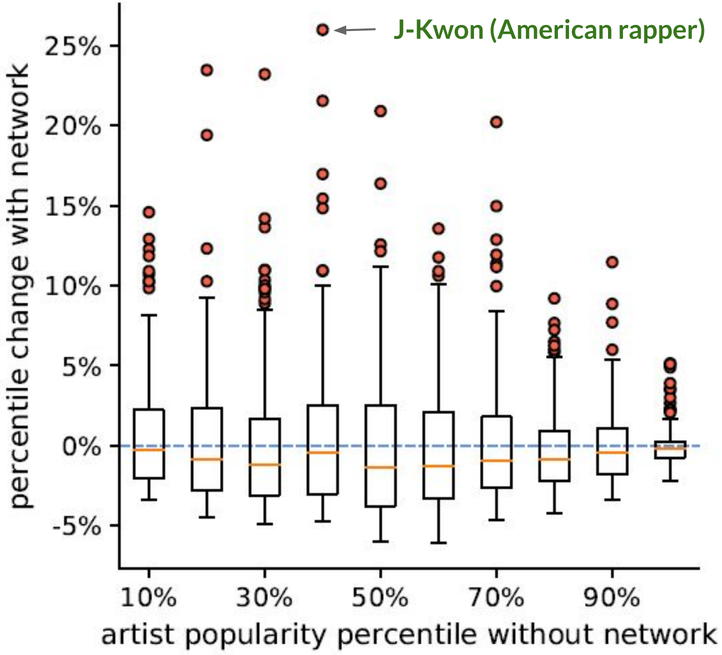
$$\hat{\mathbf{Y}}_v[t] = \underbrace{\sum_{\tau=1}^{w} \alpha_{v,\tau} \mathbf{Y}_v[t-\tau]}_{latent\ interest} + \underbrace{\sum_{(u,v)\in G} \beta_{u,v} \mathbf{Y}_u[t]}_{network\ effect}$$

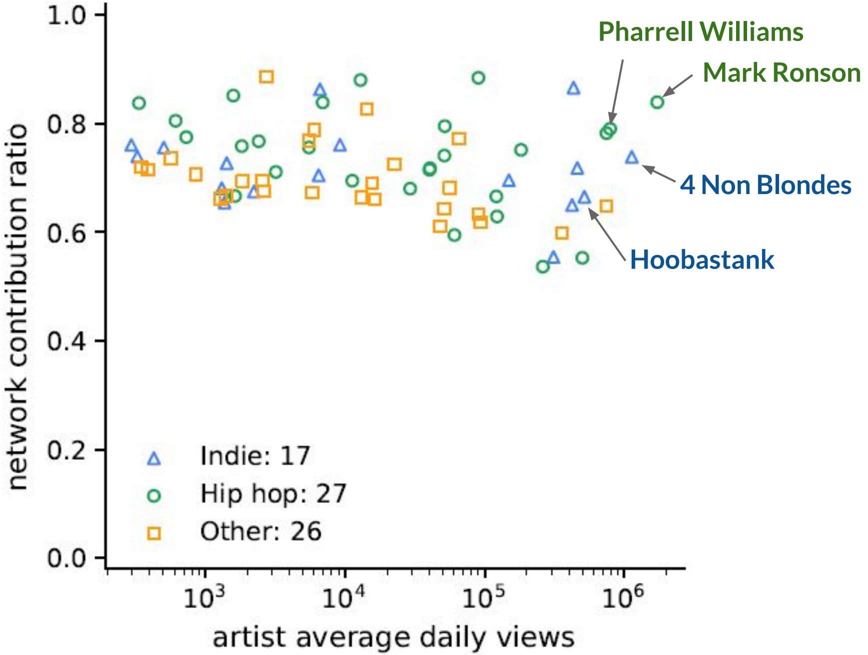




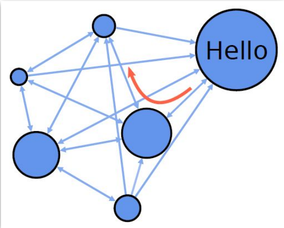
Which artists benefit the most from the recommendation network?

Estimated network contribution ratio: $\dfrac{\sum_{(u,v)\in G} \beta_{u,v} \mathbf{Y}_u}{\hat{\mathbf{Y}}_v}$





Summary



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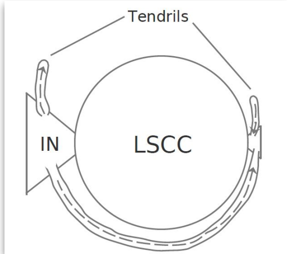

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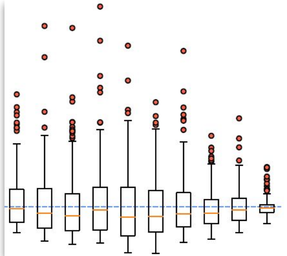

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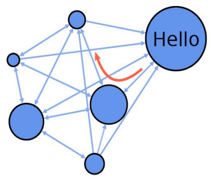
(a) A model taking account of network information

(b) Estimating link strength for each recommendation link

SCAN ME



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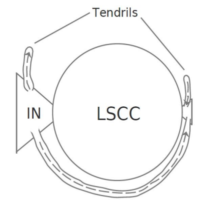

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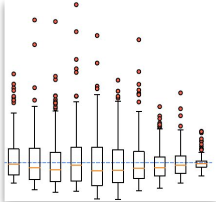

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Future work

- Measuring link properties, e.g., diversity/novelty between video pairs
- Training a shared RNN model on videos with similar dynamics