Semantics-based Expansion of Search Queries Enforcing Lateral Thinking

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***Abstract*—Web search engines are equipped with query expansion facilities to reformulate a seed query and improve retrieval performance. However, such techniques are usually used in accordance with traditional Information Retrieval approaches, which do not distinguish between creative and conventional uses of languages, or between literal and non-literal meanings. But to support a more creative search, with the ultimate objective of being surprised or inspired by the results, non-literal relationships between queries and the texts that they match should be facilitated. This paper presents a query expansion method with a lateral thinking approach, by suggesting, starting from a *seed term* given by the user, a set of lists of terms representing conceptual paths, each of which starts from the seed term. Each term in the path is reached by traversing pre-identified relationships in a given semantic network, while the selection of a specific term is driven by the assessment of a distance metrics between terms. The paper also presents a software implementation of the method, which can be accessed as a mobile web app.**

***Keywords*–Lateral Thinking; Computational Creativity; Search Queries; Semantics.**

I. INTRODUCTION

Lateral thinking [1], the term was coined by the physician Edward De Bono, is an attitude for addressing problems through an indirect and creative approach. Lateral thinking leverage reasoning that is not immediately obvious, involving ideas that may not be obtainable by using only traditional step-by-step logic. When we search for something, we are used to follow traditional pattern-based approaches. But in any patterning system, how argued by De Bono, there is an absolute, and even logic, need for something like lateral thinking, in order to yearn for something new that can further trigger creative and innovative behaviors [2].

The most common engines for searching resources over the Web evolved a lot. Currently, they do not just search for resources that exactly match keywords representing users' criteria. Indeed, most of them are equipped with query expansion facilities [3], whose aim is to reformulate a seed query to improve retrieval performance. Common query expansion techniques involve: finding synonyms of words, finding all the various morphological forms of words by stemming each word in the search query; fixing spelling errors and automatically searching for the corrected form or suggesting it in the results; weighting the terms in the original query.

In [4], a classification of automated query expansion techniques is presented. Such a classification is organizaed into: (*i*) linguistic analysis, which leverages global language properties such as morphological, lexical, syntactic and semantic word relationships; (*ii*) corpus-specific (global) techniques, which analyze the contents of a full database to identify features used in similar ways; (*iii*) query-specific (local) techniques, which take advantage of the local context provided by the query; (*iv*) search log analysis techniques, which are based on the idea of mining query associations that have been implicitly suggested by previous users; (*v*) web data techniques, which are based on anchor texts that are often succinct descriptions of the destination page and as such, can be very similar to search queries. However, such techniques are usually used in accordance with traditional information retrieval approaches, which do not distinguish between creative and conventional uses of languages, or between literal and non-literal meanings [5]. But to support a more creative search, with the ultimate objective of being surprised or inspired by the results, non-literal relationships between queries and the texts that they match should be exploited.

This paper presents a query expansion method enforcing a lateral thinking approach, by suggesting, starting from a *seed term* given by the user, a set of lists of terms representing conceptual paths, each of which starts from the seed term. Each term in the path is reached by traversing pre-identified relationships in a given semantic network, while the selection of a specific term is driven by the evaluation of a distance metrics between terms.

The method does not stick to any specific implementation constraint or to any specific knowledge resource needed for implementing the method itself. However, the paper proposes an implementation of the method based on the use of Wordnik[6] as the knowledge base the conceptual paths belong to, and the Lin similarity method [7], applied to WordNet[8], for evaluating the distance between terms. The described implementation has been also released as a mobile web application named LaSearch [9].

The rest of the paper is organized as follows. Section II reports about some computational creativity works for query expansion and engines for inspiring creativity. Section III presents the proposed query expansion method. Section IV describes the architecture of the query expansion engine and its current implementation. Finally, Section V presents the conclusions and future works.

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II. Related Works

Considering the classification elaborated in [4], and briefly presented in the Introduction, the proposed method belongs to the family of linguistic analysis techniques, which are typically based on the exploitation of dictionaries, thesauri, or other similar knowledge representation sources. Some related initiatives are here reported.

Concept creation is based on the ability to hypothesize and create new concepts to suit a given situation [10]. [11] presents a model of exploratory creativity that uses the WordNet ontology [12] as a basis for inducing the concepts that WordNet appears to lack and which should be profitably added.

Analogical expressions use terms from one domain of discourse to allude to terms in another systematically parallel domain of discourse. Analogy is thus useful when one knows of, or suspects, the existence of a given concept but does not know how it is lexicalized (e.g., *the bible of Islam* to mean the *Koran*). [13] uses a lexical ontology like WordNet to resolve analogies to be used for query expansion. [14] envisages a creative process that can take any given target description and using a pre-stored collection of domain descriptions, identifies potentially creative source domains with which to re-interpret the given problem.

Concept combination is a family of conceptual mechanisms whereby a concept is used as a referential proxy for another strongly associated one, e.g., *lexical metaphors* or *polysemy*. For instance, metaphor is a highly-generative conceptual phenomenon that can be used to create a wide range of linguistic expressions that refer to the same concept [15]. The metaphor process could be directly applied if we wish to retrieve documents that allude to a search concept figuratively rather than literally, in order to expand the search query with plausible figurative lexicalizations of this concept. With this respect, [16] introduces a computational model based on creative metaphors to address non-literal meanings of terms in information retrieval systems.

Bisociation [17] seeks to combine elements from two or more incompatible concepts or domains to generate creative solutions and insight. [18] provides a formal definition of bisociation in order to facilitate bisociation by connecting the knowledge bases of an intelligent agent in the context of a concrete problem, situation or event.

Finally, recent proposals of *inspiration and creative search engines* are worth mentioning. Seenapse[19] is an inspiration engine that helps people to come up with creative ideas, by allowing users to browse mental associations made by people all over the world, in order to expand their own possibility of having a Eureka moment. YossarianLives[20] is a metaphorical search engine, designed to spark creativity by returning disparate but conceptually related terms. ELISE (Evolutionary Learning Interactive Search Engine) aims to decrease search results precision in order to keep some diversity in the retrieved documents. ELISE is based on the cost-efficient Parisian approach and interactive evolutionary algorithms to specialise existing search engines with evolved user profiles [21].

III. Overall Approach

The proposed method is based on the exploitation of a semantic network aiming at suggesting a set of query expansions in the form of paths of terms all starting from a seed term specified by the user as the initial search criterion. A conceptual path is a list of terms that belong to the semantic network and that can be reached by traversing a given relationship in the semantic network itself, starting from the seed term. The length of the path, which depends on the number of iterations of the algorithm at the core of the proposed method, is decided by the user, while the method defines the criteria for traversing the semantic network and applied to build the conceptual paths.

At each iteration, the method first identifies the most ”promising” current paths to expand, and then, for each of them, builds all the possible expansions. For each path, all the terms that in the semantic network can be reached from the tail of the path (the tail of a path is the last term added to the path), by traversing a given relationship, are used to generate the same number of expansions. Specifically, if the tail of a path is related to *n* terms, not yet belonging to that path, *n* expansions of the path will be produced where only one term will contribute to each path. The most ”promising” paths are identified by ranking the tails of the paths with respect to the defined *expansion divergence* function, which is computed by applying a distance metrics between terms. In particular, the *expansion divergence* function, which represents the lateral thinking component, privileges those terms that are closer to the mean distance of all the possible candidates with respect to both its generator (i.e., its preceding term in the path) and the seed term. The mean distances are taken as references, because the method wants to add a new term to a path by expressing a lateral thinking attitude in a ”prudent” way, that is, avoiding that the distances of an added term from both its generator and the seed term increase too much and too fast (i.e., in very few iterations). In addition, the method requires that a term can be added to a path if its distance from the seed term is higher than the distance from its generator term (*Expansion Constraint*).

As a convention, in the rest of the paper, any lower case letter represents a term, and in particular, *t* represents the seed term. The description of the algorithm is supported by the following definitions.

A. Definitions

Definition 1 (Relatedness): the Relatedness relationship *rel* between terms is a linguistic or semantic relation in a given semantic network *SN*, i.e., $(x, y) \in$ *rel* if *y* is directly linked to *x* in *SN*.

Definition 2 (Conceptual Path): A conceptual path (*cp*) starting from the seed term t_1, and having lenght equal to *n*, is a list of *n* terms belonging to *SN* that can be reached, starting from t_1, by traversing the Relatedness relationship.

$$cp = [t_1, t_2, ..., t_n], \\ where\ \forall\ t_k\ (t_k, t_{k+1}) \in rel, k = 1...n-1. \tag{1}$$

Definition 3 (Possible Expansion): the Possible Expansion *PExp*(x) of a generic term *x* is the set of terms *y*, such that $(x, y) \in$ *rel*, where $y \neq x$ and $y \neq t$.

$$PExp(x) = \{y|(x, y) \in rel, y\} \neq xandy \neq t. \tag{2}$$

Definition 4 (Term Distance): the Term Distance *dist*(x, y) between the terms *x* and *y*, is the distance between *x* and *y*, in

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accordance with a given metrics (e.g, a linguistic or semantic distance metrics).

Definition 5 (Mean Distance): the Mean Distance *md*(*PExp*(*x*), *y*) of the terms in *PExp*(*x*) with respect to a given term *y*, is the arithmetic mean of the Terms Distance between each term *w* in *PExp*(*x*) and *y*.

$$md(PExp(x), y) = \sum_{w \in PExp(x)} \frac{dist(w, y)}{|PExp(x)|} \tag{3}$$

Definition 6 (Local Mean Divergence): the Local Mean Divergence *lmd*(y, x) of a term *y* in *PExp*(*x*) is the absolute value of the difference between the Mean Distance between *PExp*(*x*) and *x*, and the Terms Distance between *x* and *y*.

$$lmd(y, x) = |md(PExp(x), x) - dist(x, y)|, \quad where\ y \in PExp(x) \tag{4}$$

Definition 7 (Absolute Mean Divergence): the Absolute Mean Divergence *amd*(y, x) of a term *y* in *PExp*(*x*) is the absolute value of the difference between the Mean Distance between *PExp*(*x*) and *t*, and the Terms Distance between *y* and *t*.

$$amd(y, x) = |md(PExp(x), t) - dist(y, t)|, \quad where\ y \in PExp(x) \tag{5}$$

Definition 8 (Expansion Divergence): the Expansion Divergence *div*(y, x) of a term *y* in *PExp*(*x*) is the sum of the Local Mean Divergence of *y* in *PExp*(*x*) and the Absolute Mean Divergence of *y* in *PExp*(*x*).

$$div(y, x) = lmd(y, x) + amd(y, x) \tag{6}$$

Definition 9 (Suggested Paths): the Suggested Paths *SPaths*(t, h, max_{exp}) of the term *t* in *h* iterations (hops) is the set of conceptual paths, all having *t* as the head, having length equals to *h*+1, and resulting by *h* iterations of the algorithm in Figure 1, in which, at most max_{exp} terms are expanded at each iteration.

Definition 10 (Expansion Constraint): Given a conceptual path $cp = [t, t_1, ..., t_h]$ belonging to *SPaths*(t, h, max_{exp}), and any two adjacent concepts $t_k and t_{k+1}$ in *cp*, the Term Distance between the seed term *t* and t_{k+1}, must be greater than the Term Distance between *t* and t_k.

$$dist(t, t_{k+1}) > dist(t, t_k), \quad where\ t_k\ and\ t_{k+1} \in cp = [t, t_1, ..., t_h], \quad cp \in SPaths(t, h, max_{exp}), k = 1, ..., h-1. \tag{7}$$

The rationale behind the Expansion Constraint is to enforce the following two principles:

- *laterality*, that is achieving an incremental growth of the lateral thinking attitude in the expansion of the seed term at each iteration (hop);
- *reliability*, that is guaranteeing that whenever a *boundary* term (i.e., a term presenting the maximum distance value with respect to the seed) is considered in a given hop, it will not be expanded in the subsequent hop; intuitively, a *boundary* term saturates the admissible lateral thinking attitude, and thus, the fitness of the terms belonging to its possible expansions cannot be properly characterized.

```
procedure SPaths(t, h, max_exp)
    expansion = {[t]}                          ▷ an ordered set of paths
    hop = 0;
    while hop < h do
        k,n = 0;
        result = ∅;                            ▷ an ordered set of pairs
        while k < max_exp AND n < expansion.size do
            path = expansion.get(n);
            tail = path.get(hop);
            for succ ∈ PExp(tail) do
                if succ satisfies expansion constraint then
                    append(path,[succ],new_path);
                    result.add({new_path, div(succ, term)});
                    k++;
            n++;
        result.sort();  ▷ sort the pairs in result in ascending order
    with respect to the values of the second element of each pair
        expansion = ∅
        for {path, divergence} ∈ result do
            expansion.add(path);
        hop++;
    return expansion
```

Figure 1. The Suggested Paths algorithm

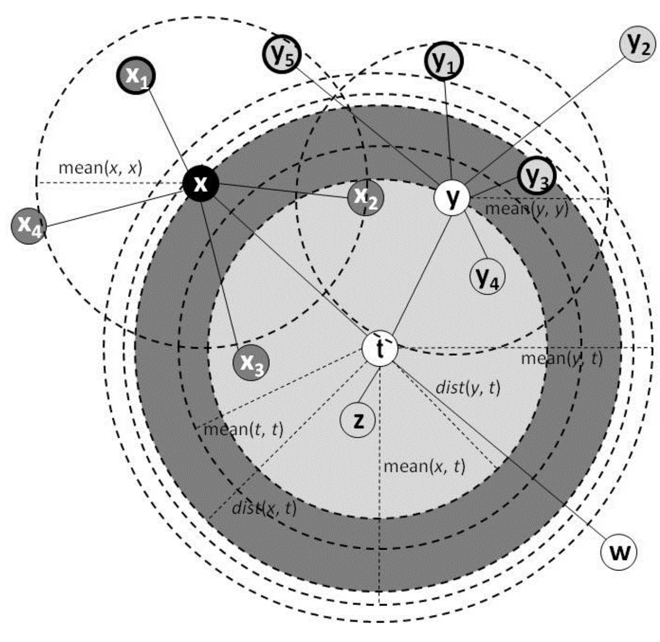

Figure 2. An example of term expansion and terms suggestion

B. Example

Here, an example of application of the presented method. Figure 2 elaborates about *SPaths*$(t, 2, 2)$, that means to search for conceptual paths of length 3 (applying two iterations of the algorithm in Figure 1), by expanding at most two terms at each iteration.

TABLE I. VALUES ABOUT TERMS IN *PExp*(*t*)

term	*dist(term, t)*	*lmd(term, t)*	*amd(term, t)*	*div(term, t)*
y	0.287	0.044	0.044	0.088
x	0.390	0.059	0.059	0.117
w	0.488	0.157	0.157	0.315
z	0.159	0.172	0.172	0.344

TABLE II. VALUES ABOUT TERMS IN *PExp*(y)

y_i	*dist*(y_i, y)	*lmd*(y_i, y)	*dist*(y_i, t)	*amd*(y_i, t)	*div*(y_i, y)
y_1	0.240	0.027	0.461	0.028	0.056
y_2	0.387	0.120	0.607	0.174	0.293
y_3	0.176	0.091	0.375	0.058	0.149
y_4	0.175	0.093	0.236	0.197	0.290
y_5	0.359	0.092	0.486	0.053	0.145

TABLE III. VALUES ABOUT TERMS IN *PExp*(x)

x_i	*dist*(x_i, x)	*lmd*(x_i, x)	*dist*(x_i, t)	*amd*(x_i, t)	*div*(x_i, x)
x_1	0.227	0.054	0.560	0.153	0.208
x_2	0.281	0.000	0.261	0.145	0.145
x_3	0.314	0.033	0.232	0.175	0.208
x_4	0.302	0.021	0.573	0.166	0.187

At the first iteration, the algorithm finds that *PExp*(t) = $\{x$, y, z, $w\}$. Consequently, it builds the following set of paths $\{$[t, x], [t, y], [t, z], [t, w]$\}$, and then orders these paths with respect to the Expansion Divergence of their tails.

At the second and last iteration, the algorithm has to select the most promising two current paths to expand, on the basis of the Expansion Divergence value of their tails, which are shown in Table I. According to such values, the paths [t, y] and [t, x] are further expanded. Then, the Possible Expansions of y and x, that are *PExp*(y) and *PExp*(x), respectively, are computed, and corresponding paths are built.

PExp(y) = $\{y_1$, y_2, y_3, y_4, $y_5\}$, but y_4 does not satisfy the Expansion Constraint, since *dist*(y_4, t) $<$ *dist*(y, t), as can be seen by considering Table I and Table II. At the same time, *PExp*(x) = $\{x_1$, x_2, x_3, $x_4\}$, but x_2 and x_3 do not satisfy the Expansion Constraint since *dist*(x_2, t) $<$ *dist*(x, t) and *dist*(x_3, t) $<$ *dist*(x, t), as can be seen by considering Table I and Table III.

Table IV summarizes by ordering terms in *PExp*(y) and *PExp*(x) with respect to their Expansion Divergence values, plus the information regarding the respect of the Expansion Constraint. According to that, the final Suggested Pahs are provided, such that *SPaths*(t, 2, 2) = $\{$[t, y, y_1], [t, y, y_5], [t, y, y_3], [t, x, x_4], [t, x, x_1], [t, y, y_2]$\}$.

IV. IMPLEMENTATION

In this Section, we introduce the prototypical implementation of the approach presented in the previous section for expanding search queries. For the realization of the algorithm, we adopted: (i) the open linguistic knowledge base Wordnik, as semantic network for computing the possible expansions of terms, and (ii) the Lin metrics [7], computed by exploiting the hyponym hierarchy of the WordNet lexical database, as linguistic similarity criteria. According to these choices, which rely on agreed and robust solutions for natural language processing, we have:

- the *Relatedness* relation *rel* is represented by the *Same Context* relation in the Wordnik thesaurus, which links terms that might be used in a similar context;
- the *Term Distance* is computed as the complement of the Lin similarity value, i.e.:
  $\textit{dist}(x, y) = 1 - \textit{sim}(x, y)$, where $0 \leq \textit{sim}(x, y) \leq 1$ is computed according to the Lin similarity.

In Table V, we show some examples of expansion of the seed term "innovation", obtained according to the current implementation. Each row of the table reports the five best results computed by performing *#hop* iterations of the algorithm, hence achieving paths of different lengths. In the experiment, the constant max_{exp} has been fixed to 10, in order to bound the computational cost of the algorithm. The ranking is then computed according to the least *Expansion Divergence* (see Definition 7).

TABLE IV. ORDERED *Expansion Divergence* VALUES.

$term_i$	*div*($term_i$, *term*)	*Laterality*
y_1	0.056	YES
x_2	0.145	NO
y_5	0.145	YES
y_3	0.149	YES
x_4	0.187	YES
x_1	0.208	YES
x_3	0.208	NO
y_4	0.290	NO
y_2	0.293	YES

TABLE V. RESULTS OF THE EXPANSION OF THE TERM 'INNOVATION'

#hop	*result*
1	[innovation, investment] [innovation, achievement] [innovation, technology] [innovation, strategy] [innovation, research]
2	[innovation, research, management] [innovation, achievement, adventure] [innovation, research, education] [innovation, investment, risk] [innovation, strategy, enterprise]
3	[innovation, achievement, adventure, mystery] [innovation, achievement, enterprise, mission] [innovation, investment, risk, result] [innovation, research, investigation, observation] [innovation, achievement, enterprise, ambition]
4	[innovation, achievement, adventure, romance, poetry] [innovation, investment, risk, result, change] [innovation, research, management, manager, fund] [innovation, achievement, adventure, tale, legend] [innovation, strategy,enterprise, project, test]

A. LaSearch Architecture

The developed *LaSearch* tool (Lateral Search) is a Web-based application, developed in Java, whose main components are depicted in Figure 3. The client side has been designed as a mobile application, which interacts with a REST Web Server exposing (i) the query expansion procedure (Section III), implemented in the *Query Builder*, and (ii) methods for gathering data from external repositories or search engines, implemented in the *Data Source Library*.

The core component is the *Expander*, which implements the *suggested expansion* procedure, as defined in the algorithm in Figure 1, relying on: (i) the *Thesauri Manager*, which computes at each hop the *possible expansion* of the given terms according to the integrated thesauri, e.g., Wordnik is currently supported; (ii) the *Ranker*, which is responsible for assessing the *expansion divergence* of the terms at each hop; (iii) the *Similarity Reasoner*, for computing the linguistic *term distance*. The latter, in turn, depends on the NLP module, based on WordNet and the Semantic Measures Library (SML)[22], which provides the implementation of the Lin similarity metrics.

Finally, at the current status of the implementation we integrated in the *Data Source Library* three connectors for

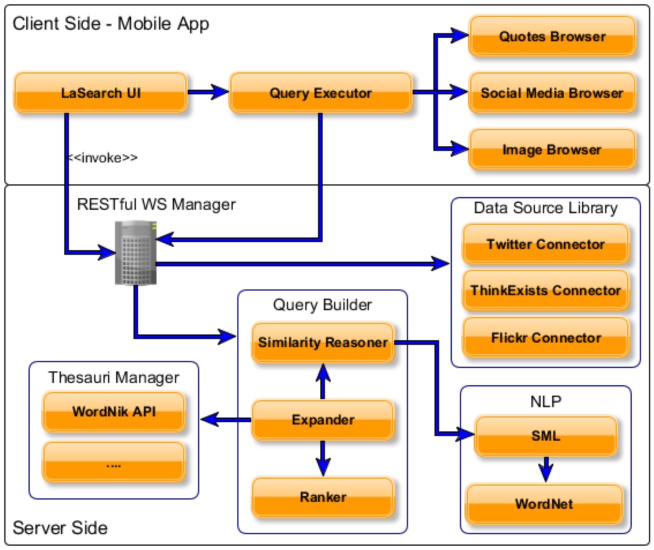

Figure 3. Architecture of the implemented prototype

extracting: (i) *hashtags* from Twitter, through the Rite-Tag API[23]; (ii) images from Flickr, through the exposed APIs[24]; (iii) quotations from ThinkExists, by using the boilerpipe library[25].

B. *Mobile Application*

The client side of the current prototype (upper part of Figure 3) is implemented as a mobile application, runnable on Android devices. It allows the user to input a term to be expanded, specifying the length of the *conceptual path*, i.e., the number of hops to be executed by the algorithm (Figure 4.a). The results of the expansion can be browsed (Figure 4.b), in order to select the terms to be used as search request by the *Query Executor*. The latter invokes the *Data Source Library*, which in turn retrieves data from a set of external repositories through the connectors implemented on the server side. In particular, we focused on three categories of data considered of particular interest in this context, namely, quotations, images, and user-generated contents on social media platforms.

The results collected by the *Query Executor* are then aggregated and presented to the user by specific browsers that allow the user to navigate the results. As an example, Figure 4.c shows popular Twitter *hashtags* related to the keyword *risk*, while Figure 4.d shows images retrieved on Flickr using the keyword *adventure*.

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we presented a method for the expansion of search queries, based on the use of a semantics-enabled approach, tailored at enforcing lateral thinking mechanisms in order to achieve more creative, inspiring and evocative results. Our initial results have been implemented in a tool, *LaSearch*, that allows the users to expand a *seed* term, obtaining conceptual paths whose terms are reached by traversing pre-identified relationships in a given thesaurus and evaluating linguistic distance metrics. Query expansions are then used to gather results from external sources, such as images and quotation repositories, or social media.

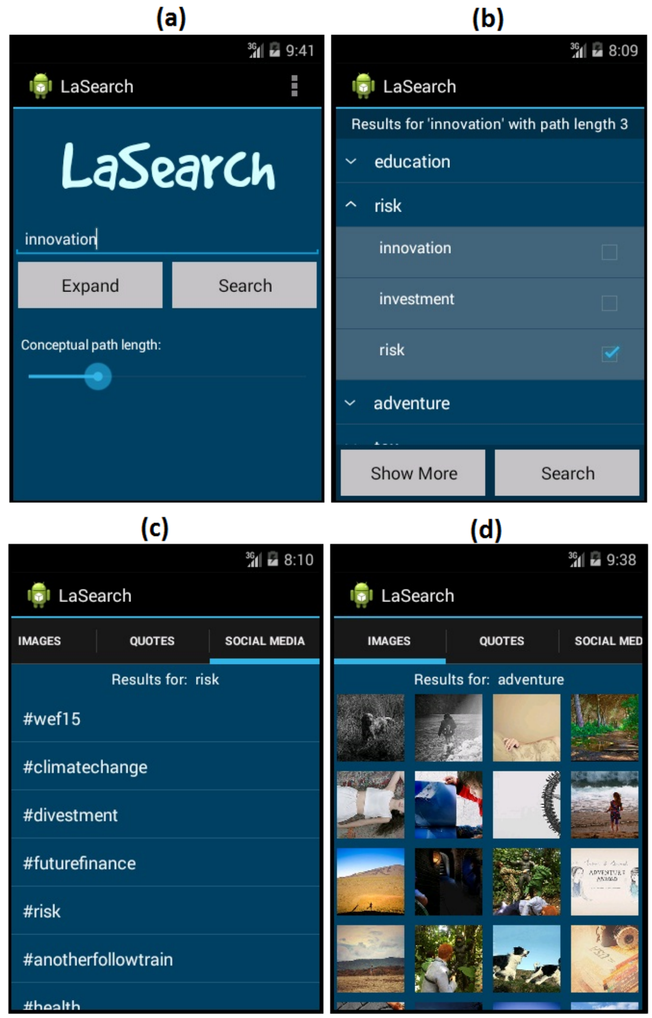

Figure 4. Screenshots of the user interface

The preliminary results presented in this paper open up several directions for future research. First of all, we plan to push forward the empirical evaluation of our proposal, to assess the quality of the results as perceived by human users. For what concerns the performance point of view, first experiments are encouraging and show that during the interactive usage of the tool, expansion and search tasks can be performed in an acceptable amount of time and memory resources.

Secondly, since the method is sensitive to the used semantic network and the relationship(s) in it (in the current implementation we used Wordnik as the semantic network, and ”same context” as the relationship), we plan to test additional knowledge sources (e.g., dbpedia [26], ConceptNet [27]), and relationships in them, as well as to consider, in the identification of terms in a path, criteria depending on the domain of corresponding concepts, in order to select terms from different contexts, which would be much related to lateral thinking. Furthermore, another initiative could be to integrate heterogeneous creativity-based approaches (e.g., analogies, metaphors [28]) for suggesting terms to the conceptual paths.

Finally, the most challenging initiative is go towards a formal definition of *lateral attitude*, introducing a computable metrics in order to be able to assess its increment at each iteration of the method. Many expansion results shown in Table V, such as [*innovation, research, education*], [*innovation, investment, risk*] or [*innovation, achievement, enterprise, ambition*], are significant examples of the kind of expansion we want to achieve. Indeed, while the terms in the paths incrementally diverge from the seed from a semantic perspective and, intuitively, increase their 'laterality', at the same time they maintain a figurative connection with it. However, translating this intuition into a structured method still remains an open issue. One could argue that precise calculation rules prevent creativity, while introducing random and chaotic behaviors could foster lateral thinking. So, is it finally sufficient to be crazy, free and nonjudgmental to be more creative [29]? We guess that it is not as simple as that.

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