

Surprising Patterns In Musical Influence Networks

Flavio Figueiredo¹

Tales Panoutsos¹

Nazareno Andrade²

¹ Universidade Federal de Minas Gerais

² Enveritas

Contact {flaviovdf, tales.panoutsos}@dcc.ufmg.br

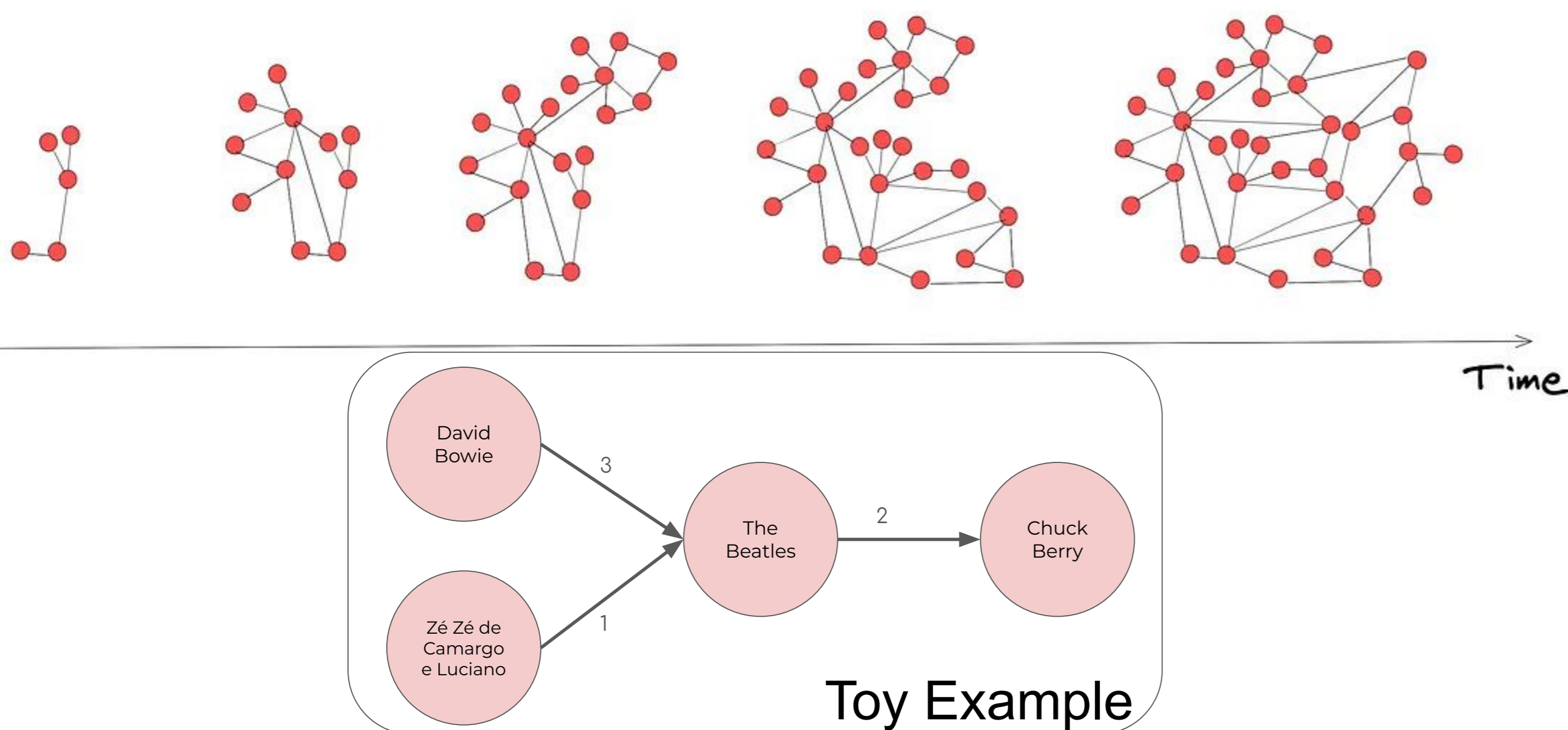
Introduction

We model artistic influence as evolving time influence networks. Next, we use centrality metrics to uncover surprising patterns of influence across time.

Hypothesis

Past Rank: Assumes the node's rank stays the same as time $t-1$.
Regular Growth: Assumes the node's rank changes linearly over time.

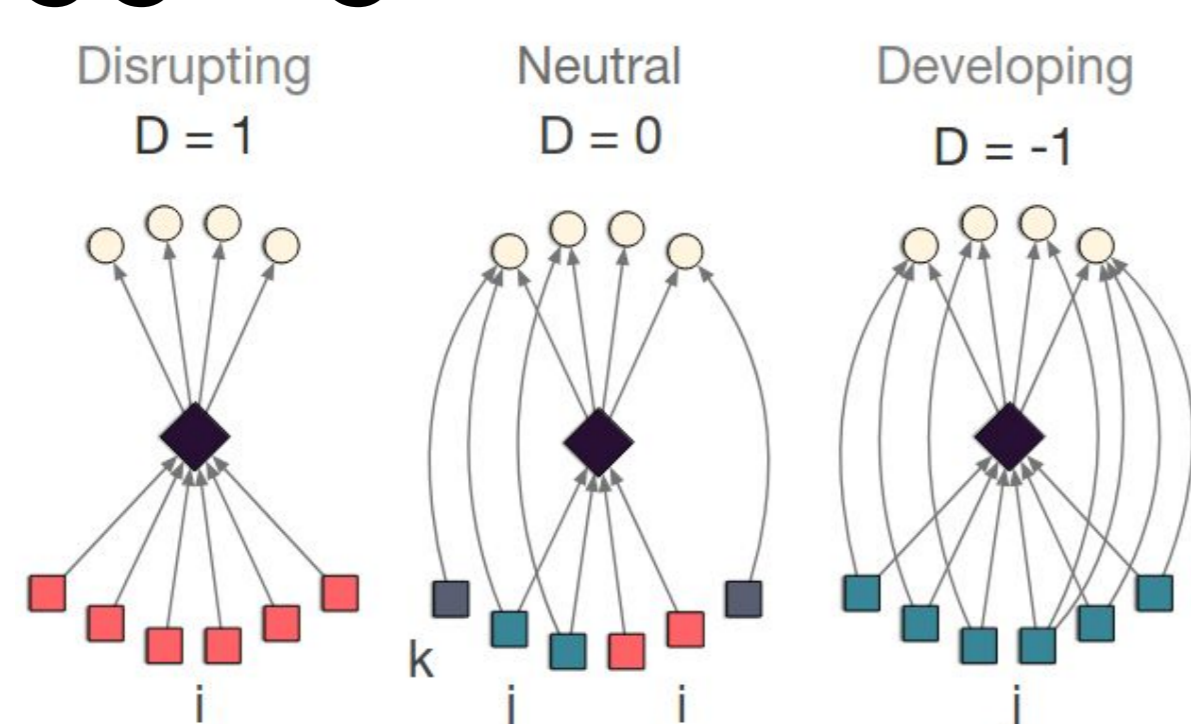
Musical Influence Networks



- **MINs: Time Evolving and Cumulative:**
 - **Nodes:** artists.
 - **Edges:** influence between artists.
 - **Edge weight:** number of times one artist cites another as an influence.

Centrality Metrics

- **PageRank:** measures how central is a node based on random walks
- **Disruption:** measures how disruptive is an node. Aggregation of influence



Bayesian Surprise

$$Sup(\mathcal{H}, \mathcal{D}) = \sum_{h=1}^{|\mathcal{H}|} D_{KL}(p(\theta_h | \mathcal{D}) || p(\theta_h))$$

Surprise is a node level score. For a single node, it sum several hypothesis H

Beta posterior for node position at time $t+1$ after we observe $t+1$

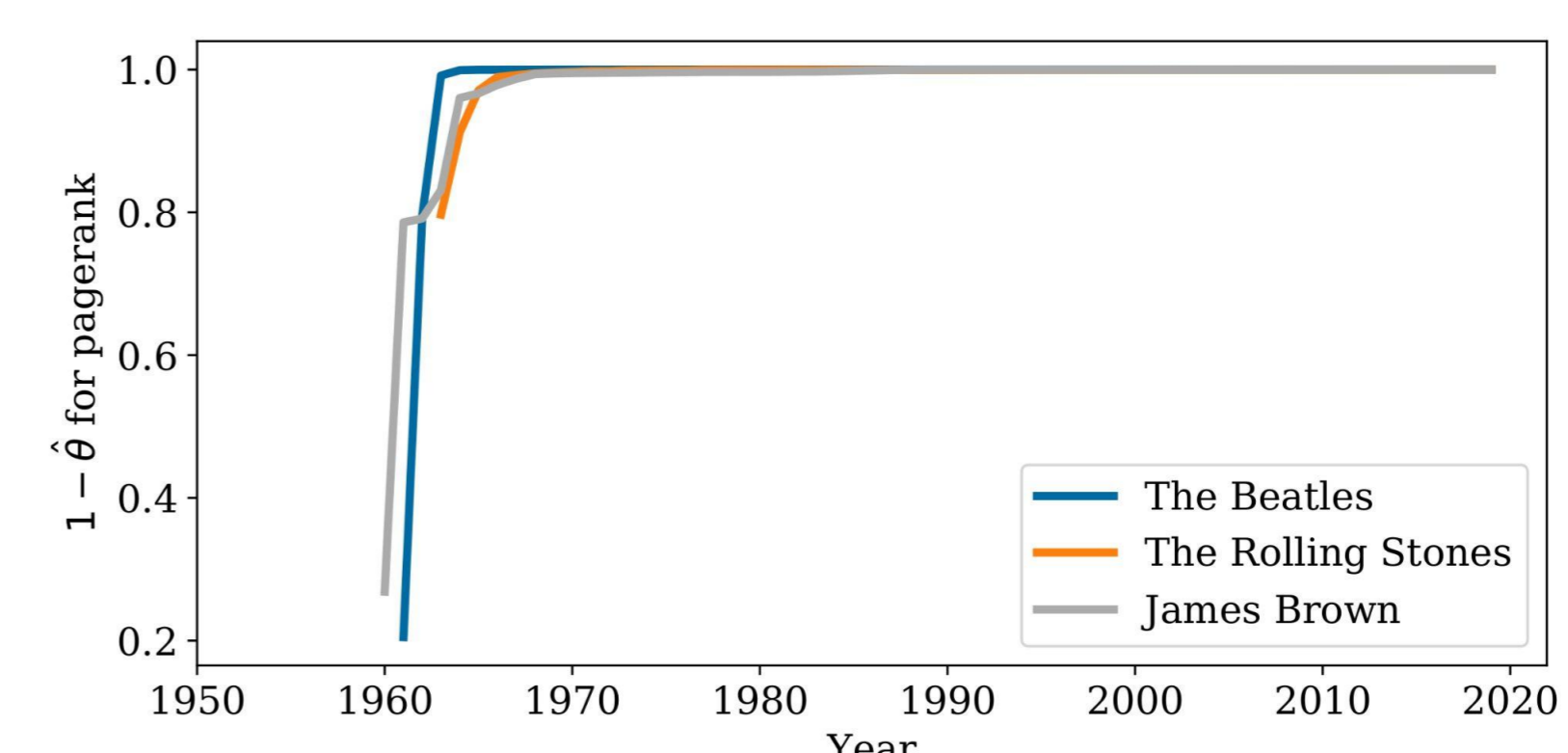
Beta prior position at time $t+1$. Based on several hypothesis. Computed before $t+1$

Datasets

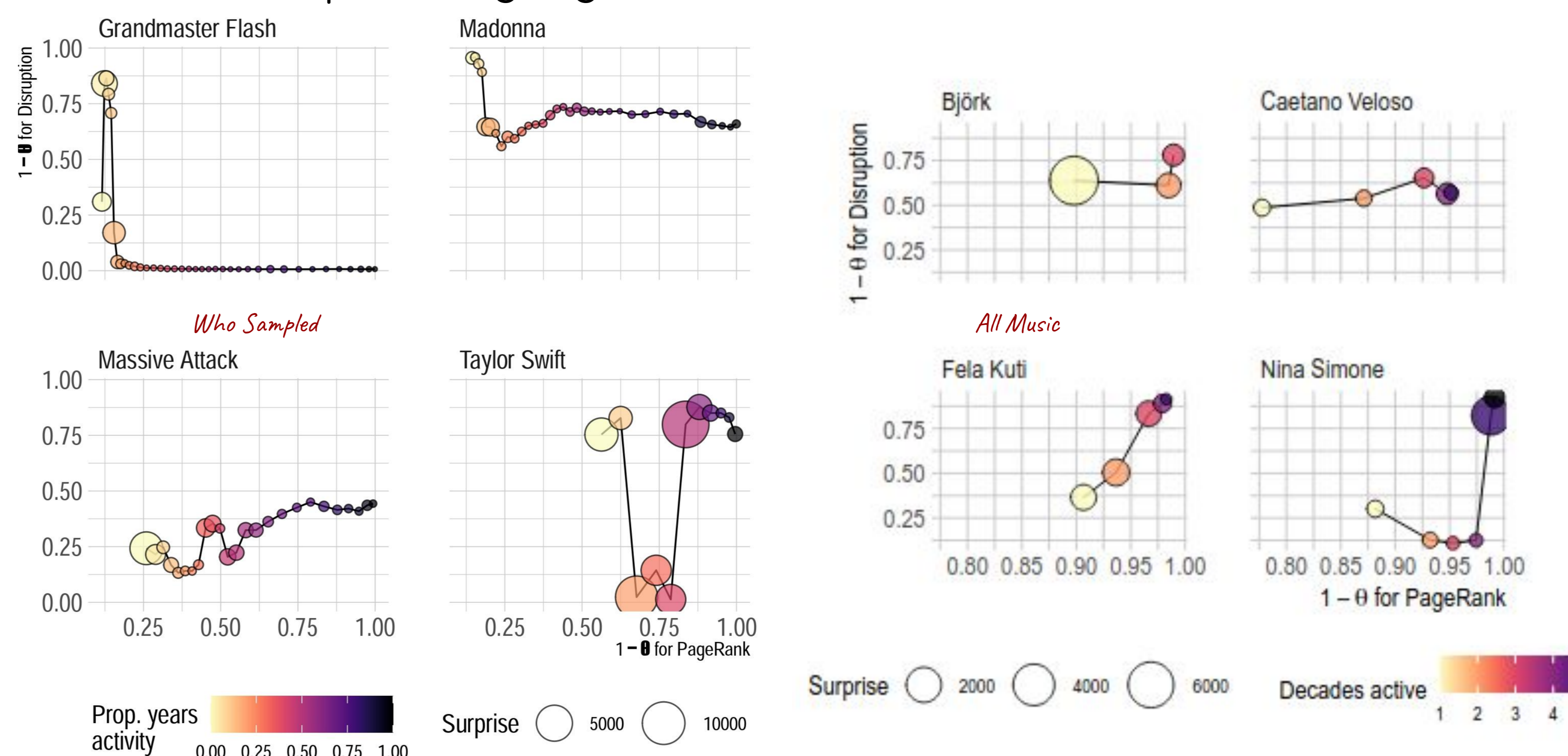
- **WhoSampled:** Tracks and catalogs music samples, covers, and remixes (weights are the number of samples).
- **AllMusic:** Provides detailed information about how artists influence one another (all weights are equal to 1).

Results

Centrality Scores Tend to Converge. Hard to see difference



Surprise Highlights Differences at the Node Level!!!



Conclusions

- Bayesian Surprise for rankings (first)
- Analysis on the temporal nature (via of music influence networks via Surprise).
- Captures patterns at the node level