Temporal Communication Motifs in Mobile Cohesive Groups

Matteo Zignani, Christian Quadri, Michela Del Vicario, Sabrina Gaito, Gian Paolo Rossi

Abstract In this paper we focus on cohesive social groups that communicate and establish relationships by mobile phone. Through a methodology which identifies cohesive groups and extracts their temporal motifs, we show how the members of social groups interact by means of calls and text messages. Our analysis rests on an anonymized mobile phone dataset, which is based on Call Detail Records (CDRs). This dataset integrates the usual voice call data with the text messages sent by one million mobile subscribers in the metropolitan area of Milan over the span of 67 days. The findings of our study concern both the structural characterization of cohesive groups and the temporal patterns emerging from the interactions among their members. Structurally, cohesive groups are small and people comprise them in ways similar to other social networks or instant messaging services. Temporally, we observe that communication patterns between pairs of group members are predominant, especially for text message communications, where the nature of the medium tends to lead toward ”blocking” interactions. Finally, if members participate in more complex communication patterns, text messages make the diffusion of common information easier.

1 Introduction

Human life is typically group life. People belong to a number of groups for purposes of sharing interests [5], achieving a common goal and/or providing mutual help: whatever the kind of the group, its members keenly interact, communicate and exchange information [4, 25]. As these tightly knit groups are fundamental build-

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ing blocks of social networks, they have been investigated by means of sociological methods, social network analysis and complex networks theory; recently they have also become the subject of studies on large scale data provided by online social media [2, 1]. Despite the large body of work devoted to study groups and communities in social networks [3, 16], their identification and characterization remain challenging. Moreover, the identification is often carried out on a static representation of the relationships, thus losing one of the main aspects of cohesive groups: the dynamics of frequent interactions [17]. In fact, communications and exchanges of information within a group are fundamental for keeping it alive and may lead to the formation of temporal communication patterns[20, 23]. The temporal patterns of these cohesive groups have been only partially investigated, also due to the limited number of temporally annotated data available [26], thus leaving the many questions about their formation and information spread process largely unresolved.

In this paper we leverage the temporal network [6] built on top of a large dataset of mobile Call Detail Records (CDRs) to detect and characterize the cohesive groups formed by mobile operators subscribers. Then, we investigate how members communicate within groups by identifying their temporal motifs; we also examine how the information spreads within groups by performing a motifs analysis. More specifically, the contributions we make in our paper can be summarized as follows:

- We identify cohesive groups as the locally maximal quasi-cliques in the on-phone interaction graph and show that the cohesive groups so extracted from the mobile operator's data exhibit size and membership patterns similar to other social networks or modern instant-messaging services. Specifically, small cohesive groups (consisting of 5 to 7 people) are predominant in our mobile phone dataset and the average number of groups an individual participates in is 6.
- We identify and count all the temporal motifs generated by call and text message interaction events among the members of the cohesive groups and examine their main characteristics. We distinguish between temporal motifs generated by call events and those generated by text messages since we wonder if the nature of the medium impacts the nature of the communication patterns. In fact, except for the single event motif, the most frequent motifs in calls and text messages are diverse. Motifs involving more than two people are more frequent in call events than in text message, with the latter reproducing motifs typical of a call conversation, i.e. a sequence of tit for tat. Finally, adopting the motif categorization proposed in Paranjape et al [14], we identify "blocking" and "not blocking" behaviors in interactions; also, we confirm the results of the previous study, showing the prevalence of blocking interactions through text messages.
- We study information diffusion processes in the temporal motifs and propose a categorization of the temporal motifs involving at least 3 nodes and 3 communication events. The categorization is based on two variants of a diffusion model. This allows us to evaluate whether or not a temporal motif can promote the diffusion of information so to reach all the motif participants. On the basis of the above variants we also propose an index which measures the propensity of a group to adopt temporal motifs facilitating the diffusion of information that will reach all members. Results suggest that *a*) temporal motifs promoting a shared

piece of information are more frequent through text message interactions; and *b*) large groups are characterized by temporal motifs which make the spreading of a piece of an information to all motif participants harder.

The paper is organized as follows. In Section 2 we describe the mobile phone dataset and the methodology to identify the cohesive groups and extract the temporal motifs from the sequence of call/text message events. In Section 3 we analyze the structural properties of the identified cohesive groups and examine the main characteristics of the temporal motifs capturing the communication patterns within the groups. Finally, in Section 4 we summarize our contributions and results.

2 Dataset and methods

2.1 Dataset

We carried on our investigation on cohesive groups and their temporal motifs by mining a large anonymized dataset of Call Detail Records (CDRs) provided by one of the major telecommunication companies in Italy. For billing purposes, the mobile operator records an entry in the charging database whenever an event occurs, i.e. a subscriber makes/receives a call or a text message. Among the many information recorded, we retain the sender's and receiver's IDs to build the users' interaction network and the initial time of the on-phone communication event to detect the temporal motifs. The information provided in the database covers the metropolitan area of Milan for a period of 67 days, namely from March 26 to May 31, 2013; before the era of instant-messaging services. During this period approximatively 63 million phone calls and 20 million text messages were exchanged among around one million of subscribers [12, 13].

On-phone interaction network. Following the standard approach in literature we represent the interaction network as a directed graph whose nodes are the operator's customers and whose edges connect two customers who interact by calls or texts and are directed from the sender to the receiver of the communication. Also, to overcome the inter-operator bias issue, we filter out CDRs where the sender or the receiver is subscribed to another operator. After applying the filter, we extract only the interactions with social relevance. To this end, for calls we consider the pairs of users whose sum of call durations exceeds one minute and whose total number of interactions is higher than 3, while for text messages the only relevant pairs are those with a total number of interactions higher than 3. Through the filtering on duration and frequency, we are able to remove accounts/users whose behavior (degree, in/out degree) resembles call centers or customer cares. The main properties of the so constructed on-phone interaction network are summarized in Table 1.

Table 1: Summary of the properties of the on-phone interaction network. The first three columns report the number of nodes, the number of links and the density of the network, respectively. $\hat{k}$ indicates the average degree. The last two columns report the percentage of nodes in the giant connected component and the average clustering coefficient $\hat{c}$.

Order	Size	Density	$\hat{k}$	% nodes in GCC	$\hat{c}$
289448	429273	$1.02 \cdot 10^{-5}$	3	78%	0.12

2.2 Cohesive group identification

The identification of cohesive groups, which is a central problem in both graph theory and social network analysis, entails different methods - from community detection [18, 3] to enumeration of particular maximal subgraphs [11, 8]. In this work we focus on the latter approach, more suitable when looking for highly tight-knit groups; moreover, community detection methods have been shown to return loosely connected subgraphs on networks built on top of on-phone communications, barely interpretable as social groups [21].

Among the different formalizations of cohesive group, we adopt a relaxation of the notion of clique, the *quasi-clique*. The notion of clique well embodies one of the main properties of a cohesive group, i.e. the mutuality [1], but the completeness of the subgraph is too strict a constraint. In literature many definitions weakening the notion of clique have been proposed, from n-cliques or n-clubs to k-core. Here we use the notion of quasi-clique or γ-clique, since it allows us to quantify how much we loosen the completeness constraint, while guaranteeing the reachability of the group members, a further property of cohesive groups. Formally, given a graph $G = (V,E)$, a γ-clique is a subgraph G_S spanned by S, a subset of V, that is connected and γ-dense. G_S is γ-dense if $|E(G_S)| \geq \gamma\binom{V(G_S)}{2}$. In this work we use $\gamma = 0.8$. Following our approach, the identification of cohesive groups turns into the enumeration of all quasi-cliques of maximum cardinality. To accomplish this task we adopt the Uno's enumeration algorithm [22] which returns all the locally maximal quasi-cliques in a given graph. Then, since Uno's algorithm does not guarantee the connectedness of the returned quasi-cliques, for each quasi-clique we verify whether it is connected or not, discarding the unconnected ones. This way, from the on-phone interaction network, which merges call and text message communications, we identify all the connected locally maximal quasi-cliques, representing the cohesive groups.

[1] By mutuality we mean that all pairs of group members interact with one another.

2.3 Temporal motifs identification

Network motifs were originally introduced into complex networks analysis as "patterns of interconnection incurring at numbers that are significantly higher than those in randomized networks" [9], i.e., they are defined as equivalence classes of isomorphic subgraphs[2] whose number of occurrences in the data is significantly higher than that in a reference system. Successive works generalized this definition to include the case of temporal networks. In [7] temporal motifs are defined as equivalence classes of temporal subgraphs whose events happen at a distance smaller than a fixed value and are consecutive, while in [14] $\delta-$temporal motifs are introduced as sequences of edges that are time-ordered and confined within a temporal interval of length δ. In this paper we followed the definition given by [7] as here we are interested in investigating communication dynamics and information diffusion within groups with a more event-focused point of view that accounts for the consequentiality of information exchanges. Authors in [7] first formally define temporal subgraphs by extending the concept of subgraph to the case of temporal networks. Starting from the definition of adjacency and connectivity of events, they derive that of connected temporal subgraphs. Two events are Δt-adjacent if they have at least one node in common and the time difference between the events is smaller than Δt. Also, they are Δt-connected if there is a sequence of Δt-adjacent events between them. Then, a connected temporal subgraph is a set of events that are pairwise Δt-connected and such that the events in which each node is involved are consecutive. They provide an algorithm that returns all temporal subgraphs with up to n_{max} events and their critical time window sizes. Then, we need to compare the critical sizes to Δt in order to identify the Δt-connected subgraphs.

Temporal motifs are then detected by introducing an equivalence relation on the temporal subgraphs as an extension of the concept of subgraph isomorphism, that is based on the representation of sequences of events as directed multi-graphs. Specifically, two temporal subgraphs are equivalent if they have the same topology, i.e., if their underlying directed multi-graphs are isomorphic and their events occur in the same order. In practice, temporal motifs are detected by using existing algorithms that exploit a mapping of the temporal subgraphs into directed colored graphs to solve the graph isomorphism problem. Refer to [7] for details about the algorithms. In our methodology, for each group, we apply the aforementioned algorithm to two temporal subgraphs; the first generated by the call interactions, the second by text messages. Specifically, we extract all the different temporal motifs within a time window $\Delta t = 1$ *hour* and with a maximum number of events $n_{max} = 4$.

[2] Two graphs $G_1(V_1, E_1)$ and $G_2(V_2, E_2)$ are isomorphic if there exists a one-to-one mapping of the vertices, $\sigma : V_1 \rightarrow V_2$, such that $\sigma(V_1) = V_2$.

2.4 Temporal motifs categorization

The sequence of the interaction events imposed by temporal motifs may drive the diffusion of a piece of information among the participants of a motif. Thus, we exploit the status of the motif participants after a diffusion process terminates. This is to categorize motifs depending on whether or not all members hold the same information.

As we allow the circulation of multiple pieces of information, each node in the temporal motif initially holds a different one. The diffusion process unfolds following the temporal structure of the motif, i.e. the ordered sequence of directed links. Consequently, the initiator of the diffusion process is the source of the first link in the motif. To complete the full description of the process, we also need to allow the target of a directed link to update its information. With respect to this updating rule we contemplate two possible variants. In the first variant (*Rule 1*), the target discards the in-coming information if it has already received it, whereas in the second variant (*Rule 2*) the target keeps accepting and holding the last information obtained. At the end of the diffusion process we categorize the temporal motif according to the final information held by its nodes. If all the nodes have the same information, we say the motif is *aligned*. An example of the two variants of the diffusion process is reported in Fig.1a. In the first case we apply Rule 1 and the final pieces of information held by each node are different, so that the temporal motif is not aligned, while in the second case the temporal motif is aligned.

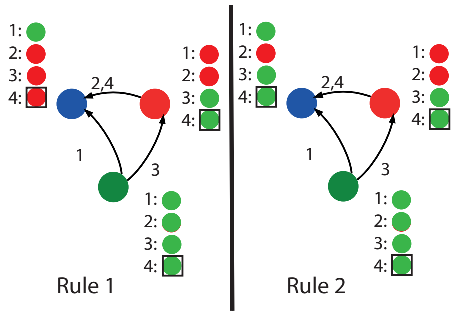
On the basis of the above categorization, we assign to each cohesive group g an *alignment index AI*, defined as the fraction of aligned temporal motifs over the total amount of motifs characterizing the group g:

$$AI(g) = \frac{\sum_{m \in M(g)} \mathbb{I}_{aligned}(m) N(m)}{\sum_{m \in M(g)} N(m)} \tag{1}$$

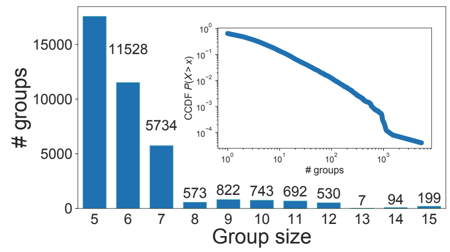
where $M(g)$ denotes the set of temporal motifs characterizing the group g, $N(m)$ counts how many times the motif m occurs in the communication sequence of the group g and $\mathbb{I}_{aligned}$ is the indicator function of the event: "the motif m is aligned". By the *alignment index*, we measure the tendency of a group to use aligned temporal motifs for their interactions, so promoting a single and shared piece of information after the motif ends.

3 Results

By means of the above methodology we identify more than $38,000$ on-phone cohesive groups, which involve about 23,800 operator's subscribers. We will show that on-phone cohesive groups are statistically similar to other groups found in different socio-technological networks. From a temporal viewpoint, we observe that, although interaction patterns between pairs of group members are predominant, in



(a)



(b)

Fig. 1: In (a) the application on a temporal motif of the two variants of the diffusion process. The numbers on the links indicate the ordered sequence of interaction events. Close to each node we report the piece of information held by the node after each step. In the second case (Rule 2) the final information is common to each node (green information), i.e. the motif is aligned; while in the first case (Rule 1) we observe two different pieces of information after the diffusion ends, i.e. the motif is not aligned. In (b) the histogram of the size of the on-phone cohesive groups. In the inset of the figure, the distribution of the number of cohesive groups per user.

call communications we show a tendency to overcome bilateral interactions. Moreover, if members participate in group communication patterns, text messages make the diffusion of common information easier.

Cohesive groups size and membership. The size of a group is one of the main aspects of a social environment, since it influences the strength of relationships, the intensity of participation in group activities and the consonance of aims [10]. In Fig. 1b we show the probability distribution function of the size. It highlights that small cohesive groups ($k = 5,6$) are predominant in mobile phone networks. Moreover the short tail of the distribution - its maximum value is 15 - indicates a substantial difference w.r.t. community detection approaches [21]. By comparing the cohesive group size with the size measured on online social networks or instant-messaging applications [24, 19, 10], we observe that their sizes are very similar.

Groups could form around common interests or existing social structures - family, workmates, teammates - so an individual may likely participate in different social groups. To this aim, in the inset of Fig. 1b, we report the distribution of the number of cohesive groups a user belongs to. The distribution follows a heavy-tail trait, i.e. most of users belong to few cohesive groups, but people participating in many cohesive groups do exist. In particular, half of the population share at most 2 social groups, while the average number of cohesive groups per user is 6. Similar results have been observed in other social networks, such as Flickr [10] or LiveJournal[24].

Temporal motifs. By means of the algorithm for the extraction of the temporal motifs presented so far, we identify 81 million motifs for calls and 18 million motifs for texts; corresponding to approximatively one thousand unique temporal motifs. Here we examine the occurrences of the motifs and identify the most frequent interaction patterns within cohesive groups, since the algorithm returns the counting of each motif in each group. In Fig.2 we report the 13-most frequent temporal motifs involving call interactions only, along with the frequency of the same temporal motifs measured on text message events. In both cases the temporal motif corresponding to a single call/text is the most frequent. In call interactions the most frequent motifs include conversations among more than two people, like out-stars and in-stars (motifs 3 and 5 respectively in Fig.2). By comparing the two distributions we also observe that in text interactions, motifs 2,4,7,9 are much more frequent than in calls. These temporal motifs correspond to a sequence of interactions within a couple of nodes; they are due to the nature of the medium, since the only way to talk by texting is a sequence of tit for tat, so generating typical bursty interaction patterns [15]. Thus, the most used interaction patterns in calls and text messages are diverse, with the former medium preferred when more than two people interact and communicate in a short time. Hence, despite on-phone communications have been thought to connect just pairs of people, in call interactions we show evidences of a need of overcoming bilateral interactions.

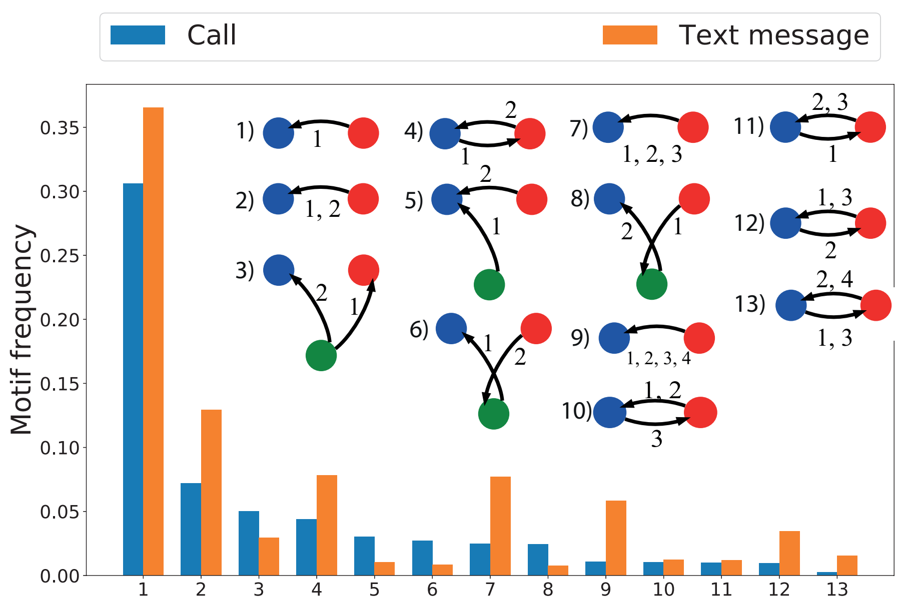
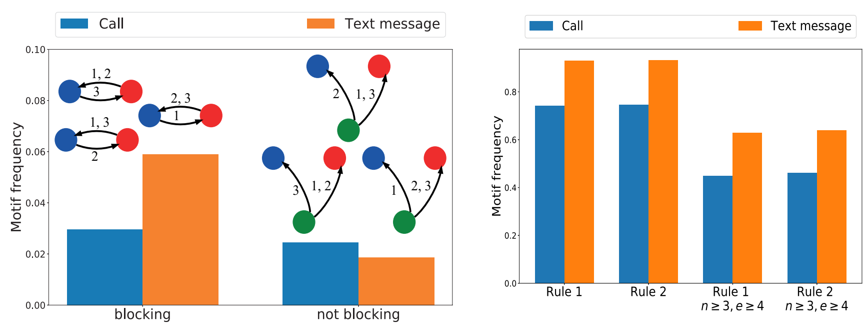


Fig. 2: The 13-most frequent temporal motifs in call interactions (blue bar). The orange bars represent the frequency of the motifs in text interactions. The temporal motifs in texts do not correspond to the most frequent ones in calls. The index on the x-axis corresponds to the id of the motifs placed inside the figure.

Albeit each temporal motif reveals a specific dynamic of the interaction patterns, we can group temporal motifs which reproduce a common behavior. Specifically, here we adopt the motif classification proposed in Paranjape et al [14] which identifies ”blocking” and ”not blocking” temporal motifs. A motif is said to be blocking when an individual has to wait for a reply from another person before interacting with another individual. A typical tit for tat between two people is blocking. In Fig.3a we show all the blocking temporal motifs on top of the bar plot. Each temporal motif is made by 3 events between two nodes with at least a link in either direction. Differently, ”not blocking” temporal motifs capture situations where an individual does not wait for a reply and proceeds to communicate with others. The three not-blocking temporal motifs have been reported in Fig.3a. We observe that these motifs are characterized by a single source interacting with different targets. In Fig.3a we also report the fraction of blocking/not blocking motifs in call and text interactions, respectively. In text messages blocking interactions are much more common w.r.t. calls, where blocking and not-blocking interactions are quite balanced. Also in this case, the inability of a single text message interaction to reproduce a call conversation leads to the prevalence of the specific behavior, which does not appear in call interactions.



(a) (b)

Fig. 3: In (a) the fraction of temporal motifs corresponding to ”blocking” and ”not blocking” behaviors in calls (blue bar) and texts (orange bar). Motifs belonging to each category are reported on top of each category bar. In (b) the fraction of aligned temporal motifs according to the variants of the diffusion process ($Rule1$ and $Rule2$) in calls (blue) and text messages (orange). In the last two groups, the fraction of aligned motifs has been computed on motifs composed by at least 3 nodes and 3 events.

Aligned Temporal Motifs Although the previous categorization has highlighted an interesting difference between text message and call temporal motifs, it is limited to a small subset of the identified temporal motifs. To extend the categorization to all temporal motifs, we adopt a simple diffusion process driven by the sequence of the events in a temporal motif which returns whether or not a motif is aligned, i.e. all nodes hold the same piece of information after the diffusion process ends.

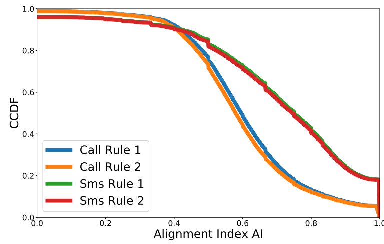
In Fig.3b we report the fraction of the aligned temporal motifs in call and text interactions. Here we observe that aligned motifs are more prevalent in text messages than in voice calls whatever the variant of the diffusion process; however this is due to the high frequency of 2-node temporal motifs which are always aligned. To remove this bias, we focus on more complex motifs where the pieces of information have to circulate among more than two nodes. Specifically, we analyze temporal motifs composed by at least 3 nodes and 3 events. In Fig.3b we show the fraction of aligned motifs over the amount of complex motifs in both text messages and calls. We observe the same general trait, indeed text message interactions tend to more frequently promote aligned temporal patterns than voice calls.

Aligned Cohesive Groups To distinguish if the above observation results from the high activity of a few cohesive groups which favor aligned interaction patterns in text messages or it is a behavior common to most of groups, we compute the alignment index (see Section 2.4) for each group, using both variants of the diffusion process. In Fig.4a we show the distribution of the alignment index AI for text messages and voice calls. The difference between the two distributions further stresses the previous observation. In fact, the probability of observing cohesive groups which interact almost completely ($AI \geq 0.8$) through aligned text motifs is 2/3-fold higher that the counterpart in call interactions.

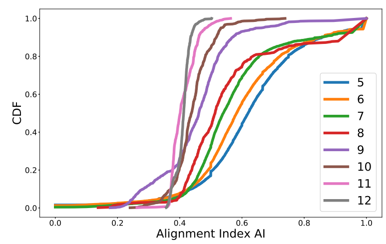
Since we have information about the size of cohesive groups, we wonder if in large groups is harder that each member holds a common piece of information after a temporal motif ends. We cope with this issue by correlating the alignment index and the size of the cohesive groups. As shown in Fig.4b and 4c, we examine the distribution of the alignment index as a function of the size. In both text and call interactions we observe the same trait, i.e. in larger group ($size \geq 9$) the usage of aligned temporal motifs is not widespread, indeed most of these groups have an index alignment between 0.4 and 0.6. Conversely, most of the small groups are characterized by an alignment index between 0.6 and 0.8; thus they tend to interact by aligned temporal motifs. In general, members of larger groups less frequently interacts by temporal motifs which promote a shared piece of information; rather many times their communications favor the spreading of different pieces of information.

4 Conclusions

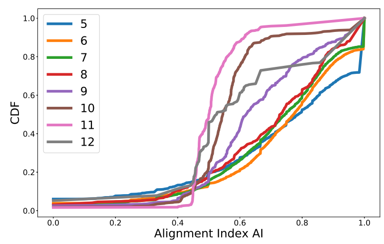
In this paper we proposed a methodology to detect in mobile phone data cohesive groups, whose statistical properties are similar to those found in online social networks or instant-messaging applications. Through the extraction of their call and text temporal motifs, we unveil how the members of social groups interact. We also propose a novel classification of temporal motifs, which rests on diffusion processes. Finally, we introduce a metric which quantify the capacity of a group to share a piece of information among the participants of a communication pattern.



(a)



(b) Calls



(c) Text messages

Fig. 4: In (a) the probability distribution (complementary cumulative distribution function) of the alignment index AI computed for each cohesive group. The alignment index has been computed using both the variants (Rule1 and Rule2) of the diffusion process. In (b) and (c) the cumulative distribution function of the alignment index grouped by the size of the cohesive groups.

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