SoulMate: Short-text author linking through Multi-aspect temporal-textual embedding

{Saeed Najafipour, Saeid Hosseini}*, Wen Hua, Mohammad Reza Kangavari, and Xiaofang Zhou

Abstract—Linking authors of short-text contents has important usages in many applications, including Named Entity Recognition (NER) and human community detection. However, certain challenges lie ahead. Firstly, the input short-text contents are noisy, ambiguous, and do not follow the grammatical rules. Secondly, traditional text mining methods fail to effectively extract concepts through words and phrases. Thirdly, the textual contents are temporally skewed, which can affect the semantic understanding by multiple time facets. Finally, using the complementary knowledge-bases makes the results biased to the content of the external database and deviates the understanding and interpretation away from the real nature of the given short text corpus. To overcome these challenges, we devise a neural network-based temporal-textual framework that generates the tightly connected author subgraphs from microblog short-text contents. Our approach, on the one hand, computes the relevance score (edge weight) between the authors through considering a portmanteau of contents and concepts, and on the other hand, employs a stack-wise graph cutting algorithm to extract the communities of the related authors. Experimental results show that compared to other knowledge-centered competitors, our multi-aspect vector space model can achieve a higher performance in linking short-text authors. Additionally, given the author linking task, the more comprehensive the dataset is, the higher the significance of the extracted concepts will be.

Index Terms—Author Linking, Short Text Inference, Word2Vec, Temporally Multifaceted, Semantic Understanding

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1 INTRODUCTION

GENERATING the subgraphs with similar vertices finds important applications in numerous domains: (i) In recommender systems [1][2], the members in a subgraph can enrich the history of other cold-start members [3][4][5]. (ii) In community detection, the subgraphs can identify groups of correlated users [6][7]. (iii) In propagation networks [6][8], the group-based immunization policies [9] [10] can better control the burst of contagions (i.e. gossips). Nowadays, the social networks record the commonly brief textual contents of the authors that are generated in a high-throughput rate. Given a graph G of short-text authors and the query author n_q, our aim is to find a subgraph $\tilde{g}_q$ comprising of highly similar authors to n_q. The NP-hard subgraph mining problem can be initiated by the computation of edge weights between authors and completed by a stack-wise graph-cutting algorithm. As the main step in obtaining of subgraphs, several approaches [11][12] have been proposed to compute the similarity weight among authors. However, the nature of short-text contents causes certain obstacles. Such *challenges* are instantiated as follows:
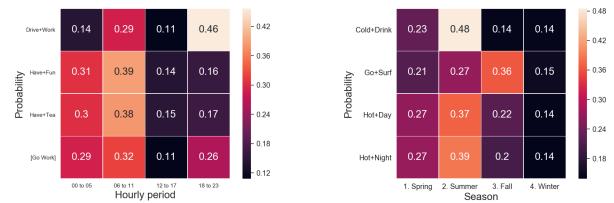
Challenge 1 (Mismatched Author Contents)

Short-text contents are typically informal and include abbreviations, misspellings, and possible errors. For in-stance, "afternoon" is informally used as "arvo". Similarly, "Brisbane" (in Australia) is usually abbreviated to "BNE" and called as "Brissie". As a result, current text mining approaches (e.g., topic modeling [13][14] and other heuristics [15][16]) may not gain sufficient statistical signals and *mismatch* the textual contents of the similar authors. Consequently, the correlation edge weight between the pair of authors will be calculated incorrectly.

Challenge 2 (Context Temporal Alignments)

Vector representation models analyze each word in the context of others. GloVe [17] consumes word pair co-occurrences and CBOW [18] predicts a word given the surrounding context. However, the state-of-the-art models [19][20] ignore the reality that the word proximity patterns alter in various temporal facets. To witness the fact, we set up an observation on our Twitter dataset [15].

(a) Hour dimension   **(b)** Season dimension
Fig. 1: Co-occurrence probability

As Fig. 1 demonstrates, the distribution probabilities for word pairs can differ in various temporal dimensions. While most people talk about going to work between 6 to 11 am, half others drive to work in the evening (Fig. 1a). People mostly tweet about *Cold+Drink*, *Hot+Day*, and *Hot+Night* during the summer and such word pairs proximate far less during the winter (Fig. 1b).

Challenge 3 (Ignoring Conceptual Relevance)

Recent works in finding author similarities

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Concept	Tweet #1	Tweet #2
overconsumption	I've drunk so much tea today!	they told me to mince two cabbages today. cabbage nightmares
resistance	Everything against me, I'm still here	@H, You feel that burn? muscles working, you becoming fit.
dullness	No ones up. Boring.	Can't help it. Depression just hits me in the face
wish	Would love to join @m but I'm exhausted!	@a so sad!, sending you hugs thoughts and love x

TABLE 1: Conceptual relevance

[21][22][23][24], compute the textual relevance between authors through exact or approximate matching. Though the Skip-gram [20][17] enriches the contents using word vectors to optimize the similarity weights between authors. Using external knowledge bases (e.g. WordNet and Wikipedia) can relax the negative effects of the noisy contents [25]. However, after all textual enrichments, while the contents belonging to a pair of authors completely or partially turn up irrelevant, we need to how they share some common concepts. As instantiated in Table 1, where the tweets (#1 and #2) belong to distinct authors and the *contents* are mainly irrelevant, they may still reflect conceptual relevance (e.g. *overconsumption* in row 1). Hence, a new approach must confront the above obstacles.

Contributions. While *our* previous work [25] detects the concepts of a single tweet with the help of an external knowledge base (KB), the proposed framework in this paper identifies concepts through unsupervised clustering in the tweet space itself, thus eliminating the bias and deviation caused by a KB. Furthermore, the concept distribution of all the tweets is aggregated for each author, which is then utilized as an important feature for determining author similarity. We also enrich the short-text inference models with semantic vector space approaches to further understand the contextual (contents+concepts) relationships between short-text authors. Moreover, inspired by *our* previous work [16], we devise a temporal-textual embedding model to track the temporal alignments of the short text contents. Our contributions are fourfold:

- To the best of our knowledge, we develop the first neural network-based temporal-textual embedding approach that can enrich short-text contents using word vectors that are collectively learned through multiple temporal dimensions.
- We analyze two clustering methods of DB-Scan and K-medoids in extracting various concepts from a corpus.
- We design a stack-wise graph-cutting algorithm to extract the maximum spanning trees (subgraphs) from the authors weighted graph.
- We propose a temporal-textual framework that can achieve better effectiveness in generating of the highly relevant short-text authors.

The rest of our paper is as follows: in Sec. 2, we study the literature; in Sec 3, we provide the problem and our framework; in Sec. 4 and 5 we respectively explain our model and experiments. The paper is concluded in Sec. 6.

2 RELATED WORK

As briefed in Table 2, the related work comprises word embedding, user similarity, and semantic understanding.

2.1 Word Embedding

Word embedding [26] accurately associates each word in documents with a meaningful continuous vector. The applications are multidisciplinary and involve Information Retrieval (IR), Natural Language Processing (NLP) [27] [28] [29], and Recommendation Systems (RS) [30] [3] [31] [32]. Traditional LSI [33] approach captures the relevance between terms and concepts through *Singular Value Decomposition*(SVD), while *Bag-of-Words*(BOW) [34] disregards the order of words and considers the word frequencies. Expectation-Maximization(EM) can equip the BOW model [35] [36] to reduce ambiguity in machine translation. The continuous BOW (CBOW) [18] ensures that the words with similar meanings will be constituted by close embeddings in the latent space. The *Word2vec* [20] extracts meaningful syntactical and semantical regularities from word pairs and is classified into CBOW and skip-gram. While the Global Vector model (GloVe) [17] consumes word pair co-occurrences to accomplish word embedding, the CBOW model [18] predicts a word given the surrounding context. Based on our Twitter dataset, the CBOW model surpasses the GloVe approach in the standard analogy test (Section 5.2.1). Vector representation has other types: Paragraph2Vec [37], ConceptVector [30], Category2Vec [38], Prod2Vec [31]. Moreover, [13] includes *topic models* to collectively generate a word from either Dirichlet multinominal or the embedding module. [38] enriches the embedding with Knowledge Graphs to eliminate ambiguity and improve similarity measures. However, the state-of-the-art models [19][20] ignore the fact that the word proximity patterns alter in different temporal facets. Even temporal models [39] [40] rely on a single temporal aspect and pretermit semantical relations [41]. But our embedding model can employ an infinite number of temporal facets.

TABLE 2: Literature

Category	Approachs	Refferences
Word Embedding	Embedding Only	[35][18][42][17]
	Graph Analysis	[14][24][43][38]
	Matrix Factorization (MF)	[22][1][44][45][24][20]
	Temporal	[39][40][46][4]
User Similarity	Collaborative Filtering	[5][47][24][48][43]
	Neural Networks	[49][50][20][51][52]
	Graph Analysis	[14][11][24][43][53]
	Author-Oriented	[21][22][23][24]
	Temporal	[54][21][55][46][4]
Semantic Understanding	Neural Networks	[56][37][18][57]
	Expansion	[58][59][60][61]
	Topic Modeling	[22][62][63][23]
	Concept-Oriented	[25][64][65]

2.2 User Similarity

The similarity between users can be computed by their contextual information through a similarity function (e.g. Cosine or Pearson). Subsequently, the collaborative filtering [47], graph-theoretic model [53], or other classification methods [66] [67] can be used to group pertinent users. Embedding models like User2Vec [50] and Mllda [52] utilize associated vectors to find the order of user relations. Other embedding models like node2vec [49] and DeepWalk [51] are motivated by the skip-gram approach and treat each user as a node in social networks. Author2Vec [11] combines the content and link information of the users to better predict the true connection between individuals. [21][22][23][24] compute the user similarity through exact

and approximate textual matching. In contrast, [20] maps users to a latent space. Unlike [55] which proposes a distributional representation for user temporal contents, majority of other embedding models neglect the time factor. Hence, we integrate multi-facet time-based clusters into text embedding to infer both the temporal and textual correlations between users.

2.3 Semantic Understanding

Textual semantics can be learned through various approaches. Early NER methods [68] [69] employ classification techniques to label the entities in a document. However, NER models cannot function effectively on noisy short-text contents. Topic models [63][62] exploit latent topics through word distributions. However, since they do not effectively retrieve the statistical cues from short-text contents, the semantic labeling task is left out abortive. Recent state-of-the-art models like CBOW [18] and ParagraphVEC [37] are proved to be beneficial to the understanding of the textual contents. Expansion models [60] are inspired by query expansion techniques [58] [59] [61] and enrich initial textual contents by complementary relevant contents. More recent Deep Neural Network models such as CNN [57] and RNN [56] facilitate short-text understanding through classification. The labeling and feature extraction modules can further promote human language inference. Some other works [65] [64] [25] exploit global concepts from the corpus to better represent the semantics in each document. More specifically, the derived concepts from microblog brief contents can increase noise tolerance and improve short text semantic understanding. Hence, our proposed framework employs clustering modules besides embedding procedure to simultaneously take advantage of concepts and contents.
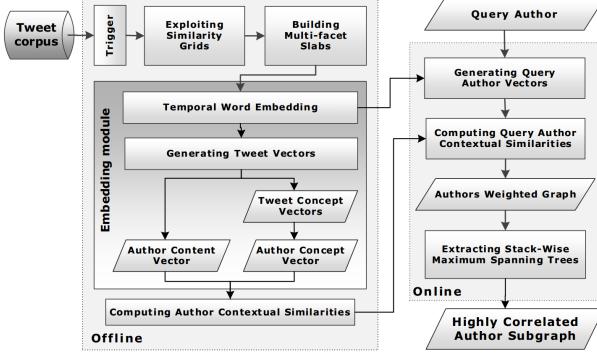

Fig. 2: Framework

3 PROBLEM STATEMENT

In this section we elucidate preliminary concepts, problem statement for author linking, and our proposed framework.

3.1 Preliminary Concepts

We commence with definitions as formalized below:

Definition 1. *(node) Every Node, denoted by $n_i \in \mathbb{N}$ represents a distinguished author of short-text contents in a social network.*

Definition 2. *(short-text message) $m_j \in \mathbb{M}$ advocates a short-text that is composed and published by an author n_i. Each message has an identity (m_j), the associated author (i.e. n_i), and the time-stamp ($m_j.t$). Accordingly, $\mathbb{M}$ ($\mathbb{M} = \{M_1, M_2, \ldots, M_n\}$) includes all short-text contents, where M_i delineates the set of short-text messages that are owned by the author n_i.*

Definition 3. *(latent temporal facets) The associated time-stamp can be interpreted by multiple time facets, where each facet represents a latent parameter z^k in $\mathbb{T} = \{z^1, z^2, ..., z^t\}$.*

Definition 4. *(temporal slab) Each latent temporal dimension z^x can comprise η splits $z^x = \{s_1^x, s_2^x, ..., s_\eta^x\}$, e.g. 7 splits for day dimension where each split advocates an individual day in the week. Accordingly, the Unifacet Temporal Slabs are built via the merging of similar splits.*

Definition 5. *(vector representation) Given the corpus of textual contents $\mathcal{C}$, for elucidation purposes, the word embedding model conveys each vocabulary $v_i \in \mathbb{V}$ with a distinguished real-valued vector $\vec{v_i}$ which is obtained in conjunction with other word vectors.*

Definition 6. *(authors weighted graph) $G = (\mathbb{N}, \mathbb{L})$ is the authors' weighted graph which includes all the authors $\mathbb{N}$ with pertinent links $\mathbb{L}$ between them. The link $l_{ij} \in \mathbb{L}$ describes the similarity weight between two authors (n_i, n_j) and can be computed using various approaches.*

Definition 7. *(query subgraph) The query subgraph denoted by $\tilde{g}_q \subset G$ contains the set of authors that are highly correlated with the input query user $n_q \in \mathbb{N}$.*

We not only use the vectorization for words, but also devise a textual time-aware model to represent the tweets, concepts, and authors by vectors.

3.2 Problem Definition

Problem 1. *(extracting hierarchical time-aware slabs) Given the set of authors $\mathbb{N}$, messages $\mathbb{M}$, and the temporal latent factors $\mathbb{T}$, we aim to extract the set of uni-facet temporal slabs through uniting similar splits in each facet. The child temporal facets are hierarchically affected by the parent dimension(s).*
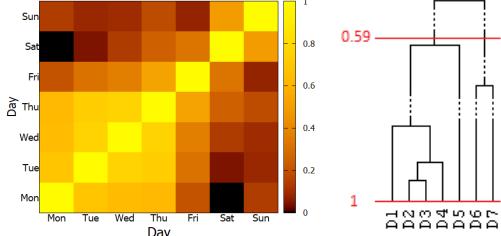*The weighted graph reflects the similarity between authors.*

Problem 2. *(computing contextual similarities) Given the set of temporal facets $\mathbb{T}$ and the messages of each author (e.g. M_i for n_i), we aim to compute the correlation weight between each pair of authors ($l_{ij} \equiv Link(n_i, n_j)|\forall n_i, n_j \in \mathbb{N} \& l_{ij} \in \mathbb{L}$).*

Problem 3. *(author linking) Given the author weighted graph G, we aim to mine the single query subgraph $\tilde{g}_q$ containing the set of authors, where all of them are highly correlated with every query author $n_q \in \mathbb{N}$.*

3.3 Framework Overview

Intuitively, the problem of author linking (Prob. 3) can be divided into two steps: (1) to compute the similarity weights between authors (Prob. 2). (2) to employ a stack-wise graph cutting algorithm to optimize the number of exploited subgraphs and maximize the intra-subgraph correlations. Figure 2 illustrates our framework for linking authors of short-text contents through a multi-aspect temporal textual embedding model. In the offline part, we use the microblog contents to acquire the multi-facet grids that reflect the similarity weight between temporal splits (e.g. 24 hourly splits). Subsequently, we employ clustering models to build uni-facet time-based slabs by merging similar splits. We propose and investigate a temporal-textual embedding model to construct tweet vectors by comprising word vectors. Author content vectors are similarly formed through uniting vectorized tweets. We then cluster similar tweets to explore hidden concepts, where each tweet concept vector corresponds to a set of concepts. Inherently, the tweet concept vectors together form the author concept vector. Accordingly, each author can be collectively represented by the *content* and *concept* vectors (so-called *context*), that can be further utilized to compute the similarity weight

between any given pair of authors. In the online part, we aim to discover a subgraph that includes a set of highly correlated authors to the query author. We firstly generate the contextual vectors of the query author and update the authors' similarity matrix. Finally, we employ a simple but effective stack-wise graph cutting algorithm to extract the output subgraph - as maximum spanning trees.

(a) TF-IDF similarity matrix **(b)** Day slabs
Fig. 3: The day latent facet

Day Slabs
{D1=Monday,D2=Tuesday,D3=Wednesday,D4=Thursday,D5=Friday }
{D6=Saturday,D7=Sunday }

TABLE 3: Day Slabs, threshold set to 0.59

4 METHODOLOGY

4.1 Offline Phase
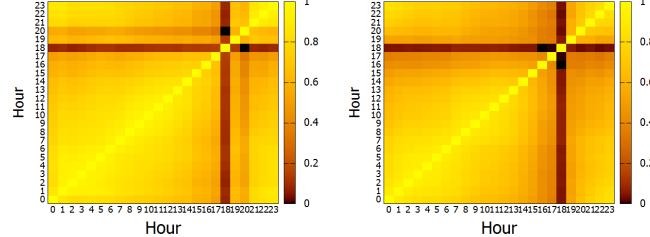
4.1.1 Constructing multi-facet dynamic slabs

For the similarity matrix, we measure the *Textual* sameness between each pair of splits (e.g. Sunday and Monday in day dimension). To proceed, we congregate the textual contents of each temporal split. Accordingly, every temporal facet can be assigned with a vector where every cell will contain the short-text contents in the relevant split. We use a modified *TF-IDF* algorithm (Eq. 1) to find the weight of each word in the textual contents of every temporal facet:

$$\hat{\mathbf{w}}(t_i, S_k^l) = \frac{f(t_i, S_k^l)}{Max_{(t \in S^l)}\{f(t, S_k^l)\}} \times Log \frac{N}{N(t_i)} \quad (1)$$

Here, N designates the total number of the splits and $N(t_i)$ is the number of splits at which the term t_i has appeared. While S_k^l is the textual contents of split k of the latent facet l, $\frac{f(t_i, S_k^l)}{Max_{(t \in S^l)}\{f(t, S_k^l)\}}$ normalizes the term frequency. Correspondingly, every split can be signified by a vector $\vec{S}_k^l$ where the cells contain the weights of the terms. Eventually, a similarity measure (e.g. *Cosine*) can report how correlated each pair of splits are. The number of dimensions, (e.g. binary facets of z^h and z^d for the hour and day latent factors) can be decided based on the sparsity of the dataset as well as the complexity of the solution. Note that people behave differently at the same hour during various days, take weekdays and weekends into consideration. This shows how the child facet can be affected by its parent latent factor. Hence, unlike our prior work [16], we heed the effects of the parent(s) on the child temporal facets. For instance, $z_h \subset z_d$ elucidates that the hour dimension comes under the sway of the parent temporal dimension (i.e. z_d). As implemented in [16], the bottom-up *Hierarchical Agglomerative Clustering* (*HAC* via *complete linkage*) can bundle similar temporal splits in each latent temporal facet to shape the final temporal slabs. The *threshold* of the HAC model may place impertinent splits into the same cluster or incorrectly toss relevant splits to separate slabs. Figure 3 depicts both the similarity grid and the clustering dendrogram for the

day dimension. On the one hand, threshold 1.0 will place the everyday entity in a distinctive slab (no clustering). On the other hand, threshold 0.59 results in more meaningful slabs as reported in Table 3 (weekday versus weekends). Since we consider the influence of the parent facets, for the hour dimension, we will need to consider two similarity matrices (one for each daily slabs). Figure 4 illustrates the hour similarity grids based on which the dendrograms are obtained as shown in Figure 5. Note that as reported in Table 4, we will have two sets of clusters for the hour dimension, where each of them are devoted to the pertinent daily slab.

(a) *weekdays* **(b)** *weekend*
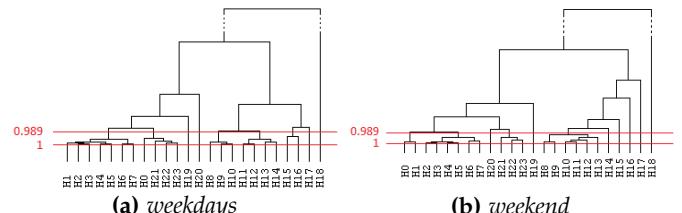**Fig. 4:** Hour similarity grids based on daily temporal slabs

(a) *weekdays* **(b)** *weekend*
Fig. 5: hourly slabs hierarchical dendrograms

Monday till Friday (0.989)	Saturday and Sunday (0.989)
{1,2,3,4,5,6,7}{8,9,10}	{0,1}{2,3,4,5,6,7}
{11,12,13,14}{15,16}{17}	{8,9,10,11,12,13}{14}{15}{16}
{18}{19}{20}{21,22,23,0}	{17}{18}{19}{20}{21,22,23}

TABLE 4: Extracting hour slabs affected by the day slabs

4.1.2 Word embedding models

Informal short-text contents come with excessive noise and writing errors. Hence, as discussed in Challenge 1 (Section 1), recent text mining approaches including topic models [13][14] fail to obtain significant statistical cues to match the textual contents of the similar authors. On the other hand, the correlation weight between a pair of microblog authors (u, v) will be computed incorrectly when their respective exact textual contents (O_u, O_v) are considered. To cope with this challenge, the semantic vector space models [70, 20, 18, 17, 33] retrieve the vector representation of each word. As the first solution to correctly compute the semantic relevance between authors, one can construct a decently ordered list of similar words to each comprising word v_i in an author's contents o_u, denoted by $\vec{v}_i^o$. Accordingly, the textual contents of each author will be represented by a new *encyclopedic semantic representation* form (O'_u) where every word $v_i \in O_u$ will be replaced by the top ζ most similar words from the associated vector $\vec{v}_i^o$. To this end, we can choose four embedding models: *Singular Value Decomposition*(SVD) [70], Skip-gram [20], CBOW [18], and also GloVe [17]. SVD computes the word vectors without training and using matrix operations over the co-occurrence matrix. For three models the well-trained vectors are iteratively enumerated through complex operations (e.g. forward and backward propagation). While the CBOW model estimates the center word of the window by the one-hot vector of

the surrounding context (order is important), the skip-gram calculates the co-occurrence probability of the surrounding words with the middle word. Nevertheless, both models return the word vectors that are trained in the hidden layer. GloVe consumes the word co-occurrence matrix, where the model converges toward the optimized values in context and main vectors.

4.1.3 Temporal word embedding

As elucidated in Section 1, the word proximity patterns change in various temporal facets. However, current word embedding models [19][20] ignore this reality. Also, notice that the CBOW algorithm can pass the word analogy test better than other vector space models (Sec. 2.1). Hence, we devise our novel time-aware embedding model based on CBOW, named as TCBOW, to better track the multi-aspect temporal-textual variations in short-text contents. Note that the temporal slabs monotonically capture the temporal alterations in textual contents through the clustering of similar splits in each temporal dimension. Accordingly, we argue that the time-aware embedding should gain an understanding of each of the slabs and subsequently predict unforeseen observations through merging the knowledge from all the slabs. Hence, we firstly devise a TCBOW module which functions on the slabs of all latent factors.

Figure 6 depicts the diagram for the slab-based TCBOW where k is a single slab in dimension $l \in \mathbb{T}$. The input layer contains the number of C one-hot encoded input words $\{\mathbf{x}_{k\{1\}}^l, \mathbf{x}_{k\{2\}}^l, ..., \mathbf{x}_{k\{C\}}^l\}$ where C is the size of the window and the number of vocabularies is denoted by $|\mathbf{V}_k^l|$. The hidden layer $\mathbf{h}_k^l$ is N-dimensional and $\mathbf{y}_k^l$ represents the output word. The one-hot encoded input vectors are connected to the hidden layer via $\mathbf{W}_k^l$ weight matrix and $\mathbf{W}_k^{'l}$ associates the hidden layer to the output. We employ [18] to compute both weight matrices of $\mathbf{W}_k^l$ and $\mathbf{W}_k^{'l}$. Given surrounding vocabs, Stochastic Gradient Descent maximizes the conditional probability of the output word.
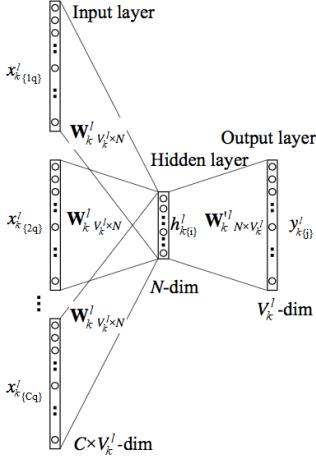

Fig. 6: CBOW

The hidden layer output is the average of one-hot input vectors that utilize the slab-based weights of $\mathbf{W}_k^l$ (Eq. 2).

$$\mathbf{h}_k^l = \frac{1}{C} \times \mathbf{W}_k^l . (\sum_{i=1}^{C} \mathbf{x}_{k\{i\}}^l) \tag{2}$$

We also employ Eq. 3 to calculate the input from the hidden layer to every node in the output layer. Here $\mathbf{V}_{k\{\mathbf{w}_{k\{j\}}^l\}}^{'l}$ is the jth column of the output matrix $\mathbf{W}_k^{'l}$.

$$\mathbf{u}_{k\{j\}}^l = {\mathbf{V}_{k\{\mathbf{w}_{k\{j\}}^l\}}^{'l}}^T . \mathbf{h}_k^l \tag{3}$$

Finally, we can apply the soft-max function on $\mathbf{u}_{k\{j\}}^l$ to attain the output layer $\mathbf{y}_{k\{j\}}^l$ (Eq. 4).

$$\mathbf{y}_{k\{j\}}^l = \frac{Exp(\mathbf{u}_{k\{j\}}^l)}{\sum_{j'=1}^{\mathbf{V}_k^l} Exp(\mathbf{u}_{k\{j'\}}^{'l})} \tag{4}$$

Given slab k in the facet l and relying on embedding weights ($\mathbf{W}_k^l$), $\vec{\mathbf{v}}_{k\{i\}}^l$ can denote the embedded vector for each word i in the hidden layer. The *cosine* function (Eq. 5) can determine the slab based similarity between each word pair (i, j).

$$\mathcal{S}_{Cosine}(\vec{\mathbf{v}}_{k\{i\}}^l, \vec{\mathbf{v}}_{k\{j\}}^l) = \frac{\vec{\mathbf{v}}_{k\{i\}}^l . \vec{\mathbf{v}}_{k\{j\}}^l}{|\vec{\mathbf{v}}_{k\{i\}}^l| \times |\vec{\mathbf{v}}_{k\{j\}}^l|} \tag{5}$$

The vocabulary corpus can be denoted by V_k^l where $\vec{\mathbf{v}}_{k\{i\}}^l$ and $\vec{\mathbf{v}}_{k\{j\}}^l$ are the subsets of slab-based vector $\vec{\mathbf{V}}_k^l$. To continue, we invoke two attributes to better infer the correlation intensity between each pair of words (i, j) in temporal slabs.

- *Level* ($\mathcal{S}_{level}(l, \vec{v}_i, \vec{v}_j)$) explains how extended each pair of words correlate together in all the temporal slabs of a single latent facet of l.
- *Depth* ($\mathcal{S}_{depth}(l, \vec{v}_i, \vec{v}_j)$) infers how the pair of words correlate in each slab, while hierarchically impacted by parent temporal dimension(s).

Eq. 6 formalizes the level-wise similarity between the vectors of the words i and j, where $\tilde{\mathbf{A}}_k^l$ is the normalized accuracy of the analogy test for slab k in dimension l.

$$\mathcal{S}_{level}(l, \vec{v}_i, \vec{v}_j) = \sum_{k \in l} \tilde{\mathbf{A}}_k^l \times \mathcal{S}_{Cosine}(\vec{\mathbf{v}}_{k\{i\}}^l, \vec{\mathbf{v}}_{k\{j\}}^l) \tag{6}$$

Similarly, Eq. 7 shows the depth similarity between the hidden layer vectors of the pair (i,j). Note that we propose two static methods for the latent facet class. Suppose that the hour facet is directly impacted by the day dimension $z_h \subset z_d$, in this case, if the current facet in the loop is the day, $l.child()$ can return the child facet, the slabs from hour factor. In contrast, if the hour is the current level, $l.parent()$ can obtain the pointer to the day temporal dimension.

$$\mathcal{S}_{Depth}(l, \vec{v}_i, \vec{v}_j) = \sum_{k \in \tau_l^b} \sum_{q \in \tau_{l.child()}^b} \tilde{\mathbf{A}}_q^{l.child()}$$
$$\times \mathcal{S}_{Cosine}(\vec{\mathbf{v}}_{q\{i\}}^{l.child()}, \vec{\mathbf{v}}_{q\{j\}}^{l.child()}) \tag{7}$$

Here τ_l^b and $\tau_{l.child()}^b$ are the set of unifacet temporal slabs that are respectively associated with the current level (l) and its child dimension. Accordingly, $\tilde{\mathbf{A}}_q^{l.child()}$ denotes the normalized accuracy of the analogy test for slab q of the child facet for l dimension. Here the cosine similarity is computed for the hidden layer vector representation of the words (v_i, v_j) in two layers of the child ($l.child()$) influenced by the parent (l). Note that the similarity feature for all the slabs of the child latent factor $l.child()$ (denoted by q), are impacted by corresponding slab k in the parent latent factor (i.e. l). Note that Eq. 7 only comprises two latent facet, that is the current layer l and its direct child $l.child()$. However, given any temporal dimension, the depth property should include the effect of children facets. To this end, we generalize Eq. 7 to Eq. 8 to recursively call the depth property toward the leaf nodes ($l.child() \neq Null$).

$$\mathcal{S}_{Depth}(l, \vec{\mathbf{v}}_i, \vec{\mathbf{v}}_j) = \begin{cases} \sum_{q \, \in \, \tau_l^b} \tilde{\mathbf{A}}_q^l \times \mathcal{S}_{Cosine}(\vec{\mathbf{v}}_{q\{i\}}^l, \vec{\mathbf{v}}_{q\{j\}}^l) \\ \qquad + \mathcal{S}_{Depth}(l.child(), \vec{\mathbf{v}}_i, \vec{\mathbf{v}}_j) \\ \qquad\qquad\qquad if \; l.child() \neq Null \\ \\ \sum_{q \, \in \, \tau_l^b} \tilde{\mathbf{A}}_q^l \times \mathcal{S}_{Cosine}(\vec{\mathbf{v}}_{q\{i\}}^l, \vec{\mathbf{v}}_{q\{j\}}^l) \\ \qquad\qquad\qquad\qquad otherwise \end{cases}$$
(8)

Eventually, the correlation intensity ($[-1, 1]$) between each pair of words (i, j) can be collectively evaluated by both the {level and depth}-wise attributes, Eq. 9:

$$\overline{\mathcal{S}}_{Cosine}(\vec{\mathbf{v}}_i, \vec{\mathbf{v}}_j) = \sum_{l \, \in \, \mathbf{T}} (\mathcal{S}_{level}(l, \vec{\mathbf{v}}_i, \vec{\mathbf{v}}_j) + \mathcal{S}_{Depth}(l, \vec{\mathbf{v}}_i, \vec{\mathbf{v}}_j))$$
(9)

After computing the similarity between each pair of words, we obtain B^{TCBOW} as a $|V| \times |V|$ matrix, where each row i is associated with a single vocabulary v_i and the resulting word vector $\vec{v}_i$ can represent the similarity between v_i and other words. $\vec{V}^{TCBOW}$ denotes the set of the word vectors in B^{TCBOW} grid.

Inherently, the dimension of vectors in $\vec{V}^{TCBOW}$ equates to the number of words (i.e. $|V|$) and turns out to be much more than $|d|$, which is the dimension of vectors in the hidden layer. Due to complexity, such a high dimension can negatively affect efficiency. To address this challenge, we propose $\vec{V}^C$ which collectively computes the word vectors based on each of the slabs in all the latent facets. To compute these collective word vectors, we take into account the effect of the word vectors of $\vec{V}_k^l$ of each slab S_k^l by multiplying those vectors into their normalized analogy accuracy $\tilde{A}_k^l$.

We compute the collective word vector $\vec{v}_i^C$ for each word v_i using two attributes of *level* and *depth*. Unlike $\mathcal{V}_{level}(l, i)$ which only includes the slabs for the current latent facet (Eq. 10), the depth property $\mathcal{V}_{depth}(l, i)$ hierarchically considers the effects from all the parent latent facets.

$$\mathcal{V}_{level}(l, i) = \sum_{k \, \in \, l} \tilde{\mathbf{A}}_k^l \times \vec{v}_{k\{i\}}^l$$
(10)

$\mathcal{V}_{level}(l, i)$ considers the slabs in the same latent facet. Similarly, Eq. 11 calculates the depth property.

$$\mathcal{V}_{Depth}(i) = \begin{cases} \sum_{q \, \in \, \tau_l^b} \tilde{\mathbf{A}}_q^l \times \vec{v}_{k\{i\}}^l + \mathcal{V}_{Depth}(l.child(), i) \\ \qquad\qquad\qquad if \; l.child() \neq Null \\ \\ \sum_{q \, \in \, \tau_l^b} \tilde{\mathbf{A}}_q^l \times \vec{v}_{k\{i\}}^l \qquad\qquad otherwise \end{cases}$$
(11)

Here l is the current layer and i is the index of words for which the collective vector is computed. Like Eq. 8, the depth property behaves recursively.

$$\vec{v}_i^C = \sum_{l \, \in \, \mathbf{T}} (\mathcal{V}_{level}(i) + \mathcal{V}_{Depth}(i))$$
(12)

Ultimately, the final collective word vector for each word v_i, denoted by $\vec{v}_i^C$, will be attained by the summation of level and depth functions (Eq. 12).

4.1.4 Generating tweet vectors

Given the word vectors that are constructed by the temporal embedding model (Collective), we now need to generate *tweet vectors*. *Summation* and *Averaging* are two simple but effective approaches to combine word vectors in each tweet and obtain the outcome tweet vector. While the summation approach generates vectors with bigger values and augments the computation time, the average method places the resulting vector between input vectors, which can better represent the blending. The Tweet vector is computed by merging the vectors of the comprising word (Eq. 13).

$$\vec{m}_i^{Avg} = \frac{\sum_{j=1}^{|m_i|} \vec{v}_{m_i[j]}}{|m_i|}, \quad \vec{m}_i^{Sum} = \sum_{j=1}^{|m_i|} \vec{v}_{m_i[j]}$$
(13)

Here, $|m_i|$ denotes the number of words in each short-text m_i and $\vec{v}_{m_i[j]}$ constitutes the word vector for the jth word in m_i. Tweet vectors can represent the comprising word vectors. However, short-text instances might refer to different concepts when context differs. Therefore, understanding of the concept(s) to which the tweets correspond matters in recognition of the authors' orientations. To this end, we need to dynamically discover the concepts that are shared among each group of tweets. Hence, any upcoming unclassified tweet can be conceptually grouped into one of the existing tweet clusters. We utilize two popular clustering methods of DBScan [71] and K-Medoids [72], which differ in nature. Where DB-Scan detects the densely grouped tweets, K-medoids discover the outliers, that have been cast-out by the DB-Scan algorithm. Nevertheless, we employ the well-known *Euclidean distance* to measure the space between cluster points (Eq. 14).

$$Distance_{Euclidean}(\vec{v}_i, \vec{v}_j) = \sqrt{\sum_{p=1}^{d} (\vec{v}_{i\{p\}} - \vec{v}_{j\{p\}})}$$
(14)

Here d denotes the dimension of word vectors and p indicates the index of any word vector (e.g. $\vec{v}_i$). Nevertheless, given the list of exploited clusters, we can present each tweet m_i with the *tweet concept vector*. The new vector lists the dissimilarities between each tweet m_i and each of the concepts that are the center point of each cluster, Eq. 15.

$$\forall_{j=1}^{|C^f|} \; \vec{m}_i^f[j] = Distance_{Euclidean}(\vec{m}_i, \vec{c}_j^f)$$
(15)

Here, $|\mathbb{C}^f|$ shows the number of clusters that are extracted using any clustering method of f. Where $\vec{m}_i^f$ shows the tweet concept vector that is computed using f, and $\vec{c}_j^f$ symbolizes the center tweet vector of the jth cluster that is extracted using the same clustering model (i.e. f). Finally, $\vec{m}_i^f[j]$ denotes the jth entry of the $\vec{m}_i^f$. Furthermore, $\mathbb{C}$ as the chosen set of clustering models ($f \in \mathbb{C}$) can collectively include two features from the type of clustering (k-medoid and DB-Scan), and whether the tweet vectors are constituted from summation or average of comprising word vectors. For instance, $Sum - DB$ can specify an f clustering model where the tweet vectors are constructed by the summation of word vectors and the employed clustering model is DB-Scan. It is noteworthy that the Tweet concept vectors tend to impose the smaller grid of $\mathbb{R}^{|\mathbb{C}^f|}$.

4.1.5 Generating author vectors

We explain in detail the approach we take to associate each author with content and concept vectors. Recall that each tweet vector is constructed via the merging of the vectors of the words it comprises. Similarly, we can apply the summation or average operators on tweet vectors to obtain the author's content vector. Let m_j be a tweet from the set of tweets composed by the author n_i ($m_j \in M_i$) where $\vec{m}_j$ denotes the vector for m_j. It is easy to see that the sum and average vectors for author n_i can be computed using Eq. 16.

$$\vec{n}_i^{Content-Sum} = \sum_{m \in M_i} \vec{m}, \quad \vec{n}_i^{Content-Avg} = \frac{\sum_{m \in M_i} \vec{m}}{|M_i|}$$

$$(16)$$

$\vec{n}_i^{Content-Sum}$ and $\vec{n}_i^{Content-Avg}$ respectively represent the sum and average author content vectors. Rather than considering operational functions (sum and average), let us consider statistical approaches. Here, we aim to predict the vector of an unobserved tweet that is deemed to be semantically aligned toward the preferences of the author n_i. While topic-modeling [14] seems to be the best solution for document generation, we extend the embedding model of the tweet vectors by the K-Fold statistics. Let d be the dimension of the tweet content vector. Hence, we can conveniently discover the maximum probability for each value to be assigned to the corresponding item in the author's content vector. To this end, we partition the range [-1,+1] into ς number of bins (In here $\varsigma = 10$). For each index in the author vector, we consider the bin which contains the values from the majority of the tweet vectors on the same index. The selected bin will represent the weight with the highest probability for the current index in author vector.
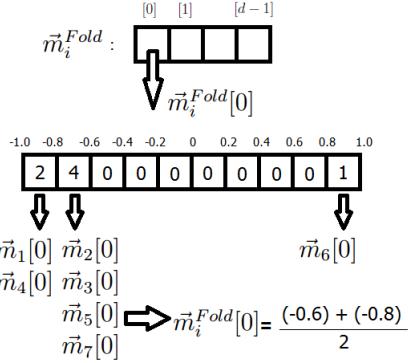

Fig. 7: (Fold)

As instantiated in Fig. 7, the bin [-0.8,-0.6] reports the values from four tweets and demonstrates that with more than 50% chance, the index zero of the author vector will be assigned between -0.8 and -0.6. For the bins with equal numbers, we utilize a linked list and distribute the prediction chance accordingly. Similar to the author's content vector, we can aggregate the tweet concept vectors of each author to construct the author's concept vector ($\vec{n}_i^{Concept}$). The concept vectors are low in dimension and dynamically carry the knowledge of concepts through clustering. However, content vectors come with less complexity and include the information of the tweets which are possibly ignored in DB-Scan or misclassified by K-medoid. The eventual author similarity should include the impacts from both content and concept vectors (Eq. 17) that is adjusted by α.

$$\forall_{i=1}^{|U|}\forall_{j=1}^{|U|}, \ X_{ij}^{Total-\alpha} = \alpha \times X_{ij}^{Concept} + (1-\alpha) \times X_{ij}^{Content}$$

$$(17)$$

Because of the difference in dimensionality, it is not inherently feasible to consolidate content and concept vectors of the authors. Given U as the set of authors, we should compute the similarity between each pair of authors to build the distinctive correlation matrices using concept and content vectors, respectively denoted by $X^{Concept}$ and $X^{Content}$. The impact from correspondent matrices can be merged by α to maximize the final performance.

4.2 Online Phase

In the online phase, we aim to mine a set of authors that are highly correlated to the query author n_q. Two duties are undertaken in online phase: Including query author and extracting stack-wise maximum spanning trees.

4.2.1 Including query author

This duty is divided into two tasks of *generating query author vectors* and *computing query author contextual similarities* that are quite similar to what we explained in Section 4.1. Firstly, we need to generate the author vectors for the query author n_q. This is especially necessary for the cold start authors. Because by posting a single tweet, the conceptual alignment of the author may evolve.

Given the set of current tweets ($M_q = \{m_1, m_2, ..., m_r\}$) belonging to n_q, we can generate corresponding tweet vectors $\vec{M}_q = \{\vec{m}_1, \vec{m}_2, ..., \vec{m}_r\}$ using precomputed $\vec{V}^C$. This step is not time-consuming as the language model is already generated in the offline phase.

What is the usage for Trigger? Trigger follows frequent intervals to continuously rebuild the slabs and subsequently construct the vector representations. This is especially useful to include the tweets of new authors where it can partially affect the embedding results. Therefore, the new tweets will be included in the embedding process in the offline phase as soon as the trigger is released.

Using the tweet vectors we can easily retrieve the n_q's content vector $\vec{n}_q^{Content}$. Correspondingly, we need to find the distance between each tweet $m_i \in M_q$ and the cluster centroids which results in the set of tweet concept vectors $\vec{M}_q^f = \{\vec{m}_1^f, \vec{m}_2^f, ..., \vec{m}_r^f\}$. Here f denotes the selected clustering approach. Accordingly, the author concept vector $\vec{n}_q^{Concept}$ can be computed by averaging of the vectors in $\vec{M}_q^f$. Given the content $\vec{n}_q^{Content}$ and concept $\vec{n}_q^{Concept}$ vectors of the query author n_q, we can respectively update $X^{Content}$ and $X^{Concept}$ author similarity matrices which are accomplished through measuring the similarity between n_q and others. Eventually, graph $G = (\mathbb{N}, \mathbb{L})$ can represent the authors weighted graph, where $\mathbb{N}$ is the set of nodes (authors) and $\mathbb{L}$ denotes the set of undirected edges with similarity weights.

4.2.2 extracting query author subgraph

We now aim to exploit the subgraphs with highly correlated authors which further comprises the query author n_q. In general, we can address the challenge through Lemma 1. Inspired by the Lemma 1, we devise the Stack-Wise Maximum Spanning Tree (SW-MST) approach (Algorithm 1) to calculate the MST for each of the highly correlated subgraphs in G. As algorithm 1 shows, we firstly push the edges into the empty stack S in ascending order, where the links with the lower weight are pushed downward. Correspondingly, we initiate an empty graph $G' = (\mathbb{N}', \mathbb{L}')$ to store the resulting spanning trees. To continue, we iteratively pop the edges from the stack and add them to $\mathbb{L}'$ and append the corresponding nodes to $\mathbb{N}'$. We repeat the process until every $n_i \in \mathbb{N}$ is added to the $\mathbb{N}'$. The G' will finally include a set of maximum spanning-trees. In other words, the algorithm 1 firstly extracts distinctive subsets of the graph in the form of maximal cliques and subsequently exploits an MST out of the cliques. Finally, each exploited MST can represent a highly correlated author subgraph.

Lemma 1. *Linking a set of highly correlated authors to the query author n_q can be facilitated by the inner-author edge weights.*

Proof. Given a fully connected weighted graph which represents the weight of contextual similarity between author vectors, the subgraph $\tilde{g}_q$ comprising n_q will result in the maximum spanning tree with the biggest average edge weight. With this logic, the node n_q will be highly correlated to every node in $\tilde{g}_q$ via either of the direct or indirect link(s).

Algorithm 1 Stack-Wise Max. Spanning Tree (SW-MST)

Input: G
Output: G', S
1: $\mathbb{N}' = \emptyset, \mathbb{L}' = \emptyset, \mathbb{N}'' = \mathbb{N}, \mathbb{L}'' = \mathbb{L}, S = \emptyset$
2: **while** $\mathbb{L}'' \neq \emptyset$ **do**
3:    $l = Min(\mathbb{L}'')$
4:    $S.push(l)$
5:    $\mathbb{L}''.remove(l)$
6: **end while**
7: **while** $\mathbb{N}'' \neq \emptyset$ **do**
8:    $l = S.pop()$
9:    $\mathbb{L}'.append(l)$
10:    **if** $l[0] \notin \mathbb{N}'$ **then**
11:      $\mathbb{N}'.append(l[0])$
12:    **end if**
13:    **if** $l[1] \notin \mathbb{N}'$ **then**
14:      $\mathbb{N}'.append(l[1])$
15:    **end if**
16:    **if** $l[0] \in \mathbb{N}''$ **then**
17:      $\mathbb{N}''.remove(l[0])$
18:    **end if**
19:    **if** $l[1] \in \mathbb{N}''$ **then**
20:      $\mathbb{N}''.remove(l[1])$
21:    **end if**
22: **end while**
23: $G' = (\mathbb{N}', \mathbb{L}')$
24: return $G', Avg(\mathbb{L}')$

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5 EXPERIMENT

We conducted extensive experiments on a real-world twitter dataset [15] to evaluate the performance of our model in short-text author linking. We ran the experiments on a server with 4.20GHz Intel Core i7-7700K CPU and 64GB of RAM. The codes are available to download [1].

5.1 Data

Our Twitter dataset [25] includes 8 million English tweets in Australia, collected via *Spritzer Twitter Feed*. The sampling was done at various times of the day for a complete year. We then used *Twitter API* to select approximately $4K$ users from streaming tweets and retrieved up to 1000 records from their Twitter history. Finally, we attained $\approx 1M$ geo-tagged *tweets* which are all composed in Australian territory. The dataset contains 305K vocabs and is made of 65M collocations.

5.1.1 Baselines

The baselines in computing of the similarity weights between authors are listed as follows. Note that the author's similarities can be computed by measuring the similarity between author vectors.

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1. https://sites.google.com/view/temporal-textual-embedding

- $SoulMate_{Concept}$: As explained in Section 4.1.5, this method renders the authors with the closeness of their tweets to each of the concepts.
- $SoulMate_{Content}$: this embedding approach [18] obtains the tweet vectors and then combines them to form author content vectors.
- $SoulMate_{Joint}$: this model regulates α to combine the author's similarities through concept and content vectors (Section 4.1.5).
- Temporal Collective: this model computes the collective word vector through multi-facet temporal embedding [16][73] and then enriches the textual contents of each author by replacing each word with its top ζ most similar words. Finally, TF-IDF can measure the textual similarity between authors.
- CBOW Enriched: this model uses CBOW [18][74] to produce the distributed representation of the words. Given the enriched textual contents of the authors, the model employs the Jaccard coefficient to compute the textual similarities.
- Document Vector: this model [75] computes the similarities between authors using TF-IDF statistics.
- Exact Matching: this straightforward baseline exactly matches the short-text contents of the authors.

5.2 Effectiveness

5.2.1 Basic Comparison of Vector Space Models

In this section, we firstly apply the Google word analogy task [20] to compare the effectiveness and efficiency of the vector representation models. The vector representation baselines (Section 4.1.2) are four-fold: SVD [70], Skip-gram [20], CBOW [18], and GloVe [17]. *SVD-15:15000* limits the word pair co-occurrences between 15 and 15000. Also, the numerical extension in GloVe-30 highlights the number of training epochs. The analogy test aims to discover the model that on the one hand, suits best to the short-text noisy contents, and on the other hand, is the best candidate for time-aware embedding. The test includes $\approx 20K$ syntactical and semantic questions like "a is to b as c is to ?", where each competitor suggests a word to alter the question mark.
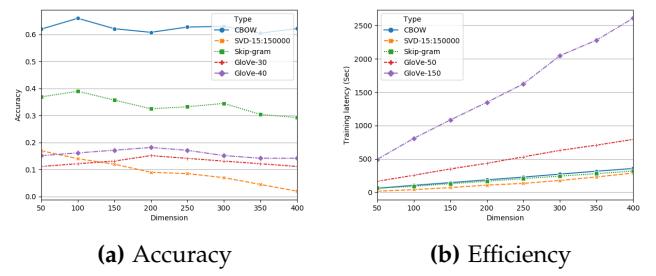

(a) Accuracy   **(b)** Efficiency
Fig. 8: Performance of the vector space models

Fig. 8a reports the accuracy of the analogy task on the twitter dataset (Section 5.1), where the dimension varies. Our dataset suffices the words for only $\approx 7K$ questions, resulting in lower numbers. The CBOW model overpasses all rivals and SVD performs the least as it lacks the training phase. Conversely, the CBOW as the most noise-resistant model surpasses skip-gram because it better involves the context of the words in the training procedure. Finally, notice that excessive noise in microblog contents leads to a sparse and oversize co-occurrence matrix which significantly reduces the performance of the GloVe model.

Our online author linking framework must handle millions of the short-text contents, where the vector representation module forms the underlying time-aware module. So as illustrated in Fig. 8b, we compare the efficiency of vector space methods. We notice that due to the lack of training procedure the temporal latency of the SVD model is the least. Furthermore, for the models with training, the CBOW and skip-gram closely gain the highest efficiencies. However, the GloVe models take the highest time in training which is naturally due to the huge size of the input co-occurrence matrix. Hence, we conclude that CBOW is better than other models in both effectiveness and efficiency.

TABLE 5: Precision of author similarity in subgraph mining

	Score Distribution	
	textual↑ conceptual↑	textual↓ conceptual↑
$SoulMate_{Concept}$	0.07	0.30
$SoulMate_{Content}$	0.43	0.05
$SoulMate_{Joint}$	**0.67**	**0.32**
Temporal Collective	0.63	0.01
CBOW Enriched	0.48	0
Document Vector	0.21	0
Exact Matching	0.39	0.01

5.2.2 Comparison of the Author Subgraph Mining Methods

In this part, we compare our approaches to linking authors with well-known competitors (Section 5.1.1). As the first step, the author's similarity matrix of each baseline model can establish the author weighted graph. We propose three algorithms to calculate author similarities ($SoulMate_{Concept}$, $SoulMate_{Content}$, and $SoulMate_{Joint}$). Eventually, given the originated weighted graph, each model can employ SW-MST algorithm (Section 4.2.2) to acquire the final author subgraphs, as Maximum Spanning Trees (MST).

Benchmark- Since the authors within each spanning tree should exceedingly correlate, as Table 5 shows, we evaluate the baselines through assessing the similarity between authors in the same exploited subgraphs. To this end, we first obtain the set of MSTs out of G' (output of SW-MST) which comprises any of 50 arbitrarily chosen authors. We then pick top 5 MSTs with at least 5 nodes that possess the highest average edge weights. Finally, given the top 10 most similar tweets from each pair of authors in the selected MSTs, we consider the votes of 5 local (Australian) experts. The possible votes are defined as follows:

- score 0: neither textually or conceptually similar.
- score 1: minor textual and conceptual similarity.
- score 2: high textual and conceptual similarity.
- score 3: minor textual but high conceptual similarity.

Subsequently, we compute the average of the votes given to each pair of tweets and round it to the nearest lower integer. We then count the tweet pairs with the scores of 2 and 3 for each one of the author similarity calculation methods. The precision metrics are then calculated by dividing the number of 2 and 3 scores (admitted by the average of experts' votes) by the total number of selected tweet pairs in subgraphs. $SoulMate_{Concept}$ is devised to detect the conceptual similarities, where the textual relevance is minor. Moreover, the $SoulMate_{Content}$ can trace the textual and conceptual relevance. However, since $SoulMate_{Joint}$ combines both modules through parameter adjustment (α=0.6), it gains the highest votes for both conditions. It is interesting to see that where the textual similarity between short-text contents is very low and all textual models including Temporal Collective, CBOW, Document Vector and Exact matching fail (perform less than 2%), $SoulMate_{Concept}$ can detect the semantic correlation between authors by 30%. Notice that the higher the number of exploited concepts, and the better the clustering models, $SoulMate_{Concept}$ model can gain a better precision. Table 5 shows, where the textual similarity is low, $SoulMate_{Concept}$ can still find (precision %30) the conceptually relevant author pairs. Conversely, $SoulMate_{Content}$ can track textual similarity (%43). To briefly mention, $SoulMate_{Joint}$ as our final model performs more accurately than other baselines. Note that based on our peripheral experiments on Temporal word embedding (Section 4.1.3), where the accuracy of $\vec{V}^{TCBOW}$ in generating of the tweet vectors is 0.881, the dimension is quite large (the number of words ($|V|$)). Hence, we employ the collective manner $\vec{V}^C$ which offers a lower precision of 0.861 but in contrast, provides a much smaller dimension (the size of hidden layer vectors ($|d|$)).

5.2.3 Effect of embedding on author content vectors

We here study the impact of several parameters on the effectiveness of author contents vectors. We compare *CBOW* versus *Collective* that are respectively the best non-temporal and temporal embedding models. To form the tweet vectors, the word vectors can be combined using summation or averaging. The tweet vectors can also form the author's content vectors through various aggregations, such as Average, Summation, and 10 Fold model.

Benchmark - The experts label the top 10 most similar tweets with the mentioned scores that were previously defined in the benchmark part of Section 5.2.2. We also deploy averaging and rounding to the bottom integer method, as we did in the previous section, to take into account the votes of all the experts. We then consider the computed score as the final score for each selected pair of tweets. Inspired by [76], we propose two weighted precision equations of 18 and 19 to compare the effectiveness of the methods: Note that in both equations, the pertinent scores are prefixed by ρ (e.g. the number of items for score 1 is denoted by ρ_1).

$\mathcal{P}_{Conceptual}$: The weighted precision formulated in Eq. 18 pays more attention to the pairs with high conceptual but low textual similarity which leads to the high numerical coefficient of 3 for ρ_3 and the null significance for ρ_0. Here, the precision is normalized by multiplying the sum of the score counts by 3 in the denominator.

$$\mathcal{P}_{Conceptual} = \frac{\rho_1 + \rho_2 \times 2 + \rho_3 \times 3}{3 \times (\rho_0 + \rho_1 + \rho_2 + \rho_3)} \quad (18)$$

$\mathcal{P}_{Textual}$: As verbalized in Eq. 19, both textual and conceptual similarities gain the same importance in $\mathcal{P}_{Textual}$ metric. This enforces the same coefficient of 2 for ρ_2 and ρ_3.

$$\mathcal{P}_{Textual} = \frac{\rho_1 + (\rho_2 + \rho_3) \times 2}{2 \times (\rho_0 + \rho_1 + \rho_2 + \rho_3)} \quad (19)$$

While among the embedding methods, the time-aware

TABLE 6: Weighted precision of user content vectors

Embedding method	Author content vector combination type	Tweet vector combination type			
		Average		Summation	
		$\mathcal{P}_{Textual}$	$\mathcal{P}_{Conceptual}$	$\mathcal{P}_{Textual}$	$\mathcal{P}_{Conceptual}$
CBOW	Average	0.547	0.433	0.645	0.511
	Summation	0.547	0.433	0.645	0.511
	10 Fold	0.594	0.442	0.668	0.477
Collective	Average	0.568	0.453	**0.652**	**0.538**
	Summation	0.568	0.453	**0.652**	**0.538**
	10 Fold	0.602	0.461	**0.676**	0.493

approach (collective embedding) is better than CBOW, the summation works better than average in the aggregation of word vectors. The 10 fold algorithm gains a higher precision for $\mathcal{P}_{Textual}$ in the aggregation of tweet vectors. However, since the 10 Fold approach performs low for $\mathcal{P}_{Conceptual}$, we opt for other aggregation algorithms that support both of the weighted precisions. Since the normalized vector for the summation method is very similar to the average approach, both precisions come with similar results. Regarding author content vectors, while summation and averaging methods are the same, we select the average operator for the lower decimal values and the less computational complexities.

5.2.4 Impact of Short-text Vector Clustering

To extract the concepts from microblog contents, we need to cluster the tweet vectors. We aim to select those thresholds that can maximize the number of exploited clusters (concepts), and simultaneously maintain a satisfying quality. Hence, in this section, we compare the performance of various clustering models. Note that we use K as the number clusters for K-medoids and ϵ as the radius for DBSCAN. Where the thresholds vary, it is both tedious and time-consuming to test the quality of clusters by human experts. Therefore in this section, we firstly study the cohesion and separation properties of the clusters using two well known methods of the Silhouette score [77] and the Davies-Bouldin index [78]. Subsequently in Section 5.2.5, we limit the range of thresholds first and then ask the experts to evaluate the quality of clusters.

(a) K-Medoid: Quality

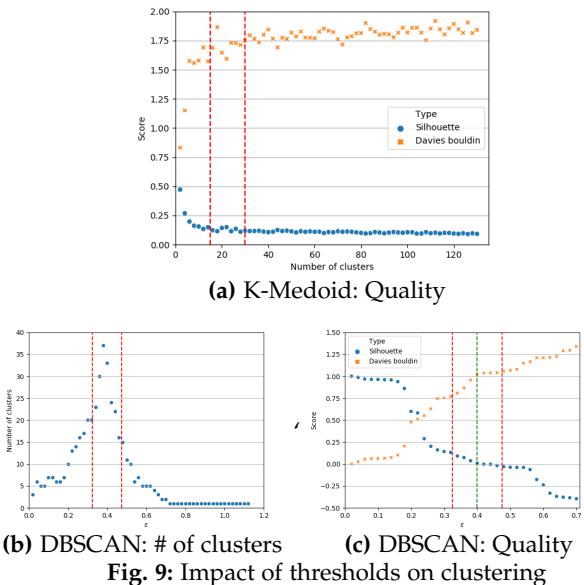**(b)** DBSCAN: # of clusters   **(c)** DBSCAN: Quality

Fig. 9: Impact of thresholds on clustering

Fig. 9 illustrates the impact of thresholds on clustering. In general, the lower the Davies-Bouldin index and the higher the Silhouette score, the better the threshold will

be. For K-medoids as depicted in Fig. 9a, we select the range [15,30] where the number of clusters is higher and the indicators highlight a good clustering quality. Subsequently, from the selected range we choose the values, 20, 22, 24, and 26 for K, where they return a higher number of high-quality clusters. Similarly, Fig. 9b and 9c study the impact of ϵ on the number and the quality of clusters in the DBSCAN method. Fig. 9b shows the number of clusters where ϵ varies. Here the threshold range of [0.325,0.475] supports the highest number of clusters, which is more than 15. Consequently, Fig. 9c can analyze the clustering scores against various ϵ values, where we aim to find the thresholds in the selected range. We notice that when the value of ϵ grows bigger than 0.4, both the number of concepts and the quality metrics reduce. We then nominate 0.36,0.38,0.4, and 0.42 for ϵ to maximize the number of high standard clusters.

5.2.5 Selection of Clustering Thresholds

We limited the range of thresholds in Section 5.2.4. In this section, we choose the best final clustering thresholds that are voted by human experts.

Benchmark - To select the best thresholds in K-medoid and DBSCAN, we consider the clusters that have been retrieved by each threshold. We then choose the top 10 most similar pair of tweets from each tweet cluster, where the similarity measure is carried out by the well-known TF-IDF method. Subsequently, the human experts of five determine the similarity of the pairs through majority voting using $\rho_0,\rho_1,\rho_2,$ and ρ_3 that are then used to compute $\mathcal{P}_{Textual}$ (Section 5.2.3). The best threshold should generate the clusters with the highest weighted precision.
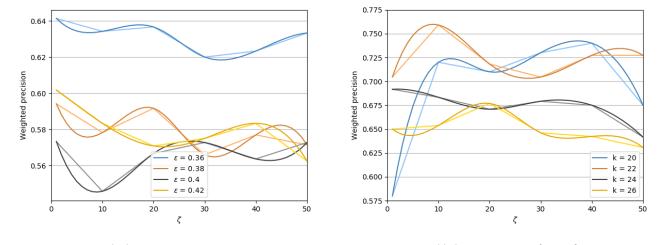

(a) DBSCAN   **(b)** K-Medoids

Fig. 10: The weighted precision by ζ for various thresholds

Fig. 10 depicts the weighted precision based on the selected thresholds when the ζ (Section 4.1.2) varies. For DBSCAN (Fig 10a), the value of 0.36 for ϵ can demonstrate the best performance for all ζ values. However, other thresholds turn up untrusted with many perturbations where ζ varies. As Fig. 10b illustrates none of the thresholds performs significantly better than the others. Nevertheless, for $K = 22$, the k-medoids model gains the highest quality at $\zeta = 10$ and maintains the approximate precision for different values of ζ.

TABLE 7: Precision of user concept vectors

Embedding	Author concept vector cluster type	Tweet vector combination type			
		Avg		Sum	
		$\mathcal{P}_{Textual}$	$\mathcal{P}_{Conceptual}$	$\mathcal{P}_{Textual}$	$\mathcal{P}_{Conceptual}$
CBOW	K-Medoids ($K = 22$)	0.10869	0.08405	0.10869	0.08405
	DBScan ($\epsilon = 0.36$)	0.09166	0.06666	0.09166	0.06666
Collective	K-Medoids ($K = 22$)	**0.17291**	**0.12638**	**0.17291**	**0.12638**
	DBScan ($\epsilon = 0.36$)	0.16388	0.12592	0.16388	0.12592

5.2.6 Impact of Clustering on Authors Concept Vectors

As elucidated in Section 5.2.3, in this section we evaluate the precision of author concept vectors via two weighted metrics of $P_{Conceptual}$ and $P_{Textual}$. As shown in Table 7, we report the weighted precisions based on three variations: (1) embedding type (CBOW vs. Collective), (2) the type of combination (Avg vs. Sum) for word vectors in generation of tweet vectors, (3) clustering type (K-Medoids vs DBSCAN) in constructing author concept vectors. As shown in Table 7, our proposed time-aware collective model can outperform the CBOW model in both weighted precisions, where the overall improvement for $P_{Textual}$ and $P_{Conceptual}$ are approximately 7 and 4 percent. The K-Medoids clustering performs better than DBSCAN. This is because the DBSCAN model can ignore outliers. We notice that the time-aware collective model performs the best @K=22, where the CBOW gains the lowest results. Since the normalized summation vectors resemble the average approach, their corresponding precision results turn the same. We can, therefore, overlook the impact of combination type in tweet generation.

5.2.7 Effect of vectors on Author Subgraph Mining

Author similarity matrices (denoted by $X^{Concept}$ and $X^{Content}$), can be combined by α to form the contextual author similarity matrix, denoted by $X^{Total-\alpha}$ (Section 4.1.5). We study the impact of α on the effectiveness of our approach that is measured by $\mathcal{P}_{Textual}$ and $\mathcal{P}_{Conceptual}$.
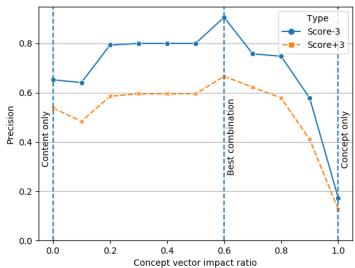

Fig. 11: Impact of α (Concept impact ratio) on effectiveness

As shown in Figure 11, $X^{Total-\alpha}$ provides the best precision in both metrics when α is set to 0.6. It is found that the effectiveness of author subgraph mining stops growing at $\alpha = 0.6$. We notice that the decrease in performance becomes faster when α increases over 0.8. This can be explained by two rationales: First, the number of exploited concepts are limited to the current dataset, Second, the importance of the embedding process, reflected by $X^{Content}$, cannot be sacrificed in favor of the concept matrix.

6 CONCLUSION

In this paper, we devise a novel framework that consumes short-text contents (e.g. tweets) to exploit subgraphs including highly correlated authors. To this end, we first need to link authors through computing the similarity edge weights between them, which results in the authors' weighted graph. Primarily, the time-aware word embedding model considers temporal-textual evidence to infer the similarity between temporal splits in multiple dimensions (e.g. Monday and Tuesday in day dimension) and collectively computes the word vector representations. Subsequently, we obtain short-text vectors and *author content vectors* using primary word vectors. Similarly, *author concept vectors* represent how every author is relevant to each of the short-text clusters. We then fuse the content-based and conceptual author similarities to calculate the correlation weight between each pair of authors. Consequently, given the authors' weighted graph, the stack-wise graph cutting component in our framework can extract the maximum spanning trees that establish the subgraph of linked authors. The result of the extensive experiments on a real-world microblog dataset proves the superiority of our proposed model in short-text author linking. Moreover, we notice that compared to DBSCAN, the k-medoids clustering can better discover the concepts from tweet contents.

Naturally, the short-texts differ in significance (e.g. popularity). Hence, to nominate the concepts from short-text clusters, we should not only consider the relevance of the short-texts but also grant higher importance to the concepts of those with higher popularity. We leave this task for future work.

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