



Investigating Influencer Endorsements: A Data-Driven Exploration

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Agenda

- 
- **Business Motivation**
 - **Model Design & Implementation**
 - Text Analysis
 - Social Network Analysis
 - **Case study**
 - **Exploring Instagram**
 - **Summary**

Business Motivation

- Influencer marketing is increasingly important
- Adidas pursues this strategy with great success (e.g., Kanye West)
- But, so far the effort is largely ad-hoc or relies on much manual effort
- Current approaches fails to consider unstructured data in social media
(text, networks, image, video)
- Thus, a decision support system would be a great of asset

Where did we start ?

A social news aggregation, web content rating, and discussion website



www.reddit.com

Why Reddit ?

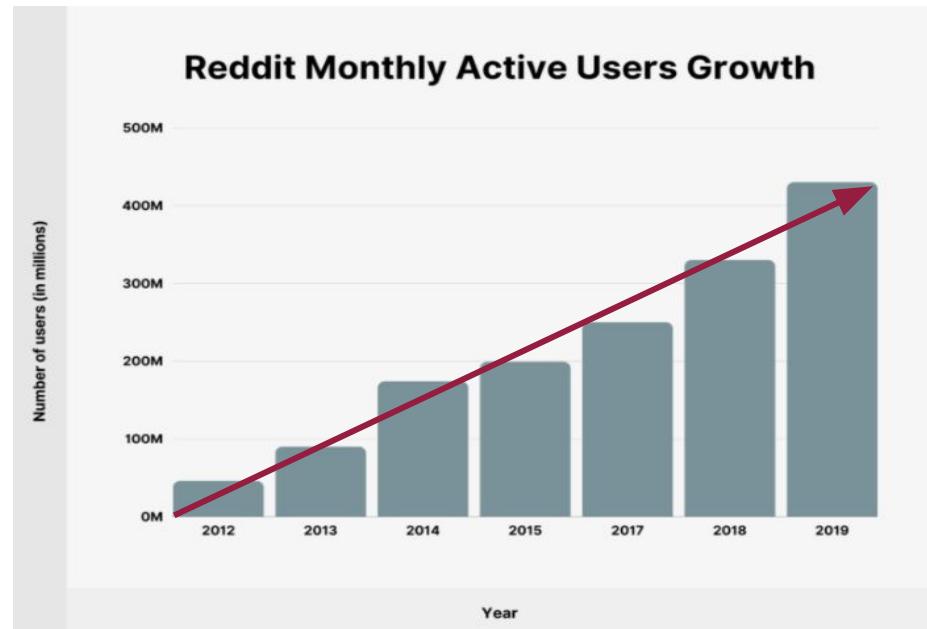
Reddit has over 430 million monthly active users. An increase of 30.3% from a year earlier.

- **52 million daily active users** access Reddit.^[6]
- **25% of US adults** use Reddit.
- In 2020, Reddit was ranked the **7th most popular social media app in the US**.
- **303.4 million posts** were shared on Reddit in 2020, a 52.4% year-over-year growth.
- **2 billion comments** were shared on Reddit in 2020.

It also allows for analysis of long-form social media instead of just short messages (twitter)

Reddit - a great source for data collection

- From 2015 to 2019, the number of Reddit monthly active users **has grown by 258.33%**. And it continues to grow in 2020 and 2021 ...^[6]



Source: <https://backlinko.com/reddit-users>

What is a subreddit?

Subreddit name

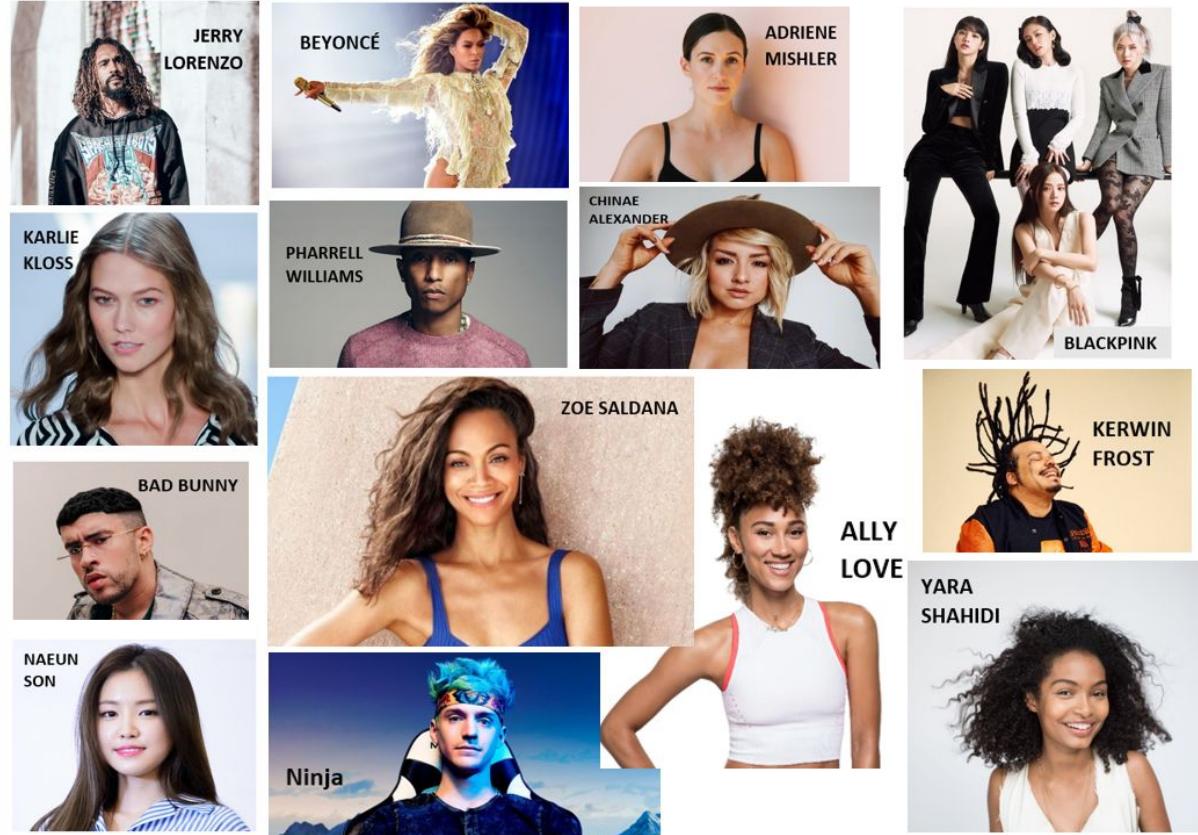
Information on the Subreddit

Information on the post

The screenshot shows the homepage of the **r/beyonce** subreddit. At the top, there's a header with the subreddit name, a profile picture of Beyoncé, and a "Joined" button. Below the header is a "Create Post" button and a pinned post by moderators. The pinned post is titled "BLACK PARADE" and includes a YouTube link. To the right of the pinned post is the "About Community" section, which displays the community's name (Beyoncé Giselle Knowles-Carter), member count (85.1k), online members (60), and creation date (Nov 12, 2011). Further down the page is a "Community Options" dropdown menu. On the left side, there's a "Filter by flair" section with categories like "Beyoncé in Pop Culture", "Question for the hive", and "Live performances". The main content area shows several posts, with the top one being a link to a free Beyoncé documentary. Red arrows from the left boxes point to specific elements: the first arrow points to the "r/beyonce" text in the header; the second arrow points to the "About Community" section; and the third arrow points to the "Beyoncé in Pop Culture" filter category.

The influencers we started with:

Mr. Brooks Clemens gave us a list of influencers who are sponsored by Adidas.^[5] We picked 14 of them for our research.



About the Data

- Types of data collected : ***user information, text data, image data***^[5]
 - Total posts collected : 39K+ comments, which are summed to **22M words**
 - The number of users : **62K+ (For network analysis)**
 - Data was collected from their respective subreddit and based on **n-gram search**.

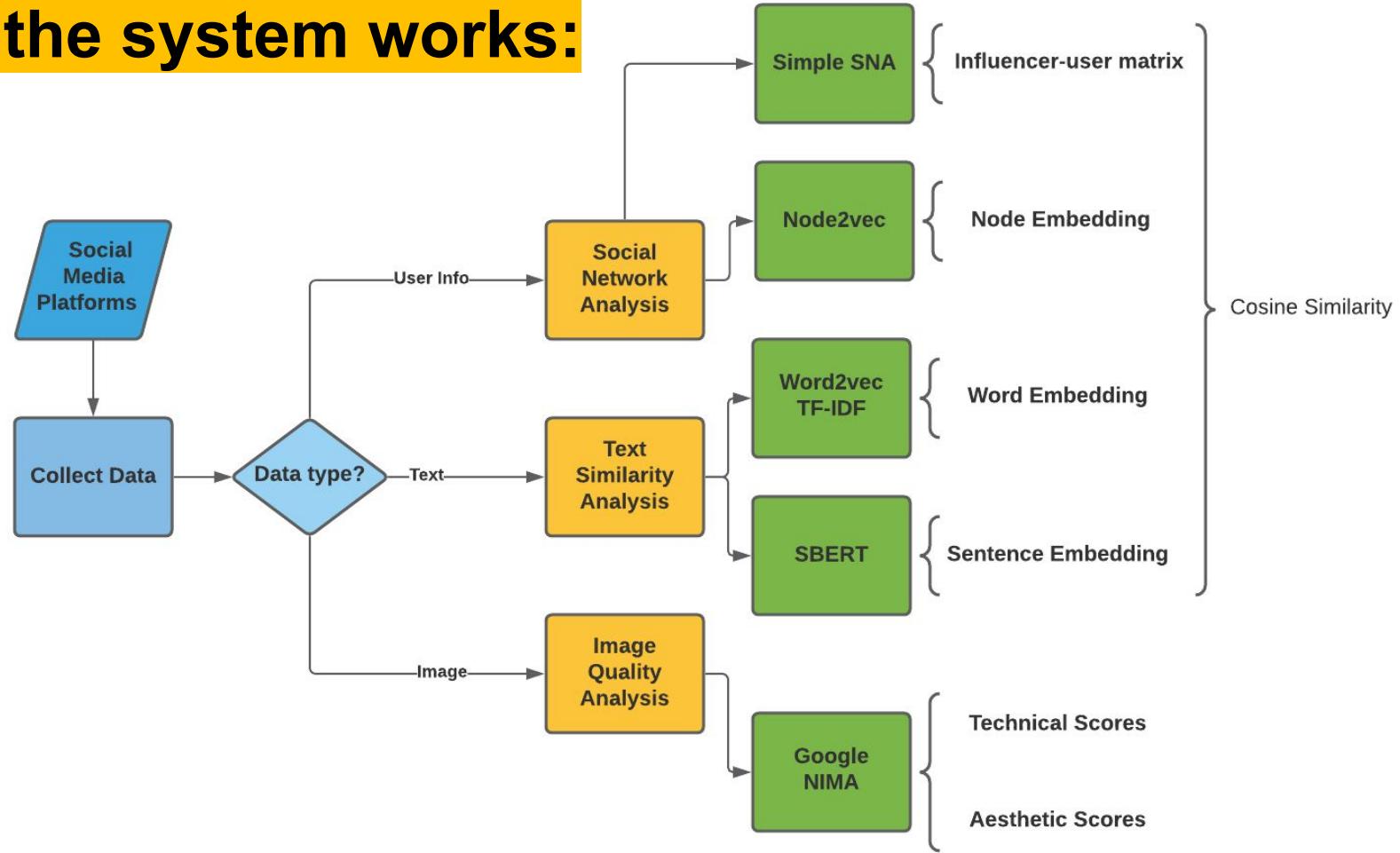
Collected Data

- ❖ Data is grouped into two versions for implementation testing and case study:
 - Version 1: 14 Celebrities is sponsored by Adidas
 - Version 2: Two adidas sponsored Korean celebrities + another eight picked Korean celebrities (based on stage style and popularity)

The design goal of the system is to:

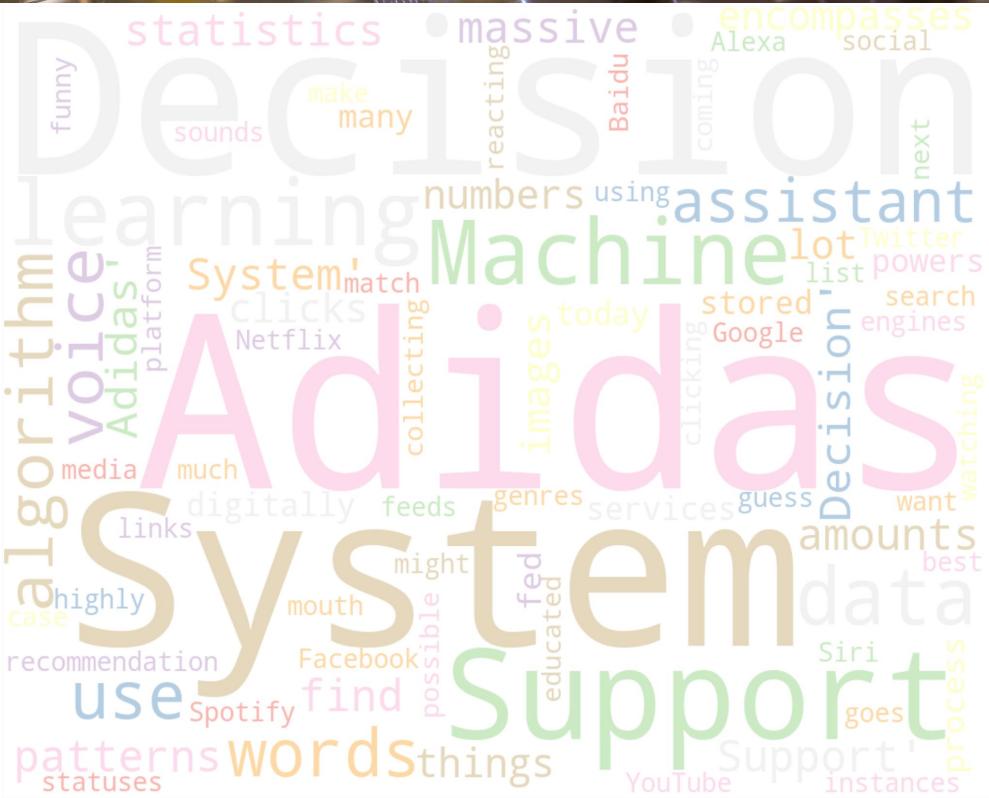
- **Build a computational, data-driven, and generalizable system**
- **Support the business decisions with little human intervention**

How the system works:



Why Text Analytics?

- **Text analytics** is the automated process of translating large volumes of unstructured text into quantitative data to uncover insights, trends, and patterns. [18]
 - Combined with data visualization tools or other statistical models, this technique enables companies to understand the story behind the numbers (the transformed text) and make better decisions. [18]



How Text Analytics benefits business analysis?

We wanted the models to look at the conversations between celebrities' fans to capture different cultural patterns buried in the unstructured text data.

It helps our business to have a better understanding of:

- how similar the way fans/users talk about the influencers
- the type of customers each influencers can reach
- similarity and dissimilarity of language habits between the customer segments
- how the fans view the influencers

The List of Popular Text Mining Techniques

01	Word2vec + TF-IDF	<ul style="list-style-type: none">Word embeddingsVectors of numeric representations of wordsSelf-trained model
02	Sentence_Transformers	<ul style="list-style-type: none">Sentence embeddingsBERT based, state of the art model10+ pre-trained models from billions of words
03	GloVe + TF-IDF	<ul style="list-style-type: none">Word embeddingsPre-trained model1M+ words
04	TF-IDF	<ul style="list-style-type: none">Term frequency-inverse document frequencyReflects importance of a word to a document
05	Sent2vec	<ul style="list-style-type: none">Sentence embeddingsGood on small dataset (pre-trained models)Crashed with large dataset due to RAM limits
06	Doc2vec	<ul style="list-style-type: none">Document embeddingsVectors of numeric representations of docsSelf-trained model

The Models in Our Decision Support System

We finally decided to include the following two models to our decision support system based on performance and computational speed.

01

Word2vec + TF-IDF^[3]

- Word embeddings
- Vectors of numeric representations of words
- Self-trained model

02

Sentence_Transformers

- Sentence embeddings
- BERT based, state of the art model
- 10+ pre-trained models from billions of words

“Embedding” : A Task-specific Dictionary

- In the context of machine learning, an **embedding is a low-dimensional, learned continuous vector representation of discrete variables** into which you can translate high-dimensional vectors.^[8]
- Generally, embeddings make ML models more efficient and easier to work with, and can be used with other models as well.
- For example, when applied to text, we can learn the semantic meaning of a word by observing what other words it frequently appears next to. And then we can generate a list of embeddings, which can be seen as a task-specific dictionary.

The Models in Our Decision Support System

01

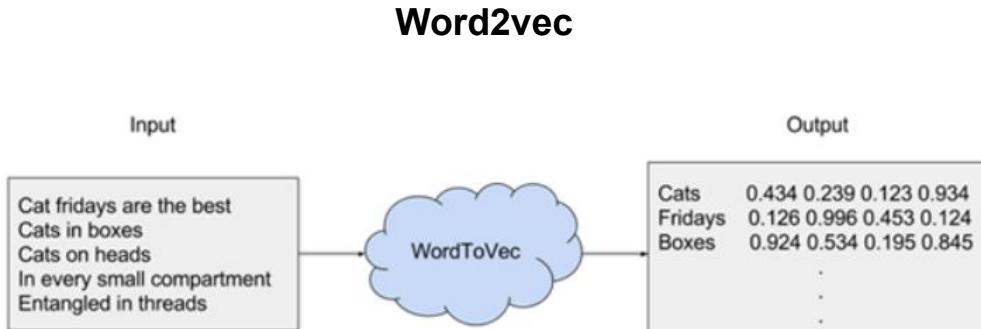
Word2vec + TF-IDF

02

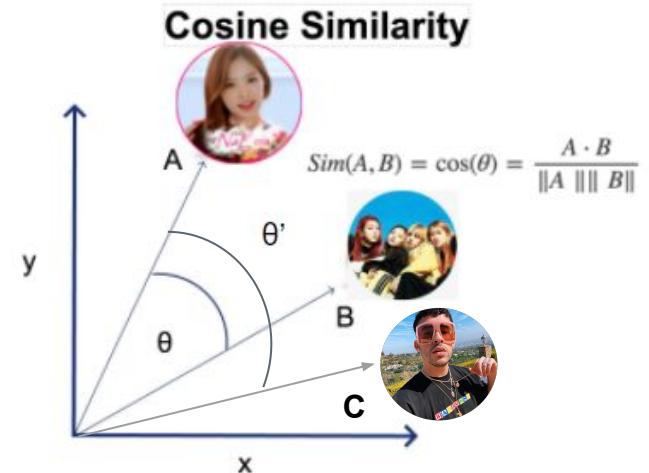
Sentence_Transformers

Word2vec and Cosine Similarity

- Word2Vec is an algorithm that accepts text corpus as an input and outputs numerical representations for each word
- Cosine similarity is a metric used to measure how similar the documents are irrespective of their size.



Source: <https://jalammar.github.io/illustrated-word2vec/>



The Dictionary Captures Semantic Meaning

A famous example of the concept of analogy:



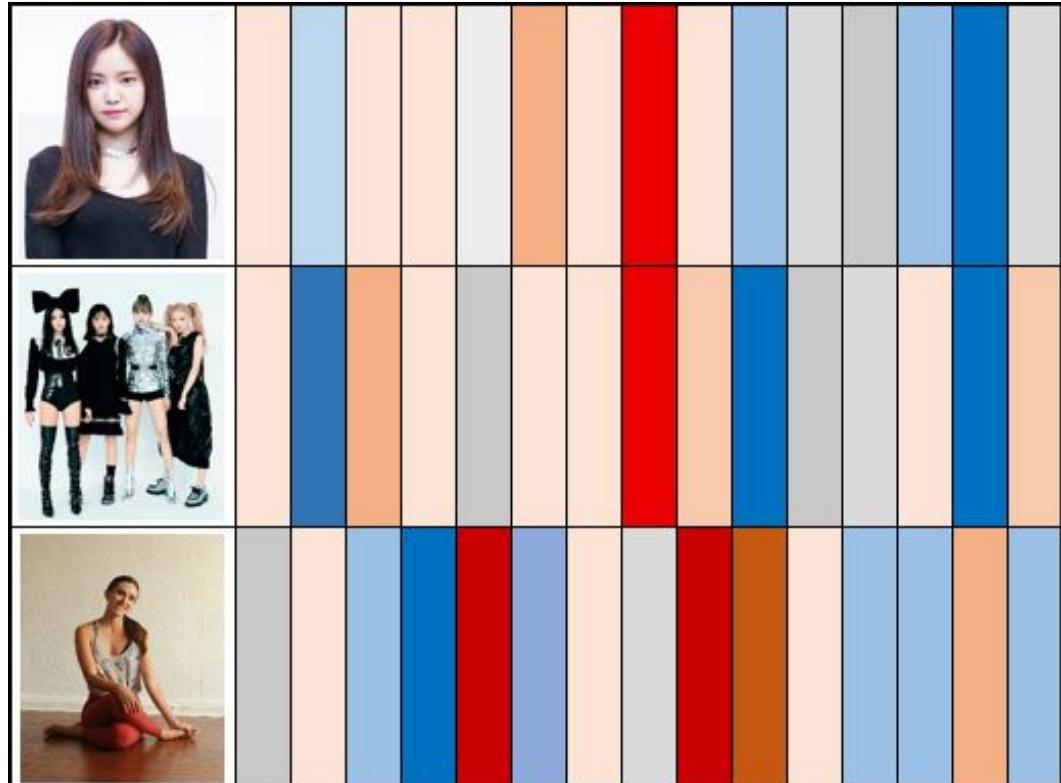
The resulting vector from "king-man+woman" doesn't exactly equal "queen", but "queen" is the closest word to it from the 400,000 word embeddings in this collection.^[1]

Analogy for Our Case

We can clearly perceive that the users talked about Naeun Son and BlackPink in a more similar way.

We can use this information to find :

- overlaps among the users' culture
- specific groups of customers



Word2vec - How to Validate the Dictionary

- This is an unsupervised method, so we do not have a ground truth to evaluate if the model has captured the semantic meaning of the words
- We used the most similar words of a specific word ["kpop"] as the evaluation metrics

Top 3 of the most similar words to "kpop"	
Words	Similarity Score
"makestar"	0.783166170
"broadcasting"	0.725594878
"blackpink"	0.672631085

Word2vec - How to Validate the Dictionary

“Makestar”:

Makestar, which will present the projects that stars and fans make together, is a two-way communication window that helps their communication.

“Broadcasting”:

Music programs of South Korea are broadcast weekly, with different artists performing on the shows to promote their music.

[more examples...](#)

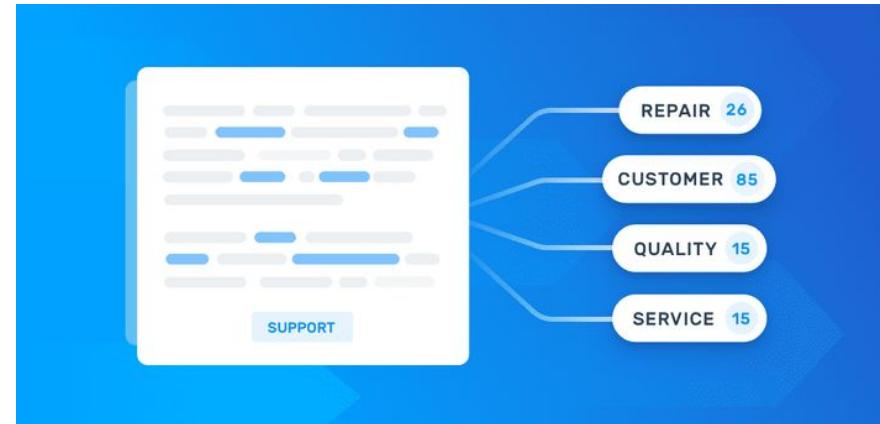
The screenshot shows the Makestar website interface. At the top, there's a navigation bar with links for Projects, Shop, Artists, Event, Polls, Forums, Music, and FAQ. On the right side of the header, there are links for Login, a search icon, and a shopping cart icon. Below the header, there's a secondary navigation bar with tabs for Artist, Animation, and Fanmade, along with links for All Categories, Funding, and Pre-order. The main content area displays a grid of project cards. There are four rows of cards, each containing two or three items. Each card includes a thumbnail image, the project title, a brief description, and a status indicator (e.g., Pre-order, Limited period, Closed). Some cards also mention specific artists like ATEEZ, ASTRO, DONGKIZ, Whee In, G-reishy, VERIVERY, and WEi.

Project Title	Description	Status
ATEEZ [ZERO : FEVER Part.2] VI...	Buy ATEEZ [ZERO : FEVER Part.2] from MAKESTAR and get the...	Pre-order
ASTRO 2nd Full Album [All Yo...	Buy ASTRO 2nd Full Album [All Yours] from MAKESTAR and get t...	Limited period
DONGKIZ 4th Single Album [Y...	Buy DONGKIZ [Youniverse] from MAKESTAR and get a limited...	Pre-order
UP10TION [Light UP] 1:1 Meet...	Encore Event for UP10TION and HONEY10! Buy UP10TION [Light...	Limited period
Whee In [Redd] Pre-Order	Buy Whee In [Redd] at MAKESTAR and get the limited edition...	Limited period
G-reishy [M] Signed Album & ...	Special time with G-reishy, who came back after a year and six...	Limited period
VERIVERY SERIES 'O' [ROUND ...	Buy VERIVERY SERIES 'O' [ROUND 1 : HALL] from MAKESTAR and ge...	Limited period
WEi [IDENTITY : Challenge] Meet&Call vol.2	Buy WEi [IDENTITY : Challenge] from MAKESTAR and get the...	Limited period

How to Reflect the Importance and Relevance of a Word?

TF-IDF, is a numerical statistic that is intended to reflect how important a word is to a document in a collection.

- Documents with similar, relevant words will have similar vectors
- It also helps discover the uniqueness of the language habits of the certain customer groups



Similarity - Wording Relevance and Semantic Meaning



Top 3 of the most similar influencers to "Beyonce"

Influencers	Similarity Score
"Zoe Saldana"	0.869546415
"Pharrell Williams"	0.865572384
"BlackPink"	0.863266794

Top 3 of the most similar influencers to "Pharrell Williams"



Influencers	Similarity Score
"Beyonce"	0.865572384
"Jerry Lorenzo"	0.856141943
"Bad Bunny"	0.834991535

The Models in Our Decision Support System

01

Word2vec + TF-IDF

02

Sentence_Transformers

SBERT with Sentence_Transformers

- BERT, machine learning technique for natural language processing pre-training developed by Google, published in 2018
- Sentence BERT (or SBERT) was developed by UKP Lab from Darmstadt University of Technology in Germany
- It provides an increasing number of state-of-the-art **pretrained models for more than 100 languages**, fine-tuned for various use-cases.

Social Network Analysis (SNA)

Social network analysis is the process of **investigating social structures** through the use of networks and graph theory.

It characterizes networked structures in terms of nodes and the ties, edges, or links that connect them.



Source: <https://gatton.uky.edu/about-us/stay-connected/news/2020/links-center-social-network-analysis-workshop-success>

How SNA Benefits Business Analysis

In the private sector, businesses use SNA to support activities such as:

- customer interaction and analysis
- information system development analysis
- marketing and business intelligence needs

In our case, we performed SNA to reveal information about the influencer's fanbase activities, overlaps, and interactions



SNA with Influencer-User Matrix

- We created an **influencer-user (I-U) matrix** to compute cosine similarity scores
 - Find the number of occurrences of each users for each influencer
 - Compute the cosine similarity between the vectors of occurrences
 - Sorting the results and find the closest ones

	User #1	User #2	User #3	User #4	User #5
Jay	3	0	7	2	1
Influencer1	2	1	2	0	0
Influencer2	0	6	2	1	0

$$\text{cosine_similarity}(\begin{bmatrix} 3 & 0 & 7 & 2 & 1 \end{bmatrix}, \begin{bmatrix} 2 & 1 & 2 & 0 & 0 \end{bmatrix}) = 0.84 \checkmark$$

$$\text{cosine_similarity}(\begin{bmatrix} 3 & 0 & 7 & 2 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 6 & 2 & 1 & 0 \end{bmatrix}) = 0.31$$

How I-U Matrix Tackles Business Questions

Beyonce

```
model.best_sub("Beyonce", n=2)  
['Bad Bunny', 'Pharrell Williams']  
-----  
model.best_complete("Beyonce", n=2)  
['Adriene Mishler', 'Jerry Lorenzo']
```



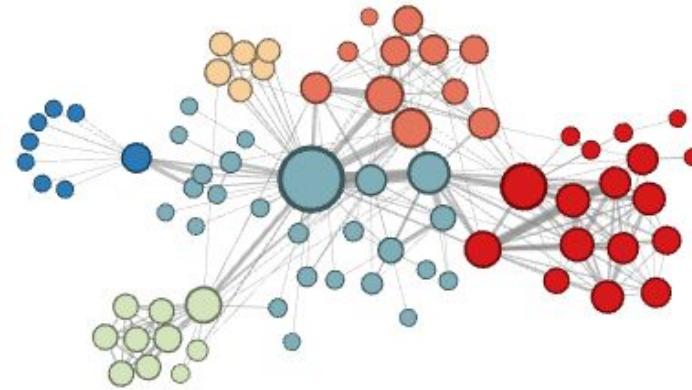
Naeun Son

```
model.best_sub("Naeun Son", n=2)  
['BlackPink', 'Bad Bunny']  
-----  
model.best_complete("Naeun Son", n=2)  
['Kerwin Frost', 'Zoe Saldana']
```



SNA with node2vec

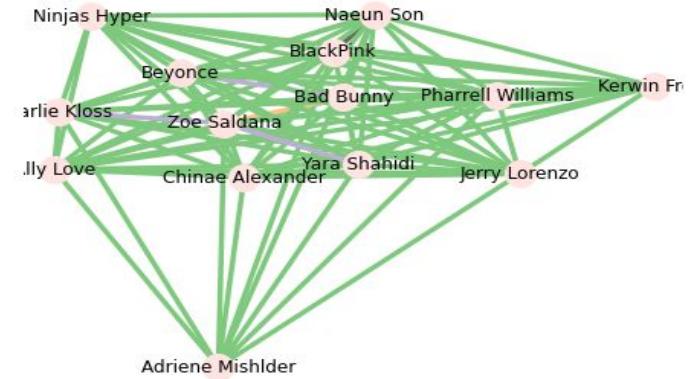
- Developed by Stanford
- Built upon the idea of word2vec
- Convert high dimensional data/information into a low-dimensional representations^[2]
- By studying the relationship between the nodes, business can generate the insights of the people to whom the influencers reached
- A node embeddings (or influencer's fanbase dictionary) will be generated:
 - Can be used for various analysis, like K-means clustering



Node2vec - Generate an Node Dictionary

Data for SNA	
Celebrity (Nodes)	Usernames (Edges)
Beyonce	User01
....

Graph



Embedding

T-SNE Plot
Node2vec Built-in Feature
K-means Clustering

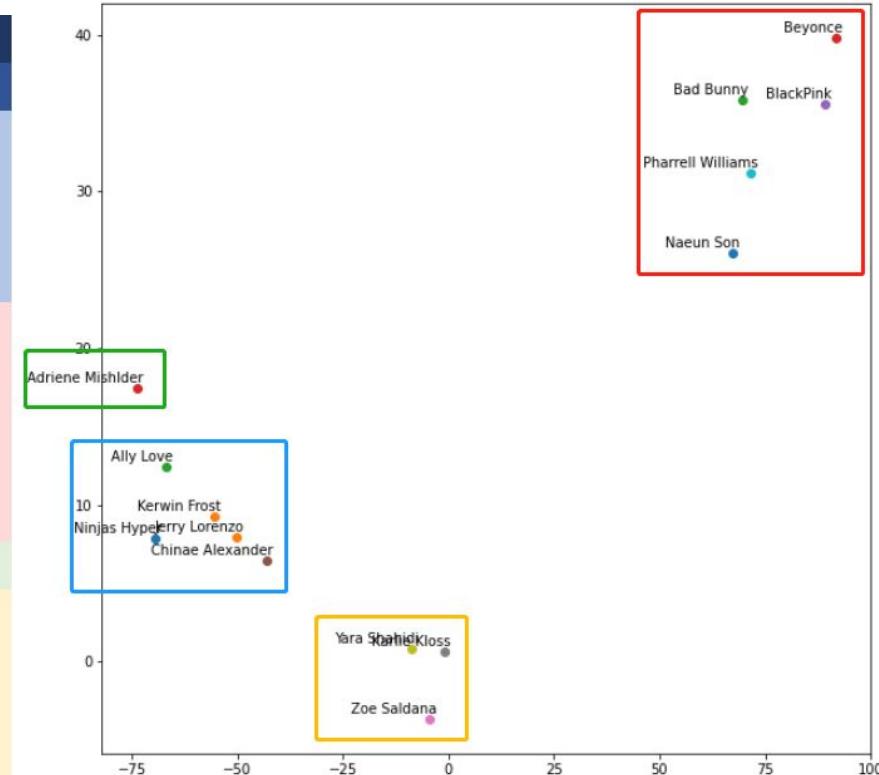
Usages

Nodes	Embeddings
Beyonce	-0.1315, 0.7745, ...
....
Naeun Son	0.8516, 0.1442, ...

Influencers' Fanbase Segments

K-means Clustering with $k = 4$

Groups	Influencers
Group 1	Ninjas Hyper
	Jerry Lorenzo
	Kerwin Frost
	Ally Love
Group 2	Bad Bunny
	Beyonce
	BlackPink
	Pharrell Williams
Group 3	Naeun Son
	Adriene Mishler
	Chinae Alexander
Group 4	Zoe Saldana
	Karlie Kloss
	Yara Shahidi



CASE STUDY

Business Question

Due to a controversy, if we had to substitute Naeun Son and BlackPink with someone else, who would be the ideal candidate?



=

?



=

?

Case study - Background

To better understand the international market, as well as to demonstrate the potential usage of the decision support system we built, we specifically picked 8 more korean groups/individuals (based on popularity, stage style, etc.) along with “Black Pink” and “Naeun Son” to conduct a case study.^[11]

Groups	Ranking	Reddit Subscribers
Black Pink	#2	122k
IZ*ONE	#5	27.4k
BTS (boy group)	#1	214k
NCT (boy group)	#6	29.4k
GFriend	#9	23.8k

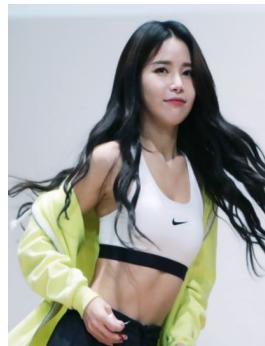
Individuals	Groups	Ranking	Reddit Subscribers
Naeun Son	Apink	#14	7.5k
Seolhyun	AOA	(Nike)	4k
Sana	TWICE	#2	102K
Solar	MAMAMOO	#7	18.5k
Miyeon	GI-DLE	#4	15k

Case study - Hypothesis

- ❖ Either Solar or Seolhyun could be the most similar individual to Naeun Son.
Naeun and Seolhyun look very similar to each other and Naeun and Solar are both prominent members of a girl group.
- ❖ IZ*ONE could be the most similar girl group to BlackPink based on ranking (#5 & #2) and origin (Seoul, South Korea)
- ❖ Sana and Miyeon could be very unique in this datasets since their stage positionings and artistic style are very different from the other groups or individuals.^[11]



≈



≈



Naeun

Solar

Seolhyun

Case study - Data



Data for Text Mining^[5]:

- ★ # of comments: 23381
- ★ # of words: 15M+

Data for SNA^[5]:

- ★ # of Influencers : 10
- ★ # of observations: 49274
- ★ # of users: 35147

Case study - Text Mining (word2vec+Tf-idf)

```
most_similar("BlackPink",
              Pairwise_similarities,
              'Cosine Similarity',
              topn=2)
```

Name: BlackPink
Similar Influencers:
Celebrity: iZone : 0.7479952518415461
Celebrity: GFriend : 0.7131607796176859

```
most_similar("Naeun Son",
              Pairwise_similarities,
              'Cosine Similarity',
              topn=2)
```

Name: Naeun Son
Similar Influencers:
Celebrity: Seolhyun : 0.6698078801647593
Celebrity: Solar : 0.6178915677265608

"Followers of BlackPink talk 74.79% similar to followers of IZ*ONE on reddit "

Case study - Social Network Analysis (basic decision modeling)

```
model.best_sub("Naeun Son", n=2)  
['Seolhyun', 'GFriend']
```

```
-----  
model.best_complete("Naeun Son", n=2)  
['Sana', 'Miyeon']
```

To find the most
similar celebrity

```
Model.best_sub ("BlackPink", n=2)  
['GFriend', 'NCT']
```

```
-----  
model.best_complete("BlackPink", n=2)  
['Sana', 'Miyeon']
```

Average execution time: 1 min 16s

To find the most
dissimilar celebrity

Case study - Social Network Analysis (node2vec)

Name: Case Study for Korean Influencers

Type: Graph

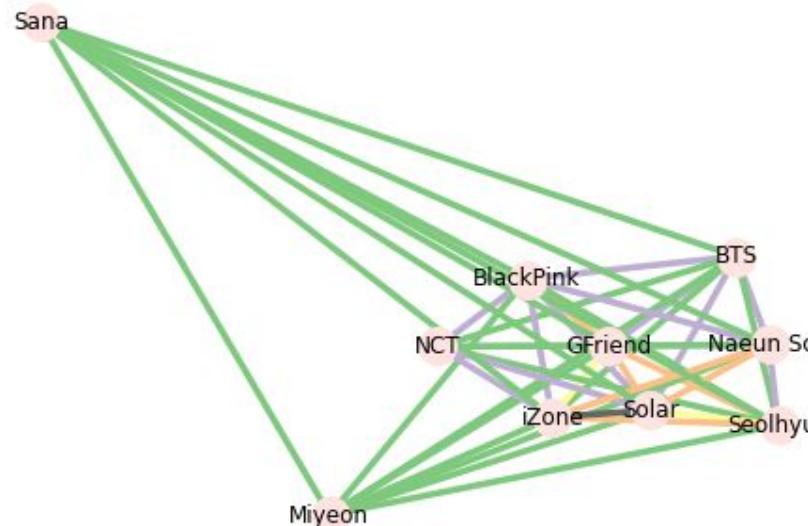
Number of nodes: 10

Number of edges: 43

Average degree: 8.6000

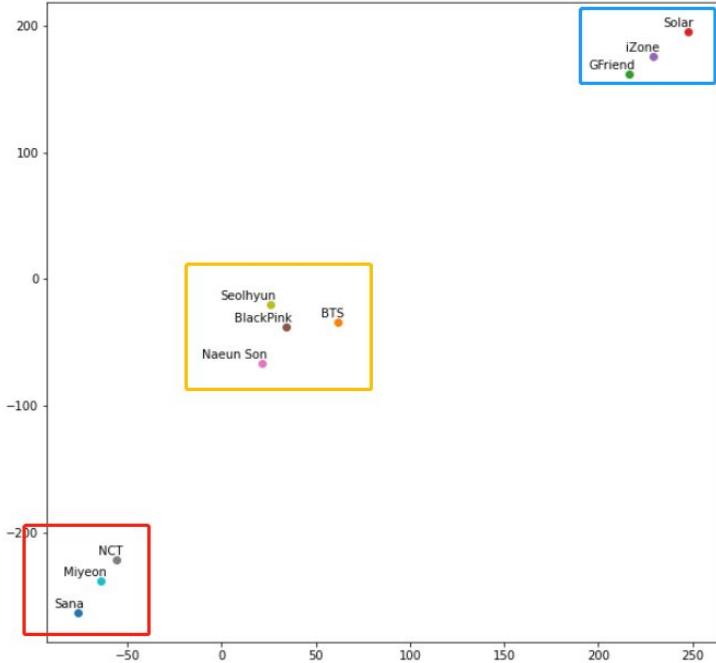
Average execution time: 188 ms

-
node2vec saved **97.52%** of execution time



Case study - node2vec

T-SNE Plot



node2vec built-in feature

```
model.wv.most_similar("Naeun Son", topn=4)  
(the groups were filtered out)
```

```
[ ('Seolhyun', 0.9898267984390259),  
 ('Solar', 0.9860391616821289),  
 ('Miyeon', 0.9639727878570557),  
 ('Sana', 0.9561481475830078) ]
```

```
model.wv.most_similar("BlackPink", topn=4)  
(the individuals were filtered out)
```

```
[ ('iZone', 0.996224582195282),  
 ('GFriend', 0.9955752491950989),  
 ('BTS', 0.9739093589782715),  
 ('NCT', 0.9657029318809509), ]
```

Conclusion

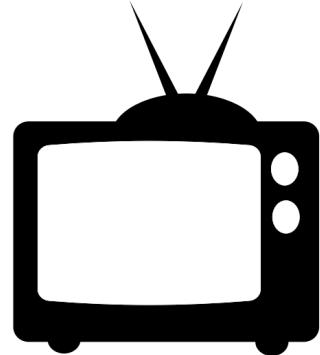


And the winners are...

LIMITATION & FUTURE WORK

Data

1. Different backgrounds.
2. Not all of them on Reddit .
3. 22% of users aged from 18 to 29 (as of February 2019)^[6]
4. We observed that the functionality Reddit API is not constant when we try to extract large amounts of data at once.



Text Mining

Limitations:

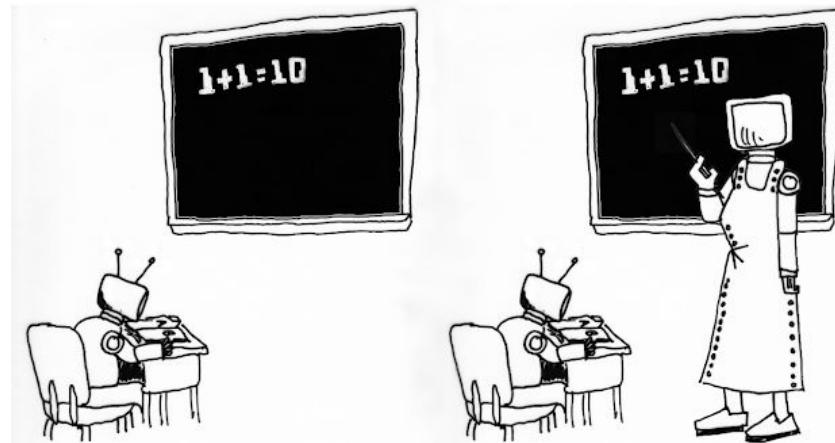
- No ground truth that can help measure the performance of the models
- Better performing models need labeled data

Potential Future Work:

- Additional preprocessing of data & vetting of the processed data
- Move on to supervised models

UNSUPERVISED MACHINE LEARNING

SUPERVISED MACHINE LEARNING



Limitations on the SNA

- A small number of nodes will limit the performance (e.g. we only had 14 influencers in the dataset)
- The data is unbalanced, so the model still could be biased.

The data says we need more data.



Potential Future Work of SNA

- Expand the influencer list to conduct a larger scope of case studies
- Collect data periodically (e.g. every 3 month) to study seasonal patterns and capture the fandom changes over time
- Node2vec can be applied for online product recommendations



Using a well-structured thoroughly documented API to collect data for a project.



Using a Web-Scraper to make a request for each individual page of data, increasing data collection time and network usage.



Possibilities on Analyzing Instagram Stories



allymisslove



nadyaokam...



chnaealex...



celinecelines



meagankong



adrienelouise



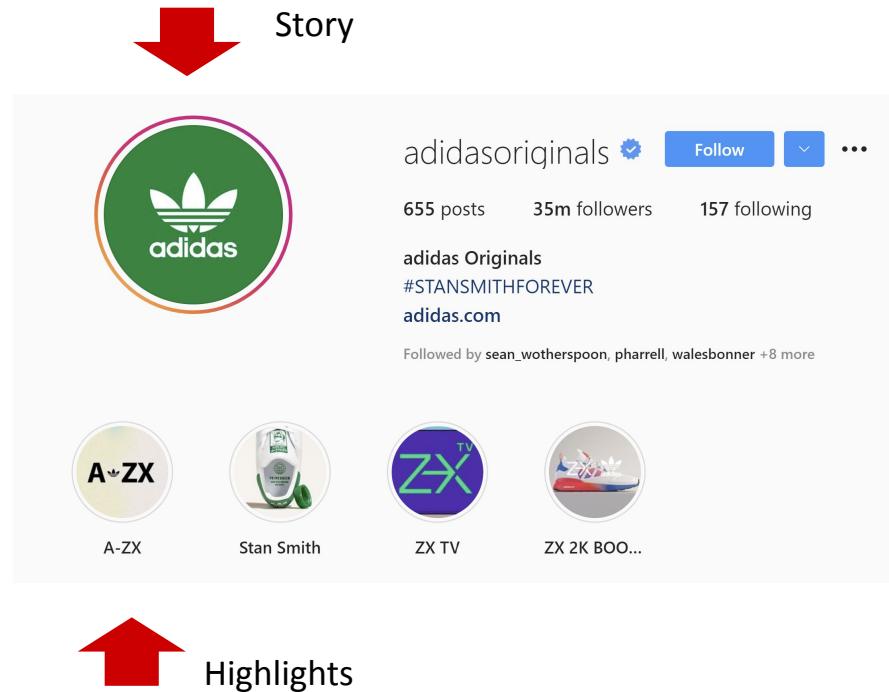
jerrylorenzo



zoesa

What are Instagram Stories?

- "Share all the moments of your day, not just the ones you want to keep on your profile"
- Ephemeral: expires 24 hours after posting
- Can be permanent if user add it as a highlight



Business Value of Understanding Stories

- Understand celebrities' different aesthetics (visual feeling)
- Avoid style overlap when marketing one product
- Tailor product endorsement matchup with celebrities' show style



Jerry Lorenzo

Bad Bunny

Problems to Solve

Getting
Instagram
Stories



Detecting
images with
Adidas logos

1

Computationally assessing image quality

How effectively they convey the visual idea?

2

Classifying images by style

How do they convey the visual idea uniquely?

Getting Instagram Stories

Open source API - Instaloader:

- Python Module, Ready to use
- Full capability of downloading media along with its metadata

Local output:

- Media (jpg for image, mp4 and jpg thumbnail for videos)
- Metadata (zipped json file)



Instaloader

<https://instaloader.github.io/index.html>

<https://instaloader.github.io/as-module.html#module-instaloader>

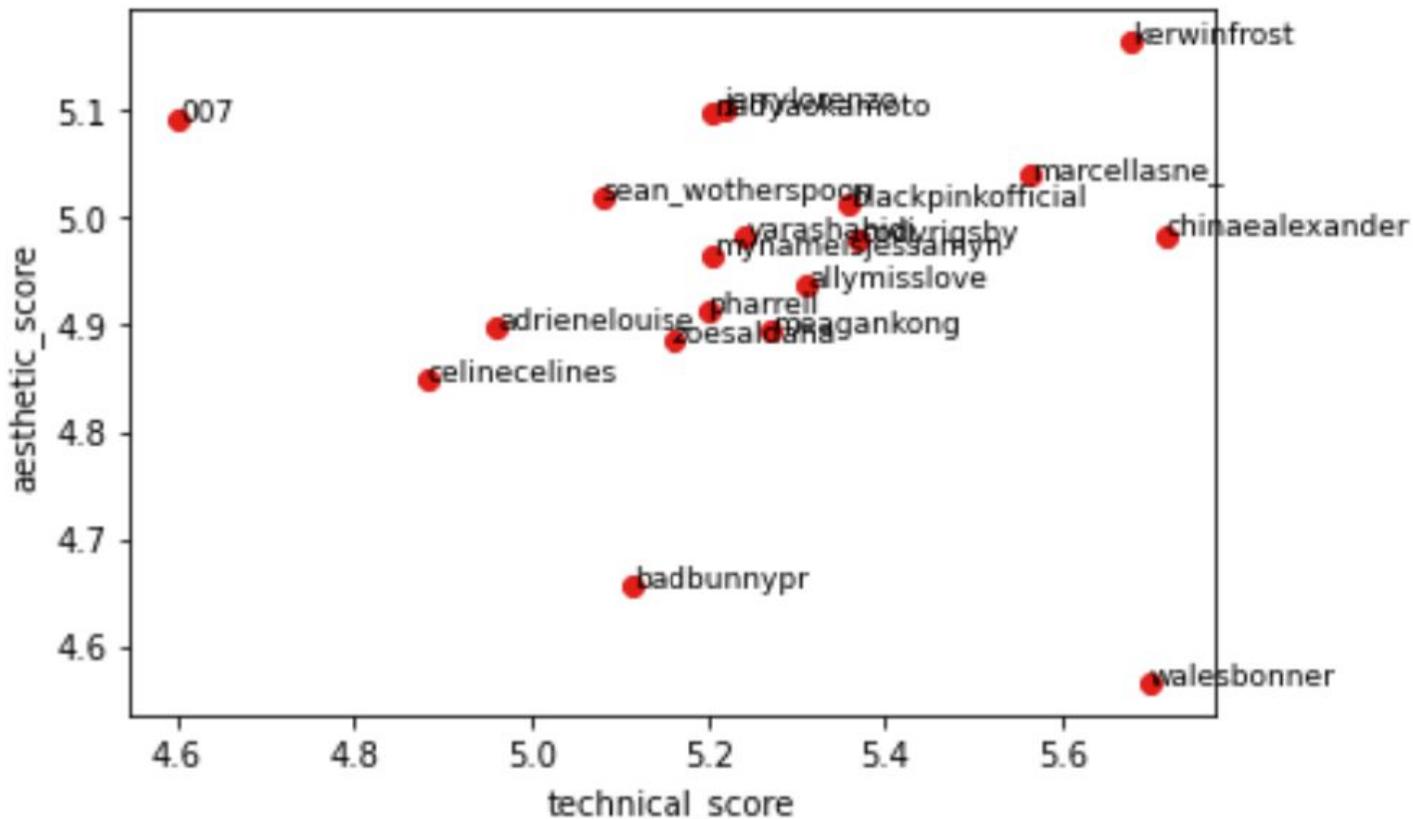
Limitations on Getting Instagram Stories

- Need to create an instagram account and follow all target users
- No way to catch expired stories
 - Need to run the script on 24-hour intervals to get all stories
- 429 Too Many Requests
 - Sometimes throw this error at around 200 fetches
 - Need multiple accounts to scrape the data

Google NIMA

- A Neural Image Assessment model
- Quantification of image quality and aesthetics
 - Technical Score: Looking good? Noise, blur, compression artifacts...
 - Aesthetic Score: Attractive? Beautifulness, human perception of good feeling.
- Trained with histograms of human ratings for every image
- Produces a distribution of ratings for any given image — on a scale of 1 to 10, assigning likelihoods to each of the possible scores
- Calculates a mean score correlates closely with human perception.

Assessing Instagram Stories Quality



Analyzing Images with Google NIMA

Technical: 5.3163

Aesthetic: 5.4846



Wales Bonner



Karlie Kloss

Technical: 4.3772

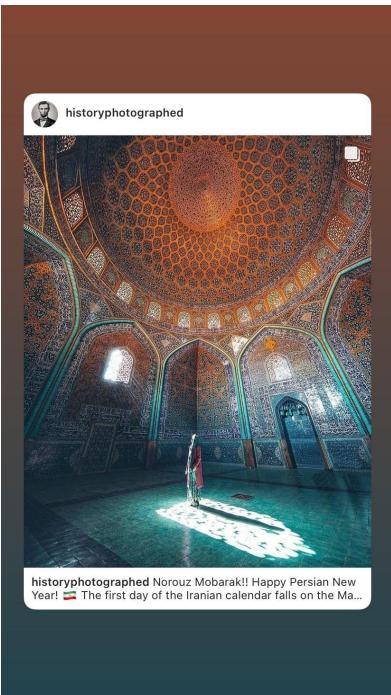
Aesthetic: 4.3204

- Blurry
- Text on top
- Color Fades out
- Color composition not ideal

Analyzing Images with Google NIMA

Technical: 4.2074

Aesthetic: 6.0637



Technical: 5.5548

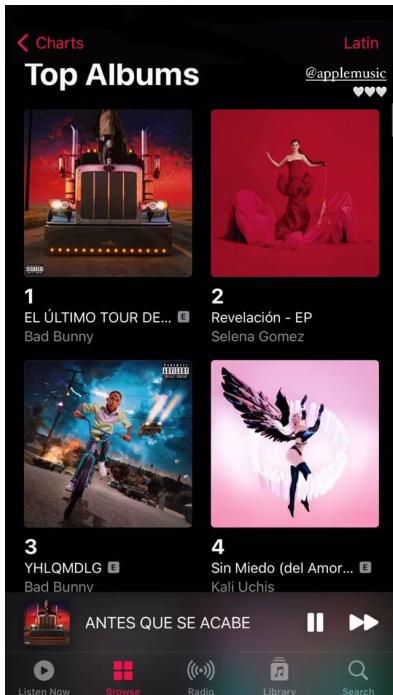
Aesthetic: 4.0486

Adriene Mishler

Analyzing Images with Google NIMA

Technical: 4.5234

Aesthetic: 5.9242



Bad Bunny

Technical: 4.2735

Aesthetic: 3.2516

Analyzing Images with Google NIMA

Technical: 6.2090

Aesthetic: 5.6127



Technical: 4.6019

Aesthetic: 4.3183

Black Pink

Analyzing Images with Google NIMA

Technical: 4.9158

Aesthetic: 5.9319



Chinae Alexander



Technical: 5.1978

Aesthetic: 3.6918

Classifying Images by Style

- Vislab by Sergey Karayev - a set of Python modules for visual recognition
 - Features: based on color dependency, composition, visual attention...
 - Architecture: Fine-tuned Caffe Deep convolutional Framework
 - Dataset: 80K flickr images with 20 style labels
 - Style labels based on Optical techniques, Atmosphere, Mood, Composition styles, Color and Genre.
 - Scalability:
 - Crossing-platform: train from flicker and test on pinterest, AVA
 - Add own training set with labels

<https://sergeykarayev.com/files/1311.3715v3.pdf>

<https://github.com/sergeyk/vislab>

<http://vislab.berkeleyvision.org/>

20 Style Labels



Macro



Bokeh



Depth-of-Field



Long Exposure



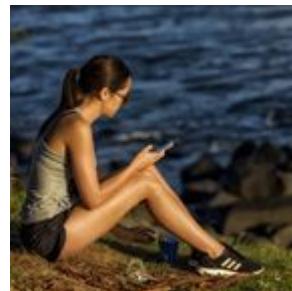
HDR



Hazy



Sunny



Serene



Melancholy



Ethereal

20 Style Labels



Minimal



Geometric



Detailed



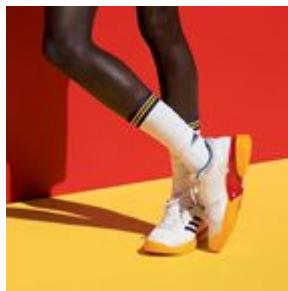
Texture



Romantic



Pastel



Bright



Noir



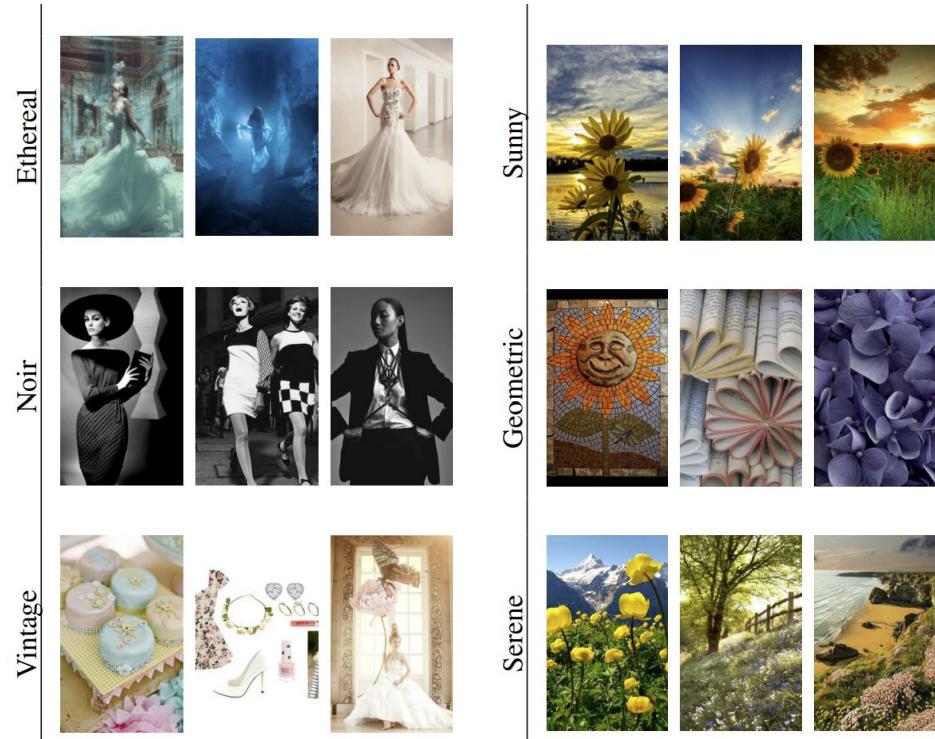
Vintage



Horror

Classifying Stories by Style

- We can get all images of same style.
- Combine with query of celebrities to explore each one's dominant visual style.
- Helps making marketing strategies
 - Minimal overlap
 - Target specific groups



Query: "dress".

Query: "flower".

Limitations of Image Style Classification

- Pre-trained model with fixed labels
- For better customized performance, need to define own style labels and manually label the training data, then retrain the classifier.

Thank you!

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APPENDIX

Word2vec - Skipgram

The pink boxes are in different shades because this sliding window actually creates four separate samples in our training dataset:

Jay was hit by a red bus in...

by	a	red	bus	in
input		output		
red		by		
red		a		
red		bus		
red		in		

The quick brown fox jumps over the lazy dog. →

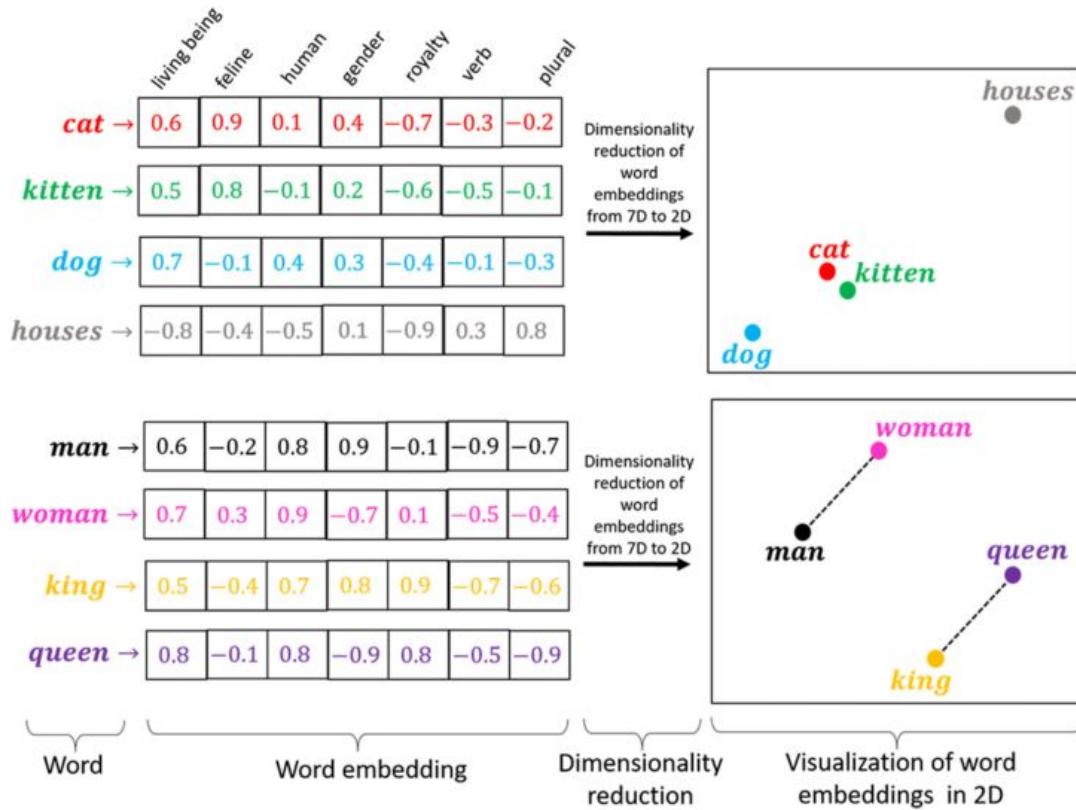
(fox, quick)
(fox, brown)
(fox, jumps)
(fox, over)

Word2vec

It did twice dimension reduction during the process:

a corpus of words → a list of unique words with vector representations

vectors → 2D embeddings



Word2vec - Evaluation Metrics

Top 3 of the most similar words to "*adidas*"

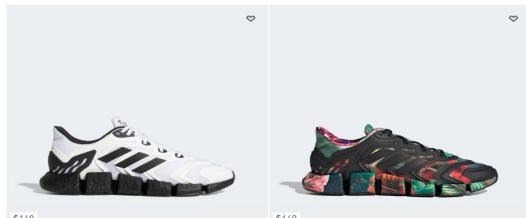
Words	Similarity Score
"yzy"	0.754484594
"pharrellwilliams"	0.694894612
"climacool"	0.676122606



search for:

"CLIMACOOL VENTO" [1]

GENDER ▾ PRICE ▾ COLOR ▾ ACTIVITY ▾ BEST FOR ▾ COLLECTION ▾ PATTERN ▾ TECHNI



\$140
Climacool Vento Shoes
Men's Running
8 colors - recycled materials

PHARRELL • ATHLETIC & SNEAKERS [2]

GENDER ▾ PRODUCT TYPE ▾ PRICE ▾ COLOR ▾ ACTIVITY ▾ COLLABORATION ▾

Pharrell x Athletic & Sneakers x Clear All



\$140
Pharrell Williams Primeknit Superstar Shoes
Originals
2 colors - new

How the TF-IDF Calculated

We have the following four documents:

- D1 "The sky is blue"
- D2 "The sun is bright today"
- D3 "The sun in the sky is bright"
- D4 "We can see the shining sun and the bright sun"

After removing stop-words, the bag of words table is as follows:

	blue	bright	can	see	shining	sky	sun	today
D1	1	0	0	0	0	1	0	0
D2	0	1	0	0	0	0	1	1
D3	0	1	0	0	0	1	1	0
D4	0	1	1	1	1	0	2	0

$$\text{IDF}(t) = 1 + \log \left(\frac{\text{Total number of documents}}{\text{Number of documents containing } t} \right)$$

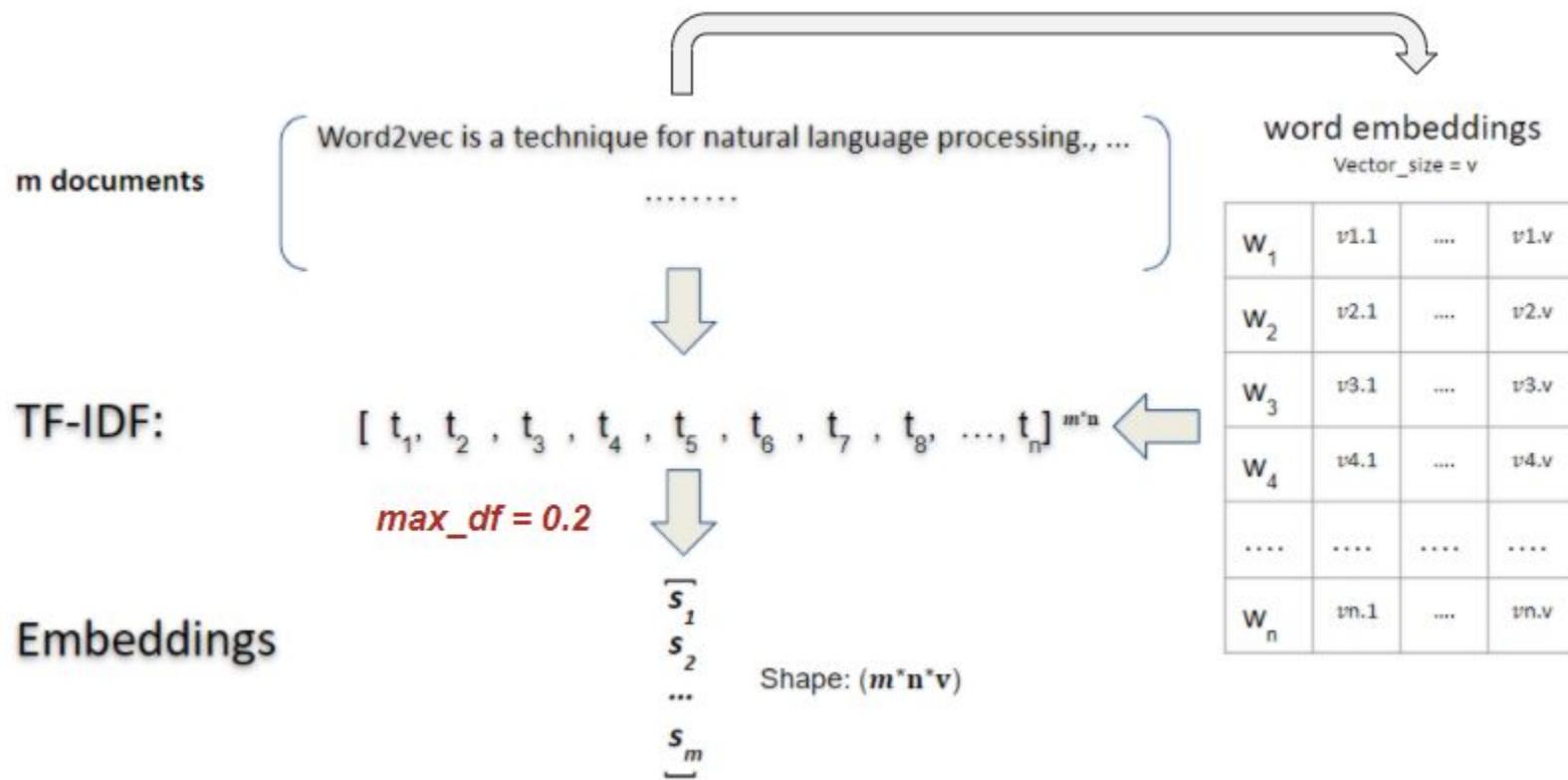
$$\text{TF}(t, d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in the document } d}$$

$$\text{TFIDF}(t, d) = \text{TF}(t, d) \times \text{IDF}(t)$$

How the model works

1. Treat 14 celebrities as 14 documents
 - $m = 14$
2. Top 30% of unique words based on frequency across all the documents [9]
 - *the number of unique words = 100,000*
 - $n = 100,000 * 0.3 = 30,000$
3. Based on a paper released by Google, the vector size of word2vec embeddings can be determined by the following formula: [10]
 - $v = 10M^{0.25} \approx 57$
4. The shape of the final embeddings is: **(14,30000,57)**

How the model works



SBERT Implementation

One of the best available models for Semantic Textual Similarity (STS) is:

stsbert-large - STSb performance

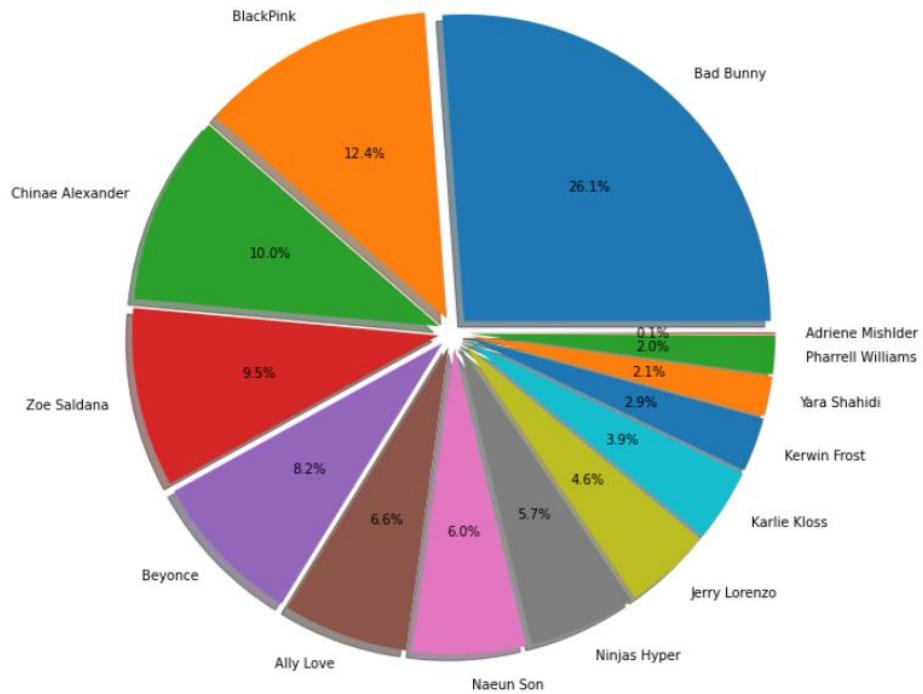
Top 2 of the most similar influencers to "BlackPink"

Influencers	Similarity Score
"Naeun Son"	0.690971255
"Karlie Kloss"	0.671959343

Top 2 of the most similar influencers to "Naeun Son"

Influencers	Similarity Score
"BlackPink"	0.690971255
"Beyonce"	0.666431148

SNA Implementation

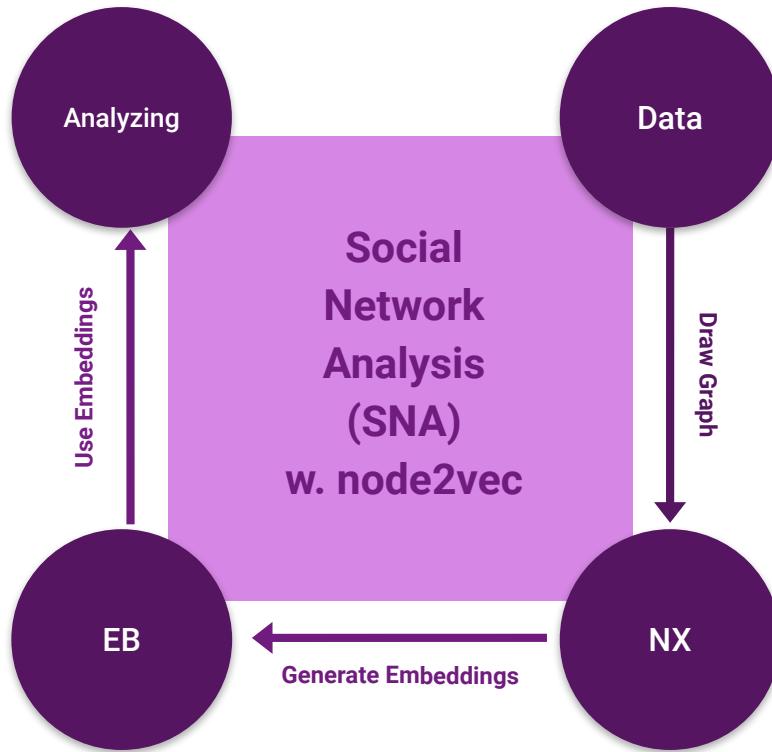


```
model.crosstable()
```

Celebrity	Celebrity	Value
Ally Love	Adriene Mishilder	3.0
Bad Bunny	Adriene Mishilder	0.0
	Ally Love	41.0
Beyoncé	Adriene Mishilder	0.0
	Ally Love	26.0
	...	
Zoë Saldana	Kerwin Frost	6.0
	Naeun Son	9.0
	Ninjas Hyper	23.0
	Pharrell Williams	24.0
	Yara Shahidi	82.0

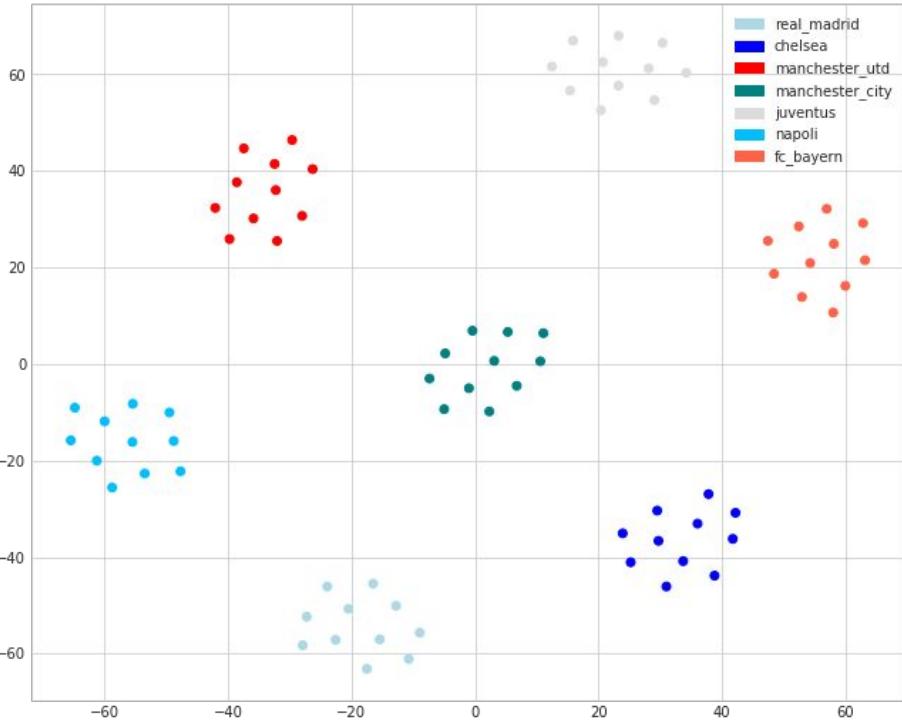
Length: 91, dtype: float64

SNA with node2vec



SNA with node2vec

Usage 2: T-SNE Plot



Usage 1: node2vec built-in feature

```
model.wv.most_similar("Celebrity 12",topn=5)
```

```
[('Celebrity 1', 0.9880407452583313),
 ('Celebrity 8', 0.9570997071266174),
 ('Celebrity 4', 0.9056358766555786),
 ('Celebrity 6', 0.8254547381401062),
 ('Celebrity 5', 0.7046592545509338)]
```

Usage 3: K-means Clustering

Group 1

	0	...	n
Celebrity 1	-0.019673	...	
0.085747			
Celebrity 3	-0.011764	...	
0.091183			

[2 rows x n columns]

....

Group k

	0	...	n
Celebrity 4	0.022665	...	0.011859
Celebrity 5	0.018963	...	0.010145

[2 rows x n columns]

SNA Implementation

Average execution time: 150 ms

node2vec saved **99.98%** of execution time

Computing transition probabilities: 100%  14/14 [00:10<00:00, 1.27it/s]

Generating walks (CPU: 1): 100%  15/15 [00:00<00:00, 129.07it/s]
CPU times: user 177 ms, sys: 3.78 ms, total: 181 ms
Wall time: 199 ms

e.g. One of the outputs of training process

Usage 1: node2vec built-in feature

```
model.wv.most_similar("Naeun Son", topn=2)
[('BlackPink', 0.9982033967971802),
 ('Beyonce', 0.988198926448822)]
```

Potential Future Work of Text Mining

Remove boilerplate to increase the informativeness and uniqueness of the “documents” for each celebrity.^[4]

**In textual analysis, Boilerplate is a combination of words that can be removed from a sentence without significantly changing the original meaning*

```
[('bot', 'action', 'performed', 'automatically'), 4186),  
 ('action', 'performed', 'automatically', 'please'), 3454),  
 ('performed', 'automatically', 'please', 'contact'), 3454),  
 ('automatically', 'please', 'contact', 'moderator'), 3454)]
```

Case study - node2vec

K-means Clustering

Group 1

	0	1	2	...	13	14	15
Sana	-0.089618	-0.071649	-0.003039	...	-0.043400	-0.102120	0.014032
NCT	-0.109779	-0.097330	0.032881	...	-0.048294	-0.241587	0.031689
Miyeon	-0.144210	-0.067727	0.037089	...	-0.058805	-0.197231	-0.010469

[3 rows x 16 columns]

Group 2

	0	1	2	...	13	14	15
BTS	-0.186073	-0.159345	0.043289	...	-0.118391	-0.346044	0.027395
BlackPink	-0.186074	-0.117281	0.071182	...	-0.112053	-0.334396	-0.008005
Naeun Son	-0.139308	-0.119381	0.069812	...	-0.106206	-0.317578	-0.010998
Seolhyun	-0.220078	-0.148290	0.036138	...	-0.085400	-0.346950	0.023048

[4 rows x 16 columns]

Group 3

	0	1	2	...	13	14	15
GFriend	-0.234220	-0.147478	0.064113	...	-0.101717	-0.409747	-0.007356
Solar	-0.260542	-0.194174	0.086498	...	-0.134705	-0.450908	0.024723
iZone	-0.236252	-0.178684	0.092774	...	-0.120792	-0.407976	0.011584

[3 rows x 16 columns]