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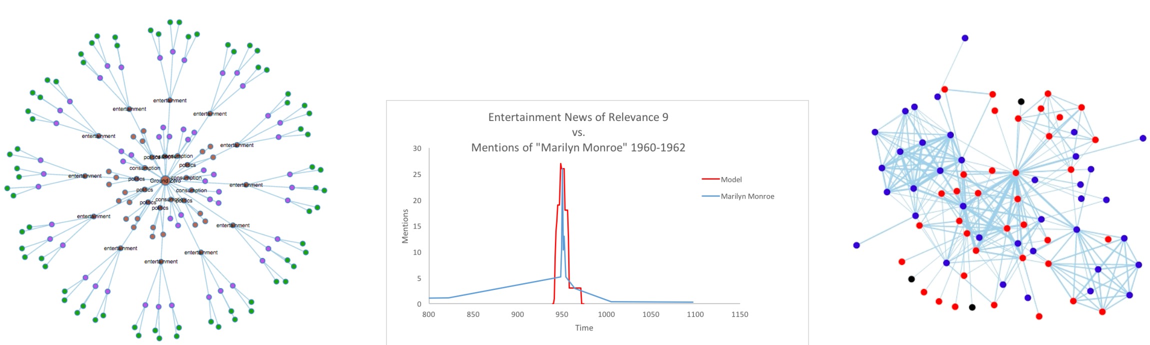
Summary

The choice to accept and spread information is inherent in people. Throughout time, we see attempts to communicate in evolving forms. Our goal is to analyze information spread by understanding the modes by which people communicate and the information they convey from the 1860s to now. First we designate news as falling under categories of consumption, politics, and entertainment. We then define the importance of an item by its relative novelty, accessibility, attractiveness, and compatibility to determine an overall relevance factor.

Our model enhances the information diffusion model to account for conflicting information and the distribution of what category of news is most popular for a given era. We then translate this information to a graphical node model to determine the spread of a news item given a certain category and relevance factor.

We built a network simulator based on our model that processes information spread for different eras, categories, and importance. From these simulations and a comparison of real data from media archives, we find the characteristics of mass appeal. Our model accurately depicts the spread of news like Abraham's Lincoln's death and the erection of the Berlin Wall. Finally, we expand our model and simulation to account for competing sources, changing topography (like a city compared to a rural town), and isolation to determine a strategy for optimizing information spread.



(a) (b) (c)

a) A capture of the simulation running randomly generated information through a network modeling year 2015. b) A comparison between the volume output of the model for high relevance entertainment news and the mentions of "Marilyn Monroe" in the Washington Post from 1960-1962. The peak corresponds to the news of her death. c) Red and Blue information pieces with equal relevance factors of 10 were released simultaneously. Blue was released in a more connected hub.

Contents

Characterizing information importance and the effect on the spread in various graph topologies

Control # 54740

February 1, 2016

1 Introduction

1.1 Context and Motivation

Over time, the methods we use to communicate has evolved and grown from small networks of groups with limiting connections to the massive array of transmission associated with the internet. In any sense, one thing has remained constant and that is the inherent practice of seeking and sharing news. Communication Theory suggests this is for a few fundamental reasons: to persuade, to give or provide information, to seek information and to express emotions. These basic desires drive the ways in which we build our networks and determines the importance of each interaction.

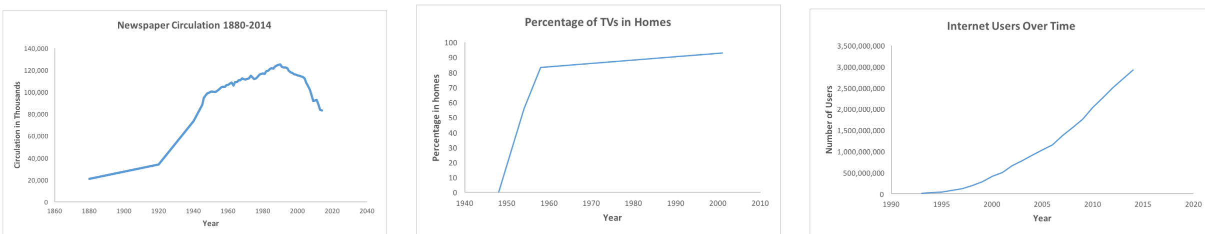
We seek to develop a mathematical model of social networks to analyze communication at its core. To do this, we need to understand the modes by which people communicate, the information people convey and accept, the science of implanting news and the effects these all have on the resulting spread of the news.

1.2 Assumptions

A few assumptions are taken in order to allow the model to run smoothly.

- We assume topical distribution trends are uniform throughout a given era.
- We assume noteworthy news has overcome the threshold of noise and disregard static traffic of information.
- We assume a discretized time variable, updating the status of the existence of an information string in each node at regular intervals.
- We assume that the probability of someone registering and paying attention to some string of data, or indeed sharing this piece of data along mediums of communication is also random.
- Finally, we assume that when a node decides to share data, it shares it with all of its neighbors.

Additional small assumptions specific to pieces of the model will be outlined at appropriate times.



(a) (b) (c)

Figure 1: a) Newspaper circulation trends over time. b) Percentage of TVs in US households over time. c) Number of internet users over time. Currently, 40.6% of the world is connected to the internet.

2 Data Analysis

2.1 Trends of News Sources

The reach of information has exploded over the past 150 years. In today's society, information from nearly anywhere can propogate into the mainstream media. These connections and spreads can bring about amazing consequences and this phenomenon is seen across time. By compiling data from census reports, statistical assessments and available databases, we determine the trends of four information transfer mediums: newspaper, radio, television, and the internet. The industrial revolution brought a massive increase in newspaper production in that the number of newspapers and subsequent circulation increased dramatically. In the 20th century, radio and TV began to replace newspapers as major sources of information, and in more recent history, the internet has massively expanded the spread of information and is in the works of replacing outdated media outlets as a primary source. Newspaper circulation skyrocketed from 1880 to 1940, until radio broadcasting began to gain influence. In 1920, only about 3 million homes had a radio set, but that number reached nearly 30 million by the end of the 1930s. By 1945, 80% of homes had a radio set and that number continued to grow into today, in which radios are in virtually every car and every home. The introduction of TV saw an even greater increase with only 0.4% of households having a set in 1948, to 55.7% four years later. The trend only continued from there. Finally, the age of the internet has exceeded the trends of the previous mediums and seen unparalleled rapid expansion. These trends can be seen in Figure 1(a-c) depicting the true data found.

The introduction of each new medium contributes to an eventual downfall of the others. Although there may not be an extinction of any one as they serve to compliment each other, it is shown that the increased usage of a novel medium brings a decrease in relevance of the current and past types. However, innovative sources like the internet combine the functions of newspapers, radio, and television with eNews, internet podcasts and instant streaming, respectively. This could serve to make outdated methods irrelevant and, consequently, obsolete.

2.2 What is news?

Ultimately, the question at hand is, what makes a news story? How does one piece of information gain relevance over another? For the purpose of this paper, we define ”news” as a piece of information that overcomes two thresholds: the threshold of penetration and the threshold of retention. We are concerned with the information that has the potential to have a wide spread and/or lasting impression. The threshold of penetration is the minimum number of mentions across various sources for a piece of information to catch wind. The threshold of retention is the minimum amount of time a piece of information is relevant enough to be shared. Essentially, in everyday news there is a level of noise of information that the story must overcome to be considered.

In order to enforce what qualifies as news, we look at major news stories throughout the past 150 years to get an accurate idea. To compare with actual data, we tracked the volume change of phrases mentioned in newspapers and other media types over periods of time. To begin, a phrase was chosen in terms of its relevance to the time period. Then we tracked the mentions of this phrase in a database of over 10 million archived newspapers from 1836-1922 and in the Washington Post from 1960-1963. The volume of mentions of the phrase per day was then recorded over a time interval.

We introduce two similar pieces of news and explore their ability to break above the thresholds. First, we examine the volume over time of mentions of the word "Lincoln" in newspapers from 1864-1866. As seen, there is a consistent level of noise until April 15, 1865, corresponding to the assassination of President Lincoln.

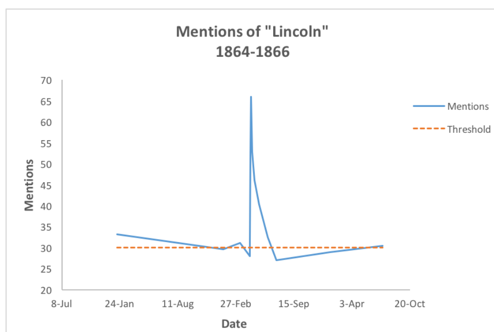


Figure 2: Mentions of "Lincoln" over time in US newspapers from 1864-1866.

After a time period, the mentions return to the threshold, even delving below as the phrase becomes less relevant over time. This is also seen in a current, but similar scenario from 2012. There is an equal distribution of mentions of "Osama Bin Laden" and "Moammar Gaddafi" until a single source released mention of Osama Bin Laden's death into a communication network, signaling a spike in his mentions. This is clearly a piece of information that reflects our definition of news.

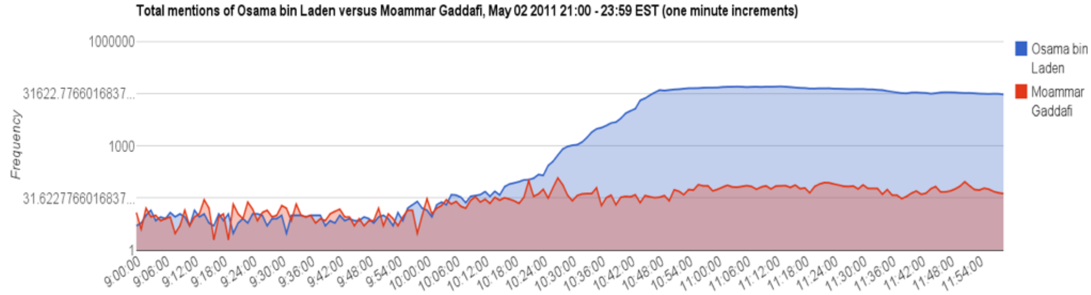
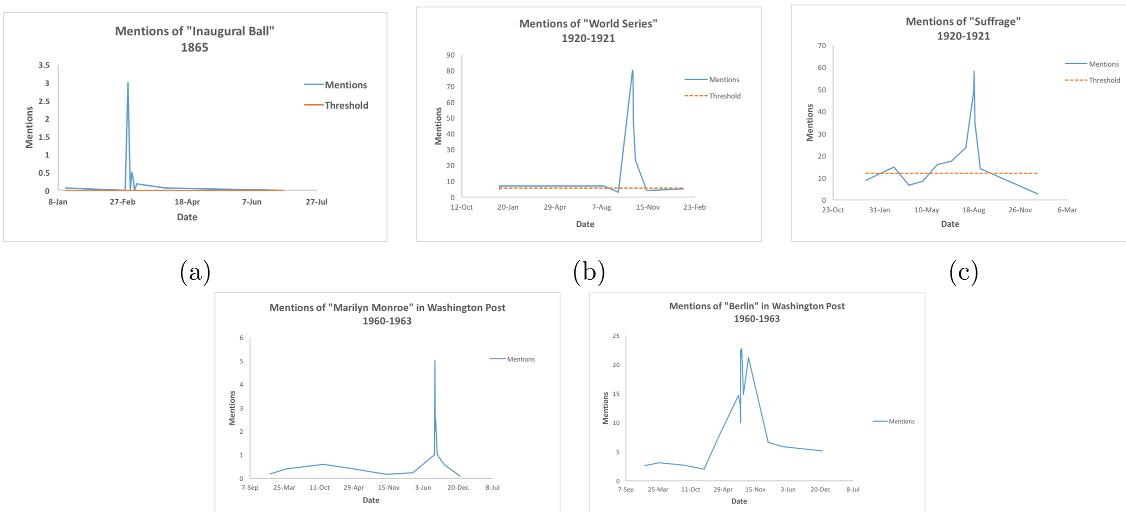


Figure 3: Mentions of the phrase "Osama Bin Laden" over time. The plot of "Moammar Gaddafi" is included as an equivalence reference.



(a) (b) (c)

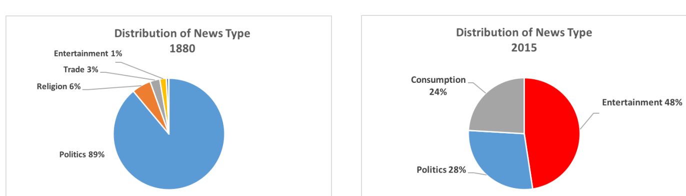
(d) (e)

Figure 4: a) Mentions of "Inaugural Ball" in newspapers from 1864-1866. Peak corresponds to Lincoln's 2nd Inaugural Ball. b) Mentions of "World Series" in the early 1920s. Peak corresponds to a Cleveland victory. c) Mentions of "Suffrage" in the early 1920s. Peak corresponds to the ratification of the 19th Amendment. Notice the dip below threshold after the news as the phrase held less relevance. d) Mentions of "Marilyn Monroe" from 1960-1962. The peak corresponds to her deadly overdose in 1962. e) Mentions of "Berlin" from 1960-1962. The peak shows the date of erection of the Berlin Wall. Notice the retention of the news.

Across the board, this shape and trend is seen for differing types of news in all eras, topics, and importance to the period.

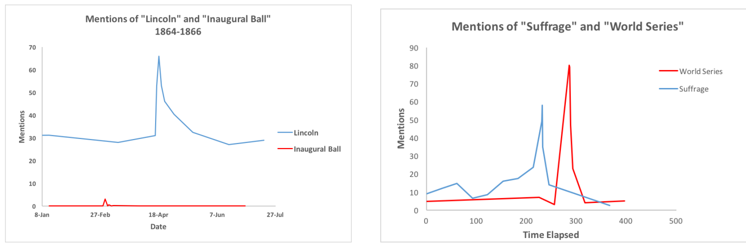
2.3 Trends of Topical Distribution

Finally, we examine the change over time of topical distribution in news sources. In spreading news, we categorize the highest ranking stories as falling into categories of consumption, politics, and entertainment. That is, the majority of news stories are most relevant in the realm of the aforementioned categories. Again compiling data from census reports on the circulation of different types of newspapers over the years, statistical data on radio and TV broadcast breakdown, and finally examining the top ten news sources with the highest internet traffic for information type, we arrive at a topical distribution for the type of information being spread over time. There is a clear trend away from political news towards entertainment which is reinforced by the comparison of phrase volume distributions within eras.



(a) Circulation proportion of newspaper type in 1880.

(b) News type by user volume of the top ten visited websites in 2015.



(a) (b)

Figure 6: Comparison of a political news story and entertainment piece of 1865 (a) and 1920 (b).

3 Models

3.1 How Information Spreads

In order to understand the nature of any piece of information and its spread throughout a network, we first note the ways in which information can travel. Hence forth, we will consider that communication is either *active* or *passive*. Active communication requires focus on the part of both the sharer and receiver of information. A notable example would be newspapers, the journalists and editors of a newspaper must certainly pay attention as they place stories in the next day's run, and those that consume newspapers have to focus on consuming the text presented. Conversely, some mediums are passive in nature. Such examples, such as radio and at times television, only require the focus of one of the participants, the one sharing the information, while the person receiving it need not focus and may instead focus on such things as, say, driving their car or tasks around the home. A note here should be made about the internet. The internet is distinctly upload-oriented which has often been used as one of its major selling points, the freedom of people to express themselves universally. In addition, the internet is at times both passive and active, there are articles one can read, interactive games, but at the same time streaming services such as Netflix, Spotify, and podcasts. While the internet has not yet branched out largely to those areas traditionally held by passive media, steps are being taken, such as the listening to podcasts in the car rather than radio.

3.2 Previous models and limitations

The comparison to diffusion is largely seen in modeling information spread. The model has a basic form of

$$\frac{dA(t)}{dt} = i(t)[P - A(t)]$$

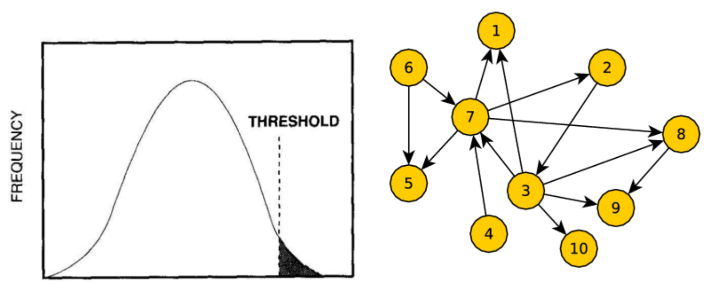
In this sense, A(t) are the individuals that have received the information, P is the total population, and $i(t)$ is a diffusion coefficient. The diffusion coefficient can be expanded to include an addition factor independent of the number of current individuals prevalent to the information, a multiplicative factor accounting for internal effect of imitation on the spread of the knowledge, or a combination of the two. These models are outlined below.

$$i(t) = \begin{cases} \alpha \\ \beta A(t) \\ \alpha + \beta A(t) \end{cases}$$

These coefficients can be implemented in the above equation and can be solved to determine the volume of people prevalent to information at given times.

This model effectively maps the increase spread of diffusion given internal and external influence qualities. However, it lacks in versatility and does not account for other factors which will enhance or inhibit the spread of information.

In modeling the spread of information in a graph, previous work can most often be categorized by two distinct model types. The Threshold model is defined by a system wherein people begin to adopt a position if a certain ratio of their neighbors adopt it. Newer solutions falling under the category of a cascade model suggest an alternative explanation for how information spreads in social networks. In this model type, each node infected with information has a certain probability to infect each of its neighbors. In this manner, one node can actually begin an information cascade, simply by spreading something that is infectious, which is analogous to viral media.



(a) (b)

Figure 7: Basic representation of threshold (a) and cascade (b) models.

3.3 Diffusion Model with Multiple Sources

We herein introduce an enhanced model of information diffusion that accounts for the factors lost in the previous model. In order for our model to accurately describe the adoption of a story into mainstream news and track the resulting spread, we take into consideration the following factors:

- The topical distribution of newsworthy items has changed over time and is not, nor has ever been, equal among topics. In a community oriented towards one subject, an item of that subject will spread quicker than one from a different subject. The topic of the item will affect the spread among a population and is an internal factor.
- Different items have varying levels of importance to a community as a whole. Some items with high importance, like the assassination of a President, will span the gaps of interest distribution in a population. The importance of a item will affect the spatial spread the information as well as the speed with which it accomplishes this spread and is an external factor. The importance of an item is determined by a number of characteristics as well:
  - Novelty or Shock (ability to spark interest without back story)
  - Accessibility (ability of any individual to understand)
  - Attractiveness (impact of news on individual)

- Compatibility (alignment with societal values and/or acceptable notions)

These considerations combined give a total *Relevance Factor* which we will model scaled from 1 to 10. This relevance factor will determine the rate of spread of the information to the connected nodes of the network. An item with a high relevance factor will have high probability of penetration, velocity, and retention. We remind the reader that an item run through our model has already been categorized as "news" and therefore exceeds the respective threshold. Thus, we herein assume an item will propagate to some extent and model the subsequent spread of the item with respect to its relevance factor.

Let y(t) denote the number of individuals who are prevalent to a piece of information. In order to accurately model the topical distribution for a given time, we designate a certain percentage of individuals to be "interested" in each topic based on compiled data of the time. For example, for a model of 1880, 89% of the individuals will be politically oriented and 7% will be entertainment. We are not insinuating that real individuals have single-minded interests, but simply that the percentages of interest of a community will change given the relative distribution of the time, modeled by designating percentages of nodes, or individuals. This will in turn account for the respective effect of item topic on spread. If a news piece is topically relevant to one community, it will naturally spread between individuals within that community, but also has the potential to leak to individuals of other communities. Essentially, an entertainment individual will still hear and share news of a high profile political story, and vice versa. The key in this cross-community sharing lies in the relevance of the information itself. A low relevance political story will spread slowly in an entertainment network, and a high relevance political story will still spread quickly in a consumption network despite the conflicting interest. This concept can be modeled in the following way.

$$\Delta y = R(t)\{[\beta_1 y_1(t) + \eta_{12} y_2(t)]\,(N_1 - y_1(t)) + [\beta_2 y_2(t) + \eta_{21} y_1(t)]\,(N_2 - y_2(t))\}\Delta t$$

Or generally,

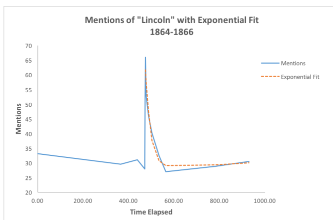
$$\Delta y = R(t)\{\sum_{i=1}^{n}\sum_{\substack{j=1\\ j\neq i}}^{n} [\beta_i y_i(t) + \eta_{ij} y_j(t)]\,(N_i - y_i(t))\}\Delta t$$

Each i represents the components of a different topical community. For example, N_1 denotes the community interested in entertainment, N_2 in politics, etc.. β_1 represents the rate at which an individual in community 1 will spread an information piece relevant to his community. η_{12} represents the rate at which he will spread the information to someone who does not know the information in a different community. β_2 and η_{21} are equivalent variables for an individual in community 2. For a piece of information relevant to one community, it will spread quickest between nodes of this community, slower between those nodes and conflicting nodes, and slowest through two nodes of conflicting interest to the story. Generally, when information i is released $\beta_j < \eta_{ji} < \eta_{ij} < \beta_i$ where i and j range from 1 to the number of categories and $i \neq j$.

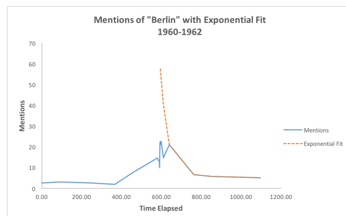
In determining the final number of individuals prevalent to the information in a given time, the function is multiplied by an external relevance factor, R(t). This accounts for information that spans the gaps in community interest. Although as a community we value some news pieces more than others, there are certain viral news stories that bridge these differences. As a people, we are affected by major political changes, influenced by mass entertainment, and impacted by new innovations. Although we are trending away from political news towards technological and entertainment oriented news as a constant influx of information, spikes of important stories will make their way to the individuals of all communities.

R(t) can be dynamic in time and allows for consideration of the characteristics described above. In general, items rise and decay exponentially at a speed proportional to their relevance. For example, an item that is novel but not necessarily impactful will have a quick ascent in volume followed by a quick decay. Whereas an item that is novel, impactful, and accessible will have a quick ascent and slow decay corresponding to high penetration and retention.

This property is reinforced in volume data collected from real event spread.



(a)



(b)

Figure 8: An exponential function is fit to the decay of mentions over time.

Phrase	R-Square Value
Berlin	1.00
Lincoln	0.96
Marilyn Monroe	0.89
Suffrage	0.90
WS	0.94

Figure 9: The R-Squared values of fits for the aforementioned news stories. An exponential decay function in our model is clearly physically reasonable.

The accuracy of the fit is shown in the above table. Thus far we have shown that the spread of a piece of information is dependent on various internal and external influence factors contributing to a combined relevance factor that varies with time. We have also shown the ability to model and predict the nature of R(t) given the characteristics of the incident information.

3.4 Network Model

To further our model, we base it in graph theory, with the goal being to observe the flow of information in a population of people connected by different means of communication, or different types of edges. In considering the nature of avenues of news, a few considerations are readily apparent. Some forms of communication are distinctly consumption-oriented in nature where one merely gets information from these mediums, such as newspapers, radio, and television. This is represented on a digraph as a directed edge. Conversely, they have an opposite that represents itself as merely an edge; forms of communication that are upload-oriented in nature include telegraphs, the internet, and talking.

Take a node, 0, at time t, (going into an internal state, $\mathcal{I}_{0,t}$) with inward connections to nodes { 1, 2, ..., j } and outward state (the state the node is transmitting to its neighbors) represented at time t by $n_{i,t}$. We represent the absorption of information by:

$$(\mathcal{I}_{0,t,k} = n_{k,t-1} \cdot P_{N_0})$$
$$(\mathcal{T}_{0,t} = \prod_{k=1}^{j} (1 - \mathcal{I}_{0,t,k}))$$
$$(\mathcal{I}_{0,t} = -\mathcal{T}_{0,t} + 1)$$

Given that any $n_{i,t}$ has a value of 0 or 1, this calculation multiplies 1 or 0 by another 0 or 1, determined by P_{N_0}, a function that semi randomly decides whether to share something or not. Then, in the next step, we subtract this number from 1, meaning that if 0 notices the information shared by a specific node, it zeroes out the entire equation, if not, it stays at 1. From then, we modify our final result so 1 switched to 0 and vice versa.

Now, while this is a method to update the internal belief of a node, it does not necessarily signal to other nearby nodes this information. We update their external beliefs, what they share to the public, after a gestation period, G, from time t_0, in the following manner, where P_{S_0} denotes a 0 or 1 in the same sense as P_{N_0}, but for sharing rather than noticing:

$$n_{0,t} = \delta_{t,t_0+G} \cdot P_{S_0} \cdot \mathcal{I}_{0,t}$$

Now, one may note that this is only ever one at a single time slice, as it uses the Kronecker delta to denote the time when this is put out into the open, as it is a pulse of information, not a sustain signal. In reference to previous literature, this very much resembles a modified Independent Cascade model for social networks or an SIR epidemic model but with increased intricacy.

3.5 Network Versatility

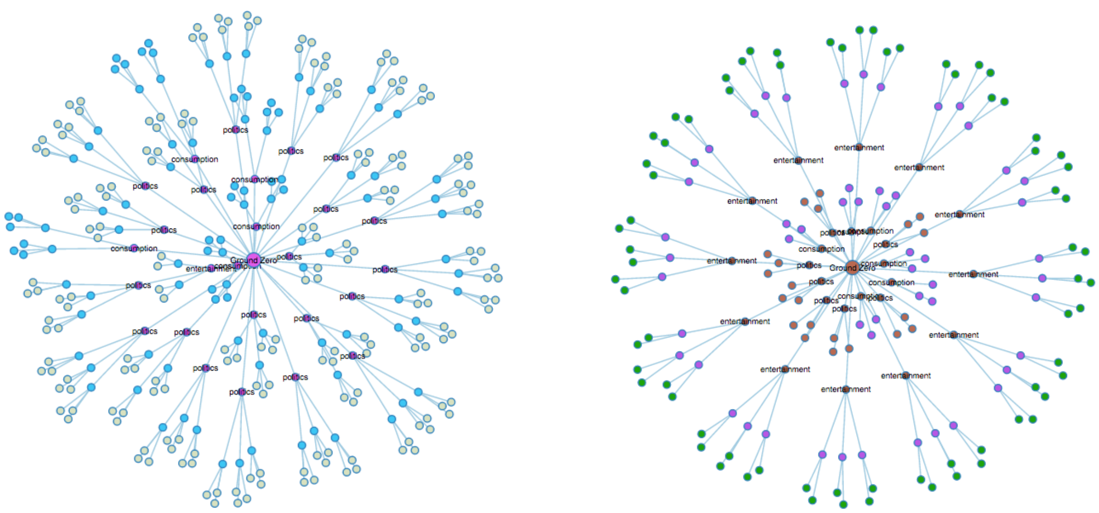
While our model as it stands is already quite versatile and can represent a good deal of scenarios, a few important problems stand out immediately. While we have a gestation period for vertices, we lack any means of transmitting data from two connected points over a timescale longer than 1 step. To that end, we bifurcate our vertices into two subcategories, real nodes and ghost nodes. A real node is simply a node weve described above, it represents a person in our model, and is where we care about information residing or not. A ghost node, on the other hand, is mathematically equivalent to a real node, except that $P_{S_0} = P_{N_0} = 1$. In addition to this specialized nature of them noticing and transmitting data, a ghost node between (0, n) also only has two connections, one inward from 0, and one outward towards n. To expand even further on this model, if we want the speed of a connection between two nodes to be v, to model time it takes to transfer between them as v steps, which one would want for things such as newspapers moving on trains, we represent this as the ghost node having a gestation period of $v - 1$. Finally, to account for the worldly scenario of an individual forgetting a piece of news, we represent the internal state of node 0, that has believed something at time t_0, at times after t_0, as:

$$(\mathcal{I}_{0,t} = \mathcal{I}_{0,t_0} \cdot P_{V_{0,t}})$$

Note here that $P_{V_{0,t}}$ is 0 or 1, based on a weighted number generator, however, it changes over time. As $t - t_0$ increases, $P_{V_{0,t}}$ will tend towards 1, as people become more forgetful of information over time. Now, instead of our model simply having people retain information, we can have people receiving information, forgetting it, then receiving it again from another source. Much like how people hear news from an initial source, like the newspaper or Facebook, go about their day and forget it, then hear about it again from someone in the home.

4 Simulations

The parameters mentioned above were placed in a simulation with a few additional modifications. As mentioned in Section 3.3, we categorize news as falling into one of three functions: politics, entertainment, and consumption. The nodes follow the proportional topical distribution of each time era. We only allow data to originate from one source and the nodes themselves can only hold one string at a time until another piece of data overrides it. We run the simulations on two networks representing the cultures of the 1880 and 2015. The differences include the topical proportions, and spread layouts. These correspond to the media categories and sources of the times. Finally, the simulation allows for a random generation of information input (order, type, relevance) or a controlled news input. A few simulations are represented below.



(a) (b)

Figure 10: Randomly generated news simulated in the 1880 (a) and 2015 (b) model. Notice the differences in community proportions and graph connections.

4.1 Validity of Simulation

For the validity of the model, we simulate news of varying topic and relevance and compare it with real world data collected.

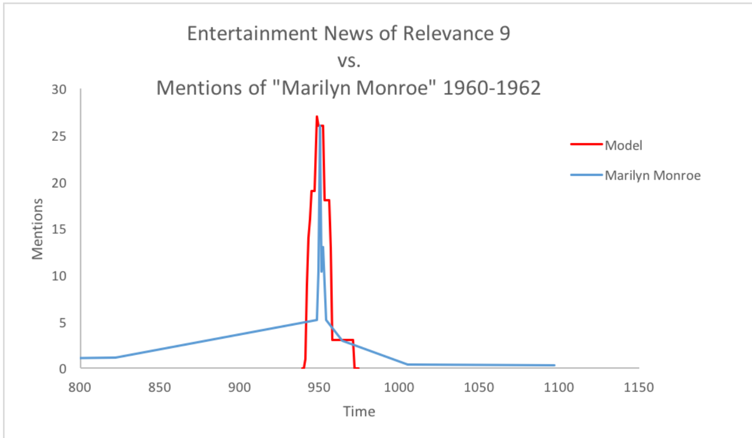
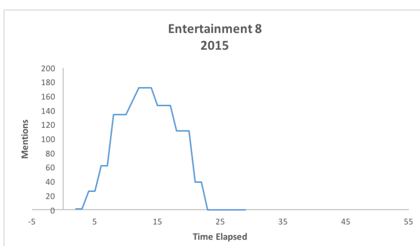
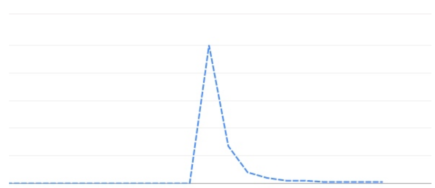


Figure 11: The volume of mentions in time of an entertainment item of relevance 9 and the data compiled around Marilyn Monroe's death.

As seen, the components of the real data are accurately reflected in the model. This news was highly relevant with high novelty, attractiveness, and accessibility. The death of Marilyn Monroe would have clearly had a high relevance factor in the time and that is reflected in the model. In a similar sense, our model for current spread and distribution reflects the news of Alan Rickman's death in January 2016 when compared with volume data from Google Trends.



(a) Model simulation of entertainment news (8) in the 2015 model.



(b) Real world trend of mentions of "Alan Rickman" over a given time.

From these comparisons, we validate our model.

4.2 Robust Nature of Simulation

To test the robust nature of our model, we evaluate the predicted propagation of current news in past networks and vice versa. Take, for example, the announcement of Osama Bin Laden's capture and death. This would be considered political news of relevance 10. Also, consider the announcement of Kim Kardashian's pregnancy, an entertainment relevance of 6. We then test this information in our 1880 network to model its spread. The results are shown below.

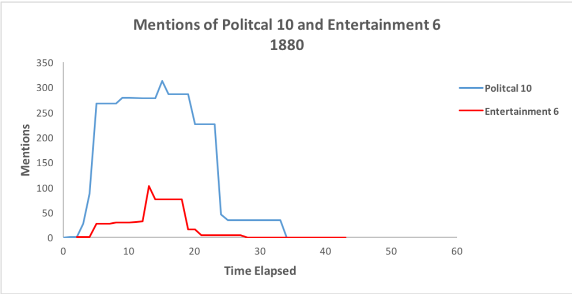


Figure 13: Simulation run on 1880 network with news of political relevance 10 and entertainment relevance 6.

To get a sense of the accuracy of the data found, notice the similarities between real volume data of Abraham Lincoln's assassination and news of the inaugural ball. The maximum height of mentions is significantly lower for the entertainment news as well as the retention period. We confidently state that the model well reflects real scenario data across time periods.

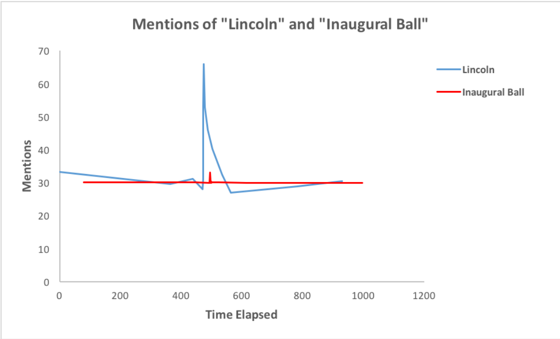


Figure 14: The volume spread of Lincoln's assassination and his earlier inaugural ball. The inaugural ball data has been shifted linearly in time to see direct comparison.

5 The Future of Communication

In looking to the future, we first note on the source changes over time. As mentioned, there are active and passive news sources as well as upload and consumption based sources. Upload-oriented networks, in and of themselves, are capable of doing all the things a consumption-oriented network can do and more and will, then, dominate when the resources needed to sustain both are present. However, as those two modes of communication fight with each other for relevance, active and passive media act differently, complimenting each other. While there is indeed a good deal of area in our media consumption space that the two will vie for, active media sees more communication in a given period of time, while passive media has occupancy space advantages in some senses. For example, passive media can be consumed while driving or completing other tasks where active cannot. In this sense, the two complement each other and neither can get rid of the other entirely. As it stands, the internet is immune to competition as it encompasses qualities of all the above-mentioned. A new source of media must either improve an excelling feature or remove flaws that inhibit information spread of the future.

A common occurrence in science fiction is the idea of a neural uplink, transmission of information between minds directly. It is inherently faster than the internet, as it drastically shortens the gestation period. Additionally, it combines all types of communication expertly effectively layering the models of interaction. The components of face-to-face conversation can be enhanced by the speed of internet connection. A model of this mode would include multi-faceted edges that would behave in compounding fashion. As it trends, we would expect the nodes to further represent entertainment as news, but with this new wave of technology, it is impossible to predict if individuals will lose community sense and begin to function on a personal premise given the immediate availability and personal nature of media associated with a neural uplink.

6 Sensitivity Analysis

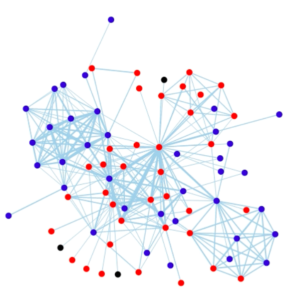
Our base model has a few fixed parameters in simulating the spread of information throughout a network. We address the impact of these parameters by varying them in the following ways.

6.1 Competing Sources

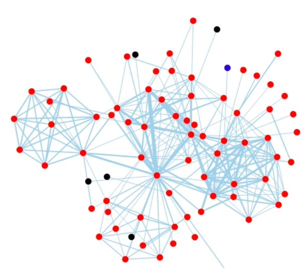
To study the propagation of news, we limited the number of source nodes to one. In this way we effectively tracked the singular path of this item. We have altered our simulation to include two competing sources of news in an interconnected system. When two sources of information of the same type are released simultaneously into the network, we follow the subsequent spread.

6.1.1 Varying Levels of Importance

We assume that there is a 50/50 chance for dominance when the two pieces of data meet at a node. Upon setting up this model, two simulations were run, one where the two pieces of information are equally believable, and one where one is much more believable than the other, or having higher relevance. The results are just as one would expect, with the first splitting equally the graph and the second being overrun by the more popular belief. In this sense, we can see how misinformation that suits our preconceived notions spreads, it is more believable to us and thus blots out real information in the network.



(a) Equal value.

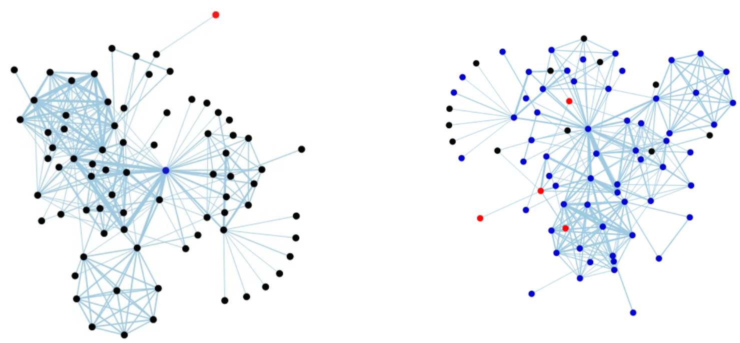


(b) Unequal value.

Figure 15: The spread of information of higher value spreads quicker and further than that of a lower value. This is amplified if the competition is increasingly uneven.

6.1.2 Varying Initial Connectivity

For two sources of equal believability, the placement of the initial prevalent nodes hold increasing importance. This is akin to equal news beginning in a rural village as opposed to a large city. We find that the item beginning in a more connected node reaches a larger amount of subsequent nodes in a shorter time. This notion is physically reasonable in that less people will be prevalent to and, thus, willing to accept, town gossip over city news.



(a) Intial sources. (b) Spread after time.

Figure 16: It is clear to see the respective spreads of red and blue information items and how their initial position or connections influenced this.

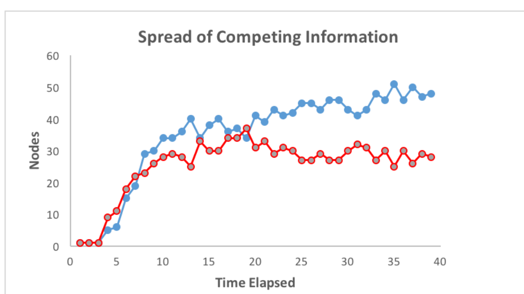


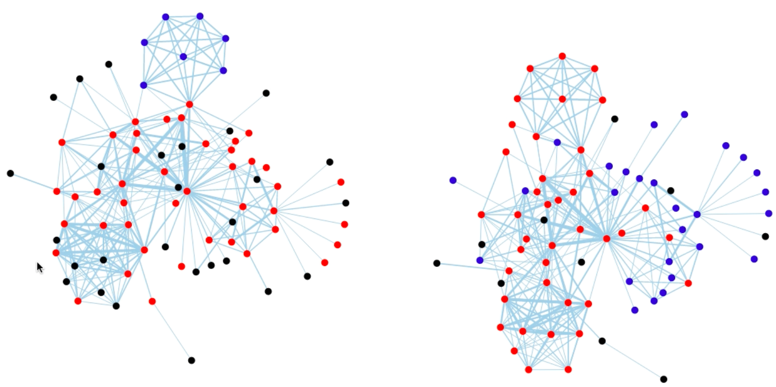
Figure 17: Red and Blue information pieces with equal relevance factors of 10 were released simultaneously. Blue was released in a more connected hub.

Recall the internet volume data surrounding the news of Osama Bin Laden's capture and death (Figure 3). The distribution closely resembles the spread of competing information (Figure 17). As "Osama Bin Laden" became a more relevant phrase, its volume and spread overtook that of a similarly oriented phrase "Moammar Gaddafi". We further prove the validity of our model through this comparison.

6.1.3 Varying Connection Distances

Finally, we alter the model to vary the distance between connections, making it so it takes longer to move across certain edges than others. There are now groupings of connectivity that vary in size and spread which allows us to simulate differing topologies both of our graph and the physical world. For example, an interconnected island shares a network with the mainland. It takes a fair amount of time to move information between them by boat, but the said information propogates much faster both on the island and the mainland themselves. This differs from the previous simulation in that the connective speeds as well as the connectivity volume are varied.

As before we consider two items that are equally relevant or believable. We find that the information originating on the island remains isolated to that island, whereas the mainland niformation dominates the mainland. Again, we also consider news beginning with a higher relevance or believability, this time on the less connected island, and news with a lower value, now beginning on the mainland. The two views establish an equilibrium with roughly the same adopting nodes.



(a) (b)

Figure 18: The resulting spread of two pieces of information beginning in an isolated (blue) and connected (red) community, respectively. (a) represents equal relevance information simultaneously spread and (b) higher relevant information (blue) released in the isolated community.

Finally, we note that if the data from the mainland is more relevant, the data on the island dies out quite quickly, and becomes a footnote in history. In these ways we can explicitly determine that physical isolation, much like social, is detrimental for the spread of information. If beliefs start out isolated by the topology of our social networks, they must make up for it in other ways simply to remain relevant.

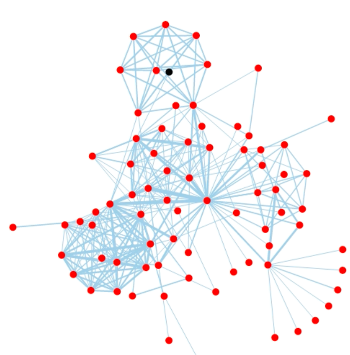


Figure 19: Higher relevance information (red) is initiated in a connected community simultaneously with information (blue) initiated in an isolated community.

6.2 Optimization of Spread

From these simulations we can also make statements about an optimaztion of spread strategy. This information is useful for individuals or groups interested in conveying information to a maximum number of people. This analysis furthers the expected belief that in order to maximize spread, the information needs to have high relevance, topical importance, and a carefully selected initial source. A node with many edges is not necessarily more connected if the surrounding nodes are weak. Ideally, a piece of information needs to be novel, accessible, attractive, and compatible. It needs to, in some way, be able to be characterized with the dominant topic of the time. Finally it needs to be initiated in a carefully selected initial place with the highest connectivity–both in personal node connections and global community connections. In these ways, the spread of an information piece an be optimized.

7 Conclusion

Throughout the development of our model one thing is clear: there is a definite relationship between the importance of a piece of information and its resulting spread. However, this importance is a combination of many factors separately intrinsic to the item and the community. We have extensively shown that our model can account for changes in these factors and accurately reflect the penetration, spread, and retention of the information. Although all news items will spike and decay in varying levels, they follow a consistent model. Thus, by examining the spread of an item, we can extrapolate the underlying factors that contribute to its relevance. Conversely, by knowing the characteristics of an information piece, we can predict the resulting spread. Finally, we can use this knowledge to strategically spread an information item to the furtherest bounds.

7.1 Strengths and Weaknesses in the Models

In total, our model is extremely multifaceted and inclusive. The diffusion model allows for varying levels of importance to be directly seen in the resulting volume of mentions. It is easily translated for an increasing number of interest categories or types of news and models the interactions of a news piece between the categories. The graph model excels in versatility: spatial distance can be represented based on assigning velocities to edges, different mediums can be assigned for the propagation of information based on velocities and direction of edges. For the model as a whole, the immense versatility allows us to see clear relationships between information with different levels of importance based on a number of inherent characteristics and the respective spread of that item.

However, our model is not without weaknesses. We are unable to show model true preferences of individuals, only the preferences of the network as a whole. The connections are generated randomly so the real scenario of having more connections with like-minded people within certain communities is lost, even if the overarching preference of the community is preserved. The model relies on discrete time values and some elements of weighted randomness in deciding how information is noticed and shared. In addition, our model involves a static graph in that no nodes appear or disappear and no edges change.

7.2 Supplements and Future Work

Although this model and the analysis of communication is far-reaching, further work on this topic may be done to move closer and closer to real world simulation. First and foremost, one could fully account for the changing nature of human interactions over time. It would further the model to include the proportional array of ways an individual communicates and how that has changed over time. Although individuals and their relationships are discrete, synthesizing it in some way with continuous time would improve this model. Finally, a way to accurately vary learning a news item from a mass media source versus a personal connection in order to map the resulting internal effect on the spread of that item by the individual would serve to further the model.

8 Appendix

Link:
`http://54.174.181.233`

The simulation utilizes the models developed in the paper to highlight nodes in a cascade effect in order to represent the spread of information across custom-made networks. The nodes and their interconnecting links as a whole are inspected following the mathematical model, and each time-step in the simulation follows the logic (based off the relevance factor) in order to determine if and when a node is infected by the overriding news event.

The simulation was designed so that a user could either activate an indefinitely−long simulation with a number of randomly generated news events, or release a singular controlled and customized news event in order to study its spread through a system. In addition to that, the simulation could be altered to release two similar news events at two user-chosen hubs in order to model the spread of competing information.

After running an event (or a number of events) for a chosen time, the user can select the "compile option and the simulator will then process the information and present the data in a tabular format for the user to utilize.

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