Semantic Annotation for Enhancing Collaborative Ideation

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ABSTRACT

Enhancing creativity has been paid a lot of attention recently, especially with the emergence of online collaborative ideation. Prior work has shown that, in addition to the exposure of diverse and creative examples, visualising the solution space enables ideators to be inspired and, thus, arrive at more creative ideas. However, existing automated approaches which assess the diversity of a set of examples fail on unstructured short text due to their reliance on similarity computation. Furthermore, the conceptual divergence cannot be easily captured for such representations. This research in progress introduces an approach based on semantic annotation to overcome these issues. The solution proposed formalizes user ideas into a set of annotated concepts and a matching mechanism is then used to compute the similarity between users' ideas. We aim also to create a visualisation of the solution space based on the similarity matrix obtained by a matching process between all ideas.

KEYWORDS

Collaborative Ideation, Semantic Annotation, Ontology, Matching.

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1 INTRODUCTION

One major issue in the context of research transfer is to identify possible application areas for research results. Collaborative ideation can provide a promising approach for supporting possible application scenarios for existing research. However, existing research has shown that the divergent thinking strategy with the "brainstorming method" has shown remarkable success so far [1].This technique seeks to increase the number of ideas generated based primarily on the exploration of others' ideas while restricting criticism. Moving brainstorming from a collocated setting to an open online platform setting (as done by several open innovation platforms[1]) yields several benefits: (1) the crowd allows the generation of a large number of ideas and (2) its heterogeneity increases the potential for ideas [9]. However, new challenges arise in distributed large-scale ideation processes, for example, (a) many ideas are basic, mundane and repetitive [7] and (b) the number of ideas makes it economically unfeasible to sift through all ideas [7]. Existing approaches use either human facilitators (experts that guide the idea generation process by providing inspirational images, similar ideas or though questions to the users) [7, 8] or the presentation of inspiring examples [2, 3] to the ideators to tackle these challenges.

A variety of research has been conducted trying to enhance the crowd ideation creativity using the presentation of examples. Indeed, the exposure of other ideas can influence ideators both positively (i.e. finding more ideas) and negatively (i.e. fixation; focusing on one idea). Moreover, research demonstrated that presenting a set of mundane ideas leads an ideator to fixation [5]. By contrast, presenting a set of inspiring (creative and diverse) ideas leads an ideator to generate more creative ideas [2–4]. However, a major issue in collaborative ideation is "how to find inspiring ideas from hundreds" [6].

A lot of effort in research has been made to select a set of inspiring ideas from a large collection of crowd ideas [4]. Existing approaches regarding exploration either browse and search for examples [12], extract schemes from examples and search for the ones that allow analogical transfer for a new idea [13] or systematically select a set of inspiring examples [2, 3]. We paid special attention to the approaches that select a set of inspiring examples systematically. Selecting a set of inspiring examples requires two criteria [2]: creativity of individual examples and diversity of examples. Various mechanisms have been already developed for the first criterion [2, 13], however, assessing the diversity of examples is still under development.

Current research is in line with approaches that assess the diversity (i.e. low similarity rating) of inspiring examples automatically. The ideators often provide ideas only in a short text, because they often spend a limited time within the ideation process [6]. Existing approaches which use machine learning do not perform well for such unstructured short texts [3] due to *conceptual divergence* (i.e. using different vocabulary to describe the same meaning), which cannot be captured from such representation. We describe in this research in progress an approach based on semantic annotation to overcome this problem. The semantic annotation is the process of enriching and representing information with semantics [10]. Our approach is to annotate concepts in an unstructured short text that describes the idea. The knowledge captured will then be interactively corrected by the user: When a concept has different meanings, which refer to different entities in Wikidata using SPARQL, an image of each entity is shown to the ideator. The ideators then select the image for the concept they think best reflects their idea (i.e. disambiguation of the meaning). These corrected concepts and their

[1] OpenIDEO (https://openideo.com/), Quirky (https://www.quirky.com)

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retrieved superclasses from Wikidata are then stored. Once the concepts are stored, a matching system is applied to compute similarity between ideas. This similarity can be used, on the one hand, for assessing the diversity of examples and, on the other hand, creating a visualisation of the solution space by computing the similarity matrix of all ideas.

The rest of the paper is organised as follows: Section 2 presents related works. Section 3 introduces an illustrative example of our approach. Section 4 provides a description of the solution proposed. Section 5 summarises our contributions and future work.

2 APPROACHES FOR ASSESSING DIVERSITY

Our literature review reveals two categories of approaches addressing the problem of assessing diversity based on a set of examples, namely, "automated approaches" and "human-machine approaches". These are introduced briefly as follows.

2.1 Automated Approaches

The works proposed in [15] and [16] measure the diversity of a set of ideas by calculating the statistical similarity between ideas using latent semantic analysis (LSA)[2]. However, other approaches [8, 9] use LSA to determine the depth and breadth of ideas. Recent work [14] has used a statistical similarity matching between ideas based on GloVe[3]. The authors of this work argue that GloVe not only agrees well with classical models, such as LSA, but also provides a more nuanced semantics, i.e. GloVe not only distinguishes the meaning between two words based on quantitative features, but also captures differences based on word analogies (such as king and queen).

One key disadvantage of the automated approaches is that they fail for unstructured short text. Furthermore, the statistical similarity used by the works mentioned above does not account for conceptual divergence (i.e. different vocabulary, relationships and meaning behind the concepts used) between ideas expressed by different ideators.

2.2 Human-Machine Approaches

Another common mechanism to assess the diversity of a set of examples is to combine human judgments and machine learning techniques (i.e. crowd-powered approaches). Research has identified a major drawback of these approaches. They rely on "micro tasks" from a crowd which are often tedious and repetitive. Therefore, the engagement of the ideators diminishes quickly [2].

Siangliulue et al. propose performing these tasks by specific workers from MTurks [2], however, this requirement is challenging due to the lack of knowledge of workers for creative tasks. A more recent research in [9] proposes that these tasks (rating, similar ideas and combination) should be explicitly performed by ideators themselves and not by external workers. However, the work does not check whether this strategy is perceived as tedious by the ideators. In another work, these tasks are implicitly performed by ideators themselves using a spatial organisation of ideas (i.e. a whiteboard space), where users can arrange their own ideas and those of others. The work also demonstrated that the visualisation of the solution space is useful for idea generation[3], but the spatial organisation demands additional mental effort from the users. Our goal, similar to the work mentioned previously, is to get similarity ratings to create a visualisation of the solution space and provide the user with inspiring examples. However, our similarity measure is based on an automatic matching system in contrast to spatial features.

In the context of semantic technologies, our literature research yielded ontologies used for the management of ideas [19]. However, these approaches look at ideas from an external perspective and do not try to extract meaning from the idea descriptions.

3 ILLUSTRATIVE EXAMPLE

We present an example in the subsequent section which illustrates the various steps involved in our approach. The scenario consists of identifying similarity between ideas to assess the diversity (i.e. low similarity) of a set of examples.

The examples chosen are two ideas which have been presented in a workshop about "Urban Security Technology". The ideas are as follows:

- *Idea 1* – Signal-Window – Window from a heat-sensitive material, that lights up if a person is in the room during a fire.
- *Idea 2* – Rescue Indication facade – The facade indicates in which floor there are people that need to be rescued.

The input of our approach is the idea description. Natural language processing (NLP) is used to extract concepts. Once the concepts are extracted, the next step is to link those concepts to entities from an external knowledge base. The main challenge of this step is the validation of the concepts extracted. Therefore, a validation is performed by showing the ideator a set of images and asking which one reflects his idea. These images are obtained from the corresponding entities in Wikidata. The concept of "window", for instance, in *idea1* corresponds to an entity "window" in Wikidata. This entity has a linked image and additional information; this image is shown to the ideator. The image selected by the ideator for each concept allow us to store the correct concepts along with their superclasses. As a second step, a matching system is used to calculate semantic similarities between the concepts that represent the ideas. The matching system implements three metrics: structural, terminological and linguistic, to identify the similarity between the concepts of the ideas.

We have applied the GloVe technique, which uses statistical similarity to assess diversity between these two ideas, as an evaluation; we then compared the result with our approach.

The similarity result obtained by measuring the vector distance of the GloVe representations of the two ideas shows that the similarity measured is very low, meaning that the two ideas are considered different by this technique. However, using our approach, the ideas are considered similar, due to the high similarity value calculated by system matching of the annotated concepts extracted. In the first idea, for instance, the concepts ’window’ and ’room’ identified have "architecture element" as a superclass, which is the same for the concepts ’facade’ and ’floor’ in the second idea. Furthermore, the concepts ’people’ and ’person’ are equivalent using the superclasses, since ’people’ has type ’person’. These results are very promising and allow for a more detailed evaluation of our approach.

[2] Latent Semantic Analysis (LSA) is a theory and method for extracting and representing the contextual-usage meaning of words by statistical computations applied to a large corpus of text [17]

[3] https://nlp.stanford.edu/projects/glove/

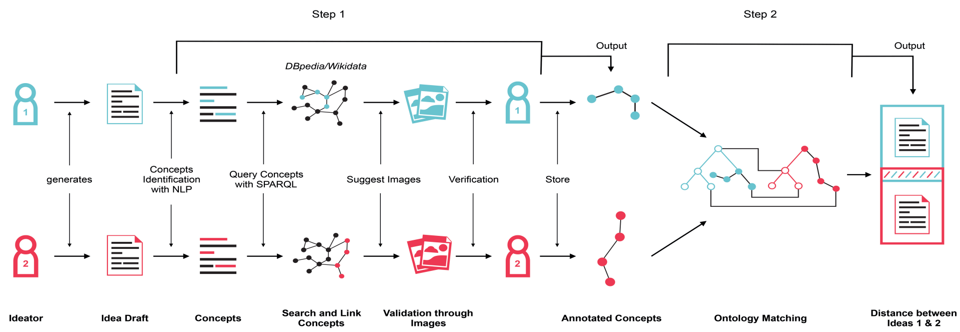

Figure 1: Process of Annotating and Matching Concepts for Assessing Diverse Ideas

4 THE PROPOSED APPROACH

The approach we propose in this research in progress consists of extracting, annotating and matching concepts from textual descriptions of ideas. More specifically, it exploits the structural conceptualization through the extracted concepts from idea descriptions. A matching system is used to calculate the semantic similarity between ideas based on their ontological concepts. The process of our approach is illustrated in Figure 1. The figure provides a general summary of the solution proposed. It consists of two successive steps, as described below.

The step "Concepts Annotation" consists of annotating the concepts that reflect the conceptualization behind the user's ideas. This step can be further divided into "Concepts Identification", "Search and Linking Concepts", and "Validation of the Concepts Extracted".

During the "Concepts Identification" phase, the concepts which represent the idea are extracted from short unstructured text that describes the user's idea. We have used NLP to perform this extraction: The unstructured short idea description passes through a case-conversion, stop-word elimination as text cleaning, tokenization and normalization (stemming lemmatization). This phase is performed using the Stanford NLP API[4]. The output of this phase is a set of normalized tokens (nouns and verbs).

During the "Search and linking Concepts" phase, the concepts selected and their superclasses are stored. To perform this phase, the entities identified in the previous phase are linked to DBpedia/Wikidata[5] entities using the SPARQL language. Once the query on an identified concept is performed and the corresponding entity in Wikidata is retrieved, a relationship "Same As" is created between those two entities. In addition, all information about the Wikidata entity is stored. However, it is possible that some SPARQL queries do not return any results, because some identified concepts of a user's idea cannot be found in Wikidata due to the heterogeneity of the ideator's vocabulary. In this case, our approach is to find possibly related Wikipedia entries for the entity by employing an automated search engine query (limited to Wikipedia sites) and picking the first result as the concept. A SPARQL query is then performed again on the entity found by this approach (i.e. matched entity). Once the SPARQL query returns information about this matched entity, an equivalent relationship is created between the concept of the ideator's idea and the matched entity found by querying.

During the "Validation of the Extracted Concepts" phase, the annotated concepts which describe the user's idea are validated. The knowledge captured (i.e. the corresponding entities that refer to concepts of an idea) must be validated somehow, since an idea concept may refer to many entities in Wikidata. A set of pictures is shown to the ideator to validate which entities should be stored. Each picture is a combination of the concepts' images of an idea that refers to the entities in Wikidata. For If the user's idea is as follows: "Window from a heat-sensitive material", the concept here, "window" refers to two entities in Wikidata (Q35473: window as an architectural structure or Q835016: window as a widget - as a graphical user interface element). In such a situation, two pictures are exposed to the ideator, each of which contains a combination of concepts' images of an idea. The first image contains an image of a window (as an architectural feature) plus an image of heat-sensitive and an image of a material. However, the second image contains an image of a window (as a computer), plus an image of heat-sensitive and an image of a material. If the situation arises that there are no images linked to the concept in the external knowledge base, we propose handling this by falling back on showing the concept names along with the abstract of the concept description. We have used the context of different identified concepts to reduce the number of the pictures generated (i.e. the application domain). When the ideator selects which image reflects his/her idea, the concepts captured, along with the corresponding entities, are stored. In addition, the superclasses of the corresponding entities obtained from external ontologies (Wikidata or any external knowledge base that supports a SPARQL endpoint) up to the concept "Thing" are also stored (for instance, if the concept "car" is identified, the superclass "vehicle" and their superclass "Object" are also stored).

Contrary to the related works, we do not consider the image selection task to be as tedious as rating, because of the visual component and the greater variety in the content for each idea. In addition, unlike external crowds, the ideator has knowledge about his/her own idea.

The next step, "Matching Mechanism", consists of matching the concept annotated in the first step to assess the similarity of ideas. The matching process receives two or more of a set of concepts

[4]https://nlp.stanford.edu/
[5]Our approach uses DBpedia/Wikidta as external knowledge-base (https://www.wikidata.org/ http://dbpedia.org/)

(along with their superclasses) as input and generates a set of semantic correspondences between the concepts annotated that are being processed as output [11, 18].

The matching process used in our approach is based on our prior studies proposed in [20] and [18]. Firstly, the process conducts a comparison of every pair of ideas defined as input to match all users' ideas. For every pair of ideas, it starts by extracting their annotated concepts. Secondly, the matching process computes the similarity between the entities using terminological, structural and linguistic matchers. We have combined three different string similarity measures, namely the Levenshtein distance, Jaro distance and SLIM-Winkler distance, to cover the maximum terminological heterogeneity [18]. We have used WordNet as an external dictionary to detect synonymous and antonymous concepts. The approach uses Lin algorithm [21] on WordNet[6] to compute linguistic similarity. The process uses the external structure of the external knowledge base (DBpedia/Wikidata) to compare superclasses, more specifically upper cotopic similarity, to reduce the conceptual heterogeneity [20]. Thirdly, the matching process combines the similarities obtained by each matcher in a unified matrix (i.e. a similarity matrix is obtained for each matcher). This unified matrix is achieved using a combination strategy that gives the priority to the similarity calculated by WordNet. In other words, the similarity is retained if the similarity value calculated using WordNet is greater than the similarity value calculated using one of the string matching algorithms or structural measures. Otherwise, the similarity is retained using the average aggregation method. Fourthly, once the combined matrix of similarity value is obtained, the matching process applies a filter to select the most relevant one. This is achieved using the maximum strategy with a threshold, i.e. the process selects the maximal similarity value that is greater than a given threshold for each line of the unified similarity matrix.

Finally, the most relevant similarity value between two ideas is stored in a matrix of all matched ideas producing a pairwise similarity measure of all ideas. This pairwise similarity can be used to, on the one hand, select a set of highly diverse ideas (by minimizing similarity) and, on the other hand, to visualise an overview of the similarity between all ideas generated by using dimensionality reduction algorithms to place the idea on a 2D surface.

5 CONCLUSION AND PERSPECTIVES

The approach proposed in this research in progress aims to assess automatically the diversity of a set of ideas based on a semantic annotation approach. It consists of two main parts: (1) concepts annotation and (2) a matching mechanism. Firstly, the concepts annotation is performed by concept identification, then search and linking concepts with Wikidata entities and a validation through user-based selection of images are carried out. Secondly, these annotated concepts along with their superclasses are used as a support to calculate the similarity between ideas using ontology-matching techniques. By using semantic annotation, we mitigate the problems of related work in the automatic calculation of idea similarity: statistical matching gives inferior results on short text and conceptual divergence. Using our approach, we can assess the similarity of two ideas, which can then be used further to select a set of diverse ideas (low similarity rating) that inspires the user to generate more creative ideas. Furthermore, we use the similarity ratings obtained to provide a visualisation of the solution space to give ideators an overview of the collaborative effort. We are currently continuing the experimental study by (1) validating our approach regarding extraction and matching, (2) comparing our approach with an automatic approach that uses GLoVe in more detail and (3) conducting a usability test for the image selection.

We will build an ontology in future work that covers a large number of concepts that appear in all users' ideas. Furthermore, we will use this ontology to employ semi-automatic idea recombination. Another approach would be to employ the analogical transfer techniques used by [13].

[6]https://wordnet.princeton.edu

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