PeRView: A Framework for Personalized Review Selection Using Micro-Reviews

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April 24, 2018

Abstract

In the contemporary era, social media has its influence on people in making decisions. The proliferation of online reviews with diversified and verbose content often causes problems inaccurate decision making. Since online reviews have an impact on people of all walks of life while taking decisions, choosing appropriate reviews based on the podsolization consisting is very important since it relies on using such micro-reviews consistency to evaluate the review set section. Micro-reviews are very concise and directly talk about product or service instead of having unnecessary verbose content. Thus, micro-reviews can help in choosing reviews based on their personalized consistency that is related to directly or indirectly to the main profile of the reviews. Personalized reviews selection that is highly relevant with high personalized coverage in terms of matching with micro-reviews is the main problem that is considered in this paper. Furthermore, personalization with user preferences while making review selection is also considered based on the personalized users' profile. Towards this end, we proposed a framework known as PeRView for personalized review selection using micro-reviews based on the proposed evaluation metric approach which considering two main factors (personalized matching score and subset size). Personalized Review Selection Algorithm (PRSA) is proposed which makes use of multiple similarity measures merged to have highly efficient personalized reviews matching function for selection. The experimental results based on using reviews dataset which is collected from (www.YELP.COM) while micro-reviews dataset is obtained from (www.Foursquare.com). show that the personalized reviews selection is a very empirical case of study.

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1 Introduction

Online reviews for almost any product or service have been influencing the people’s decision making process. A reviewer basically produces an assessment about a company, service, or any other task Vasconcelos et al. [37]. In these days, we can find a variety of ample reviewers in different web sources. For instance, in online shopping, web services such as (http://Amazon.com) provide hosts reviews as a part of the online shopping experience. This part provides a clearly assessment and product ranking that helps and assist their and other customers in determining which product is the most suitable for their need Agarwal et al. [2]. Moreover, this is the reason that many businesses are focusing on getting better reviews to promote their businesses based on the best reviews that are personally considering such similar consistency [29] [28].

Intuitively, customers are more inundated by the variety of comments that made during numerous reviews. In this case, it is not clearly enough which review comments are worth or not for the readers attention, and this is worsened by two factors, the length and the verbosity of many reviews. It is more increasingly that is more difficult to discover and determine the personalized review that has a higher relevant experience Bodke et al. [5]. Furthermore, high personalized quality reviews identification and selection is a hard task for the customers which is potential topic that has been more focusing of substantial research Chen et al. [7].

Recently, social networking has been growing intensively and has been became more established from year-to-year. In this case, the emergence of new type of online reviews has been discovered which called micro-reviews service Nguyen et al. [30]. Micro-review is prevailing since the emerging trends in social media and micro-blogging which is alternative source of information for the reviewers to find more interested information to read. Micro-reviews are consisting, short, and focused, as well as they are nicely complementing, elaborate, and verbose nature of full-text reviews focusing on a specific of an item Chong et al. [11]. Moreover, the micro-review cannot be properly expanded more than 140 characters which means that the reviewers should be focusing on aspect of the venue that are more important to the investigators (users) [18].

(www.YELP.COM) and (www.Foursquare.com) are popular social web sites that is in the meanwhile most customers used, provide online reviews section for public. For instance, (www.YELP.COM) provides reviews on restaurants while (www.Foursquare.com) provides micro-reviews that are more concise and focused on the feedback. People who wanted to visit a restaurant and before making a decision, generally find reviews in these social web sites where these reviews are related to restaurants across the globe. Many researchers contributed towards analysis of online reviews [14 17 19 29].

In this paper, we present an approach to selecting the personalized reviews that are highly relevant with high personalized coverage in terms of matching with a selecting sub-set of micro reviews. The selected sub-set contains more focused and concise by reflecting the true opinion of individuals. Moreover, selected sub-set of micro-reviews are not verbose and do not contain unnecessary information. The idea is to select a personalized subset of reviews, pertaining to any restaurant or service, that exhibit high personalized coverage in terms of matching with micro-reviews sub-set. For the purpose of matching it is essential to have text mining approaches and lexical dictionary such as WordNet to have comprehensive matching strategy. Our matching strategy includes different personalized matching criteria such as syntactical, semantic and sentiment matching. These diversified personalized matching approaches are merged to have a significant personalized matching function based on two factors (personalized matching score and the reviews selected size) that can be used to have high satisfactory reviews. Towards this end, we proposed a framework named
PerView with an underlying algorithm named Personalized Review Selection Algorithm (PRSA) which takes micro-reviews and reviews as input and produce selected reviews. PRSA employs the matching function aforementioned and personalized preferences as well for effective review selection process.

In this paper, the real time online reviews of restaurants and corresponding micro-reviews are collected from two different datasets (www.yelp.com) and (www.foursquare.com) respectively. These reviews and micro-reviews for more than 50 restaurants formed the dataset for experiments. In this case, the high quality personalized preview selection is proposed to select a subset of the personalized reviews that are highly correlated and related to the selected micro-reviews sub-set. The first contribution in this paper is that proposing a micro-review sub-set selection instead of relying on the whole set of the micro-review. The selected sub-set of micro-reviews algorithm based on select the set of micro-reviews that covers the whole domain. Then, the second contribution in this research is on the framework named PeRView which facilitates online personalized review selection. The framework also supports personalization by considering preferences of end users by building a personal profile for each user (reviewers). Then, based on the third contribution of this paper which design a personalized evaluation metric of reviews selection, the highly personalized reviews set that coverage significant consistence of the selected micro-reviews are selected based on considering two main factors (average personalized matching score and sub-set size).

The rest of the paper is structured as follows. Section 2 related works and preliminary. Section 3 presents the proposed methodology. Section 4 presents experimental results. Section 5 throws light into conclusions drawn and recommendations for future research in the area of review selection.

2 Related Works and Preliminary

2.1 Related works

This section reviews important literature related to online review selection. [10] employed selection concept with data mining concepts but it was meant for personnel selection. They built a framework for selection of personnel. Meng et al. [26], proposed a recommendation method known as Keyword-Aware Service Recommendation (KASR). They used personalized recommendations where personalized concept has similarities of the work of this paper. User preferences are used for personalized ratings. Bhatia et al. [3], proposed a method for review selection process using micro-reviews. Bhatia et al believed that micro reviews are concise and they are best used for validating reviews and choose good reviews that match with micro-reviews as much as possible. Our work is close to this work but we improved it further and also personalized. Nie et al. [32] employed LDA for music, images and text. As far as LDA is concerned, our approach in this paper is reusing LDA to get an improved form for review selection process. [15] focused on making topic models in Twitter. They employed LDA for empirical study on topic modelling in Twitter. [33] on the other hand studied and used LDA for detecting Twitter topics.

Blei et al. [4] investigated the utility of LDA for topic modelling. As topic modelling can reveal explicit details of a document, this method was used for text modelling and document classification. Mason et al. [25] employed LDA for micro-summarization of online reviews to render useful information to end users. They used unsupervised and supervised methods for empirical study. They employed multiple aspects in the research such as entity recognition, summarization and sentiment analysis. lappas et al. [20] focused on review selection. Their work was meant for
filling the gap between review summarization and review selection processes. They considered it as combinatorial optimization problem. Tsaparas et al. [36] studied user reviews made online and explored a method for selecting a comprehensive collection of reviews that make sense. Various complexity coverage problems are addressed analyzing them.

Ganesan et al. [13] made it explored an unsupervised approach for generating summary of opinions. They proposed a methodology for generating ultra-concise summaries of sentiments. They achieved it by using some heuristic algorithms. Lu et al. [23] opined that micro-reviews are concise and more meaningful than reviews. They studied probabilistic models based on LDA for topic suggestion for micro-reviews. This approach is based on sentiments. Nguyen et al. [28] also used micro-reviews in order to have efficient selection of reviews. They used micro-reviews to obtain salient features of reviews and finally select best reviews. This work is also similar to our work in this paper. However it follows crowdsourced approach. Similar work is found in Nguyen et al. [28] where micro-reviews are used to test coverage and choose reviews. Selvam [34] employed Integer Linear Programming (ILP) and unified classification for review selection with the help of micro-reviews.

Nguyen et al. [31] continued their research on micro-reviews. They explored review synthesis for summarization of micro-reviews for making them more compact and readable. Nguyen et al. [20] studied mining of massive textual data in order to obtain heuristics for achieving selection problem. They proposed a subset selection procedure by extending Neyman-Pearson feature selection approach. More on feature selection algorithms is found in [27], [38] and [6]. Liu et al. [21] [27] on the other hand used feature selection approach used in data mining and its utility in reducing complexity in data mining procedures. Lu et al. [22] used short comments and investigated the problem of rated aspect summarization of target entity to have knowledge on such data. Lappas et al. [16] proposed a method for finding top-k web service recommendations where selection of recommendations is based on a hybrid similarity metric. Adomavicius et al. [1] explored user modelling with multi-criteria for generating recommendations. Chorley et al. [12] studied the users of online review web site Foursquare.com. They focused on finding personality of users based on their visiting patterns and other content based analysis. Based on the reviews made by users, they tried to estimate different aspects of users personality.

Chen et al. [9] studied user generated content (UGC) available in Foursquare.com for investigating diversity of tips, venue categories, and measuring of tips for sentiment analysis. Tao et al. [34] focused on web information gathering by using personalized ontology. Personalized data of end users is used for information gathering. In the literature many approaches are found for review selection. However, they used different approaches for review selection. Some of them used micro-reviews for finding coverage of reviews and select them. In this paper we improve review selection based on micro-review approaches based on matching score ranking using Mutual Information (MI) feature ranking approach which helps the proposed system to avoid the similar matching score that intuitively accrue in some cases.

2.2 Preliminary

Review is an evaluation of a publication or product or service. Reviews have influence on quick understanding and sometimes even making decisions as well. It may reflect relative merit of publication or service. Consumers of a product or service may write a review on it. Review which is denoted as $R$ generally contains more information while micro-review has limited and concise information. In this case, we have to define some relational terms in term to fully understand the
main problem. Literary, reviews and micro-reviews comments are a set of words where the single
word mathematically denoted as $W$. Although, the review is a group of sentences that are part of
a review denoted as the following equation 1:

$$ R_{R \in R} = \{s_1, s_2, ..., s_n\} = \sum_{i=1}^{R} S_i $$

Where $s$ is denoted as a sentence and it is define as a set of words as the following equation 2 shows:

$$ S_{s \in R} = \{s_1, s_2, ..., s_n\} = \sum_{i=1}^{S} W_i $$

The term Micro-Review which is denoted as MR is also defined as a group of words denoted as
the following equation 3 shows:

$$ MR_{N \in R} = \{W_1, W_2, ..., W_n\} = \sum_{i=1}^{N} W_i $$

Where $N$ is the size of the micro-reviews. Moreover, the corpus of rewrites in our case which
is denoted as $G_{\text{numberofreviews}}$ is defined as a collection of reviews and micro-reviews that are
available in the dataset which is mainly denoted as the following equation 4 shows:

$$ G_{C \in R} = \{D_1, D_2, ..., D_n\} = \sum_{i=1}^{C} D_i = \sum_{i=1}^{C} C_{R} \sum_{j=1}^{C} R_{C_{R}} + \sum_{k=1}^{C_{MR}} M_{R_{C_{MR}}} \text{ (4)} $$

Where $C_R$ and $C_{MR}$ are the number of the reviews and micro-reviews separately. The person-
alization term also refers to the fact that the review selection is associated with a user and his/her
preferences. Moreover, the term Preferences which is denoted as $P$ is defined as a set of likings of
user denoted as the following equation 5 shows:

$$ P_{P \in R} = \{P_1, P_2, ..., P_n\} = \sum_{i=1}^{P} P_i $$

where $P_i (1 \leq i \leq n)$.

The term Preferences of Previous Users which is denoted as $pp$, is defined as set of preferences
of previous users denoted as the following equation 6 shows.

$$ PP_{PP \in R} = \{PP_1, PP_2, ..., PP_n\} = \sum_{i=1}^{P} P_i $$

where $PP_i (1 \leq i \leq n)$.

Another term is the Matching Function which is denoted as $F$, is defined as the following
equation 7 shows:

$$ F_{\text{Score}}(r, mr) = \sum_{i=1}^{R} \sum_{j}^{MR} \min(r_i, mr_j) $$

4
where \( s \) is a sentence in \( R \) and \( MR \) are a reviews and micro reviews. The function also considers \( P \) and \( PP \) while checking similarity. Selection Coverage which is another term in our problem that is denoted as \( \text{Coverage}(R) \) and it is defined as the maximum number of micro-reviews matching with limited number of reviews that satisfy user preferences as it shown in equation \( 8 \)

\[
\text{Coverage}(R) = MR^{\text{max}}(\{|R \subseteq MR|\}, \left(\frac{P}{|MR|}\right))
\]

The main criteria of the selection majority in this problem is the Selection Efficiency which refers to the efficiency of a review \( R \). In another word, the Selection Efficiency is nothing but fraction of relevant sentences in \( R \) that satisfy user preferences as the following equation \( 9 \) shows:

\[
\text{Efficiency}(R) = \frac{|R'|}{|R|}
\]

The process of reviewing became easier of late, thank to web applications and web portals where reviewing is facilitated. \([\text{www.YELP.COM}]\) and \([\text{www.Foursquare.com}]\) are best examples for reviews and micro-reviews respectively. With the emergence of social networking, the reviews and micro-reviews on various entities are growing exponentially. Therefore, it is essential to have automated mechanisms to choose genuine and high-quality reviews. Such reviews can help in making well informed decisions or gain knowledge quickly from the knowhow of other people who have already experienced merits and demerits of certain service rendered. However, it is a challenging to identify such genuine and high-quality reviews. Especially finding such reviews with high coverage is NP-hard. Many researchers contributed towards it. The review selection is studied in \([14, 17]\) and \([19]\).

Recently Nguyen et al. \([30]\) proposed a mining technique that considers micro-reviews and coverage of micro-reviews on given entity as an objective function to discover reviews that reflect genuine and high coverage content that is very useful to users. They considered a product or service for which reviews are taken from Yelp.com and micro-reviews are taken from Foursquare.com. They also treated micro-review as a tip or recommendation. Choosing micro-reviews related to a product as objective function for matching with reviews and selection of reviews appeared meaningful approach as the micro-reviews of same service reflect short recommendations. Considering micro-reviews as coverage made sense. However, personalization in review selection is the research area which is not yet explored. This is the basis for the research which needs to investigate further to evaluate the research questions given below. The main research objective is Personalized Review Selection Using Micro-Reviews. Selection of reviews based on matching coverage of micro-reviews needed further optimization. Therefore, we consider it as an optimization problem.

3 Proposed Methodology

Social media helps to know about user personality, products and even services though the customers reviews and their interests and emotions that can be demonstrated as comments during the reviewing. In another word, reviewers comments can have extracted by monitoring person’s social activities as well as the reviewing controlling and visualizing systems that enable to provide personalized data/services and their opinion (comments). Our proposed system aims to facilitate the mining of reviews and micro-reviews in order to discover personalized reviews that satisfy the user preferences. This section provides the methodology that used to investigate the process of achieving personalized review selection using micro-reviews through our proposed system. A framework of
our proposed system as part of the methodology technique which guides the research to be carried out to understand the whole approach. It provides various components that can be used to complete the research and evaluate the work.

3.1 Data Collector

The first stage of our proposed system is the Data collector. The ability to find specific information and websites is becoming increasingly essential for a typical end-user whilst browsing the web. This is essentially one of the main reasons as to why crawler software exists in which to provide users a mirror of the web, either for archive purposes or simply to find relevant information using search keywords. The basic model that we used to do the data collector is the Web crawlers model implementation which is illustrated in Figure 1. In this basic model there is a sequential web crawler staring from the Seeds which can be any list of starting URLs. In order of starting page visits, which is determined by frontier data structure (http://www.Yelp.com). Datasets are collected from two sources. The first one is the (http://www.Yelp.com) and the second one is the (http://www.Foursquare.com). Reviews dataset on restaurants is collected from (http://www.Yelp.com) while the micro-reviews dataset which is related to the same entities is collected from (http://www.Foursquare.com).

3.2 Pre-processing

The second stage of our proposed system is the pre-processing stage. In this stage the Data Pre-processors first removes slang and abbreviated words using commonly used slang in social media posts and Web pages. Web pages data also consist of spelling mistakes which badly effect the information extraction process. The pre-processing stage in our approach has made the datasets per-processing to provide appropriate data (reviews and micro-reviews comments) from the raw data in two phases:

3.2.1 Stop Word Removal

Stop words are the words in the set of documents (corpus) containing certain words that do not make any difference in the text clustering process.

3.2.2 Stemming Process

A stemming process which identifies root words and removes all derived words. The well-known class Porter Stemmer algorithm is reused here for stemming mechanism.

3.3 Profile Builder

This submodule extracts useful information from Web pages and maintains history to build user (reviews) profile. Our approach for the profile builder has three main stages. The first stage is the pre-processing stage where the input for this stage is unstructured text data from the reviews dataset. In this stage the stop words are removed which are the words in the set of documents (corpus) containing certain words that do not make any difference in the text clustering process. Then, the stemming process is done which identifies root words and removes all derived words. The well-known class Porter Stemmer algorithm is reused here for stemming mechanism. The
Figure 1: Basic crawlers Flowchart Implementation
next stage is Keywords extraction and dictionary builder which consists the high frequently words after applying the Histogram of Words (WoF). Moreover, Profile constructor extracts customer’s preferences by using Alchemy API. It takes unstructured text and acquires knowledge by presenting the semantic richness hideaway in sentiment relevant to those entities. The system keeps extracted user sentiments, keywords, entities in users profile repository for futurity utilize. The final stage is the profile builder by using TF/IDF matrices creator. In this stage, the TF/IDF stands for Term Frequency/Inverse Document Frequency which is a standard measure to reflect the importance of a word to a document with respect to the corpus. Based on the return results of the TF/IDF each document is assigned to one category to build the profile for this document. Figure 2 shows the main flowchart of the profile builder that is used in this paper.

3.4 Sub Micro-Review Set Selection

The user preference or the sub micro-reviews set selection is the main significant step that has been proposed in this paper. Based on the mathematical model of the best micro-review set selection, the most relevant sub-set of micro-reviews is going to generated and selected. The main mathematical model as well as the relevant micro-review sub-set selection are described below:

In this section, we will explain the necessity of micro-review sub-set selection in our PeRView approach by selecting a small set of micro-reviews that cover as many reviews as possible, with few sentences. Mathematically, we call the Micro-Review $MR_{N \in \mathbb{R}}$ efficiency covers the whole Review set $R_{R \in \mathbb{R}}$ if a Micro-Reviews sentence $S_{S \in MR_{S}}$ matches the Review comment. In another word, Micro-review $MR_{N \in \mathbb{R}}$ covers any review $R_{R \in \mathbb{R}}$ if there is a sentence $S_{S \in MR_{S}}$ matches $R_{R \in \mathbb{R}}$. Intuitively, we can define the selection problem of the Micro-Reviews sub-set by denoting that the Micro-Reviews sub-set $T_{N \subseteq MR}$ is a sub-set of Micro-Reviews $t_{MR \in \mathbb{R}}$ that the Reviews set $T_{R}$ is covered by at least one sentence from the Micro-review $MR_{N \in \mathbb{R}}$sentences. Formally, we can define the whole problem as equation 10 shows below:

$$T_{R} = t_{MR} \in T_{MR \in \mathbb{R}} : \exists S_{S \in t_{MR}} \in MR_{N \in \mathbb{R}}, R_{R \in \mathbb{R}}, F(S, R) = 1$$  (10)

we say that $T_{MR}$ sub-set covers the Review topic $T_{R}$ by defining the coverage of review $R$ as the following equation 11

$$Cov(MR) = \frac{T_{MR}}{T_{R}}$$  (11)

We can extend this definition to the case of a collection of a subset of micro-reviews. For a set of micro-reviews $S \subseteq MR$, we define the coverage of the set $S$ as equation 12 shows below:

$$Cov(S) = \frac{|\bigcup_{MR \in S} T_{MR}|}{T_{R}}$$  (12)
Figure 2: Profile Builder Flowchart Implementation
3.4.1 Efficiency Selection Criteria

In some cases, some micro-reviews may have high coverage which means that many sentences that are not relevant to any topic of the review at all. To avoid such similar case, the efficiency selection criteria should be used. For a micro-review set $MR_{N \in R}$ let assume that $MR_{mr}$ of such “relevant” sentences which cover at least one review topic as show in 13:

$$Mr_{mr} = \{S_{s \in MR} \in MR_{N \in R} : \exists t_{MR} \in T_{MR}, F(S, t) = 1\} \quad (13)$$

Then, the define the efficiency $eff(MR)$ is define as a fraction of “relevant” sentences in MR. Which is formally can be written as the equation 14 shows:

$$Eff(MR) = \frac{|MR_{mr}|}{|MR|} \quad (14)$$

Extending the definition of efficiency to a collection of micro-reviews is a little more involved. We need a way to aggregate the efficiency of the individual micro-reviews. In this case we use the average efficiency of a set S is defined as the average efficiency of the micro-reviews in the set. Formally, we can define that as the following equation 15:

$$Eff_{Average}(S) = \frac{\sum_{MR \in S} Eff(S)}{|S|} \quad (15)$$

The algorithm, shown in Algorithm 1, proceeds in iterations each time adding one review to the collection $S$. At each iteration, for each review $MR$ we compute two quantities. The first is the gain $gain(MR)$, which is the increase in coverage that we obtain by adding this micro-review to the existing collection $S$. The second quantity is the cost $Cost(R)$ of the review $MR$, which is proportional to the inefficiency $1 - Eff(R)$ of the review, that is, the fraction of sentences of $MR$ that are not matched to any review. We select the micro-review $MR^*$ that has the highest gain-to-cost ratio and guarantees that the efficiency of the resulting collection is at least $\alpha$, where $\alpha$ is a parameter provided in the input. The intuition is that reviews with high gain-to-cost ratio cover many additional tips, while introducing little irrelevant content, and thus they should be added to the collection.

3.4.2 Micro-Reviews Selection

The whole system flowchart of the micro-reviews selection is illustrated in the Figure 3.

3.5 Our Proposed Framework Personalized Reviews Selector (PeRView)

The proposed framework that we claimed in this paper is called PeRView which is mainly designed to facilitate the mining of reviews and micro-reviews in order to discover personalized reviews that satisfy the user preferences is illustrated in Figure 4. Our proposed system framework has three main stages. The first stage is the data collector stage which is used to collect all the reviewers, micro-reviewers, while the second stage is the pre-processing stage. Finally, the third stage of our proposed system is the Personalized Review Selection Algorithm (PRSA) which captures user preferences and model them although it performs comparison of micro-reviews with reviews sentence
Figure 3: Micro-reviews sub-set selection
Algorithm 1 Micro-Reviews Selection Algorithm

Input: Set of Micro-reviews MR, Set of Reviews R, Efficiency function Eff; Threshold T: selection number of the micro-reviews, parameters $\alpha, \beta$

Output: Set of Micro-reviews $S \subseteq MR$ of size T.

1: $S = \emptyset$
2: if $|S| < T$ then
3:  for all $MR \in R$ do
4:    $gain(MR) = Cov(S \cup MR) - Cov(S)$
5:    $Cost(MR) = \beta(1 - Eff(MR)) + (1 - \beta)$
6:  end for
7:  $\epsilon = MR \in R : Eff(S \cup MR) \geq 0$
8:  if $(\epsilon == 0)$ or $\max_{MR \in \epsilon} \text{gain}(MR) == 0$ then
9:    Break
10: end if
11: $MR^* = \arg\max_{MR \in \epsilon} \frac{\text{gain}(MR)}{\text{cost}(MR)}$
12: $S = S \cup MR^*$
13: $R = R / MR^*$
14: end if
15: return $S$

The proposed framework takes input as micro reviews, and their corresponding that related to same entity. Also, it takes the reviews and user preferences as another input in the whole input stage which is done by doing the data collector stage. Then, it makes use of the proposed algorithm named Personalized Review Selection Algorithm (PRSA) which performs various activities on the given inputs. First of all, it captures user preferences and model them. Afterwards it performs comparison of micro-reviews with reviews sentence wise by employing syntactic similarity. Then it employs semantic similarity using lexical dictionary known as WordNet [24]. The topic modelling concept is employed by using Mutual Information Ranking mechanism (MI) which is used to rank the similarity scoring to select the best one. Then sentiment polarities of micro reviews and reviews are compared to make a decision to include them. Afterwards, the matching function is applied in order to discover personalized reviews that reflect high coverage, high quality and satisfy user preferences.

Algorithm 2 takes set of reviews of chosen restaurant, set of micro-reviews of same restaurant, user preferences for personalization and matching threshold as input and produces set of reviews that exhibited high quality and coverage. For each review all micro-reviews are compared for similarity. Similarity is found syntactically, semantically and polarities related to sentiments. Then the similarities are merged to have final quantitative value. The number of micro-reviews matching with review as much as possible determines its coverage. This is verified by suing given threshold and the reviews are finally selected. Syntactic similarity is achieved by using keyword similarity model found in [24]. Each sentence in a review denoted as $s$ and each micro-review denoted as $mr$ are associated with a vector as it shown in equation \[16\]

\[
\text{SyntacticSimilarity}(s, mr) = \cos(s, mr)
\]  

Since syntactic similarity is based on keywords present in the review and micro-review, standard
Figure 1: Overview of PerView framework.
Algorithm 2 Personalized Review Selection Algorithm

Input: Set of reviews $R$, set of micro-review $MR$ related to $R$, user preferences $P$, threshold $t$

Output: Set of reviews that with high quality and coverage $R'$

1: initialize $R'$ to hold result
2: for each review $r$ in $R$ do
3:   for each sentence $s$ in $r$ do
4:     $count \leftarrow 0$
5:     for each micro review $mr$ in $MR$ do
6:       $sim_1 \leftarrow \text{find - Syntactic - Sim}(s, mr)$
7:       $sim_2 \leftarrow \text{find - Semantic - Sim}(s, mr)$
8:       $sim_3 \leftarrow \text{find - Sentiment}(s, mr)$
9:       $sim \leftarrow \text{Ranking - evaluation}(sim_1, sim_2, sim_3)$
10:      if $s$ covers $mr$ and $P$ with $sim$ then
11:         increment $\rightarrow count$
12:     end if
13:   end for
14: if $count \geq t$ then
15:   add review $\rightarrow R'$
16: end if
17: end for
18: return $R'$

TF – IDF (Term Frequency Inverse Document Frequency) approach is used to know relative importance of a word. With respect to semantic similarity a review and micro-review are similar if they describe same concept though the words are different.

 Associates topic of each micro-review with probability distribution of topics. It shows which are very important for given micro-review. The similarity of topic distributions is used as measure semantic similarity between a micro-review and a review sentence. The distance measure between two probability distributions used is Jensen-Shannon Divergence. If divergence is more, it indicates lesser in similarity as it shown in equation 17:

$$\text{SemanticSimilarity}(s, mr) = 1 - JSD(\theta_s, \theta_{mr}) \quad (17)$$

Where $s$ refers to sentence in a review and $mr$ refers to a micro review. Probability distribution of sentence and micro review are denoted as $\theta_s$ and $\theta_{mr}$ respectively. Then the third similarity is sentiment similarity. It refers to the fact that sentiment of review and micro-review should match. Sentiment polarities are computed as discussed in [8] and shown in equation 18:

$$\text{SentimentSimilarity}(s, mr) = \text{Polarity}(s) \times \text{Polarity}(mr) \quad (18)$$

By merging these three similarity measures, a final matching function is computed which returns either 0 or 1 indicating binary decisions such as not matching and matching. The similarity knowhow is used to have a binary classifier which determines match or not match based on the given threshold.
4 Experimental Results

The experimental results of the proposed system are based mainly on the objective experiments which shows the effectiveness of the proposed approach. Finding a set of micro-reviews that covers as many reviews as possible which is used later to select the best reviews is the main contribution of the proposed system. In this section, first, we describe the datasets that are used in the experimental results. This is followed by the evaluation metric that is used to select the best set of reviews. Then, we discuss the experimental results that the proposed system is achieved.

4.1 Dataset

The reviews and micro reviews dataset have been collected from different websites such as (www.YELP.COM and www.Foursquare.com) which are used for experiments. Observations are made with matching percentages of reviews with each micro review. Dataset corpus is collected from two sources. They are (www.YELP.COM) and (www.Foursquare.com). Reviews on restaurants are collected from (www.YELP.COM) while the micro-reviews related to the same entities are collected from (www.Foursquare.com). Several datasets pertaining to different restaurants for which reviews and micro-reviews available are collected from those sources.

4.2 Evaluation Metric

In case of evaluate select the most significant set of reviews that has the highest Personalized coverage score, there are two main factors that we have include in our elevation and selection formula. Personalized matching score and reviews set size are the main factor that our evaluation metric should considers. In such a similar case, our evaluation problem definition differs depending on the choice the minim set that has the higher personalized coverage score. In this case, we define the efficiency personalized scoring function $PerEff_{min}$ which is defined as the minimum set of selected reviews $S$ that has a higher personalized coverage score. Formally, we define the minimum efficiency selected set by:

$$PerEff_{min} = \min_{R \in S} (R)$$  \hspace{1cm} (19)

The $Personalized - Eff_{min}$ in our evaluation case problem is that each individual Personal selected review must have a personalized similarity score that by computing the personalized efficiency score should be at least $\alpha$ as a constraint which presents the personalized coverage evaluation score. Formally we define the that as:

$$PerEff_{min}(S) \geq \alpha$$  \hspace{1cm} (20)

Since the size of the personalized selected reviews set is the second factor that our evaluation should consider it. Therefore, we define such an optimization function called maximization of the personalized coverage score $MaxPerCoverage$, where the reviews personalized similarity scores are restricted to the personal selected reviews subset size in such should have an efficiency personalized score at least $\alpha$. In this case the $MaxPerCoverage$ optimization function can be used for obtaining an optimal evaluation solution.

In case of define the $MaxPerCoverage$ optimization evaluation function, let assume that $X_i$ is obtained as personalized similarity score that associated with each personal review $R_i$ and based on
that each individual personal review has been selected. Also, denoting that \( R_i \) is the personalized selected set. Although, lets assume that \( Y_i \) is the sub personalized review size that associate with each personal selected set \( S_i \). We also define another parameter called \( C_i \) that associated with each personal subset \( S_i \), with \( C_i = 1 \) denoting that selected such a personal subset \( S_i \) is covered by at least one of review (personalized matching score) in the selected set, and \( C_i = 0 \) in the otherwise.

Intuitively, to maximize the \( \text{MaxPerCoverage} \) score for any personalized selected subset based on the main factors that we have defined above, we define the optimization problem in our case as a problem with a set of constraints to maximize the \( \text{MaxPerCoverage} \) evaluation score such as:

\[
\text{maximize } \sum_{j=1}^{m} C_i = \text{Persimalirity}(s, mr) \tag{21}
\]

The evaluation objective function as it is defined in 21 maximizes the \( \text{MaxPerCoverage} \) evaluation score based on some constraint. The first constraint is defined in 22 which ensues the number of selected reviews (sub-personalized set size) does not exceed \( K \) which means at least one personal review covers the whole set.

\[
\text{subject to } \sum_{i=1}^{n} X_i \leq K \tag{22}
\]

In additional to that, the second constraint is defined in 23 which ensures that average personalized similarity matching scores (that covers the whole selected set \( S_i \) based on the personalized average score) and also based on the size of its set \( Y_i \) to compute the average personalized similarity scoring at least one review that covers \( C_i \) must be selected.

\[
\sum_{i:S_j \in S,R_i} \sum_{i=1}^{n} \frac{X_i}{Y_i} \geq C_i \forall s_j \in T \tag{23}
\]

Other constraints which are define in 24 and 25 are required to ensure that the value of both average personalized similarity score as well as the \( \text{MaxPerCoverage} \) evaluation score between the range 0 and 1:

\[
X_i = \{0, 1\} \tag{24}
\]

\[
C_i = \{0, 1\} \tag{25}
\]

Therefore, it is well known that the main aims of the \( \text{MaxPerCoverage} \) optimization function is to always select the personal review set whose adding maximizes the personalized coverage score and it should be closer than the other reviews based on the approximation personalized ratio for the \( \text{MaxPerCoverage} \) which is formally defined in the following equation:

\[
\text{Approximation Personalized’ ratio} = (1 - \frac{1}{\ell}) \tag{26}
\]

Where \( \ell \) is defined as the natural logarithm. In other word, we define the \( \text{MaxPerCoverage} \) score is based technically on the \( \text{Per-Eff}_{\text{min}} \) efficiency score that has approximation personalized ratio as it defied in 26. Finally, we present the \( \text{MaxPerCoverage} \) algorithm that basically based on many iterations that in each iteration by adding new review (based on the personalized similarity score)
on the collection set $S_i$ based on the personalized matching $X_{per_i}$ score and the set size $S_i$ that is automatically updated upon each new review has been added to the set. In this case, to evaluate each subset, in each iteration that we select one individual review $R$ based on the personalized matching score between the closest reviews $R_{R \in R}$ set and the micro-reviews set $MR_{M \in R}$ we compute two quantity scores. The first score is the information gain based of the personalized selected review $gain(R_{per})$ which increase the maximization the personalized coverage score based on the average personalized similarity score and the size of the reviews set. Formulary, it is defined in the 27

$$PerGain(R_{set}) = \left( \frac{\sum_{i=1}^{n=size(y_i)} X_{per_i}}{n} \right)$$

(27)

Which in our maximization optimization case [28] will increase the $MaxperCoverage$ score by adding each new closest review (personalized one) to the collected set $S_i$ based on its personalized similarity score.

The second quantity score is the $Cost(R_{per})$ of the personal review $R$ which is mathematically presents the efficiency personalized score that based on the next formula.

$$PerCost(R_{set}) = 1 - (PerEff_{min} = min_{R_{set} \in S(R_{set})})$$

(28)

Finally, we select the personalized review set that get the highest gain and cost ration based on the personalized matching similarity score as well as the size of the personalized reviews set. The $MaxPerCoverage$ algorithm that is mainly designed to evaluate and select the best personalized review result set is described in algorithm 3 below.

**Algorithm 3 MaxPerCoverage Evaluation Algorithm**

**Input:** $R_i$ selected review, $x_i$ personalized matching score, $y_i$ initial reviews set size;

**Output:** Selected Personal Reviews set $PerC_{R_{set}}$ that has the highest personalized evaluation score $PerC_{R_{set}}$.

1: Set the total number of Selected set $T = \sum_{i=1}^{n} S_i$
2: Set the set size for each Reviews set $Y_i = |S_i|$
3: for all $S_i$ do
4: Compute the Personalized Evaluation Scores for each set based on
5: $PerC_{R_{set}} = \{gain(R_{set}), Cost(R_{set})\}$
6: Compute the Personalized Gain score for each set based on
7: $PerGain(R_{set}) = \left( \frac{\sum_{i=1}^{n=size(y_i)} X_{per_i}}{n} \right)$
8: Compute the personalized Cost score for each set based on
9: $PerCost(R_{set}) = 1 - (PerEff_{min} = min_{R_{set} \in S(R_{set})})$
10: end for
11: Get the size of the $PerGain(R_{set})$ scores $C_{R_{set}}$
12: Get the size of the $PerCost(R_{set})$ scores $C_{R_{set}}$
13: Evaluate the set of $PerGain(R_{set})$ and $PerCost(R_{set})$
14: for $K1 = 1$ to all $PerGain(R_{set})$ do
15: for $K2 = 1$ to all $PerCost(R_{set})$ do
16: if $PerGain(R_{set})$ and $PerCost(R_{set})$ is the personalized highest scores, then
17: Get the index of the Personalized Reviews set $PerC_{R_{set}} = index(R_{set})$
18: end if
19: end for
20: end for
21: return $PerC_{R_{set}}$
4.3 Matching

In our experimental results, the personalized matching between any review and the micro-review is the main objective of the proposed system. In this case, the proposed system is mainly aiming to established that by achieving a reasonable level of quality personalized matching which the proposed system is represented by the threshold personalized coverage value. The review in this case is selected based on the personalized coverage selection algorithm that we have discuss which would be a good reflection of main review personalized coverage scope.

In our experimental result we choice different coverage threshold score in case of showing the probability of the personalized matching. Figure 5 shows the different threshold value selection based on the personalized reviews coverage scoring (personalized matching score). We can see that as much as our threshold value selection is significant strong personalized sub-set such as (90%) or (100%) the number of the personalized reviews selection will monotonically decreased. As it is shown in Figure 5, the number of the personalized reviews selection number is decreased from 15 (reviews) when the threshold value is 50% (personalized coverage-matching score) to 13 (reviews) when the threshold value is increased to be 60%.

![Figure 5: Personalized Matching (Coverage Thresholds) Results](image)

It is significantly clear that the coverage thresholds value is affect the percentage of the achievement score (personalized selection accuracy) as it is shown in Figure 6 where the best accuracy score for the best personalized reviews selection was in the threshold value (50%) where the total number of the personalized selected reviews is 15 out of dataset reviews which achieve approximately 83.33% accuracy. Then, the achievement accuracy is being decreased among all the other threshold values to reach to (5.55%) in the threshold value (100%) which is significantly tough, but
our proposal system is still able to select the best personalized reviews based on that criteria.

4.4 Coverage and Personalized Efficiency Selection

In term to clarify the investigation stage of the proposed system for the personalized review selection. In this section, we describe the effectiveness of the MaxPerCoverage Evaluation Algorithm on selection the best personalized reviews based on both the personalized average matching score and the reviews set size. Table 1 shows an example on the MaxPerCoverage scoring algorithm based on selecting a threshold value (90%). During the experimental results, we can notice that the personalized reviewers set that has been selected has satisfied about (61.74%) as an average MaxPerCoverage score based on selecting (90%) MaxPerCoverage threshold value.

Comparing with the other thresholds values, Figure 7 shows the relation between the set size and the average personalized matching score as it has been based on through the MaxPerCoverage selection algorithm.

We can notice that as much as the average personalized matching score for the whole sub-set is highly coverage and the personalized reviews set size is used to evaluate our selection accuracy, the performance results will be monotonically increased. As it is shown in Figure 7 the highest MaxperCoverage accuracy was (61.74%) based on the total average personalized matching score and set size which is (15 reviews). Based on the set-size, two optimal and best personalized reviews sets will be evaluated. One with the size 15 which achieves 61.74% while the other one with size 13 which achieves 56.18%.
Table 1: Example Reviews Selection based on the *MaxPerCoverage* Scoring Algorithm

| ID | Review Selection Sentence                                                                 | Threshold | MaxPerCoverage |
|----|-------------------------------------------------------------------------------------------|-----------|----------------|
| 1  | "Me and my friends stayed there this weekend and it was GREAT. Like everyone says, from the outside it looks outdated (just like you see in the pictures), but the rooms are in great shape. They are clean and comfortable. 4 of us stayed in one room and we had plenty of space. The bathroom was clean and they provide the needed amenities. Also, the owners are amazing! They gave us rides back and forth to the festival and we never had to wait long (the motel is about 10 minutes away, a little more with the Coachella traffic). We also really enjoyed talking to them on the rides, they are very fun and nice. It is a bit pricey, but so is every other hotel/motel on Coachella weekends....etc. | 90%       | 0.909          |
| 2  | Not Selected                                                                             | 0.5       |                |
| 3  | Not selected                                                                             | 0.388     |                |
| 4  | Not selected                                                                             | 0.625     |                |
| 5  | Not selected                                                                             | 0.857     |                |
| 6  | Not selected                                                                             | 0.727     |                |
| 7  | Not selected                                                                             | 0.8       |                |
| 8  | Not selected                                                                             | 0.611     |                |
| 9  | Not selected                                                                             | 0.8       |                |
| 10 | Not selected                                                                             | 0.625     |                |
| 11 | "City Center Motel is the BEST place to stay if you are in town. I recently stayed here for Coachella 2014, and all I can say is WOW. The rooms were amazing, with a more updated look and nice TV. In addition to the nice room, the service i received was more than i could ask for. The owners were very nice and tried their very best to make our experience here memorable. During the festival they even offered us a ride to and from the festival whenever we needed it which was awesome because it was only 10 minutes away and they knew how to avoid all the main traffic. Overall, i would recommend staying here when in town, it surely was worth it. Although the outside of the motel looked outdated, the saying goes, ""never judge a book by its covers""") | 1.0       |                |
| 12 | Not selected                                                                             | 0.4       |                |
| 13 | Not selected                                                                             | 0.625     |                |
| 14 | Not selected                                                                             | 0.875     |                |

"I was driving from Sacramento to Phoenix and decided to stop overnight in Indio (no reservations). I drove around late at night to find a place to sleep and learned there was a big dog show in town and many motels had no vacancies. Luckily, I stopped at the Bhakta’s City Center Motel. It’s not instantly available from the freeway, but it’s a little dream place. My room was updated in every way: bed, linens, bathroom fixtures, flooring, and more. There was a nice/large flat screen TV on the wall, nice toiletries in the bathroom, and a microwave and refrigerator. This is ""the season"" in Indio and my room was $69. The family/owners are extremely friendly and helpful...and available 24/7....etc.""
Figure 7: MaxPerCoverage based on the Average Personalized Matching Score and Reviewers Set-size
5 Conclusion

In the wake of proliferation of review contents over Internet and their importance in the contemporary world for decision making it is essential to choose high quality personalized reviews that are mainly consist on the main reviewed topic. In this paper we proposed a framework named PeRView which is meant for supporting selection of high quality personalized reviews based on using a sub-set of micro-reviews which consistency more accurate than the reviews based the proposed selection algorithm (MRS). The methodology used for review selection process exploits a sub-set of micro reviews that highly covers the whole domain of the micro-reviews set in order to validate and select the best personalized reviews. Since the select sub-set of micro-reviews are short descriptions, they are used to match with reviews and based on the maximum personalized coverage of the selected sub-set of micro reviews in the reviews, selection decisions are made based on the proposed evaluation metric. In order to find the personalized similarity between a sentence in review and micro review, three kinds of personalized similarity measures are defined and merged. They are known as syntactical similarity which is based on traditional $TF/IDF$, semantic similarity and sentiment similarity based on sentiment polarities. Basically, the evaluation metric is designed based on these personalized similarities as well as the size of the selected reviews to make the final decision for selection the best reviews set. Personalized user preferences are accommodated in the framework to have more qualitative reviews. The experimental results show that the proposed system is able to select the best personalized reviews based on the toughest threshold value (personalized coverage score) which is a 100% accuracy.
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