



# VEGAN

## TWITTER ANALYSIS

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# WHO ARE WE?



Viktor



Konstantin



Lennert



Artur



Wouter

# DISCUSS THESE POINTS FOR AN EFFICIENT PRESENTATION



PRESENTATION OF 20 MINUTES



DISCUSS INSIGHTS IN MANAGERIAL PRESENTATION

DISCUSS TECHNICALITIES IN TECHNICAL PRESENTATION



Q&A OF 20 MINUTES



INDIVIDUAL QUESTIONS FOR 7 MINUTES



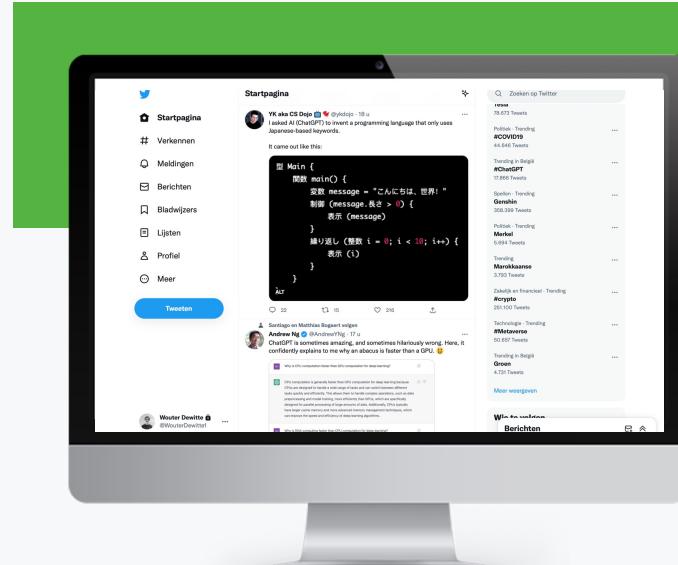
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# MANAGERIAL PRESENTATION

A presentation about insights and conclusions

# LEARN THE WAYS OF TWITTER FOR OPTIMAL INSIGHTS

These properties make Twitter different from other platforms



## HOW IS TWITTER DEFINED?

"Twitter is a **microblogging**, **social** networking service owned by American company Twitter, Inc., on which users **post** and **interact** with messages known as "tweets". "



Short messages with a concise message



Source of information

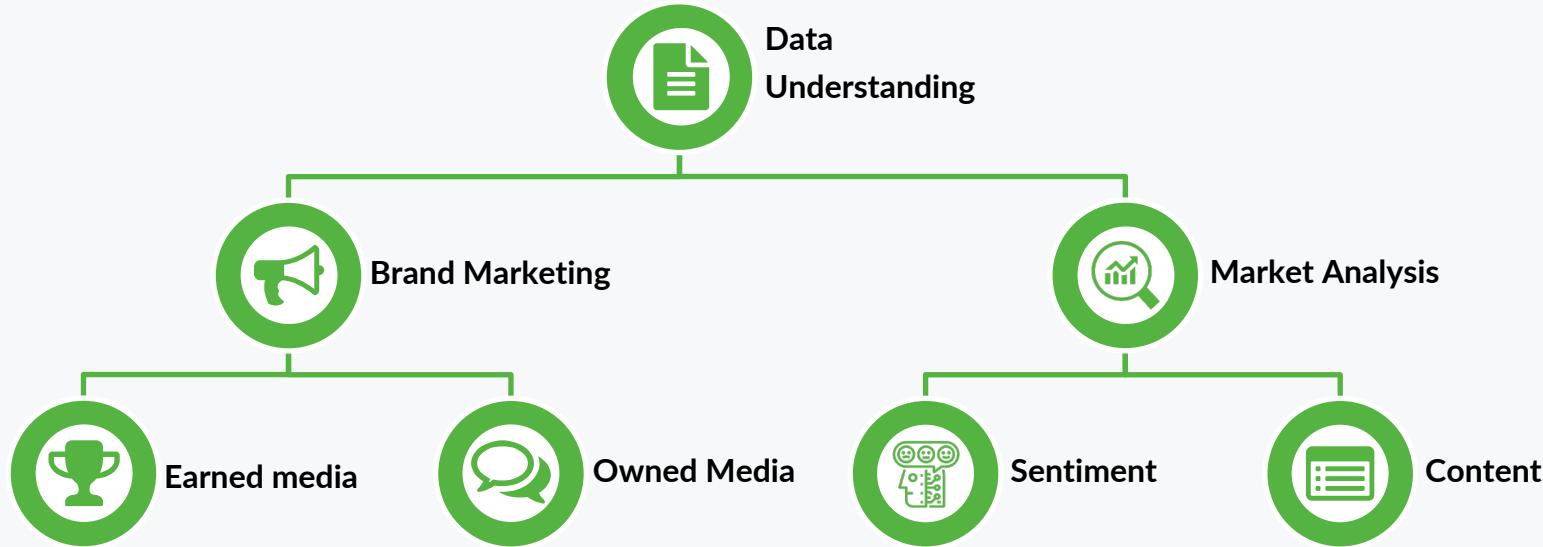


Large network of interconnected users

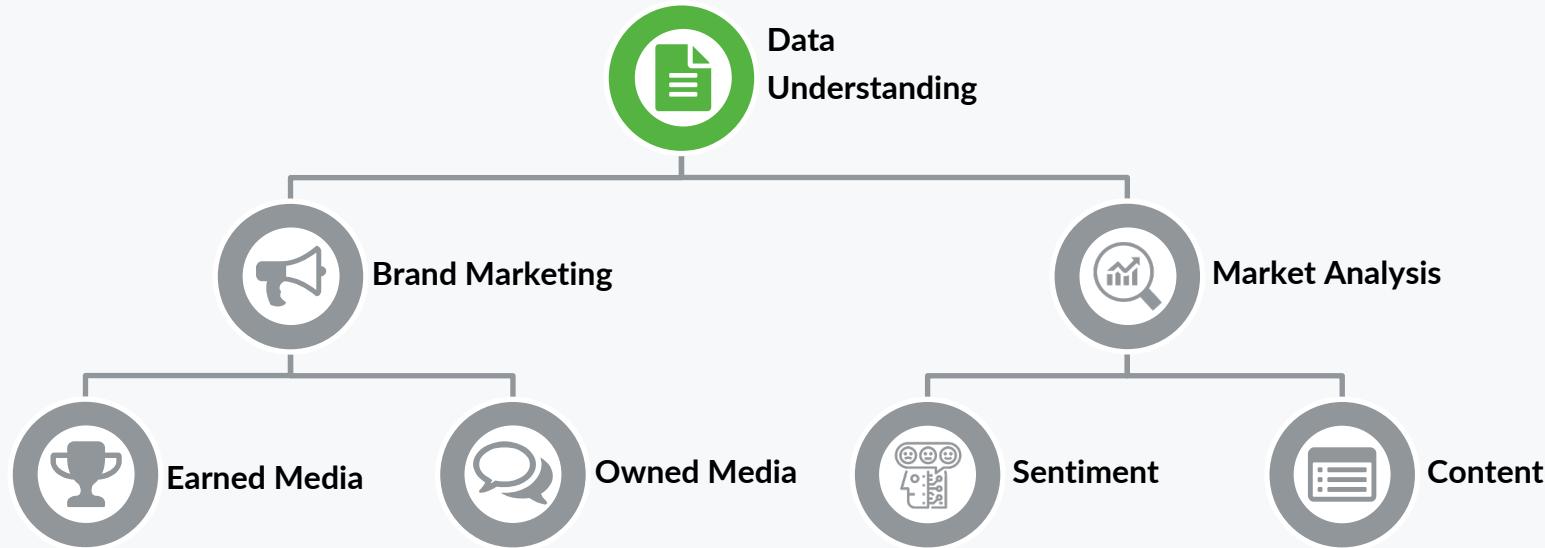


Interactive platform

# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS



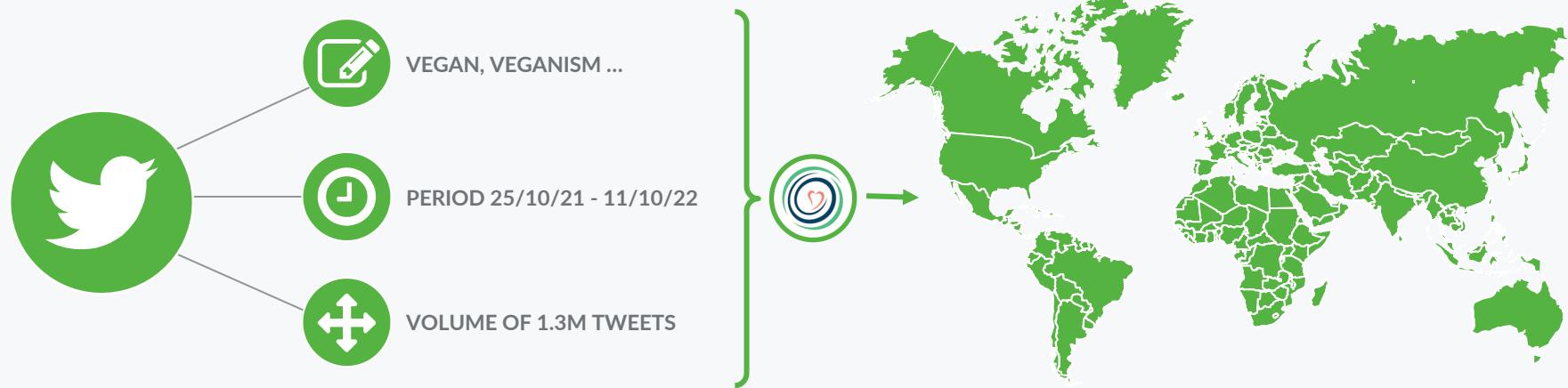
# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# UNDERSTAND YOUR DATA TO CREATE VALUABLE INSIGHTS

Understand the data and then check the generalizability





# CONCLUSION FROM THE MODEL

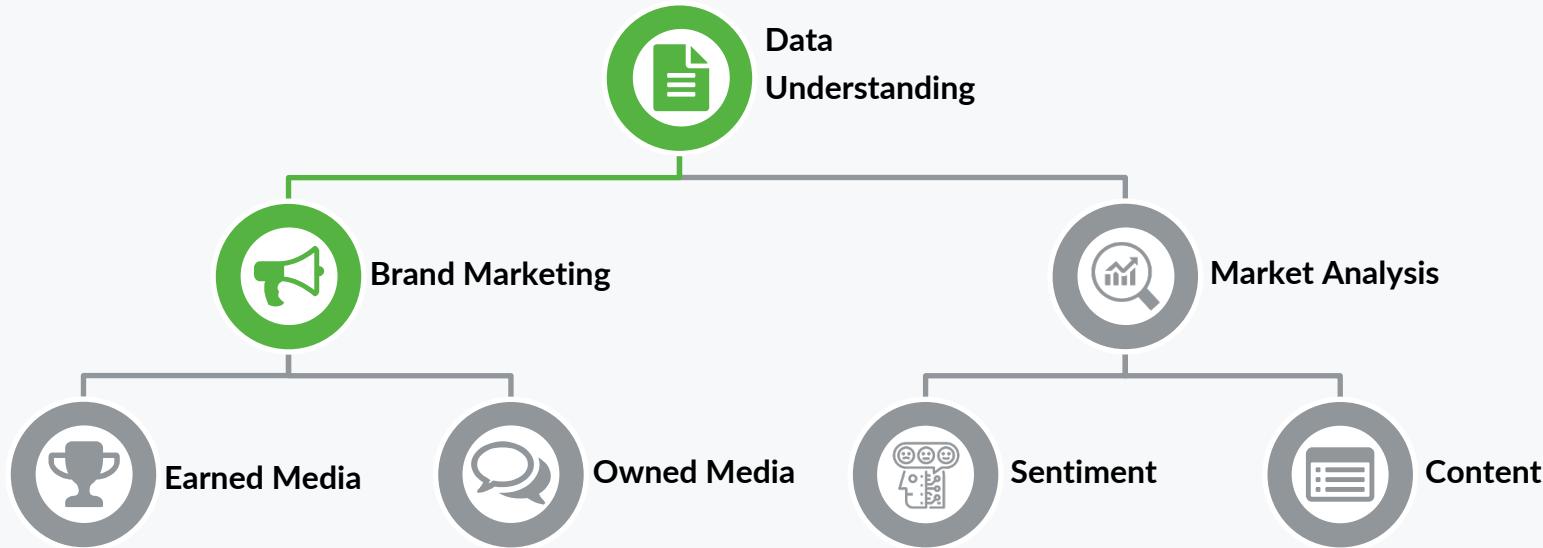


The features extracted from the data have **predictive power** for the ETF performance

The data is **representative** of the **global vegan market**

The data is a **valid source** for the extraction of **other useful insights**

# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS



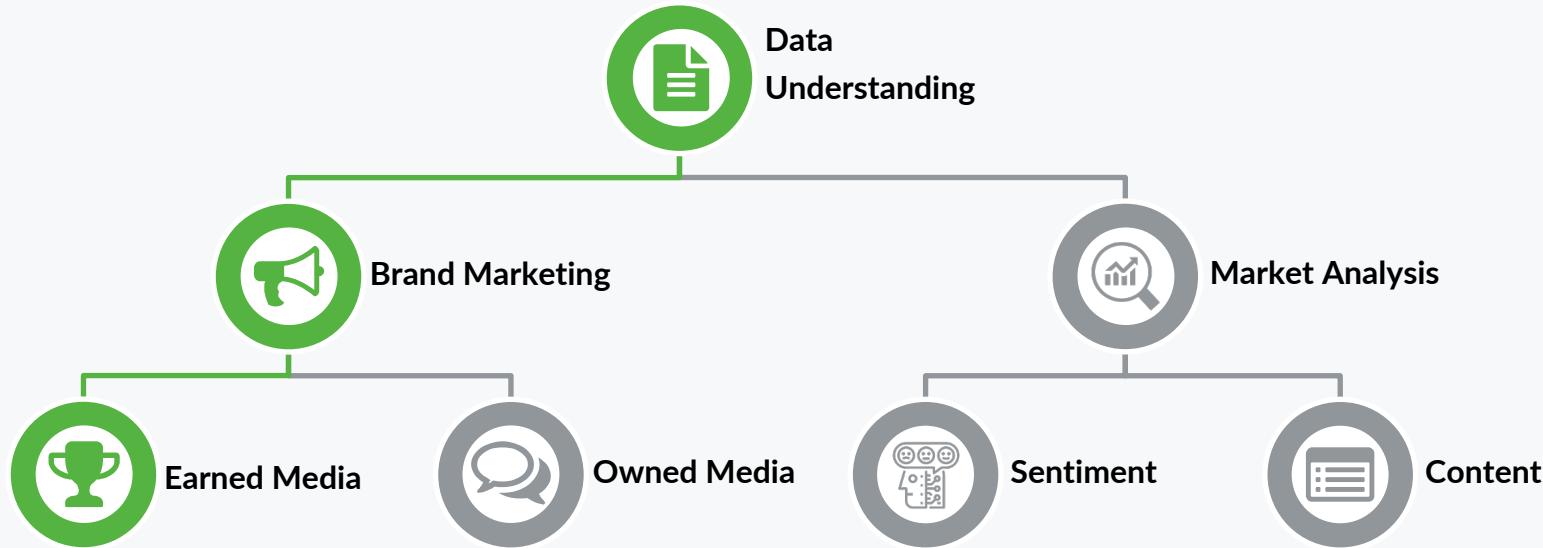


# USE INSIGHTS TO MAXIMIZE BRAND MARKETING IMPACT TO DEVELOP YOUR BRAND

6 reasons why branding and thus brand marketing is so important for your business



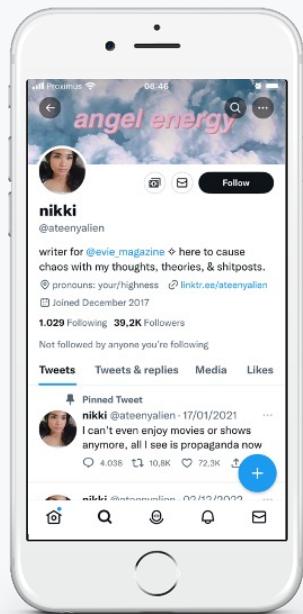
# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# OPTIMIZE YOUR EARNED MEDIA BY USING INFLUENCERS DEFINED BY THRESHOLDS

Make use of 3 thresholds and one tip to find influencers



## AMOUNT OF FOLLOWERS

High amount of followers shows **high popularity**



## LEVEL OF ENGAGEMENT

High level of engagement shows **high influence**



## FREQUENCY

High frequency shows active account



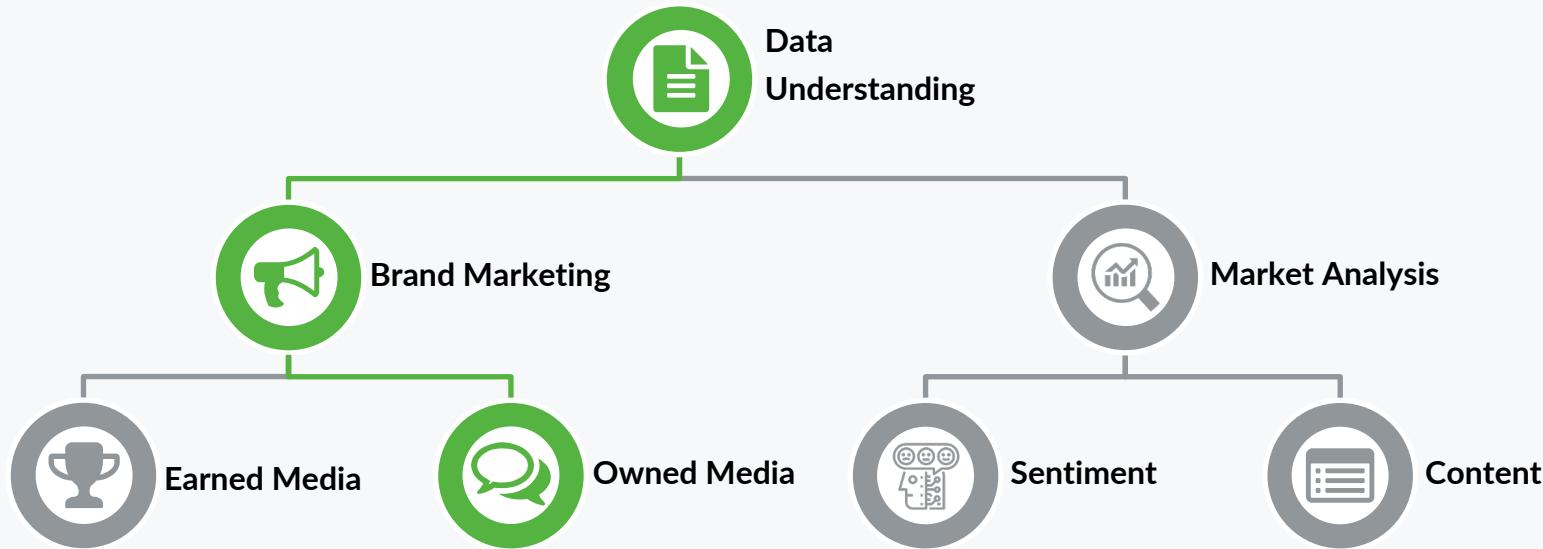
## NEWER ACCOUNTS

Newer account means **higher engagement**

## Top Influencers

1	amaneku_organic
2	ateenyalien
3	itsTFC
4	MissAudreyBoo
5	teonawrites

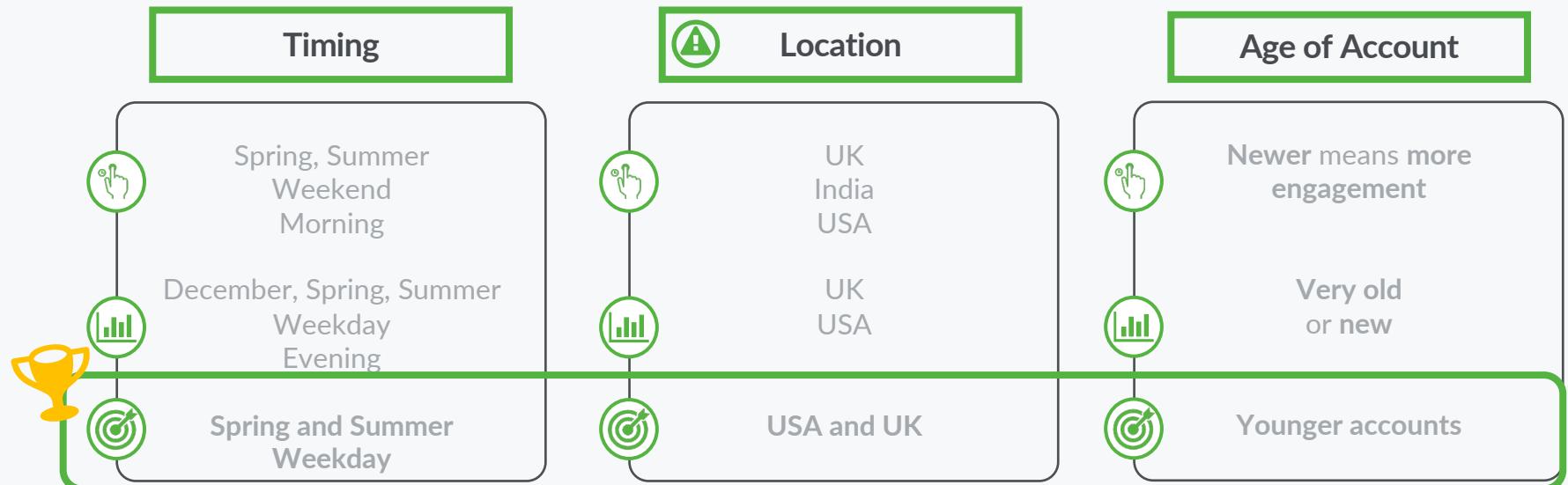
# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# OPTIMIZING OWNED MEDIA BY POSTING IN SUMMER IN USA AND UK AND TARGETING NEW ACCOUNTS

Optimize the use of your owned media based on 3 different categories





# OPTIMIZING OWNED MEDIA BY MAXIMIZING ENGAGEMENT RATE

Use these do's and don'ts to create better-performing tweets



TARGET NEWER ACCOUNTS



POST OFTEN IN FEBRUARY, JUNE, JULY AND NOVEMBER



USE TEXT AND AVAILABLE SPACE



DON'T FOLLOW TOO MANY ACCOUNTS



DON'T POST FREQUENTLY FROM MARCH TO MAY



DON'T BE OBJECTIVE OR NEGATIVE



# GOOGLE TRENDS



## SEASONAL EFFECTS

Summer and especially winter seasons peak



## INCREASE UNTIL 2020

General popularity on Google from 2010 to 2020 increased exponentially



## STAGNATING TREND

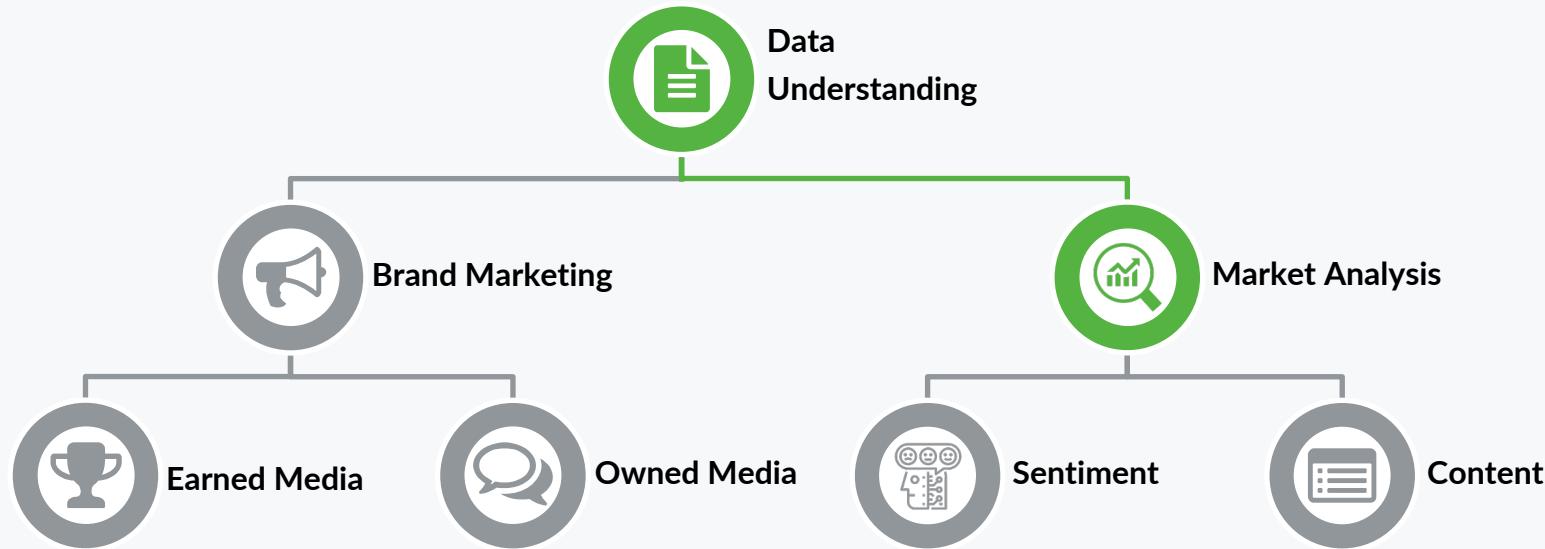
In 2020 popularity peaked and stagnated the following years



## FORECAST

We expect the seasonality effects to be still present and about the same popularity for the following 3 years

# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# USE INSIGHTS TO KNOW MORE ABOUT YOUR MARKET AND HAVE THE ADVANTAGE

## RISK REDUCTION

Market analysis will help your decision-making so there will be less risk.



## TARGETING

With market knowledge, you can target the right customers.



## EMERGING TRENDS

Staying ahead means spotting new opportunities and trends.



## GROWTH OPPORTUNITIES

Knowing the market gives you the opportunity to grow and expand.



## LEARN FROM MISTAKES

Marketing analytics can explain mistakes from the past.

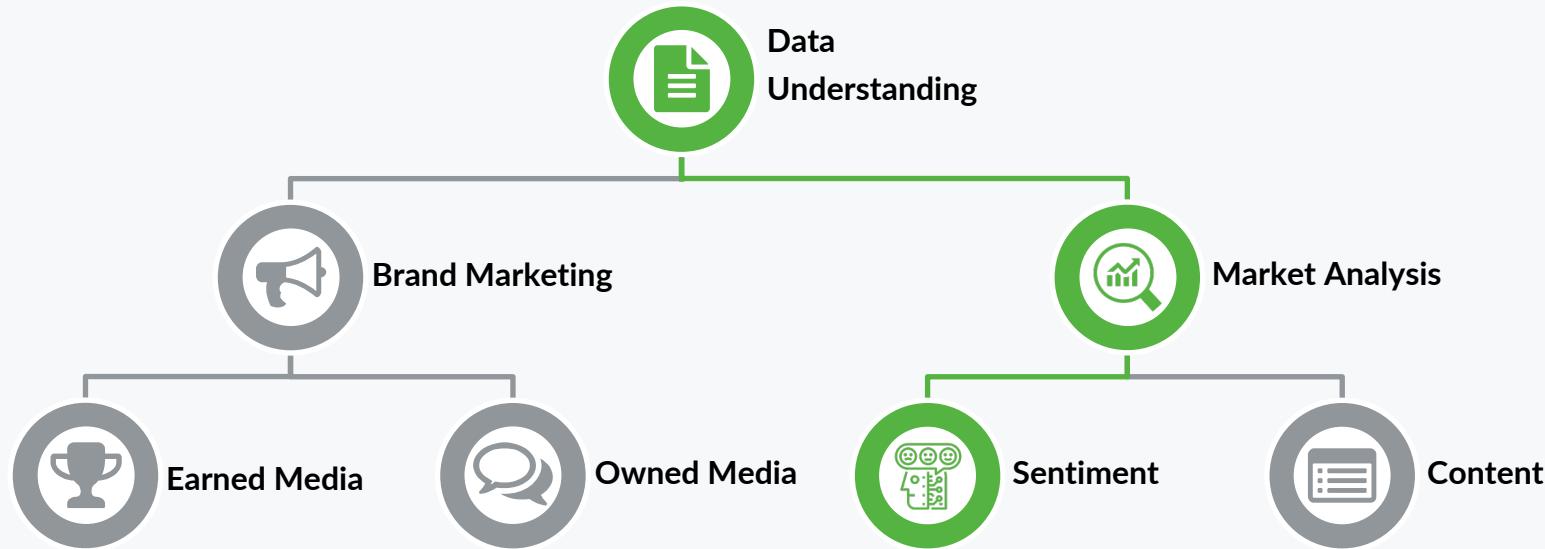


## REVENUE PROJECTION

Forecast your future revenues by using your market analysis.



# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# LEARN ABOUT THE EMOTIONS AROUND YOUR BRAND TO KNOW WHEN THE REACTION IS MOST POSITIVE

2 periods of the year that have better sentiment

01

## WINTER SEASON

Because of good intentions for the new year

02

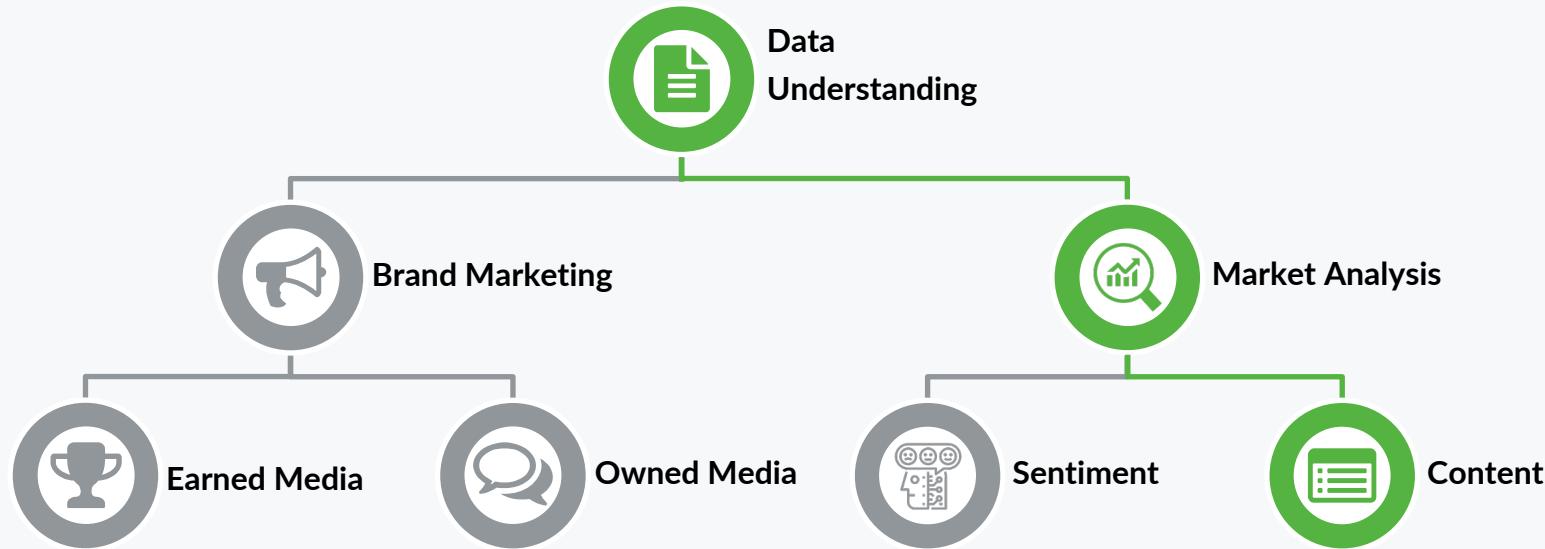
## JUST BEFORE SUMMER

Because of the healthy summer goals

Sentiment means the **emotion**, **expressions**, and **feelings** that people **express** in tweets.



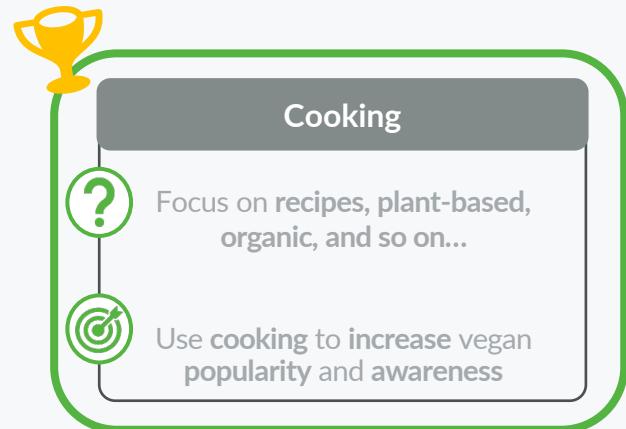
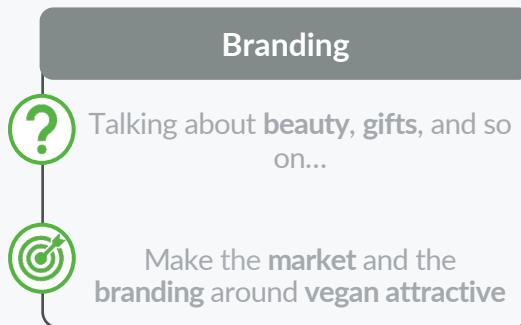
# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS



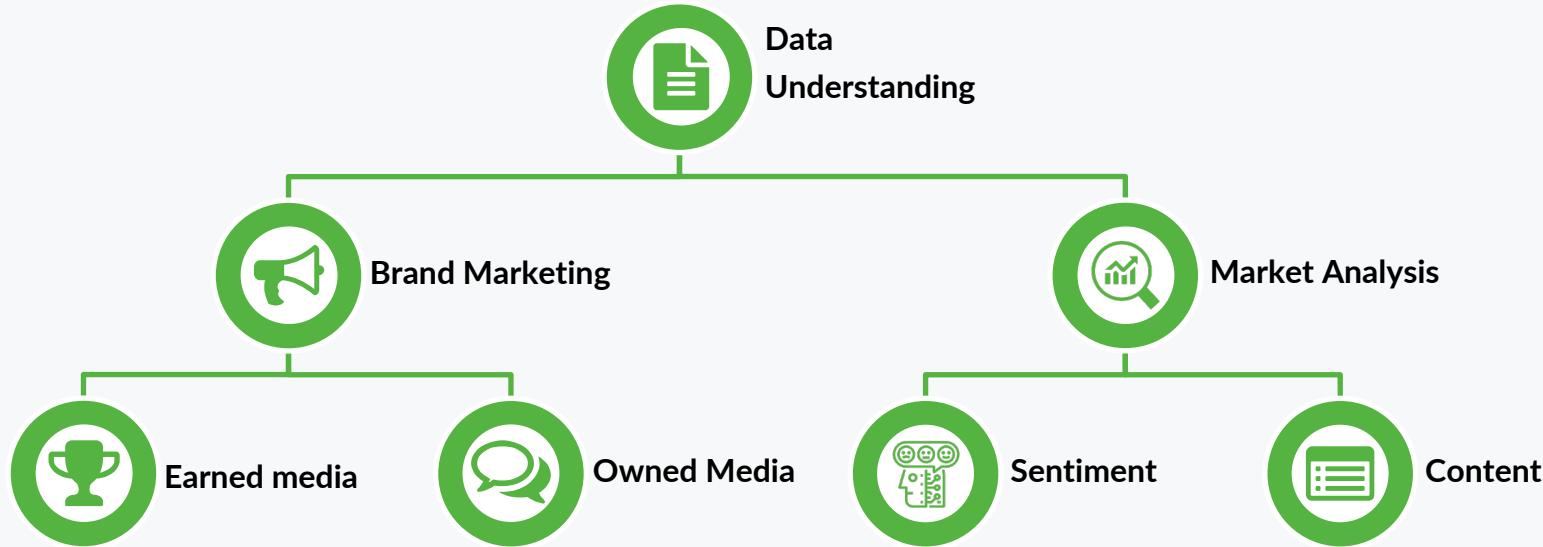


# LEARN ABOUT THE CONTENT OF YOUR BRAND TO KNOW WHAT TO POST ABOUT

These three topics define our vegan brand on Twitter



# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS

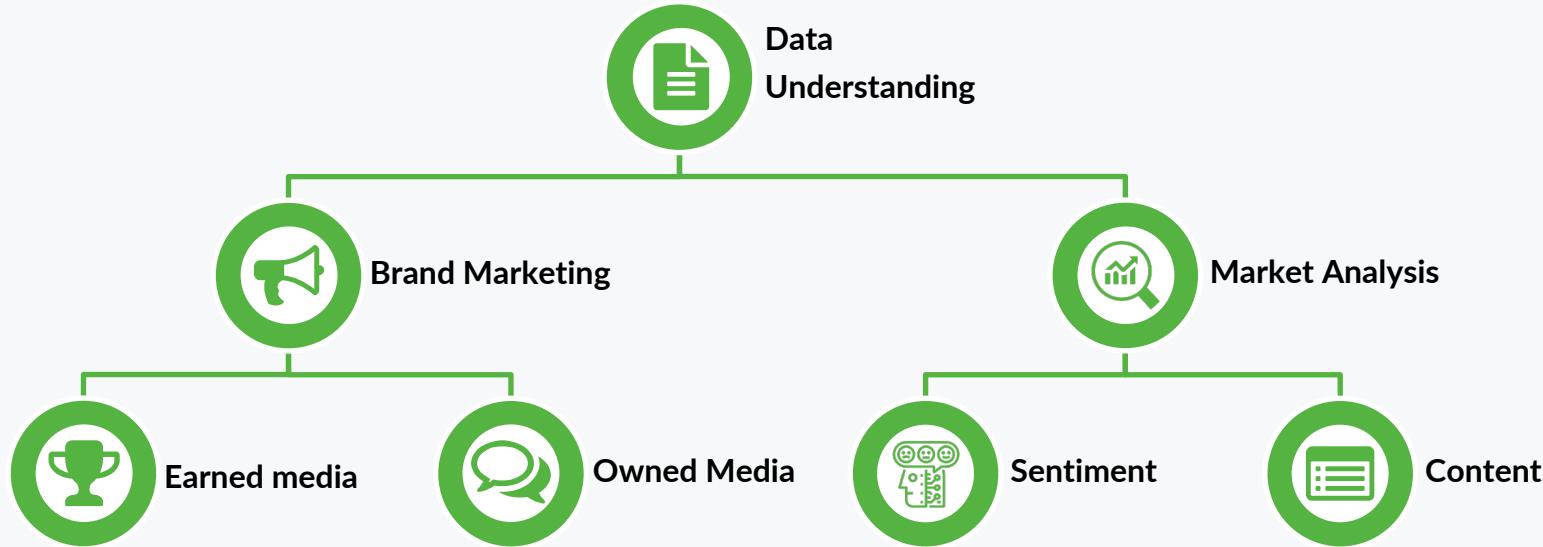




# TECHNICAL PRESENTATION

A presentation about our models and technical implications

# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# LIMITATIONS OF THE DATA AND SOFTWARE

Know the **limitations** so that you can create meaningful results.

## Out of Memory Error

Not enough memory to compile model 2 on whole dataset, only able to use 5% of the tweets

## Data limitations

Not able to obtain further information on the user: limiting network analysis



## Not able to translate tweets

Not able to translate tweets due to PC memory constraints

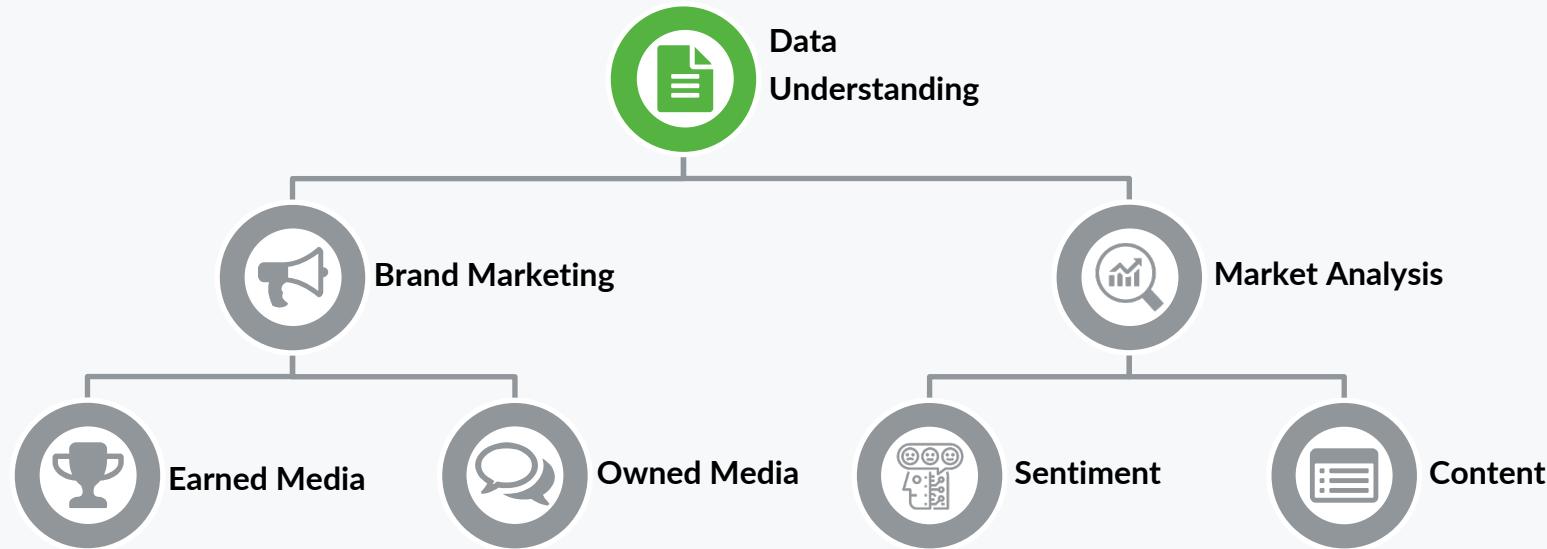
## No replies

No information on the replies was available

## Missing data

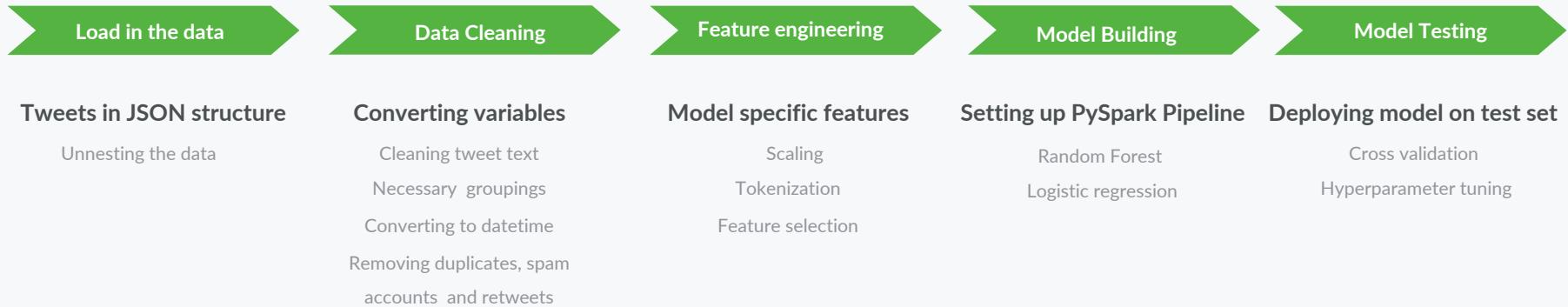
Very little information on the geographic location of the tweets

# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# GENERAL ML PIPELINE





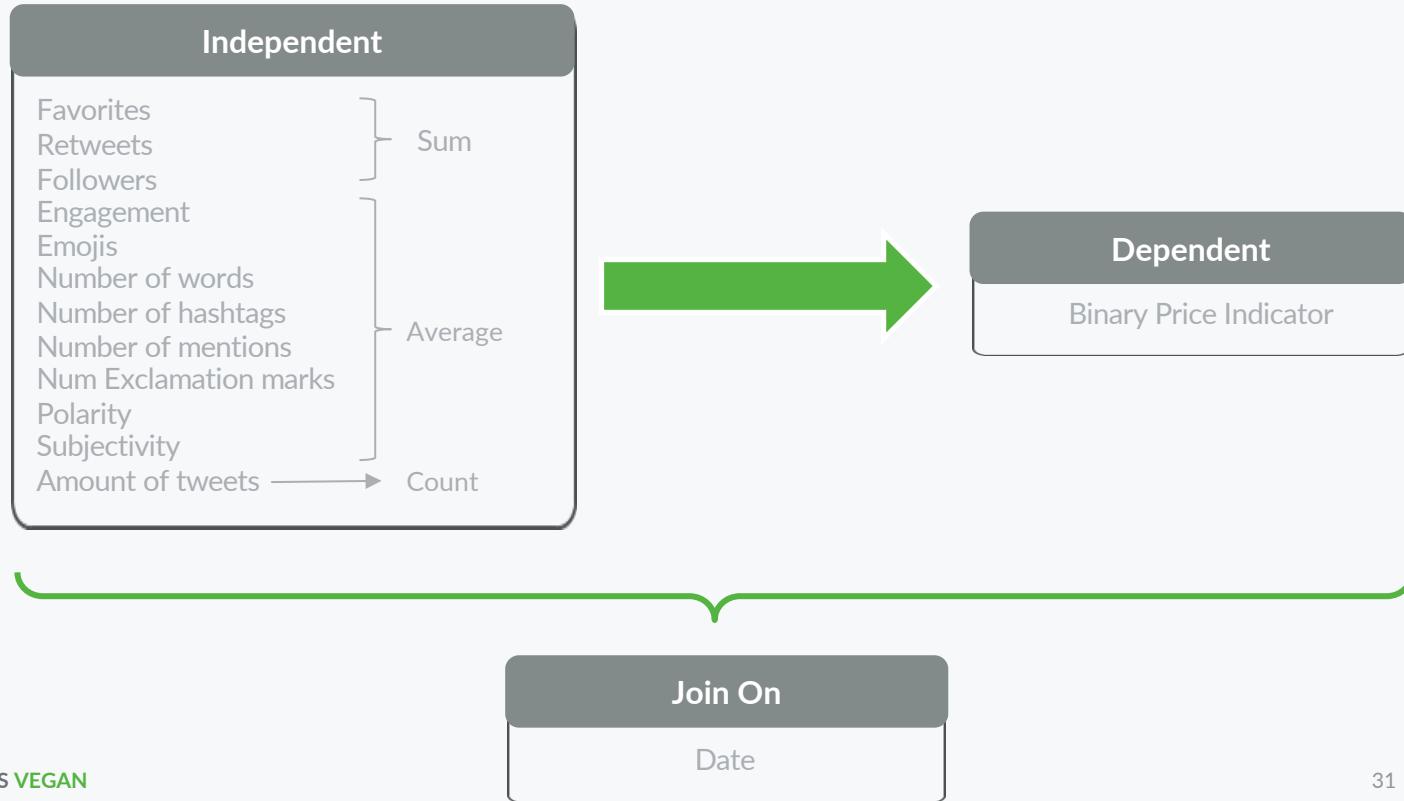
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## MODEL 1 : PREDICTING VEGAN ETF TRACKER





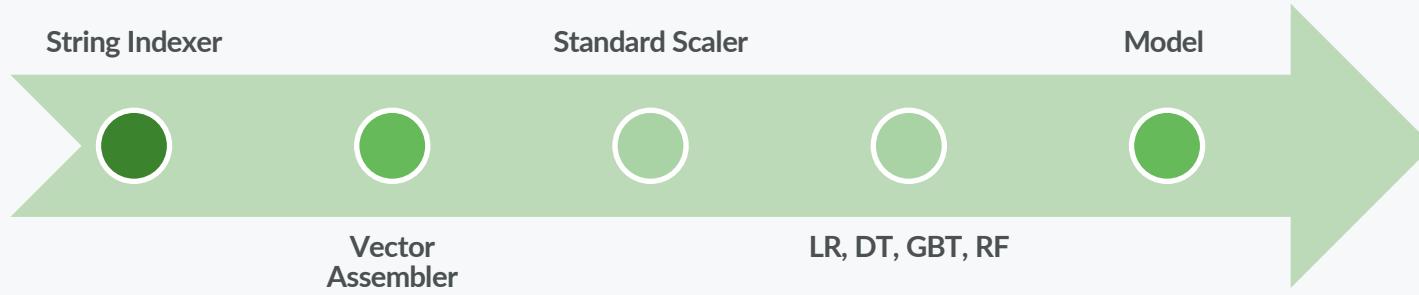
# BASETABLE CREATION FOR ETF PREDICTION





# ML PIPELINE VEGAN TO PREDICT BINARY ETF TRACKER

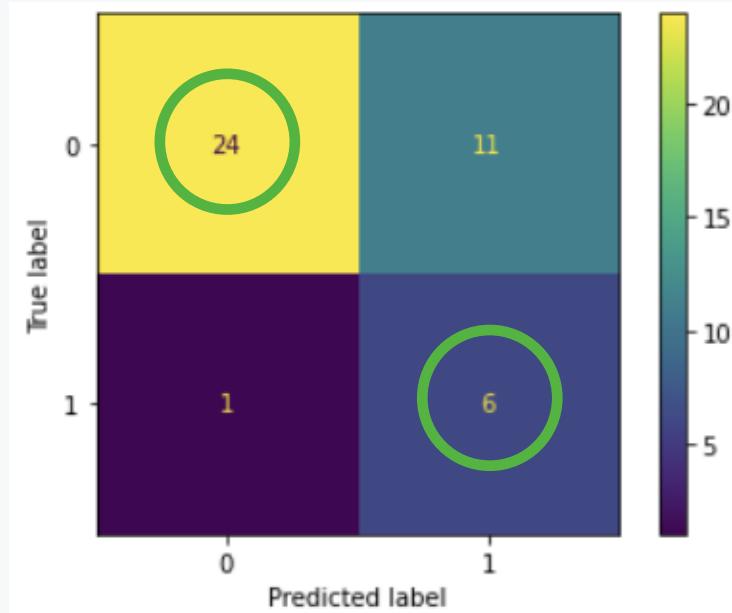
Showing the different steps in the binary predictive ETF model



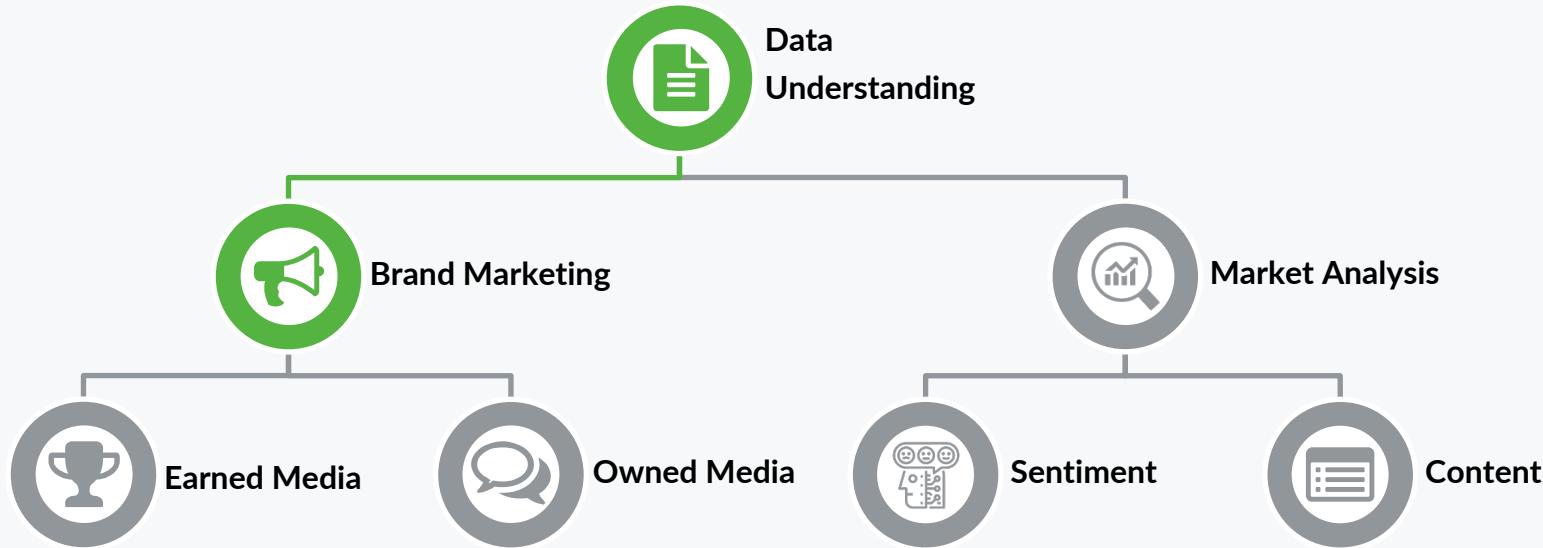


# VISUALIZATION OF MODEL EVALUATION BINARY ETF TRACKER

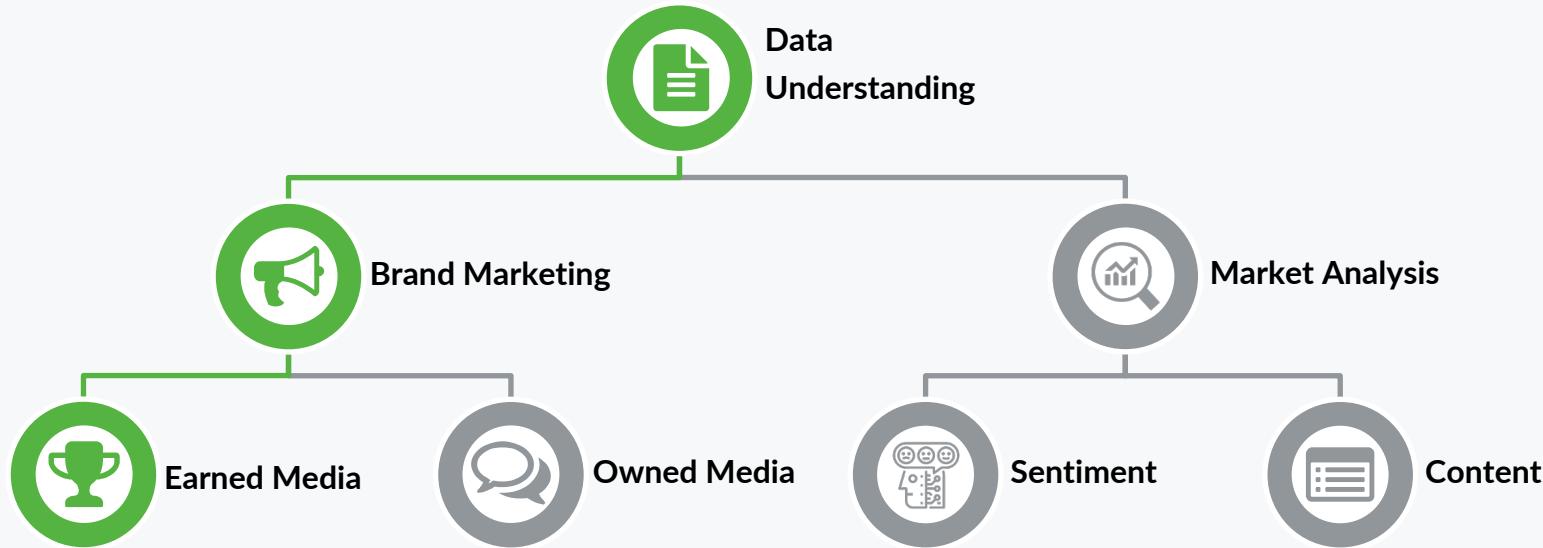
Sensitivity = 85% , Specificity = 69%



# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS



# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# OPTIMIZE YOUR EARNED MEDIA BY USING INFLUENCERS

Explanation of thresholds and the function that determines the influencer accounts



## 10.000 FOLLOWERS

High amount of followers shows high popularity



## 4% LEVEL OF ENGAGEMENT

High level of engagement shows high influence



## 2 TWEETS PER WEEK

High frequency shows active account

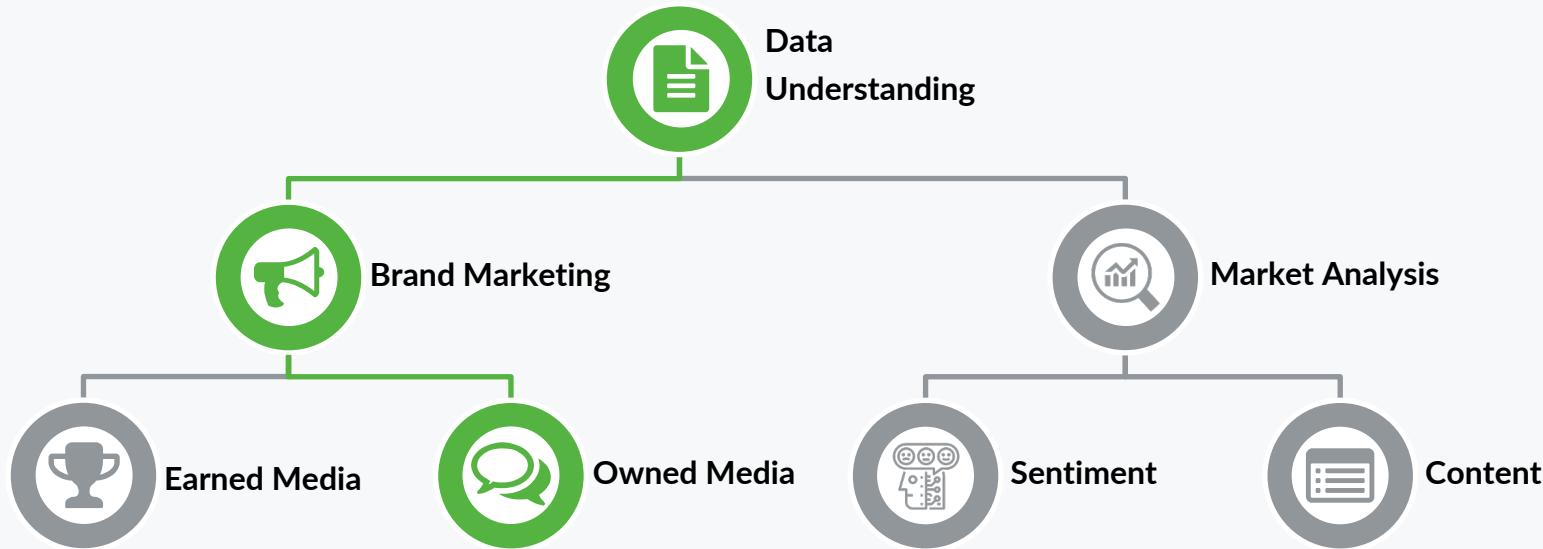


Group the information of followers,  
engagement and frequency per user

Join all the information in one table

Filter the information on the  
thresholds so that we only have  
relevant information

# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS



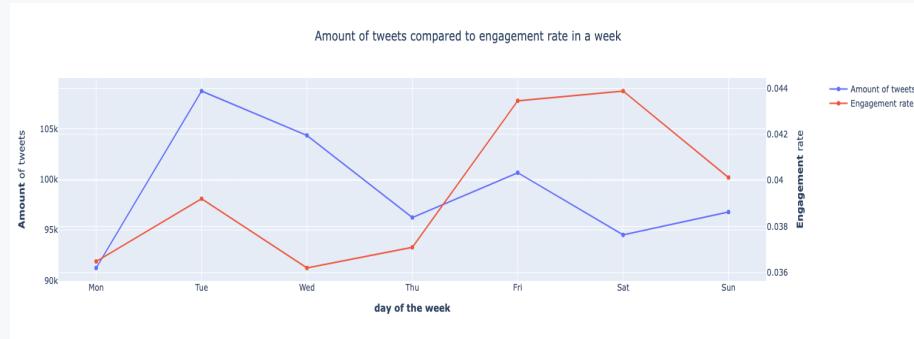


# OPTIMIZING OWNED MEDIA BY USING DATA



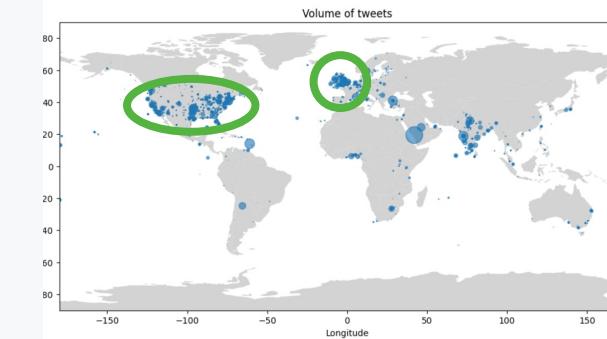
## Post in Spring/Summer and Weekdays

These periods have high volume and engagement



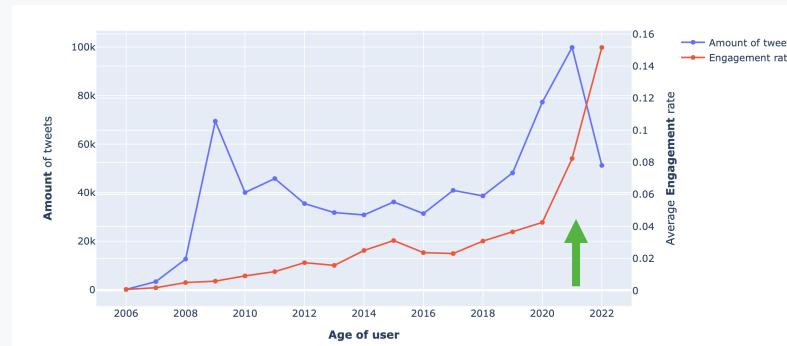
## USA & UK

These regions show much larger volume



## Target younger accounts

These show much higher engagement





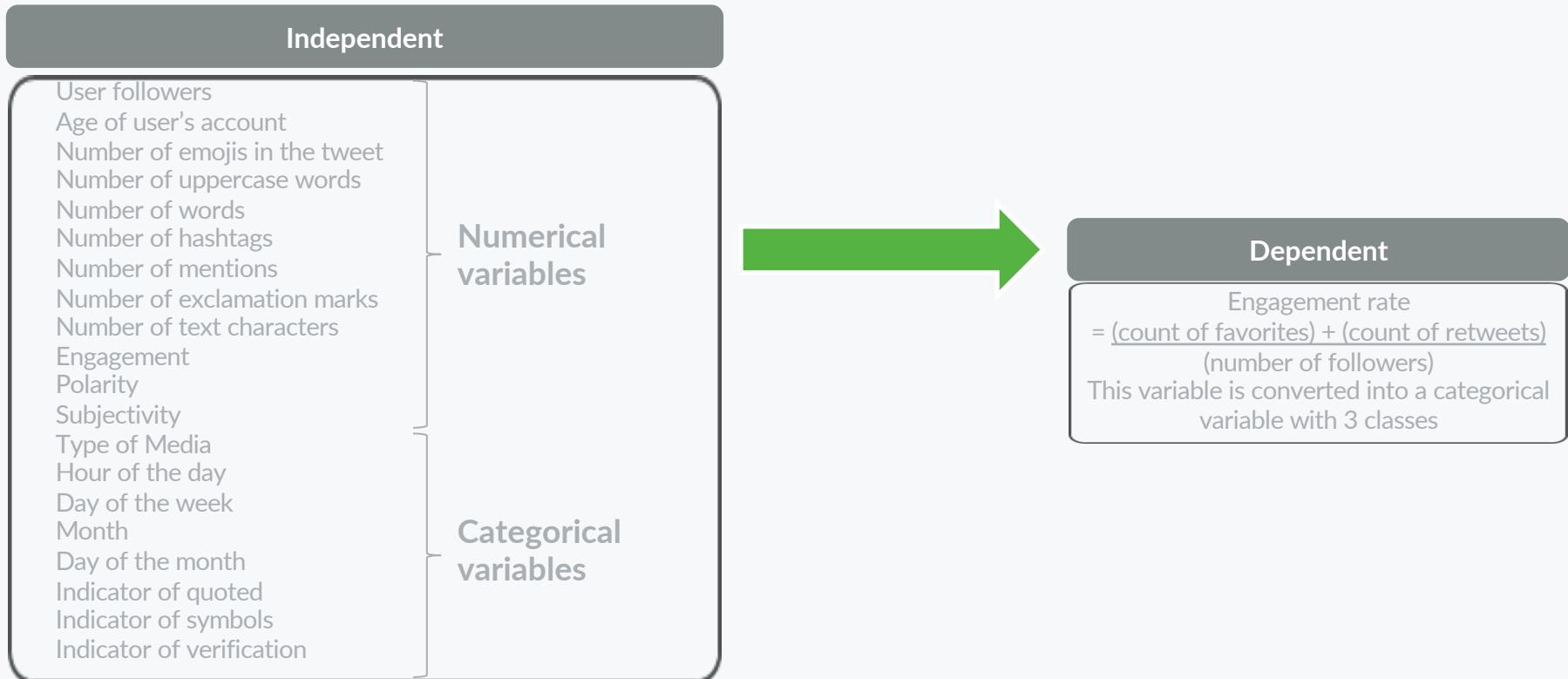
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## MODEL 2: PREDICTING ENGAGEMENT



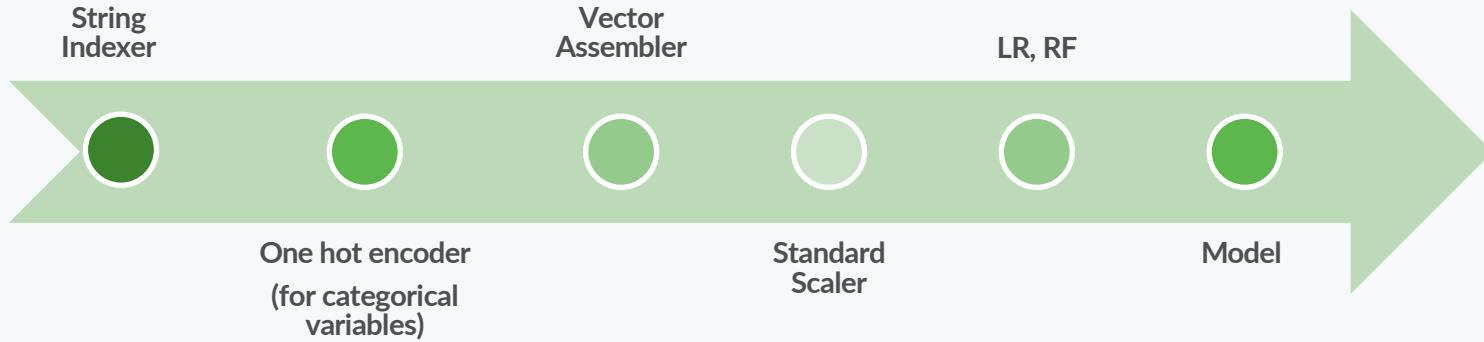


# BASETABLE CREATION FOR ENGAGEMENT PREDICTION





# ML PIPELINE VEGAN TO PREDICT CATEGORICAL ENGAGEMENT SCORE





# MODEL PERFORMANCE

Random Forest with weights:

F1 : 0.8139

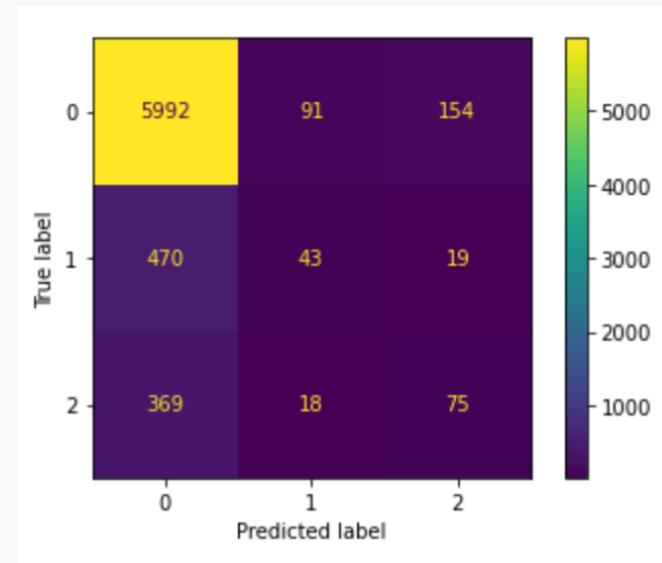
RECALL : 0.8446

PRECISION : 0.7748

WEIGHTED\_TPR : 0.8450

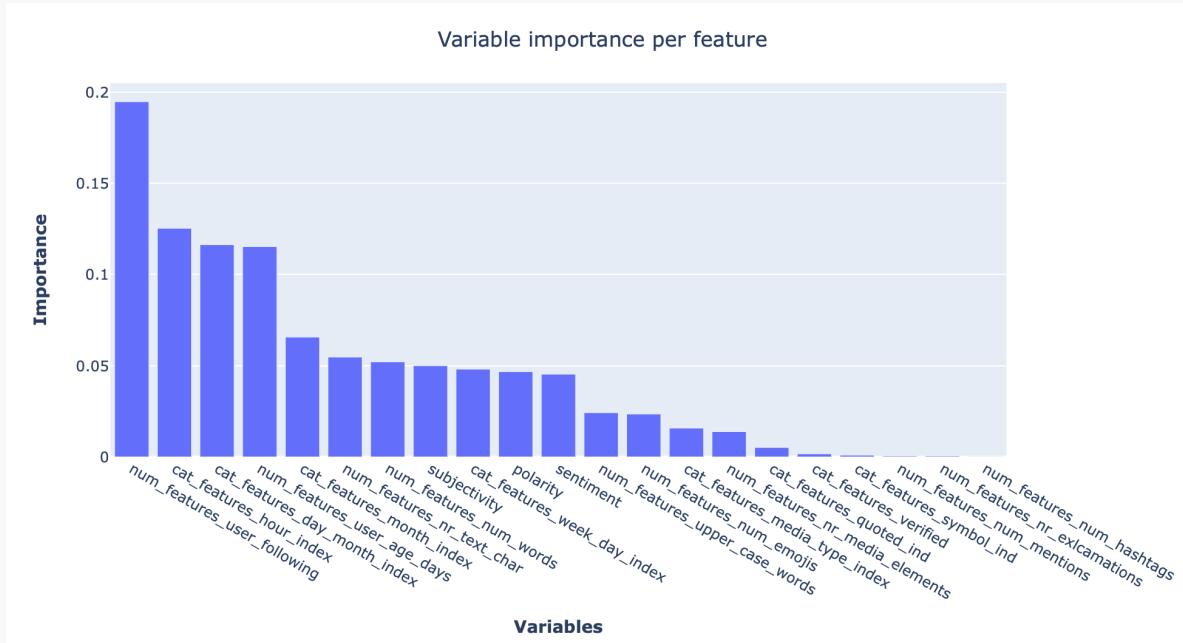
WEIGHTED\_FPR : 0.7430

Confusion matrix Random Forest model with Ajudsted weights for class imabalance





# VARIABLE IMPORTANCE





## MODEL 3 : FORECASTING BASED ON HISTORICAL DATA

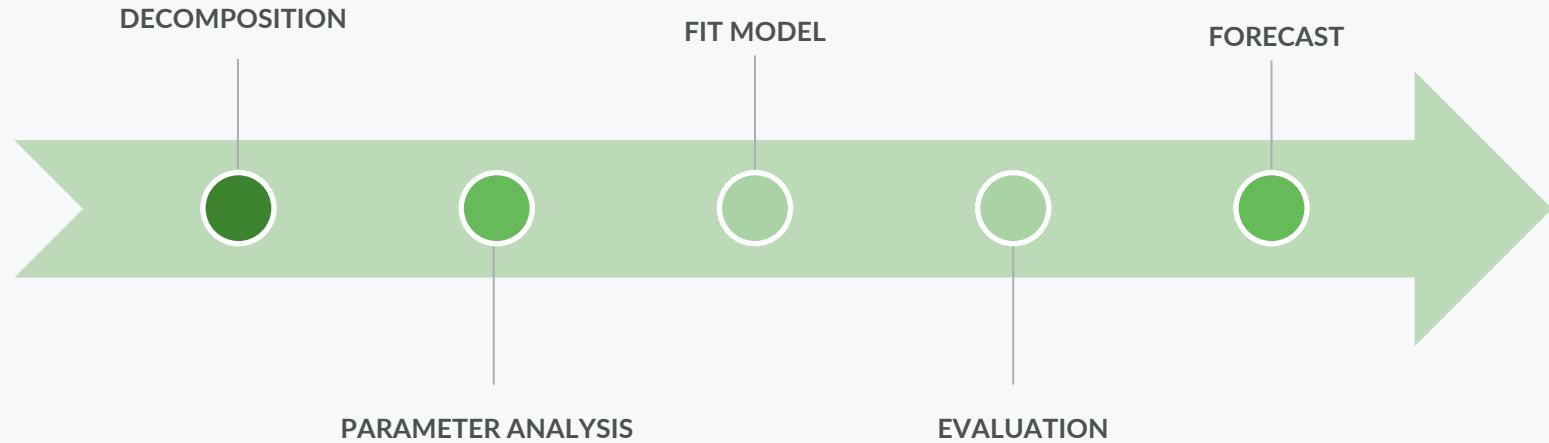
USING SARIMA





# GOOGLE TRENDS SARIMA

Seasonal Autoregressive Integrated Moving Averages



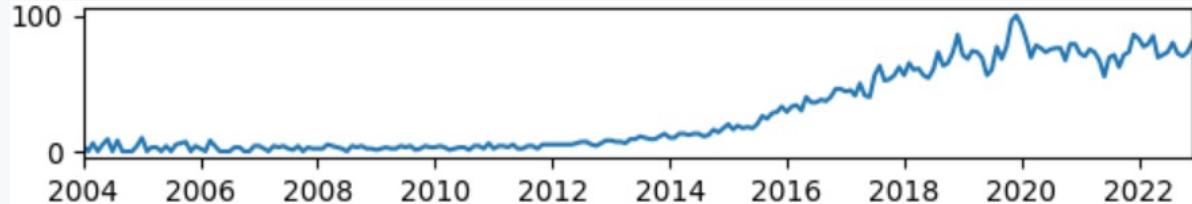


# GOOGLE TRENDS SARIMA

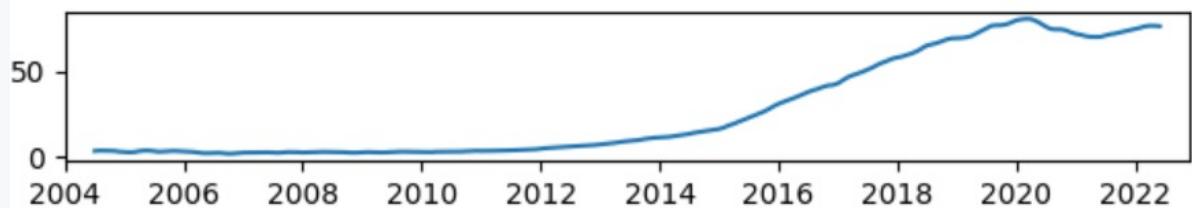
DECOMPOSITION



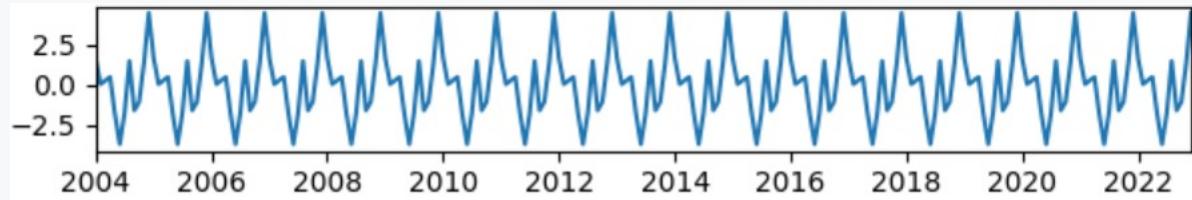
Google Trends: Vegan  
from 1st of january 2004 till  
11th of december 2022



Trend  
component isolated



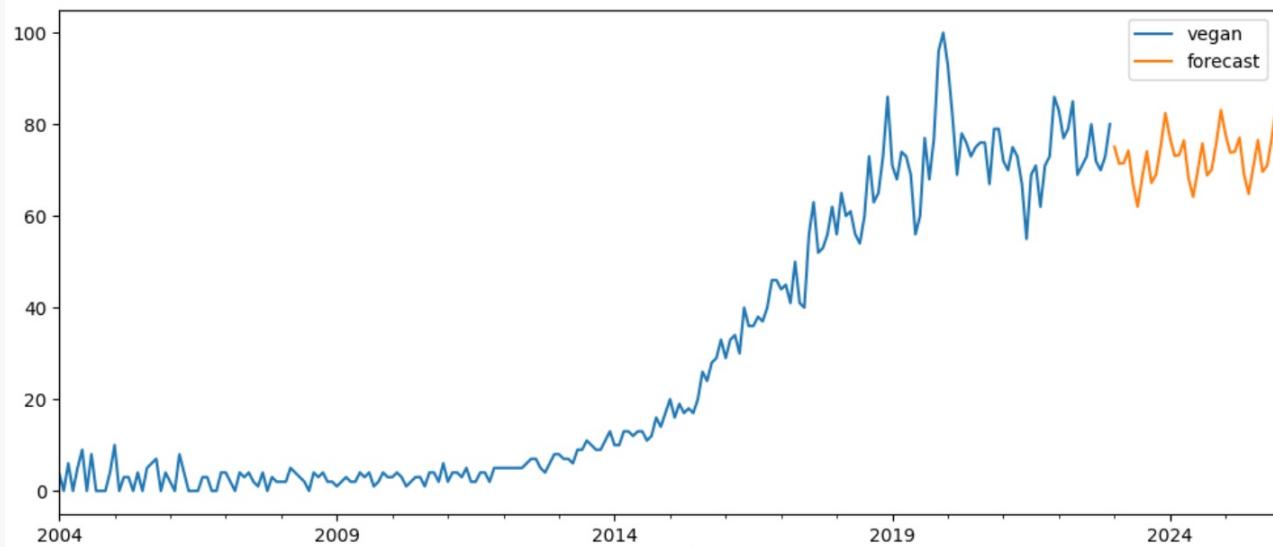
Seasonality  
component isolated





# GOOGLE TRENDS SARIMA

FORECASTING



Forecasts  
for 3 consecutive years



Trending  
same trending levels next 3  
years



Seasonality  
Seasonality plays a  
significant role



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## MODEL 4 : PREDICTING CHANGES IN GOOGLE TRENDS

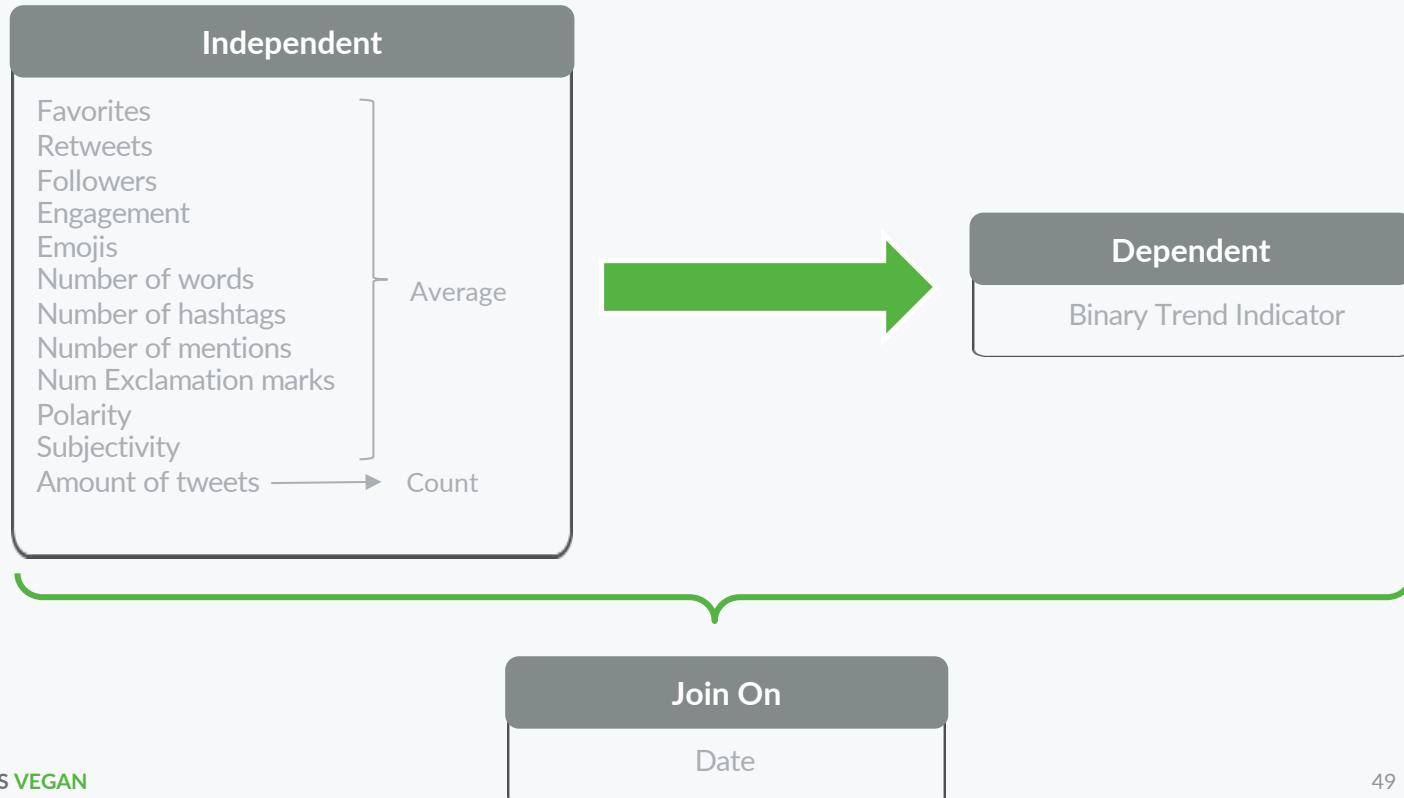
Based on Twitter data

# Google Trends





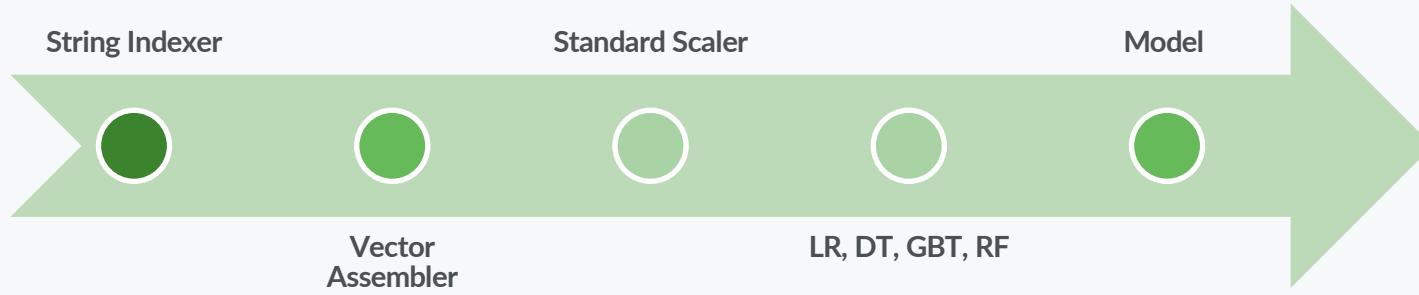
# BASETABLE CREATION FOR GOOGLE TRENDS PREDICTION





# ML PIPELINE VEGAN TO PREDICT BINARY GOOGLE TRENDS

Showing the different steps in the binary predictive Google trend model





# CONCLUSION GOOGLE TREND PREDICTION

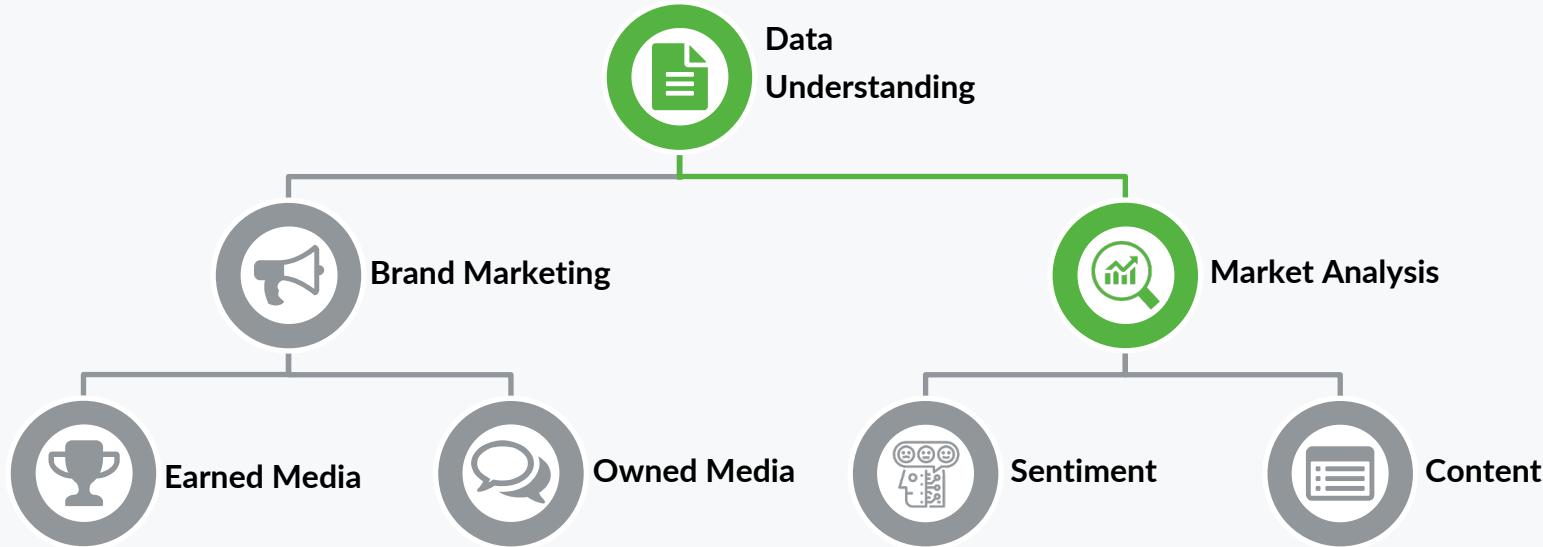


Based on our **evaluation metrics** we found there is no predictive power in this model

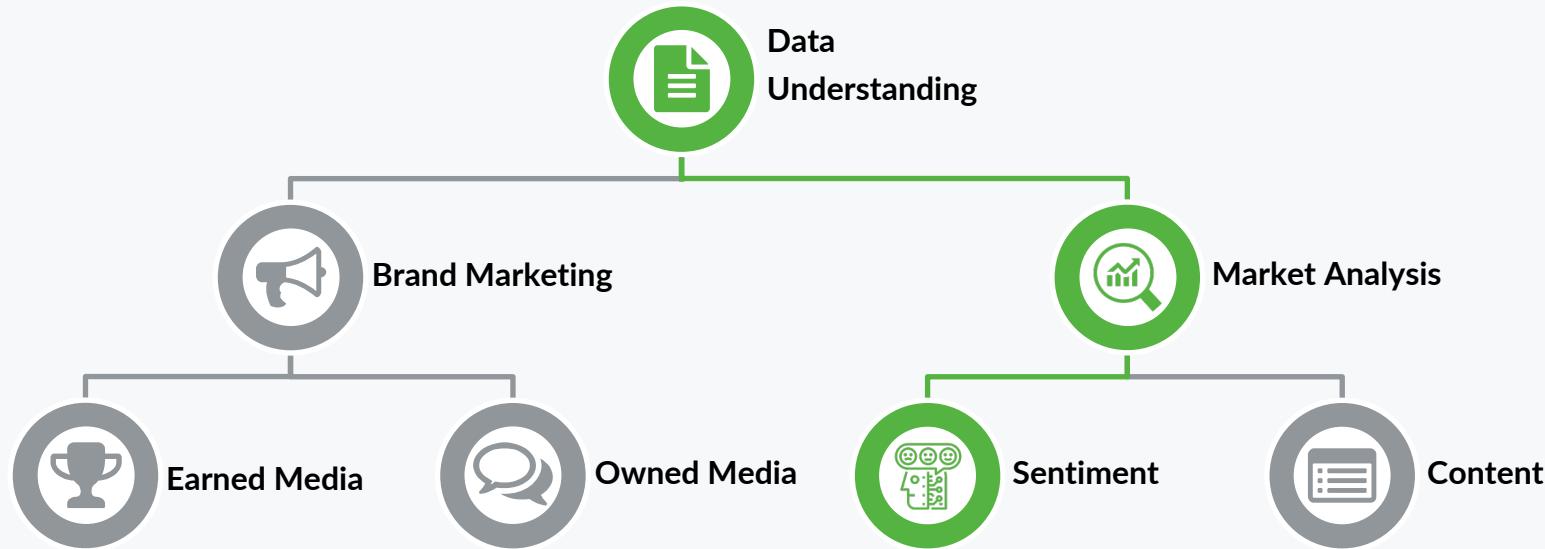
We found **no evidence** to use Twitter data for **Search Engine Optimization** in this context

This outcome is **against our expectations** so further research is advisable

# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS



# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# LEARN ABOUT THE EMOTIONS AROUND YOUR BRAND TO HAVE THE ADVANTAGE

Using Vader and TextBlob packages to perform sentiment analysis

01

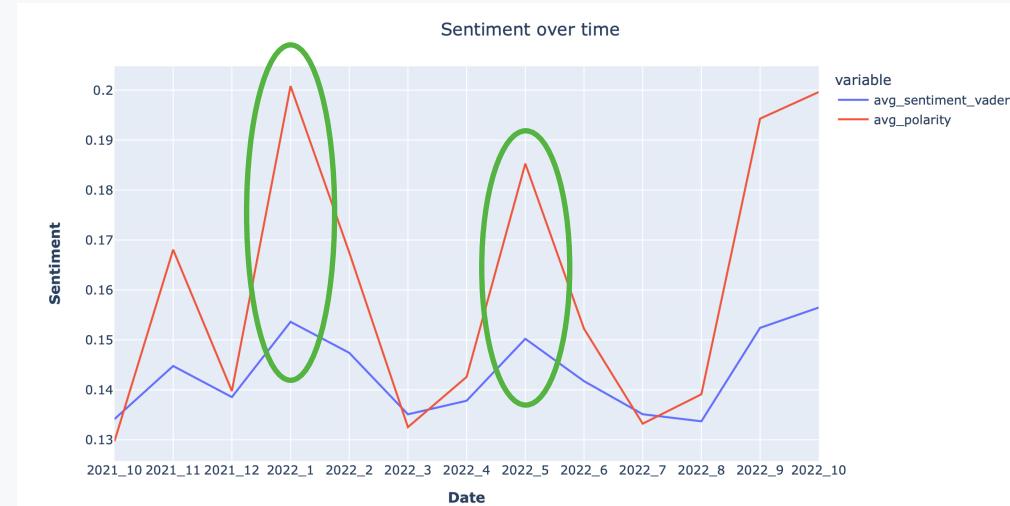
## Vader Package

Lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media

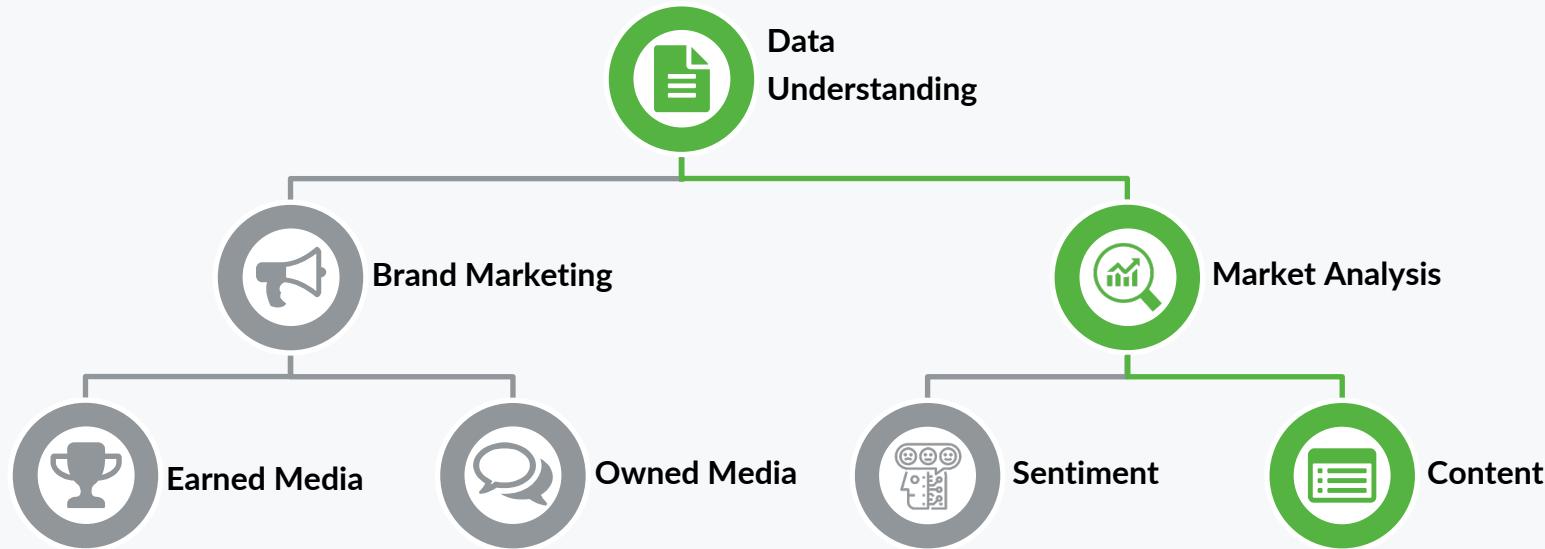
02

## TextBlob Package

Using pre-defined dictionary and averaging over all words in text



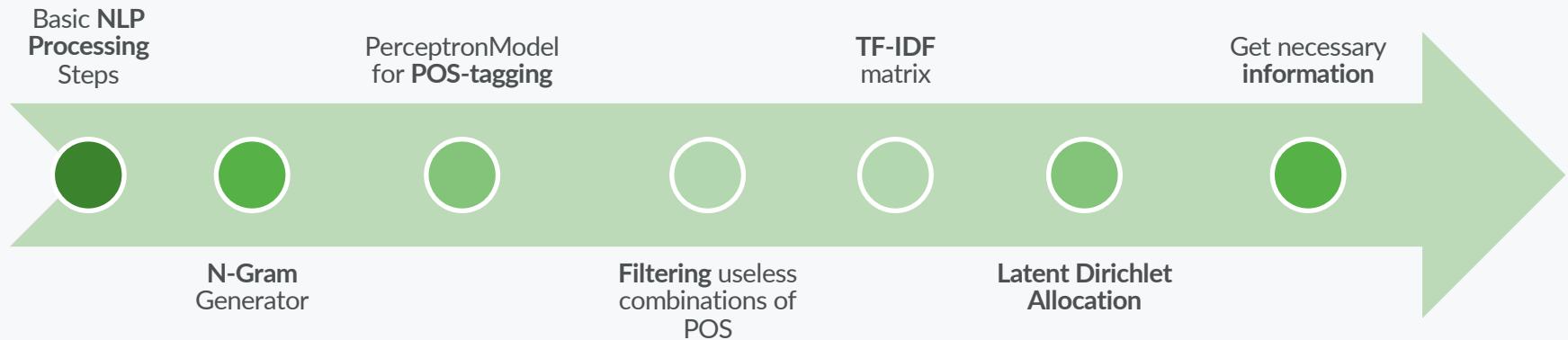
# VALUE TREE THAT SHOWS THE VALUE IN DIFFERENT LAYERS





# USE SPARK NLP TO PERFORM **TOPIC MODELING** AND LEARN ABOUT THE TOPICS

Showing the different steps in the topic modeling Spark NLP process





# CREATE A WORD CLOUD TO HAVE AN OVERALL IDEA ABOUT THE TOPICS



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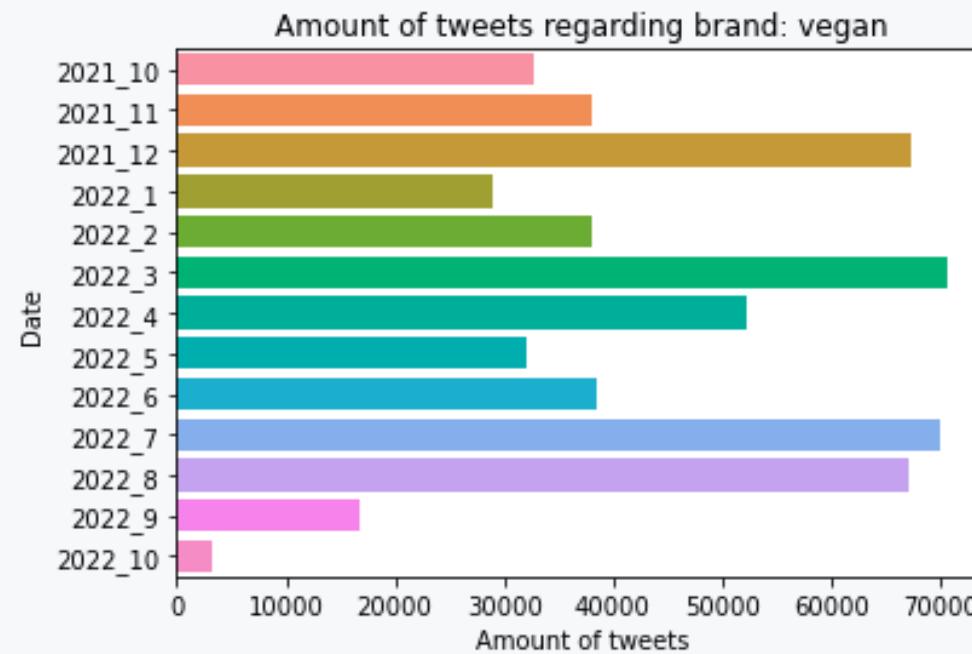
# TIME FOR Q&A!

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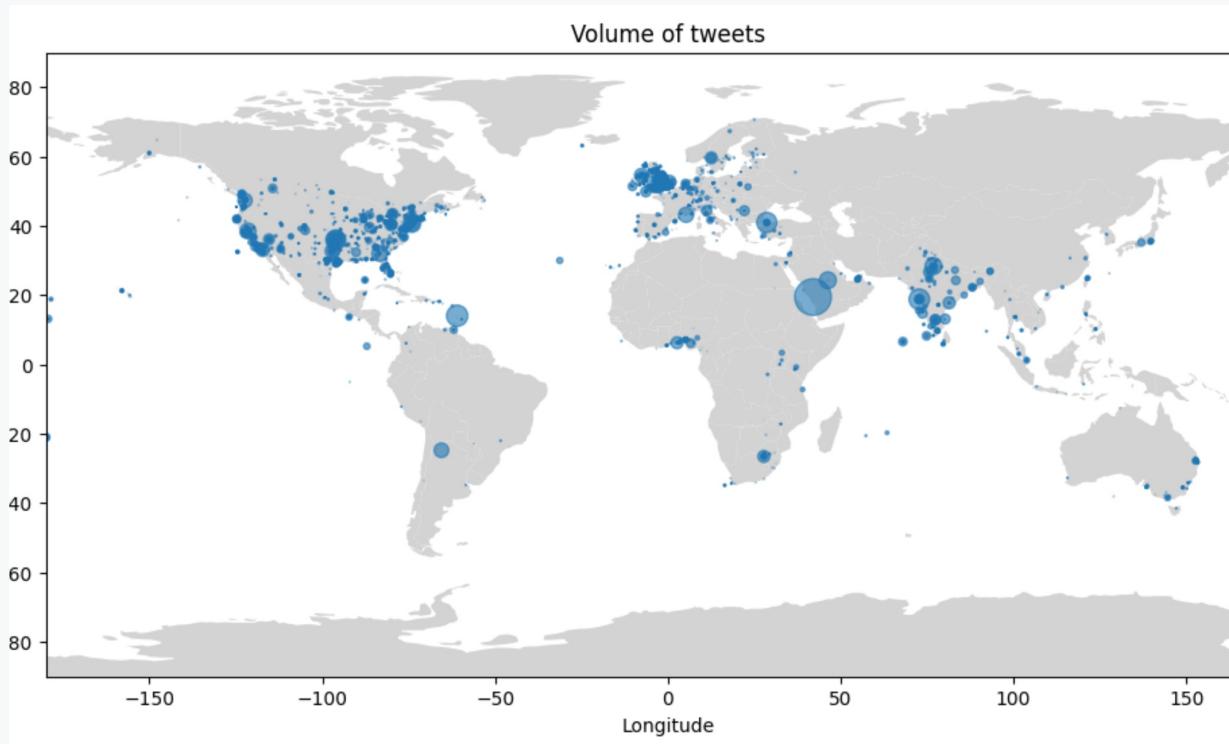
# APPENDIX

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# VOLUME

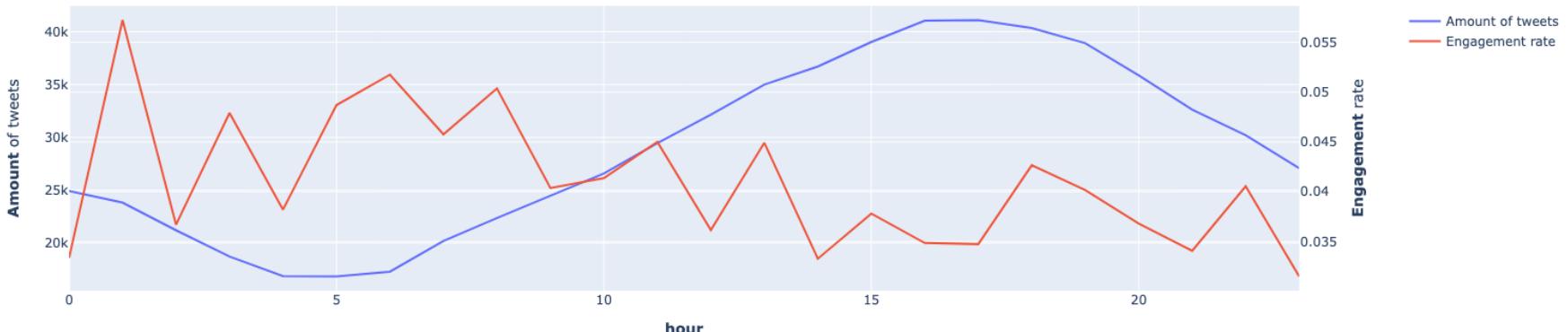


# LOCATION



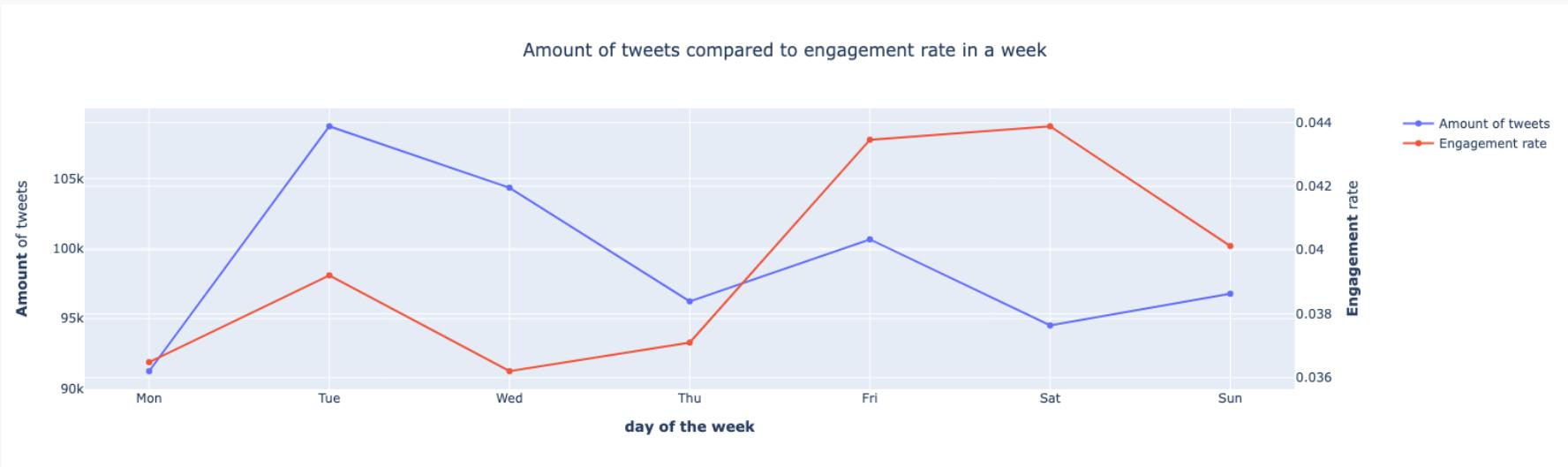
# TIMING

Amount of tweets compared to engagement rate in a day



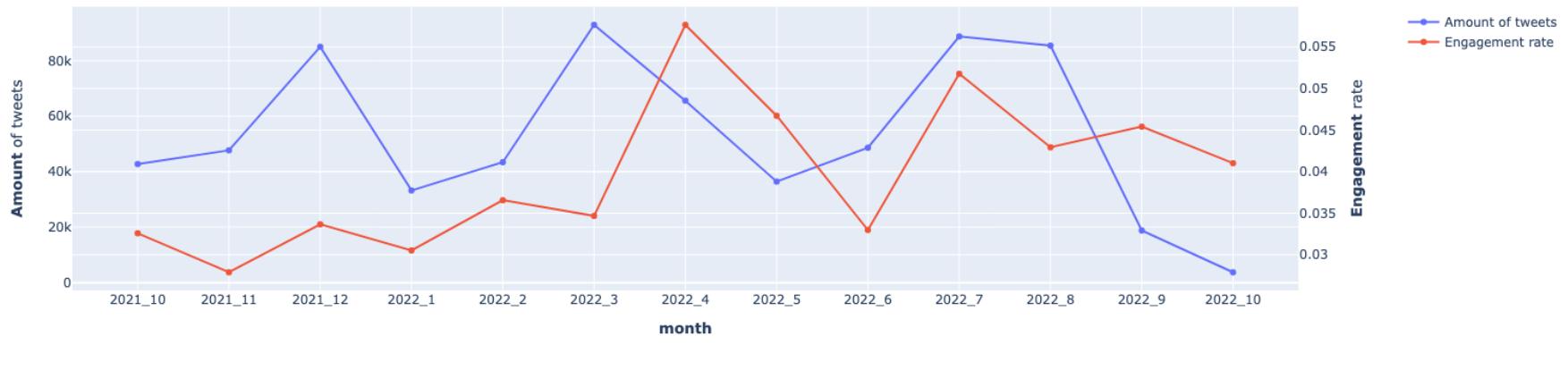
# TIMING

Amount of tweets compared to engagement rate in a week

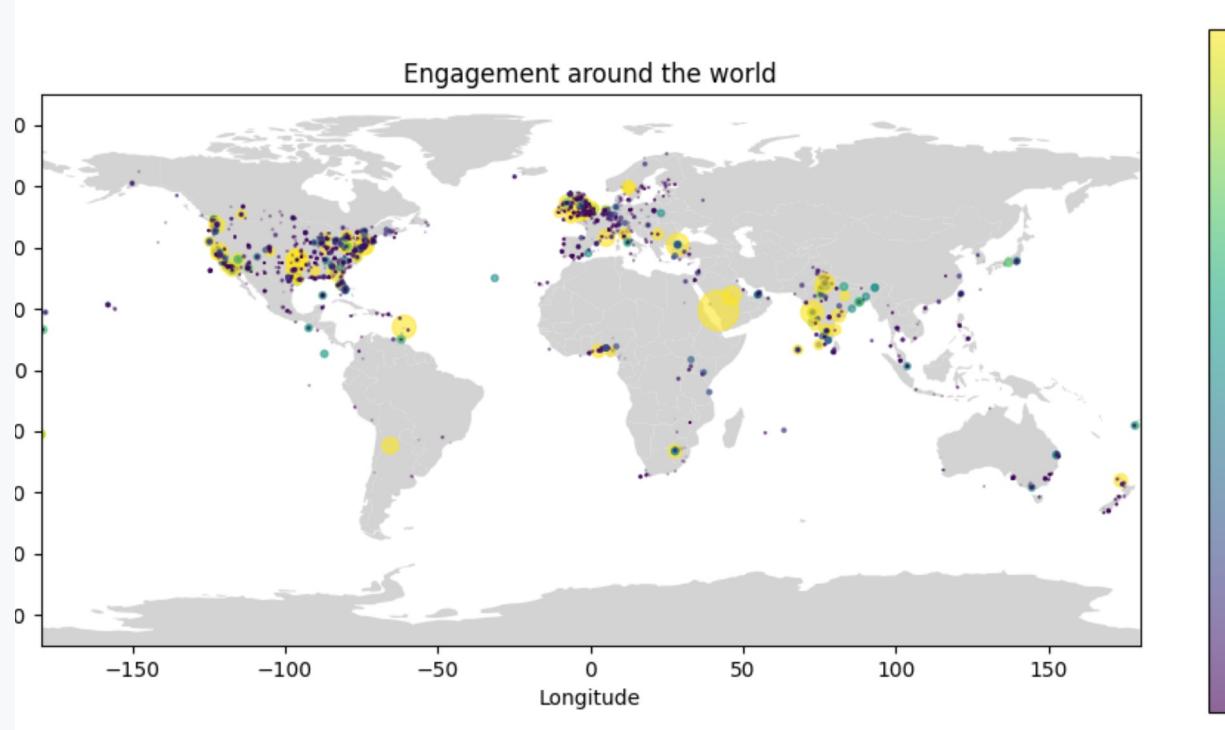


# TIMING

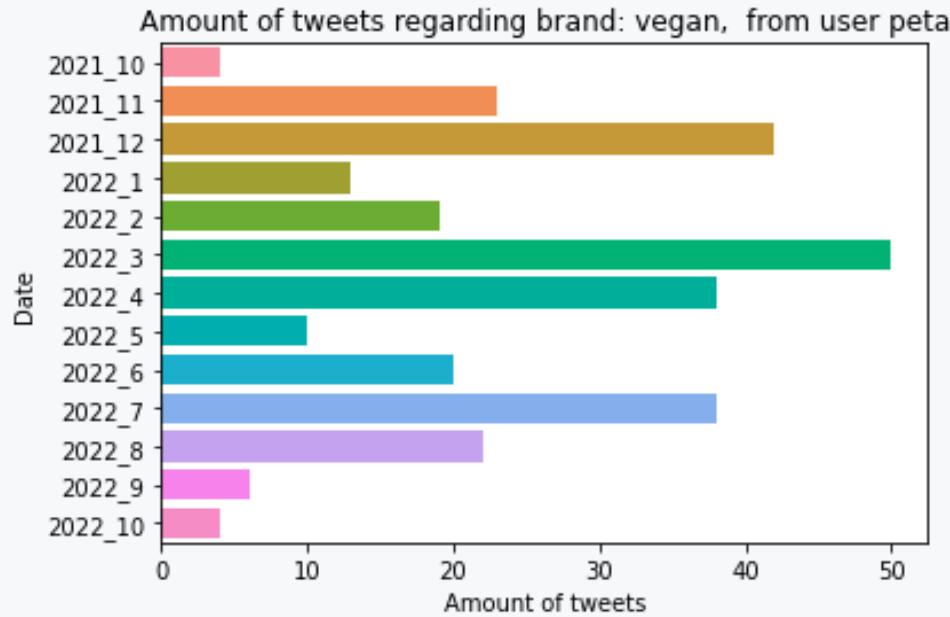
Amount of tweets compared to engagement rate in a day



# ENGAGEMENT AROUND THE WORLD



# BRAND FOLLOWER'S IMPORTANCE



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# BRAND FOLLOWER'S IMPORTANCE

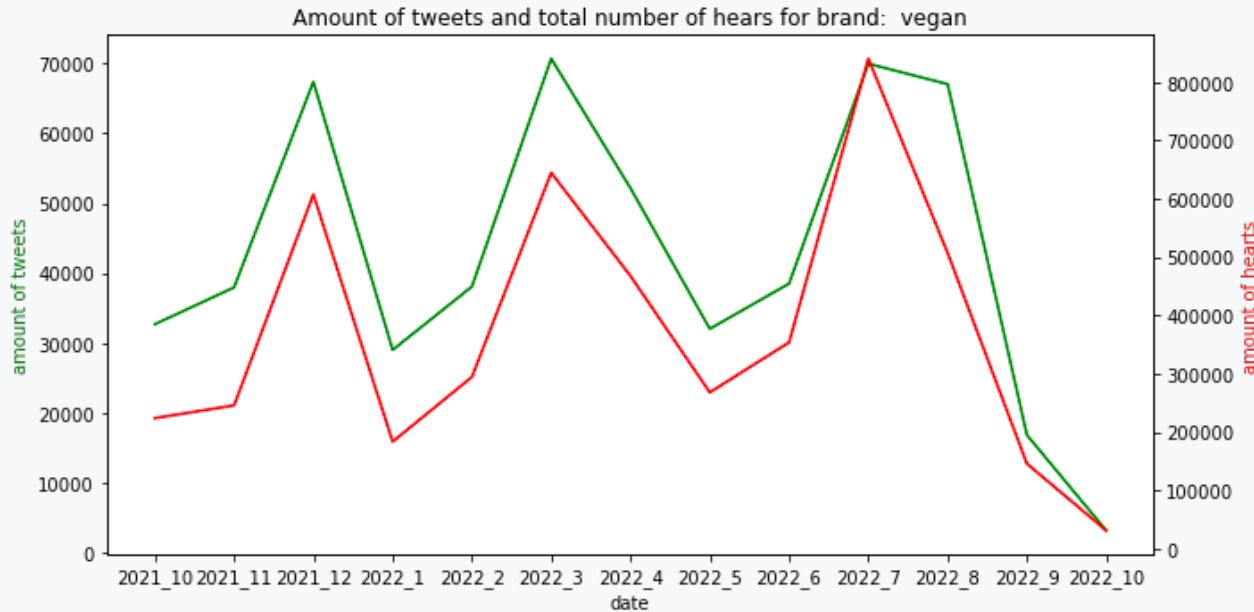
Account with the highest weight

name	screen_name	amount_of_followers	count_of_tweets	weight
PETA	peta	1082775	289	312921975
Lady Gaga	ladygaga	84876971	2	169753942
The New York Times	nytimes	53818201	2	107636402
Reuters	Reuters	24739056	4	98956224
Kompas.com	kompascom	8296037	9	74664333

Account with the highest weight with more than 50 tweets

name	screen_name	amount_of_followers	count_of_tweets	weight
PETA	peta	1082775	289	312921975
Vegan Future	veganfuture	173086	339	58676154
vegnews	VegNews	176977	231	40881687
Vegan Posters	veganposters	9645	3831	36949995
Mystic Mist Healing	TheMysticMist	4629	6622	30653238

# NUMBER OF LIKES

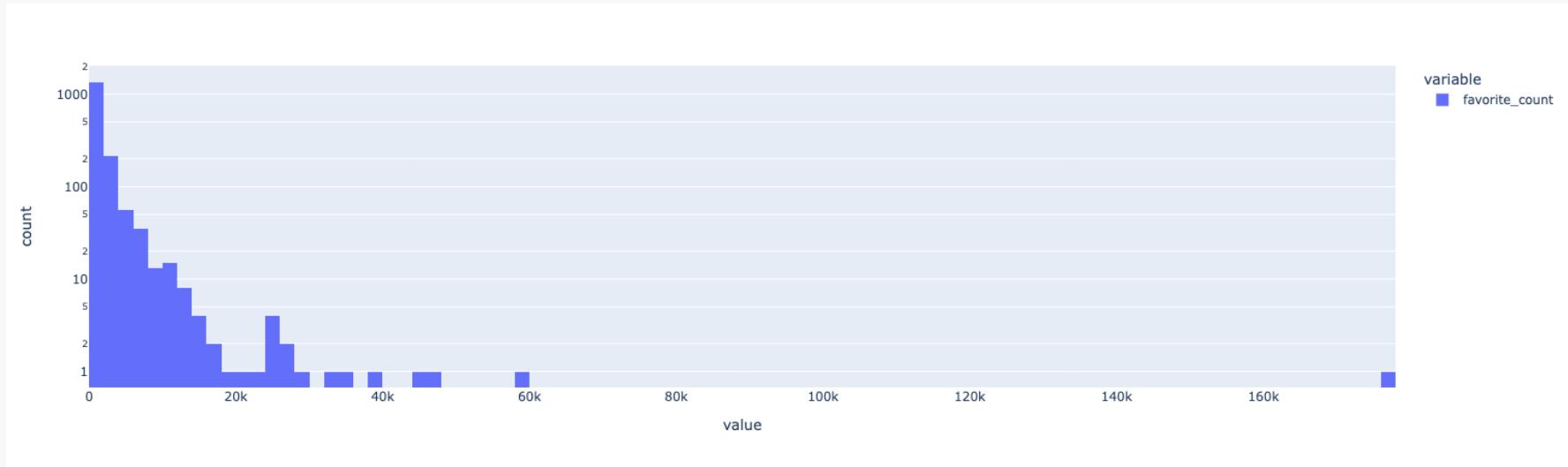


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# NUMBER OF LIKES

<b>name</b>	<b>MaxFollowersCount</b>
Lady Gaga	84876971
CNN	58738132
The New York Times	53833653
BBC News (World)	37368190
The Economist	26981263
Kourtney Kardashian	26324023
Reuters	25387151
A.R.Rahman	24192397
Nicki Minaj	23311089
Fox News	22083552

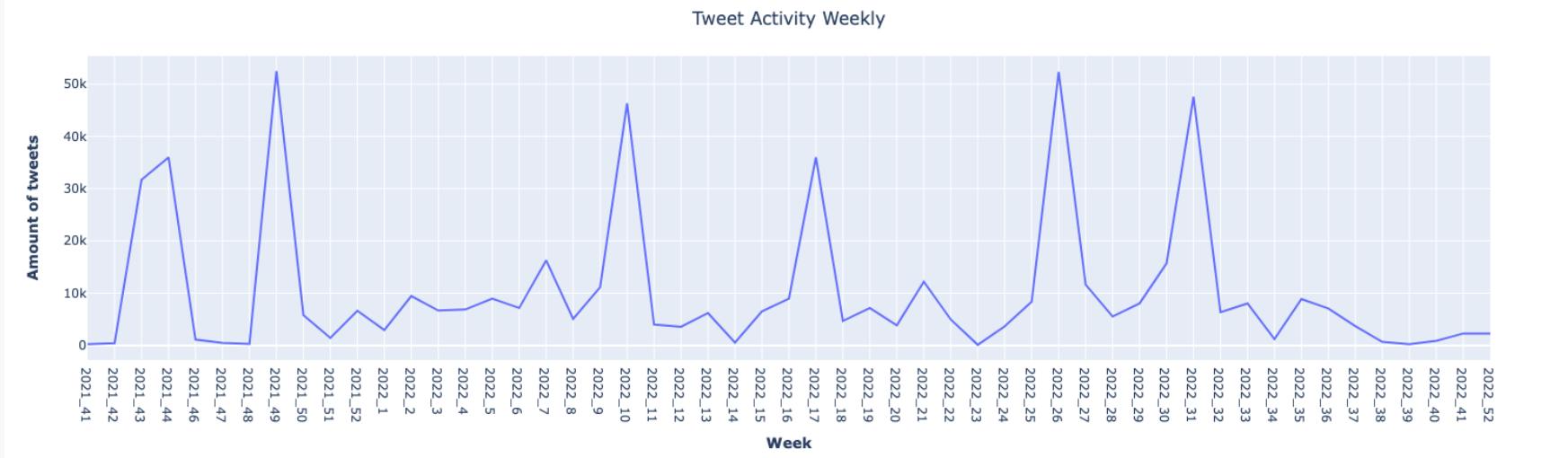
# FAVOURITES PER TWEET



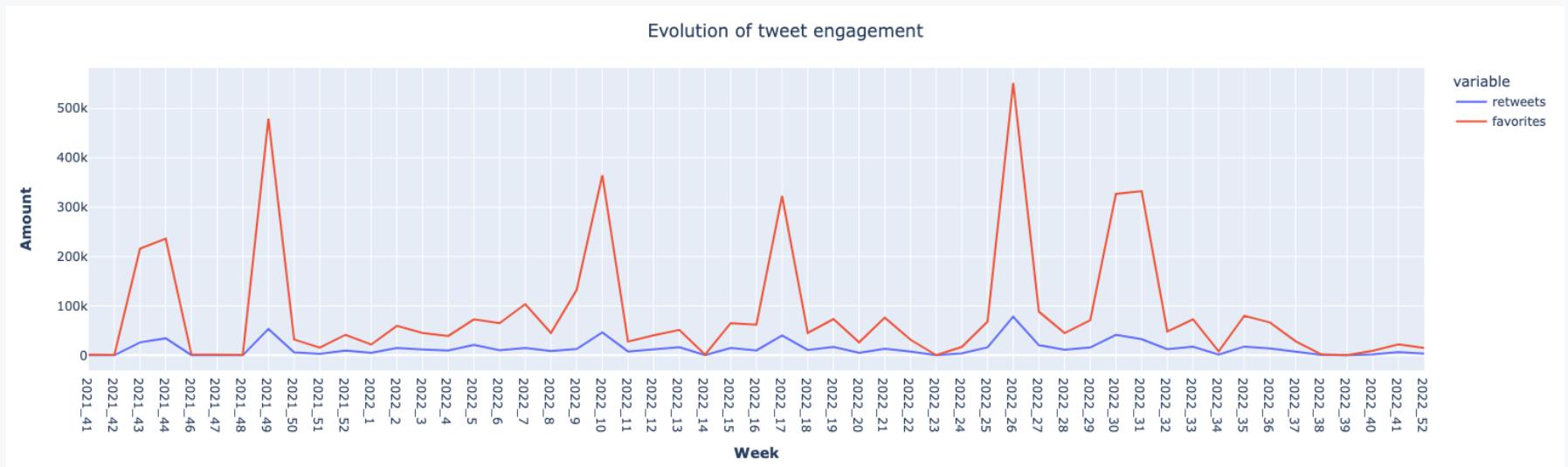
# EVOLUTION OF TWEET ACTIVITY MONTHLY



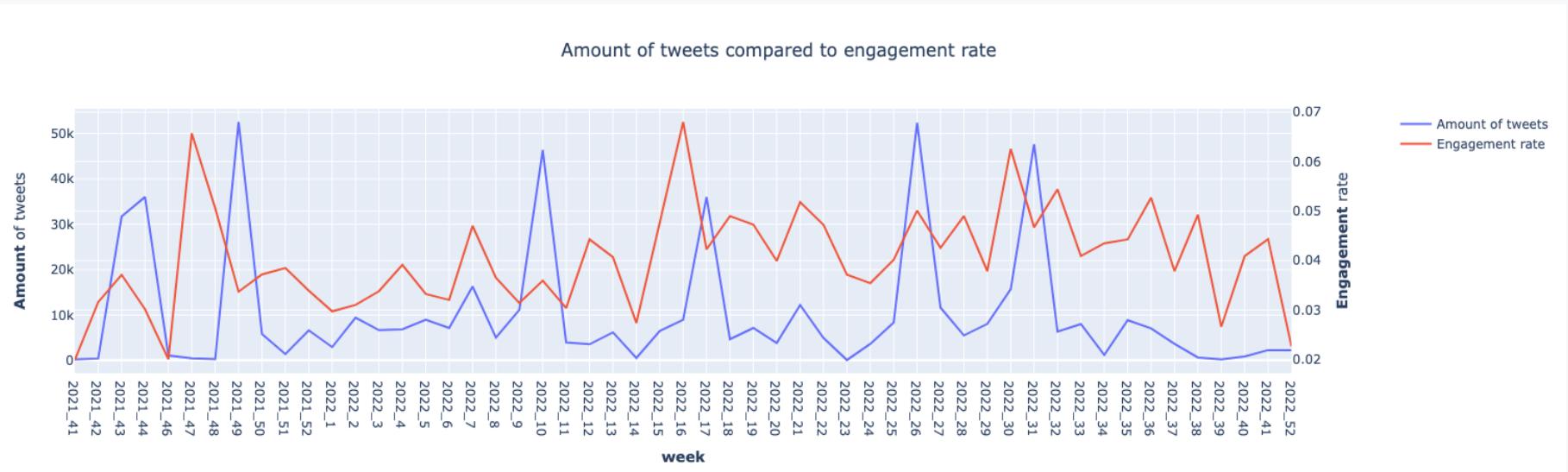
# EVOLUTION OF TWEET ACTIVITY WEEKLY



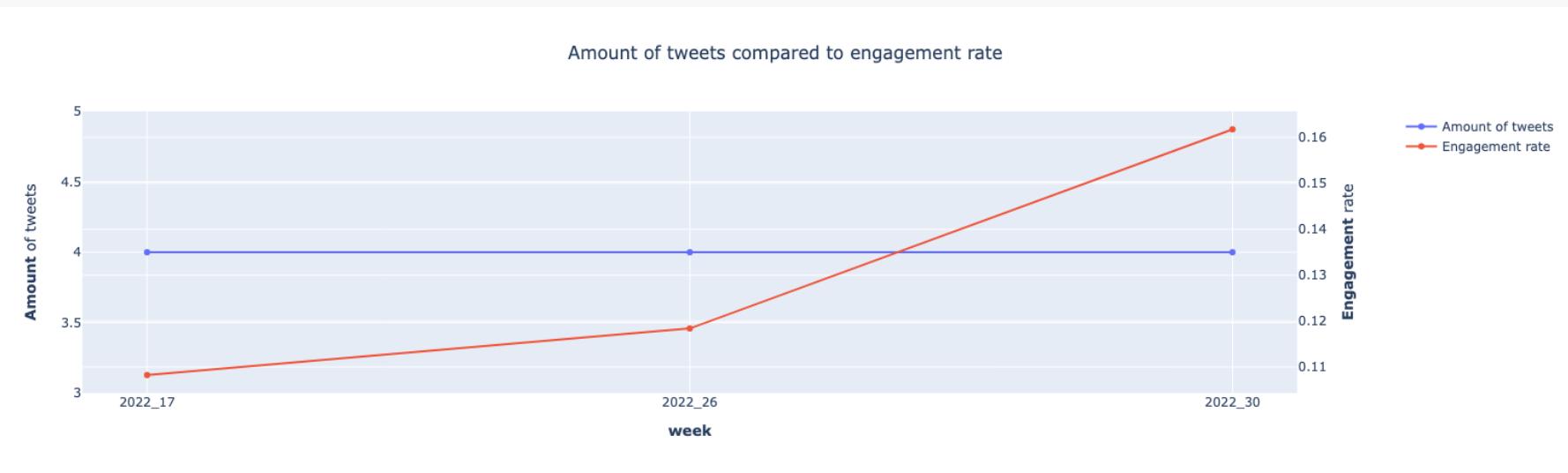
# EVOLUTION OF TWEET ENGAGEMENT



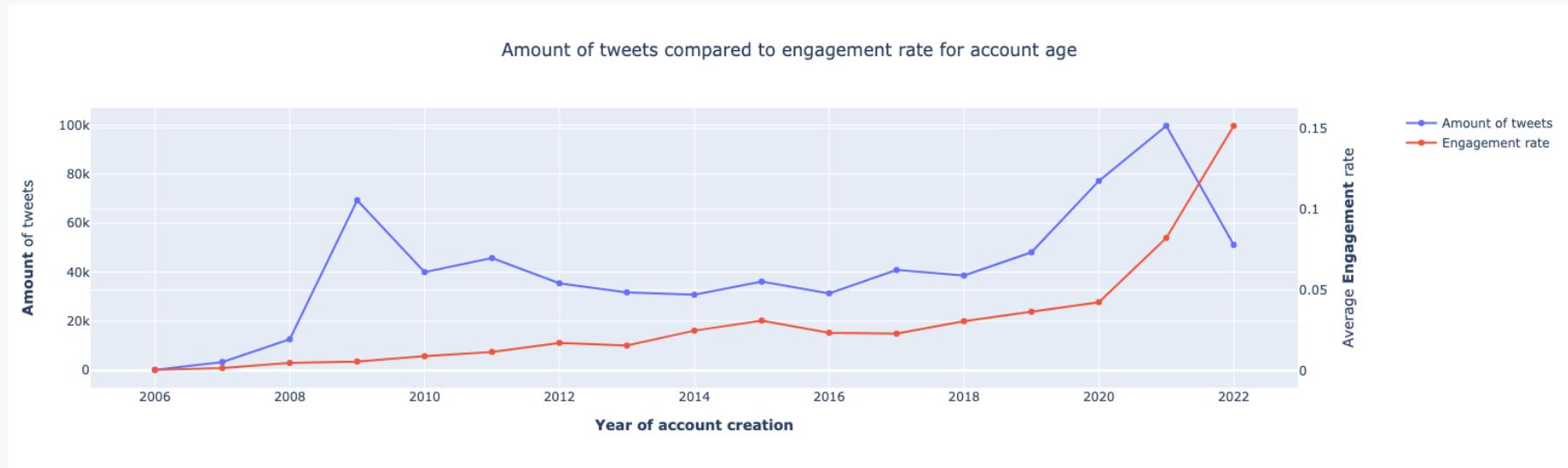
# LEVEL OF SOCIAL MEDIA ACTIVITY VS ENGAGEMENT



# VOLUME OF INFLUENCER ACTIVITY VS LEVEL OF ENGAGEMENT



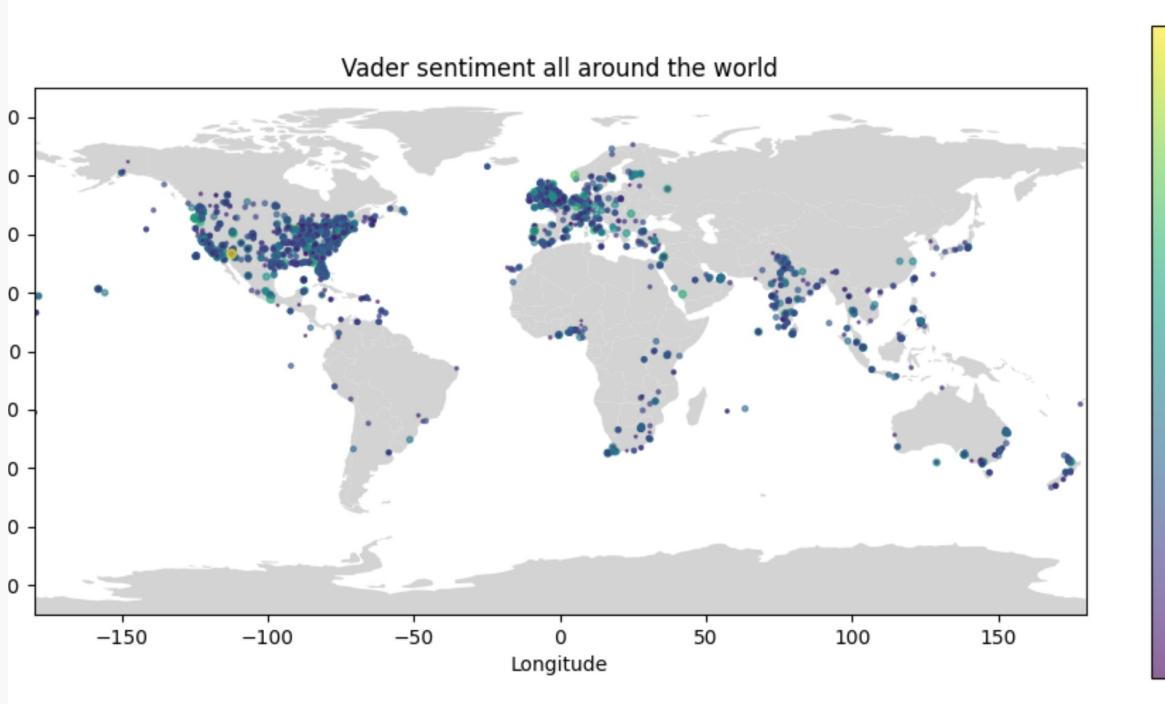
# AGE OF ACCOUNTS WITH ENGAGEMENT AND VOLUME



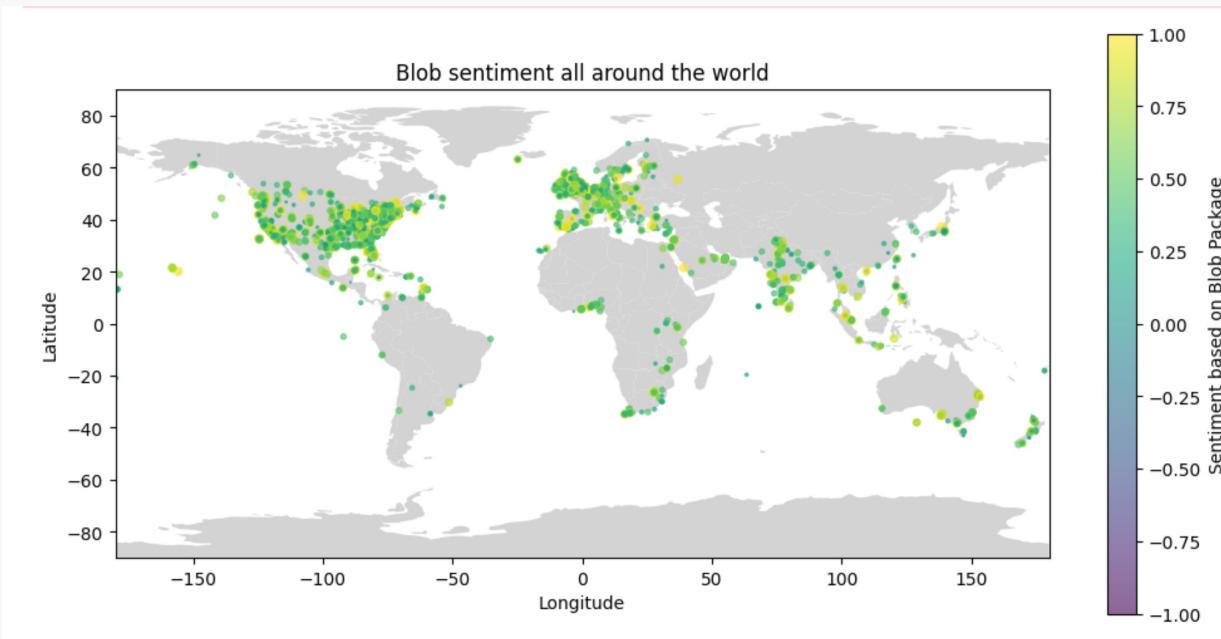
# Sentiment per week



# Vader sentiment around the world



# Blob sentiment around the world



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# Variable importance Random Forest

Feature	Importance
user_following	0.194689
hour of the day	0.125309
day of the month	0.116302
account age	0.115249
month	0.065632
number of text characters	0.054684
number of words	0.052102
subjectivity	0.049946
weekday	0.048056
polarity	0.046693
sentiment	0.045300
number of upper case words	0.024228
number of emojis	0.023503
media type index	0.015749
number of media elements	0.013839
quoted tweet	0.005118
verified account	0.001654
symbol indicator	0.000929
number of mentions	0.000500
number of exclamations	0.000473
number of hashtags	0.000043

# Coefficients logistic regression:

For the users the account is following and account age

# 1) Look at the number of users the accounts is following

```
coefs_df.filter(F.col('Feature') == 'num_features_scaled_0').show()
```

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
num_features_scaled_0	0.21893131811186922	-0.07389076709476614	-0.14504055101710314

# 3) Age of the account in days

```
coefs_df.filter(F.col('Feature') == 'num_features_scaled_7').show()
```

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
num_features_scaled_7	0.14229672200470173	-0.02227923167135...	-0.12001749033334655

# Coefficients logistic regression:

For the number of text characters and the number of words in the tweet

# 6) Look at the text characters of the tweet

```
coefs_df.filter(F.col('Feature') == 'num_features_scaled_9').show()
```

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
num_features_scaled_9	-0.00644509745984...	-0.00938912471622577	0.015834222176070754

# 7) Look at the number of words of the tweet

```
coefs_df.filter(F.col('Feature') == 'num_features_scaled_3').show(truncate = False)
```

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
num_features_scaled_3	-0.00997985303923987	0.0012823808209239502	0.008697472218315938

# Coefficients logistic regression:

For the subjectivity, polarity and sentiment of the tweet

```
# 8 + 9) Look at the subjectivity, polarity and sentiment of the tweet
coefs_df.filter((F.col('Feature') == 'subjectivity') |
                 (F.col('Feature') == 'polarity') |
                 (F.col('Feature') == 'sentiment')).show(truncate = False)
```

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
sentiment	-0.05737200701348562	0.01000923729822799	0.04736276971525765
polarity	-0.007370786667381791	-0.0170725622750061	0.024443348942387838
subjectivity	-0.02215712103128041	-0.0215743758010151	0.043731496832295706

# Coefficients logistic regression:

For the number emojis and the number of upper case words in the tweet

```
# 11 + 12) Look at extra characters: number of emojis and number of upper case words
coefs_df.filter((F.col('Feature') == 'num_features_scaled_1') |
                 (F.col('Feature') == 'num_features_scaled_2')).show(truncate = False)
```

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
num_features_scaled_1	-0.0030855051461838724	0.008212959466056984	-0.005127454319873103
num_features_scaled_2	-0.0024891964088818714	6.398308953780299E-4	0.001849365513503825

# Coefficients logistic regression:

For the hour of the day

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
cat_features_hour_index_OHE_1	0.007768756020498764	0.05309877031656413	-0.06086752633706288
cat_features_hour_index_OHE_10	0.028058668600232733	0.020143892489595513	-0.04820256108982826
cat_features_hour_index_OHE_12	-0.007419555674138468	0.053780576862951394	-0.04636102118881294
cat_features_hour_index_OHE_0	-0.0216374315914389	0.054329718299690036	-0.03269228670825114
cat_features_hour_index_OHE_17	-0.009045650739182473	0.03734296658004055	-0.028297315840858057
cat_features_hour_index_OHE_3	5.06836835806825E-4	0.023520230478031652	-0.02402706731383848
cat_features_hour_index_OHE_2	0.04759111549946655	-0.02828521840595907	-0.01930589709350748
cat_features_hour_index_OHE_13	0.004627108100162384	0.00965453107742652	-0.014281639177588899
cat_features_hour_index_OHE_20	-0.009789667909068133	0.023705827998245756	-0.013916160089177608
cat_features_hour_index_OHE_21	0.0038846739245690094	0.0032827424337155764	-0.007167416358284537
cat_features_hour_index_OHE_16	-0.02470949625550453	0.030957223407659062	-0.006247727152154522
cat_features_hour_index_OHE_9	0.020411954678321707	-0.02134574348760665	9.337888092849805E-4
cat_features_hour_index_OHE_22	0.006199848253685338	-0.013398022556215238	0.007198174302529899
cat_features_hour_index_OHE_4	-0.026938348306833778	0.017870254429369493	0.009068093877464318
cat_features_hour_index_OHE_23	0.009072946141219482	-0.020433415046513786	0.011360468905294322
cat_features_hour_index_OHE_19	0.00786142568349386	-0.02263508665826263	0.014773660974768746
cat_features_hour_index_OHE_5	0.010759507854698763	-0.02860075225935315	0.017841244404654386
cat_features_hour_index_OHE_18	0.003858814451203442	-0.02199034619716972	0.018131531745966278
cat_features_hour_index_OHE_11	0.013759032139171339	-0.032551362140502214	0.0187923300133092
cat_features_hour_index_OHE_8	-0.003240295953822237	-0.028783364754317094	0.032023660708139334
cat_features_hour_index_OHE_14	0.017103250756872967	-0.05005516091700063	0.032951910160127676
cat_features_hour_index_OHE_15	0.0038284700656728734	-0.04253996489718813	0.03871149483151527
cat_features_hour_index_OHE_7	-0.028786001317671693	-0.0176545815381141	0.04644058285578583

# Coefficients logistic regression:

For the day of the month

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
cat_features_day_month_index_OHE_6	0.036024875871627456	0.05661534155052849	−0.09264021742215592
cat_features_day_month_index_OHE_4	−0.044698943898271254	0.11045424772999039	−0.06575530383171913
cat_features_day_month_index_OHE_9	−0.01236441337162952	0.06771125078322807	−0.055346837411598515
cat_features_day_month_index_OHE_5	0.0760187260578621	−0.031800651847148406	−0.044218074210713644
cat_features_day_month_index_OHE_14	0.020894747755976224	0.022077200760737863	−0.04297194851671406
cat_features_day_month_index_OHE_10	−0.020873748996749913	0.0533695577775577	−0.0324958087808079
cat_features_day_month_index_OHE_8	0.014988753759103881	0.00954814347963806	−0.02453689723874197
cat_features_day_month_index_OHE_30	−0.015191053906148406	0.0359674836598773	−0.020776429753728867
cat_features_day_month_index_OHE_2	0.01026178333876439	0.010354790220189914	−0.020380968554066334
cat_features_day_month_index_OHE_27	−0.0034050049957552644	0.013624323189912623	−0.010219318194157343
cat_features_day_month_index_OHE_11	0.00617665064391543	0.003112425702156344	−0.009289076346071762
cat_features_day_month_index_OHE_25	−0.02264304154453164	0.03022794329567801	−0.00758490175114631
cat_features_day_month_index_OHE_19	−0.00549186718441076	0.012363793082463062	−0.006871925898022
cat_features_day_month_index_OHE_31	0.013623606757205419	−0.013320669705766841	−3.0293704693857773E−4
cat_features_day_month_index_OHE_3	−0.0010449587077753417	−0.00349582935353440345	0.004540788061319361
cat_features_day_month_index_OHE_28	0.001707324790631941	−0.007082892163440611	0.005375567372808645
cat_features_day_month_index_OHE_29	0.008360406217704524	−0.02147715389547158	0.01311674767776708
cat_features_day_month_index_OHE_20	0.015167325771216943	−0.029775529090042954	0.014608203318826046
cat_features_day_month_index_OHE_22	0.011764580506433387	−0.0377917196321009	0.026027139125667523
cat_features_day_month_index_OHE_7	−0.053453081425344946	0.02414337329321806	0.02930970813212685
cat_features_day_month_index_OHE_24	0.0194265425905904	−0.04976387442376958	0.03033733183371053
cat_features_day_month_index_OHE_16	0.06279931623820924	−0.09552427511164592	0.032724958873436676
cat_features_day_month_index_OHE_12	0.01138945820205512	−0.050037523685671784	0.038648065483616656
cat_features_day_month_index_OHE_26	−0.05149314377416043	0.0108859459266100314	0.04063368450806013
cat_features_day_month_index_OHE_21	0.00598204022824045	−0.049790763163285456	0.04380872293504502
cat_features_day_month_index_OHE_1	0.006146450655558484	−0.05855713647109144	0.052410685815532966
cat_features_day_month_index_OHE_23	0.004337456335799106	−0.061071298686690444	0.05673384235089134
cat_features_day_month_index_OHE_13	−0.008216816490115563	−0.049038149044345815	0.057254965534461404

# Coefficients logistic regression:

For the month of the year

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
cat_features_month_index_OHE_3	0.0032435586499102967	0.022605645590216494	-0.025849204240126773
cat_features_month_index_OHE_5	0.00669860420495559	0.017137325771302635	-0.023835929976258215
cat_features_month_index_OHE_1	0.05564209123908551	-0.040886129618752765	-0.014755961620332702
cat_features_month_index_OHE_4	0.0034387008779550323	0.009160783641865532	-0.012599484519820577
cat_features_month_index_OHE_10	1.3467152387964192E-4	0.0015697896518880466	-0.00170446117576768
cat_features_month_index_OHE_12	-0.010846801154359351	0.012024195574231884	-0.0011773944198725252
cat_features_month_index_OHE_6	-0.011170943698131859	8.561980753634834E-4	0.010314745622768406
cat_features_month_index_OHE_11	-0.005118515705167424	-0.009672580201042169	0.014791095906209601
cat_features_month_index_OHE_2	-0.00649771240947244	-0.01300426747945528	0.01950197988892772
cat_features_month_index_OHE_8	0.004234064206301132	-0.024396587609881167	0.020162523403580056
cat_features_month_index_OHE_7	-0.003971900196553123	-0.016892237280445588	0.020864137476998737

# Coefficients logistic regression:

For the day of the week

Feature	Coefvalue_class_0	Coefvalue_class_1	Coefvalue_class_2
cat_features_week_day_index_OHE_Thu	4.186560202989838E-4	0.0387257898325645	-0.03914444585286348
cat_features_week_day_index_OHE_Sun	0.007387957539618533	0.003065247079718391	-0.010453204619336917
cat_features_week_day_index_OHE_Fri	0.01663920597789385	-0.007710391210414071	-0.00892881476747976
cat_features_week_day_index_OHE_Tue	0.0034353399217008536	0.002773781263825663	-0.006209121185526465
cat_features_week_day_index_OHE_Sat	-0.004136082947720673	0.00951032466785686	-0.00537424172013618
cat_features_week_day_index_OHE_Wed	-0.006137857568483364	-0.02032483468394185	0.02646269225242523