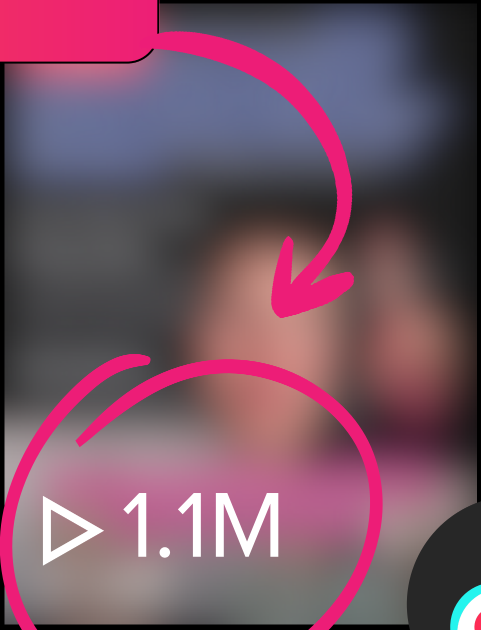
HOW WE HACKED TIKTOK TO GET

1,000,000 views

IN 14 DAYS!



AND YOU CAN TOO

THIS IS A REALLY F*CKING COOL STATISTICAL ANALYSIS

Made for anyone who posts on social media.

But... it's really long, and super detailed... with a lot of math.

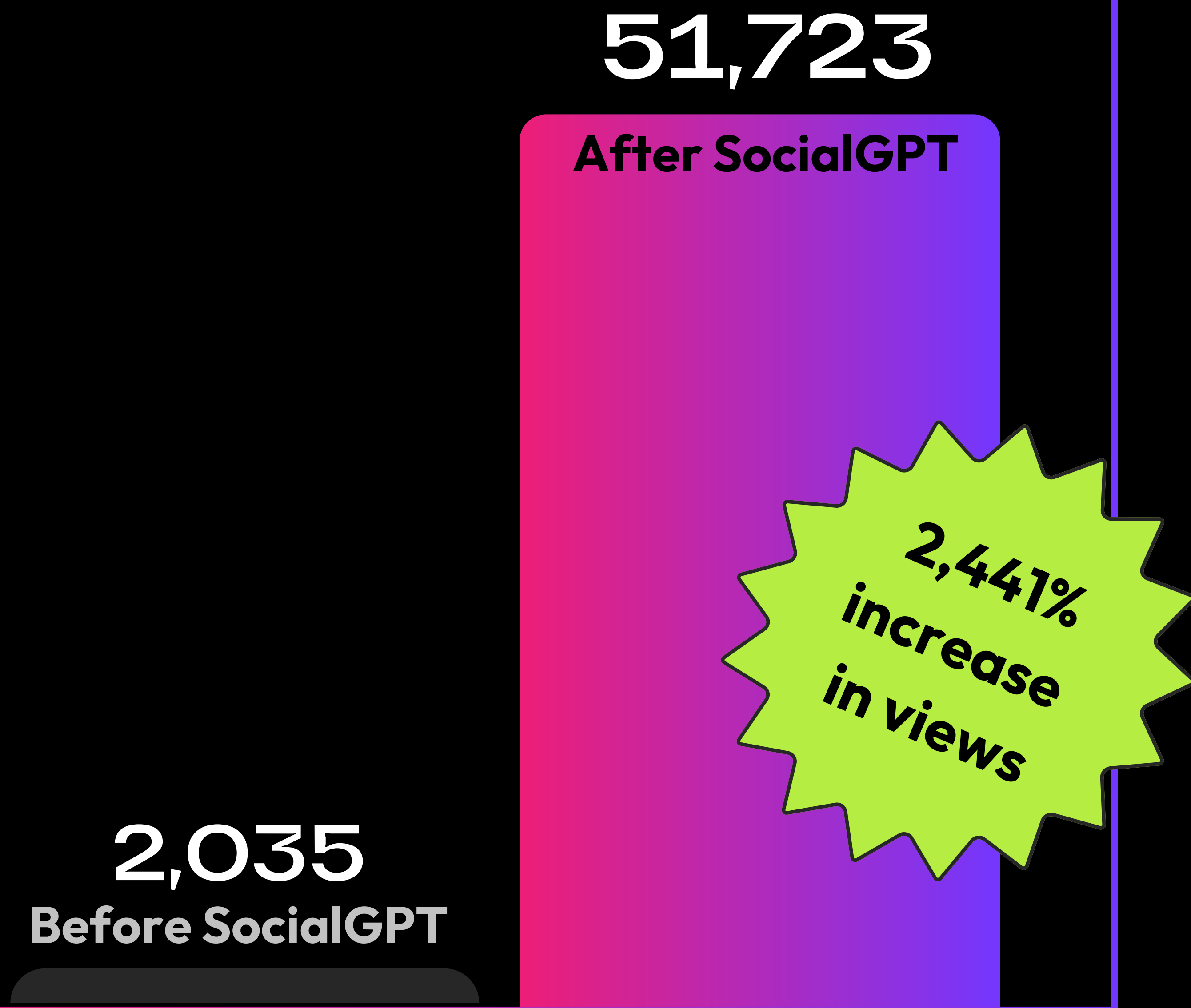
This is the data we use to hack a TikTok account.

Want us to do it for you?

sales@scrollmark.com

NO, FOR REAL.

Here are the average views we had, before optimizing using our growth-hacking algorith, and after.



AVG. TIKTOK VIEWS

IT WORKS.

WE CRACKED FYP

Most marketers feel like TikTok virality is random. ***So we tested it.*** By analyzing 31 videos across every metric, we reverse-engineered what really drives reach and engagement.

In 14 days, our latest video got 1.1M+ views.

HERE'S THE EXACT FRAMEWORK SO YOU CAN DO IT TOO.

Templates Included

HOW WE DID IT.

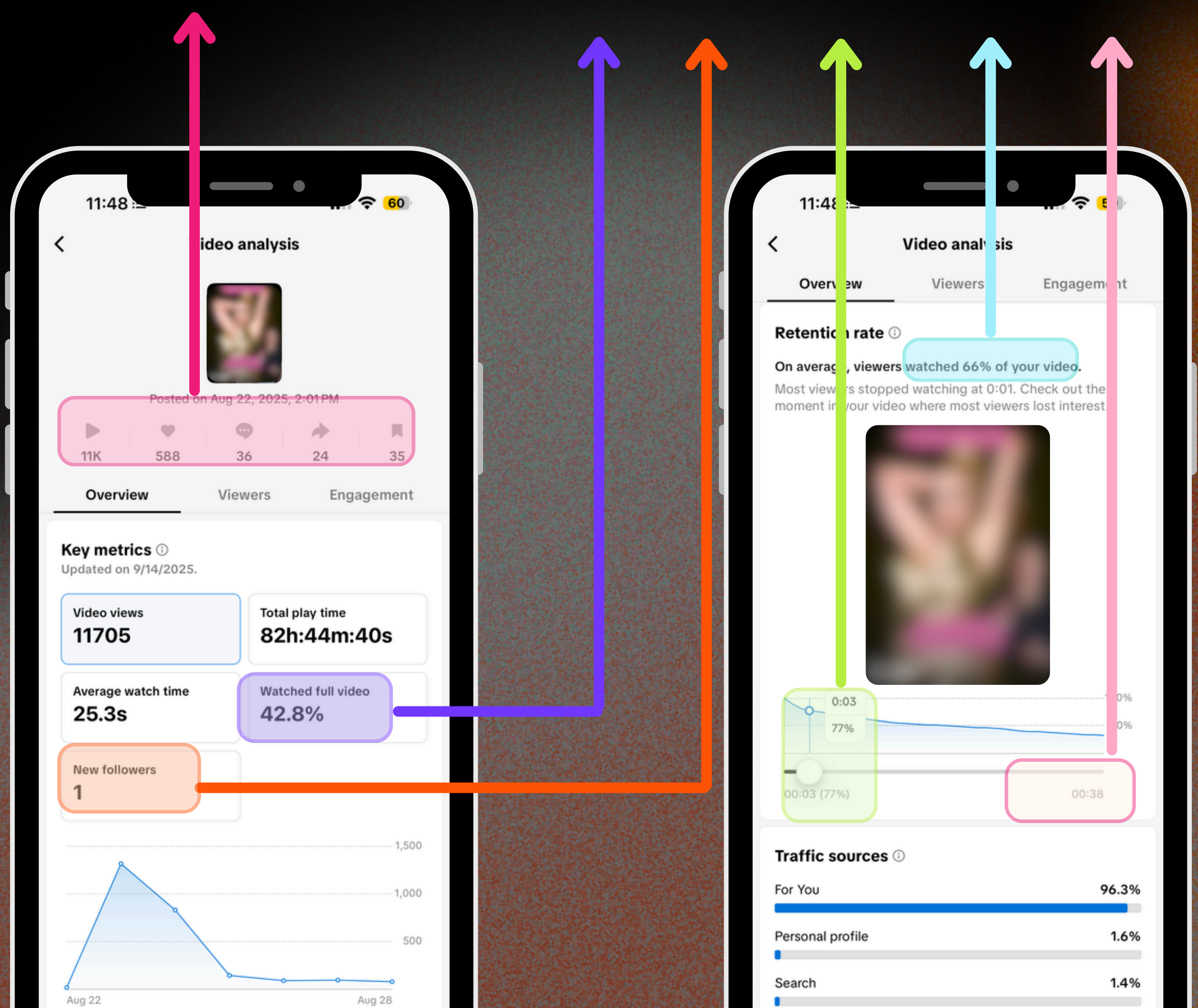
FIRST THING'S FIRST. GRAB YOUR DATA.

We took the **31 most recent videos on our channel** and pulled the most important metrics directly from TikTok analytics, to end up with a table like **below**.

We used correlation + regression analysis to see which metrics actually map to reach and engagement. Then we built a framework you can copy, test, and scale.

Don't worry, we'll walk you through how to compute the relevant correlations!

Views	Likes	Comments	Shares	Saves	Watched Full Video	New Followers	0:03s Retention	Retention	Duration
11k	588	36	24	35	42.8%	1	77%	66%	0:38

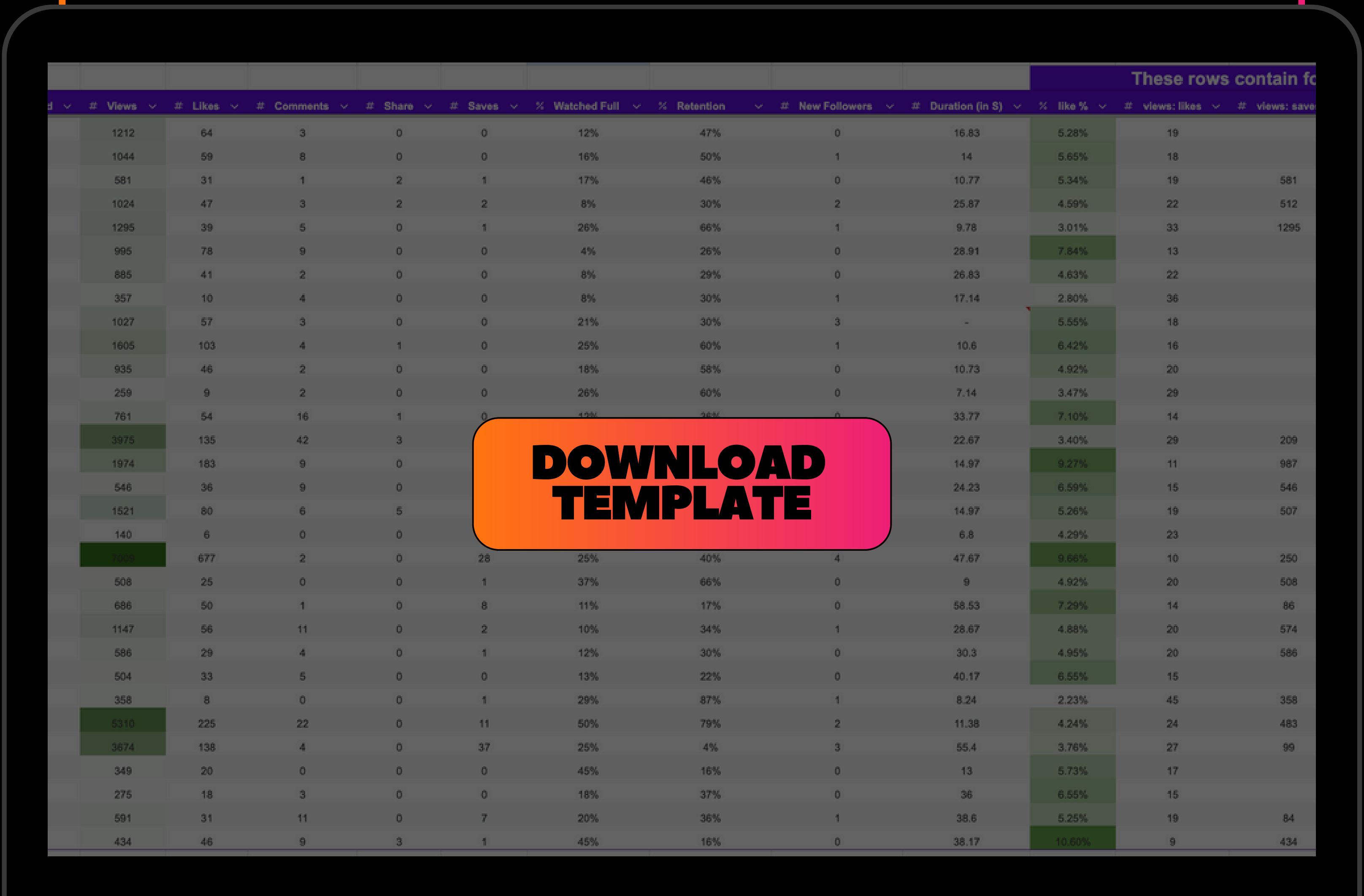


USE OUR TEMPLATE.

We crafted a template to help! Click the button below to download our table template.

Then, open TikTok, navigate to "Analytics", and start entering in your video data.

Yes, it's tedious :(If you'd like to skip this part, use **SocialGPT** to read your data and compute this analysis automatically!



									These rows contain fo		
# Views	# Likes	# Comments	# Share	# Saves	% Watched Full	% Retention	# New Followers	# Duration (in S)	% like %	# views: likes	# views: save
1212	64	3	0	0	12%	47%	0	16.83	5.28%	19	
1044	59	8	0	0	16%	50%	1	14	5.65%	18	
581	31	1	2	1	17%	46%	0	10.77	5.34%	19	581
1024	47	3	2	2	8%	30%	2	25.87	4.59%	22	512
1295	39	5	0	1	26%	66%	1	9.78	3.01%	33	1295
995	78	9	0	0	4%	26%	0	28.91	7.84%	13	
885	41	2	0	0	8%	29%	0	26.83	4.63%	22	
357	10	4	0	0	8%	30%	1	17.14	2.80%	36	
1027	57	3	0	0	21%	30%	3	-	5.55%	18	
1605	103	4	1	0	25%	60%	1	10.6	6.42%	16	
935	46	2	0	0	18%	58%	0	10.73	4.92%	20	
259	9	2	0	0	26%	60%	0	7.14	3.47%	29	
761	54	16	1	0	[illegible]	[illegible]	0	33.77	7.10%	14	
3975	135	42	3	[illegible]	[illegible]	[illegible]	[illegible]	22.67	3.40%	29	209
1974	183	9	0	[illegible]	[illegible]	[illegible]	[illegible]	14.97	9.27%	11	987
546	36	9	0	[illegible]	[illegible]	[illegible]	[illegible]	24.23	6.59%	15	546
1521	80	6	5	[illegible]	[illegible]	[illegible]	[illegible]	14.97	5.26%	19	507
140	6	0	0	[illegible]	[illegible]	[illegible]	[illegible]	6.8	4.29%	23	
[illegible]	677	2	0	28	25%	40%	4	47.67	9.66%	10	250
508	25	0	0	1	37%	66%	0	9	4.92%	20	508
686	50	1	0	8	11%	17%	0	58.53	7.29%	14	86
1147	56	11	0	2	10%	34%	1	28.67	4.88%	20	574
586	29	4	0	1	12%	30%	0	30.3	4.95%	20	586
504	33	5	0	0	13%	22%	0	40.17	6.55%	15	
358	8	0	0	1	29%	87%	1	8.24	2.23%	45	358
5310	225	22	0	11	50%	79%	2	11.38	4.24%	24	483
3674	138	4	0	37	25%	4%	3	55.4	3.76%	27	99
349	20	0	0	0	45%	16%	0	13	5.73%	17	
275	18	3	0	0	18%	37%	0	36	6.55%	15	
591	31	11	0	7	20%	36%	1	38.6	5.25%	19	84
434	46	9	3	1	45%	16%	0	38.17	10.60%	9	434

RUN A CORRELATION ANALYSIS. (OR USE AI TO RUN IT)

Once your data is in the spreadsheet, you need to see which metrics actually drive reach and engagement.

We ran both a rank-based (Spearman) and linear (Pearson) correlations, plus a standardized regression to see relative "weights."

Don't be scared! If you have no idea what that means, we have a copy-paste ready AI prompt for you to use which will compute it for you, and draw conclusions.
Skip to the next page.

In case you're curious

What is Spearman's Correlation?

What is it?

Tests monotonic relationships (how things move together in rank order).

Why it matters

Tells us if higher saves = higher views, even if not perfectly linear.

What is Pearson's Correlation?

What is it?

Tests linear relationships (straight-line fit).

Why it matters

Shows how strongly two metrics move together in raw values.

You are a data analyst for social video. I will upload a CSV exported from a TikTok analytics spreadsheet.
Please analyze it end-to-end and return a marketer-friendly report with clear conclusions and next actions.

DATA EXPECTATIONS & MAPPING

Columns may be named slightly differently. First, standardize to these canonical names (ask me to map if missing):
- video_title
- date_posted
- views
- likes
- comments
- shares
- saves
- new_followers
- duration_s (duration in seconds; if in mm:ss, convert to seconds)
- watched_full_rate (as a fraction or %, e.g., 0.28 or 28%)
- retention_rate (avg watch time / duration; fraction or %)
- category (free text like "pop culture", "dance", etc.)

If any column is absent, ask me for the correct mapping before continuing. Strip thousands separators, coerce numerics, and treat % strings as percentages. Drop rows with views <= 0. Keep a copy of the cleaned dataset for reference.

DERIVED METRICS (add these columns)

- like_rate = likes / views
- comment_rate = comments / views
- share_rate = shares / views
- save_rate = saves / views
- follow_rate = new_followers / views
- engagement_rate_public = (likes + comments + shares) / views
- engagement_rate_all = (likes + comments + shares + saves) / views (use this as "Engagement_Rate" in the report)

ANALYSES TO RUN

A) Correlations (report both Spearman and Pearson):
Targets:
1) Views (reach)
2) Engagement_Rate (use engagement_rate_all)
Features to test (include only if present): duration_s, retention_rate, watched_full_rate, like_rate, comment_rate, share_rate, save_rate, follow_rate, and one-hot encoded category dummies (e.g., cat_pop_culture).
Output two neatly formatted tables:
- Table 1: Correlation with Views (Feature, Pearson_r, Spearman_rho)
- Table 2: Correlation with Engagement_Rate (Feature, Pearson_r, Spearman_rho)

B) Standardized multiple linear regression predicting Views:
- Standardize (z-score) numeric predictors.
- Include the same features listed above (avoid perfect multicollinearity with category dummies).
- Report standardized coefficients (betas) in descending magnitude with 95% CIs if possible.
- Name this "Table 3: Standardized Coefficients Predicting Views".
- Briefly discuss collinearity and how it can flip signs for overlapping signals.

C) Category performance summary:
- Group by category and report: posts (n), avg_views, median_views, avg_engagement_rate, avg_save_rate, avg_duration_s.
- Name this "Table 4: Category Performance Summary".

D) Benchmarks:
- For key metrics (duration_s, retention_rate, watched_full_rate, engagement_rate_all, like_rate, share_rate, comment_rate, save_rate), compute median, 75th percentile, and max.
- Name this "Table 5/6: Key Metric Benchmarks (Median / P75 / Max)".

E) Visuals (only if the environment supports plotting):
- Scatter: Views vs duration_s
- Scatter: Views vs retention_rate
- Scatter: Views vs watched_full_rate
- Scatter: Views vs save_rate
- Scatter: Engagement_Rate vs watched_full_rate
For each, add a LOWESS or linear trendline and a one-sentence takeaway in plain English.
If plotting is not possible, provide a short textual interpretation.

QUALITY CHECKS

- Show row count, date range, and % of rows with missing data for key fields.
- If any metric is extremely skewed, note it and avoid over-interpreting tiny samples.
- Do not drop “low view” rows unless views == 0; instead, call them out as potential noise.
- If unit detection finds % vs fraction inconsistencies, fix and state what you did.

EXECUTIVE SUMMARY (WRITE FOR MARKETERS)

Start the report with a one-page brief that a non-technical marketer can act on:
- Top 3 positive drivers of Views with plain-English explanations and numbers (e.g., “Save rate (Spearman ~0.40) tracks with higher reach”).
- Top 3 negative or neutral drivers of Views.
- Top 3 positive drivers of Engagement_Rate and 2–3 negatives (e.g., longer videos may raise interactions per view while lowering completion).
- Clear targets based on the 75th percentile: recommended length range, retention target, watched-full target, save-rate goal.
- Category advice: which categories to double down on vs. retire or reframe.
- A short “what to try next week” checklist (runtime target, hook for saves, cadence of micro-payoffs, end-of-video prompt).

FINAL OUTPUT FORMAT
----

1) Executive Summary (bullets + one short paragraph narrative)
2) Table 1: Correlation with Views (Pearson, Spearman)
3) Table 2: Correlation with Engagement_Rate (Pearson, Spearman)
4) Table 3: Standardized Coefficients Predicting Views
5) Table 4: Category Performance Summary
6) Tables 5/6: Key Metric Benchmarks (Median / P75 / Max)
7) Visuals with captions (if supported)
8) Caveats (sample size, outliers, collinearity, measurement bias)

NOTES

- Keep explanations simple (“what it means” and “what to do with it”).
- Use percentages with one decimal place where helpful.
- If the dataset is very small (<25 posts), include a caution about statistical stability and treat results as directional.
- If anything critical is missing, pause and ask for clarification before proceeding.

Copy this massive prompt

Once you do that, you’ll get a report that looks something like the following pages.

Want us to do it for you?

sales@scrollmark.com

WHAT DRIVES VIEWS?

WHAT DRIVES VIEWS?

Now let's look at real data.

TOP POSITIVE DRIVERS OF REACH (IN OUR TEST ACCOUNT)

The GOOD Stuff

- **Save Rate (ρ = 0.41)**: In our dataset, saves showed the strongest relationship to reach. Videos that people saved were consistently the ones pushed further.
- **Follow Rate (ρ = 0.40)**: When a video led to new follows, it almost always correlated with high reach.
- **Pop Culture Content (ρ = 0.22)**: Videos tied to cultural or topical moments outperformed other categories.
- **Duration (ρ = 0.21)**: Longer runtimes actually helped reach in this dataset, even though TikTok advice often leans toward "shorter is better."

Feature	Target	Pearson_r	Spearman_rho
Save_Rate	Views (Reach)	0.38	0.41
Follow_Rate	Views (Reach)	0.03	0.4
cat_pop culture	Views (Reach)	0.39	0.22
Share_Rate	Views (Reach)	-0.05	0.22
Duration_s	Views (Reach)	0.29	0.21
Retention_Rate	Views (Reach)	0.06	0.09
Like_Rate	Views (Reach)	0.22	0.08
cat_carosaul	Views (Reach)	-0.04	0.07
Watched_Full_Rate	Views (Reach)	0.33	0.03
cat_personality	Views (Reach)	-0.09	0.01
Comment_Rate	Views (Reach)	-0.17	0
cat_moment in my life	Views (Reach)	-0.06	0
cat_dance	Views (Reach)	-0.26	-0.16
cat_360 camera	Views (Reach)	-0.14	-0.29

Surprising!

General TikTok advice says "the shorter the better".

Our analysis showed longer videos were more positively linked to higher reach.

WHAT DRIVES VIEWS?

Now let's look at real data.

NEUTRAL/MIXED SIGNALS (IN OUR TEST ACCOUNT)

The WEIRD Stuff

- **Retention (ρ = 0.09) and Watched-Full (ρ = 0.03)**: These didn't map clearly to reach on their own. Some high-completion videos did well, others didn't — suggesting these only matter in combination with other factors.
- **Likes (ρ = 0.08)**: Likes-per-view weren't a strong predictor of distribution.
- **Comments (ρ = 0.0):** Comments had truly no correlation with reach. They're important for community engagement, but don't drive views at all... at least not for our test account.

NEGATIVE ASSOCIATIONS (IN OUR TEST ACCOUNT)

The BAD Stuff

- **Dance (ρ = –0.16) and 360 Camera (ρ = –0.29):** These categories underperformed in our test account.

Feature	Target	Pearson_r	Spearman_rho
Save_Rate	Views (Reach)	0.38	0.41
Follow_Rate	Views (Reach)	0.03	0.4
cat_pop culture	Views (Reach)	0.39	0.22
Share_Rate	Views (Reach)	-0.05	0.22
Duration_s	Views (Reach)	0.29	0.21
Retention_Rate	Views (Reach)	0.06	0.09
Like_Rate	Views (Reach)	0.22	0.08
cat_carosaul	Views (Reach)	-0.04	0.07
Watched_Full_Rate	Views (Reach)	0.33	0.03
cat_personality	Views (Reach)	-0.09	0.01
Comment_Rate	Views (Reach)	-0.17	0
cat_moment in my life	Views (Reach)	-0.06	0
cat_dance	Views (Reach)	-0.26	-0.16
cat_360 camera	Views (Reach)	-0.14	-0.29

Surprising!

General TikTok advice says to bait for comments.

Our analysis shows comments had truly no correlation with reach, literally had zero effect (positive or negative).

TL;DR

In our test account, to get better **reach**:

- We have to target saves & follows. When people save our videos, and follow us, we get better reach.

- Our ideal video length is 25-35 seconds. Shorter videos did worse!

WHAT WE DID WITH THIS DATA

- We started baiting for saves. *i.e. 'save this video for the next time you go shopping for kitchen-gadgets'*
- We stopped posting videos shorter than 25 seconds.
- We added "follow us" CTAs i.e. '*follow us for more unbelievable pop-culture facts*'

Important note: Every TikTok account is different. You'll find that your account different metrics to target. That's why you need to run this analysis yourself on your own data!

WHAT DRIVES ENGAGEMENT?

WHAT DRIVES ENGAGEMENT?

Now let's look at real data.

(IN OUR TEST ACCOUNT)

TOP POSITIVE DRIVERS OF ENGAGEMENT

The GOOD Stuff

- **Duration (Spearman 0.56)** In this dataset, the longest videos generate the most engagement per view. Probably because longer content creates more "surface area" for comments, jokes, or shares.
- **Pop culture content (0.37)** Just like with reach, topicality drives audience energy. Pop culture themes fuel engagement-heavy discussions.

NEUTRAL/MIXED SIGNALS (IN OUR TEST ACCOUNT)

The WEIRD Stuff

- **Personality (0.06)** Engagement rate is neither strongly helped nor hurt by personality-style videos in this dataset.
- **Carousel (0.02) and Moment in my life (–0.09)** Statistically flat. These don't move the needle much.

Feature	Target	Pearson_r	Spearman_rho
Duration_s	Engagement_Rate	0.52	0.56
cat_pop culture	Engagement_Rate	0.41	0.37
cat_personality	Engagement_Rate	0.06	0.06
cat_carosaul	Engagement_Rate	-0.03	0.02
cat_moment in my life	Engagement_Rate	-0.1	-0.09
cat_360 camera	Engagement_Rate	-0.19	-0.25
cat_dance	Engagement_Rate	-0.36	-0.31
Watched_Full_Rate	Engagement_Rate	-0.26	-0.32
Retention_Rate	Engagement_Rate	-0.34	-0.34

Surprising!

Once again, longer videos generated the most engagement!

That means, long videos are great for this account, not just to drive views, but also to drive likes, comments, shares, and saves.

WHAT DRIVES ENGAGEMENT?

Now let's look at real data.

NEGATIVE ASSOCIATIONS (IN OUR TEST ACCOUNT)

The BAD Stuff

- **Dance content (–0.31)** Dance posts actively lower engagement per view. They may get views (sometimes), but they don't invite interaction.
- **360 camera (–0.25)** Similarly weak for engagement.
- **Watched-Full Rate (–0.32) and Retention Rate (–0.34)** This is counterintuitive but important: ***videos with high completion/retention actually correlate with lower interaction per view***. This makes sense if you think about it: people who watch silently all the way through don't always like/comment/save. The ones sparking conversation are often messier, punchier, or polarizing... they might interrupt watch-through but boost engagement.

Feature	Target	Pearson_r	Spearman_rho
Duration_s	Engagement_Rate	0.52	0.56
cat_pop culture	Engagement_Rate	0.41	0.37
cat_personality	Engagement_Rate	0.06	0.06
cat_carosaul	Engagement_Rate	-0.03	0.02
cat_moment in my life	Engagement_Rate	-0.1	-0.09
cat_360 camera	Engagement_Rate	-0.19	-0.25
cat_dance	Engagement_Rate	-0.36	-0.31
Watched_Full_Rate	Engagement_Rate	-0.26	-0.32
Retention_Rate	Engagement_Rate	-0.34	-0.34

Surprising!

Wait what?! Retention had a NEGATIVE correlation with engagement!

That means that if we're purely targeting engagement, ***retention doesn't matter***.

TL;DR

In our test account, to get better **engagement**:

- We need to double-down on our longer, more in-depth, pop-culture explainer videos.
- Other formats do NOT drive as much engagement.

WHAT WE DID WITH THIS DATA

- We completely cut out all other formats and only focused on pop-culture green-screen explainers.
- We also completely cut out our retention-focused video formats, as those didn't drive as much engagement.

Important note: Every TikTok account is different. You'll find that your account different metrics to target. That's why you need to run this analysis yourself on your own data!

STANDARDIZE LINEAR WEIGHTS

(PREDICTING VIEWS)

WHAT PREDICTS VIEWS?

HERE'S WHAT PREDICTS VIEWS:

Duration (0.84) By far the biggest driver of views. Longer videos in this dataset predict more reach, even stronger than saves or retention. This suggests TikTok rewarded your ~20–40s+ formats.

Retention Rate (0.46) → Strongly positive. Videos that people stick with (avg watch % vs total length) independently boost reach.

Watched-Full Rate (0.43) → Another strong positive. Completion still matters when modeled properly, even if it looked weak in the simple correlations.

Together, Retention + Watched-Full confirm: quality of watch time is a huge multiplier when duration is accounted for.

Share Rate (0.09) and Like Rate (0.07) → Small positives. Nice to have, but not the core engine.

Save Rate (–0.05) → This flips! Saves looked strong in correlation, but once you factor in duration/retention, they don't add unique explanatory power — they're overlapping with "good video" signals. Saves still matter to TikTok, but in this set they're not the independent driver.

Comment Rate (–0.08) → Slight negative. Higher comment density didn't push reach in this model (could even hurt, if those comments come on polarizing or niche posts).

Predictor	Std_Coefficient
Duration_s	0.84
Retention_Rate	0.46
Watched_Full_Rate	0.43
Share_Rate	0.09
Like_Rate	0.07
Save_Rate	-0.05
Comment_Rate	-0.08

WAIT WHAT?!

Saves looked great on their own, but their power is largely explained by the fact that saved posts were also longer and had higher completion rates. Duration + Retention are the real "muscles" under the hood.

WHAT THIS MEANS

- If we want reach, optimize for length + watch-through first.
    - → Longer runtimes with high completion % are the strongest drivers.

- Saves, likes, shares are still useful signals… but they're more like symptoms of a good video, not the root cause in your dataset.

- Comments don't correlate with reach. Treat them as community-building rather than algorithm fuel.

COMPARING BOTH MODELS.

Correlation with Views & Engagement (Pages 9-16)

What we learned

- Saves and follows correlated strongly with reach.
- Pop culture content consistently helped both reach and engagement.
- Duration showed a positive relationship with reach and engagement, longer videos outperformed the common “shorter is better” advice.
- Comments and likes didn’t meaningfully correlate with reach (they’re better treated as community signals than distribution drivers).

Predicting Views (Pages 17-19)

What we learned

- When modeled together, duration, retention, and watched-full rate were the strongest independent predictors of reach.
- Saves, while strong in simple correlations, lost independent weight once duration and watch-through were accounted for.
- In other words: saves and shares matter, but they overlap with the signals TikTok already gets from quality watch time.
- Comments showed a slight negative relationship here too, reinforcing that they don’t fuel distribution in this dataset.