



Fordham University Consultancy Project MS in Marketing Intelligence

July 26th 2018
New York



THANK YOU

for giving us this great opportunity
to work with real-world data, and

THANK YOU

Lindsey, Ashleigh,
Professor Peter Johnson,
and any others
for the help and support.

INTRODUCING OUR TEAM



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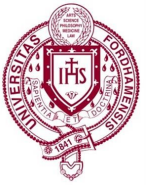
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MURONG XI



QINZI XU



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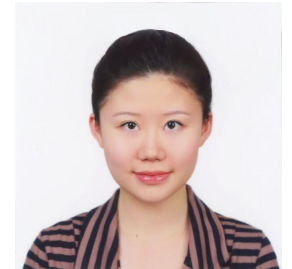
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WEI ZHANG



JIN LUO



YUQING CHEN



HAOTIAN WU



QIAOCHU CAI



GEZHI ZHUANG



JUENAN CHEN



FANGQING YUAN

PRESENTATION OBJECTIVES

Develop strategies to build audience on social media

After today, we hope to help you:

- Forecast future views and engagement rates
- Create more engaging titles for video posts
- Take advantage of the most effective publishing times
- Better manage posts through video categorization
- Exploit the potential of sponsored videos





1

TIME SERIES FORECASTING

Make forecast about future view and engagement rate for four Scripps networks.

2

COMPETITIVE COMPARISON

Comparing Food Network's performance with its strongest competitor -- Tasty

3

FOOD NETWORK KPI ANALYSIS

Discussing significant variables that will affect view and engagement rate

4

CATEGORIZATION

Assign meaningful categories to posts and examine the performance of categories

5

SPONSORED VS. NON-SPONSORED VIDEOS

Learn more about how sponsored videos are performing against non-sponsored videos

6

CONCLUSION

Concluding the presentation summarizing findings



Scripps Networks KPI Trends and Forecasting



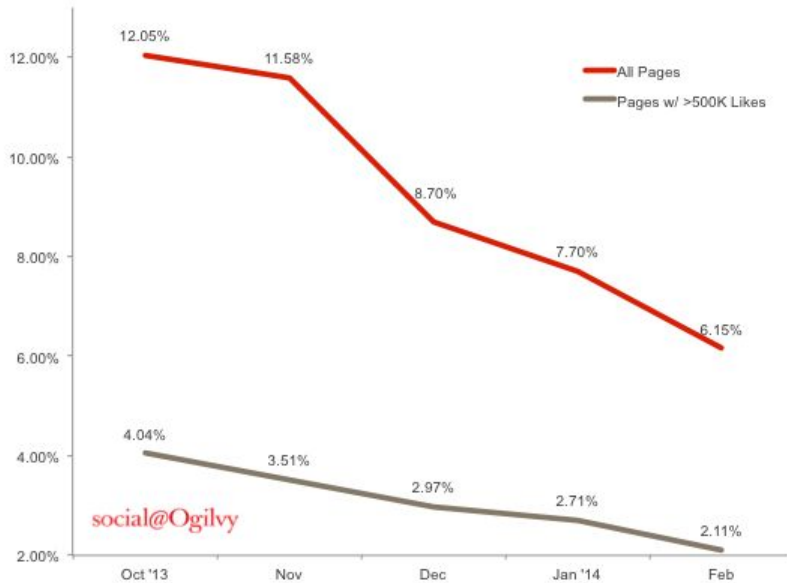
1





Changes in Facebook algorithm is influential

Average Organic Reach of Content Published on Brand Facebook Pages



social@Ogilvy
Analysis of 100+ Facebook Brand Pages around the world with more than 48 million total fans conducted by Social@Ogilvy in February 2014. Please see our report, "Facebook Zero" at <http://social.ogilvy.com> for details.

Source of Information:
<https://www.falcon.io/insights-hub/industry-updates/social-media-updates/facebook-algorithm-change/#/GEN>



Fall of organic reach and engagement

Trend was observed in 2014, where organic reach rate for brand pages was already down to 6%.



Latest algorithm update

Focusing on prioritizing posts from friends, family, and groups instead of business and brand.



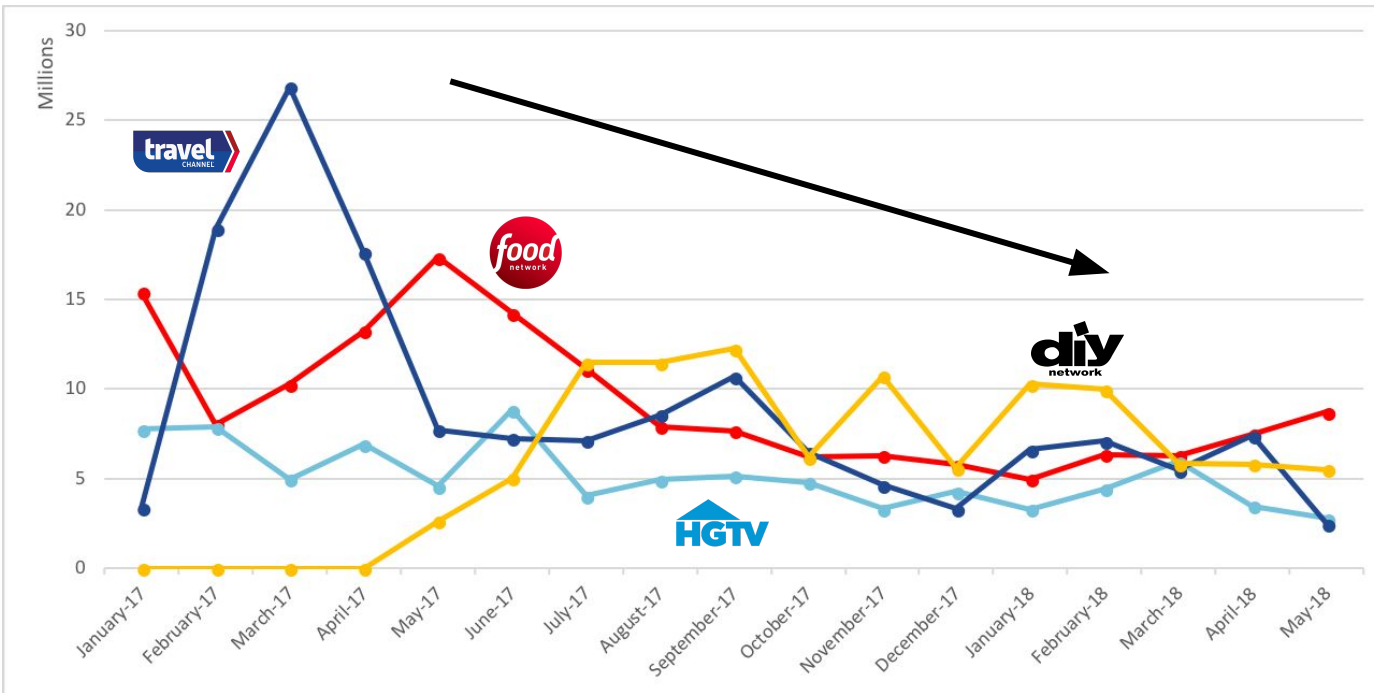
Decline continues in 2017

From January to June 2017, the average number of engagement with branded content on Facebook fell more than 20%.

ARE SCRIPPS NETWORKS FACEBOOK PAGES AFFECTED?



Views per Video by Month (January 2017 - May 2018)



We can see a clear decline in view per video started early 2017, reflecting changes in Facebook algorithm.



Food Network is leading in both **May 2017** and **2018** performance



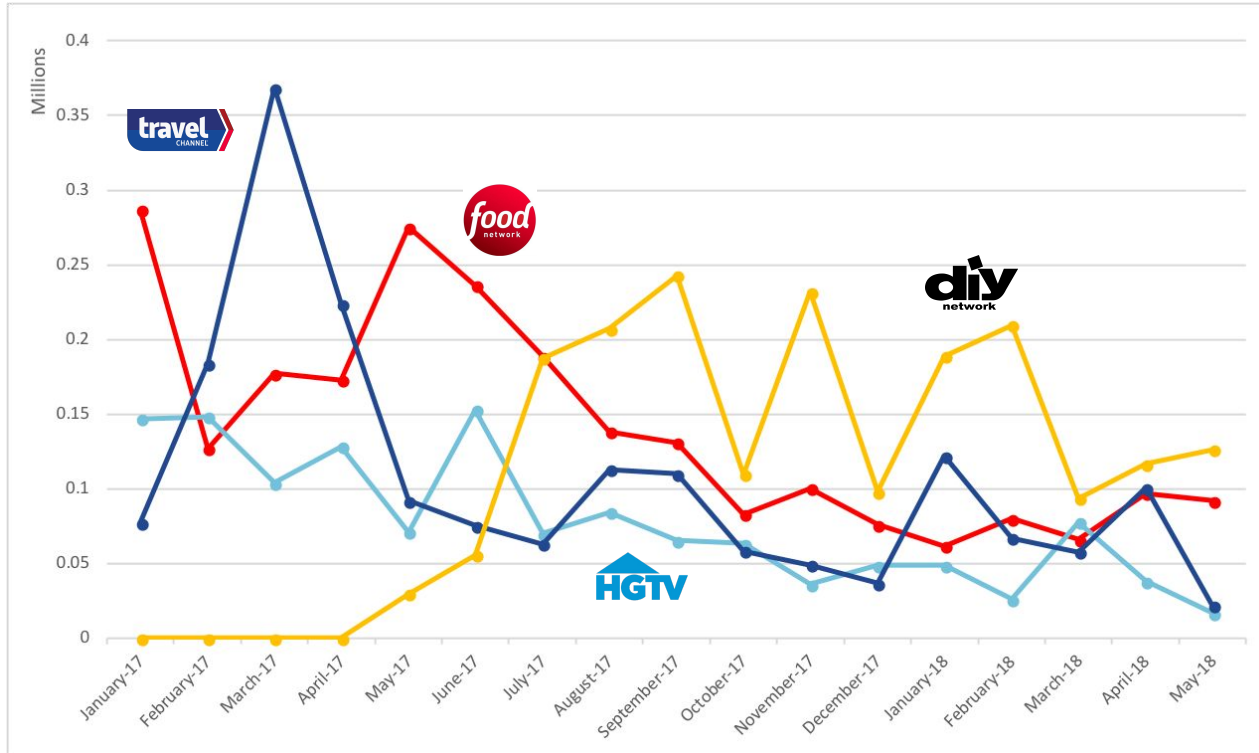
DIY started off low, but is outperforming all three other networks

Source of data: 10K records from Tubular

WHAT ABOUT ENGAGEMENT NUMBER?



Engagement per Video by Month (January 2017 - May 2018)



Source of data: 10K records from Tubular

Same declining trend is observed in engagement per video by month.



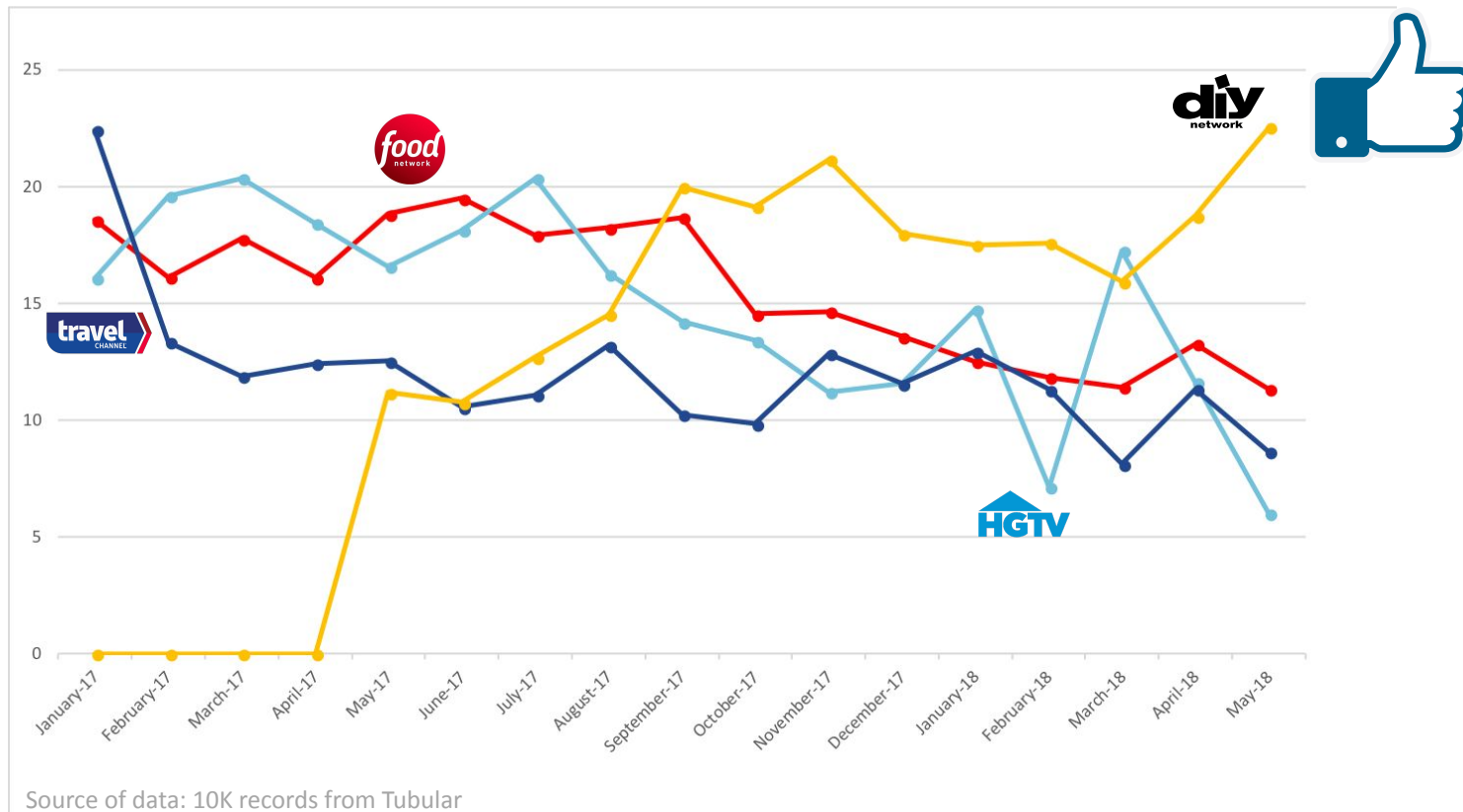
Views and **engagement** are highly correlated, but with engagement number being more volatile.



DIY is outperforming all three other channels.

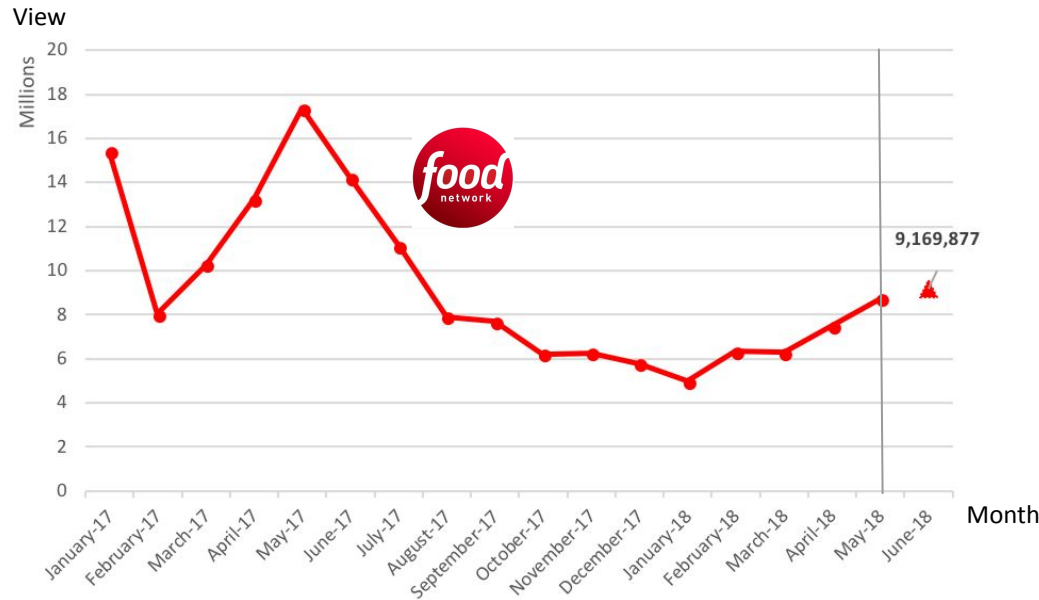


Engagement Rate per Video by Month (January 2017 - May 2018)

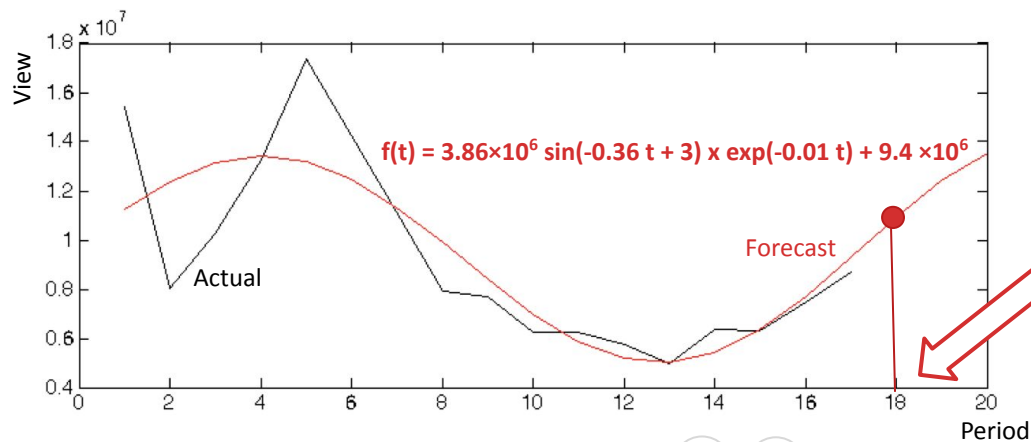




Forecast of View per Video in June 2018



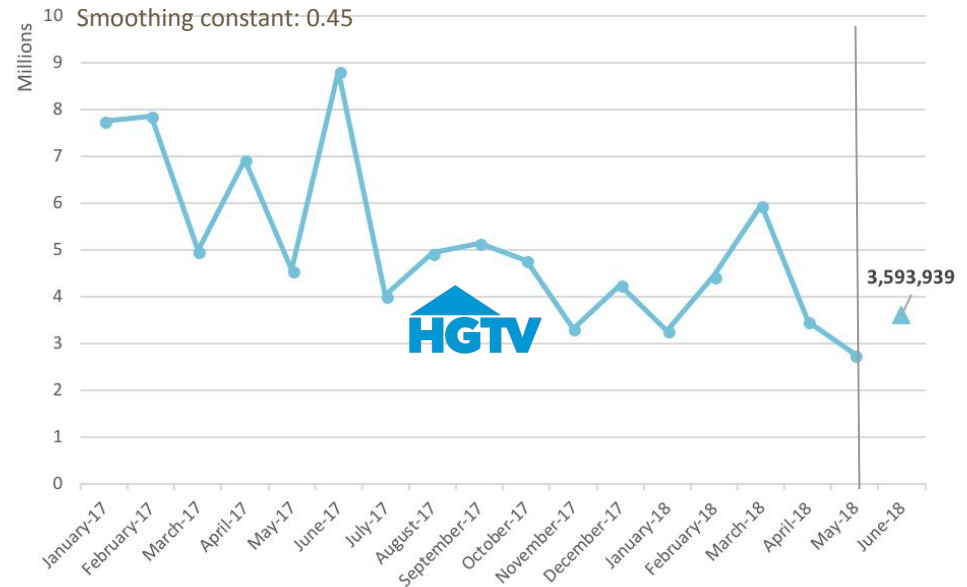
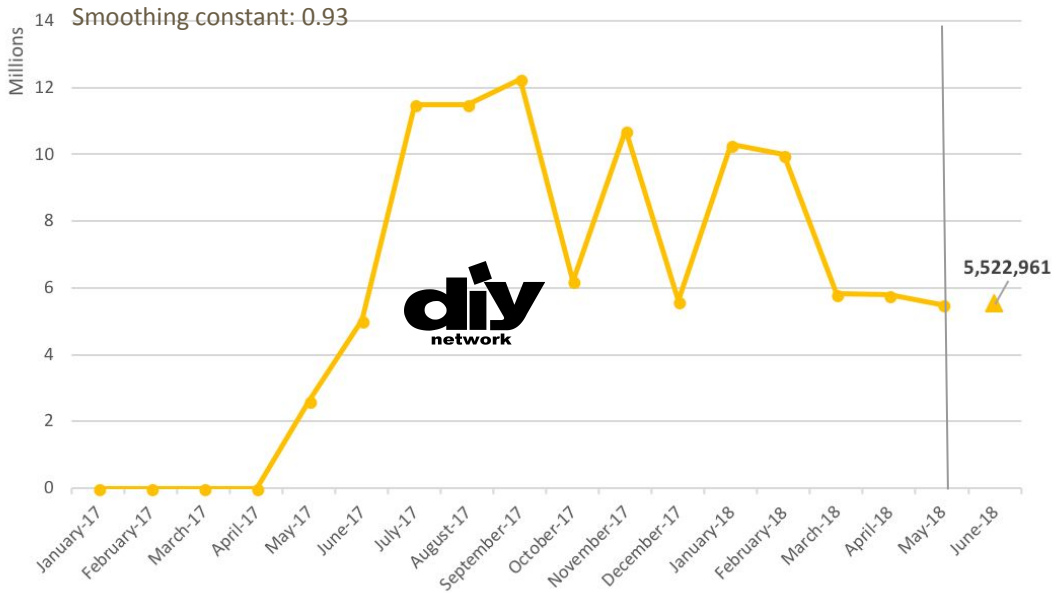
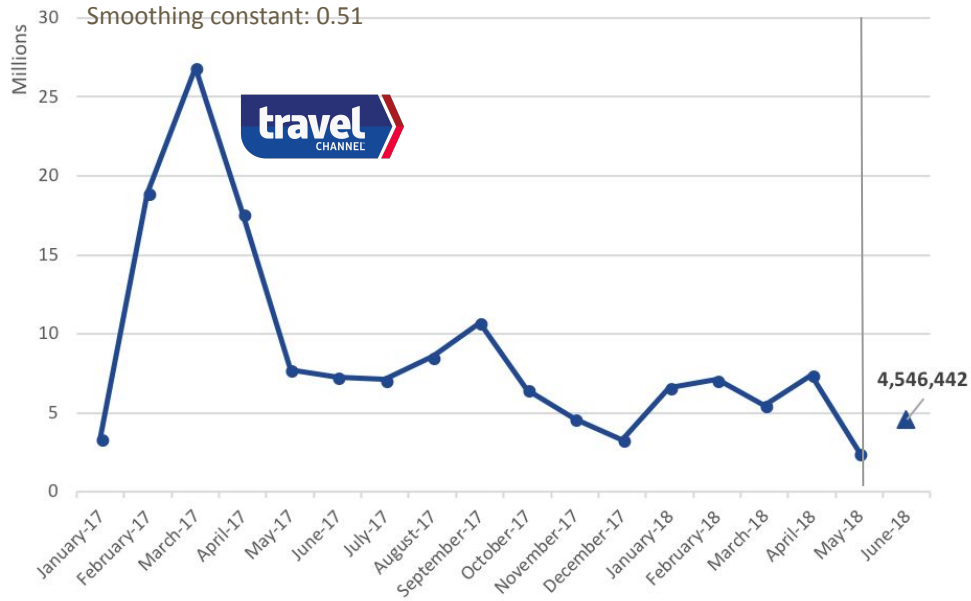
The forecasted average view was calculated using the function, by setting t=18.



June 2018 = Period 18

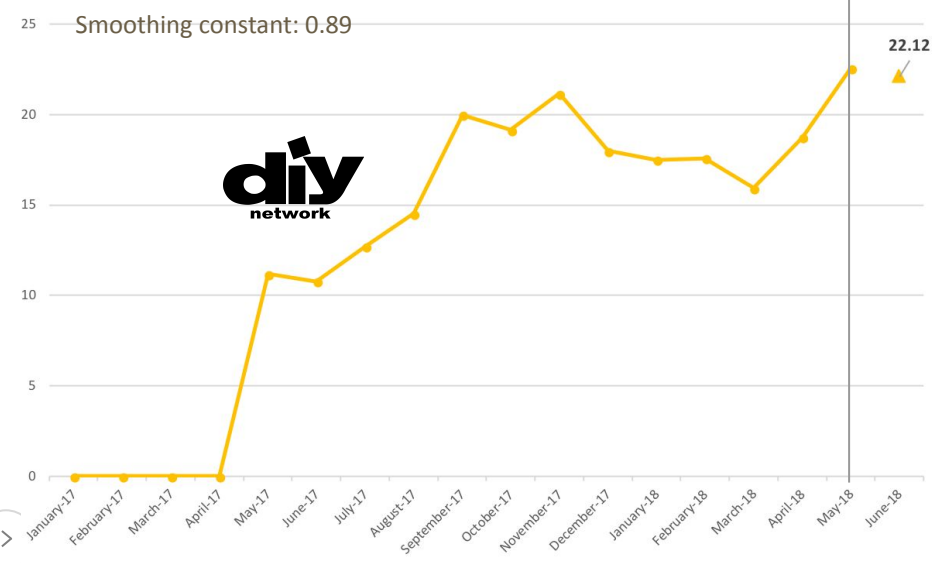
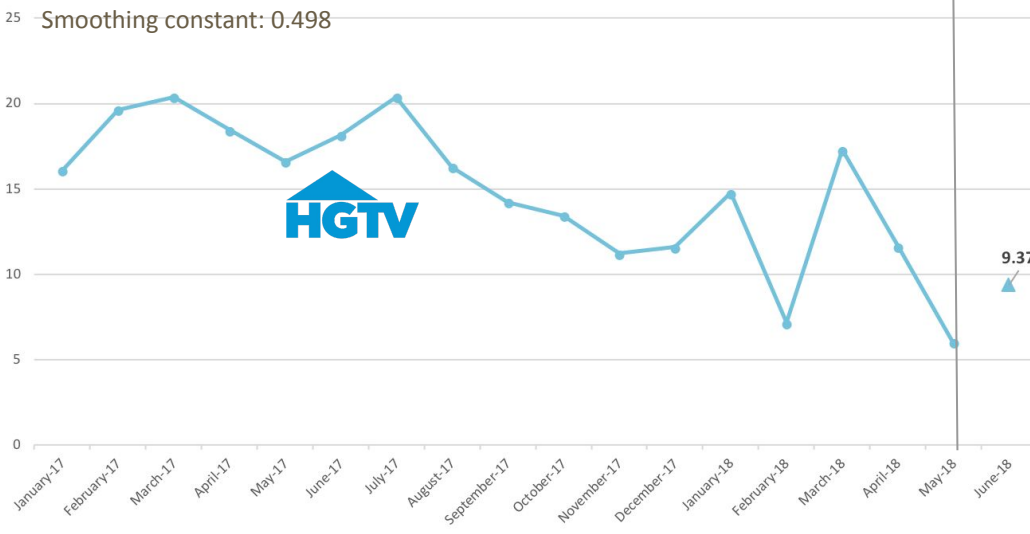
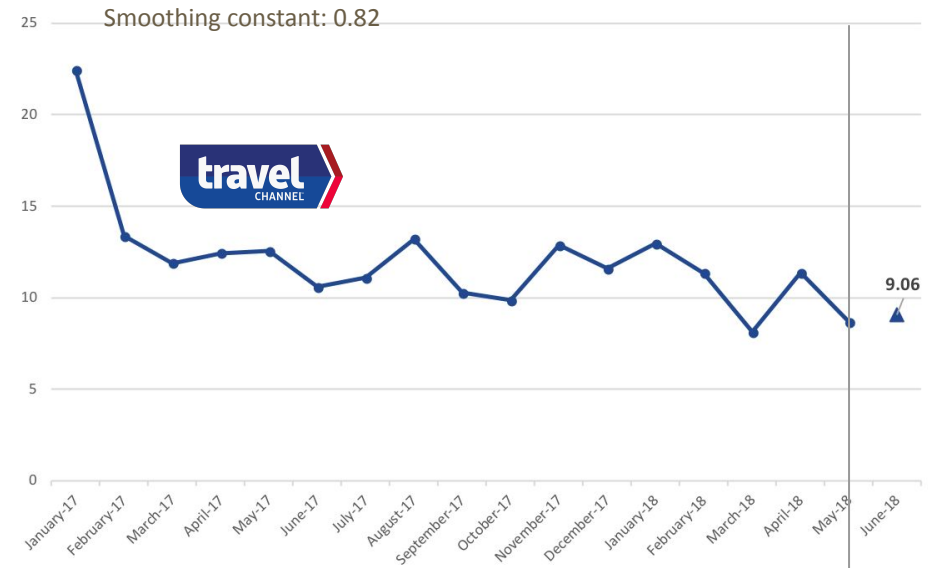
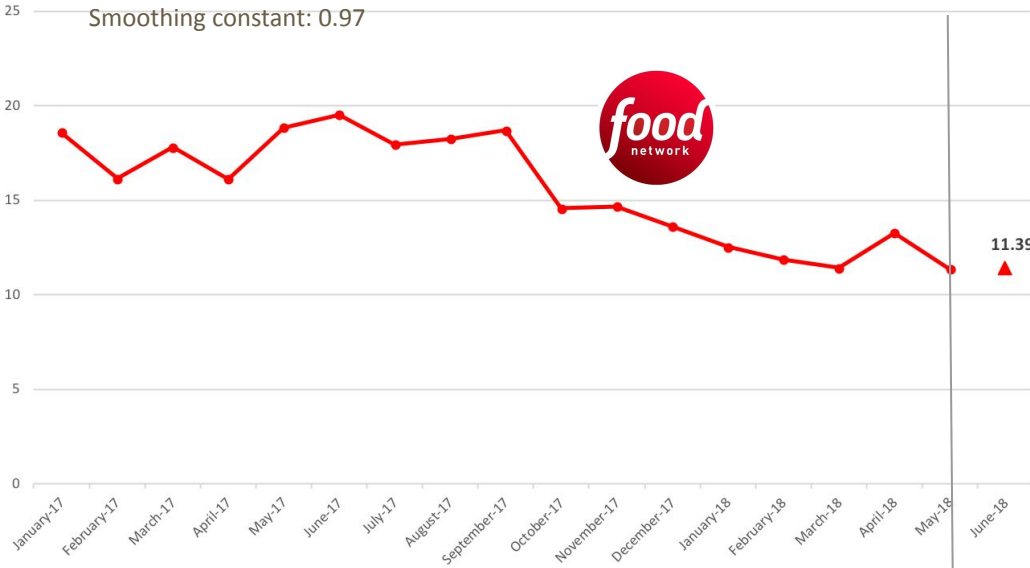


VIEW FORECASTS LOOK GOOD!





ENGAGEMENT RATE EXPECTED TO RISE!



Competitive Comparison

Food Network vs. Tasty



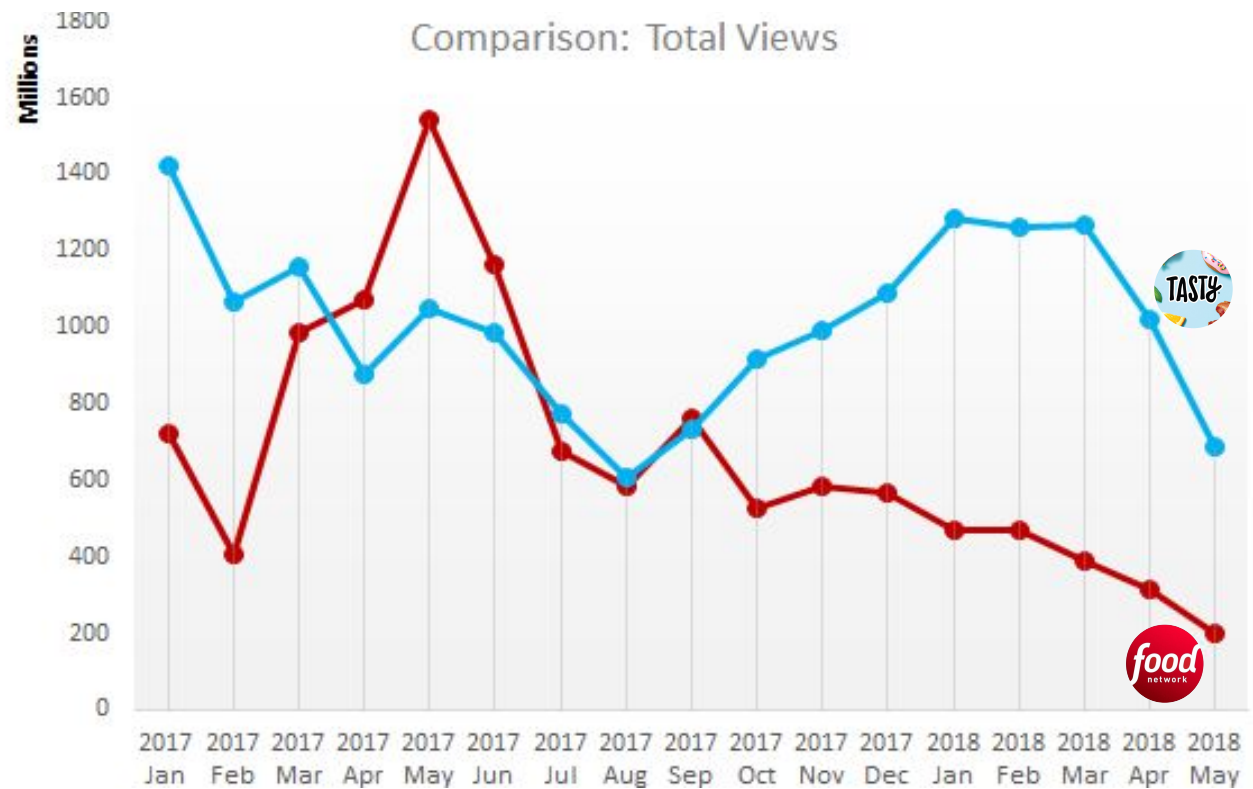
2



THE GAP IS CLOSING



Total Views (Jan 2017- May 2018)



FN peak in May 2017

Tasty peak in January 2018



FN's declining since October 2017

BOTH declining since January 2018

Source of data: 10K records from Tubular





Count of Videos (Jan 2017- May 2018)

★ As the count of videos decreases from the last quarter of 2017, total views also decrease.



Source of data: 10K records from Tubular

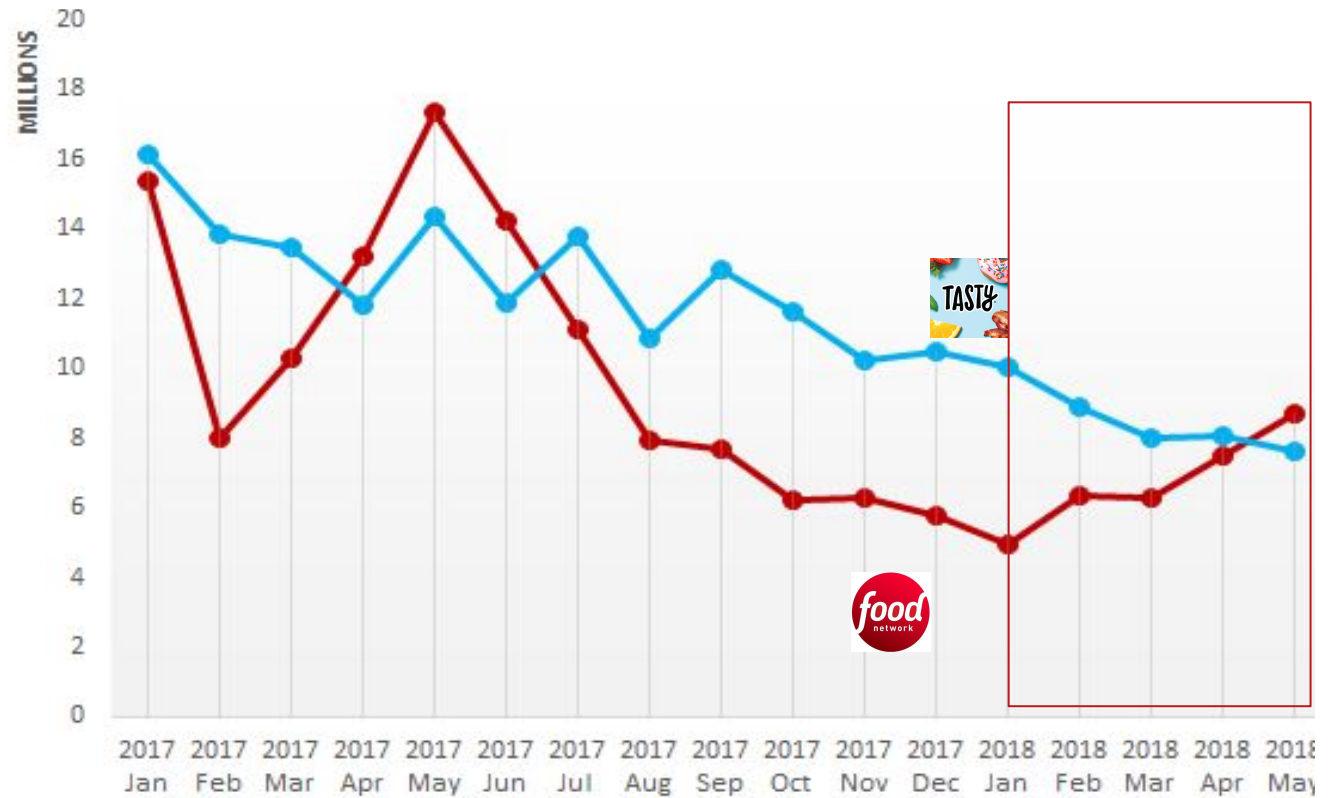




Views per Video by Month (Jan 2017- May 2018)




As the count of videos and total views **decrease** from January 2018, views per video **increase** and reach the peak in May 2018.





Source of data: 10K records from Tubular

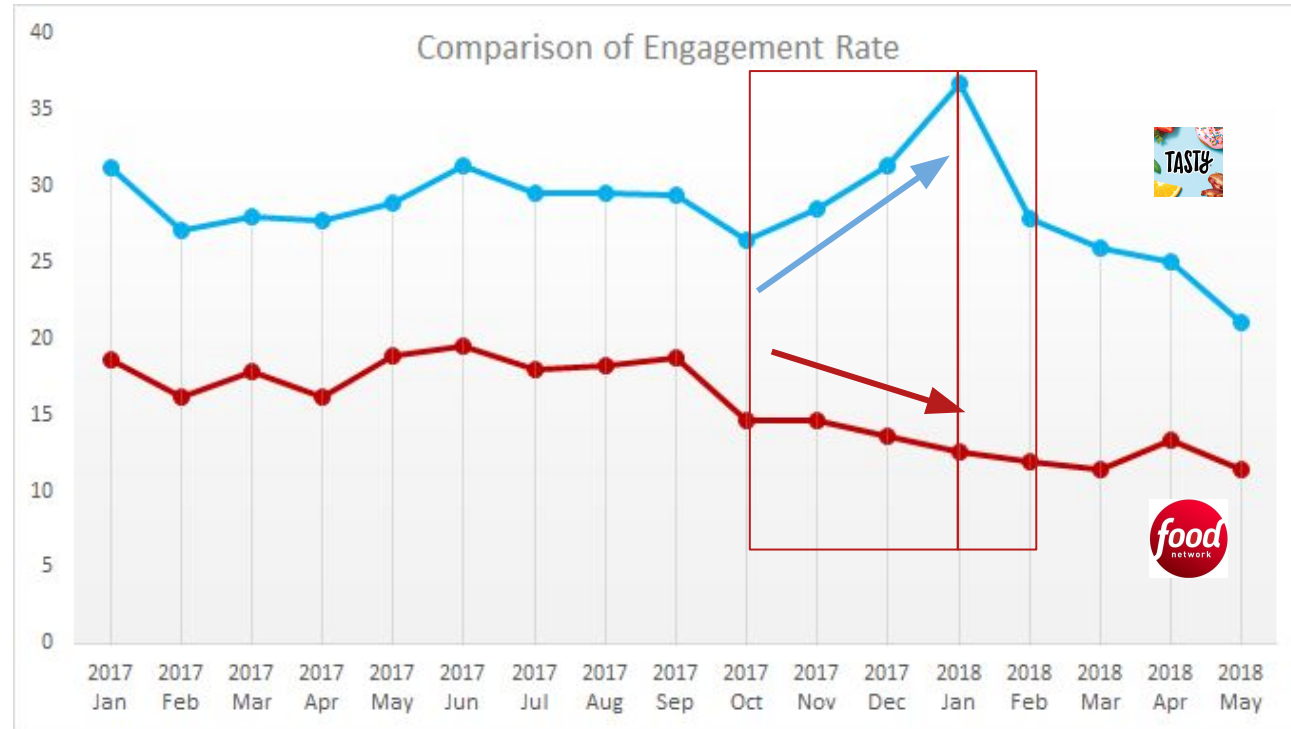


Engagement Rate per Video by Month (Jan 2017- May 2018)

 Tasty increased significantly from October 2017 to January 2018

 Tasty decreased significantly in February 2018

 FN continuously decreased during the same period



Source of data: 10K records from Tubular



What leads to the differences between Food Network & Tasty?



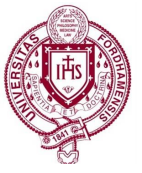
PUBLISHING TIME

Certain publishing time of the videos generates more views.



TITLES MATTER

The differences in titles have an effect on the performance.



DIFFERENCES

Publishing Time

Time of Day to publish the videos



HYPOTHESIS 1

Publishing time of day has significant effects on views performance.



METHODOLOGY

Explore the relationship between publishing time and views

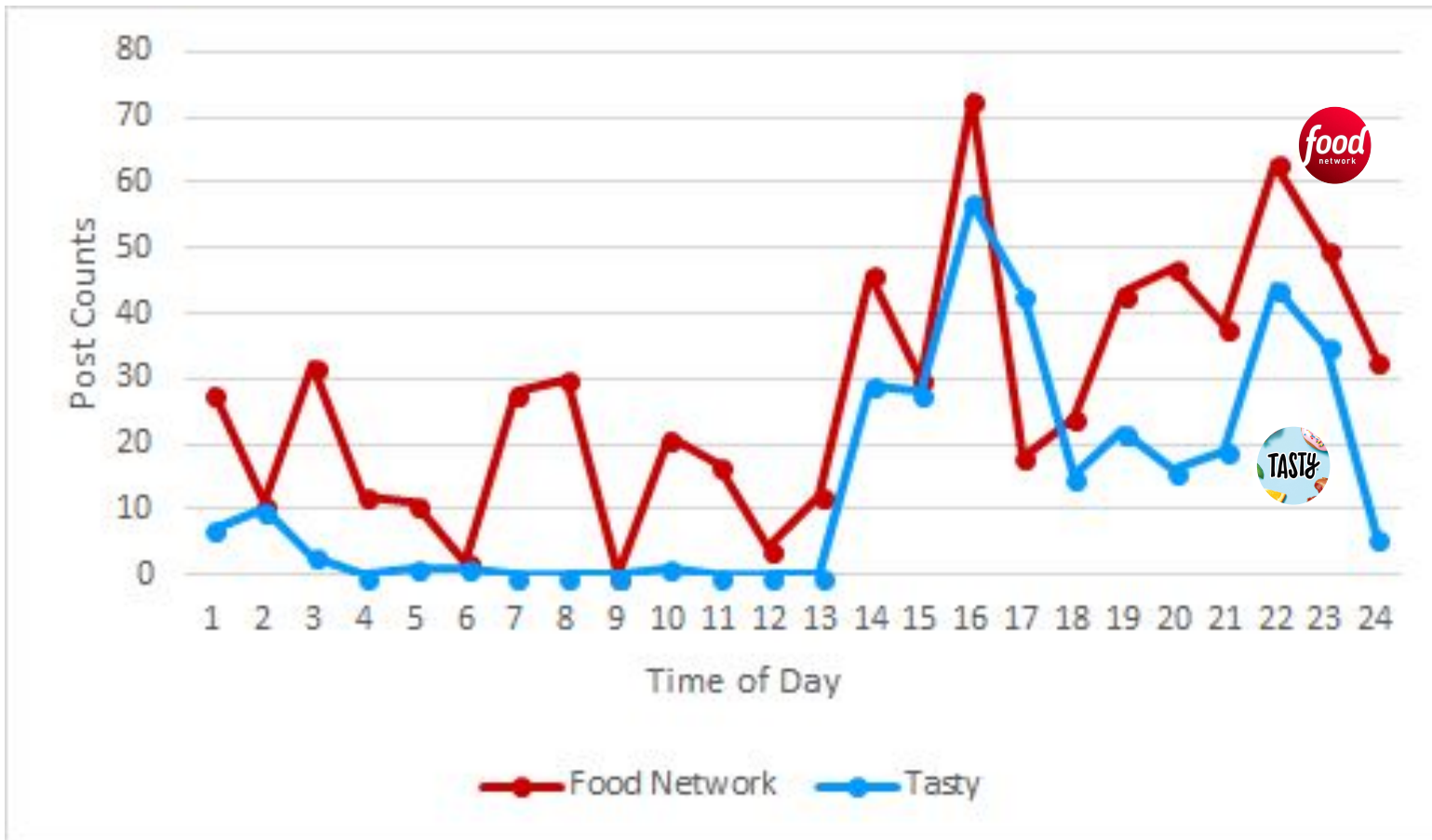


FINDINGS

Certain publishing times of day generate more views.



Count of Videos (Jan 2017- May 2018)



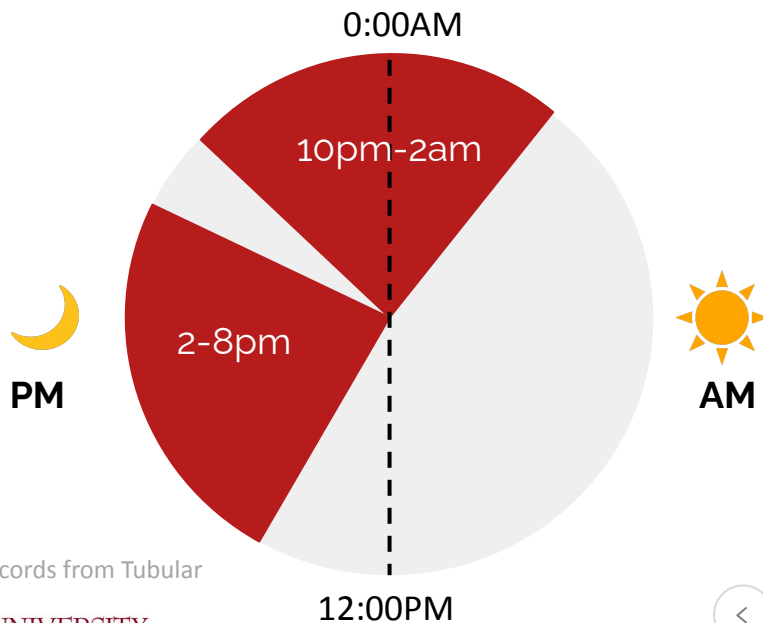
Source of data: 10K records from Tubular



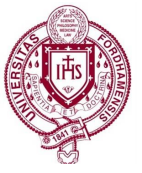
Does Publishing Time Affect Views?

 **Yes!**

Here are the publishing times in a day that generate more views according to the Regression:



Source of data: 10K records from Tubular



DIFFERENCES

Titles Matter



HYPOTHESIS 2

Different title contents lead to different performances.



METHODOLOGY

Conduct text analysis over Food Network and Tasty's video titles of each month during the selected time period (Oct. 2017 - Jan. 2018)



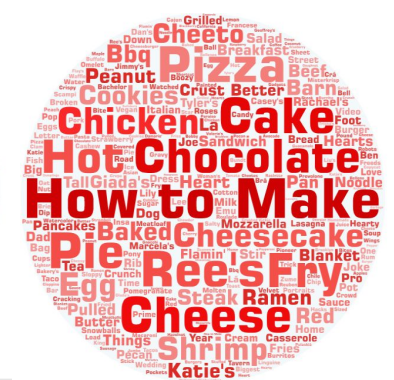
FINDINGS

Tasty demonstrates more variety in titles.



Title Word Frequency (Oct 2017- Jan 2018)

- FN shows incredible consistency in titles while Tasty shows much more variety.



October, 2017

November, 2017

December, 2017

January, 2018



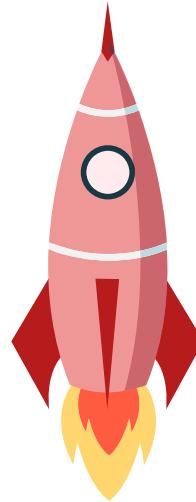


54.5% FN VIDEO TITLES START WITH "HOW TO MAKE"

Create More Videos Titles Without "How To Make"

🌀 Titles With "How to Make"

- How To Make Giada's Chicken Carbonara
- How To Make Bacon-Wrapped Turkey Roll
- How to Make Oreo-Stuffed Ice Cream Sandwich
- How To Make Giada's Lemon and Pea Alfredo
- How to Make In-N-Out-Inspired Animal Style Burger
- How To Make Katie's Crème Brûlée
- How To Make Ree's 5-Star Salisbury Steak
- How to Make Swiss Roll Pumpkins
- How To Make A Beauty and The Beast Inspired Dinner
- How To Make Pot Roast with Red Wine



🌀 Titles **Without** "How to Make"

- Mirror Glaze Cake
- Scalloped Potato Roll
- Steak Dinner For Two FULL RECIPES:
 - 5 Exceptional Egg Hacks
 - Banana Bread Bottom Cheesecake
 - 8 Desserts in 1 Sheet Tray
 - 7 Dorm-Friendly Microwave Meals
 - French Omelette Vs. Japanese Omelette
 - Spinner Cookies

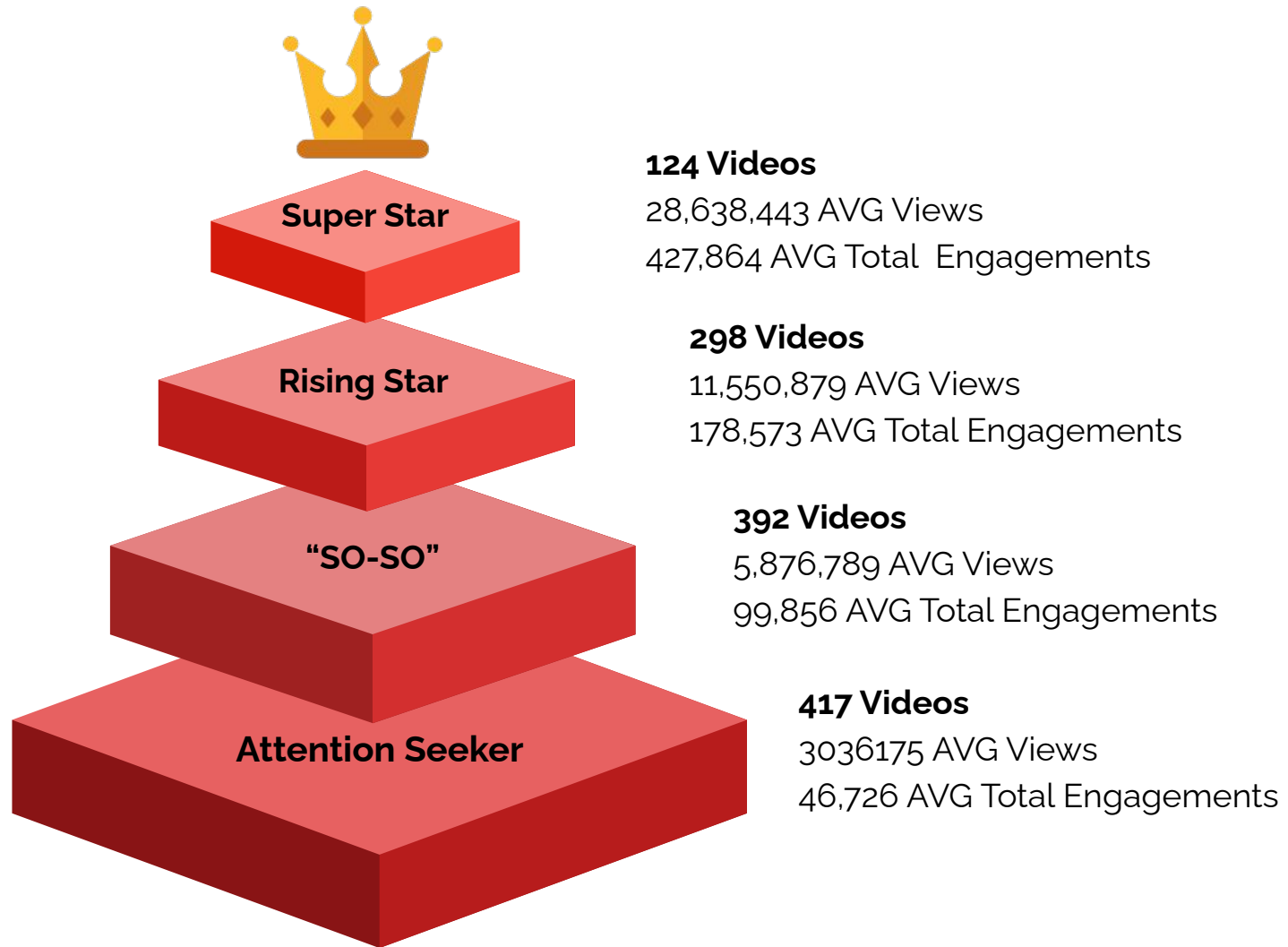
MORE VIEWS

Videos without "How to Make" titles perform better in terms of Views.

TITLE FEATURES OF DIFFERENT SEGMENTS BASED ON PERFORMANCE



Video Posts Segments



*Source of data: 10K records from Tubular
*Tools: SPSS Ward's Clustering

Looking at Food Network KPIs





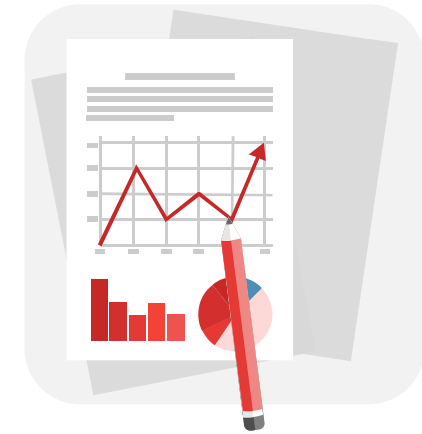
KPIs being discussed

- Views
- Engagement Rate



Hypothesis

Month, day-of-week, and time-of-day that the videos are posted have significant effect on view, engagement rate, and view daily growth rate of the posts.



Methodology

Hedonic regression



INDEPENDENT VARIABLES

HEDONIC REGRESSION

Breaking down KPIs into variables that may determine performance

DEPENDENT VARIABLES

Count of Videos

Total number of posts per month



Month

Shows seasonality



Day-of-Week

On weekends or weekdays



Time-of-Day

When is the video posted



V30 and Log(V30)

Total views in the first 30 days

- Logarithm of V30 was taken to increase validity of regression



Daily Growth Rate

Shows how fast the views grow daily



Engagement Rate

Engagement rate per video





WHAT DOES THE REGRESSION TELL US?



Variables significant to V30

- Count of Videos
- Month



View Generators (from highest to lowest)

DECEMBER						
M	T	W	T	F	S	S
28	29	30	1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	1
2	3	4	5	6	7	8

MAY						
M	T	W	T	F	S	S
28	29	30	1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	1
2	3	4	5	6	7	8

APRIL						
M	T	W	T	F	S	S
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	1	2	3	4
5	6	7	8	9	10	11





WHAT DOES THE REGRESSION TELL US?

! Variables significant to V30

- Count of Videos
- Month

👎 ...and months that have been lacking behind

NOVEMBER						
M	T	W	T	F	S	S
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	1	2	3	4
5	6	7	8	9	10	11

JANUARY						
M	T	W	T	F	S	S
28	29	30	1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	1
2	3	4	5	6	7	8

SEPTEMBER						
M	T	W	T	F	S	S
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	1	2	3	4
5	6	7	8	9	10	11





WHAT DOES THE REGRESSION TELL US?



Variables significant to Daily Growth Rate

- Month
- Day-of-Week



View Boosters (from highest to lowest)

DECEMBER						
M	T	W	T	F	S	S
28	29	30	1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	1
2	3	4	5	6	7	8

MAY						
M	T	W	T	F	S	S
28	29	30	1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	1
2	3	4	5	6	7	8

APRIL						
M	T	W	T	F	S	S
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	1	2	3	4
5	6	7	8	9	10	11



Views increase faster during weekdays



WHAT DOES THE REGRESSION TELL US?

! Variables significant to Daily Growth Rate

- Month
- Day-of-Week

👎 ...and months that are slow

NOVEMBER						
M	T	W	T	F	S	S
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	1	2	3	4
5	6	7	8	9	10	11

JANUARY						
M	T	W	T	F	S	S
28	29	30	1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	1
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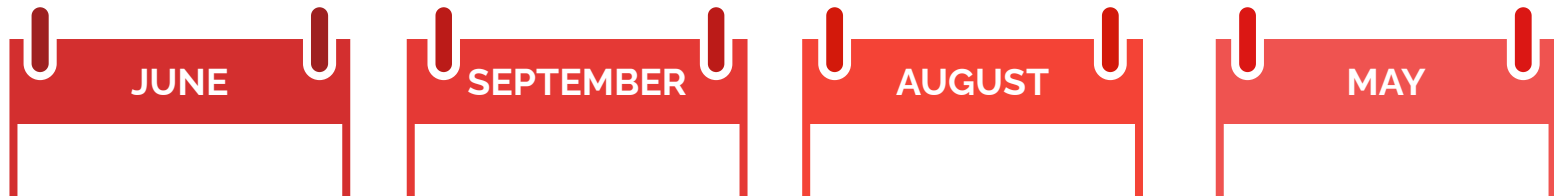
SEPTEMBER						
M	T	W	T	F	S	S
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	1	2	3	4
5	6	7	8	9	10	11



! Variables significant to Engagement Rate

- Month
- Day-of-Week

👍 People are more engaging around these months (from highest to lowest)



👍 ...and are more willing to engage over the weekends

NOTE THAT...



SEPTEMBER						
M	T	W	T	F	S	S
31	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	1	2	3	4
5	6	7	8	9	10	11

Focusing more on post QUANTITY

- One of the months that expected to generate the least view and daily growth rate
- BUT expected to reach high engagement rate

DECEMBER						
M	T	W	T	F	S	S
28	29	30	1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	1
2	3	4	5	6	7	8

Focusing more on post QUALITY

- Expected to generate most view with the highest view daily growth rate
- BUT expected to reach lowest engagement rate

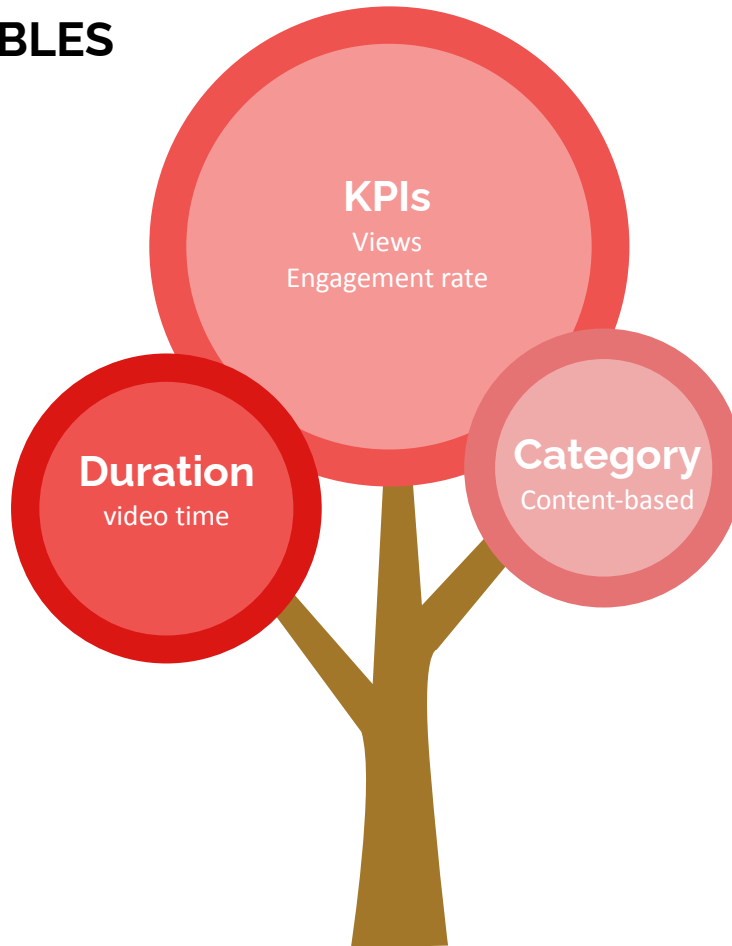
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Categorization





VARIABLES



HYPOTHESIS

- KPIs will perform differently in different categories
- KPIs will perform differently with different durations

METHODOLOGY

- SPSS- ANOVA & T-TEST for understanding the significance for correlation between variables
- Tableau- analysis result visualizations

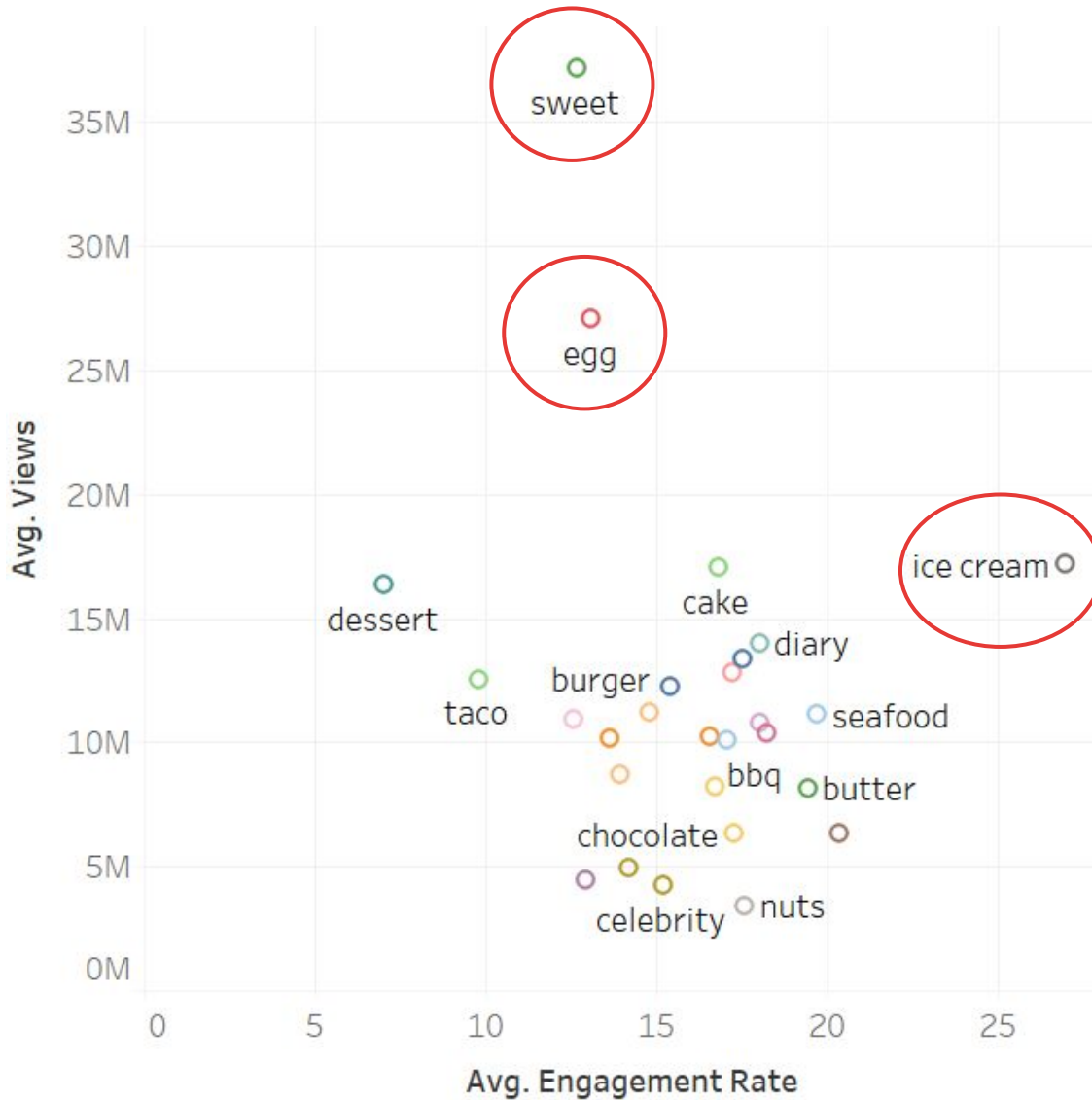
KPIs VS. CATEGORY

Category is significantly correlated with each KPIs index

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
views	Between Groups	3.075E+16	26	1.183E+15	3.863	.000
	Within Groups	3.435E+17	1122	3.062E+14		
	Total	3.743E+17	1148			
engagement rate	Between Groups	5382.953	26	207.037	3.084	.000
	Within Groups	75313.571	1122	67.124		
	Total	80696.524	1148			

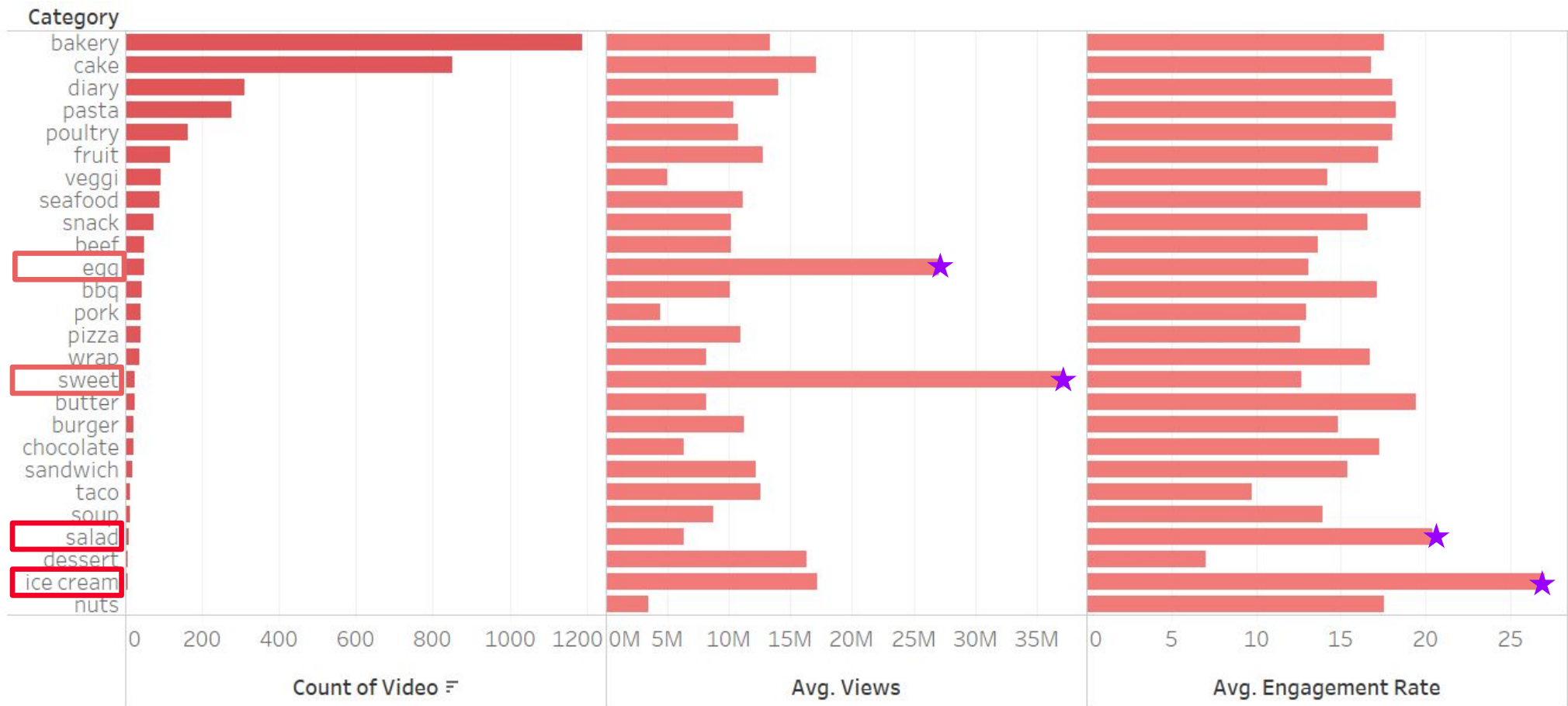
KPIs VS. CATEGORY



- Sweet has the highest views followed by egg
- Ice cream has the highest engagement rate
- Category related to dessert performed much better than other categories

KPIs VS. CATEGORY

- Salad and ice cream are the categories with high potential, so count of videos for those categories should be focused upon
- Videos related to sweet and egg also can be produced more as they are high on views





Duration > 60

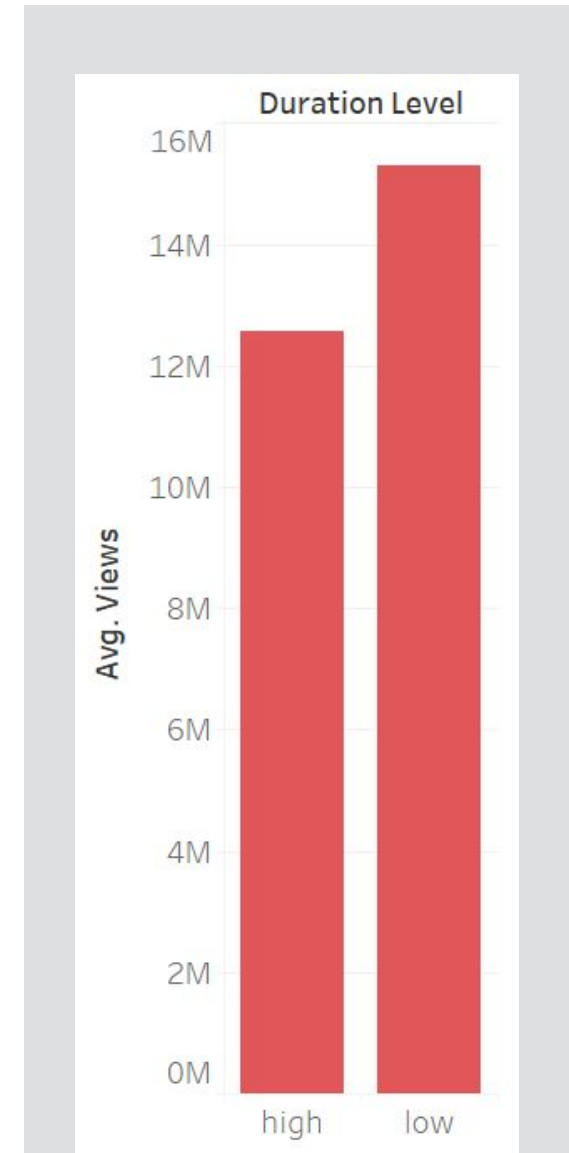
High level

Duration <= 60

Low level

T-test Result

		Levene's Test for Equality of Variances	
		F	Sig.
views	Equal variances assumed	23.116	.000
	Equal variances not assumed		
engagement rate	Equal variances assumed	1.168	.280
	Equal variances not assumed		



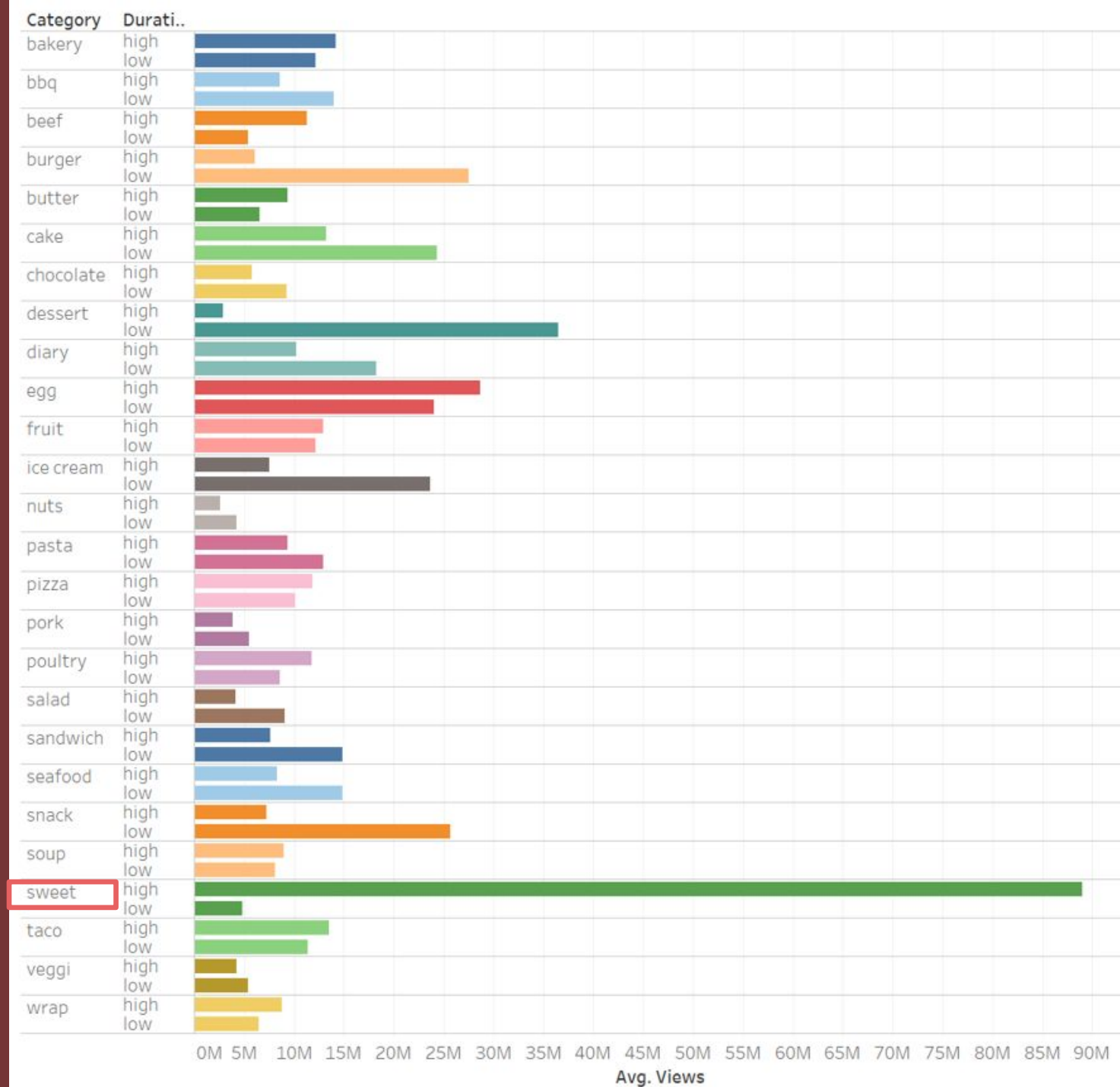
When comparing these two levels, there is significant difference on views, but there is no significant difference on engagement rate.

KPIs vs. duration

For most categories:

- Views and duration level are *negatively* correlated

SWEET category is an exception!



LOOKING AT VIDEOS THAT ARE “STICKY”



Definition: Videos that continues captivating attention after 30 days of posting are considered as “Sticky” videos.



Daily Growth Rate of Engagement after Day 30*

$$\left[\left(\frac{\text{Total Engagement}}{\text{Engagement in the first 30 days}} \right)^{\frac{1}{\text{New Observation Period Length}}} \right] - 1$$



Daily Growth Rate of Views after Day 30*

$$\left[\left(\frac{\text{Total Views}}{\text{Views in the first 30 days}} \right)^{\frac{1}{\text{New Observation Period Length}}} \right] - 1$$



- Four Stickiness Levels:**
- Winning Streak**
 - Nice Shot**
 - Average Performer**
 - Flash**

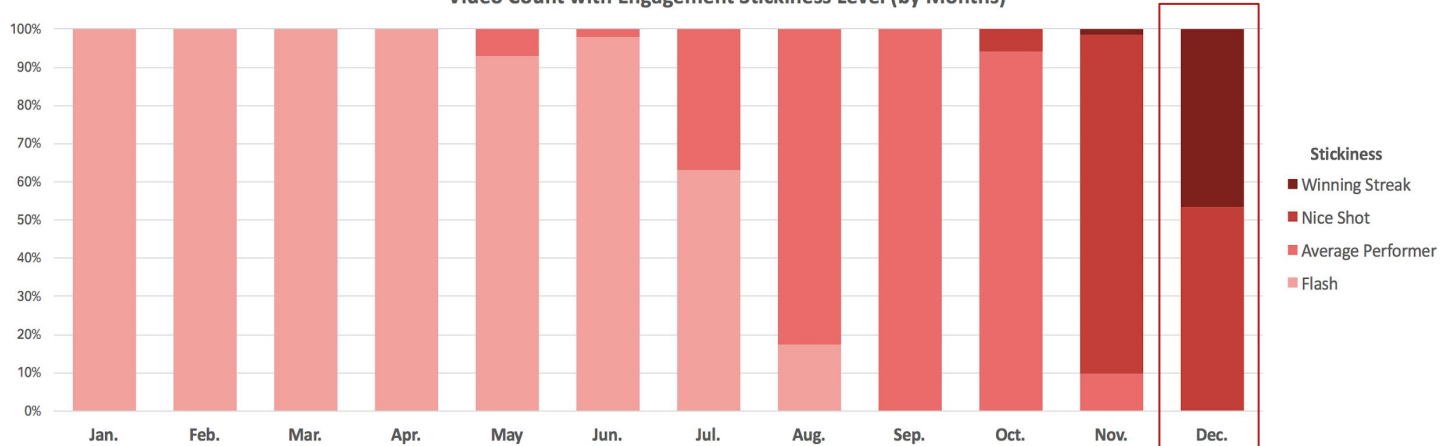
Category Data Source: Socialbakers_FB
Variables Source: 10K records from Tubular
Effective Results:: 824 rows*



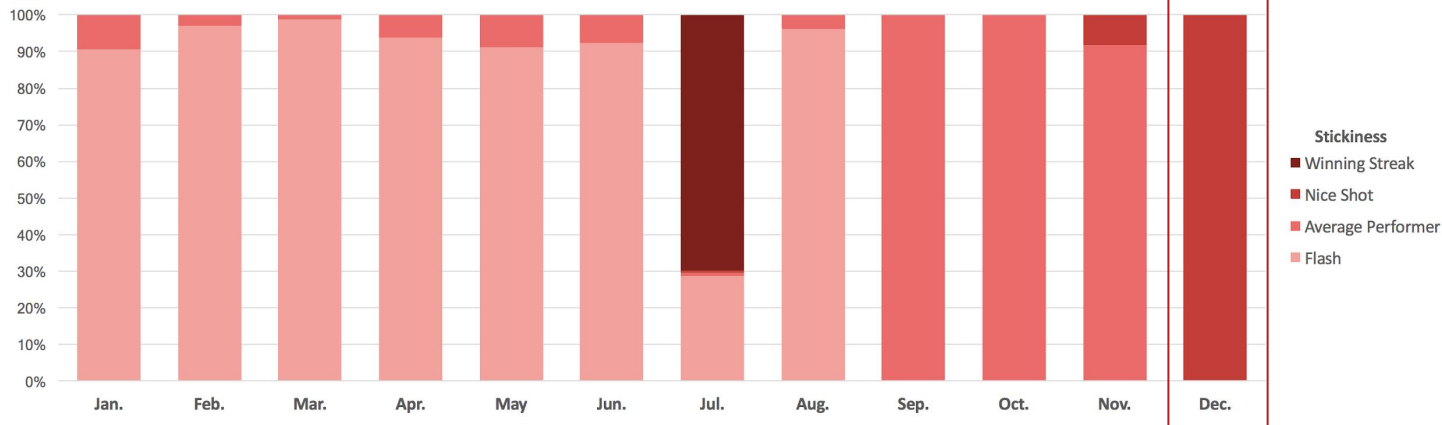


Hypothesis: Stickiness is relative to video posted month.

Video Count with Engagement Stickiness Level (by Months)



Video Count with View Stickiness Level (by Months)



Finding:
Videos posted in the late few months of the year have higher stickiness.



Hypothesis: Certain categories tend to have higher stickiness



Finding:

More videos in **Cake** and **Bakery** categories have high stickiness.

*The average stickiness of "How to" videos is Lower than videos without "How to" in title.



Analysis of Sponsored vs. Non-sponsored Videos



5





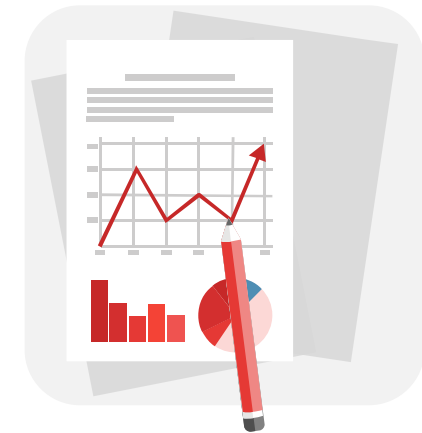
KPIs being discussed

- Status of video-Sponsored vs. Non-sponsored
- Views
- Engagement Rate
- Categories



Hypotheses

- “Sponsored videos will have fewer views (or lower Engagement rate) than non-sponsored videos.”
 - Rationale: viewers may assume that sponsored videos have a bias toward their product and service and be less engaged.



Methodology

- Test- to test the significance
- Tableau for result visualization

DOES VIDEO STATUS AFFECT ENGAGEMENT?



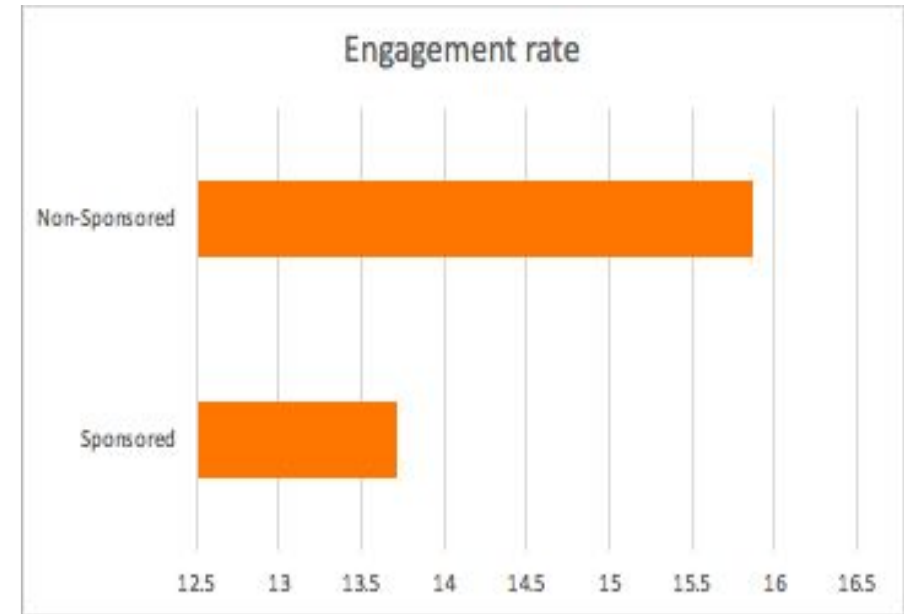
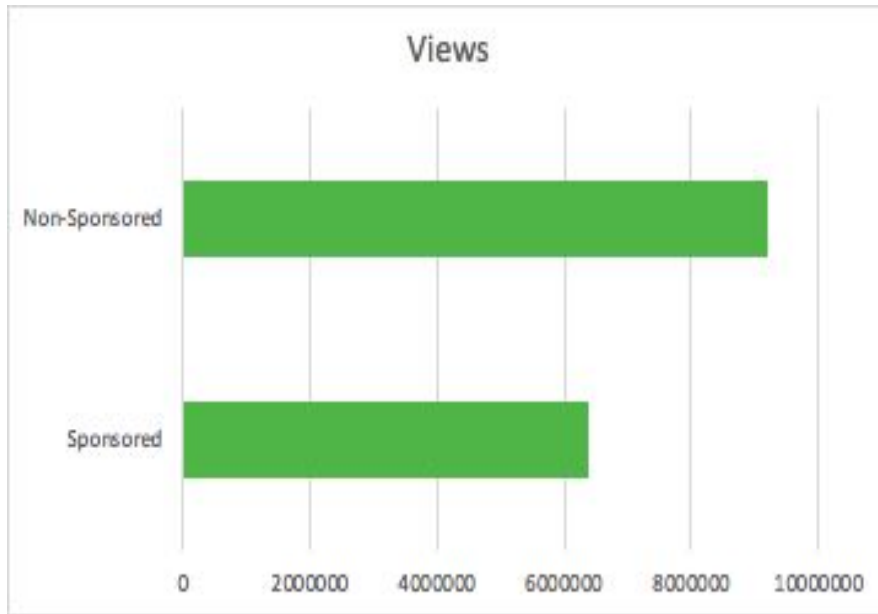
	SponsoredStatus	N	Mean	Std. Deviation	Std. Error Mean
Engagement Rate	0	1226	15.8706191	8.75328280	.249991778
	1	30	13.7149747	7.82182642	1.42806359
Views	0	1226	9196239.25	11562929.2	330234.642
	1	30	6365116.00	5982782.50	1092301.64

No significant difference in the KPIs of the 2 types of videos

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Engagement Rate	Equal variances assumed	.461	.497	1.336	1254	.182	2.15564437	1.61378497	-1.0103718	5.32166058
	Equal variances not assumed			1.487	30.804	.147	2.15564437	1.44977981	-.80196400	5.11325274
Views	Equal variances assumed	1.746	.187	1.336	1254	.182	2831123.25	2118595.14	-1325258.6	6987505.12
	Equal variances not assumed			2.481	34.537	.018	2831123.25	1141130.05	513394.955	5148851.54

DO VIEWERS LIKE NON-SPONSORED MORE THAN SPONSORED POSTS ON THEIR SOCIAL FEEDS?



- **Non-sponsored videos** perform slightly better in views (30.7%) and engagement rate (15.3%) than sponsored videos
- Since there is no significant difference in the views and engagement rate, focus on the sponsored group would be equally beneficial
 - They perform equally well and can be further leveraged

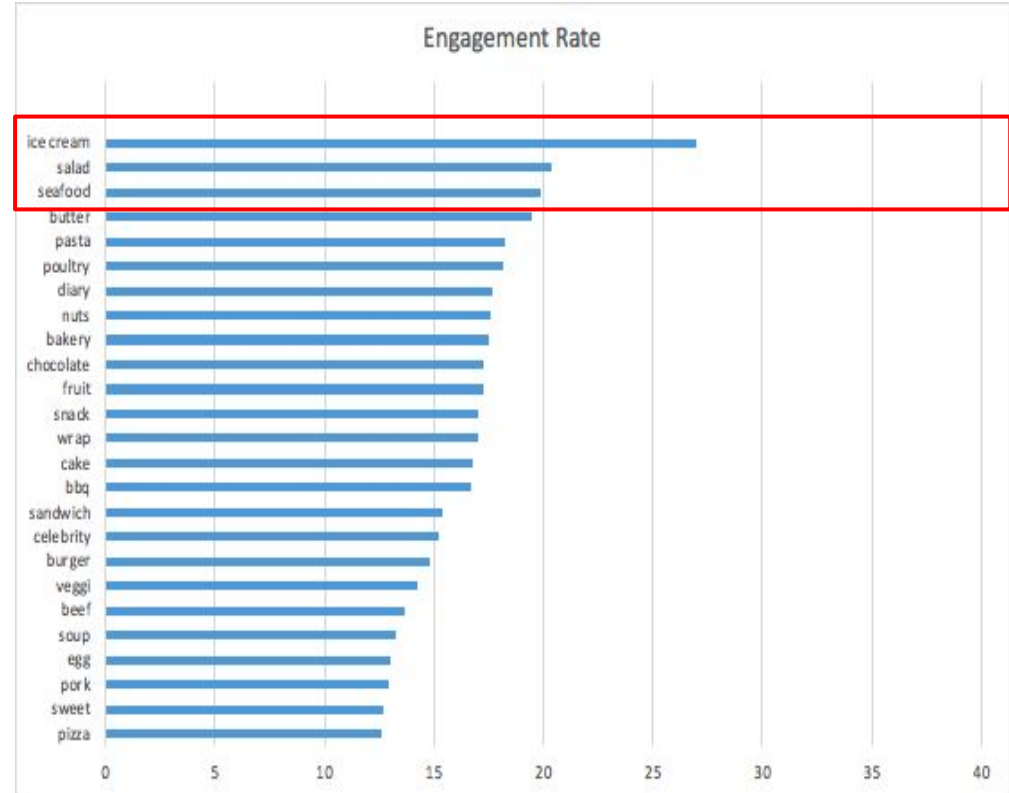
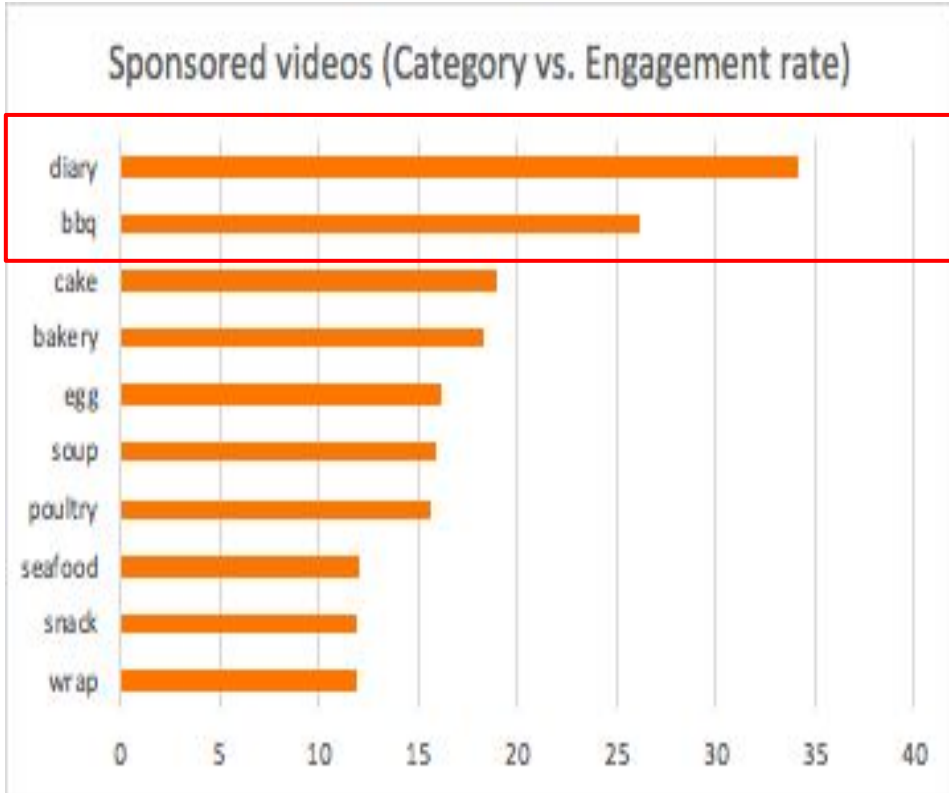
NURTURE VIEWS AND ENGAGEMENT WITH FOCUS ON TOP PERFORMING CATEGORIES



Categories of Sponsored videos

VS.

Categories of Non-Sponsored videos



- While maintaining focus on the top performing videos, company can also upload more videos that has a good overall engagement rate (including both sponsored and non-sponsored)
 - Such as Ice-cream, salad, seafood, pasta, dairy etc.

6

Conclusion



PRESENTATION OBJECTIVES

Develop strategies to build audience on social media

After today, we hope to help you:

- Forecast future views and engagement rates
- Create more engaging titles for video posts
- Take advantage of the most effective publishing times
- Better manage posts through categorization
- Exploit the potential of sponsored videos



TO CONCLUDE THE PRESENTATION



1

Optimistic future forecast!

2

**More posts after 2pm to generate more views.
More variety in title development!**

3

Identified *View Generators* and *View Boosters*, as well as months that people feel more “engaging”.

4

**27 categories are generated
Ice cream and salad are high potential categories;
Cake category has the highest stickiness
Low duration videos has higher views**

5

Sponsored videos would be a great potential focusing on categories with high engagement



THANK YOU
Q&A

