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SocialText: A Framework for Understanding the Relationship between Digital Communication Patterns and Mental Health

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***Abstract*—As social media platforms have grown to form the foundation of modern digital communication, digital text message datasets that document interpersonal exchanges on these platforms have proliferated. These exchanges comprise a rich corpus of social context data, which can provide insight into how mental health challenges manifest in social contexts. To date, researchers have employed a variety of methods for extracting mental health-centric features from digital text communication data, including natural language processing, social network analysis, sentiment analysis, time series analysis, and discourse analysis. However, there is a marked divide in current literature between qualitative and quantitative feature extraction methods. To effectively identify and analyze key underlying social contexts and related mental health factors from digital text communication data, researchers must extract a comprehensive corpus of features from raw textual data streams. In this paper, we present a generalized framework for extracting features from digital text communication datasets that leverages methodological approaches from diverse fields. This framework will serve to bridge the gap between quantitative and qualitative research approaches to analyzing digital text communications with respect to mental health.**

I. INTRODUCTION

Approximately 3.2 billion people actively use social media worldwide. The pervasive nature of traditional SMS messaging and the growing popularity of social networking applications like Facebook and WhatsApp have yielded a rich landscape of digital textual communications (DTCs). DTCs are particularly promising for addressing the current widespread mental health crisis. Over 43 million American adults suffer from a mental health or substance abuse condition, and treatment remains difficult to access for many [1]. For individuals facing periods of stress, depression, and loneliness, DTCs provide a window into their mental state, coping behaviors and social support network [2]. However, despite the richness of their features, DTCs remain largely unexplored in existing mobile sensing frameworks. Moreover, approaches to analyzing DTC features remain largely split along quantitative-qualitative lines. In this paper, we introduce a novel framework that seeks to remedy this divide by addressing both low-level (i.e. message sentiment, social network structure) and high-level (i.e. platform usage) features. First, we provide a brief overview of the related literature. Then, we present our framework and explain how our feature extraction recommendations align with the related literature. Finally, we present several examples of how our framework can be used, with a focus on mental health.

II. RELATED WORK

Recent literature has drawn attention to the role of DTCs in a variety of social and mental health contexts; these include social support [3], stress [3], [4], communication satisfaction [5], personality traits [6], [7], loneliness [8], depression [9]–[11], bipolar disorder, PTSD, SAD [10], mood [12]. DTC features vary widely from study to study and across qualitative and quantitative domains. Some studies rely on self-report measures to gauge predictors of mental health patterns (e.g. Facebook usage). Others rely on raw features extracted from textual message content [4], [11]. Still others aim to relate mental health outcomes to variations in temporal patterns and social network topology [3], [9]. Few studies, however, have leveraged a combined feature space that affords insights from both qualitative and quantitative research practice. Our framework addresses this gap in the literature with a methodology-agnostic topology that can be adapted to qualitative, quantitative, and mixed-methods domains.

Researchers have emphasized multimodal approaches to mental health monitoring via sensor technologies, some of which are generalizable to a variety of conditions and others of which focus on a single condition. Mohr et al. and Abdullah and Choudhury's frameworks mapped raw sensor data to higher-level features features to several mental health domains [2], [13]. Aung et. al presented a tripartite framework that addresses *measurement*, *inference*, and *management*. Burns et al. demonstrated the utility of context sensing for a mobile intervention for depression [14]. While these and other existing frameworks have indeed situated mobile sensing as a critical tool for understanding mental health in context, none, to our knowledge, have focused exclusively on DTCs. By extending multimodal approaches in sensing for mental health to include DTCs, we introduce an opportunity to extract richer social contexts and improve our understanding of the role of DTCs in mental health behaviors.

III. FRAMEWORK OVERVIEW

The goal of the *SocialText* framework is to provide a clear, comprehensive method for creating informative, organized feature spaces, used to analyze the social semantics of DTC data. Figure 1 provides a comprehensive visual overview of *SocialText*, which provides an avenue for logically deconstructing DTC datasets, beginning with *modality* and ending with *message features*. Alongside each layer, we present

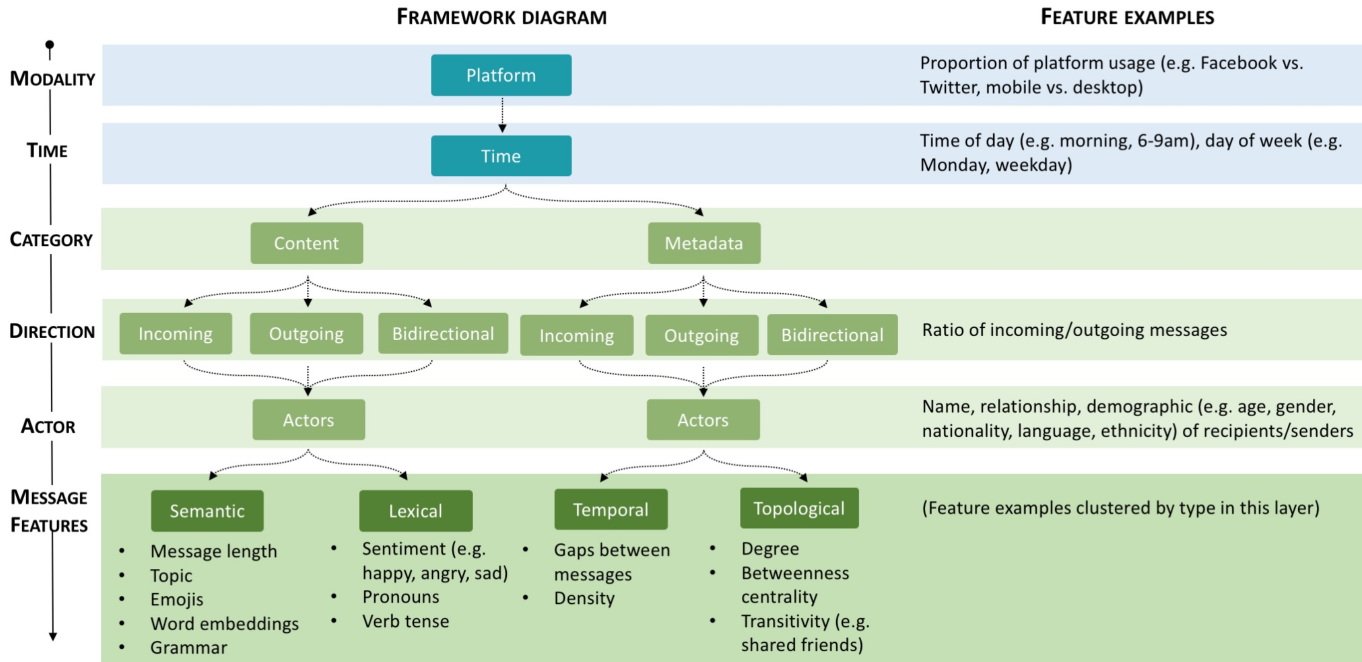

Fig. 1. Framework Diagram

examples of features that can be extracted at each layer of the framework. These features, as well as their relevance to characterizing social contexts and mental health states, are discussed in detail below.

A. Modality

Modality pertains to both the software and hardware via which users send and receive DTCs. A unique modality can be defined in terms of the software platform (i.e. Facebook, SMS) and/or device used (i.e. laptop, phone). Grouping platform and device together in the modality layer allows for a range of hardware/software integrations to be considered and keeps the *SocialText* framework platform agnostic. Furthermore, texting behavior (e.g. time, vocabulary, emojis) can change across different platforms. Not accounting for these differences may bias experimental results. For example, wifi-enabled SMS messaging via iMessage is native to Apple's desktop operating system, OSX, making it easy for iPhone users to rely on their laptops to send DTCs. Conversely, Android users have historically had to rely on third-party software to use their laptops to respond to SMS messages.

B. Time

Time refers to the time window of interest (i.e. hour, day, week). Appropriate time windows vary depending on the desired outcome variable; for example, observing momentary state anxiety vs. persistent trait anxiety. While daily fluctuations in DTC are like to reflect fluctuations in state-level measures, trait-level provide informative baselines. Researchers should take care to select an appropriate time window, as the dimensionality of subsequent feature spaces can vary drastically depending on the chosen window. Additionally, in addressing mental health outcomes, different temporal contexts have different meanings. For example, the number of messages an individual sends in a week may remain relatively constant while daily messaging patterns vary. An individual may shift from a weekend pattern of consistent engagement with her social circle to short episodes of high engagement with prolonged lapses after each episode. While these patterns may appear similar in an aggregated week-level measure, analysis of daily message rates may reveal granular communication patterns in flux and may provide evidence of fluctuations in an individual's mental state.

C. Category

Category distinguishes between two distinct categories of features: content and metadata. *Content* features describe patterns inherent in individual and aggregate DTCs. Content features include shared vocabularies and interpersonal differences in message semantics between members of a social network. *Metadata* features highlight the times and frequencies with which members of a social network exchange messages and the respective impact of these factors on the structure of the social network as a whole. Metadata features include timestamps, direction (incoming/outgoing), and actors. The insights provided by each are different by nature of their construction; therefore, separating these feature spaces is crucial for modeling approaches to be effective. However, in order to accurately infer social context from digital text messages, researchers must account for factors related to both content and metadata.

D. Direction

Direction comprises three different message classifications: incoming messages, outgoing messages, and bidirectional messages. Bidirectional messages refer to the entire message corpus, irrespective of whether messages are incoming or outgoing. Bidirectional message features reveal factors like discussion quality and conversation dynamics. Incoming and outgoing messages can reveal ego-centric aspects of the underlying social context. Outgoing message features, in particular can reveal how relationships between an individual's communication practices and her mental state. For example, sending more messages in the morning vs. at night may be tied to conditions such as loneliness and depression. On a conversation-specific level, the ratio of incoming to outgoing messages can inform our understanding of social dynamics between actors, such as the communication patterns and overall connectedness of an individual's social circle. From this ratio, we may also be able to distinguish between different types of relationships (i.e. family, friends, inner circle) based on incoming message characteristics.

E. Actor

The ***Actor*** layer encapsulates information pertaining to DTC senders and recipients. This layer allows for distinction between unique conversations (i.e. messages between roommates vs. messages between family members). Actors can be qualitatively classified in terms of their interpersonal relationships (e.g. romantic partner, friend, family member). These relationships can either be explicitly requested from study participants or derived by examining features of exchanged messages in terms of content and metadata. Additionally, this layer reveals high-level features centering group and individual conversations. If an individual is more engaged in group conversations than in individual conversations, he may experience more difficulty forming close social connections. Researchers can also use the actor layer to compare and contrast engagement in group vs individual conversations in terms of demographic information. For instance, females may engage with each other differently than they engage with males. Furthermore, varying gender ratios in group conversations may play a role in the resulting social dynamics.

F. Message Features

The ***Message Features*** layer addresses the different content-based and metadata-based features of message subsets. This layer does not further partition the data but rather enumerates the aggregated features that can be calculated based on individual messages. With respect to the content and metadata sub-trees, we have defined two sub-categories for each sub-tree in the *message features* layer of the framework. The content features sub-tree consists of lexical and semantic features, while the metadata sub-tree is broken down into temporal and topological features. *Lexical* features refer to vocabulary and term-related qualities of message content. *Semantic* features capture the relationships between words within a set of messages and the significance of these relationships to the overall tone and meaning. *Temporal* features refer to time-sensitive message characteristics. *Topological* features refer to social network structures, commonly derived from social network analysis methods.

IV. Message Feature Extraction

A. Content

1) Semantic

Semantic features of textual content describe the relationship between different linguistic structures and their effect on the overall meaning of a given text. Semantic features can be inferred by examining both the syntax of messages and the context within which an individual is communicating. Inference typically involves breaking a sentence down into its axiological components and relating these components to similar messages. Researchers may be interested in identifying semantic patterns within individual conversations, comparing individual and group conversations, or identifying temporally dense clusters of messages, depending on the mental health condition they are investigating.

One of the most prevalent methods for semantic feature extraction in existing mental health applications is *word embedding*, which fundamentally consists of mapping a word to a vector using a dictionary. In the context of DTCs, word embeddings can describe structural organization of words in a text messages; for example, a message can be represented by a one-hot encoded vector where 1 stands for the position of the word in the message and 0 is any other position. Word embedding techniques can be classified as either frequency (i.e. representation of term frequency) or prediction based (i.e. probabilistic relationships between words). Frequency-based embedding methods include Count Vector, Term Frequency-Inverse Document Frequency (TF-IDF), and Co-occurrence Vector.

Count Vector creates a dictionary of N unique terms in a corpus C of documents:

$$C = \{D_1, D_2 ... D_d\}$$

where d is the number of documents. Count Vector then counts the number of occurrences of each term n in each document, resulting in a d x n matrix CV of term frequencies. Considering the case where C is defined as a conversation between 2 individuals and $D_i, i\epsilon\{1...d\}$ is an individual text message, CV may reveal words that are unique to one of the participant's vocabularies, as well as common response phrases and terms (e.g. "You're Welcome" after "Thank You").

TF-IDF consists of two separate calculations: *term frequency* and *inverse document frequency*. *Term frequency* is defined as f_t/N, where f_t is the number of times a term t appears in a document and N is the number of terms in the entire document. *Inverse document frequency* is defined as $log(N_d/n_t)$, where N_d is the number of documents and n_t is the number of documents a term t has appeared in. Term frequency is calculated the same way as each row of the Count Vector method is calculated. *Inverse document frequency* discerns term relevance by finding high frequency terms that appear in a subset of the given documents. This subset distinction is important because high frequency words that appear in every document are less likely to be relevant to the documents but rather language in general. In the context of DTCs, if documents are defined as text messages where N is the total number of messages in a conversation, TF-IDF can identify words that characterize conversations and thus reveal interpersonal relationships and social contexts. Co-occurrence matrices provide a representation of term co-occurrence (the number of times a pair of words occurs) within a specific context window (e.g. two words before and after a term in a document). Co-occurrence matrices preserve the semantic relationship between words; for example, e.g. "sad" and "lonely" are more related than "sad" and "jogging".

Prediction-based word embedding techniques leverage neural networks to establish probabilistic relationships between words and have been used for classifying DTCs in mental health and identifying syntactical relationships within DTCs [15]. *Word2Vec*, one of the most popular techniques, is a combination of two techniques: *Continuous Bag of Words (CBOW)* and *Skip-gram*. *CBOW* is a probabilistic method for identifying term relevance in a given context. Conversely, *Skip-gram* is a method for predicting context given a word. Skip-gram models demonstrably out-perform context prediction models and can effectively capture two semantics for a single word (e.g. 'Apple' can refer to the company or the fruit). The ability to identify topical shifts in text conversations between members of diverse social networks allows researchers to classify interpersonal relationships and highight variations in communication style that may be contextually relevant to mental health outcomes.

2) Lexical

DTC lexica reflect individual communication styles and provide insight into personal traits, relationship quality, and mental state, among other factors. Text mining techniques can help us to represent DTC data and identify lexical patterns that relate to individuals' personality traits, such as neuroticism [7]. Linguistic Inquiry and Word Count (LIWC) is one of the most popular lexical feature extraction methods and has been rigorously validated in the context of psychometric analysis of textual data [16]. LIWC is a dictionary-based approach that assigns words to relevant psychological categories (e.g. inhibition, emotion, close relationships) and counts the number of words in each category over multiple texts.

DTCs often include frequent use of abbreviations, acronyms, emoticons, misspelling, and hashtags. These features are critically important for understanding a message's context and factors such as an individual's personality characteristics. Sentiment analysis is another popular technique that extracts subjectivity and polarity from text and predicting participants' mental health state. Additionally, researchers have identified predictive relationships between psychological states (e.g. depression, stress, anxiety, etc) and the dictionary of words from an individual's communications. The use of functional language has also been related to personality traits. For example, pronouns are useful linguistic elements that can help identify focus, which, in turn, can show priorities, intentions, and processing [16].

B. Metadata

1) Temporal

The time at which individuals send and receive DTCs can reveal much about underlying social context, including interpersonal relationships and communication styles. Many researchers have examined temporal patterns across DTCs from the perspective of chronemics and social information processing theory. Chronemics describes the role of time in communication and provide nonverbal behavioral indicators. Social information processing theory describes the nonverbal contexts and relationship-mediation aspects of digital communication. To characterize temporal patterns, we use two primary metrics: (1) *gaps*, defined as the difference between the time at which 2 unique messages were sent or received, and (2) *density*, defined by the probabilistic density estimation of exchanged messages within a specific context.

Gaps are useful for capturing conversational dynamics. Response latency patterns highlight conversational features like turn-taking, trust, and engagement. Consistently low intra-conversation response latencies may indicate a close relationship between two actors. Latency has also been shown to be related to social engagement and patterns of isolation; if an individual takes longer than usual to respond to a close friend's messages, the latency could indicate a shift in that relationship dynamic or intentional social withdrawal.

Density is another metric for identifying temporal patterns in DTC datasets. Density is quantified by using probabilistic distribution functions. It is particularly versatile, as researchers can adjust the granularity (e.g. messages per second, hour, day) to suit different temporal contexts. In the context of DTCs, comparing the distributions of an individual's unique conversations over a given time window can reveal underlying relationship differences. For example, *monochronic* (maintaining one conversation at a time) and *polychronic* (engaging in multiple, parallel conversations) individuals can be identified by comparing conversation-specific density estimations within the same time window. In the context of communication style, density can be used to gauge individual differences in engagement and conversational style via DTC platforms. For example, imbalance in the density of incoming and outgoing messages in the context of a conversation can reveal symptoms of social withdrawal and loneliness in the sender and/or receiver.

While low-level patterns in the temporal dynamics of DTC messages are informative for state-level mental health outcomes, more generalized patterns may also be of interest as they can help establish ground truth for population-specific behaviors and personality-driven communication patterns. Furthermore, as social media becomes more integrated into our personal lives, temporal patterns in text message data can help researchers better identify temporal patterns in life events (e.g. elections, birthdays, going to school).

2) Topological

The topology of an individual's social circle can provide significant insight into personality traits. For example, extroverted

Citation	Modality	Time	Category	Direction	Actor	Message Features	Health Outcome
[3]	Facebook	Months	Metadata	Incoming	Friends	Temporal/Topological	Stress, Social Support
[4]	Twitter	Month	Content	Outgoing	All Actors	Semantic/Lexical	Stress
[5]	SMS	Day	Metadata	Outgoing	Friends/Family	Temporal	Communication Satisfaction
[6]	Twitter, Instagram	Multi-year	Metadata/Content	Outgoing	All Actors	Semantic/Lexical	Personality Traits
[7]	SMS	All times	Content	Outgoing	All Actors	Semantic	Neuroticism
[8]	SMS	Month	Metadata	Outgoing	All Actors	Temporal	Social Anxiety, Loneliness
[9]	SMS	Week	Metadata	Incoming/Outgoing	All Actors	Temporal	Depression
[10]	Twitter	Multi-year	Content	Outgoing	All Actors	Semantic/Lexical	Depression, BPAD, PTSD, SAD
[11]	SMS	Day	Content	Incoming/Outgoing	All Actors	Semantic/Lexical	Depression, Suicide
[12]	Twitter	Months	Content	Outgoing	All Actors	Semantic/Lexical	Mood

TABLE I
EXISTING LITERATURE TABLE. *PTSD: Post-Traumatic Stress Disorder, SAD: Seasonal Affective Disorder, BPAD: Bipolar Affective Disorder*

individuals may form connections with others in different ways than introverted individuals. Furthermore, social network topology emerging from social stimuli such as physical proximity has proved effective in improving mental health monitoring [17]. In the context of DTCs, social network topology can be inferred by constructing graphical networks from a dataset of text messages. In such networks, individual actors serve as nodes and their messages serve as directed edges, which can be classified as outbound, inbound, and direction-ignored for feature extraction. Different network scales for feature extraction are necessary, depending on the size of social circle overlap among a dataset's actors. When the inter-connectivity between actors in different individuals' social circles is low or zero, we can only focus on the communication partners within each social circle, separately, as these circles are disjoint. When inter-connectivity is high, as for a dataset collected from a close cohort (such as college students enrolled in the same class), we should also take global topological measures into account because shared connections are prevalent.

We formally propose three network scales, ranging from least to most connected: *egocentric*, *local*, and *global*.

An *egocentric* network $G_e = (V_1, E_1)$ contains the vertex set:

$$V_1 = \{p, a_1...a_n\} \tag{1}$$

where p is an individual, n is the network size, and a_i, $i\epsilon\{1...n\}$, is any actor besides p in her social network.
This network also contains the edge set E_1 of all messages exchanged between the individual p and any other actor a_i, $i\epsilon\{1...n\}$ besides p in the network:

$$E_1 = \{\{p, a_1\}...\{p, a_n\}\} \tag{2}$$

We hypothesize that egocentric networks are most widely present because no information needs to be collected from the partners in the dataset.

A local network is a complete graph $G_l = (V_1, E_2)$. G_l contains (1) as well as the edge set E_2, which contains all messages exchanged between actors, *including* p. A global network encompasses the messages of all individuals in the dataset captured in a given time window.

To capture the topology, we draw upon three major network metrics: (1) *degree*, the number of edges connecting an individual with others, to approximate the level of social activeness; (2) *betweenness centrality*, defined by the proportion of shortest paths in a network that go through a vertex, to describe how central in the encounter network a subject is, and; (3) *transitivity*, which as a global measure is defined by the proportion of closed connected triples (i.e. triangles) out of all connected triples in a network and as a local measure the proportion of closed connected triples connected to a vertex out of all connected triples centered on the vertex. Transitivity quantifies the propensity for a network to exhibit (global) and a subject to be present in (local) triangular relations, which is an indicator of community forming. Given a comprehensive dataset, researchers can infer the nature and quality of social connections between conversation partners. More generally, researchers can compare different social network constructions to infer information about demographic differences between users of different social networks.

V. Discussion

Table I provides a list of selected relevant studies that utilize DTC data to study mental health outcomes. In this table, we map each study onto the *SocialText* hierarchy, demonstrating its flexibility in characterizing mobile mental health sensing studies irrespective of study design. Perhaps more importantly, *SocialText* is useful for revealing important methodological overlaps in the existing literature. For example, Elhai et. al. [9] studied depression with respect to temporal patterns in SMS data while Nobles et. al. [11] studied the semantic and lexical features of a similar dataset. While these studies choose different time windows (or, rather, *Time* layer selections), they are similar along all other dimensions of *SocialText*'s structure. By using *SocialText* to identify similar studies, such as [9] and [11], researchers can streamline the process of creating new methodological approaches from the best aspects of existing approaches. Thus, *SocialText* facilitates the development of novel methodologies for mobile mental health sensing.

While Table I identifies similar methodological approaches across existing literature, it also evidences a clear separation between the consideration of metadata features and content features in mobile sensing for mental health contexts. For example, while Gopalakrishna Pillai et al. [4] used a feature space extracted related to both content and metadata, their ultimate findings focused on syntactic and lexical components rather than temporal ones. Burke & Kraut [3], on the other hand, leveraged temporal and topological features, but not semantic or lexical ones. Content and metadata features alone can be informative for predicting mental health outcomes. However, understanding the deeper dynamics of social interactions, such as the evolution of personal speaking style over time or across relationships, is critical and cannot be easily derived from either content or metadata information alone. We argue that considering both the content and metadata feature spaces will yield richer insights into the complex dynamics of diverse mental health conditions. *SocialText* unites content and metadata message features together in a single hierarchy, making it easier for researchers to leverage all features in combination. Thus, *SocialText* assists researchers in developing more comprehensive mental health models from mobile sensing data.

VI. Conclusion

Analysis of DTCs remains an open research area at the intersection of mental health and computing. DTCs afford rich features related to social context but remain largely unexplored in existing mobile sensing frameworks. Previous approaches to analyzing DTC features address quantitative and qualitative separately. In this paper, we have introduced a novel framework, SocialText, that defines a hierarchical structure for extracting features from DTC datasets. Each layer of the *SocialText* framework intentionally highlights features that can be derived from raw sensor data and used to identify social context and, thus, better predict mental health outcomes from DTCs. While the upper layers define important variables for data partitioning, the lowest layer identifies categories of features that can be extracted from the messages themselves. Features pertaining to the semantics and lexicon of message content can characterize conversational context, while temporal and topological features can reveal social network ties and temporal messaging patterns. Considering all message features in combination provides a comprehensive characterization of the effect of social dynamics of DTCs on participants' mental states. Researchers can use *SocialText* to further classify existing literature in mobile sensing for mental health, identify similar studies in this space, and leverage aspects of multiple methodologies to characterize or predict mental health states. We anticipate that *SocialText* will provide a novel path forward for exploring the multifaceted role of DTCs in mental health.

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