Competition for popularity and identification of interventions on a Chinese microblogging site

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Abstract

Microblogging sites are important vehicles for the users to obtain information and shape public opinion thus they are arenas of continuous competition for popularity. Most popular topics are usually indicated on ranking lists. In this study, we investigate the public attention dynamics through the Hot Search List (HSL) of the Chinese microblog Sina Weibo, where trending hashtags are ranked based on a multi-dimensional search volume index. We characterize the rank dynamics by the time spent by hashtags on the list, the time of the day they appear there, the rank diversity, and by the ranking trajectories. We show how the circadian rhythm affects the popularity of hashtags, and observe categories of their rank trajectories by a machine learning classification algorithm. By analyzing patterns of the ranking dynamics we identify anomalies that are likely to result from the platform provider’s intervention into the ranking, including the anchoring of hashtags to certain ranks on the HSL. We propose a simple model of ranking that explains the mechanism of this anchoring effect.

Introduction

Studying public attention is important from various aspects including governance, public security, intelligence, marketing, and pandemic management [1,2]. With the development of digital technology, social media have permeated into the society and become an inevitable source of information for many. An increasing part of the public obtains the latest information from social media, expresses opinions and attitudes there. This results in a strong competition for visibility and popularity partly because of their obvious relation to power and financial gain. Due to the large number of users and the volume of activity, changes in popularity happen at a high pace. As the novelty of the hot topics fades rapidly with time [3], public attention shifts to new, current trending topics. Popularity trends on social media can be regarded as a proxy of collective public attention. In the social media ecosystem, microblogging sites are important platforms because of the conciseness of the messages, the high turnover speed and the open online social networks of their users. Microblogging sites are complex interacting systems where users generate content and disseminate information through posts, reposts, comments, likes and mentions, and where emergent phenomena occur like macroscopic collective behaviors triggered by some pieces of information [4].

Detecting and indicating the trends in popularity is important since they reflect most concerned issues by the public in real time, which is highly relevant for a number of issues, including the popularity of cultural products, market changes [5], government
policy-making, and elections [6]. In order to inform costumers, microblogging site providers like Twitter or Sina Weibo present trending lists based on some statistical measures. The lists have twofold roles: first, they indicate popularity of given topics, second, they boost popularity of those topics which manage to get to the list. Therefore there is a competition in getting to the list and staying there as long as possible.

Twitter trending list shows hot topics around the globe. Research studies have analyzed the dynamics of trending topics through comprehensive statistical analysis from the aspects of lexical composition, trending time, trend re-occurrence [5], etc. There have been different factors identified, which contribute to the success of a topic, like novelty of the piece of information and the resonance level of the messages spread as well as the influence of certain members of the propagating network [7]. The evolution of Twitter trends is characterized by phases of burst, peak and fade [8] and the patterns of temporal evolution of popularity of hashtags have been ordered into six different categories [9].

The economic and political relevance of popularity of items on online media is an incentive to the service providers to intervene into the trending lists. A linear influence model [10] was introduced to capture the network effect on endogenous diffusion of hashtags on Twitter trending list and demonstrate evidences of manipulation [11] on the observed dynamics. Certain trending topics on Twitter may be opportunistically targeted with desirable qualities by spammers [12]. Recent studies on Twitter trends have found likely presence of coordinated campaigns in AstroTurf version to influence and manipulate public opinion during the Covid crisis in Mexico [13].

The Chinese microblogging site Sina Weibo is geographically more limited but larger than Twitter in terms of number of daily and monthly active users [14]. Although it has generated less academic publications than Twitter, it has attracted considerable research attention due to its enormous user participation and profound role in mainland China where Twitter is blocked [41]. The Hot Search List (HSL) on Sina Weibo, with a role similar to Twitter trending list, is a major source for people from mainland China to obtain real-time information about the popularity of topics. Research on Weibo hot topics has focused on topic dynamics from the perspective of time, geography, demographics, emotion, retweeting, and correlation [15], on similarities and differences to Twitter [16,24], emergence mechanisms [17], patterns of popularity evolution [18], prediction [19–21], social emotions and diffusion patterns [22] as well as impact of censorship [23].

The ranking of trending contents on social media changes over time, following the rise and fall of public attention dynamics: Old trends vanish and new trends emerge. The search volume for hashtags indicates their popularity and on Sina Weibo this quantity is the main underlying for the ranking list HSL, as reflected in the name of the list. Sina Weibo HSL claims to publish the ranking of the top 50 most popular hashtags based on a multi-factor index [25]. Due to its opaque algorithm of determining and ranking hashtags on the HSL, Weibo has been target of criticism for making financial gains as the HSL serves as an advertising tool to boost popularity. Sina Weibo responded to the criticism on 23 August 2021 and released what it called the rule of capturing the “hotness” $H$ of a hashtag at a certain time [26], in the form of the following formula:

$$H = (S_H + D_H + R_H) \times I_H,$$

where search hotness $S_H$ refers to the search volume, including manual input search and click-and-jump search, discussion hotness $D_H$ is for the amount of discussion, including original posting and re-posting, reading hotness $R_H$ represents the volume of readings in the spreading process of the hashtag, and interaction hotness $I_H$ refers to the interaction rate of hot search results page. The rank of a hashtag on the list increases or decreases reflecting the relative popularity of the topic to other topics at a certain
The amount of time a hashtag stays on the list indicates the degree of its ability to attract consistent public attention.

The exposure of hashtags on the HSL has a great promotional effect; thus, many are keen to be on the list, resulting in strong competition and manipulation attempts. Studies reveal that hashtags from different topical categories differ in time length of prehistory (from birth till first appearance on the HSL) and the types of accounts involved in the propagation. Celebrity and entertainment-related hashtags are often associated with marketing accounts which can be influenced by social capital. Recent findings indicate the possibility of algorithmic intervention from the platform provider towards Covid-related hashtags on the HSL during the Covid-19 pandemic. Research indicated that human editorial decisions were involved in the curation of Weibo trending topics with the aim of increasing user engagement and that Weibo actively facilitates the production and spread of online contention to attract more users through a range of recommendation mechanisms built into the platform, including the trending topic list and channels such as Sina-owned official accounts. As contents on social media can influence social perception, studying the dynamics of both ranking position and duration of the hashtags on the HSL can deepen our understanding about the dynamics of public attention, its relation to hashtag prehistory, and reveal ways of interventions on social media platforms.

In this paper, we study the attention dynamics on Sina Weibo by digging deeper into the characteristics of the hashtags on the HSL. We describe the patterns of the ranking position and duration of hashtags, introduce ranking trajectory classification, and uncover its relationship with the prehistory and the time of the day when the hashtag first appears on the HSL. We identify anomalies which can be attributed to intervention into the ranking by the service provider and propose a model of anchoring to explain the anomalous ranking dynamics of hashtags on the HSL.

Materials and methods

Sina Weibo Data

Sina Weibo Hot Search List is a convenient tool for netizens to follow hot topics, news events, and celebrity gossip, and has gone through several reforms. In 2014, a real-time Hot Search List was launched on the client with an updating frequency of once every ten minutes, allowing users to see the latest hot information anytime, anywhere. The updating frequency later accelerated to every minute in 2017. Until 2021 there used to be one or two advertisement rank positions included in the top 50 ranks. The datasets used in this research are available in a GitHub repository.

Sina Weibo HSL contains the names of the hashtags, their ranks, and the search volume hotness which is the base of the ranking (see Eq. (1)). We crawled the data from Sina Weibo HSL, with a frequency of $\Delta t = 5$ minutes from 22 May 2020 to 29 September 2020. Since the commercial advertisements randomly occupied the HSL at the third and the sixth ranks, in order to get a constant length of non-advertisement hashtags on the HSL at each timestamp, we removed all the advertisement hashtags which are labeled with “Recommendation (荐)”, re-ranked the original HSL and took the top $L = 48$ hashtags for each timestamp, with $L$ being the length of the list. Weibo

Since 2021, Weibo went through another reform that the advertisements hashtags are randomly placed between ranks 3 and 4 or ranks 6 and 7, without a rank number associated in front of the advertisements, resulting in maximum 52 hashtags on the HSL, excluding the imposed positive energy recommendation position above all ranks which is often promotion for positive contents. Sina Weibo has also separated a new list specifically for entertainment and celebrity-related hashtags, though in the normal HSL there are still entertainment-related hashtags. Our data was collected from the period before the reform.

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was punished by the cyberspace authority of China to suspend the update of HSL for one week in June 2020 due to its interference with online communication [32], which causes a gap in the data (see Fig. 1). We then did our major analysis based on the data after the punishment. We took all the hashtags that have appeared on the HSL in a two month period from 17 July to 17 September 2020, and crawled all the posts containing these hashtags in their prehistory from birth till first appearance on the HSL.

**Ranking dynamics**

**Measures**

A popular hashtag $i$ enters the HSL at time $t_i$ at rank $r_i(t_i)$ ($1 \leq r_i \leq L$) and disappears from it at time $T_i$. The rank of this hashtag changes with time producing a trajectory $r_i(t)$ until it disappears from the HSL. In order to capture the ranking characteristics of hashtags at different ranks, we use the measure rank diversity [33,34]. Rank diversity $D(k)$ measures the number of different hashtags at rank $1 \leq k \leq L$ during a given period of time $t_{\text{min}} \leq t \leq t_{\text{max}}$:

$$D(k) = \sum_t \sum_i \delta(k, r_i(t)) \phi_{i,k}(t), \quad (2)$$

where $\delta(\cdot, \cdot)$ is the Kronecker delta and $\phi_i(t)$ is the indicator, which is 1 if hashtag $i$ has not been at rank $k$ until time $t$ and 0 otherwise.

Rank diversity has been studied extensively. It is known that these quantities are characterized by profiles: For high ranks, their diversity have small values, while the behavior for lower ranks depends on whether the system is closed (only the rank changes but the items do not) or open (when items arrive on and leave from the list). In closed systems the dynamics at low ranks is also suppressed leading to low values of $D$ and a maximum at intermediate ranks, while in open systems these quantities grow monotonously, as it can be shown by simple diffusive models [33–35]. An open system can be considered as a part of a very large closed system.

The duration $d_i$ of a popular hashtag on the HSL measures the time over which it is able to attract consistent public attention:

$$d_i = T_i - t_i. \quad (3)$$

The highest rank $r_i^{\text{min}}$ of a hashtag measures its maximum relative ability to attract public attention during its whole lifetime on the HSL:

$$r_i^{\text{min}} = \min_{t \in [t_i, T_i]} r_i(t). \quad (4)$$

**Categorization of rank trajectories**

The rank trajectory $r_i(t)$ is uniquely defined for $\forall$ hashtag $i$. Some hashtags have short lifetime on the HSL, others can attract popularity for a longer period of time; some go rapidly to high ranks, others never reach that level. Are there similarities between different shapes of the trajectories and can they be ordered into categories? Here we use machine learning techniques to find characteristic patterns in these rank trajectories. In order to deal with rank time series of different lengths, we use Dynamic Time Warping (DTW) [36] as a similarity measure between two time series. DTW computes the best possible alignment between two time series. Then we use k-means clustering to find clusters of characteristic shapes. The computation was done using python tslearn package [37].
Results

Circadian patterns

Human actions are largely influenced by the circadian rhythm and so are online activities. Figure 1A shows the increment of the number of hashtags per $\Delta t = 5$ minutes interval clearly demonstrating the cyclic structure during the observation period from 22 May 2020 to 29 September 2020, except for a short interruption in June 2020. Similarly in Fig. 1B, the median search volume index of hashtags on the HSL at a timestamp rises and decays in a periodic fashion. The missing of data for one-week in June 2020 is observed in both Fig. 1A and Fig. 1B, which results from the suspension of HSL by the cyberspace authority of China due to Weibo’s interference with online communication [32].

Fig 1. Circadian patterns of the Sina Weibo Hot Search List (HSL). (A) Increment of number of new hashtags per $\Delta t = 5$ minutes on the HSL during the observation period from 22 May 2020 to 29 September 2020. (B) Time series of the median of search volume index of all hashtags on the HSL at a timestamp, advertisement rank positions excluded. $H$ represents the median value hotness $H$ of hashtags on Sina Weibo HSL at a timestamp. In both (A) and (B) the one-week gap due to the suspension of HSL by the cyberspace authority of China is visible.

Rank trajectory clustering

A successful hashtag $i$ stays on the HSL between the time instants $t_i$, when it appears on the list, until $T_i$, when it finally disappears from it defining the duration $d_i = T_i - t_i$. Some hashtags stay on the list for very short time ($d_i < 10$ minutes), while some others stay for many hours. The rank of a hashtag $i$ follows a trajectory $r_i(t)$. Some hashtags’ trajectories go first up and then down, some go up and down and up again, there are also cases that hashtag’s trajectory goes up and then it disappears. Also, the speed change of the trajectories is variable, resulting in a multitude of shapes of rank trajectories.

The duration distribution of hashtags in the observation period is shown in Fig. 2A. We observe a sharp peak for hashtags with short duration and two less pronounced peaks, where the latter are characterized by similar patterns of the ranking trajectories. The vertical red line at the local minimum of 1 hour separates the duration distribution into two sections, section 1 and 2, respectively. The individual rows in Fig. 2 correspond to the clustering of the rank trajectories on each of the separated sections: Section 1 (B,C,D) and Section 2 (E,F,G). Even for hashtags with short duration on the HSL (Section 1) it is worth categorizing the rank trajectories. In most cases the rank does not change much during the lifetime $d_i$ (see Figs. 2B and C) and remains low, however, as shown in Fig. 2D, some ranks of the hashtags exhibit a clear directional motion: they go to lower rank numbers, i.e., to higher ranks and disappear from there. For the more expected rank trajectories shown from Fig. 2E to Fig. 2G, we also see
some recognizable differences. Rank trajectories in Fig. 2E first go up and quickly go down after hitting the top, without staying at a certain rank for a long time. Rank trajectories in Fig. 2F first go up, stay stable around the highest ranks with little fluctuation for a long time and then go down. Rank trajectories in Fig. 2G first go up, with more fluctuations but never surpass the previous peak, then stay stable for a long time and finally go down. In the next Section we will show how the rank trajectory shapes are related to the time of the day the hashtags first appear on the HSL.

Fig 2. Clustering patterns of hashtag rank trajectories on the Sina Weibo HSL.

(A) Distribution of hashtag duration on the HSL, divided into two sections based on local minima at 1 hour. Results of k-means clustering with 3 clusters in each section for time series data are shown, metric is dtw (dynamic time warping) distance, y-axis is normalized to the mean and the standard deviation and the x-axis by $d_i$. (B), (C), (D) correspond to duration interval from 0 to 1 hour (Section 1). (E), (F), (G) correspond to duration interval larger than 1 hour (Section 2). Red curves depict clustering centers in each category.

Anomaly detection

The dynamics of popularity as captured in the HSL should be sensitive to the actual trends and reflect the users’ overall activity patterns. The individual rank trajectories show fluctuations but after averaging one would expect smooth behaviors. However, when studying the characteristics of the hashtags’ rank dynamics on HSL, like the rank diversity or duration distribution we bumped into strange behaviors which we interpret as indications of interventions by the service provider.

Duration

Figure 3A is the $d_i$ vs $t_i (\text{mod } 24h)$ scatter plot, i.e., it shows the durations of the hashtags vs the times of the day when they first appeared on the HSL, with each point.
representing a hashtag. Hashtags tend to appear on the HSL starting from around 7 a.m. till midnight. We can see clear shapes of lower-left and upper-right triangles, separated by a stripe in the middle with a low number of points inside. The lower boundary of the upper-right triangle is very sharp, while the upper boundary of the lower-left triangle is less so. There are data points within the stripe, but the density is much less compared with the data points inside the triangles and also if we compare it to the users’ overall activity pattern (see SI Appendix). The vertical distance between the triangle boundary lines is approximately 7 hours. The existence of these triangles suggests that the hashtags, which enter the HSL after 15 p.m. tend to either disappear from the HSL on the same day or stay on the HSL during the night and disappear after 7 a.m. the next day. This is presumably related to Sina Weibo working mode, already pointed out in previous studies [17], namely that Sina Weibo practically stops working between midnight and 7 a.m. If the ranking was automated following the formula Eq. the changes from day to night should not be that sharp and the circadian pattern should follow more or less that of the people’s activity.

Fig 3. Relationship between hashtags’ duration on the HSL and the time \( t_i \).
(A) Scatter plot of hashtags’ duration on the HSL and the time of the day they first appear on the HSL. Each point is a hashtag, colored by the category it is clustered in Fig. 2.
(B) Distribution of hashtags’ duration on the HSL according to different time intervals during the day of first appearance on HSL.

Figure 3B shows the duration distribution of the hashtags as a decomposition of Fig. 2A by binned starting values of the times of the day. For each time interval, the observed distribution is trimodal. As the start time of the day \( t_i (\text{mod } 24\text{h}) \) goes on, the density of hashtags in the third mode is increasing. In Fig. 3A we see a low-density area at around 1 hour duration between the blue and the yellow dots, which corresponds to the minimum between sections 1 and 2 in Fig. 2A. Accordingly, in the duration distribution plot shown in Fig. 3B, a peak is observed for hashtags with duration shorter than 1 hour. Within this stripe there is an accumulation of pink dots corresponding to trajectories of category D, with a unique shape, namely starting at low rank and ending at a high one within a short period of time. The fact that the hashtags disappear from the HSL during their rising trend toward higher ranks might be related to platform interventions. In most other cases the more expected shape is observed, namely starting and ending from low rank and having in between some higher rank.

How are the shapes of the rank trajectories related to the time of the day the hashtags first appear on the HSL? Recall the Weibo working mode, if a hashtag’s stay on the HSL is influenced by the night break, then it will automatically have a little-fluctuation period of at least seven hours, resulting in a rank trajectory shape similar to Fig. 2F or the last part of Fig. 2G, which we color in red and green respectively in Fig. 3A. Hashtags in Fig. 2F are born closer to midnight and further
away from the hypotenuse of the upper-right triangle in Fig. 3A. This is reasonable since hashtags entering HSL close to midnight are likely exposed to the stay on the HSL during the night break. Hashtags with shape in Fig. 2G, however, are close to the hypotenuse boundary of the upper-right triangle in Fig. 3A. One possible explanation is that although these hashtags’ attention level is already in decreasing trend, their stay on the HSL are prolonged by the night break, so that when the next day begins, they are replaced by new hashtags and leave the list. The majority of hashtags with shape shown in Fig. 2G are of shorter duration, located in the dense area of the lower-left triangle colored in blue in Fig. 3A. The separation of the red and blue areas in Fig. 3A lower-left triangle tells that hashtags which quickly go down after reaching their highest ranks on the HSL lack the ability to consistently attract public attention to maintain their positions on the list. In contrast, hashtags maintain relatively stable ranks (Fig. 2F) stay longer times on the HSL, as Fig. 3A lower-left red area suggests.

Ranking

As mentioned in the Introduction, spontaneously evolving ranking dynamics have typical rank diversity patterns [33–35]. After sufficiently averaging the rank diversity, the curve shape is smoothened and depends on whether the system is open or closed, as shown in S1 Appendix.

Figure 4A shows the distribution of the enter-ranks $r_i(t_i)$ and leave-ranks $r_i(T_i)$ on the HSL. The majority of hashtags do not land on the HSL from the very bottom of the ranking list, instead they tend to enter at ranks 44 - 46 while they tend to leave from the bottom ranks. Figure 4B shows the scatter plot of the highest rank of the hashtags and their duration on the HSL. The duration exhibits a bimodal pattern with a sudden jump at rank 16, and then it decreases. Figure 4C shows the relationship between the hashtags’ enter-ranks on the HSL and their corresponding duration on the HSL. The popularity of a hashtag is reflected in its rank position and the duration it stays on the HSL. Hashtags at higher ranks are more stable and stay for longer hours on the HSL as shown by the rank diversity in Fig. 6A, thus it is strange for hashtags entering HSL at a high rank only stays for short duration.

Figure 6A shows the rank diversity of the hashtags on the HSL broken down to daytime and nighttime. The difference between the behavior during the night and day is apparent: The former is more likely to the closed systems’ characteristics with reduced activity while the latter is closer to the open systems’ features although the trend around rank 44 turns down, probably due to the fact that the hashtags’ enter-ranks $r_i(t_i)$ is shifted to the left as shown in Fig. 4A. There are apparent
anomalies in these figures at certain ranks where rank diversity values are dropping systematically as compared to what is expected from the assumption of a smooth curve for these quantities. We think that the anomalies are due to interventions by the service provider, which anchors some of the hashtags on the HSL at specific ranking positions (see Section Anchor effect).

Ranking dynamics in relation to prehistory

Before the hashtags gain enough popularity and land on the HSL, they go through different propagation routes during their prehistory. The time length of the prehistories $t_{HSL}$ differ for different hashtags [17]. Some hashtags get to the HSL in very short time after birth, while others take longer. Figure 5 shows the relationship between $t_{HSL}$ of the hashtags, the ranks they enter the HSL $r_i(t_i)$, and the duration $d_i$ of their stay on the HSL. As shown in Fig. 5A, in accordance with Fig. 4A, the majority of hashtags enter the HSL at a low rank peaking around 45. Some hashtags enter the HSL at higher ranks, however, as the prehistory gets longer, the chance the hashtag enters the HSL from a high rank is less likely. As for the properties of hashtag duration on the HSL shown in Fig. 5B and Fig. 5C, the duration against prehistory length exhibits bimodal distribution. As the prehistory length increases, the first peak drops and the second peak rises. The bimodality similar to results shown in Fig. 3 is influenced by the Weibo circadian working mode.

Fig 5. Prehistory length $t_{HSL}$, enter-ranks $r_i(t_i)$, and duration $d_i$ of hashtags on the Sina Weibo HSL.

(A) The relationship between the hashtags’ prehistory time length and the ranks they first enter on the HSL. (B) The relationship between the hashtags’ prehistory time length and the duration they stay on the HSL. (C) Parameterized probability density function of the hashtag duration on the HSL by prehistory time length, using kernel density estimation (KDE) [38], with the parameter bw = “scott” [39].

Anchor effect

In this section, we propose a ranking model with anchoring to simulate the dynamics of the hashtag ranking anomalies on the HSL.

Let us take a system of $N$ elements (for the hashtags), each element has a random initial score of values within $(0, 1)$, and rank these elements from top to bottom based on the scores. Let $r_i$ and $s_i$ denote the rank and the score of the $i$-th element, respectively. The scores change in time and that causes the rank movement of the elements. We will choose a simple dynamics: An element is randomly selected, 1 is added to its score and the ranking is changed if necessary. The idea of the anchor is the following: Set an anchor at position $A$. For hashtags whose $r < A$, it is difficult to go down the ranking list; for hashtags whose $r > A$, it is difficult to go up (note that high rank means low $r$.
The anchor represents a barrier characterized by an increment \( \delta \). Let \( \varphi(r_i) = i \) denote the selection of the element at a given rank at an instant of time.

The procedure of ranking at each step is shown below. Randomly pick one element \( j \) and \( s_j^{\text{new}} = s_j + 1 \). There are three possibilities:

(a) \( r_j < A \). Update the top \( A - 1 \) ranks, no change of the anchor element.

(b) \( r_j = A \). If \( k = \varphi(A - 1) \) and \( s_j^{\text{new}} > s_k + \delta \), update the top \( A \) rank. Otherwise, no change of ranks.

(c) \( r_j > A \). If \( \ell = \varphi(A) \) and \( s_j^{\text{new}} > s_\ell + \delta \), old anchor rank drops to \( A + 1 \), update the top \( A + 1 \) ranks. Otherwise, update ranks lower than \( A \), no change of the anchor element.

We simulate a system with 500 elements and take the top \( L = 48 \) ranks to approximate an open system.

The rank diversity of a non-intervened system has parabola-shape (see Supporting Information). The intervention produces a deep valley at the anchor position, very similar to those observed in the measured curves in Fig. 6, which shows the comparison between the real data and our model with anchoring. Figure 6A shows the average rank diversity of the observation period, separately for day and night. The measures during the day from 7 a.m to 24 p.m has larger value than during the night from 24 p.m to 7 a.m. and the night behavior is closer to that of a closed system, according to the suppressed activity during that period. At certain positions (ranks 16, 28, and 33) there are large drops in the values of the function, indicating intervention by “anchoring” hashtags at these specific ranks. The simple model of anchoring reproduces qualitatively the effect.

![Fig 6. Rank dynamics comparison between empirical data and a ranking model with anchoring.](image)

With this model we support the assumption that the observed anomalies in the ranking functions are due to intervention.

**Discussion**

Public attention is precious and it is nowadays largely dependent on online social media, therefore it is of great interest to understand the dynamics governing popularity on such platforms. Considerable effort has been devoted to this task on Twitter \cite{3,5,8} and some results are also known on Sina Weibo \cite{15,17}. In order to attract attention, people, companies, and political actors are tempted to make use of hidden manipulations besides well known tools of direct advertisements or propaganda \cite{11,12,17,28,41}. Thus popularity can emerge spontaneously via collective attention from online users who are
genuinely interested in a topic and form trends, quantified and captured by the algorithm of the platform, or trends emerge from intervention by the platform provider motivated by financial or other interests. (It should be noted that “collective attention” may also be influenced, e.g., by spamming \cite{12} or coordinated campaigns \cite{13,16}.)

In this paper, we studied the attention dynamics of trending hashtags on the Sina Weibo Hot Search List by using various measures of ranking dynamics, like entering and leaving ranks as well as duration of hashtags on HSL, rank diversity, and categories of rank trajectories. The aim of the identification of regularities in the ranking dynamics was twofold: First, contribution to the quantitative characterization of the dynamics of public attention in order to better understand its mechanism, and second, finding signatures of interventions by the service provider.

The duration of the hashtags on the HSL in relation to the time of the day they enter the list shows trimodality (Fig. 3). This is related to the fact that the appearance of hashtags on the HSL have circadian patterns (Fig. 1A). On the one hand, the pattern is caused by the circadian rhythm of the users whose activities depend on the time of the day (see \cite{S1 Appendix}, on the other hand it is imposed by the apparent working mode of Sina Weibo, which reduces the night-time flow of new hashtags to the HSL almost to zero level. The night break is reflected in the very low number of points in the stripe separating the two triangles in Fig. 3A and in the particularly sharp upper boundary of this stripe. This seven hour gap has been shown to influence the prehistory of the successful hashtags \cite{17} by contributing to the difference between shorter and longer prehistories and it creates a link between the behavior of the hashtags on the HSL and their prehistory (Fig. 5).

The observation of the extreme daily pattern is already an example that we are able to identify interventions by the service provider through anomalous behavior of the ranking dynamics. Obviously, the ranking is not automated following a plain formula like Eq. 1 but depends on human control. Even more importantly, we show an anchoring effect at some rank positions on the HSL, where rank diversity is suppressed as compared to the expected smooth behavior of this quantity. Using a simple ranking model we show how anchoring at some rank positions changes rank diversity. A further observation indicating intervention is that some hashtags on the HSL appear at high ranks and disappear in short time (Fig. 4C). Similarly, there are many hashtags that just stay on the HSL for short time which is shown in the first peak in Fig. 3B. The fact that the peak is separated from the rest of the distribution is also likely be related to intervention.

Sina Weibo is the microblogging site with world-wide the largest number of active users, who are overwhelmingly Chinese speakers. While we believe that alone the size of Sina Weibo justifies focused study, we know that most of our results are idiosyncratic. However, this is true only in a narrow sense as our results provide general lessons. We demonstrated that studying the ranking dynamics in popularity lists is worth for several reasons. First, we uncovered relationships between ranking dynamics and the circadian pattern of user activity, also establishing a link to the prehistory of items getting to the ranking list. Moreover, we identified different trajectory categories on the list, which characterize different dynamic patterns of popularity. Finally, and most importantly, we showed, how pinpointing anomalies in ranking statistics can be used to identify interventions by the service provider. As service providers have financial interests and may be under political pressure, objectivity of the ranking lists and its truth content can be questioned. Similarly to the fight against fake news, the fight against manipulation of public attention is in the interest of the society and it also needs the tools of detecting interventions.
Supporting information

S1 Appendix.  Supplementary Material to the manuscript.

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References

1. Aksoy CG, Ganslmeier M, Poutvaara P. Public attention and policy responses to COVID-19 pandemic. MedRxiv. 2020 Jan 1.

2. Dyer J, Kolic B. Public risk perception and emotion on Twitter during the Covid-19 pandemic. Applied Network Science. 2020 Dec;5(1):1-32.

3. Wu F, Huberman BA. Novelty and collective attention. Proceedings of the National Academy of Sciences. 2007 Nov 6;104(45):17599-601.

4. Eom YH, Puliga M, Smailović J, Mozetič I, Caldarelli G. Twitter-based analysis of the dynamics of collective attention to political parties. PloS one. 2015 Jul 10;10(7):e0131184.

5. Annamoradnejad I, Habibi J. A comprehensive analysis of twitter trending topics. In2019 5th International Conference on Web Research (ICWR) 2019 Apr 24 (pp. 22-27). IEEE.

6. McGregor SC, Mourão RR, Molyneux L. Twitter as a tool for and object of political and electoral activity: Considering electoral context and variance among actors. Journal of Information Technology & Politics. 2017 Apr 3;14(2):154-67.

7. Romero DM, Galuba W, Asur S, Huberman BA. Influence and Passivity in Social Media. SSRN Electronic Journal, 2010, 6913(1):18–33.

8. Asur S, Huberman BA, Szabo G, Wang C. Trends in social media: Persistence and decay. InProceedings of the International AAAI Conference on Web and Social Media 2011 (Vol. 5, No. 1, pp. 434-437).

9. Yang J, Leskovec J. Patterns of Temporal Variation in Online Media. WSDM ’11: Proceedings of the fourth ACM international conference on Web search and data mining, February 2011 Pages 177–186, https://doi.org/10.1145/1935826.1935863

10. Yang J, Leskovec J. Modeling information diffusion in implicit networks. In2010 IEEE International Conference on Data Mining 2010 Dec 13 (pp. 599-608). IEEE.

11. Zhang Y, Ruan X, Wang H, Wang H, He S. Twitter trends manipulation: a first look inside the security of twitter trending. IEEE Transactions on Information Forensics and Security. 2016 Aug 30;12(1):144-56.
12. Stafford G, Yu LL. An evaluation of the effect of spam on twitter trending topics. In 2013 International Conference on Social Computing 2013 Sep 8 (pp. 373-378). IEEE.

13. Piña-García CA, Espinoza A. Coordinated campaigns on Twitter during the coronavirus health crisis in Mexico. Tapuya: Latin American Science, Technology and Society. 2022 Apr 8;2035935.

14. Number of monthly active users of Sina Weibo from 1st quarter of 2018 to 3rd quarter of 2021. statista. [Online]. https://www.statista.com/statistics/795303/china-mau-of-sina-weibo/ [Accessed 2022 Aug 9].

15. Fan R, Zhao J, Xu K. Topic dynamics in Weibo: a comprehensive study. Social Network Analysis and Mining. 2015 Dec;5(1):1-5.

16. Yu LL, Asur S, Huberman BA. Trend dynamics and attention in Chinese social media. American Behavioral Scientist. 2015 Aug;59(9):1142-56.

17. Cui H, Kertész J. " Born in Rome" or" Sleeping Beauty": Emergence of hashtag popularity on a microblogging site. arXiv preprint arXiv:2203.14802. 2022 Mar 28.

18. Kong Q, Mao W, Chen G, Zeng D. Exploring trends and patterns of popularity stage evolution in social media. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2018 Aug 7;50(10):3817-27.

19. Zhao J, Wu W, Zhang X, Qiang Y, Liu T, Wu L. A short-term trend prediction model of topic over Sina Weibo dataset. Journal of Combinatorial Optimization. 2014 Oct;28(3):613-25.

20. Liu T, Zhong Y, Chen K. Interdisciplinary study on popularity prediction of social classified hot online events in China. Telematics and Informatics. 2017 Jun 1;34(3):755-64.

21. Zhou Y, Zhang L, Liu X, Zhang Z, Bai S, Zhu T. Predicting the trends of social events on Chinese social media. Cyberpsychology, Behavior, and Social Networking. 2017 Sep 1;20(9):533-9.

22. Fan R, Zhao J, Chen Y, Xu K. Anger is more influential than joy: Sentiment correlation in Weibo. PloS one. 2014 Oct 15;9(10):e110184.

23. Chen L, Zhang C, Wilson C. Tweeting under pressure: analyzing trending topics and evolving word choice on sina weibo. InProceedings of the first ACM conference on Online social networks 2013 Oct 7 (pp. 89-100).

24. Yu L, Asur S, Huberman BA. What trends in Chinese social media. arXiv preprint arXiv:1107.3522. 2011 Jul 18.

25. Common Questions on the Rules of Real-time Hot-Search-List, Hot-Message-List and Hot-Topic-List”. Sina Weibo. [Online]. https://www.weibo.com/ttarticle/p/show?id=2309404007731978739654 [Accessed 2022 Aug 9].

26. Weibo Hot Search Regulation Rules. Sina Weibo. [Online] https://weibo.com/1934183965/KuKyPkp8Y?type=rep [Accessed 2022 Aug 9].
27. Zhang Z, Li B, Zhao W, Yang J. A study on the retweeting behaviour of marketing microblogs with high retweets in Sina Weibo. In 2015 Third International Conference on Advanced Cloud and Big Data 2015 Oct 1 (pp. 20-27). IEEE.

28. Cui H, Kertész J. Attention dynamics on the Chinese social media Sina Weibo during the COVID-19 pandemic. EPJ data science. 2021 Dec 1;10(1):8.

29. Li M. Promote diligently and censor politely: how Sina Weibo intervenes in online activism in China. Information, Communication & Society. 2021 Oct 2:1-6.

30. Perloff RM. Mass media, social perception, and the third-person effect. InMedia effects 2009 Jan 13 (pp. 268-284). Routledge.

31. GitHub repository
   https://github.com/cuihaosabrina/Sina_Weibo_Interventions

32. China punishes microblog platform Weibo for interfering with communication. Reuters. [Online] https://www.reuters.com/article/us-china-censorship-weibo-idUKKBN23H1J2 [Accessed 2022 Aug 15.]

33. Morales JA, Sánchez S, Flores J, Pineda C, Gershenson C, Cocho G, Zizumbo J, Rodríguez RF, Iñiguez G. Generic temporal features of performance rankings in sports and games. EPJ Data Science. 2016 Dec;5:1-6.

34. Iñiguez G, Pineda C, Gershenson C, Barabási AL. Dynamics of ranking. Nature communications. 2022 Mar 28;13(1):1-7.

35. Morales JA, Colman E, Sánchez S, Sánchez-Puig F, Pineda C, Iñiguez G, Cocho G, Flores J, Gershenson C. Rank dynamics of word usage at multiple scales. Frontiers in Physics. 2018:45.

36. Müller M. Dynamic time warping. Information retrieval for music and motion. 2007:69-84.

37. Tavenard R, Faouzi J, Vandewiele G, Divo F, Androz G, Holtz C, Payne M, Yurchak R, Rußwurm M, Kolar K, Woods E. Tslearn, a machine learning toolkit for time series data. J. Mach. Learn. Res. 2020 Jan 1;21(118):1-6.

38. Terrell GR, Scott DW. Variable kernel density estimation. The Annals of Statistics. 1992 Sep 1;1236-65.

39. Scott DW. Multivariate density estimation: theory, practice, and visualization. John Wiley & Sons; 2015 Mar 30.

40. 2015 weibo user development report. Weibo Report. [Online] https://data.weibo.com/report/reportDetail?id=333 [Accessed 2022 Aug 10.]

41. Bamman D, O’Connor B, Smith N. Censorship and deletion practices in Chinese social media. First Monday. 2012 Mar 4.
Supporting Information to:

Competition for popularity and identification of interventions on a Chinese microblogging site

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SI1. Daily posts volume on Weibo

![Graph showing Weibo users' daily posts volume distribution](image)

**Figure S1.** Distribution of Weibo users’ daily posts volume according to Weibo User Development Report [1].

SI2. Examples of rank trajectories

![Graphs showing rank trajectories](images)
**Figure S2.** Examples of rank trajectories in Fig. 2D. (A) #Qutoutiao rectification# (#趣头条整改#) (B) (#Temperatures set to hit record lows in many cities this week#) #本周多城市气温将创新低# (C) #How to describe yourself having no money in one sentence# (#如何一句话形容自己没钱#)

**SI3. Rank diversity in a model closed system**

![Graph showing parabola shaped normalized rank diversity](image)

**Figure S3.** Parabola shaped normalized rank diversity in a model closed system of size 500. The top L = 48 can be considered as an open system.

**References**

[1] Center, S. W. D. 2015 weibo user development report. Weibo Report. https://data.weibo.com/report/reportDetail?id=333 (2016)