# Follow Us and Become Famous! Insights and Guidelines From Instagram Engagement Mechanisms

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## ABSTRACT

With 1.3 billion users, Instagram (IG) has become an essential business tool. IG influencer marketing, expected to generate $33.25 billion in 2022, encourages companies and influencers to create trending content. Various methods have been proposed for predicting a post's popularity, i.e., how much engagement (e.g., Likes) it will generate. However, these methods are limited: first, they focus on forecasting the likes, ignoring the number of comments, which became crucial in 2021. Secondly, studies often use biased or limited data. Third, researchers focused on Deep Learning models to increase predictive performance, which are difficult to interpret. As a result, end-users can only estimate engagement after a post is created, which is inefficient and expensive. A better approach is to generate a post based on what people and IG like, e.g., by following guidelines.

In this work, we uncover part of the underlying mechanisms driving IG engagement. We rely on statistical analysis and interpretable models rather than Deep Learning (black-box) approaches to achieve this goal. Leveraging innovative domain-relevant features, we first build classifiers to predict posts' engagement. Then, we interpret the best models to determine which type of content will generate the most engagement, maximizing influencers' and companies' profits. We conduct extensive experiments using a worldwide dataset of 10 million posts created by 34K global influencers in nine different categories. Our simple yet powerful algorithms can effectively predict engagement, making us comparable and even superior to Deep Learning-based methods, reaching up to 94% F1-Score. Furthermore, we propose a novel unsupervised algorithm for finding highly engaging topics on IG. Thanks to our interpretable approaches, we conclude by outlining guidelines for creating successful posts.

*Both authors contributed equally to this research.


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## CCS CONCEPTS

• **Information systems → Social networks**; • **Computing methodologies → Machine learning**.

## KEYWORDS

Instagram, Engagement, Popularity, Interpretable AI, Social Networks, Post Popularity

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## 1 INTRODUCTION

People post photos on Instagram (IG) for many purposes, including conveying personal identity, nurturing relationships, feeling part of a community, and promoting worthwhile content [42]. Getting approval from others is highly rewarding, to the point that engagement metrics (e.g., Likes, Comments, Views) have become addictive, especially for low self-esteem people [27]. Some people use IG for only a few minutes daily, but for others, e.g., the influencers, it has become a way of life. In short, influencers are people who can influence society. Due to their ability to reach people, companies have used them to market their products [28], so much so that influencer marketing is estimated to generate $33.25 billion in 2022 [17, 18]. Whatever the reason, everyone strives to get as much engagement as possible under their posts, even at the cost of buying it [51, 53]. For influencers, planning popular posts is time-consuming and costly, with no guarantee of success. In this regard, a tool that can predict the popularity of a post in advance would be of great interest, especially when sponsored posts are highly remunerated (e.g, Cristiano Ronaldo is paid around $1 Million for a single post [5]).

Researchers have proposed algorithms for predicting the popularity of posts, but they are far from perfect (§2.1). The first limitation is they measure engagement only in terms of likes, not incorporating stronger forms of interaction or what IG favors, i.e., the number of comments [49]. Then, the lack of a universal dataset for such predictive tasks leads to outcomes based on limited or biased data. Furthermore, these models often make use of Deep Learning (DL) models that may be difficult (or even impossible) to interpret [15, 45]. As a result, end-users must *first* create the post

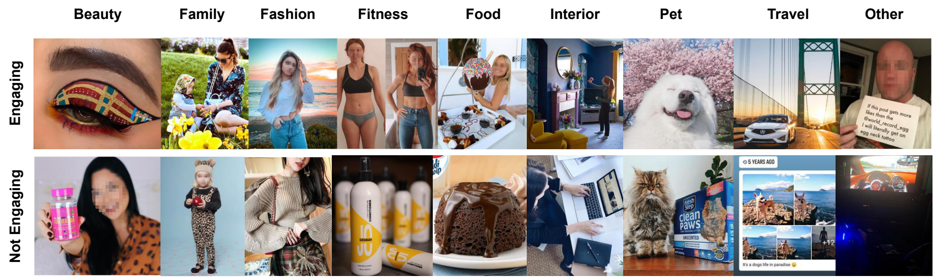



**Figure 1: Engaging and not engaging posts for each category.**

through an expensive and time-consuming process, and *then* assess posts' popularity using such black-box models.

**Contribution.** Our goal is to *understand* and *explain* the underlying mechanisms driving IG engagement. We extract domain-relevant features leveraging the well-known capabilities of DL models, but entrust the prediction to interpretable Machine Learning (ML) algorithms [32], allowing us to draw guidelines. According to the IG recommendation algorithm, we consider likes and comments as engagement metrics. We conduct extensive experiments on a recent dataset of 10M posts from 34K influencers. We demonstrate through statistical analysis that influencer tiers (i.e., their audience wideness) and categories (i.e., the primary topic they cover) are crucial to predict posts' popularity. Figure 1 shows engaging and non-engaging posts, which supports the intuition that the characteristics determining engagement differ by category.

Last, we propose a novel unsupervised approach to detect hot topics (i.e., highly engaging) for each category, which overcomes the need for domain knowledge to extract meaningful features. We summarize our contributions as follows:

- We analyze the underlying mechanisms of IG engagement, in terms of likes and comments, from a dataset of 10M posts, divided into nine categories and five tiers of influencers, leveraging statistical analysis and interpretable ML algorithms;
- We propose an interpretable model to predict posts' engagement and define handy guidelines, exploiting several features extracted by State-of-the-Art (SotA) Deep Learning models;
- We propose a novel unsupervised approach for spotting highly engaging topics in each tier and category, considering both visual and textual content;
- We release our enriched dataset upon request as a possible baseline for future works.

**Organization.** §2 presents related works. §3 describes the dataset and preliminary assessments, while the engagement prediction and interpretation are conducted in §4. The hot topic detection appears in §5, and the final guidelines are provided in §6. §7 concludes the paper.

**Transparency.** To promote transparency and reproducibility, we created a repository[1] containing exhaustive details on our study, the source code, and our dataset, which can be requested for research purposes only.

[1]https://github.com/spritz-group/FollowUs

## 2 RELATED WORKS

The popularity of IG posts has been mainly assessed by predicting the number of likes they received, usually divided by the number of followers of the posting user, or after a log-scaled transformation. Mazloom et al. [30] predicted the popularity of brand-related posts by defining engagement parameters important in marketing and using a Support Vector Regression. The authors extended further their work [29] for different categories such as activities, landscapes, people, and animals. De et al. [6] trained a Deep Neural Network (DNN) on posts' metadata (e.g., creation date, users tagged, hashtags) to predict the popularity of future posts of an Indian lifestyle magazine. Similarly, Zhourian et al. [59] approached popularity prediction as a regression and classification task, focusing on posts of Iranian business IG accounts. Rather than predicting popularity in general, Zhang et al. [57] implemented a dual-attention mechanism to predict user-specific posts' popularity. Ding et al. [8] tried to isolate the contribution of the visual content by predicting the intrinsic image popularity through a DNN. Gayberi et al. [11] extracted concepts and object features using a pre-trained model on Microsoft COCO Dataset [25] and used several Machine Learning algorithms to predict the likes of a post. Through transfer learning, Riis et al. [44] extracted visual semantics such as concepts, scenes, and objects and tried to set an explainable baseline for population-based popularity prediction. Carta et al. [3] proposed an approach based on Gradient Boosting and feature engineering of users' and posts' metadata to predict popularity in a classification fashion. Last, Purba et. al [40] attempted to create a global dataset of around 20K posts from 16K users and leveraged features extracted from hashtags, image analysis, and user history, predicting the number of likes over followers using a Support Vector Regression (SVR).

### 2.1 Limitations of Existing Literature

This section briefly describes why the past literature in the area is incomplete and how our work closes such gaps.

**Incomplete Popularity Metric.** Prior works focused *exclusively* on the number of likes to measure post popularity, which is outdated and discrepant with the current IG algorithm. The IG algorithm was changed in 2021 [49] to show users content based on their interests, not just their social graph. The shift to such *recommendation media* changed how posts became popular. The content *must* be engaged with, mainly through likes and comments, so that Instagram spreads it on many users' feeds, and only then it can become popular. Consequently, it is crucial to consider the number of comments as an indicator of engagement, given they result from a higher user effort than leaving a like [1], and thus are more relevant for the IG recommendation algorithm [49]. As far as we know, we are the first to include comments in our engagement metrics.

**Limited or Biased Dataset.** Since Meta's APIs[2] are limited, there are no public datasets to use as baselines. Most prior works collected their datasets, focusing on limited portions of the population [6, 59]. Moreover, except for Mazloom et al. [29], they do not consider the different categories and tiers of the creators. For example, a picture of a dog and a top model would become popular for different reasons. The influencer tier, instead, was not previously considered. However, the engagement rate of influencers with millions rather than a few thousand followers reaches different levels [12], and normalizing the metrics is insufficient. In §3.3, we demonstrate that influencer categories and tiers strongly influence engagement metrics ($p$-value<0.001) and thus need to be treated separately to yield accurate predictions.

**Poor Results Explanation.** As deep learning algorithms and ensemble machine learning algorithms have improved performance, recent works have largely relied on end-to-end black-box models [8, 44, 57] rather than extracting specific features to train simple regressors or classifiers [30, 59]. While the model is more accurate, it is difficult (or impossible) to understand what has been learned [15, 45, 46]. As extensively demonstrated in the landmark Nature paper by Rudin [45], interpretable models *must* be preferred to (complicated) black-box models when explainability is critical. Often, if the problem has structured data and meaningful features, there is no significant difference in performance between more complex classifiers (i.e., DNNs, ensemble methods) and simpler ones. We remind the reader that interpreting a model substantially differs from explaining it [9], as done by Riis et al. [44].[3] Furthermore, in our scenario, using a black-box model for post popularity means the user must create the post first, which can be extremely costly [5]. Thus, we use an interpretable model (i.e., a Decision Tree) to provide guidelines that can be followed *before* generating a post that wishes to gain popularity.

# 3 DATASET & PRELIMINARY ASSESSMENTS

In this section, we describe the dataset (§3.1), the engagement metrics (§3.2), the importance of dissecting the data in categories and inner tiers (§3.3), and the features we considered and extracted for the study (§3.4).

## 3.1 Dataset Description

In our work, we utilize the dataset proposed by Kim et al. [20] that contains 10,180,500 posts from 33,935 influencers collected in 92 days. The influencers are divided into nine categories, namely Beauty, Family, Fashion, Fitness, Food, Interior, Pet, Travel, and Other, depending on their content type. Furthermore, we categorize each influencer in the five well-known tiers based on their number of followers [51]: Nano [1K, 10K), Micro [10K, 50K), Mid [50K, 500K), Macro [500K,1M), Mega [1M, $+\infty$].

[2]https://developers.facebook.com/docs/instagram-api/

[3]Interpretability means that the cause and effect can be determined, while explainability indicates which parameters are linked to a prediction, explaining the phenomenon a posteriori, non-deterministically.

Each post is composed of the image, caption, metadata (e.g., publish time, location), and engagement metrics (i.e., the number of likes and comments)[4]. Similar to previous works [40, 44, 59], we normalize our target features (likes and comments) dividing them by the number of followers of the post's creator, allowing a fair comparison between posts of different users[5]. Given that creators' followers were taken only at the end of the collection, we remove posts older than thirty days, a period within the followers' growth remains mostly stable [35]. Moreover, since an IG post engagement growth usually last one to three days [12], we exclude posts younger than five days. In the end, our dataset counts 650,118 posts created by 33,935 influencers. Table 1 shows the number of posts (and influencers) per tier and category. The small presence of some categories (e.g., food, interior, pet) for very popular influencers is aligned with the actual IG categories distribution [16].

**Table 1: N. posts (influencers) for categories and tiers.**

| | Nano | Micro | Mid | Macro | Mega |
|---|---|---|---|---|---|
| **Beauty** | 8449 (546) | 7879 (537) | 6998 (387) | 745 (35) | 835 (37) |
| **Family** | 29744 (1887) | 23432 (1330) | 12740 (674) | 1267 (77) | 2145 (102) |
| **Fashion** | 49622 (3154) | 82895 (4841) | 68737 (3238) | 8833 (325) | 8987 (355) |
| **Fitness** | 5060 (301) | 6194 (424) | 6256 (342) | 352 (27) | 748 (39) |
| **Food** | 27697 (1511) | 28191 (1440) | 14805 (583) | 936 (25) | 305 (6) |
| **Interior** | 6461 (373) | 9606 (541) | 5525 (261) | 413 (13) | 404 (7) |
| **Pet** | 3416 (164) | 4073 (260) | 2929 (153) | 87 (6) | 115 (4) |
| **Travel** | 24445 (1774) | 19630 (1522) | 13098 (838) | 816 (49) | 540 (27) |
| **Other** | 73213 (2976) | 38967 (1454) | 31874 (1004) | 4255 (120) | 6399 (166) |

## 3.2 Engagement Metrics: Likes & Comments

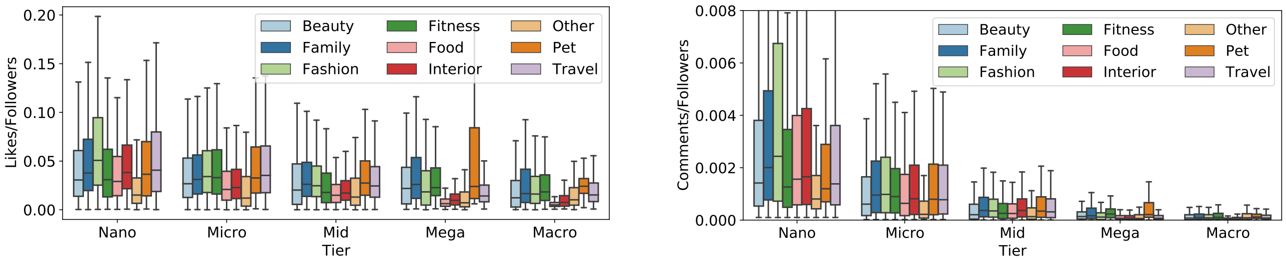
Prior works (§2) focused *exclusively* on the number of likes as a popularity metric. Nonetheless, since 2021, comments have become a crucial engagement metric to make a post popular [49]. Figure 2 shows the box plots of the likes and comments for every category and tier. There are some common trends, but commenting is less frequent than liking. Such discrepancy is justified by the two different levels of public expression they carry [1]. Comments are costly and expose users' opinions more, while likes are almost immediate and instinctive. Hence, a highly-liked post may not receive many comments. Further demonstrating the independence of the two metrics, we calculated Spearman correlation coefficients ($rho$) between the distributions of likes and comments. The result ($rho = 0.58$, $p$-value $< 0.001$) shows a moderate correlation between likes and comments, demonstrating that they need to be analyzed separately as two not-so-dependent phenomena. Thus, we consider as engagement metrics $\frac{\#Likes}{\#Followers}$ and $\frac{\#Comments}{\#Followers}$.

## 3.3 The Importance of Tiers and Categories

Do the Northern Lights create more engagement than a cute puppy? How about a pineapple pizza in Naples? As these concepts are incomparable, answering these questions a priori is difficult. Similarly, would people react analogously if a celebrity and a normal person divorced? Most likely not. Those are just a few examples behind our hypothesis: *influencers' tiers and categories significantly affect the*

[4]We did not further process these metrics, e.g., by removing spam comments, since IG algorithm accounts for quantity, and not quality [49].

[5]As a convenience, we refer to the normalized numbers simply as likes and comments.




**(a) Likes.** **(b) Comments.**

**Figure 2: Box plots of Likes and Comments for the different categories and tiers. Note that the y-axes have two different scales, giving a lower number of comments in general.**

*engagement metrics.* To demonstrate this hypothesis, we conduct a Multivariate ANOVA (MANOVA) [26], with category and tier as independent variables and the likes and comments as dependent ones. By such a statistical test, we can determine whether the mean scores of engagements differ between our nine categories and five tiers. Before conducting MANOVA, we normalize the likes and comment distributions as explained in §3.2. Among the MANOVA results, we adopted Pillai's trace test, which is robust when MANOVA assumptions are violated [50]. Pillai's trace test returned 0.0942 and 0.2646 for category and tier, respectively, with $p$-value < 0.0001. Since the $p$-value is less than the significance level $\alpha = .0001$, we reject the null hypothesis of the MANOVA and conclude that the explanatory variables (tier and category) significantly affect the values of the response variables (likes and comments). In particular, the tier resulted contributing more than the category.

## 3.4 Features Extraction

Starting from the filtered posts of §3.1, we augmented our dataset with features from each kind of data source, such as metadata, images, and text, which we now briefly describe.[6] In the process, we also employed nine SotA DL algorithms.

*3.4.1 Metadata Features.* The posts' metadata provides information on their "discoverability". This term refers to features that increase post visibility, like hashtags and mentions. Hashtags label the post's content, while mentions allow tagging someone in a post, so their followers can reach the source profile. Therefore, we created two counters to keep track of the number of hashtags and tagged users. In addition, we specify whether the post is a video, sponsored, has a location, and time-related information, for a total of 10 features.

*3.4.2 Images Features.* We extract features from images on multiple levels to fully describe the image content, including the scene, people, and aesthetic features.

**Scene features.** To describe the environment where the picture is set, we leverage the Places365 DL model [58]. The model can identify up to 365 places mapped to 3 macro categories (indoor, outdoor natural, outdoor man-made) and 16 micro categories (e.g., shopping/dining, transportation). Moreover, we perform object detection of 80 different classes mapped in 12 categories using Faster R-CNN MobileNetV3 [38]) trained on MS COCO dataset [25], counting the objects belonging to each category.

**People Features.** Using RetinaFace [7], we perform face boundaries detection and then estimate the age and gender [33] of the detected people. For each post, we save the number of females and males, and min, max, mean, and standard deviation of people's age. Furthermore, guided by the well-known impact of nudity in advertising [47], we perform nudity detection using NudeNet [37] for Beauty and Fashion categories, in which the main subject is the human body. The model determines whether 16 parts of the body (e.g., breast, belly, feet, buttocks) are exposed.

**Aesthetic features.** Taking inspiration from Guntuku et al. [4], we derive aesthetic features of the image. In particular, we first extract the percentage of red, green, and blue channels. Then, from the HSV (Hue, Saturation, Value) representation, we obtain the percentage of luminance, warm and cold colors, pleasure, arousal, and dominance scores [31, 52]. Furthermore, we leverage Kong et al. [21] model to obtain eleven high-level aesthetic features (e.g., color harmony, motion blur, content symmetry). Last, we extracted the sentiment score conveyed by the image through the model proposed by Campos et al. [2].

**Other features.** For the Pet category, we calculated pets' cuteness scores through a Cute Animal Detector [19]. In total, we obtained 80 visual features.

*3.4.3 Text Features.* From the posts' captions, we extracted features such as the caption length, the number of Emojis, and their relative sentiment [22]. Moreover, we retrieve the sentiment of the whole text leveraging Google Cognitive Services (GCP) [13], expressed as a score ($\text{Sentiment}_{\text{score}} \in [-1, 1]$, where $-1$ is negative, 0 is neutral, and +1 is positive) and magnitude ($\text{Sentiment}_{\text{magnitude}} \in [0, +\infty)$), that is representing the strength of the sentiment. We translated non-English text using GCP, and obtained five textual features in total.

# 4 PREDICT & INTERPRET THE ENGAGEMENT

Through correlation analysis, we uncover features that correlate with engagement. Then, we use interpretable models to predict engagement and develop guidelines for producing engaging content.

## 4.1 Correlation Analysis

To determine which features contribute the most to raising engagement, we correlate the features with our two engagement metrics

[6] The complete list of features is available in our repository.

(Likes and Comments). To this aim, we use Spearman's rank correlation coefficient $r_s$ [60]. This method offers the advantages of producing feature ranks, being insensitive to outliers, and not requiring any specific normalization of the data. The Spearman's correlation coefficient is based on Pearson's correlation coefficient [34] and it is defined as follows. For $n$ observations, the $n$ scores $X_i$, $Y_i X_i$, $Y_i$ are converted to ranks as $R(X_i)$ and $R(Y_i)$, and $r_s$ is computed as:

$$r_s = \rho_{R(X),R(Y)} = \frac{\mathrm{cov}(R(X), R(Y))}{\sigma_{R(X)}\sigma_{R(Y)}} \quad (1)$$

where $\rho$ denotes Pearson correlation coefficient but applied to the rank variables, $\mathrm{cov}(R(X), R(Y))$ is the covariance of the rank variables, $\sigma_{R(X)}$ and $\sigma_{R(Y)}$ are the standard deviations of the rank variables. As for Pearson's correlation coefficient, the Spearman correlation values are expressed in the range $r_s \in [-1, 1]$ along with their $\rho$-value that express their significance that is higher as much as the value is small.

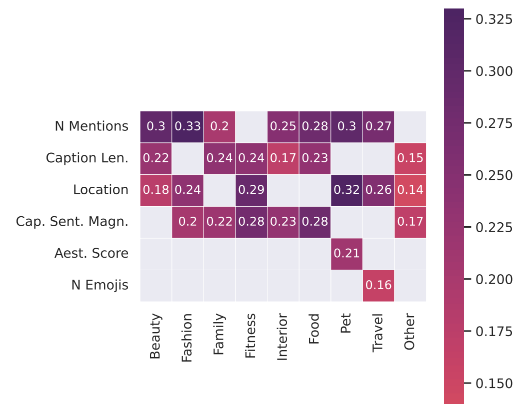
For each one of the influencers categories (i.e., beauty, fashion, etc.) and for each one of the tiers (i.e., nano, micro, etc.) we perform the correlation analysis of the features against the engagement metrics (Likes, Comments)[7]. Figure 3 reports the top-3 most correlated features to comment engagement for each category in the Nano and Mega tiers. We notice immediately how the most relevant features in different categories are very similar when the tiers are small (Nano in the figure, but also Micro). In contrast, behavior becomes category-specific as tier size increases (Mega in the figure, but also Macro). This behavior also occurs for likes. As we can see, small influencers, or users aspiring to become influencers, use similar strategies in every category. These include the use of many mentions, a long caption, and location tags.

**Likes Engagement.** By examining how features correlate to likes, it is possible to observe how the engagement mechanism differs for each type of influencer. Generally, we can notice that the strongest features are related to the images and their content rather than to the text (i.e., the caption), while almost the opposite occurs for the comments. The number of mentions generally has a positive impact on likes, even if their relevance decreases as tiers increase. A similar pattern can be observed in the number of hashtags having a negative effect, which tends to intensify in larger tiers. Availability of the location is very relevant up to the micro tier, after which it becomes category-specific.

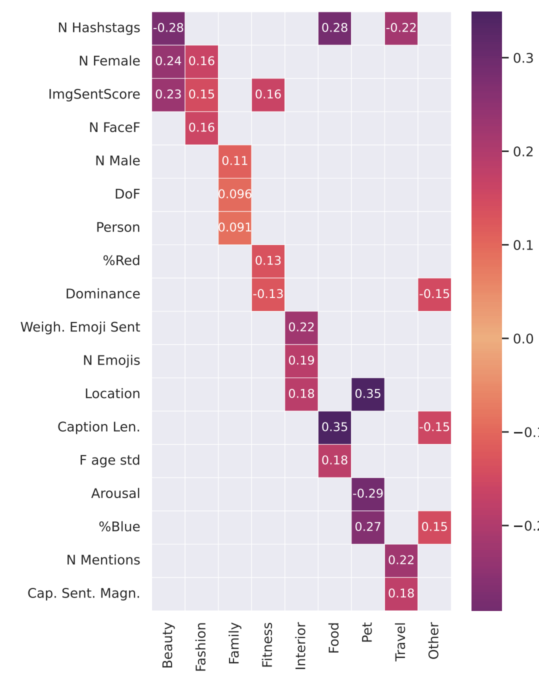
**Comments Engagement.** Similarly to the likes engagement, we observe an overall positive correlation for the number of mentions, even though the relevance goes decreasing as the tier increases. Even in this case, the number of hashtags plays an antagonist role in comments engagement, instead the presence of the location field in a post is generally helpful. This type of engagement benefits from text-specific features such as caption length, sentiment magnitude, and Emoji usage.

> ***Takeaway:*** *Likes engagement differs from Comments engagement in that they are oriented toward images and captions, respectively. Additionally, low-tier influencers tend to adopt the same strategy to grow, while high-tier influencers exhibit more category-specific characteristics.*

[7] We made all the results available in our repository.




**(a) Nano Influencers.**




**(b) Mega Influencers.**

**Figure 3: Top-3 features per absolute correlation value ($\rho$-value $< 0.001$) in comments engagement for each category.**

## 4.2 Engagement Prediction & Guidelines Methodology

Besides explaining which characteristics of Instagram posts build engagement, we also aim to form guidelines for producing the ideal engaging post. Having such guidelines for influencers saves time and money consistently since the process for producing a high-engagement post is well-defined. To this aim, we leverage interpretable models, even if this could reduce the overall accuracy. Deep learning models are well known for their capability of solving complex tasks, but by definition they work as a black box that we cannot reliably explain [45]. For this reason, we decided to utilize

**Table 2: Performance of Decision Trees (DT) against a dummy classifier (Dum.). In bold, the best scores for likes and comments for each category. Values reported are F1-Score, macro-weighted** *mean±std.*

| | Nano | | | | Micro | | | | Mid | | | | Macro | | | | Mega | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Like | | Comments | | Like | | Comments | | Like | | Comments | | Like | | Comments | | Like | | Comments | |
| | DT | Dum. | DT | Dum. | DT | Dum. | DT | Dum. | DT | Dum. | DT | Dum. | DT | Dum. | DT | Dum. | DT | Dum. | DT | Dum. |
| **Beauty** | 0.61±0.002 | 0.46±0.004 | 0.65±0.003 | 0.46±0.004 | 0.60±0.003 | 0.47±0.012 | 0.62±0.006 | 0.46±0.017 | 0.61±0.004 | 0.47±0.011 | 0.61±0.002 | 0.47±0.016 | 0.69±0.012 | 0.45±0.054 | 0.67±0.011 | 0.47±0.046 | **0.74±0.006** | 0.48±0.029 | **0.68±0.009** | 0.49±0.025 |
| **Fashion** | 0.57±0.006 | 0.47±0.008 | **0.62±0.003** | 0.47±0.001 | 0.53±0.002 | 0.46±0.002 | 0.57±0.004 | 0.46±0.004 | 0.53±0.004 | 0.47±0.004 | 0.56±0.007 | 0.47±0.002 | **0.61±0.001** | 0.47±0.009 | 0.60±0.011 | 0.48±0.015 | 0.57±0.013 | 0.46±0.011 | 0.56±0.002 | 0.47±0.005 |
| **Family** | 0.57±0.005 | 0.47±0.010 | **0.59±0.005** | 0.47±0.007 | 0.53±0.002 | 0.46±0.005 | 0.56±0.002 | 0.47±0.008 | 0.55±0.007 | 0.48±0.005 | 0.55±0.002 | 0.47±0.003 | **0.60±0.014** | 0.47±0.031 | **0.59±0.013** | 0.47±0.017 | 0.59±0.006 | 0.47±0.026 | 0.57±0.001 | 0.46±0.007 |
| **Fitness** | 0.62±0.004 | 0.48±0.005 | 0.63±0.004 | 0.47±0.009 | 0.60±0.006 | 0.47±0.009 | 0.59±0.012 | 0.47±0.006 | 0.61±0.010 | 0.47±0.009 | 0.61±0.003 | 0.47±0.010 | **0.72±0.010** | 0.45±0.045 | **0.69±0.032** | 0.46±0.023 | 0.65±0.013 | 0.49±0.016 | 0.61±0.033 | 0.48±0.010 |
| **Food** | 0.59±0.003 | 0.46±0.003 | 0.62±0.001 | 0.47±0.010 | 0.57±0.001 | 0.47±0.007 | 0.61±0.001 | 0.47±0.006 | 0.57±0.005 | 0.46±0.010 | 0.63±0.002 | 0.46±0.011 | **0.75±0.008** | 0.46±0.020 | 0.71±0.024 | 0.47±0.061 | 0.71±0.023 | 0.57±0.091 | **0.72±0.029** | 0.53±0.098 |
| **Interior** | 0.59±0.002 | 0.48±0.012 | 0.62±0.003 | 0.46±0.01 | 0.59±0.003 | 0.47±0.002 | 0.63±0.001 | 0.47±0.006 | 0.58±0.010 | 0.45±0.012 | 0.63±0.003 | 0.47±0.011 | 0.76±0.033 | 0.48±0.021 | **0.83±0.020** | 0.49±0.015 | **0.77±0.011** | 0.44±0.083 | 0.74±0.027 | 0.45±0.074 |
| **Other** | 0.58±0.002 | 0.47±0.001 | 0.57±0.0001 | 0.47±0.004 | 0.55±0.001 | 0.47±0.0021 | 0.56±0.005 | 0.47±0.002 | 0.59±0.001 | 0.47±0.006 | 0.58±0.001 | 0.46±0.005 | **0.63±0.003** | 0.46±0.013 | **0.59±0.008** | 0.47±0.023 | 0.60±0.003 | 0.46±0.005 | 0.58±0.008 | 0.46±0.012 |
| **Pet** | 0.69±0.004 | 0.47±0.019 | 0.72±0.006 | 0.49±0.009 | 0.60±0.008 | 0.45±0.018 | 0.62±0.005 | 0.46±0.007 | 0.61±0.018 | 0.46±0.006 | 0.64±0.003 | 0.47±0.024 | **0.94±0.057** | 0.42±0.042 | **0.87±0.048** | 0.42±0.042 | 0.78±0.045 | 0.51±0.032 | 0.77±0.012 | 0.5±0.065 |
| **Travel** | 0.60±0.001 | 0.47±0.0042 | 0.61±0.001 | 0.47±0.006 | 0.59±0.0012 | 0.47±0.003 | 0.63±0.002 | 0.47±0.007 | 0.58±0.004 | 0.47±0.006 | 0.64±0.009 | 0.48±0.010 | **0.72±0.008** | 0.45±0.024 | 0.67±0.050 | 0.47±0.012 | **0.72±0.010** | 0.46±0.031 | **0.71±0.017** | 0.42±0.032 |

Decision Trees (DT) [41]. By training a DT classifier to predict low or high engagement (bottom 0.75 and top 0.25 quantile), we can simply explain how to produce top engagement posts by following the binary classification tree. The paths to reach the top 0.25 quantile leaves represents guidelines for creating high-engagement posts.

#### 4.2.1 *Implementation.*

Since influencers behave differently according to their category and tier, as they want to reach a different public, we create an engagement classifier for each category and tier. Each classifier is trained and validated on 75% of the dataset and tested on the remaining 25%. To build accurate estimators for each dataset (i.e., combinations of the nine categories and five tiers – 45 in total), we fine-tune the Decision Tree Classifier through a Grid Search (cv=5) that evaluates more than 20K combinations of parameter fits to achieve the best F1-Score (macro weighted) possible. To further reduce the bias due to the random split of the dataset, we repeated the evaluation three times on three different training-test partitions. Considering low and high engagement based on 0.75 and 0.25 quantiles implies having heavily unbalanced classes that make the learning process harder. Therefore, we also introduce as tuning parameters the use of well-known under-sampling and over-sampling techniques, i.e., SMOTE and Tomek links [24, 55].

#### 4.2.2 *Results.*

The results on the test sets are reported in Table 2. All the results surpass the dummy classifier, showing our method can effectively predict posts' engagement. Moreover, the standard deviations are fairly low, suggesting the models are stable. In terms of Likes, predictions are generally more accurate for Macro and Mega influencers, raging around 60-80% F1-score (20-40% better than the dummy). The reason can be that these high-tier influencers tend to be more diversified as we found in the correlation analysis, making some characteristics more effective. Accordingly, our classifier exhibited difficulties in the lower tiers of Fashion, in which influencers tend to post similar content, and Other, in which the content was extremely diverse. On average, we reached the best performances for Pet, Interior, and Beauty. Regarding Comments, we find a behavior similar to Likes, except for the best performances for Fashion and Family, which appear for Nano influencers. A possible reason is that many Nano influencers might not know the best practices for creating engaging captions, which are strongly correlated to comments engagement as shown in correlation analysis. The best categories we predicted are Pet, Food, and Travel. Last, we reached the best Likes and Comments prediction score (94% and 87%, respectively) for the Pet Macro posts. An example[8] of guideline with a DT structures is depicted in Figure 4. Following the nodes conditions (i.e., post characteristics), a label will be assigned when reaching a leaf (i.e., bottom 0.75 or top 0.25 quantile). We will present more examples of guidelines in §6.

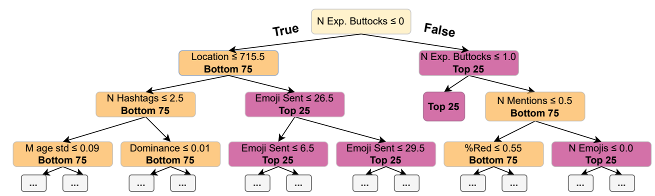



**Figure 4: Example of guidelines generated by the decision tree for category Beauty, tier nano, likes engagement. The representation is limited at a maximum depth of 3.**

#### 4.2.3 *Baselines Comparisons.*

As Mazloom et al. [29], Gayberi and Oguducu [11], and other similar studies mentioned, comparison with other works in this area is not completely possible. The main reasons are the use of private algorithms and data, and how the problem is formulated. Unfortunately, IG policies[9] never allowed automatic collection and release of common users' posts, forcing previous works to create a new (private) dataset everytime [3, 6, 11, 29, 30, 40, 59]. Moreover, given the lack of a common dataset to work on, some works focused on a regression problems [11, 40, 59], other on a classification problem [3, 6, 59], adopting different metrics, such as the log-normalized number of likes [8, 11] or the likes divided by the number of followers [40, 44, 59]. Thus, to set up baselines despite the aforementioned limitations,[10] we adopted four models: (i) $I^2$PA of Ding et al. [8] (the only one publicly released); (ii) a Decision Neural Network (Dec-NN) to represent prior works which first extract generic visual or textual features, and then trained a non-interpretable classifier (similar to [11, 29, 44]); (iii) End-to-End Deep NN (EE-DNN) for prior works that relied on end-to-end black-box DL models, giving in input both posts' images and captions simultaneously (similar to [57]); (iv) a stratified dummy classifier,[11], which predicts targets

[8]All the results are available in our repository.
[9]https://help.instagram.com/581066165581870, accessed: Sep 2022.
[10]Note that some features used in previous works were not available in our dataset, limiting the comparison.
[11]https://scikit-learn.org/stable/modules/generated/sklearn.dummy.DummyClassifier.html

based on the training set distribution. Both Dec-NN and EE-DNN extract posts' image and caption embeddings (through ResNet50 [14] and Sentence-Bert [43]); however, EE-DNN fine-tunes them before the fusion, while Dec-NN receives their early-fusion as input. The decision is taken through three ReLU feed-forward layers (sizes = 2048+768 → 256 → 128 → 2). Both NN were Adam optimized and trained for 50 epochs with early stopping (patience = 5).

The results of Table 3 show that our approach outperformed the baselines for each category, except for Fashion and Other, in which we achieved comparable performance, demonstrating the superiority of our simple DT over Deep Learning models. For the categories Beauty, Fitness, Food, Interior, Pet, and Travel, our results are statistically significantly higher than the second-best model (calculated through unpaired $t$-test, two-tailed p-value < 0.05). Particularly noteworthy is the result against I$^2$PA and EE-DNN, which represents SotA end-to-end DL models. In particular, EE-DNN performs pretty poorly, likely because fine-tuning the feature extraction modules led to overfitting. On the other hand, Dec-NN, which is more similar to our strategy, generalized better by not tuning the image and text general representations. Probably, we surpassed such baselines mainly because of the category-related features we extracted, again stressing that developing a cross-category engagement predictor could be unfeasible. Accordingly, we probably could not beat Dec-NN in the Other category because of the lack of category-related features.

Although the comparison with previous work is not completely fair for the above reasons, our results are comparable [6, 57] or better [3, 40, 44] than the ones reported on their own data. Anyhow, we remind the reader that our goal is to *explain* the engagement, not necessarily surpass the prediction of existing non-interpretable models. Last, our dataset was collected using IG APIs from business accounts and is thus shareable. We believe our dataset could serve as a baseline for future works.

**Table 3: Comparison of Mean F1-Score between our model (DT) and baselines in predicting Likes. Underlined results are statistically significantly higher (two-tailed $p$-value < 0.05) than the second-best.**

| Category | DT (Our) | I$^2$PA | Dec-NN | EE-DNN | Dummy |
|---|---|---|---|---|---|
| **Beauty** | **0.65**$_{\pm 0.055}$ | 0.587$_{\pm 0.026}$ | 0.582$_{\pm 0.097}$ | 0.362$_{\pm 0.037}$ | 0.466$_{\pm 0.024}$ |
| **Fashion** | 0.563$_{\pm 0.030}$ | **0.581**$_{\pm 0.019}$ | 0.572$_{\pm 0.043}$ | 0.327$_{\pm 0.013}$ | 0.464$_{\pm 0.008}$ |
| **Family** | **0.568**$_{\pm 0.026}$ | 0.567$_{\pm 0.019}$ | 0.507$_{\pm 0.071}$ | 0.347$_{\pm 0.042}$ | 0.476$_{\pm 0.017}$ |
| **Fitness** | **0.640**$_{\pm 0.043}$ | 0.545$_{\pm 0.026}$ | 0.511$_{\pm 0.069}$ | 0.377$_{\pm 0.062}$ | 0.478$_{\pm 0.018}$ |
| **Food** | **0.638**$_{\pm 0.077}$ | 0.550$_{\pm 0.030}$ | 0.518$_{\pm 0.053}$ | 0.464$_{\pm 0.269}$ | 0.48$_{\pm 0.031}$ |
| **Interior** | **0.660**$_{\pm 0.087}$ | 0.534$_{\pm 0.056}$ | 0.461$_{\pm 0.047}$ | 0.309$_{\pm 0.031}$ | 0.468$_{\pm 0.022}$ |
| **Other** | 0.590$_{\pm 0.026}$ | 0.540$_{\pm 0.022}$ | **0.602**$_{\pm 0.021}$ | 0.318$_{\pm 0.013}$ | 0.463$_{\pm 0.004}$ |
| **Pet** | **0.724**$_{\pm 0.126}$ | 0.564$_{\pm 0.046}$ | 0.630$_{\pm 0.127}$ | 0.342$_{\pm 0.0727}$ | 0.461$_{\pm 0.015}$ |
| **Travel** | **0.642**$_{\pm 0.064}$ | 0.570$_{\pm 0.012}$ | 0.473$_{\pm 0.044}$ | 0.342$_{\pm 0.069}$ | 0.457$_{\pm 0.016}$ |

*4.2.4 Feature Importance.* Guidelines to create engaging posts results from following the tree generated by the DT classifier. In addition, similarly to correlation analysis, the content creator can inspect the model's feature importance to determine which features are impacting the engagement predictions. Thus, we studied the features used by the models, checking whether they matched with correlation results. A representative example[12] of this analysis is shown in Table 4, which suggests good correspondence with the factors expressed in §4.1. For example, the presence of common features in small tiers, followed by category-specific features with increasing tier size. As for the correlation analysis, the number of mentions and whether a location is given resulted in importance that is inversely proportional to the tier size.

**Table 4: Features importance of category Fashion, tier micro.**

| # | Feature | Imp. |
|---|---|---|
| **1** | N Mentions | 1.0 |
| **2** | Age avg | 0.80 |
| **3** | Dominance | 0.73 |
| **4** | N Exp.Buttocks | 0.46 |
| **5** | Outdoor Natural Env. | 0.19 |

**(a) Likes.**

| # | Feature | Imp. |
|---|---|---|
| **1** | N Exp. Buttocks | 1.0 |
| **2** | N Mentions | 0.64 |
| **3** | Caption Len. | 0.18 |
| **4** | N Emojis | 0.16 |
| **5** | Cap. Sent. Magn. | 0.13 |

**(b) Comments.**

**Takeaway:** *A simple and interpretable Decision Tree can outperform Deep Learning algorithms if leveraging domain-knowledge features. Prediction results and feature importance analysis confirm the consideration drawn by feature correlation, showing how similar and dissimilar tiers and category behaves.*

## 5 SPOTTING INSTAGRAM HOT TOPICS

Our features allow us to predict a post's engagement with good accuracy, but there is room for improvement. In our *interpretable* approach, features have to be extracted a priori instead of being learned "automatically" by a deep learning model. Thus, our features are limited by our educated guesses of what could be engaging, and by the concepts obtainable through existing SotA deep learning models. For instance, if available, we would have used a love or a marriage scene detector, which is likely to produce high engagement. Although such detectors could be implemented through classical approaches (e.g., by fine-tuning an image recognition NN like ResNet [14]), we opted for defining an unsupervised strategy to detect *general hot topics*. In particular, we aim to find (if any) topics or concepts that, if present in a post, would create high engagement independently from the publisher. In this context, unsupervised means we make no assumptions on which topics are engaging (as we did to extract category-related features for §4), but rather explore users' interests [54].

From §4 we learned that likes and comments are mainly driven by the image and caption, respectively. Thus, in the next experiments, we focus on finding likes-related hot topics through visual features, and comments-related hot topics through textual features. We now present our methodology and findings.

### 5.1 Methodology

The idea behind our method is to group together semantically similar images and captions and observe whether some of these groups reach high engagement on average.

**Embeddings.** To define image and text semantic similarity, we rely on the concept of embedding. An embedding is a vector representation of an object (e.g., image, text) in which objects with similar

[12] All the results are available in our repository.

semantics have similar vector profiles [23]. Embeddings are usually extracted by taking the output of the penultimate layer of a deep neural network performing a classification task. In our experiments, we retrieved image embeddings using ResNet50 [14] pre-trained on the ImageNet dataset, and text-embeddings using Sentence-Bert [43] (in particular, in its version *all-mpnet-base-v2* [10]). Before extracting the text embeddings, we translated non-English text leveraging Google Cloud Platform [13], so to perform language detection and translation automatically.

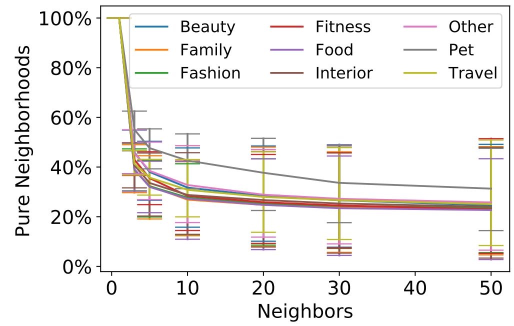
**Semantically Similar Neighborhood.** As a first approach, we could create clusters of similar images or captions, and see whether some clusters present higher engagement than others. However, as shown in the literature [36], current cluster algorithms suffer the decision of the number of clusters beforehand. Moreover, finding hot topics is challenging [56], since they could be small and lost in a big cluster. Thus, we prefer a Nearest Neighbors approach to find neighborhoods of points with similar engagement. In particular, we first divided our posts into five engagement classes determined by the percentiles [0-20, 20-40, 40-60, 60-80, 80-100], saving the thresholds of each percentile. Then, for each point, we search its N nearest neighbors, calculate their engagement average, and see whether the average falls in the same engagement class as the point under consideration. If so, that neighborhood is considered "pure", and new posts falling in it would likely produce that particular engagement class. To find the nearest neighbors, we first reduced the dimensionality of the embeddings using PCA (100 components), and then applied the Nearest Neighbor algorithm leveraging Scikit-Learn implementation [39] using Euclidean Distance as the distance metric. Figure 5 depicts the percentage of pure neighborhoods for different N = [1, 3, 5, 10, 20, 30, 50] for the mid-tier. On average, around 20% (N=50) of the points are in a pure neighborhood, which suggests that some topics are more (or less) engaging than others. The pet category presents the highest average, probably because its topics can be the species and breed of animals (visually similar), and some could be liked more (or less) than others.

## 5.2 General vs User-specific Hot topics

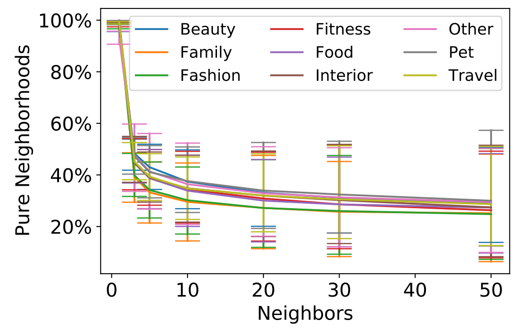
The percentage of the pure neighborhoods found in §5.1 is comprehensive of neighborhoods made only by a single influencer, i.e., not a general hot topic. In this case, we identified what we could call a user-specific hot topic, which is very useful for understanding what topic is engaging (or not) for that particular influencer. Thus, what differentiates general vs user-specific hot topics is how many influencers participate in a pure neighborhood, and with how many posts. We call this parameter *User Diversity*. To calculate it, we took inspiration from the Simpson's Diversity Index [48], used in ecology to quantify the biodiversity of a habitat. It takes into account the number of species present, as well as the abundance of each species. The diversity index $D$ is expressed as:

$$D = 1 - \frac{\sum_{i=1}^{K} n_i(n_i - 1)}{N(N-1)}, \quad (2)$$

where $N$ is the total sample size, $K$ the number of species, and $n_i$ is the number of organisms of the $i^{th}$ specie. $D$ ranges from 0 to 1, where 0 is minimum diversity and 1 is maximum diversity. In our scenario, the species are the influencers, and the organisms are the posts. Similarly, we can define an *Engagement Diversity*, which




**(a) Likes**




**(b) Comments**

**Figure 5: Percentage of pure neighborhoods in mid-tier for engagement metrics.**

measures the posts' diversity in terms of engagement. This metric is needed since we created pure neighborhoods based only on the average engagement of their posts; therefore, there can be posts belonging to different engagement classes within a pure neighborhood. To recap, by measuring the *Engagement* and *User Diversity* of our pure neighborhoods, we can define topics as depicted in Figure 6. We are more interested in the green part, since neighborhoods with high engagement diversity are less reliable. We set the threshold between low and high at 0.5.

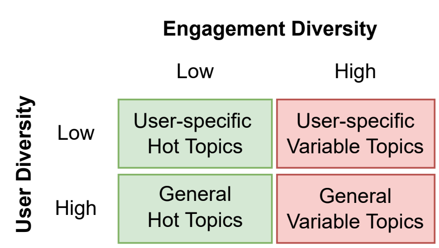



**Figure 6: Types of topics for Engagement and User Diversity.**

**Findings.** We concentrated our research of hot topics only on the highest engagement class (i.e., posts falling in the top 20% percentile), focusing on each tier and category differently. During the automatic search, we removed neighborhoods that overlapped for

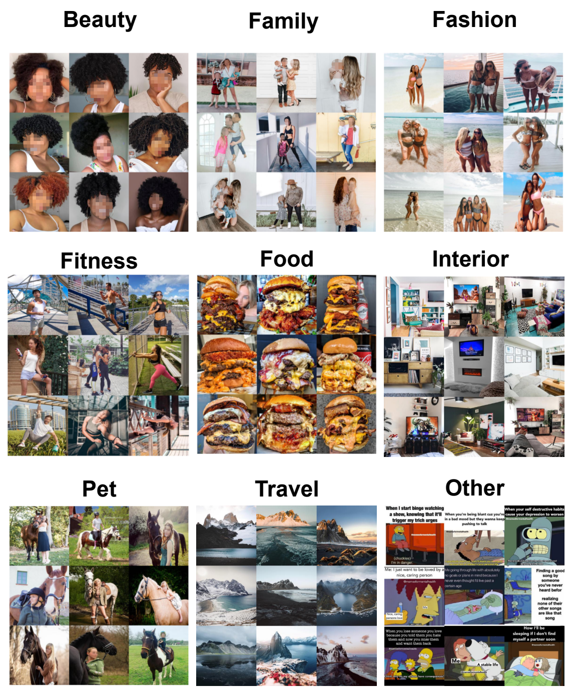



**Figure 7: Examples of hot topics found in our categories.**

more than 80% of the points. We explored the resulting neighborhoods and found several hot topics, which we did not think about in the feature extraction phase, and could not be detected by SotA models, confirming the benefits of this unsupervised research. All the neighborhoods can be browsed on our repository, while in Figure 7 we reported an example for each category. For instance, we found "mother with her child" for Family, "two (or more) girls in bikini" for Fashion, or "girl/kid near/riding a horse" for Pet. For captions, we found less category-specific hot topics and more common strategies. For instance, giveaways attract a lot of comments, since participants usually have to comment and tag other friends. Furthermore, we found the working strategy of asking users' opinions on a topic, general questions, or requests for upcoming content. More general hot topics are presented in §6.

**Takeaway:** *Instagram offers both visual and textual hot topics that are likely to generate high engagement levels. Captions tend to use similar strategies across categories despite visual hot topics being category-specific.*

## 6 GUIDELINES INSIGHTS

This section provides some guidelines to get more Likes and Comments for each category, resulting from both DT engagement classifiers (§4) and hot topics detection (§5). We also provide some suggestions to make an engaging caption.

### 6.1 Guidelines for Likes, Comments, and Topics

Each category presents different characteristics to build engagement. We now present guidelines to get more Likes and Comments along the hot topics we found.

**Beauty.** Likes are mainly driven by exposed buttocks and feet, a high image pleasure, and positive emoji sentiment. Exposed buttocks also generate many comments, as well as a low age average, having the location set, and the use of many mentions. Wavy hair is much appreciated, and hot topics include couples and eye make-up with perfect eyebrows. Users usually love when the influencers receive new make-up products, recreate famous make-up (e.g., from movies), and talk about personal problems.

**Family.** Likes and Comments are driven by similar factors. People's features like age and gender are predominant. The mean age of female subjects should be low, with a high standard deviation. This suggests that mothers with children are a hot topic, as detected in §5.2. Indoor or outdoor-natural environments are preferred, and location, colors, and the number of mentions are highly impacting. As hot topics, we found pregnancy, childbirth, and body changes, during which followers feel closer to the influencer.

**Fashion.** In terms of Likes, a higher number of mentions is suggested for small tiers, whereas colors-related features (e.g., dominance, arousal) contribute heavily to high-tier influencers. A predominant role is held by exposed buttocks, which contribute to both likes and comments. Exposed feet generate many comments, as well as outdoor pictures, short captions with many hashtags, and positive emoji sentiments. As hot topics, girls in bikinis and men with six-packs are successful. Discussing outfits for special events is highly engaging, such as traveling, going to concerts, birthdays, gallant dinners, or simply starting the week.

**Fitness.** Likes are driven by warm colors, and high dominance of female subjects with low age standard deviation, preferably in their workout outfit. A short caption with positive sentiment helps in receiving both likes and comments. Low arousal generates many comments, according to the body transformation hot topic. The caption should motivate people to try harder in their workouts.

**Food.** Males are more common and generate more likes in this category. Extreme burgers and spirits are highly appreciated, as well as perfect and very colored food compositions. Pictures in kitchens or outside restaurants help to get likes. The location is important for getting comments, as well as high arousal and a positive caption with many Emojis. The caption should include a brief description of the plate and questions about the favorite food. Pizza days, chocolate, and vegan food are often in the middle of heated discussions.

**Interior.** To get likes, indoor environments like a living room and cold colors are preferred, as well as the presence of kids and female subjects. The location is relevant for both likes and comments, but avoid commercial buildings and food pictures. Luminous and pleasant pictures generate more comments, as well as the presence of animals. A good caption combines positive Emoji sentiment, a few hashtags, and general questions, like what to do on the weekend.

**Pet.** Pictures should be in an indoor or outdoor-natural environment, use warm colors, and convey a positive sentiment to get many likes. The use of the location and mentions helps a lot for comments, as well as very high or very low animal cuteness. Among the most loved animals, we found horses, exotic animals, Siamese cats, and dogs with clothes and ribbons. Many comments will arrive along with a new family member!

**Travel.** Likes are gained primarily by female subjects and a low number of male presence, with a generally low age standard deviation and a low minimum age. This suggests that travel pictures of young friends or groups of the same age are highly engaging. To get many comments, besides the importance of outdoor-related features, the sentiment conveyed by the text should tend to be positive. Further, hashtags and mentions are crucial, and the picture should be pleasant and arousing, with low dominance. Pictures near the sea are highly appreciated, and users engage more with summer and holiday posts.

**Other.** More likes are obtained by females in indoor places with cold colors and low dominance. Many emojis and short captions help too. Men of the same age in a single picture get many comments, using a neutral sentiment in the caption. Hot topics are many, for example, football, memes, or superheroes. The captions tend to be funny and quite short.

### 6.2 Guidelines for Engaging Captions

Even if each category and tier require a specific caption to build engagement, we identified some common strategies to generate highly engaging ones. From our explorations, we identified a typical pattern among most hot captions, i.e., asking questions to the audience. Such questions can be very generic (e.g., "how do you feel today?"), or topic-specific (e.g., "which outfit do you prefer?"), which helps engage the users. Moreover, creators often ask people to perform particular actions, such as tagging or sharing content with friends. This behavior, known as *call to action*, usually generates a lot of engagement. Last, hashtags are generally at the end of the caption, often separated by the rest of the text with one point or dash per line. This behavior forces the users to click on the "View more" button to see the whole caption, generating more engagement.

### 6.3 Limitations

Our guidelines are the result of analyzing the biggest IG dataset ever released, composed of around 10M posts created by 34K influencers. Nevertheless, it does not include many categories of interest (e.g., sport, cinema, music), and what people like as well as hot topics could change over time. However, we presented two methodologies (supervised §4 and unsupervised §5) that can be applied to any category (possibly enhancing the feature set) at any time, by taking a "snapshot" of IG content produced by influencers of a target category and tier. Moreover, a reader might be concerned that the IG algorithm started considering comments to recommend posts in 2021, whereas our dataset is from 2020. We remark that our paper's aim is to explain which post's features induce users to generate more comments (which now are a crucial factor), and not how IG is now recommending posts to users. Indeed, as for likes, the main reason users leave comments is based on the posts themselves [1], not whether users see the posts.

## 7 CONCLUSION

In this work, we aimed to close the gap from previous works, explaining the underlying mechanisms of IG engagement and focusing on the interpretable models. In this way, it is possible to create engaging IG content by design, following predefined guidelines saving time and money. Through a careful and all-inclusive process of feature extraction, we trained predictors that achieved up to 94% of F1-Score. In particular, our results show that likes are mainly driven by images, while comments are primarily stimulated by captions. Further, we demonstrated how influencers' behavior becomes more category-specific as their tier increases. Last, we proposed a novel unsupervised approach for detecting and analyzing hot topics, to better understand the inner dynamics of each category.

In the future, we plan to improve the predictions through a model that integrates hot topic extraction. Furthermore, more categories should be studied, and a metric that combines likes and comments should be introduced to better understand their relationship. Regarding these metrics, they could be polished by removing fake engagement, for instance. However, as of now, we have no evidence IG algorithm is accounting for such differences. Last, geography should be taken into account to understand whether it impacts engagements mechanisms

## ETHICAL CONSIDERATIONS

We did not collect any data in this work. All the data we have used has been legitimately collected in previous work using Instagram API [20]. These data may be shared with researchers upon request to advance the field of research, and cannot be used in any other manner (e.g., for business). Images reported in this paper have only been used for research and demonstration purposes. Human subjects in the pictures are all Instagram influencers, i.e., public figures. Anyhow, we carefully blurred their faces in order to make them unrecognizable.

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