

# Meme Review Dead or Alive?

*Predicting Reader Response to Timely Memes using Machine Learning*

Phase 2

1

## Background

What we set out to learn

- How the internet affects many variants of people
- How internet memes gained and maintained popularity
- How images are shared in internet media
- How to automatically find classifiable features
- How to cluster similar looking images

3

## Motivation & Problem Definition Recap

2 out 5 Facebook posts are memes  
Memes are a great marketing tool  
Millennials LOVE memes

Online Businesses and Influencers  
Massive Data dump



2

## “Insights into Internet Memes”

It is commonly assumed that Internet memes spread virally but scientific evidence as to this assumption is scarce.

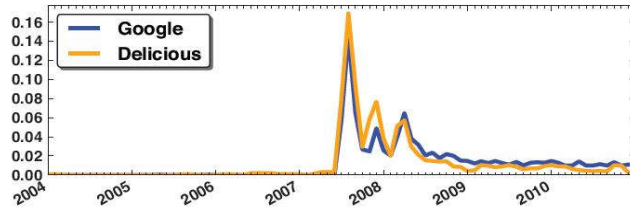
Investigate the epidemic dynamics of 150 famous Internet memes.

The analysis is based on time series data that were collected from Google Insights, Delicious, Digg, and StumbleUpon.

4



(a) instances of the “chocolate rain” meme

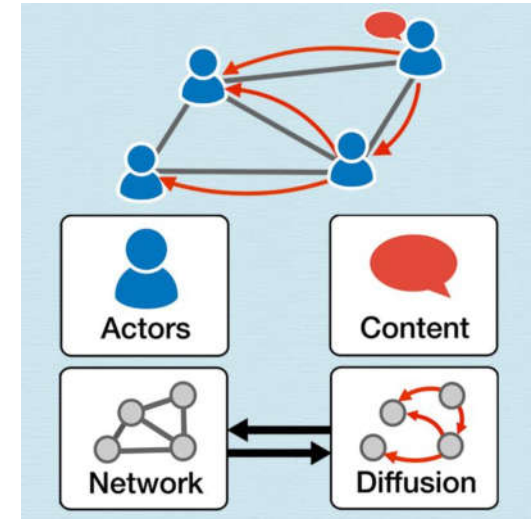


(b) two time series (retrieved from Google Insights and Delicious) reflecting the rise and decline in popularity of this Internet meme

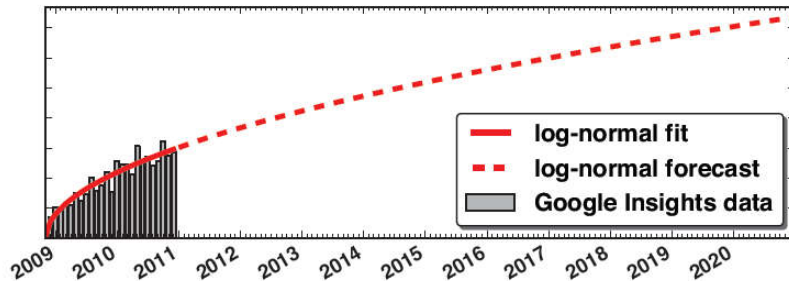
Differential equation models from mathematical epidemiology + simple log-normal distributions = a good account of the growth and decline of memes.

5

## “Predicting the Content Diffusion Path in Online Social Networks”



7



Traditional compartment models might be good but lack flexibility.

Log-normal distributions are more practical.

Thus, concluding by saying memes might be viral but only on social media platforms and not the rest of the internet.

6

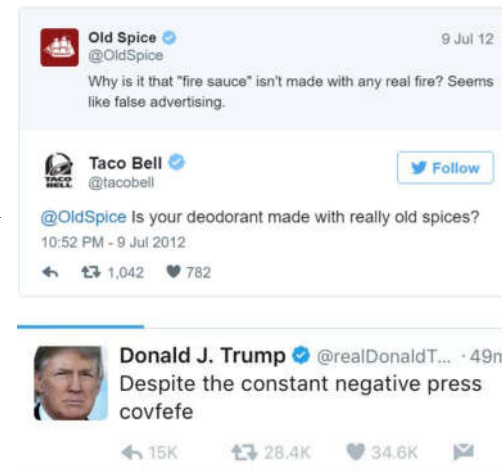
## “Marketing with Twitter: Challenges and Opportunities”

255 million monthly active users

Specific features may have more overall effect in the final decision of a user response

Holds attention + memorable

Upvotes, Author, Dates



8

## “A Study of Meme Propagation”

Memes gain momentum and then lose their popularity over time

Categorized the Memes, i.e. Political memes vs General Memes



9

## Calculating Confusing Convolutions

type	patch size/ stride	output size	depth
convolution	$7 \times 7 / 2$	$112 \times 112 \times 64$	1
max pool	$3 \times 3 / 2$	$56 \times 56 \times 64$	0
convolution	$3 \times 3 / 1$	$56 \times 56 \times 192$	2
max pool	$3 \times 3 / 2$	$28 \times 28 \times 192$	0
inception (3a)		$28 \times 28 \times 256$	2
inception (3b)		$28 \times 28 \times 480$	2
max pool	$3 \times 3 / 2$	$14 \times 14 \times 480$	0
inception (4a)		$14 \times 14 \times 512$	2
inception (4b)		$14 \times 14 \times 512$	2
inception (4c)		$14 \times 14 \times 512$	2
inception (4d)		$14 \times 14 \times 528$	2
inception (4e)		$14 \times 14 \times 832$	2
max pool	$3 \times 3 / 2$	$7 \times 7 \times 832$	0
inception (5a)		$7 \times 7 \times 832$	2
inception (5b)		$7 \times 7 \times 1024$	2
avg pool	$7 \times 7 / 1$	$1 \times 1 \times 1024$	0
dropout (40%)		$1 \times 1 \times 1024$	0
linear		$1 \times 1 \times 1000$	1
softmax		$1 \times 1 \times 1000$	0



11

## “Going Deeper with Convolutions”

- Google’s own research paper proposing the Deep Convolutional Inception Neural Net
  - By C. Szegedy & 8 others from Google Inc, University of North Carolina and
  - Published to Cornell’s ArXiv on the 17th of September 2014
- ImageNet Large-Scale Visual Recognition Challenge 2014  
1st Place Winner for Classification and Detection.

10

## Stats and Scores

Team	Year	Place	Error (top-5)	Uses external data
SuperVision	2012	1st	16.4%	no
SuperVision	2012	1st	15.3%	Imagenet 22k
Clarifai	2013	1st	11.7%	no
Clarifai	2013	1st	11.2%	Imagenet 22k
MSRA	2014	3rd	7.35%	no
VGG	2014	2nd	7.32%	no
GoogLeNet	2014	1st	6.67%	no

Table 2: Classification performance.

Team	Year	Place	mAP	external data	approach
UvA-Euvision	2013	1st	22.6%	none	Fisher vectors
Deep Insight	2014	3rd	40.5%	ImageNet 1k	CNN
CUHK DeepID-Net	2014	2nd	40.7%	ImageNet 1k	CNN
GoogLeNet	2014	1st	43.9%	ImageNet 1k	CNN

Table 4: Comparison of detection performances.

12

## “Visualizing Data using TSNE”

- T-Distributed Stochastic Neighbor Embedding
- Published by Laurens van der Maaten of Tilburg University and Geoffrey Hinton of University of Toronto
- First published to The Journal of Machine Learning Research on the 9th of November 2008

13

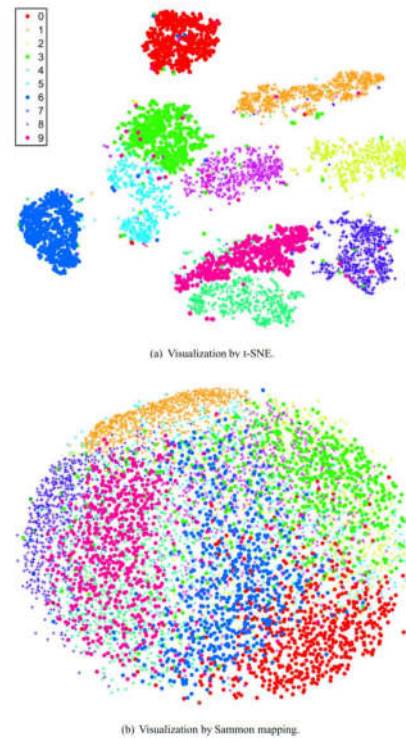


Figure 2: Visualizations of 6,000 handwritten digits from the MNIST data set.

15

## Dimension Warping

- TSNE is a Dimensionality Reduction technique
- TSNE Projection can map and cluster High Dimensional Data to a 2D or 3D Space by representing noticeable features as vectors
- Similar to PCA (Principal Component Analysis)



14

## “UMAP for Dimension Reduction”

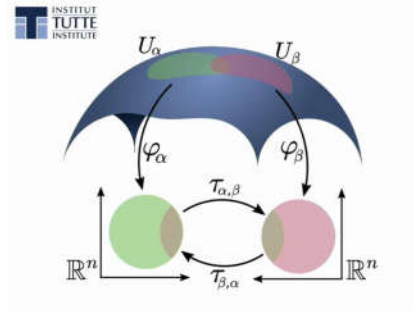
- Uniform Manifold Approximation & Projection
- Published by Leland McInnes and John Healy from Tutte Institute for Mathematics and Computing, Canada
- Is a fairly recent technique, 13th February 2018, that is rivaling the otherwise state-of-the-art TSNE.

16



# UMAP Ur Own Clusters

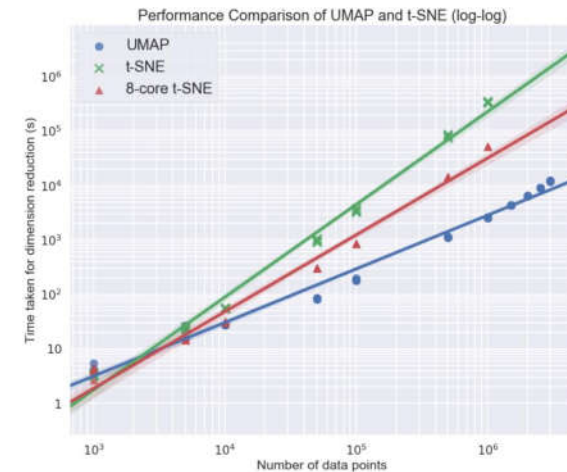
- Isn't actually about maps.  
Shocker I know...
- Processes neighbors in HD space.
- Connects clusters with other clusters with fancy topological math and neighbor graphs.
- This forms a manifold with no distortion making it uniform



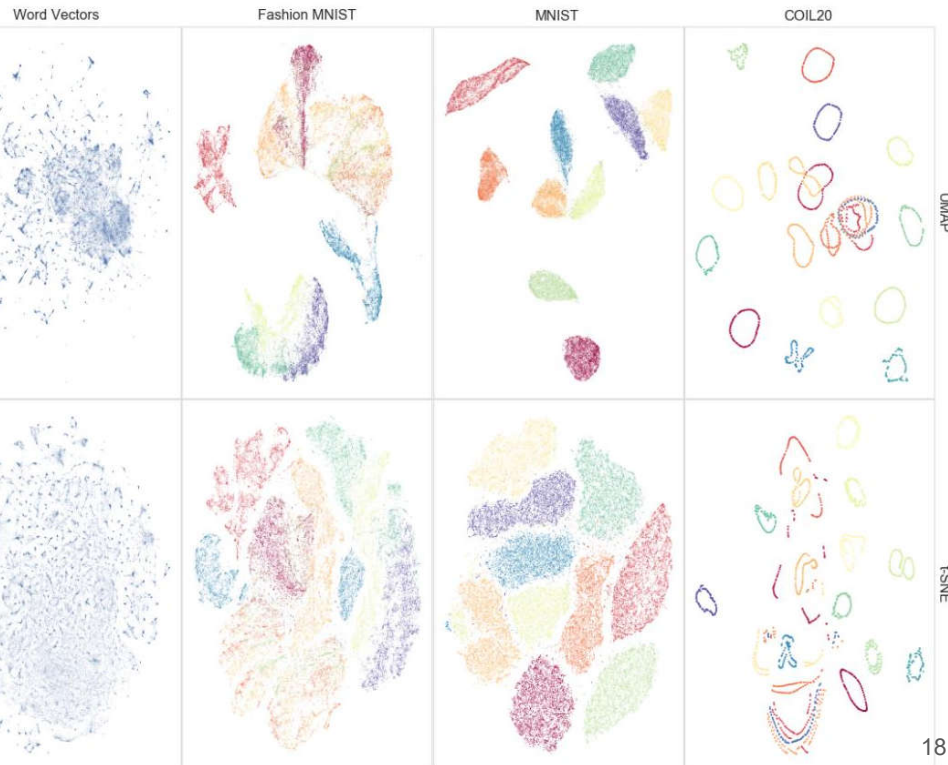
17

Table 1: Runtime of UMAP and t-SNE on various datasets

dataset	dataset size	t-SNE	UMAP
COIL20	1440x16384	20s	7s
COIL100	72000x49152	683s	121s
Shuttle	58000x9	741s	140s
MNIST	70000x784	1337s	98s
F-MNIST	70000x784	906s	78s
GoogleNews	200000x300	16214s	821s



19



18

Back to  
Meme Review

What have WE done so far?



20

## Data Source & Preprocessing Recap

Kaggle

Reddit meme dump

JSON metadata

Image Preprocessing

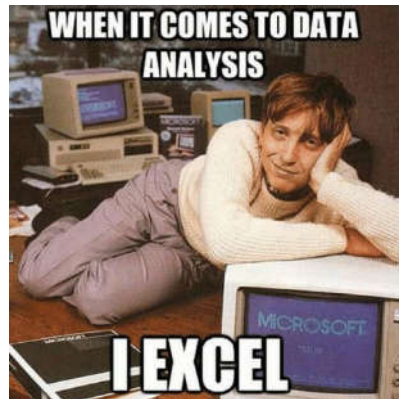
Resize Resolution

Convert All images to JPG

Process JSON metadata

Messy JSON Organization

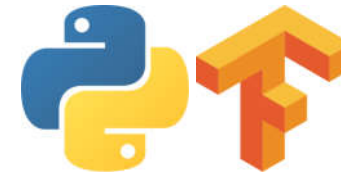
UNIX-based UTC Timestamp



21

## Data Visualization

tableau<sup>++</sup>public



23

## Neural Networks Recap

Inception

Used before the TSNE Cluster to  
produce classifiable feature vectors

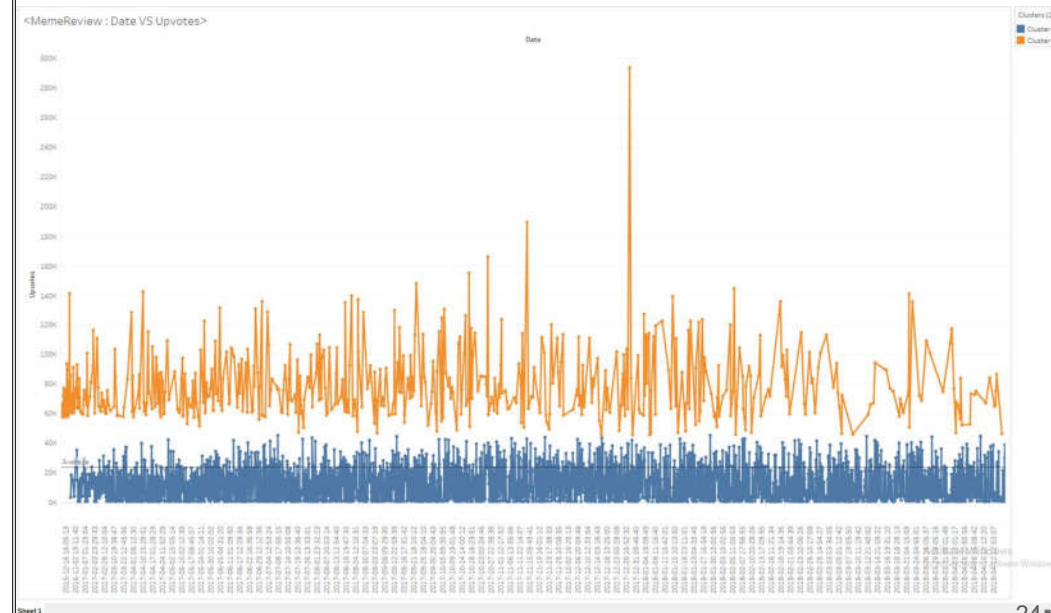
AlexNet

VGGnet



22

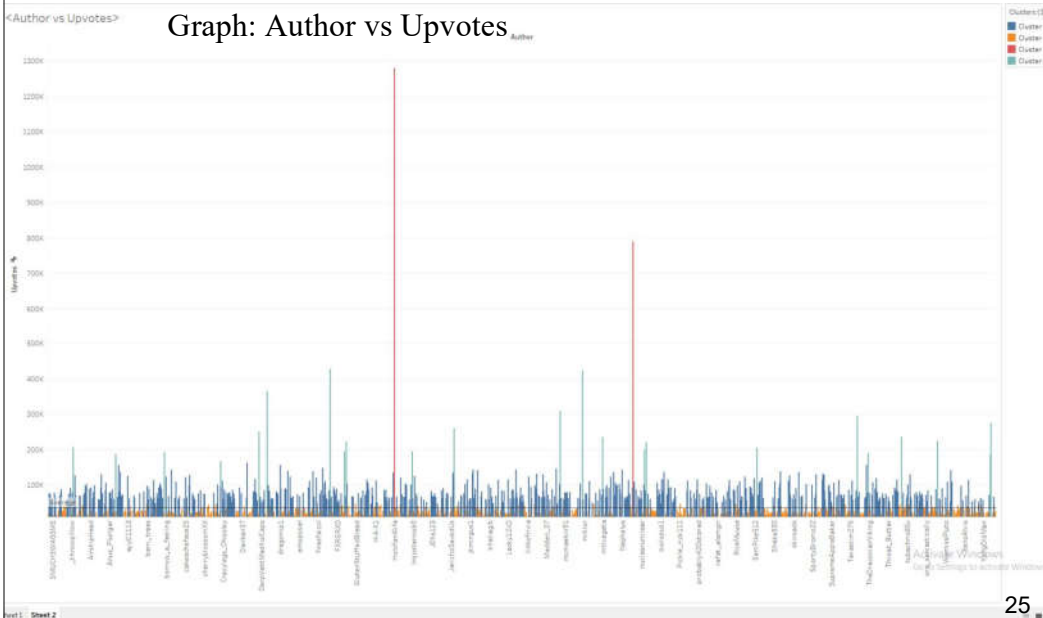
## Data Visualization of Correlations



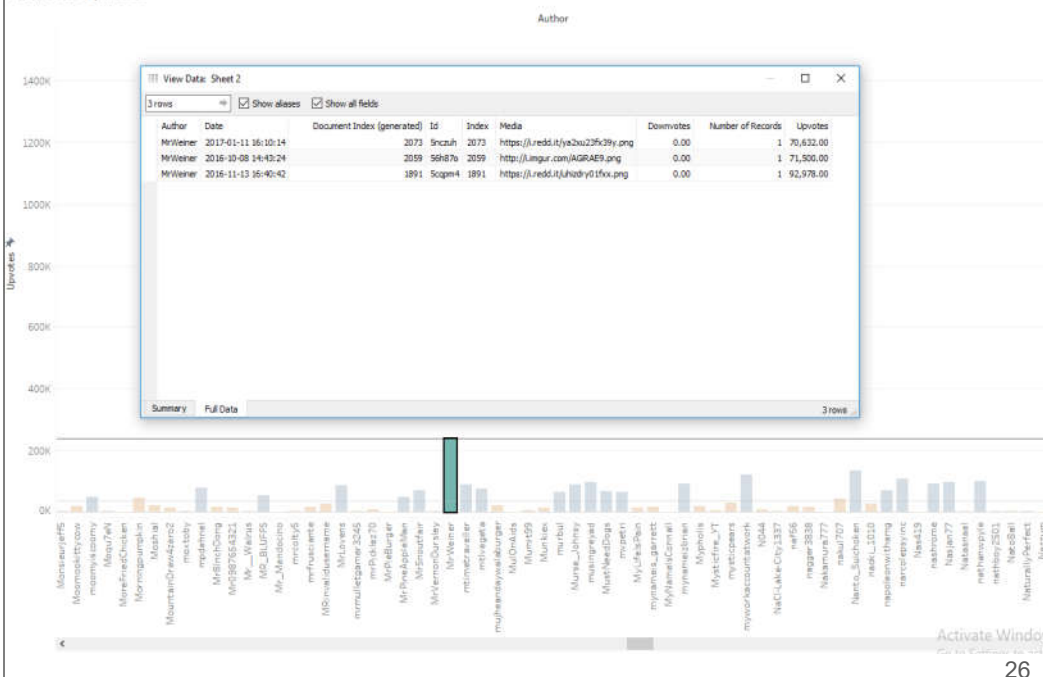
24

# Data Visualization of Correlations

Graph: Author vs Upvotes

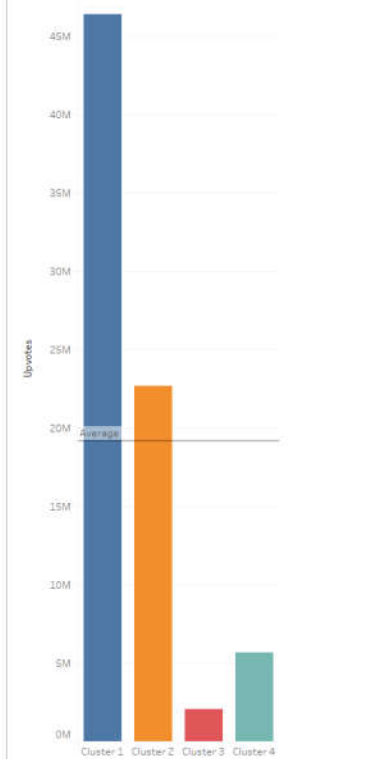


Author vs Upvotes



## Author Clusters

4 Types  
of  
"Meme-creators"

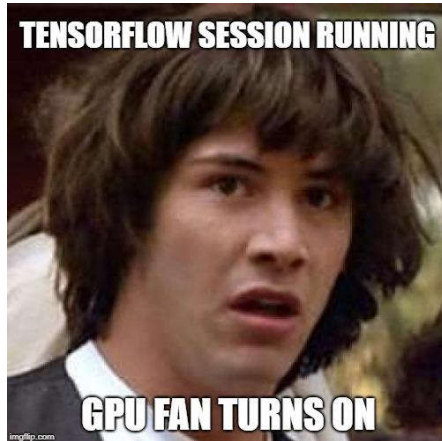




## See in Numbers

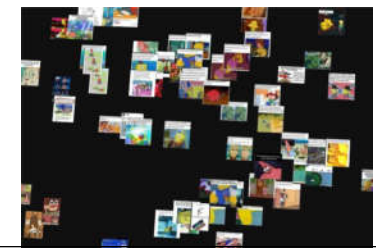
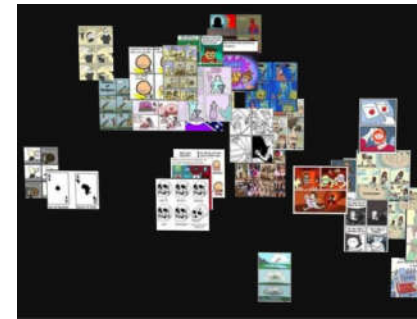
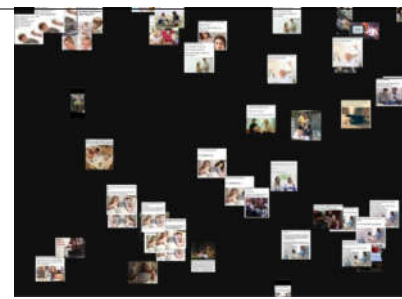
Produce image vectors from  
Inception Neural Net  
penultimate pool layer's  
weights using TensorFlow

Use previous Vectors for  
Clustering with UMAP then  
project onto an HTML Canvas  
running D3.js



29

## Clusters of Memes



31

## A UMAP Map of Memes

Population 3,326

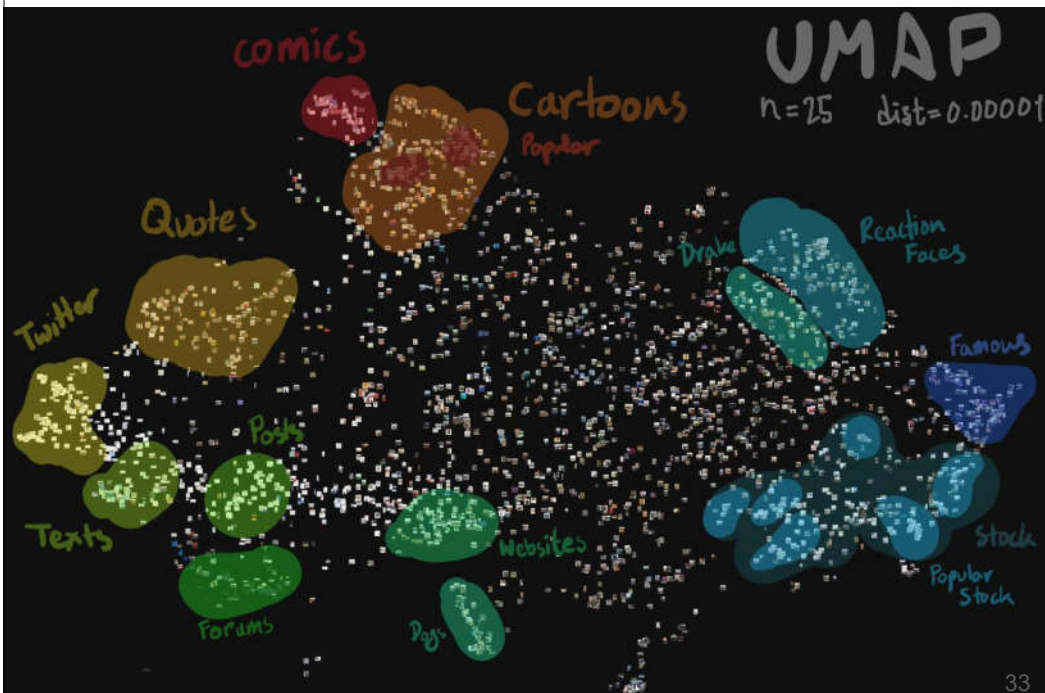


30



32

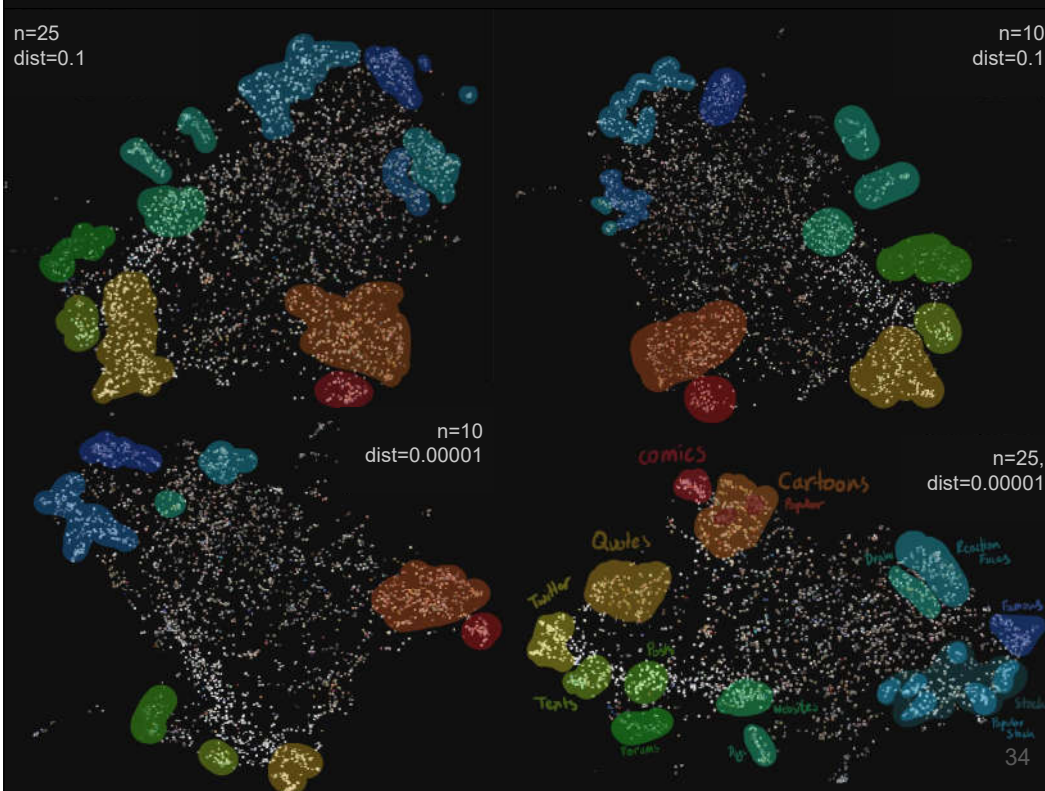




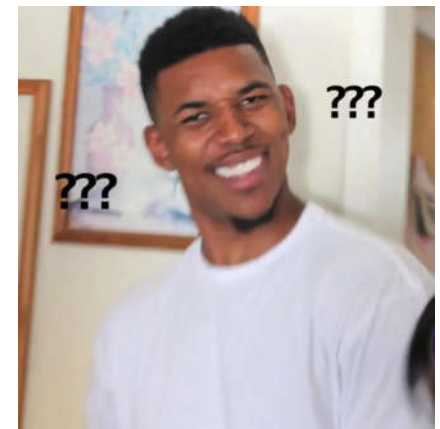
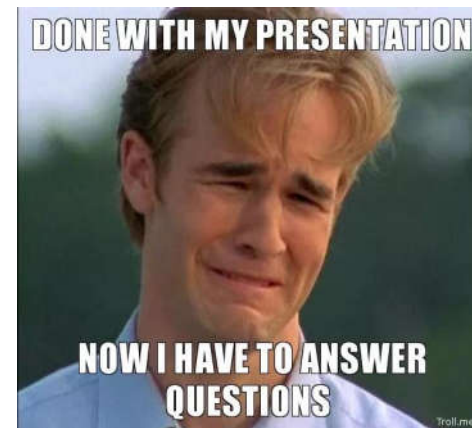
## Contributors

- **Abir Rahman**  
*Marketing with Twitter*  
*A Study of Meme Propagation*
- **Jawad Aziz Khan**  
*Going Deeper with Convolutions*  
*Visualizing Data with TSNE*  
*UMAP for Dimension Reduction*
- **Taufiq Rahman**  
*Insights into Internet Memes*  
*Predicting the Content Diffusion*  
*Path in Online Social Networks*

35



## Any Questions?



36