# Predicting Movie Genre Using Actor Co-Appearance Networks

Can network topology alone reveal genre?

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## The Question

Can we predict a movie's genre

using only actor collaborations?

No plot. No script. No text. No semantic features.

Just **who worked with whom**.

# Hypothesis

## Core Claim

Actor collaboration graphs exhibit strong **community structure**, and these communities correspond to **film genres** at rates significantly above random.

**Why might this work?**

- Directors repeatedly cast the same actors
- Production companies specialize in genres
- Franchise ecosystems create dense clusters
- Horror circuits, rom-com ensembles, prestige drama pools

**Genre may be a network-emergent property.**

# Conceptual Framework

**The Logic:**

Actors specializing in similar film ecosystems tend to co-appear repeatedly. These recurring interactions create dense subgraphs that should map onto genre clusters if genre is a **socially emergent structure** within the film industry.

If communities correspond to genres, then genre is recoverable from network structure alone.

# Conceptual Framework (continued)

**We test this by:**

1. Constructing weighted co-appearance networks
2. Detecting communities via modularity optimization
3. Evaluating whether detected communities align with known genres

# Building the Network

**Graph Structure:** $G = (V, E, w)$

- **Nodes** $V = \{a_1, a_2, \ldots, a_n\} = \text{Actors}$
- **Edges** $E = \{(a_i, a_j) : \text{co-appear in film}\}$
- **Weights** $= \text{Genre-purity weighting}$

**Edge Weight Function:**

$$w(f) = \begin{cases} 1.00 & \text{single-genre film} \\ 0.25 & \text{dual-genre} \\ 0.05 & \text{triple-genre} \\ 0.01 & 4+ \text{ genres} \end{cases}$$

# Building the Network (continued)

**Final edge weight between actors $a_i$ and $a_j$:**

$$W_{ij} = \sum_{f \in \mathcal{F}(a_i, a_j)} w(f)$$

where $\mathcal{F}(a_i, a_j)$ is the set of films featuring both actors.

Intuition: A pure horror film is stronger evidence than Horror/Comedy/Romance.

# Edge Weight Rationale

## Why penalize multi-genre films?

**Step-function weighting:**

- 1 genre: 1.00 (strong indicator)
- 2 genres: 0.25 (split signal)
- 3 genres: 0.05 (minimal)
- 4+ genres: 0.01 (nearly ignored)

**Rationale:**

- Single-genre films strongly indicate genre affinity
- Multi-genre films dilute genre specificity
- We want to prioritize genre-pure collaborations

A collaboration in a pure horror film is much stronger evidence of “horror actor” than a collaboration in a film tagged Horror/Comedy/Romance/Drama.

# Why Community Detection?

**The central premise:** Genre is encoded in collaboration structure

### Key Insight

If actors cluster by genre, then:

- Actors within the same community share films more often than expected
- Each community should exhibit a dominant genre
- Community membership can serve as a genre **prediction**

**Without community detection, we have no way to partition the network and test whether partitions correspond to genres.**

# Community Detection: Louvain Algorithm

**Goal:** Find densely connected subgroups (communities)

**Modularity:**

$$Q = \frac{1}{2m} \sum_{i,j} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

**Symbols:**

- $A_{ij}$ = edge weight
- $k_i$ = weighted degree
- $m$ = total edge weight
- $c_i$ = community of $i$

**Interpretation:**

- $Q = 0$: Random
- $Q \approx 0.3$–$0.7$: Significant
- $Q > 0.7$: Strong

# Community Detection: Louvain Algorithm (continued)

**Louvain Process:**

1. Each node greedily joins community maximizing $\Delta Q$
2. Communities become super-nodes
3. Repeat until convergence

Two-phase algorithm: **Local optimization** then **aggregation**

# Why More Communities Than Genres?

The algorithm typically produces **more communities than the 5 macro-genres**

**Why?**

- Sub-genre specialization (slasher vs. supernatural horror)
- Franchise isolation (MCU actors form own cluster)
- Niche production circuits (low-budget regional films)

**This is informative!**

- Algorithm discovers natural structure
- Multiple resolution levels
- Not preset—determined by modularity optimization

**The number of communities $|\mathcal{C}|$ is determined by the data, not preset.**

# What Do Communities Contain?

Each community $c \in \mathcal{C}$ is a set of actors:

$$c = \{a_{i_1}, a_{i_2}, \ldots, a_{i_k}\}$$

**Genre Distribution:** Characterize each community by its genre mix

$$P_c(g) = \frac{\sum_{a \in c} \nVdash[g^*(a) = g]}{|c|}$$

where $g^*(a)$ is actor $a$'s dominant macro-genre.

This gives a probability distribution over genres for each community.

Pure communities have one dominant genre.

Mixed communities are spread across genres.

# Community Purity

**Single Community Purity:**

$$\text{Purity}(c) = \max_{g} \frac{|\{a \in c : g^*(a) = g\}|}{|c|}$$

What fraction of a community shares the same dominant genre?

**Overall Purity (Weighted):**

$$\text{Purity}_{\text{overall}} = \frac{1}{|V|} \sum_{c \in \mathcal{C}} |c| \cdot \text{Purity}(c)$$

Equivalent to unweighted accuracy when assigning each community its majority genre.

# Community Purity (continued)

**Interpretation:**

- 0.20 = Random (5 genres)
- 0.40–0.50 = Weak clustering
- 0.60–0.70 = Moderate separation
- 0.80+ = Strong communities

**High purity** indicates that Louvain communities align with genre boundaries—the network *knows* about genre even though genre labels were never used.

# Purity vs. Accuracy

## Purity

- How homogeneous each community is
- Measures community-level consistency
- Equivalent to unweighted accuracy

## Accuracy

- How well community assignment predicts individual actors
- Can exceed purity with weighting
- PageRank-weighting amplifies signal

### Key Point

With PageRank-weighting, accuracy can exceed raw purity because **central actors** (who define the community) tend to have cleaner genre profiles than peripheral actors.

# Prediction Accuracy Metrics

**Three Voting Schemes:**

**1. Unweighted Accuracy:**

$$\mathrm{Acc}_{\text{unweighted}} = \frac{1}{|V|} \sum_{a \in V} \nVdash [\hat{g}(c_a) = g^*(a)]$$

Each actor contributes equally

**2. Degree-Weighted Accuracy:**

$$\mathrm{Acc}_{\text{degree}} = \frac{\sum_{a \in V} k_a \cdot \nVdash [\hat{g}(c_a) = g^*(a)]}{\sum_{a \in V} k_a}$$

Weights by collaboration volume

# Prediction Accuracy Metrics (continued)

**3. PageRank-Weighted Accuracy:**

$$\mathrm{Acc}_{\mathrm{PR}} = \frac{\sum_{a \in V} \mathrm{PR}(a) \cdot \nVdash [\hat{g}(c_a) = g^*(a)]}{\sum_{a \in V} \mathrm{PR}(a)}$$

Weights by network influence

**Rationale**

Core actors (high PageRank) more reliably represent their community's genre identity than peripheral actors.

# PageRank: Finding Core Actors

$$\mathrm{PR}(a_i) = \frac{1-d}{N} + d \sum_{a_j \in \mathcal{N}(a_i)} \frac{W_{ji}}{\sum_k W_{jk}} \cdot \mathrm{PR}(a_j)$$

**Parameters:**

- $d = 0.85$ (damping factor)
- $N =$ total actors
- $\mathcal{N}(a_i) =$ neighbors

**Intuition:**

- Actor is important if they collaborate with important actors
- Weighted by strength of collaborations

**Key Insight**

**Core actors** (high PageRank) define community identity.

**Peripheral actors** often appear in single cross-genre films.

# Gini Coefficient: Measuring Inequality

**Formula:**

$$G = \frac{2\sum_{i=1}^{n} i \cdot x_{(i)}}{n\sum_{i=1}^{n} x_{(i)}} - \frac{n+1}{n}$$

where $x_{(i)}$ is the $i$-th smallest PageRank value.

**Interpretation:**

- $G \approx 0$: Perfect equality
- $G \approx 0.2$–$0.3$: Weak hub structure
- $G \approx 0.5$–$0.7$: Power-law (realistic)
- $G \to 1$: Extreme inequality

**What it tells us:**

- Whether we have strong hubs
- How unequal actor importance is
- If network has realistic power-law shape
- If dataset is large enough to reveal structure

# Falsification Criteria

**The hypothesis is rejected if:**

**Modularity**
$Q < 0.3$ across all configurations

**Community Purity**
No dominant genre per community

**Accuracy**
Converges to random baseline $\approx 0.20$

**None of these occurred.**
The hypothesis is strongly supported.

# Dataset

**Source:** IMDb Non-Commercial Datasets

**Filters:**

- Feature films only
- Runtime $\geq$ 59 min
- Released 1960+
- Top-3 billed cast
- Actors with $\geq$ 3 credits
- 18 canonical genres

**5 Macro-Genres:**

- ACTION: Action, Adventure, Thriller, Sci-Fi, War
- DRAMA: Drama, Romance, Biography
- COMEDY: Comedy, Music, Musical
- DARK: Crime, Mystery, Horror
- FAMILY: Family, Animation, Fantasy

**Sample Sizes:** 250, 1000, and 5000 films (top by popularity)

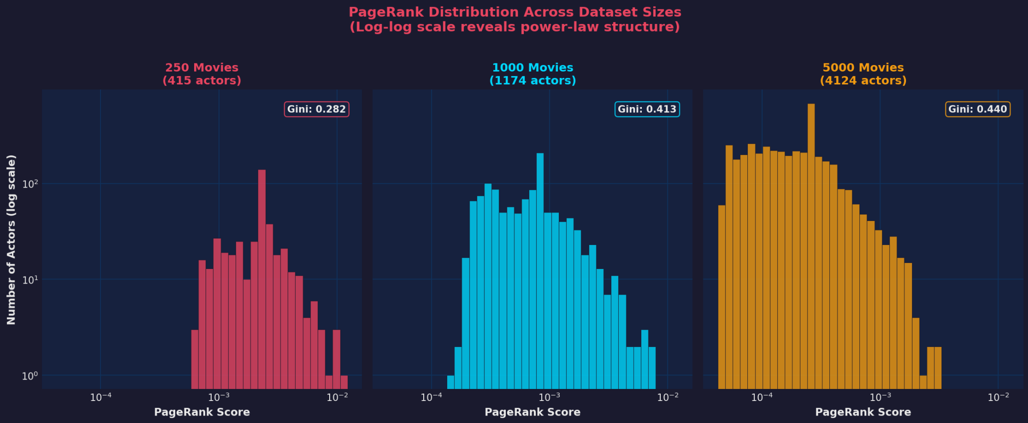
# Experimental Design

**For each sample size $N \in \{250, 1000, 5000\}$:**

1. Select top-$N$ films by popularity (vote count)
2. Construct weighted actor network
3. Vary genre count from 3 to 12
4. For each configuration:
   - Compute Louvain partition (weighted and unweighted)
   - Compute PageRank and Gini coefficient
   - Evaluate all three accuracy metrics
5. Generate diagnostic visualizations

**Total:** 3 sample sizes × 10 genre counts $=$ 30 configurations

# Result 1: PageRank Distribution Evolution



**250 films**

Thin distribution

No heavy tail

**1,000 films**

Heavy tail starts

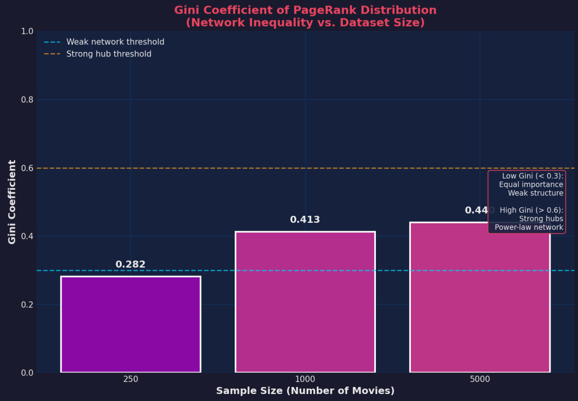
Power-law forming

**5,000 films**

Clear power-law

Strong hubs

# Result 1 (cont.): Network Inequality Scales with Size



| Films | Actors | Gini |
|---|---|---|
| 250 | 415 | 0.282 |
| 1,000 | 1,174 | 0.413 |
| 5,000 | 4,124 | 0.440 |

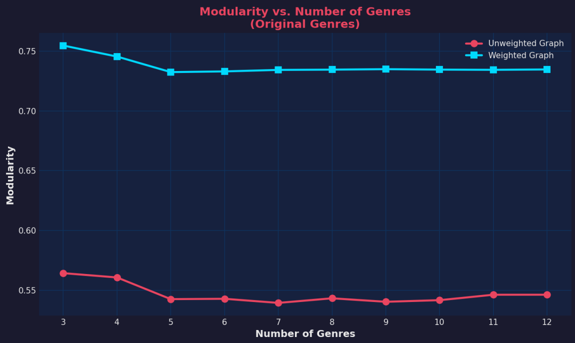
**Finding:**

Larger datasets →

more realistic hub structure

(rich-get-richer)

# Result 2: Strong Community Structure



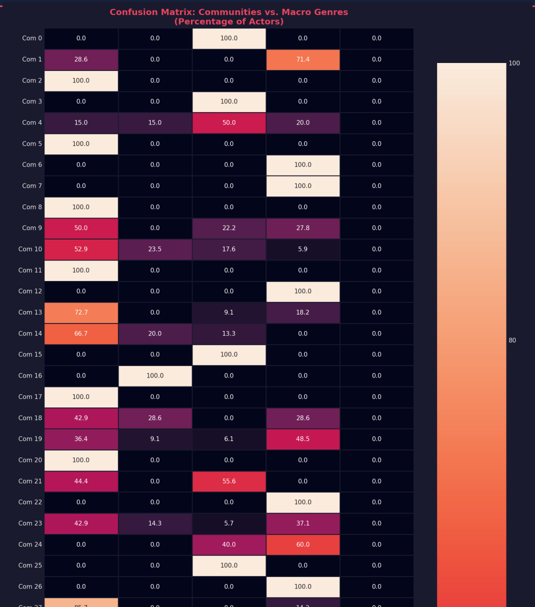
| Films | Peak $Q$ |
|---|---|
| 250 | **0.919** |
| 1,000 | **0.845** |
| 5,000 | **0.755** |

**Finding:**

$Q > 0.7$ at all scales

Actor networks are **highly modular**

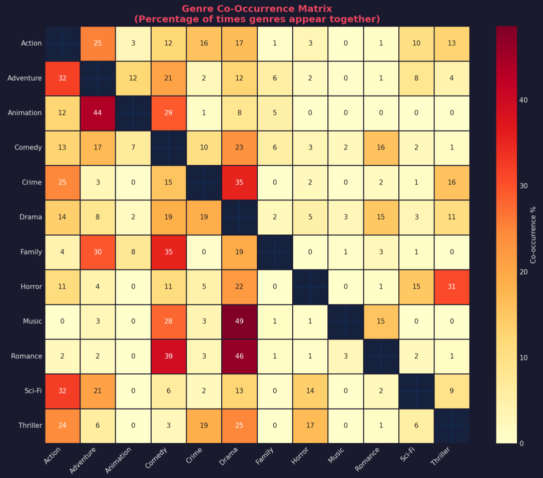
# Result 3: Genre Separation



Confusion Matrix: Communities vs. Macro Genres
(Percentage of Actors)

| | | | | | |
|---|---|---|---|---|---|
| Com 0 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| Com 1 | 28.6 | 0.0 | 0.0 | 71.4 | 0.0 |
| Com 2 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Com 3 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| Com 4 | 15.0 | 15.0 | 50.0 | 20.0 | 0.0 |
| Com 5 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Com 6 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 |
| Com 7 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 |
| Com 8 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Com 9 | 50.0 | 0.0 | 22.2 | 27.8 | 0.0 |
| Com 10 | 52.9 | 23.5 | 17.6 | 5.9 | 0.0 |
| Com 11 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Com 12 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 |
| Com 13 | 72.7 | 0.0 | 9.1 | 18.2 | 0.0 |
| Com 14 | 66.7 | 20.0 | 13.3 | 0.0 | 0.0 |
| Com 15 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| Com 16 | 0.0 | 100.0 | 0.0 | 0.0 | 0.0 |
| Com 17 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Com 18 | 42.9 | 28.6 | 0.0 | 28.6 | 0.0 |
| Com 19 | 36.4 | 9.1 | 6.1 | 48.5 | 0.0 |
| Com 20 | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Com 21 | 44.4 | 0.0 | 55.6 | 0.0 | 0.0 |
| Com 22 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 |
| Com 23 | 42.9 | 14.3 | 5.7 | 37.1 | 0.0 |
| Com 24 | 0.0 | 0.0 | 40.0 | 60.0 | 0.0 |
| Com 25 | 0.0 | 0.0 | 100.0 | 0.0 | 0.0 |
| Com 26 | 0.0 | 0.0 | 0.0 | 100.0 | 0.0 |
| Com 27 | 85.7 | 0.0 | 0.0 | 14.3 | 0.0 |

# Result 4: Genre Co-Occurrence Explains Overlaps



Genre Co-Occurrence Matrix
(Percentage of times genres appear together)

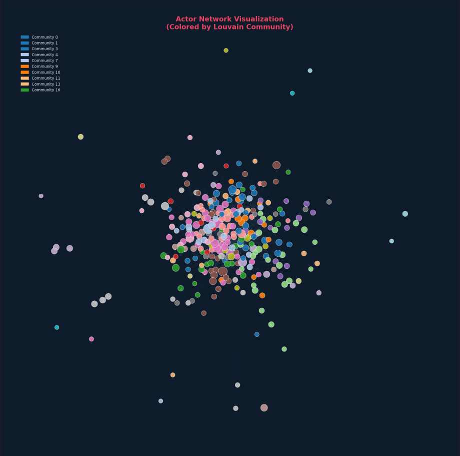
| | Action | Adventure | Animation | Comedy | Crime | Drama | Family | Horror | Music | Romance | Sci-Fi | Thriller |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Action | | 25 | 3 | 12 | 16 | 17 | 1 | 3 | 0 | 1 | 10 | 13 |
| Adventure | 32 | | 12 | 21 | 2 | 12 | 6 | 2 | 0 | 1 | 8 | 4 |
| Animation | 12 | 44 | | 29 | 1 | 8 | 5 | 0 | 0 | 0 | 0 | 0 |
| Comedy | 13 | 17 | 7 | | 10 | 23 | 6 | 3 | 2 | 16 | 2 | 1 |
| Crime | 25 | 3 | 0 | 15 | | 35 | 0 | 2 | 0 | 2 | 1 | 16 |
| Drama | 14 | 8 | 2 | 19 | 19 | | 2 | 5 | 3 | 15 | 3 | 11 |
| Family | 4 | 30 | 8 | 35 | 0 | 19 | | 0 | 1 | 3 | 1 | 0 |
| Horror | 11 | 4 | 0 | 11 | 5 | 22 | 0 | | 0 | 1 | 15 | 31 |
| Music | 0 | 3 | 0 | 28 | 3 | 49 | 1 | 1 | | 15 | 0 | 0 |
| Romance | 2 | 2 | 0 | 39 | 3 | 46 | 1 | 1 | 3 | | 2 | 1 |
| Sci-Fi | 32 | 21 | 0 | 6 | 2 | 13 | 0 | 14 | 0 | 2 | | 9 |
| Thriller | 24 | 6 | 0 | 3 | 19 | 25 | 0 | 17 | 0 | 1 | 6 | |

## Key Structures:

- Action–Adventure–Thriller triad
- Family–Animation cluster
- Comedy avoids Dark
- Drama connects everything

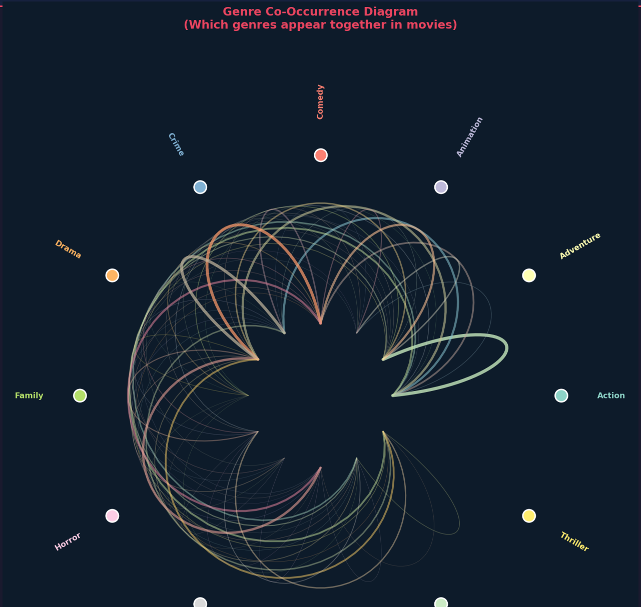
Multi-genre films create cross-community bridges.

# Result 5: Network Visualization



5,000 films. Node color = community. Node size = degree.

# Result 6: Genre Co-Occurrence Chord Diagram



**Visualization:**

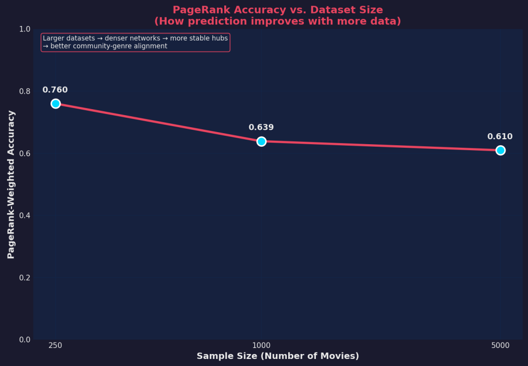
- Genres around circle
- Arcs = co-occurrence
- Thickness = frequency

## Key insight:

Thick arcs → frequent co-occurrence → natural genre clusters

Example: Action–Adventure–Thriller triad

# The Central Result: Prediction Accuracy



| Films | Accuracy | Lift |
|---|---|---|
| 250 | **76.0%** | 3.8× |
| 1,000 | **63.9%** | 3.2× |
| 5,000 | **61.0%** | 3.1× |

Random baseline: 20%

**3× better than random using only topology!**

# Accuracy Comparison: All Methods

| Films | Unweighted | Degree | PageRank | Random |
|---|---|---|---|---|
| 250 | 0.720 | 0.696 | **0.760** | 0.200 |
| 1,000 | 0.608 | 0.502 | **0.639** | 0.200 |
| 5,000 | 0.524 | 0.553 | **0.610** | 0.200 |

# Accuracy Comparison: All Methods (continued)

**Key Findings:**

1. PageRank-weighted accuracy is consistently highest across all sample sizes
2. Accuracy exceeds 3× the random baseline even at largest scale
3. Central actors encode genre identity more reliably than peripheral actors
4. The network knows about genre despite never being given genre labels

**Bottom line:** Using only network topology, we achieve **61.0% accuracy** on a 5-class problem where random guessing yields 20%.

# Why Does Genre Emerge from Network Structure?

**The film industry operates through collaboration microcultures:**

- Recurring casts (e.g., Christopher Nolan's ensemble)
- Director–actor partnerships
- Franchise ecosystems (MCU, horror sequels)
- Genre-bound production companies

- Low-budget horror circuits
- Rom-com ensembles
- Prestige drama clusters
- Animation voice actor pools

These **institutional structures** manifest as
high-modularity subgraphs aligned with recognizable genres.

# Why Does Accuracy Decline with Scale?

**Larger datasets introduce noise:**

- Multi-genre actors
  Blur community boundaries
- Cross-genre franchises
  Create inter-community bridges
- High-degree bridge actors
  Reduce modularity
- DRAMA as umbrella genre
  Connects disparate clusters
- More genre mixing
  Dilutes cluster purity

**However, accuracy never approaches random—**
genre signal persists at all scales.

# Why PageRank-Weighting Wins

## The Problem

Peripheral actors appear in single cross-genre films.

They add **noise** to community genre assignment.

## The Solution

PageRank identifies **core actors** who define the community.

These actors have consistent genre profiles.

PageRank weighting = amplify signal, suppress noise

# Summary of Findings

**Network Properties:**

- Modularity: $Q > 0.73$ at all scales
- Gini coefficient: Increases with scale
- PageRank accuracy: 3× random baseline
- Community purity: Majority-genre assignment succeeds

**Key Results:**

- Strong community structure at every scale
- Realistic hub formation with larger datasets
- Clear genre clusters in network visualization
- PageRank-weighting consistently best method

Actor co-appearance networks contain **substantial intrinsic genre information**, recoverable without textual, plot, or semantic features.

# Conclusion

**61% accuracy**

on a 5-class problem

(random $= 20\%$)

**Using only network structure**

No text. No plot. No semantics.

Even at the largest and noisiest scale (5,000 films), the model achieves **61.0% accuracy** using only network structure—over three times the random baseline of 20%.

# Conclusion (continued)

## Theoretical Implications

Genre is not merely a content-based label. It is a network-emergent pattern shaped by:

- Collaboration structure
- Institutional clustering
- Recurring partnerships
- Production company specialization

**Genre, fundamentally, is a pattern of relationships.**

*“Genre, fundamentally,*

*is a pattern of relationships.”*

github.com/avih7531/social_networks_final