



Breadth vs. Depth – Linking Network Shape to Revenues, a Study of the Dispersion of Film Trailers via Twitter

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Introduction

- Social media provides a platform where consumer communities can be mobilized
- Traditionally marketing consists of the usage of “owned media” which is a sponsored form of information dissemination
- Social networks involve “earned media”, information can flow irrespective of sponsorship

Social Media and Twitter

- Social media is user created and user generated
- One of the most popular forms of social media is Twitter
- Twitter was originally intended to provide a platform for users to provide a back and forth exchange regarding recent news and events, after the South-by Southwest film and music festival in Austin the growth of Twitter exploded
- Users communicate to one another in 140 characters or less
- Users can follow the newsfeed of other users and publicly interact through their messages and the sharing of information
- Some networks are densely connected where many of the users follow each other
- Others are quite wide, many unconnected users link additionally unconnected users

Research Question and Context

Breadth

High

Low

Depth

High

Optimal

???

Low

???

Worst

Context:

- The research context is the independent film industry in the United States between 2009 – 2012
- Independent films are conceptualized as those not produced with the backing of a major production house
- At the time of writing the average feature film cost over \$50 million dollars to produce, distribute and market
- Independent films must use less conventional means to increase demand

Network Characteristics

Network Breadth

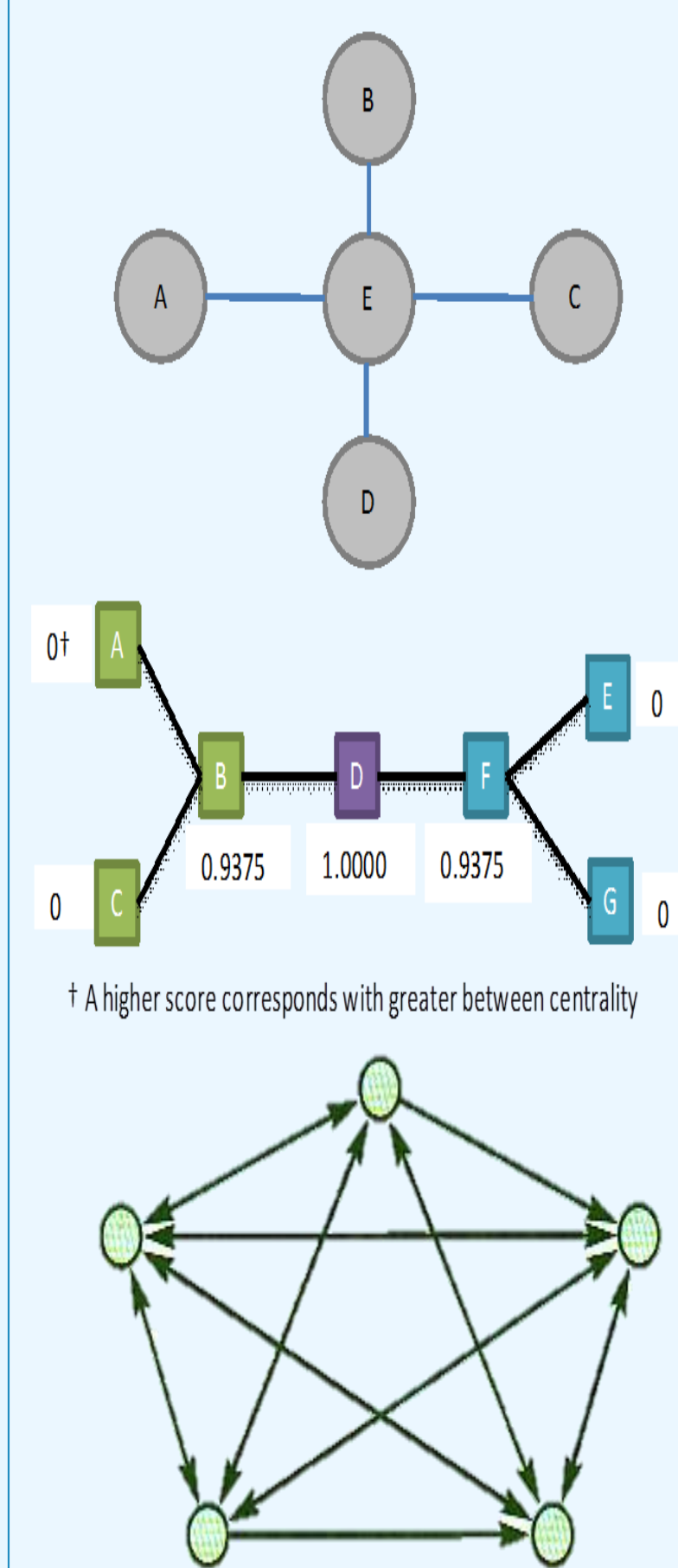
- This measure examines the average distance between users in the network
- In the example on the right, the network has very high breadth because the users are all connected by one user
- Depth is low because most users are not directly connected

Centrality

- The degree to which a user acts as a bridge between separate users
- Users who belong to multiple groups often have high centrality

Network Depth

- This indicates the level of connectedness between users in the network
- A high level of connectedness indicates that many of the users are connected to one another
- Breadth may be low because the users are all connected to one another and thus share similar networks



† A higher score corresponds with greater between centrality

Regression Equation

$$\text{Log}(\text{Rev})_i = \beta_0 + \beta_1(\text{Breadth}_i) + \beta_2(\text{Depth}_i) + \beta_3 \log(\text{Centrality}_i) + \beta_4(\text{Ratings}_i) + \beta_5(\text{Theaters}_i) + \beta_6(\text{Weeks}_i) + \beta_7(\text{Vertices}_i) + \beta_8[\text{Breadth}_i * \log(\text{Centrality}_i)] + \epsilon_i$$

Methodology

- Our sample is comprised of independent films that appeared at the Sundance Film Festival between the years 2009 to 2012
- Every category of film was included except for feature film presentations
- Feature films were omitted because of their large scale financial backing
- The final sample contained a total of 147 independent films
- We developed a network using the Node XL software program
- We focused on those who retweeted the trailer or mentioned the trailer

Hypotheses & Regression Model

Benefits of Greater Breadth

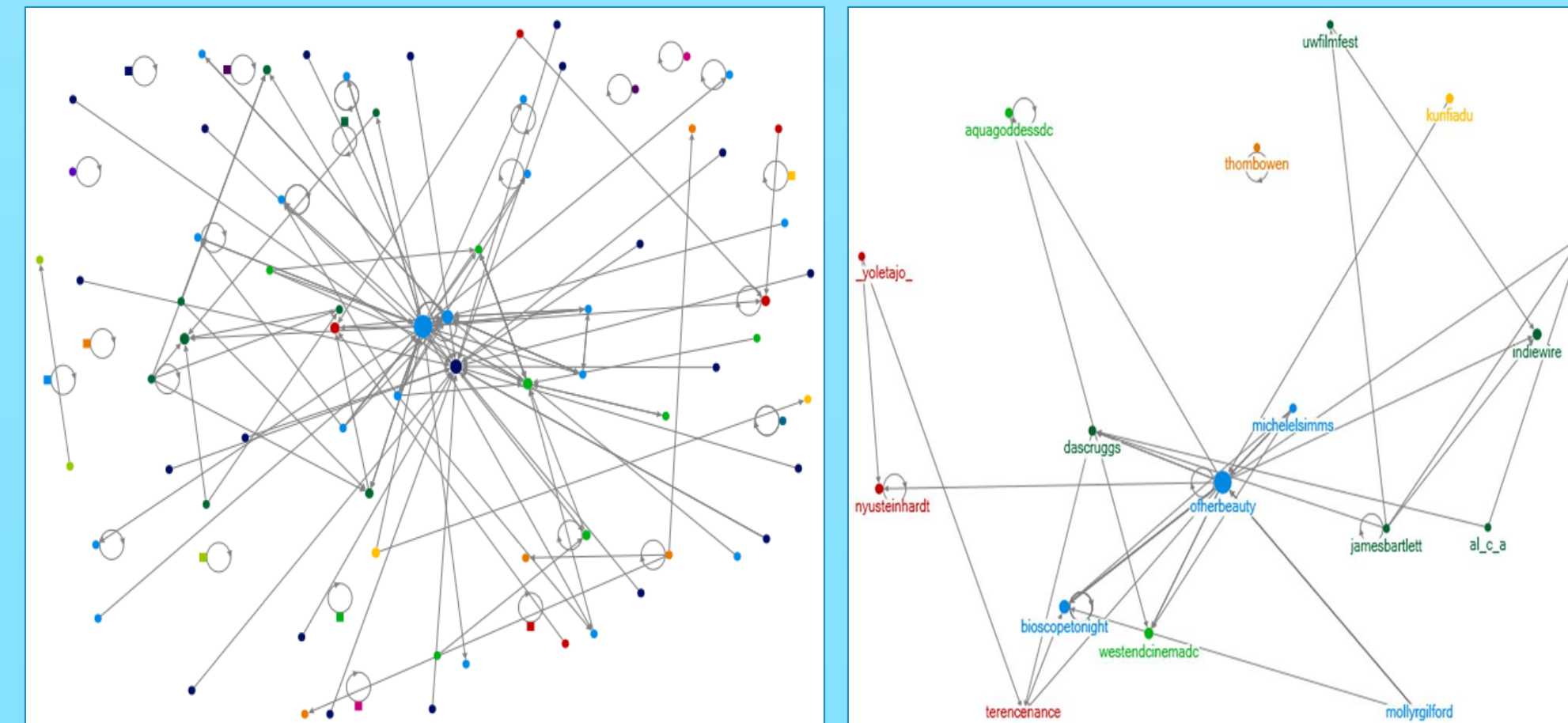
H1a: When a marketing communication spreads throughout a social network, the greater the breadth of the network the more positive the impact on box office revenues for an independent film.

Benefits of Greater Depth

H1b: When a marketing communication spreads throughout a social network, the greater the depth of the network the more positive the impact on box office revenues for an independent film.

H2: The effect of greater network on revenues for an independent film will be weakened by an individual in the network that has high centrality within it

Using Node - XL



Discussion

- The wider the network the greater the positive impact on the revenues of the film, in other words the more spread out your network the greater the impact on the revenues of the independent films. (Hypothesis 1a was supported)
- The density of the network was not found to be significant (Hypothesis 1b was not supported)
- The impact of network breadth was weakened by high centrality, the average distance between users (H2 supported)

Results

- The mean log of revenue for the films is 5.2769 with a standard deviation of 0.7767
- We found the variance inflation factors to be less than 5 thus indicating that issues of multicollinearity were unlikely to impact our results

Table 3

- Model 1 of Table 3 is the base model, containing only the control variables
- The availability measures were both significant and the number of vertices was not significant, both findings were expected
- The effects of the film's ratings were not significant, which contradicted previous work on the film industry
 - Ratings can signal the quality of a film to consumers before consumption
 - It is expected that films with good ratings will obtain higher profits than films
- Independent films are a subcategory of films, which may be less permeable to the effects of critical reviews and appeal to a subgroup of the consumer population
- The inclusion of the films in our sample in the *Sundance Film Festival* provides a degree of credibility
- Model 2 includes the independent variables while Model 3 tests our basic assumption that greater breadth and depth would have the biggest impact on the revenue
- This assumption was validated by the significant interaction of breadth and depth
- The estimates from Model 4 showcase our primary research and indicate that hypotheses 1a and 2 were supported while hypothesis 1b was not supported

Table 2 Descriptive Statistics and Pearson Correlation Coefficients, 2009-2011 (N=147)

| Variable | Mean | S.D | Min. | Max. | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---------------------|----------|----------|--------|----------|-----------|-----------|------------|-----------|----------|----------|--------|
| 1. Log (Revenue) | 5.2769 | 0.7767 | 3.4404 | 7.1071 | | | | | | | |
| 2. Breadth | 1.2200 | 0.6830 | 0.1429 | 2.8258 | 0.2344 | | | | | | |
| 3. Depth | 0.0148 | 0.0269 | 0.0011 | 1.1667 | -0.2666† | -0.2972* | | | | | |
| 4. Log (Centrality) | 1.7417 | 1.0149 | 0.0000 | 3.8850 | 0.2949* | 0.8690*** | -0.4939*** | | | | |
| 5. Ratings | 6.8898 | 0.8009 | 4.4500 | 8.0000 | 0.2300 | -0.0389 | -0.0370 | 0.0178 | | | |
| 6. Theaters | 227.8333 | 455.0775 | 1.0000 | 2620.000 | 0.6973*** | 0.1215 | 0.1215 | 0.2276 | 0.1668 | | |
| 7. Weeks | 11.8571 | 8.8223 | 1.0000 | 40.0000 | 0.5880*** | 0.0511 | -0.1683 | 0.1566 | 0.4405** | 0.4632** | |
| 8. Vertices | 140.3158 | 122.4417 | 3.0000 | 377.0000 | 0.1902 | 0.5823*** | -0.4081** | 0.6424*** | -0.1351 | 0.2033 | 0.0929 |

†p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001

Table 3 Parameter Estimates of (log) Revenue, 2009 - 2011 (N =147)

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---------------------------|-----------------------|-----------------------|-----------------------|-------------------------------------|
| Theaters | 0.0001*** (0.0002) | 0.0001*** (0.0002) | 0.0009*** (0.0002) | 0.0009*** (0.0002) |
| Weeks | 0.0285* (0.0119) | 0.0260* (0.0112) | 0.0253* (0.0110) | 0.0220* (0.0099) |
| Ratings | -0.0174 (0.1168) | -0.0568 (0.1107) | -0.0622 (0.1086) | -0.0472 (0.0969) |
| Vertices | 0.0008 (0.0009) | 0.0016 (0.0011) | 0.0016 (0.0011) | 0.0006 (0.0010) |
| Breadth (Hypothesis 1a) | | 0.8350* (0.3518) | 0.7685* (0.3477) | 1.6012*** (0.3843) |
| Depth (Hypothesis 1b) | | -6.7916 (5.3334) | -22.9920† (11.842) | -6.2063 (4.6697) |
| Log(Centrality) | | -0.3114 (0.2206) | -0.4013† (0.2242) | 0.1255 (0.2333) |
| Breadth x Log(Centrality) | | | | -0.4096** (0.1229) |
| Breadth x Depth | | | | 15.0402* (9.8639) |
| Constant | 4.8117*** (0.7847) | 4.8641*** (0.7459) | 5.1408*** (0.7535) | 4.2346*** (0.6794) |
| Adjusted R-Square | 0.5850 | 0.6665 | 0.6891 | 0.7525 |

Note: Standard errors are in parentheses
* p < 0.05, **p < 0.01, ***p < 0.001

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