Trust-Based Individualization for Persuasive Presentation Builder

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Abstract. For most people, decision-making involves collecting opinion and advice from others who can be trusted. Personalizing a presentation's content with trustworthy opinions can be very effective towards persuasiveness of the content. While the persuasiveness of presentation is an important factor in face-to-face scenarios, it becomes even more important in an online course or other educational material when the "presenter" cannot interact with audience and attract and influence them. As the final layer of our personalization model, the Pyramid of Individualization, in this paper we present a conceptual model for collecting opinionative information as trustworthy support for the presentation content. We explore selecting a credible publisher (expert) for the supporting opinion as well as the right opinion that is aligned with the intended personalized content.

Keywords: Presentation · Personalized · Trust · Opinion mining

1 Introduction

As discussed in our previous publication [1], presentations are effective way of communicating information, particularly in the field of education and e-learning. However, the content of a presentation may not be completely beneficial and persuasive to all users since it is not personalized for each recipient. Yale Attitude Change Approach [2] specifies four kinds of processes that determine the extent to which a person will be persuaded by a communication. These processes are:

1. Attention: The presenter must first address the intended audience.
2. Comprehension: The audience must understand the presented message.
3. Acceptance: The audience must accept the argument in the presentation.
4. Retention: The audience must remember the argument later.

It also elucidates the persuader main characteristic which is credibility. As defined by Yale Attitude Change Approach credibility is summarized into expertise, trustworthiness, dynamism and sociability. Despite some of the differences, for the rest of this document, we will use the terms credible, trustworthy, and expert interchangeably, as by expert we mean someone whom audience find credible and trustworthy. It has been also frequently demonstrated that highly trustworthy and credible communicators prompt a greater positive attitude toward the position they advocate than

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do others with less level of credit [3]. As Sternthal and Dholakia said in [3], if a highly credible source inhibits counter arguing, whereas a less credible source does not, cognitive response predicts the superior persuasive power of a highly credible communicator.

In Personalized Presentation Builder for Persuasive Communication, we proposed a personalization model called, Pyramid of Individualization [4]. The intention of our model is to build a system in which with the help of aggregating user's social network information, the presenter is able to personalize the content of a given presentation. The proposed personalization consists of four layers:

1. Content assembler that collects appropriate content items through demographic segmentation.
2. Language modifier that increases text readability.
3. Personality trait modifier that revises the content by predicting user's personality.
4. Individual modifier that adds items related to each individual such as quotes, images, events, information shared by close relatives or trustable public figures/organization, etc.

Our main focus in this paper is the individual modifier (the fourth layer). The design for this modifier is based on the idea of enriching the personalized content with the flavor of personal data like family history or personal opinion. A simple example could be a restaurant's online flyer to promote people to reserve the restaurant for their future events. Incorporating the individual's personal photo from past festive events may enhance the sense of positive emotion towards persuasiveness of the advertisement in comparison to using a generic restaurant advertising image.

However using personal images in the intended personalized content is only a simple example of such individualization. An image of friends in a restaurant, or a quote from them describing their happy event there, can increase the likelihood of audience trusting that place even more. Various types of data such as user likes, postings, comments or events can be used in such "individualization". Our objective in this paper is to introduce the essential components involved in collecting supporting opinions from reader's trustworthy sources to support the personalized content.

Social networks are becoming the most common place for people to post information, express their opinion, and get reviews from other users. These activities result in the generation of a rich source of information on different aspects of life. Such user-generated information ranges from health and politics to product and service reviews. However, these "opinionative information" may be generated by different people with various relations to us. The opinion can be from an iconic public figure or organization who we strongly support or from our credible colleague who we personally know. On the other hand, they also may come from someone who is part of our social network but not trusted, or with different taste and standards.

The iconic public figure and our dear colleague share a common factor, which is trustworthiness. Dictionary definitions for trust include such terms as "confidence", "reliance", "expectation", and "hope". Kim Giffin studied theory of interpersonal trust within credibility context [5]. She shows that interpersonal trust is based upon a listener's perceptions of a speaker's expertness, reliability, intentions, activeness, personal attractiveness and the majority opinion of the listener's associates.

After discussing the technical issues of improving persuasiveness of personalized content by using opinion-oriented information, we focus on the central problems around designing the actual model. The next section of this paper, the related work and the motivation behind this research has been reviewed. Following that, we present some background information about the proposed model, a general overview of our procedure, and some implementation notes. Then we discuss some conceptual results and examples. Finally we describe how this system can be improved and what work remains to be done in the future phases of the research.

2 Related Work

In general, there are two main types of textual information: facts and opinions. Multiple solutions have been proposed and specialized in factual Information Retrieval (IR). These solutions have been discussed and used in the language modifier section of our personalization system. In this paper, the main focus is on identifying and using personal opinions. In the related literature, this is usually referred to as opinion mining or sentiment analysis [6].

With the rapid growth of the user-generated content published in social networks, a tool for mining the Web to capture sentiments and opinions at a large scale becomes essential. Due to importance of collecting products and services reviews by product vendors and policy makers, we have witnessed extensive interests in this line of research [7, 8]. Their focus has mainly been designing the system suitable for organizations to analyze and aggregate their customers' attitude towards a product or service and its features along different dimensions, such as time, geographical location, and experience. In our research, our focus is to retrieve the reviews for personalizing content to persuade readers'.

Bo Pang and Lillian Lee [6] published an inclusive survey that covers methods and approaches in the field of Opinion Mining (a.k.a. Sentiment Analysis). Their focus is on techniques to address new challenges raised by sentiment-aware applications, as compared to those that are already present in more traditional fact-based analysis. They have discussed a variety of topics from material on summarization of evaluative text and on broader issues regarding privacy and economic impacts that the development of applications based on opinionative information gives rise to. Enhancing percussive personalized content can become an addition to the above topics.

There have been also many studies within the field of trust-based social recommender systems. Some preliminary literature demonstrate the advantages of applying factor of trust in recommendation marking [9, 10]. These works focus on recommender systems that consider trustworthiness factor before recommending content to the user. One of the challenges in these systems is their trust rating mechanism. Predicting trust rating between content publisher and receiver is a critical task. For instance, Golbeck and Hendler in their work on inferring binary trust relationships in web-based social networks considered those social networking sites where users explicitly provide trust ratings to other members [11]. However, for large social networks it is infeasible to assign trust ratings to each and every member so they propose an inferring mechanism, which would assign trustworthy/non-trustworthy rating to those who have not been assigned one. The missing element in their research is demonstrating the logic within an application context.

Although mining personal opinion and experience consists of a series of challenging procedures, evaluating the credibility of collected data has its own complexity. Microblogs can be sources of truthful news and also a tool to spread misinformation and false rumors. Castillo and Mendoza analyzed the information credibility of news propagated through Twitter using a classifier [12]. Their model uses features from users' tweets and re-tweeting behavior, from the text of the posts, and from citations to external sources. Based on their results, with precision and recall in the range of 70% to 80%, it is possible to classify messages as credible or not credible. On the other hand, Soo Cho [13] proposed to apply user profiling and LIWC (a text analysis software program) [14] to predict publisher's expertise. By collecting background knowledge about the publisher, the system assigns a certain level of reliability based on the subject of the content. Predicting the credibility of the content is an essential part of our individualization model and these approaches would be applicable in our proposed model.

3 Proposed Individualization Model

Nowadays, it is becoming evident that the views expressed on the web by a certain user can be influential to readers in forming their opinions on some topic [15]. In order to benefit from such a delicate concept, we need to be tactful enough with selecting an aligned opinion with our personalized contents from the right person for a particular reader. To understand the complexity of the process, consider the following scenario. We are looking to personalize an advertisement to highlight the benefits of a new tax policy. We have found a review from a democratic congressman regarding the new policy. The congressman is considered as an expert with a decent public credibility approval but the twist is the actual content reader is a republican. Due to differentiation between the expert and the reader political point of view, the expert may miss the credibility factor in the reader's eyes.

Our proposed model is a collaboration between multiple actors and assigned roles. The actors in this model are Individualization System, Reader, Expert and Author. While Individualization System acts as an automated content recommender, the reader and author are users who are interacting with the system. The expert is a user who will be known to the system through the reader. Table 1 defines some the term used in our model.

The challenge of collecting the proper supporting opinion consists of multiple sub processes. It begins with identifying the objective of the personalized content. After that we select the right expert and then collect the supporting opinion. The general overview of the process illustrated in Fig. 1.

Table 1. Summary of individualization model terminology

Actor	Role
Individualization system: the automated recommender or the personalization system	1. The personalized content can fall into personal (e.g. birthday event) and public (e.g. new tax policy) categories
	2. The system starts with authors opinion and then finds and uses supportive opinions to improve percussiveness of recommended personalized content
Reader: the intended personalized content receiver.	Authenticated to the system through his/her social network account
Expert: the expert might be the reader's close friend/family member or a public figure/organization which is trusted by the reader	Published the supporting opinion
Author: the presentation designer	Creating the presentation template and rule files

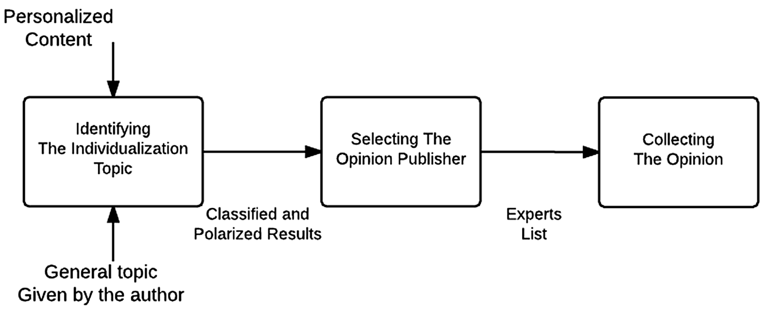

Fig. 1. General overview of individualizations model

3.1 Identifying Individualization Topic

Categorizing the personalized content is the first step towards mining supporting argument. The content main topic needs to be identified before an expert or a supporting opinion can be assigned to the personalized content. As discussed in our previous paper [4], a content assembler collects the contents by user profiling and applying author driven content rules. The content rules act like the logic to guide the recommender system with collecting, analyzing, and personalizing the content. The rules are essentially consisting of facts and goals. Facts are users' data (e.g. age, sex and income) and goals (e.g. increasing savings and higher education) are topics that author likes the personalization system to collect content for based on users' data. Once the rule is activated, the system begins with searching for information within the rule's goal context and recommends the most relevant content based on the criteria. Thus, rule goals can also be used as a way to categorize the content.

To avoid contradiction between supporting opinion and the content, the system first need to conduct polarity analysis on the content. For instance, following sentence implies a negative opinion:

"**Returns are not guaranteed** – While stocks have historically performed well over the long term, there's no guarantee you'll make money on a stock at any given point in time and you may lose all your principle".

However such an opinion is not a suitable candidate for the content as supporting opinion:

"Just made a $3,000 investment in stock last year and it turned into a $250,000 fortune within couple of years".

The polarity of a sentiment is the point on the evaluation scale that corresponds to our positive or negative evaluation of the meaning of this sentiment. A good practice is to verify whether the supporting opinion has the matching sentiment information as the intended personalized content. This achievable through existing third party public APIs like o2MC and Stanford NLP - Sentiment Analysis.

3.2 Searching for the Expert

Acquiring expertise in any domain is defined as going beyond ordinary learning from rule-based and fact-based "know-that" towards experience-based "know-how" [16]. Unfortunately, the data generated in social network accounts does not have the semantic structure which we see for product's review on a typical electronic commerce (EC) website. Such a data structure, allows publishers to build up reputation/expertness level in the community. In social networks, our tools are limited to number of likes and re-posts (re-tweets) plus polarity analysis on the comment. As illustrated in Fig. 2, our task in this part of proposed model is to generate a list of experts for a given topic.

There are two groups of experts: personal relatives and public figures/organizations. Personal relatives includes close friends and family members. Unlike well-known famous people/organizations (the second group), the system first needs to determine the quality of the relationship with the people in the first group. To achieve our goal, we rely on an unsupervised model to estimate relationship strength from interaction (e.g., communication, tagging) and common interests. By using the above idea, Xiang and Neville formulated a link-based latent variable model, along with a coordinate ascent optimization procedure for the inference [17].

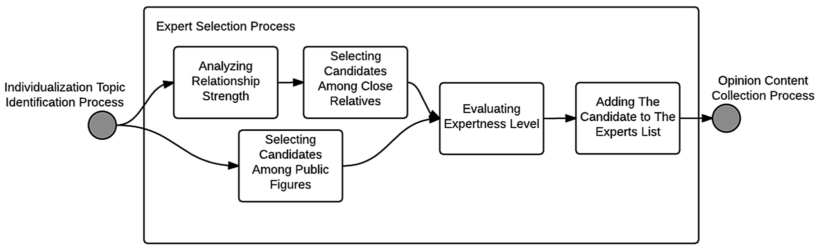

Fig. 2. General overview of expert selection process

Once the system filtered out reader's casual acquaintances with weaker relationship strength, it initiates a semantic approach to organize each of our candidates with the area of expertness within the given topic. Based on Dreyfus and Dreyfus terminology [16], this task has two phases.

1. Confirming the "know-that" factor:
   This task is summarized into processing/classifying candidate activities, and finding the total number of activities associated to the individualization topic. The activity is defined as candidate's posts and re-posts from other users. The post may also contain a link to a website which is also reflected in the classification. The goal is to define how well the candidate knows the topic.
2. Estimating the "know-how" factor:
   Well known readability indexes like flesch-kincaid [18], gunning FOG [19] or Coleman-Liau [20] are formulated to evaluate and indicate comprehension difficulty of a text or a passage. The calculated readability score for the candidate's published or the recommended content is the first source to determine the level of expertness. Although, there is no ranking mechanism in social network to build up reputation, number of followers, likes and re-posts can be applied towards estimating the reputation level.

To increase the likelihood of choosing the best possible supporting argument, the system generates a list of top experts for the given individualization topic instead of only selecting a single expert.

3.3 Collecting the Opinion

Sentiment analysis (opinion mining) [6] involves various methods and techniques that originate from Information Retrieval (IR), Artificial Intelligence (AI) and Natural Language Processing (NLP). This confluence of different approaches is explained by the nature of the data being processed (free-form texts) and application requirements (scalability, online operation) [21]. For the purpose of our research, we picked a typical opinion mining process that involves identifying, classifying and analyzing sentiment polarity. Besides, collecting the content, it conducts binary sentiment classification for instance, at emotional states such positive or negative. An overview of this section of the model is illustrated in Fig. 3.

Similar to the identifying individualization topic, in the first step, we need to identify the topics mentioned in the input data, and also associate with each topic the corresponding opinionative sentences. The available third party tools for opinion mining also allow us to distinguish between opinionative and non-opinionative phrases by performing subjectivity identification. This additional task is useful, since not all phrases that contain sentiment words are, in fact, opinionative.

The second step is to collect the supporting opinion. We need to assure that the opinion and personalized content sentiments are aligned. The same polarity analysis which we have applied for the personalized content can be reused during opinion mining. By comparing the result with the personalized content sentiment, the model can avoid creating contradiction between supporting opinion and the main content.

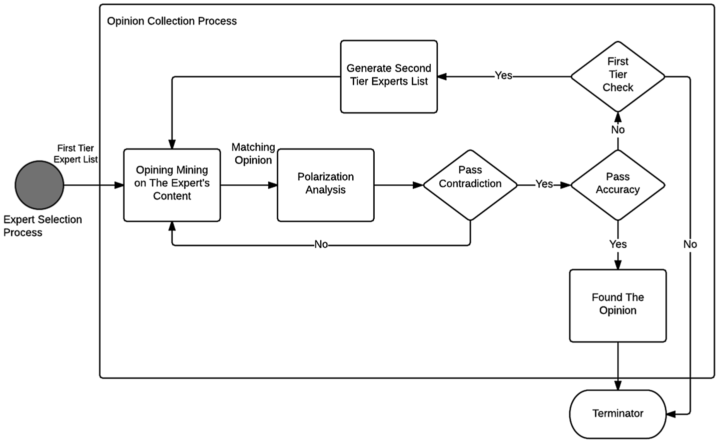

Fig. 3. General overview of opinion collection process

To simplify the comparison process, we are considering only binary polarity analysis by classifying contents into positive and negative groups. However, it is possible that the content has neutral or irrelevant sentiment category. In that case, we are not collecting opinions for the content.

Once the above steps are conducted, it is possible to select the closest matches to the target content as the supporting opinions. However, it is likely that the personalization system fails to find supporting opinions from the legitimate experts list or the accuracy level for the closest match is too low. To address the lack of supporting opinions, the model considers opinion mining through a second tier of experts recommended by the reader's preliminary experts (first tier of experts). This process is very similar to finding the first tier of expert's module. In social networks, transitivity means "the friends of my friends are my friends". The transposition of this property in our context implies "the reader trusts people who are assigned as credible sources by the reader's experts". Due to performance concerns and mitigating the risk of trustworthiness factor, we decided to not proceed with third or fourth tier sources.

4 Discussions

For a better demonstration of the methodology, we consider the following example of an educational piece on financial advice:

"Saving at least 10 to 15 % for retirement at an early age is a wise strategy. You will have to save less if you start early, and your savings will have longer to grow. Not all savings are guaranteed such as 401 K and stocks, so choose a savings option that is comfortable for you. One of the investment opportunities is in real-estate. Just four years ago, there were less than 25 annual starts in your neighborhood, and today it has grown to nearly 200 annual starts. It looks like the recovery is starting to occur even in the most exurban parts of Atlanta."

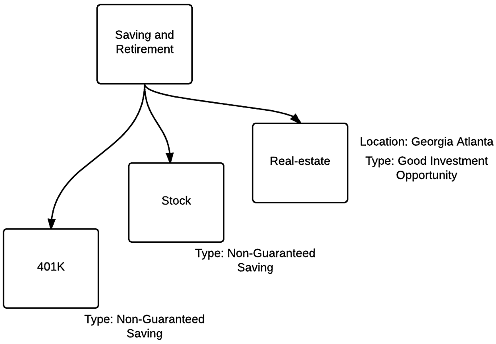

Fig. 4. Objective analysis example

The highlighted words in the above phrase are considered as objects. An object can be a product, person, event, organization or topic. Each object can be represented as hierarchy of components and sub-component. Each component in this hierarchy can have its own associated attributes. Figure 4 illustrates the relations between the objects and their attributes in the above example.

An opinion can be expressed on any component or attribute in the hierarchy. Using the mentioned tools for opinion mining in the proposed model, we are able to identify the objects as well as opinions that are likely to be relevant to the content. For instance, after searching through reader's social network, the system might generate results shown in Fig. 5. In this example, based on the generated experts list, the system decides to collect a tweet from the reader's close friends as well as a tweet from his trustable bank.

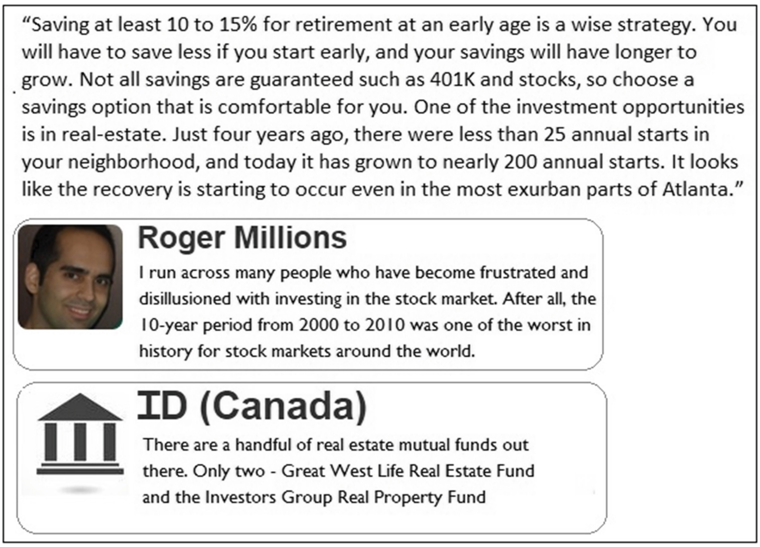

Fig. 5. Conceptual example

Our initial findings from previous publication [4] suggest that personalizing text can improve content persuasiveness. The accuracy of the result has a direct relation with the precision of the user social network contents. Based on the peer reviews on opinion mining, we identified polarity and modality at the local context with an estimated performance over 90 % precision and 50 % recall [22]. Comment threads can become another source of data for sentiment analysis and information retrieval. However, due to its unstructured nature, it requires entailment process and complex filtering methods, which is out of the scope of our work at this time.

5 Conclusion

In this paper, we have discussed our individualization model to enrich a personalization system with extracting opinion-oriented information. This model uses a corresponding 3-stage pipeline where the given content and user data will be used to collect opinionative information as supporting content to improve the overall persuasiveness of the content. The initial results demonstrate the ability of our model to increase the persuasiveness of content by enhancing it with supporting opinions from trustable sources. While further research is required to fine-tune all major parts of the model, the current design and findings are promising and show the potential use in many educational and otherwise informative applications, such as customer briefing, etc.

In addition to further research on technical aspect of the proposed system, more theoretical work is required to investigate the value of social network-based trust and who we can trust, the ethical issues associated with such persuasions (abuse of trust, privacy, etc.), the effectiveness of conflict resolution methods for opinions, and finding appropriate multimedia content from experts and the users themselves.

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