ES 491

Project Presentation

Viral Content

Aditya Tripathi
18110010

What does Virality mean?

- Virality is the phenomenon via which content gains sudden popularity. Viral content is spread through sharing via the internet.
- The sharing of videos on social sites has given rise to this phenomenon.
- The emergence of online video sharing sites and social networking have enabled users across the world to create and consume content and videos.
- The sheer volume of available videos makes it difficult for users to decide what to watch. As a result, people have come to rely on their social networks to provide viewing choices

What is the AIM of this project?

- The model is based on real-world phenomenons found in the real world social media networks.

- We seek to understand the spread of viral content on social media via the methods of diffusion of information
  - How exactly does videos go viral, what are the social contents of the video that go viral?
  - What kind of social network graph has what kind of effect on the sharing and virality of a video?
  - Which model is the real world social graph closest to? What factors (social and non-social) contribute to a virality of content/video.?
  - what pushes people to share watch the content? What interactions between content and user compels the users to watch the it?

WHAT SHOULD WE DO !!?

ABM!!

Why ABM is a Good Choice for this model ?

- In Agent Based Modelling (ABM) aggregate behaviour knowledge is not required apriori.
- ABM also incorporates probability versus determinism with balance and flexibility.
- It can generate new hypothesis.
- ABM is very good at modelling stochastic behaviour and agent environment interactions

INSPIRATION FOR THE MODEL

- No one understands the precise recipe for making a video go viral.
- Many experiments have been performed to find ways in which videos were most widely spread.
- One such research has been done by a team at Google in 2010. Broxton, where they explored on how popularity of a video is affected by social and non-social factors.
- Broxton defined social factors of a video to be the phenomenon of one person sharing a video to another person in its social graph.
- A non-social factor is getting recommendation from the platforms algorithms, say YouTube's recommendation

Category Name	Highly Shared Video %	Category Social View %	Overall Social View %
Pets & Animals	**42.3**	48.4	1.3
Nonprofits & Activism	38.8	54.7	1.4
News & Politics	31.7	47.2	6.6
Travel & Events	29.5	46.0	1.1
Education	28.8	**61.3**	2.9
Science & Technology	28.4	50.6	2.9
Sports	28.1	39.7	7.9
People & Blogs	26.7	43.8	11.4
Autos & Vehicles	23.8	42.0	2.2
Comedy	20.0	42.9	10.3
Howto & Style	19.7	38.8	2.6
Entertainment	15.6	32.4	16.9
Gadgets & Games	15.3	36.8	6.3
Film & Animation	14.0	33.3	5.0
Music	12.8	29.9	**18.2**
Shows	9.8	34.1	3.0

- They collected data using 1.5 million videos that were randomly selected from YouTube between April 2009 and March 2010.

- The data available for each video included the video category (e.g. "Pets", "Music", "News" etc) and the number of views and shares at the daily level.
- From this data, I worked upon the "Highly Shared Video %" category. This provided the data for sharing likelihood of 16 different types of videos over 30 days.
- There are 16 video types.

MODEL DESCRIPTION

AGENTS and NETWORK

- The model contains users in the social network. They are represented by turtles.Each user has a
  - Videos-viewed list
  - my-sharing-likelihood
  - number-of-times-shared
  - is_recommending?
  - previous-recommender
- A network is formed by undirected links from one turtle to other turtle. Each link has a state variable “connection-strength”, which represents the strength of connection between 2 user
- The network can be of 3 types:
  - Preferential
  - Small World
  - Random

MODEL DESCRIPTION

ENVIRONMENT

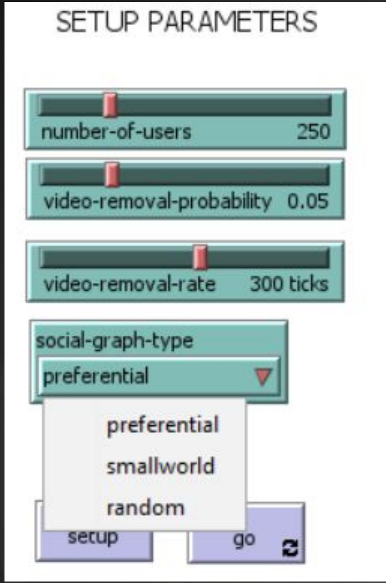
- The patches represents videos . The patches make up a square grid landscape of 33 x 33 patches with no wrapping around and each patch has the following state variables:
  - Video-type: There are 16 video types as shown earlier. Each video type has a sharing likelihood value (shown in picture)
  - video-id
  - number-of-times-viewed
  - Social-motivation-index
- Guadagno explored various hypothesis about emotions effect on the virality of a video. One of his hypothesis was that video having higher social index in terms of video being funny or cute or happy is more likely to be shared
- But was unable to reject any of them.

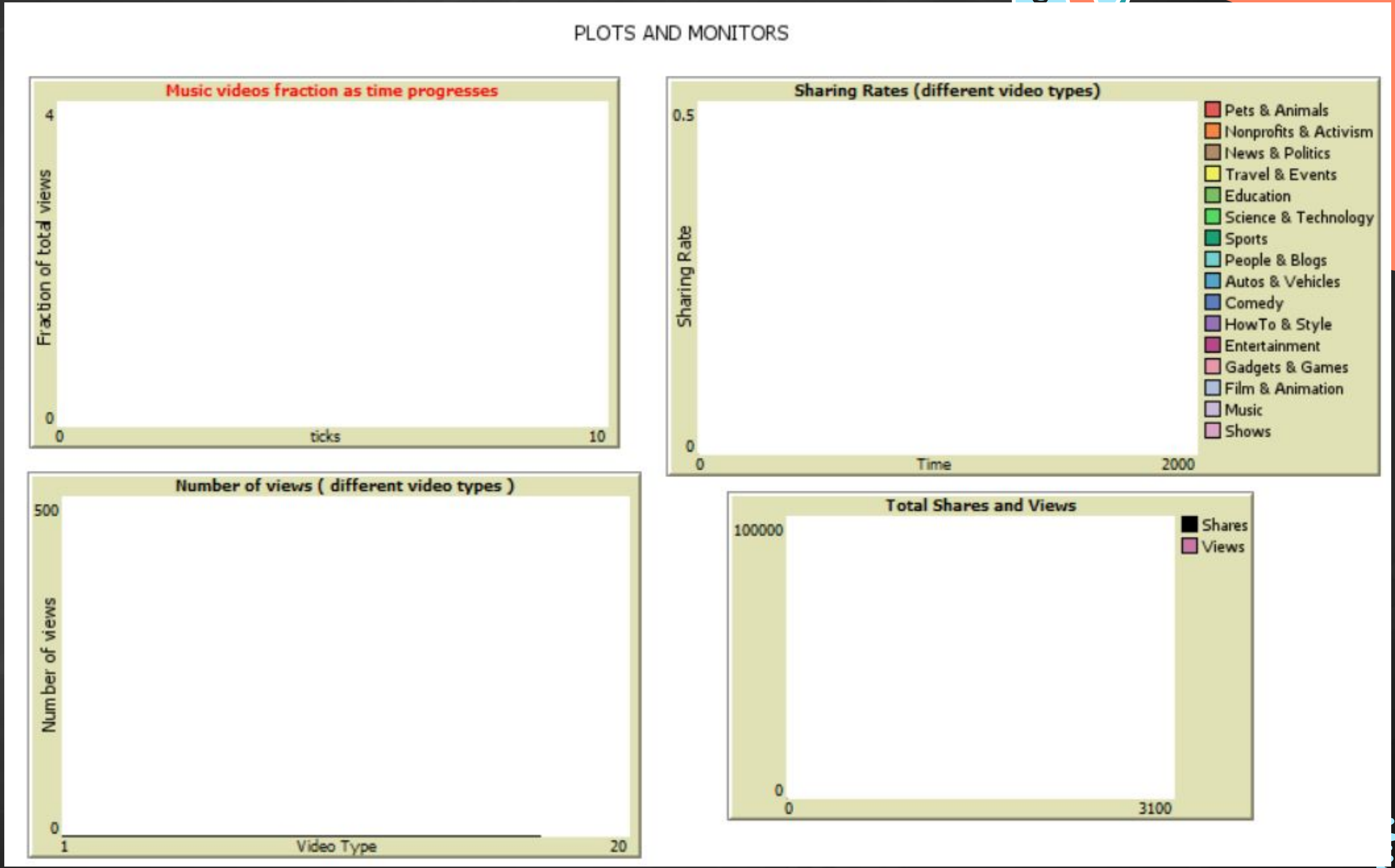
MODEL DESCRIPTION

ENVIRONMENT And TIME STEP

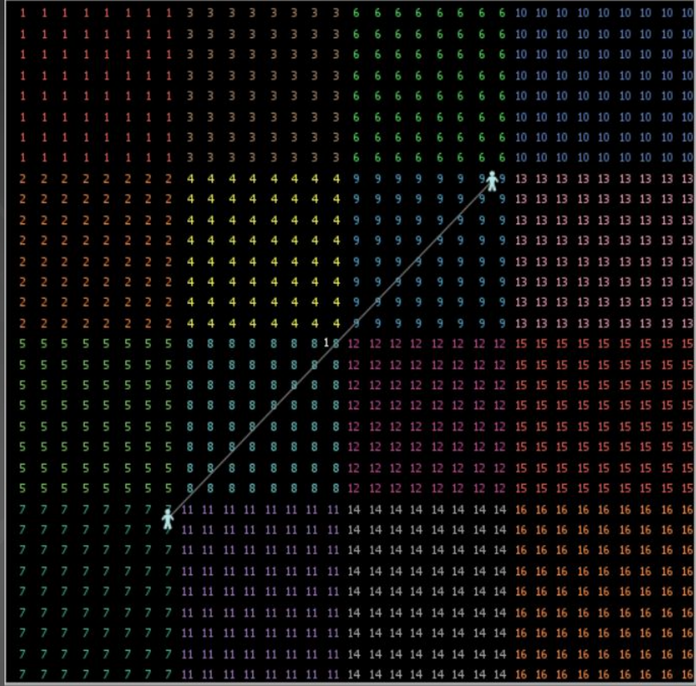
- Therefore, I expressed the emotions in terms of social motivations proposed by Nottingham (WistiaFest, 2015)
    - There are zeitgeist, opinion-seeking, experience, perseverance, kudos social-welfare, reaction, expression and utility
- The social motivation index for any video is calculated by normalizing the sum of all the indexes, unlike Guadagno, who used notion of happiness, sadness etc.
- This will server as a apt substitute for video emotion.This index will be a representation of how the social motivation of a video
- Using parameter calibration and comparing the patterns with the literature, I found that 100 ticks represents a day, and the model runs for around 31 days.

MODEL INPUT AND OUTPUT PARAMETERS





MODEL INITIALIZATION



- The network is setup with initial connection-strength to 1
- Users are created with empty viewed list, and previous recommender as nobody, and is_recommending? Is set to false. Each user has a random sharing likelihood between 0 and 1.
- Video-sharing-likelihood which is set to [42.3 38.8 31.7 29.5 28.8 28.4 28.1 26.7 23.8 20.0 19.7 15.6 15.3 14.0 12.8 9.8] as per the Broxton paper, shown in image
- The world is divided into 16 parts, each part representing a specific type of video.
- A new video is created for each patch and each video is assigned a unique video-id.
- The social-motivation-index for each video is initialized to a random list of numbers.

MODEL PROCESS FLOW

- The following actions that are executed in this order at each time step:

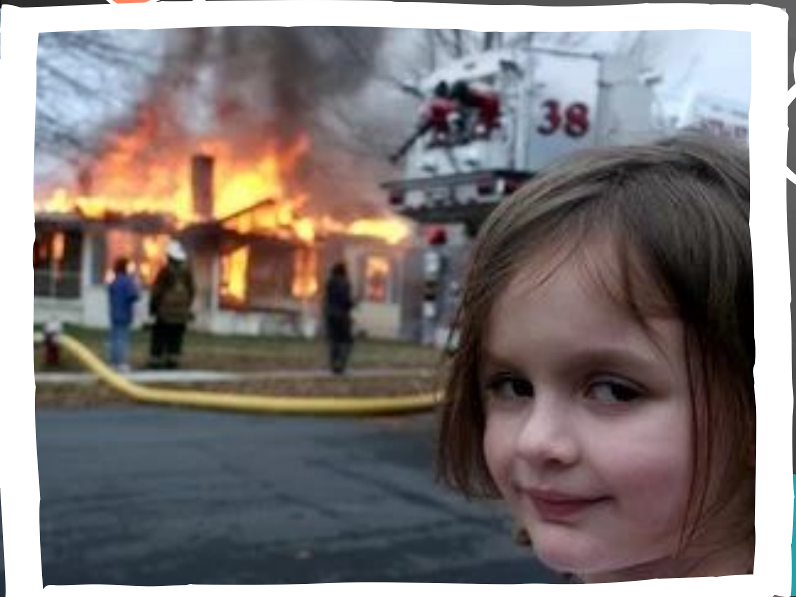
- **View :** The user watches the video on the patch the user is if it has not already viewed the same video or randomly watches the video again with a probability of 50%. If the user watches the video, then it decides if it wants to **share this video or not.**
    - **Deciding to share or not** : A cumulative of the mean of the social-indexes of the video, likelihood of sharing of the user, and the likelihood of this video being shared is computed. With the calculated probability the video is shared
      If this video is shared, then the connection strength between the user who suggested this video to this user(previous-recommender) is increased by 1.

- If the user has already viewed the current-video (video represented by the patch on which user is present currently) then it randomly tries to reach some other content . This process is done via moving the user in some random direction on some other patch, as each patch is a different video.

MODEL PROCESS FLOW

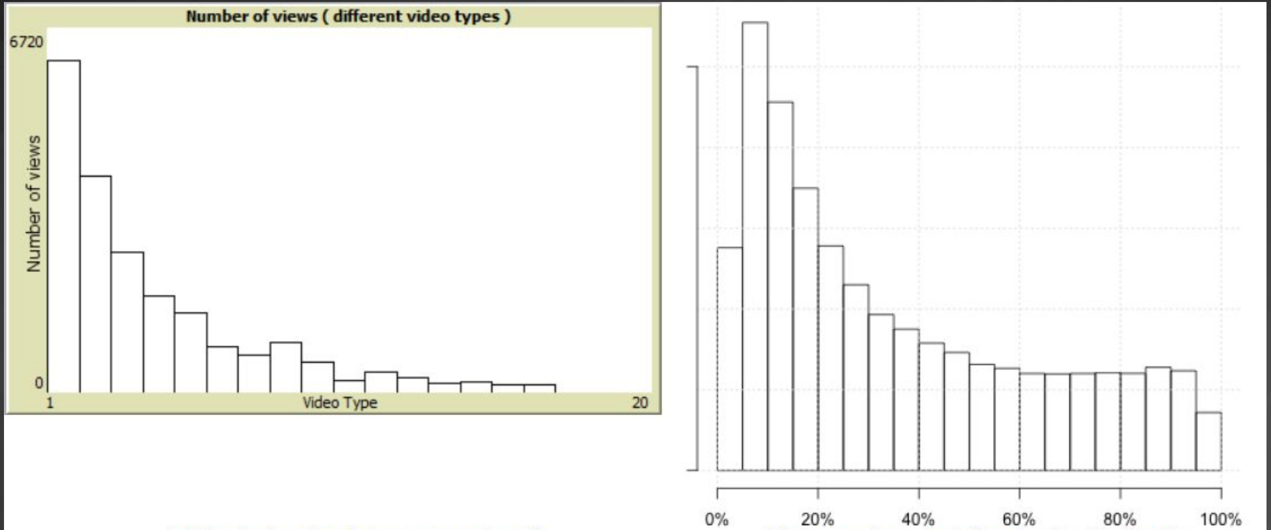
- **Watch New Video** : The user tries to watch a new video. It checks if there are any connections of it who are trying to share/recommend some video.
  If so, out of of all those users, it selects the user which it trusts the most.
  Upon finding such a user, the current user teleports to the patch of the recommender user. And the previous-recommender of the user who teleported is set to the user who shared the video.

- **Decide to remove** : After some regular interval of time (decided by the slider video-removal-rate) there is a chance that a video will be removed, and in place of deleted video, a new video will be added of the same type. The chance of deletion is also decided by a slider called video-removal-probability.



DEMO!

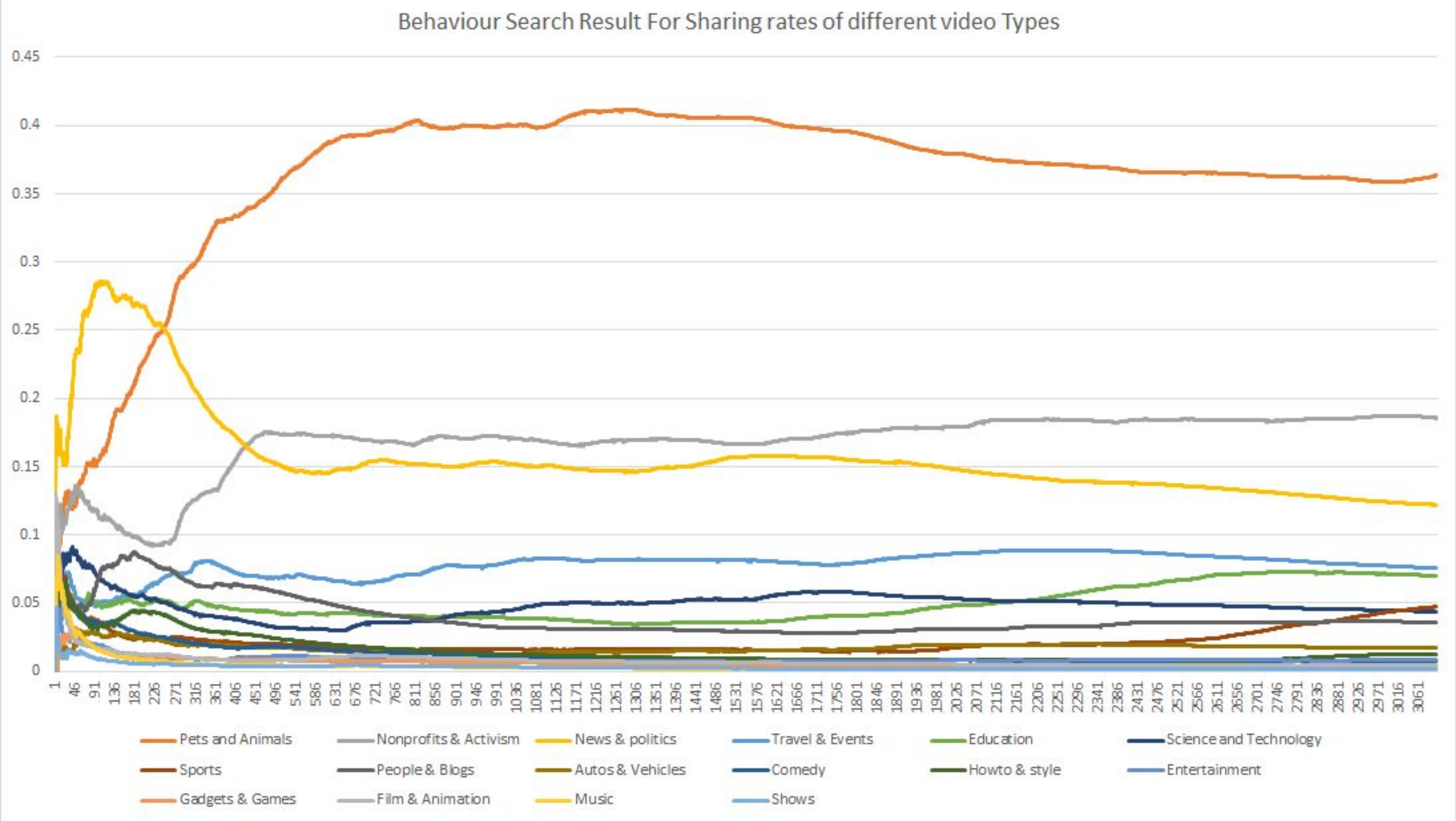
RESULTS AND RELEVANCE OF THE MODEL



(a) Simulation Plot for mean number of views for each type of video

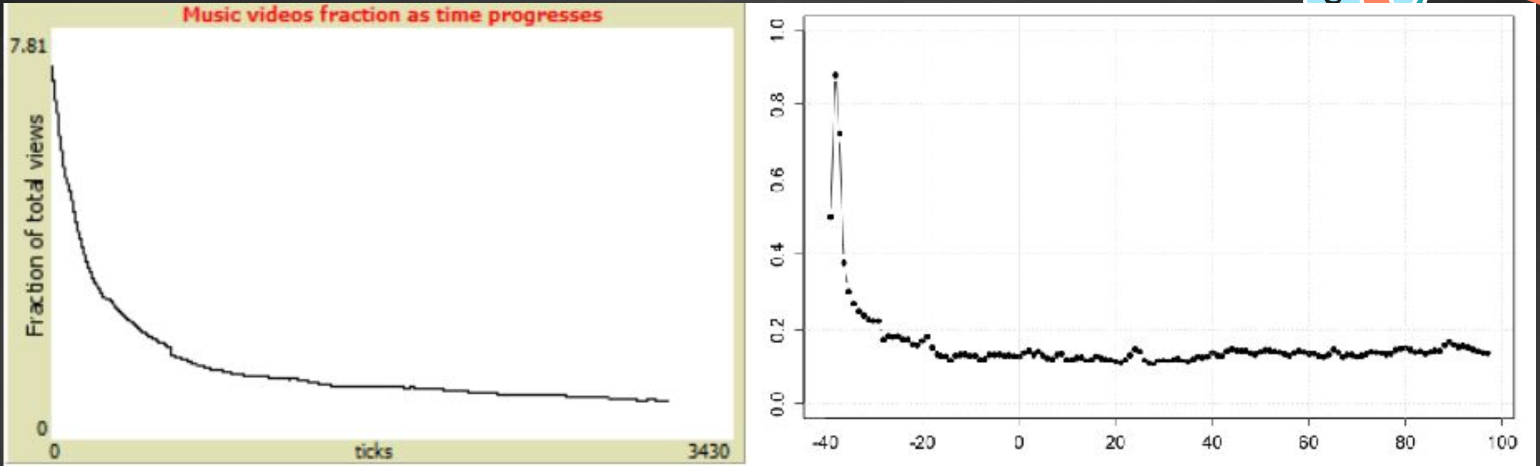
(b) Broxton's analysis for viewing distribution over 30 days

- The hypothesis of the model is that Virality is directly proportional to the sharing likelihood, the network it is used in and social parameters of a video.
- Comparison between the average number of views of different types of videos from the model and the Broxton paper. This is an emergent pattern which was not coded into the model, but is an outcome of the interactions between agents and environment.



Behaviour Search Result For Sharing rates of different video Types
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Pets and Animals
Nonprofits & Activism
News & politics
Travel & Events
Education
Science and Technology
Sports
People & Blogs
Autos & Vehicles
Comedy
Howto & style
Entertainment
Gadgets & Games
Film & Animation
Music
Shows

RESULTS AND RELEVANCE OF THE MODEL

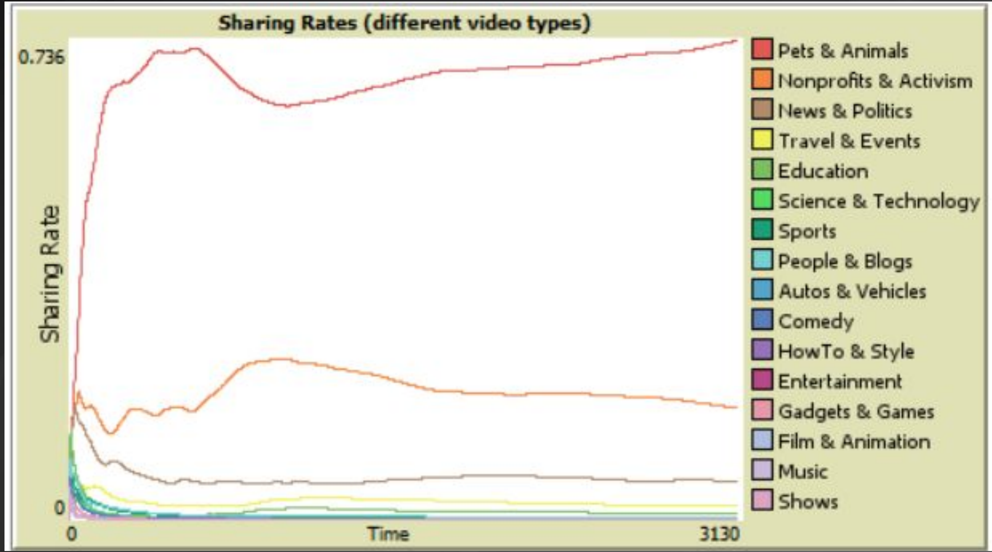


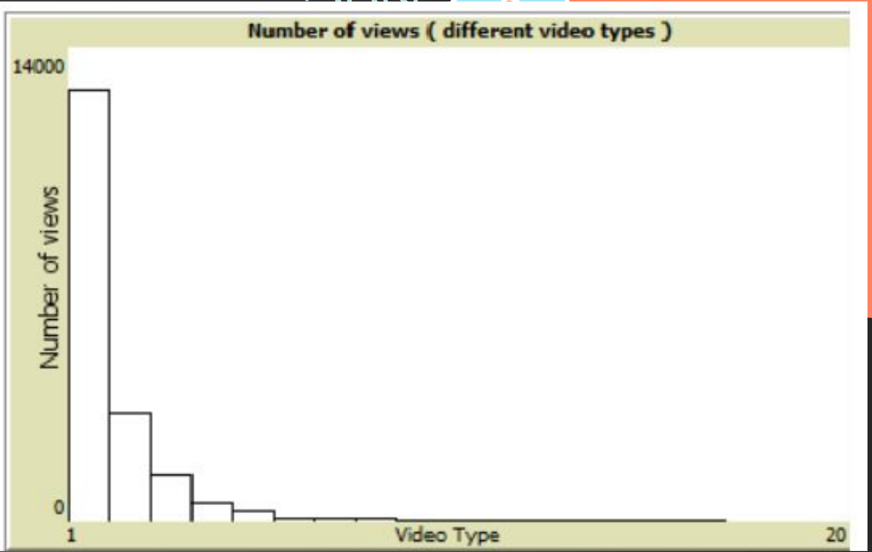
(a) Music Video sharing rates

(b) Broxton's Music video sharing fraction over time

- These are the sharing rates of just the music videos. And we can compare from the rate given in the Broxton's paper, that they are again the same.

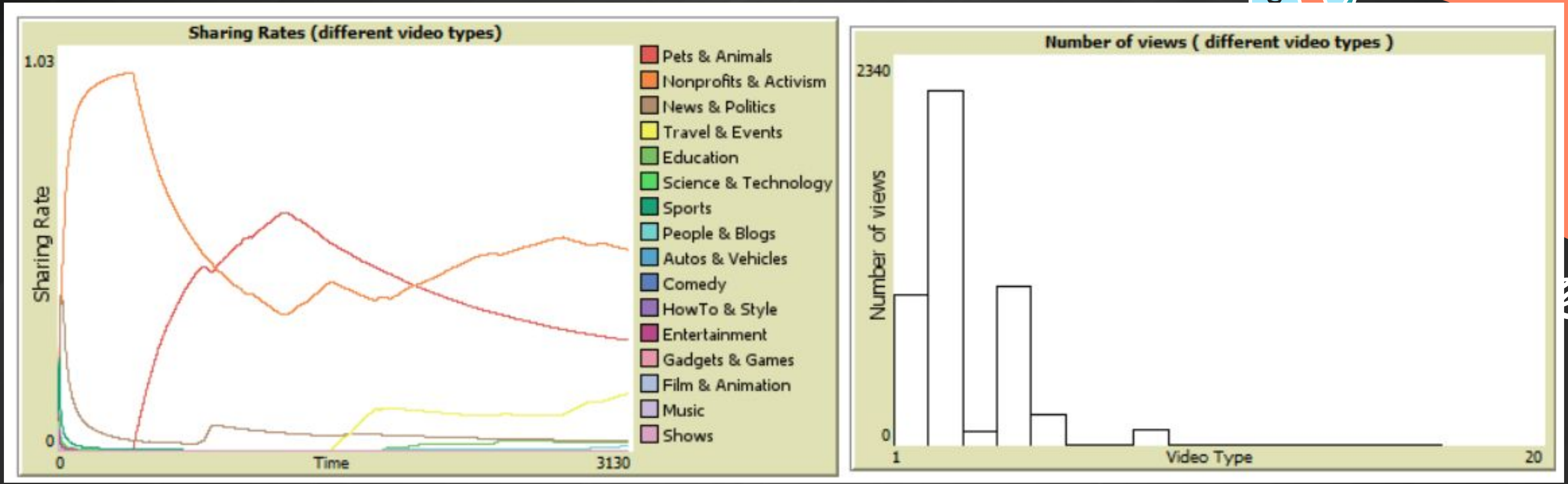
RESULTS AND RELEVANCE OF THE MODEL





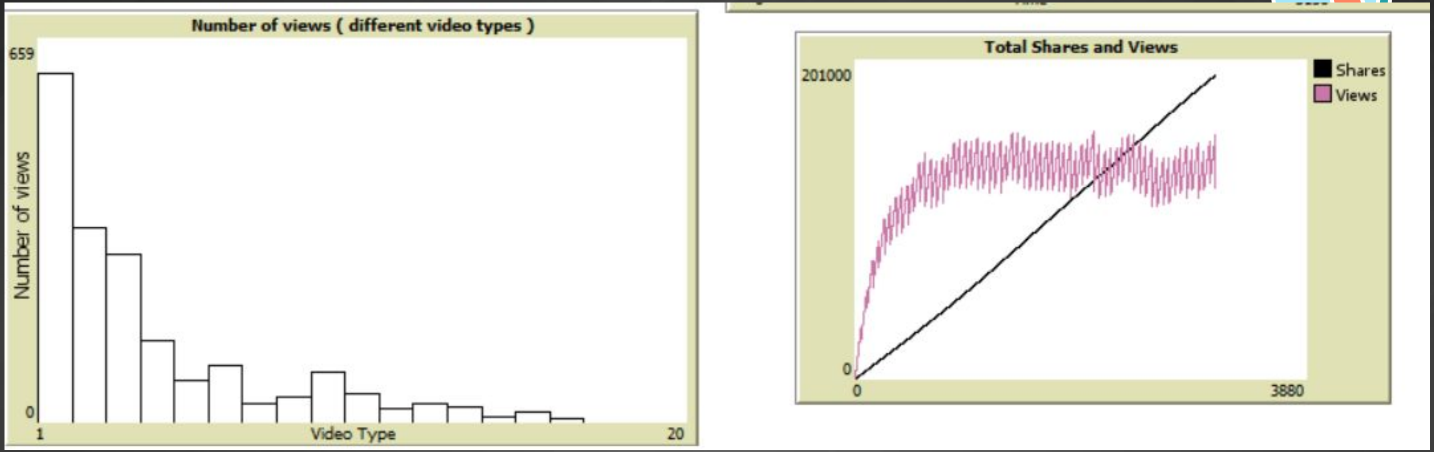
- This simulates the case when all the users are of very similar interests.
- The sharing rates does not match with the Broxton's analysis, and are very off. Also, from the viewership plot, it is easy to see that 90% of the views are for the video type 1, which has the most sharing likelihood.

RESULTS AND RELEVANCE OF THE MODEL



- This shows the sharing rate and average views for random graph. The graph is formed with 10% chance of any 2 users being connected. And the results are even worse than that of the small world model. They are completely random.

RESULTS AND RELEVANCE OF THE MODEL



- The number of views becomes almost constant when the videos are removed too frequently. The number of views are removed for the deleted video. This result also matches the expectation of the real world.

- If the videos would have been removed too frequently, then there would have had not been much about virality. However, there is not much effect in the distribution of views or the sharing rates. They are the same as expected.

RELEVANCE AND CONCLUSION

- The preferential model is the one that best replicates the real world social network. The results of preferential model were the closest to Broxton's analysis

- Other attributes such as video-deletion-rate, deletion-probability etc were also tested in Behavior Space, the network-type had by far the greatest effect on the results.

- It can be concluded that although the quality of the video is significant to its virality, the platforms in which it is transmitted have a greater effect. If the content of a video resonates with one user in a preferred network, it is more likely to be shared with someone who might enjoy it.

- This discovery may be crucial for anyone looking to make a viral video in the future, and this model will be highly relevant in such cases.

RELEVANCE AND CONCLUSION

- There are millions of people who have jobs directly related to the phenomenon of virality. There are millions of agencies and companies running whose sole purpose is to create viral ads, videos for their customers.

- People even love watching viral videos, and a lot of companies try to associate themself in order to promote their products. The ad-technique is already a very large industry, and thus knowing the parameters that can affect the virality is becoming a billion dollar business.

- There might never be a recipe for making the perfect parameters for viral video, a growing number of businesses are getting closer to it. Advertising companies are studying behaviours of users sharing the video as well as the features of the video itself to see what leads to its virality

- Unlocking the secret of viral videos to build effective viral marketing campaigns may be a game-changer in the ever-changing billion-dollar advertisement market, so studying the actions of this and other related models could be a worthwhile investment.

THANK YOU !