An open-source framework for ExpFinder integrating N-gram Vector Space Model and \( \mu \)CO-HITS

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Abstract

Finding experts drives successful collaborations and high-quality product development in academic and research domains. To contribute to the expert finding research community, we have developed ExpFinder which is a novel ensemble model for expert finding by integrating an N-gram vector space model (nVSM) and a graph-based model (\( \mu \)CO-HITS). This paper provides descriptions of ExpFinder’s architecture, key components, functionalities, and illustrative examples. ExpFinder is an effective and competitive model for expert finding, significantly outperforming a number of expert finding models as presented in [1].

Keywords: ExpFinder, Expert finding, N-gram Vector Space Model, \( \mu \)CO-HITS, Expert collaboration graph

1. Introduction

Identifying experts given a query topic, known as expert finding, is a crucial task that accelerates rapid team formation for research innovations or business growth. Existing expert finding models can be classified into three categories such as vector space models (VSM) [2, 3], document language models (DLM) [4, 5, 6], or graph-based models (GM) [7, 8, 9]. ExpFinder [1] is an ensemble model for expert finding which integrates a novel N-gram VSM (nVSM) with a GM (\( \mu \)CO-HITS)-a variant of the generalised CO-HITS algorithm [7].

As seen in Figure 1, ExpFinder has nVSM, a vector space model, as a key component that estimates the weight of an expert and a document given a topic by leveraging the Inverse Document Frequency (IDF) weighting [10] for N-gram words (simply N-grams). Another key component in ExpFinder is \( \mu \)CO-HITS that is used to reinforce the weights of experts and documents given a topic in nVSM using an Expert Collaboration Graph (ECG) that is a certain form of an expert social network. The output of ExpFinder is the reinforced weights of experts given topics.

ExpFinder is designed and developed to improve the performance for expert finding. In this paper, we highlight two main contributions to the expert finding community. First, we provide a comprehensive implementation detail of all steps taken in ExpFinder. It could also be used as an implementation guideline for developing various DLM-, VSM- and GM-based expert finding models.

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approaches. Second, we illustrate how ExpFinder works with a simple example, thus researchers and practitioners can easily understand ExpFinder’s design and implementation.

This paper is organised as follows. Section 2 describes ExpFinder’s architecture and functionalities. Section 3 demonstrates the procedural steps in ExpFinder. Section 4 provides the impact and conclusion of ExpFinder.

2. Functionality

ExpFinder is implemented in Python (version ≥ 3.6) with open-source libraries such as \texttt{pandas}, \texttt{NumPy}, \texttt{scikit-learn}, \texttt{SciPy}, \texttt{nltk}, and \texttt{networkx}. In this section, we present its architecture, key components, and their functionalities. The architecture of ExpFinder is presented in Figure 2 that consists of four key steps with the corresponding functions and their functional dependencies:

1. \textbf{Step 1 - Extract tokens and topics}: Given an expertise source \( D \) (e.g., scientific publications) of experts \( \mathcal{X} \), we extract expertise topics by using \texttt{tokenise\_doc()} in \texttt{extractor.py}. We assume that expertise topics are represented in the forms of noun phrases. For each document \( d \in D \), the function splits it into sentences. Then, for each sentence, the function removes stopwords, assigns a part of speech (POS) to each word, merges the inflected forms of a word (i.e., the lemmatisation process, for example, ‘patients’ is lemmatised to ‘patient’), and extracts single-word terms (called \textit{tokens}) and topics with a given linguistic pattern. In addition, we use a regular expression (\texttt{regex}) in Python to construct a linguistic pattern based on POS that is further used for extracting four different types of topics as shown in Figure 3. Note that we use \texttt{nltk} for performing this process. The output of this step is the list of the tokens and the list of topics for each document \( d \in D \). The set of the all tokens is denoted as \( \mathcal{W} \), and the set of the all topics is denoted as \( \mathcal{T} \).

2. \textbf{Step 2 - Estimate the weights of experts and documents given topics in nVSM}: The process includes four main steps with the corresponding functions in \texttt{generator.py}:
Figure 2: The architecture and functional workflow of ExpFinder: blue labels indicate module names of ExpFinder, and ‘Output Relation’ maps the functional component to the corresponding processing step.

Figure 3: The Python regular expression of a linguistic pattern for extracting topics in a single document

2.1. We use `generate_tf()` to estimate the term frequencies (TFs) of \( W \) in each document \( d \in D \). For this estimation, we use `CountVectorizer` in `scikit-learn`. The output of this function is the \( |D| \times |W| \) Document-Token matrix (DTM) where each entry contains the TF of \( w \in W \) in \( d \).

2.2. We use `generate_dp_matrix()` to estimate the weights of documents given \( T \) in nVSM \cite{1}. The function estimates \( nTFIDF \) of each topic \( t \in T \) by integrating the \( nTF \) weighting and the \( nIDF \) weighting. Intuitively, \( nTF \) estimates the frequency of \( t \) by averaging TFs of tokens in \( t \) where TF of each token is stored in DTM. In addition, \( nIDF \) \cite{10} is the \( N \)-gram IDF weighting method that estimates the log-IDF, \( \log \frac{|D|}{df(w_1 \wedge w_2 \wedge \ldots \wedge w_n) + 1} + 1 \), of \( t \) where \( w_1, \ldots, w_n \) are \( n \)-constituent terms in \( t \). The output of this step is the \( |D| \times |T| \) Document-Phrase matrix (DPM) where each entry contains the \( nTFIDF \) weight of \( t \) in \( d \).
2.3. Given $D$, we use `generate_ed_matrix()` to generate the $|X| \times |D|$ Expert-Document matrix (EDM) where each entry shows a binary relationship between $x \in X$ and $d$ (e.g., 1 indicates that $x$ has the authorship on $d$, and 0 otherwise).

2.4. We use `generate_pr_matrix()` to estimate the weights of experts $X$ and documents $D$ given each topic $t \in T$ in $nVSM$ [1]. The weights of $X$ are estimated by calculating matrix multiplication of $EDM^{X \times |D|}$ and $DPM^{ |D|\times |T|}$ (e.g., $ETopM = \texttt{numpy.matmul}(EDM, DPM)$ in Python). The output is the $|X| \times |T|$ Expert-Topic matrix ($ETopM$) where each entry contains the topic-sensitive weight of $x$ given $t$. The weights of $D$ are represented by $DPM$. Now, we denote $DPM$ as the $|D| \times |T|$ Document-Topic matrix ($DTopM$) where each entry shows the topic-sensitive weight of $d$ given $t$. It is worth noting that $DPM$ can be integrated with another factor (e.g., the average document frequencies of $T$) to obtain different weights for $DTopM$. However, in our approach, we set $DTopM = DPM$.

3. Step 3 - Construct ECG. We use `generate_ecg()` in `generator.py` to handle this step. The function receives $D$ and builds an ECG using DiGraph in networkx to present a directed, weighted bipartite graph that has expert nodes $V_x$ and document nodes $V_d$. The set of nodes in the graph is denoted as $V$ such that $V = V_x \cup V_d$. A directed edge points from a document node $v_d \in V_d$ to an expert node $v_x \in V_x$ if $x$ has published $d$. In this step, we also use `generate_ed_vector()` in `generator.py` to generate a $|V| \times 1$ Expert-Count vector ($c_x$) and a $|V| \times 1$ Document-Count ($c_d$) vector based on ECG. These vectors are used for the estimation of $\mu$CO-HITS in Step 4.

4. Step 4 - Reinforce expert weights using $\mu$CO-HITS. We use `run_expfinder()` in `trainer.py` to handle this step. The function receives $ETopM$, $DTopM$, ECG, $c_x$ and $c_d$, generated in (Steps 2 and 3) as parameters, and reinforces the estimation of expert weights given topics by integrating $nVSM$ and $\mu$CO-HITS [1]. For each $t \in T$, we perform the three steps:

4.1. Generate the adjacency matrix of nodes and its transpose - Given the ECG, we use `to_matrix()` in networkx to generate the $|V| \times |V|$ adjacency matrix of the graph $M$, and also construct its transpose matrix $M^T$. These matrices are required in the initialisation for running the $\mu$CO-HITS algorithm.

4.2. Normalise the weights of experts and documents given a topic - We get topic-sensitive weights of $X$ and $D$ given $t$ from $ETopM$ and $DTopM$, respectively. The output of this includes the $|X| \times 1$ Expert-Topic ($\alpha_x$) and $|D| \times 1$ Document-Topic ($\alpha_d$) vectors where each entry shows the topic-sensitive weight of an expert and a document given $t$, respectively. Then, we normalise these vectors using L2 normalisation to scale their squares sum to 1 as the initialisation for running the $\mu$CO-HITS algorithm [11].

4.3. Reinforce expert weights given a topic - We integrate $nVSM$ and $\mu$CO-HITS through $k$ iterations to reinforce expert weights given $t$. $\mu$CO-HITS is the extension of the CO-HITS algorithm [7] which contains two main properties such as average authorities $a$ and average hubs $h$ which show importance of $X$ and $D$, respectively, based on the ECG.
In addition, these properties can be defined as \( \mathbf{h} \):

\[
a(x; t)^k = (1 - \lambda_x)a(x; t)^{k-1} + \lambda_x \left( \frac{M^\top \cdot h(D; t)^{k-1}}{c_d} \right)
\]

\[
h(D; t)^k = (1 - \lambda_d)h(D; t)^{k-1} + \lambda_d \left( \frac{M \cdot a(x; t)^k}{c_x} \right)
\]

where

- \( a(x; t)^k \) and \( h(D; t)^k \) are \(|V| \times 1\) vectors which contain the reinforced expert weights and reinforced document weights, respectively, given \( t \) at \( k\text{th} \) iteration. As the initial weights of these vectors, we use the topic-sensitive weights of experts and documents estimated in nVSM. Thus, \( a(x; t)^0 = \alpha_x \) and \( h(D; t)^0 = \alpha_d \). By doing so, we integrate nVSM with \( \mu \text{CO-HITS} \). Note that \( a(x; t)^0 \) is a \(|X| \times 1\) vector, and \( h(D; t)^0 \) is a \(|D| \times 1\) vector. However, for easily implementing the HITS algorithm, we have transformed the dimension of these vectors into \(|V| \times 1\) vectors where additional entries hold the value of 0.

- \( \lambda_x \in [0, 1] \) and \( \lambda_d \in [0, 1] \) are parameters for expert and document, respectively. These are used to control the impact of topic-sensitive weights on \( a \) and \( h \), respectively. Assigning lower values indicates the higher impact of topic-sensitive weights on \( a \) and \( h \).

- \( \frac{(M^\top - h(D)t)^{k-1}}{c_d} \) is the calculation for the average authorities. The numerator performs matrix multiplication between the \(|V| \times |V|\) adjacency matrix \( M^\top \) and the \(|V| \times 1\) \( h \). The denominator is a \(|V| \times 1\) counted vector \( c_d \) generated in Step 3. To calculate this in Python, we simply apply \texttt{numpy.matmul}(M, h(D; t)^{k-1})/c_d.

- \( \frac{M \cdot a(x; t)^k}{c_x} \) is the calculation for the average hubs. The numerator performs matrix multiplication between the \(|V| \times |V|\) adjacency matrix \( M \) and the \(|V| \times 1\) \( a \). The denominator is a \(|V| \times 1\) counted vector \( c_x \) generated in Step 3. To calculate this in Python, we simply apply \texttt{numpy.matmul}(M, a(x; t)^k)/c_x.

After computing \( a \) and \( h \) at \( k\text{th} \) iteration, we apply \texttt{L2} normalisation to both \( a \) and \( h \). We use the obtained \( a(x; t)^k \) after the final iteration to construct the \(|X| \times |T|\) Expert-Topic matrix (\( \text{RETopM} \)) where each entry contains the reinforced weight of \( x \) given \( t \).

3. Illustrative examples

In this section, we illustrate how ExpFinder works. The input data\(^1\) includes three experts (i.e., \( x_1, x_2 \) and \( x_3 \)) and three documents (i.e., \( d_1, d_2 \) and \( d_3 \)) as shown in Table 1. Figure 4 presents the output examples of the steps in ExpFinder:

1. **Step 1 - Extract tokens and topics:** Given \( D \), we extract tokens \( W \) and topics \( T \). In this step, we set a maximum length of phrase to be 3 such that we only obtain phrases that have less than or equal to 3 tokens. Additionally, we use the linguistic pattern presented in Section 2.

\(^1\)The example data are also provided in our Github repository.
Table 1: The document dataset $\mathcal{D}$ used in the example: extracted phrases are highlighted in yellow, and extracted tokens are in bold.

| Docs | Experts | Text |
|------|---------|------|
| $d_1$ | $x_1, x_2$ | A prerequisite for using electronic health records (EHR) data within learning health-care system is an infrastructure that enables access to EHR data longitudinally for health-care analytics and real time for knowledge delivery. Herein, we share our institutional implementation of a big data-empowered clinical natural language processing (NLP) infrastructure, which not only enables healthcare analytics but also has real-time NLP processing capability. |
| $d_2$ | $x_1, x_3$ | Word embedding, where semantic and syntactic features are captured from unlabeled text data, is a basic procedure in Natural Language Processing (NLP). In this paper, we first introduce the motivation and background of word embedding and its related language models. |
| $d_3$ | $x_2$ | Structural health monitoring at local and global levels using computer vision technologies has gained much attention in the structural health monitoring community in research and practice. Due to the computer vision technology application advantages such as non-contact, long distance, rapid, low cost and labor and low interference to the daily operation of structures, it is promising to consider computer vision structural health monitoring as a complement to the conventional structural health monitoring. This article presents a general overview of the concepts, approaches, and real-life practice of computer vision structural health monitoring along with some relevant literature that is rapidly accumulating. |

The output of this step contains the set of 50 unique topics $\mathcal{T}$ and the set of 85 unique tokens $\mathcal{W}$. For example, extracted topics in $d_1$ include some single-token topics (e.g., prerequisite and capability) and some multi-token topics (e.g., real-time nlp processing and electronic health record).

2. **Step 2 - Estimate the weights of experts and documents given topics** - Given $\mathcal{T}$ and $\mathcal{W}$, we generate three main matrices (i.e., EDM, DTopM and ETopM) that will also be used in Step 4. To do this, we perform the following:

- Given $\mathcal{W}$, we generate $\text{DTM}^{3 \times 85}$ where each entry shows the TF of a token $w \in \mathcal{W}$ in a document $d \in \mathcal{D}$. For example, the $3 \times 1$ vector of healthcare, $\text{DTM}_{\text{healthcare}}$, is $(1, 0, 0)$ which shows it occurs only in $d_1$ (see also $\mathcal{D}$ in Table 1). As another example, we obtain $\text{DTM}_{\text{analytics}} = (2, 0, 0)$ which denotes that analytics appears twice in $d_1$.
- Given $\mathcal{T}$ and $\text{DTM}^{3 \times 85}$, we generate $\text{DPM}^{3 \times 50}$ where each entry contains the weight of a phrase $t \in \mathcal{T}$ for a document calculated in nVSM. For example, suppose that healthcare analytics is denoted as $t_1$, we then calculate nTF of $t_1$ in $d_1$ as:
  \[ n\text{TF}(t_1, d_1) = \frac{\text{DTM}_{\text{healthcare}} + \text{DTM}_{\text{analytics}}}{|t_1|} = \frac{(1 + 2)}{2} = 1.5 \]
where $|t_1|$ is a number of tokens in $t_1$. Then, we calculate the N-gram IDF of $t_1$ as:

$$n\text{IDF}(t_1) = \log \frac{|D| \cdot df(t_1) + 1}{df((\text{DTM}_{*, \text{healthcare}} \land \text{DTM}_{*, \text{analytics}})^2 + 1 + 1} = \log \frac{3 \times 1 + 1}{df((1,0,0) \land (2,0,0))^2 + 1 + 1} = \log \frac{4}{1^2 + 1} + 1 = 1.693.$$ 

Here, $\land$ is implemented in NumPy. Finally, we multiply $n\text{TF}(t_1, d_1)$ with $n\text{IDF}(t_1)$ to obtain $n\text{TFIDF}$ of $d_1$ given $t_1$ as: $\text{DPM}_{1, t_1} = n\text{TFIDF}(t_1, d_1) = n\text{TF}(t_1, d_1) \times n\text{IDF}(t_1) = 1.5 \times 1.693 = 2.540$.

- Given $D$, we generate $\text{EDM}_{3 \times 3}$ where each entry shows the authorship of an expert on a document. For example, $x_1$ is an author of $d_1$, and hence, the entry between $x_1$ and $d_1$ ($\text{EDM}_{1,1}$) equals 1. Also, $\text{EDM}_{1,3} = 0$ shows that $x_1$ is not an author of $d_3$ (See Table 1).

- Given $\text{EDM}_{3 \times 3}$ and $\text{DPM}_{3 \times 50}$, we generate $\text{ETopM}_{3 \times 50}$ where each entry contains $n\text{TFIDF}$ weight of an expert given a topic. As we explained in Section 2, we assume that $\text{DTopM} = \text{DPM}$. Now, we demonstrate the calculation for the weights of experts $X$. 

Figure 4: Illustrative examples for ExpFinder: the blue labels indicate module names of ExpFinder.
given $t_1$ ($ETopM_{*,t_1}$) in $nVSM$ as:

$$ETopM_{*,t_1} = EDM^{3\times3} \cdot DTopM_{*,t_1}$$

$$= \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \cdot (2.540, 0, 0) = (2.540, 2.540, 0)$$

Note that $DTopM^{3\times3}$ and $ETopM^{3\times3}$ are only used for the visualisation purpose. We use $DTopM^{3\times50}$ and $ETopM^{3\times50}$ for the estimation in Step 4.

3. Step 3 - Construct ECG: Given $D$, we generate an ECG which has three expert nodes and three document nodes, as shown in Figure 4. The graph is also used to generate $3 \times 1$ vectors (i.e., $c_x$ and $c_d$) that are used for the estimation of $\mu$CO-HITS in Step 4. For example, $c_{d_1} = 2$ indicates there are two documents (i.e., $d_1$ and $d_2$) pointing to $x_1$. Similarly, $c_{x_3} = 1$ indicates that there is one expert (i.e., $x_2$) who has authorship on $d_3$.

4. Step 4 - Reinforce expert weights using $\mu$CO-HITS: We use run_expfinder() in trainer.py to reinforce expert weights given topics $T$. The function receives $DTopM^{3\times50}$, $ETopM^{3\times50}$, ECG, $c_x$ and $c_d$, generated in (Steps 2 and 3) as parameters, and generate the $3 \times 50$ Expert-Topic matrix where each entry shows the reinforced weight of an expert given a topic. Now, we illustrate the estimation for the reinforced weight of $X$ given $t_1$ as:

- Given 6 nodes in an ECG, we generate the adjacency matrix $M^{6\times6}$ and its transpose matrix $M^T$ as:

$$M = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}, M^T = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

where rows and columns are labeled with the sequence $s$ (i.e., $s = (d_1, x_1, x_2, d_2, x_3, d_3)$).

- We apply L2 normalisation for the $6 \times 1$ Expert-Topic ($\alpha_x$) and the $6 \times 1$ Document-Topic ($\alpha_d$) vectors. The output of each vector is as:

$$\alpha_x = \text{L2-normalize}(ETopM_{*,t_1}) = (0, 0.707, 0.707, 0, 0, 0)$$

$$\alpha_d = \text{L2-normalize}(DTopM_{*,t_1}) = (1, 0, 0, 0, 0, 0)$$

- We reinforce expert weights given $t_1$ in 5 iterations with $\lambda_x = 1$ and $\lambda_d = 0.7$. Here, we demonstrate the calculation of average authorities $a$ and average hubs $h$ at the first iteration ($k = 1$):

$$a(X; t_1)^1 = (1 - \lambda_x)a(X; t_1)^0 + \lambda_x \left( \frac{M^T \cdot h(D; t_1)^0}{c_d} \right)$$

$$= 0 \cdot (0, 0.707, 0.707, 0, 0, 0) + 1.0 \cdot \left( \frac{(0, 2, 2, 0, 1, 0)}{(2, 1, 1, 2, 1, 1)} \right)$$

$$= (0, 2, 2, 0, 1, 0)$$

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\[ h(D; t_1)^1 = (1 - \lambda_d) h(D; t_1)^0 + \lambda_d \left( \frac{M \cdot a(X; t_1)^1}{c_x} \right) \]
\[ = 0.3 \cdot (1, 0, 0, 0, 0) + 0.7 \cdot \left( \frac{4, 0, 0, 3, 0, 2}{1, 2, 2, 1, 1, 1} \right) \]
\[ = (3.1, 0, 2.1, 0, 1.4) \]

where \( a(X; t_1)^1 \) and \( h(D; t_1)^1 \) are 6 \times 1 vectors. At the end of the iteration, we normalise these vectors by applying the L2 normalisation technique as:

\[ a(X; t_1)^1 = \text{L2-normalize}(a(X; t_1)^1) = (0, 0.667, 0.667, 0, 0.333, 0) \]
\[ h(D; t_1)^1 = \text{L2-normalize}(h(D; t_1)^1) = (0.776, 0, 0, 0.525, 0, 0.35) \]

After 5 iterations, we obtain \( a(X; t_1)^5 = (0, 0.577, 0.595, 0, 0.56, 0) \) whose labels are presented by \( s \), and hence, we use \( x_1, x_2 \) and \( x_3 \) as indexes for obtaining a 3 \times 1 vector (i.e., \( \text{RETopM}^{3 \times 50} \)).

The output is \( \text{RETopM}^{3 \times 50} \). If we use \( t_1 \) and the other two topics (i.e., natural language processing and vision technology, denoted as \( t_2 \) and \( t_3 \), respectively), we can generate \( \text{RETopM}^{3 \times 3} \) in Figure 4. This matrix can be used for two major tasks (1) finding the most expertise query for each expert (also known as expert profiling); and (2) finding the best expert for a given query (also known as expert finding).

4. Impact and Conclusion

With the growth of expertise digital sources, expert finding is a crucial task that has significantly helped people to seek the services and guidance of an expert [12]. ExpFinder is an ensemble model for expert finding that integrates nVSM with \( \mu \text{CO-HITS} \) to enhance the capability for expert finding over existing DLM, VSM and GM approaches. To our best knowledge, ExpFinder is the first attempt to provide the implementation of nVSM and \( \mu \text{CO-HITS} \) for expert finding.

The implementation of ExpFinder also provides functionalities that can be potentially useful for implementing other expert finding models. For example, our implementation provides functionality for extracting noun phrases using a linguistic pattern based on a part of speech (POS). This pattern can be easily customised in our provided code based on researchers' purposes. As another example, our Expert-Document matrix (EDM), Document-Topic matrix (ETopM), and Document-Topic matrix (DTopM) can be used to easily represent an Author-Document-Topic (ADT) graph that was used in a graph-based model in [5].

We also describe the implementation detail of ExpFinder with an illustrative example. This would help researchers and practitioners to understand how ExpFinder is designed and implemented with what core functionalities. Further, we publish the readable source code with example data. This could also be helpful to quickly get started and extend the functionalities of ExpFinder for realising different expert finding models as future work.

5. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
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6. Current code version

Ancillary data table required for subversion of the codebase. Kindly replace examples in right column with the correct information about your current code, and leave the left column as it is.
| Nr. | Code metadata description                                                                 | Value                                                                 |
|-----|------------------------------------------------------------------------------------------|----------------------------------------------------------------------|
| C1  | Current code version                                                                       | v1.0                                                                |
| C2  | Permanent link to code/repository used for this code version                               | [https://github.com/Yongbinkang/ExpFinder](https://github.com/Yongbinkang/ExpFinder) |
| C3  | Permanent link to Reproducible Capsule                                                     |                                                                     |
| C4  | Legal Code License                                                                        | MIT License (MIT)                                                   |
| C5  | Code versioning system used                                                                | git                                                                 |
| C6  | Software code languages, tools, and services used                                          | Python                                                              |
| C7  | Compilation requirements, operating environments & dependencies                            | Python environment version 3.6 or above, pandas, networkx, NumPy, scikit-learn, nltk, SciPy, Torch, Transformers, SciBERT |
| C8  | Link to developer documentation/manual                                                     | [https://github.com/Yongbinkang/ExpFinder/blob/main/README.md](https://github.com/Yongbinkang/ExpFinder/blob/main/README.md) |
| C9  | Support email for questions                                                                | ykang@swin.edu.au, hungdu@swin.edu.au                               |

Table 2: Code metadata