Table of Contents

Personalised Recommendation of Who to Follow Based on Fellowship of Followers
Marko Adamko, Pavol Navrat and Alena Kovarova ................................................................. 1

Factors affecting the effectiveness of Web 2.0 as a mobile Learning Tool in the Workplace: A Conceptual View
Bassey Orok and Abel Usoro ........................................................................................................ 6

A Study of Devising Neural Network Based Indoor Localization Using Beacons: First Results
Filip Mazan and Alena Kovarova ................................................................................................. 15
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Personalised Recommendation of Who to Follow
Based on Fellowship of Followers

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Abstract: This paper presents an approach to personalised recommendation of who to follow on Twitter. It is based on a simple observation that following the same Twitter account could be considered a fact that contributes to a possible similarity of followers. We proposed a simple scheme to elicit gradually candidates to follow which are most likely sources of microblogs that are of some interest to the user. We implemented a prototype and conducted experiments. They show that the basic idea works. We compared our system with the known “Who To Follow” application. Our system shows at least comparable performance and often gives better recommendations.

Keywords: Personalised Recommendation, Microblog, Twitter, Information Stream.

1 INTRODUCTION

Information overload is one of the significant characteristics of the present era. It manifests itself in many forms, one important of them being an information stream. The online social networking service Twitter administers the creation and sharing of microblogs called tweets. Users write and post very short (up to 140 characters) messages. Twitter distributes it to other users who subscribed to receiving messages from them by declaring themselves to be their followers. A user can also forward a received tweet (retweeting), which gives them the power to spread information broadly. In such a way, users receive streams of tweets. To put this into context, there are (as of July 2015) 645 million registered Twitter users, out of which 289 million are active ones, generating on average of 58 million tweets per day (Statistic Brain Institute, 2015). Each user faces a question: Which tweets from this huge stream ordered on a timeline should be a part of the specific stream that is shown to them?

A user can influence contents of own stream by subscribing to certain accounts as their follower. If they are too cautious, subscribing to only very few accounts, the user may miss many interesting microblogs. If they follow everyone who potentially writes something interesting, they may be flooded by so many tweets that it becomes impossible to read them all in a given time. And even this scheme does not guarantee that some interesting tweets are not missed simply because their source has not been known to the user. It is desirable to identify which tweets are good to recommend (automatically) to the user, where these tweets have to be very close to their interests. Sources or clues to user’s interests are their twitting history and their social relations.

We propose an approach to tweets recommendation that is based on identification of other accounts that are likely sources of interesting tweets. We devised a simple scheme that is able to recommend who to follow. Experiments show our approach performs similarly or better than a known solution.

The structure of the rest of the paper begins with a brief commentary of related works. This is followed by our explanation of our approach to recommendation of tweet sources. Then we give evaluation and results; and finally, conclusions and future work are presented.

2 RELATED WORKS

The present work falls within a broader context from several points of view. Connection between personalisation and user modelling has been intensively studied by many scholars (e.g. Barla 2011) and particularly in social media (Yin 2015). The role of a group of users in personalised recommendation has been stressed e.g. by Kompan (2013, 2014). Microblogs themselves are sources of valuable information and thus a subject to analysis aiming to identify opinions (Machova 2013) and sentiments (Korenek 2014) or to perform exploratory search (Zilincik 2013).

J. Chen et al. (2010) experimented with recommending content from information streams. In designing a recommender, they explored various options. They contemplated a three dimensional design space: along the first dimension, various options of how to select candidate accounts; along the second one, various options of how to use content information; and along the third one, how to use social information.

K. Chen et al. (2012) proposed a collaborative ranking model for recommending interesting tweets. The model collects preference information from many
users. This facilitates collaborative filtering that produces recommendations. Their approach is quite comprehensive. It takes into account the content of the tweet, user’s social relations and certain other explicitly defined features.

An important issue has been raised by Liu (2014) who proposed an approach to personalized tweet recommendation that aims to be privacy preserving. Their framework provides for keeping the content of tweets and users’ interests hidden from other unauthorized entities.

A tweet recommendation method would benefit from knowing user’s topics of interest. Bhattacharya et al. (2014) proposed a method to infer the topics of interest for an individual user. Their idea is to infer them from the topical expertise of the users whom the user follows.

Our idea is to exploit the social relations even further. The user is a follower of a host of other users. There are possibly many other followers of the same set of users. What do these followers have in common?

3 FELLOWSHIP BASED APPROACH

Our assumption is that on Twitter, the semantic relationship in the followership process that can be characterized as follows/is_followed is sufficiently information-rich to yield genuine recommendations of who to follow. The question is how such recommendations can be elicited from the data that represents the users and their relations, i.e. lists of followers of each particular user.

Data on each particular user (retrieved during their logging in) includes accounts that they follow. However, often a user follows dozens, if not hundreds of other accounts. To produce a realistic recommendation, this set must be substantially narrowed.

We should bear in mind that the goal is to produce personalized recommendations to the user. Therefore, any expressions of any user A are in principle possible sources of clues of their interests. In our approach, there is retrieved their timeline and extract of up to 200 most current tweets written by the user A. They are analysed to find mentions of the followed accounts in their tweets or shared tweets (retweets). Each mention or retweet increases priority of the followed account.

There are also retrieved up to 200 favourite tweets, i.e. those marked by a star by the user A, which is an attribution similar to the “like” in Facebook. Accounts who authored such tweets receive an increase of their priority.

As a result of such priority attributions, there is formed an ordered list of accounts. We take the 10 top accounts as sources of data (we consider the bottom 10 accounts to be candidates for deletion). The crucial design decision was here to determine which data will be used for creation of recommendations. It is to be noted that due to the nature of communications occurring on Twitter, the early common recommendation data model of considering a group of related individuals (Balabanović 1997) is not sufficient since that would mean considering only accounts followed by the user (i.e., their friends). Another model includes into consideration also friends of friends of the user (Facebook) or accounts followed by accounts followed by the user (Twitter) (Chen 2010). However, this model is not as suitable for Twitter as for Facebook. The reason is that users on Twitter frequently follow not only their friends, but also publicly popular individuals, be they actors, singers, sportspersons, politicians, news services, entertainers etc. Such individuals are not user’s friends.

The key point of our model is to form a group of individuals who follow one or more accounts that are also followed by the user. This is a conceptual deviation from the commonly shared view to focus on user’s friends. We start from a list of the top 10 accounts of user A (see above). The number 10 is of course only a subjectively set ad hoc parameter of our method; on the other hand, we experimented with different values. From the data on each of these accounts, there are randomly selected 100 (again ad hoc parameter) followers, all in all totalling up to 1000 users. They create user A’s fellowship of followers – FF(A).

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Users in FF(A) have at least this in common: they follow accounts that are among the top 10 accounts followed by the user A. The next step is to find out which accounts are the most followed by users from FF(A). For each account, up to 200 (yet another *ad hoc* parameter) followees are extracted.

We have now at most 200,000 accounts that are followed by someone from FF(A). Due to overlapping interests of different followers, the number is often significantly smaller, say around 50,000.

We should like to emphasize that values for the above mentioned *ad hoc* parameters are the result of extensive careful experimenting aimed at achieving quality of recommendation in a short time.

The multiset of several tens of thousands of accounts needs to be massively reduced. Bear in mind we want to make recommendation to the user A which accounts to follow. The multiset contains (occurrences of) accounts followed by those who have similar following portfolio as the user A. The first rule of thumb is obviously to use the number of their occurrences in the multiset. However, this does not suffice. Among the accounts with most occurrences in the multiset there can be found accounts that are in no way representative of the followers’ interests but simply have an extremely high number of followers. For example, singer Katy Perry has (as of time of writing this text) more than 71 million followers. In our approach, filtering out the less occurring accounts is augmented by a mechanism of weighting numbers of occurrences by numbers of followers (details of the mechanism are described below). In such a way, too popular accounts were moved down in the list.

**4 EVALUATION AND RESULTS**

We developed a prototype version of a system (MA) that implements the described approach. The MA prototype was used initially to adjust several *ad hoc* parameters of our method with the aim of increasing the quality of recommendation while maintaining a short response time.

The actual experimenting is aimed at an evaluation of the proposed approach. In order to be able to make any judgements on the quality of our recommendations, we need to solicit evaluating feedback from the users. To achieve as much objective evaluation as possible, we arranged for presenting recommendations by two different tools, i.e. by MA prototype and by the “Who To Follow” application of Twitter (WtF). Each evaluator was presented two lists of recommendations. In the first list, there were top 10 recommendations produced by MA. In the second list, there were top 10 recommendations produced by the WtF application. The user did not know which list was produced by which recommendation. The evaluator was asked to indicate in both lists those accounts that he would be interested in and would be willing to follow. An example of the two lists presented to the user is in Figure 2.

![Figure 2. An example of the two lists of recommendations presented to the evaluating user](image)

There were 24 evaluators – all of them Twitter users. First, recommendations by MA were produced solely based on numbers of occurrences of accounts in the multiset (i.e., no weighting). Results are in Figure 3, see columns WtF and MA.

Axis x shows evaluators. Axis y shows the numbers of accounts that the user decided to follow based on the recommendation of the respective tool (either WtF or MA). It is evident that the results for both tools are very similar. The users liked on average 24.6% recommendations produced by the WtF. They liked 25.4% recommendations produced by MA.
We have not been content with these results. We identified popular accounts as the reason for not-so-good performance of MA. This observation should not lead to deleting those highly popular accounts since it still may be the case that they could be interesting to the user A. This was endorsed by two evaluators who stated that they would decide to follow such accounts even if they do not fit to their scope of interest. We developed the following weighting scheme to diminish the preference of highly followed accounts (NoO stands for number of occurrences and a is an account from the multiset).

if NoO(a) > 10^7 then NoO(a) = NoO(a)/10
else if NoO(a) > 10^6 then NoO(a) = 10^6

In the second round of evaluation, the evaluators were presented recommendations produced by MA incorporating the weighting scheme. Results are in Figure 3. (See columns MA*).

In Figures 4, 5 we can clearly see that numbers of recommendations by WtF that the evaluators decided to follow are the same (24.6%). Numbers of recommendations by MA employing the weighting that the evaluators decided to follow are significantly better. On average, they decided to follow 38.8% recommendations. This result is by 14.2 percentage points better than WtF. The net improvement of MA after incorporating the weighting scheme is 13.4 percentage points.

5 CONCLUSIONS AND FUTURE WORK

In this paper we studied how to improve recommendation of Twitter accounts. This, of course, has been studied by several authors, but it remains a research topic currently. Our approach is based on a simple idea. Any user on Twitter is characterized by the set of accounts they follow. We retrieve other individuals who follow at least one of the most favourite from these accounts to form a fellowship of followers. Preferences and tastes of this group determine recommendations to the user.

Experiments, albeit limited, allow us to conclude that the approach produces better recommendations.

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Factors affecting the effectiveness of Web 2.0 as a mobile Learning Tool in the Workplace: A Conceptual View

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Abstract: Evidence gathered from extant literature shows that there exist studies on the use of Web 2.0 technologies for learning. Although a few of these studies focus on the use of Web 2.0 technologies in the workplace, other studies tend to focus on specific Web 2.0 technologies used in the workplace. However, researchers have reported a dearth in available empirical information on the use of Web 2.0 tools or technologies in the workplace for learning. This paper with the aid of models and frameworks from multiple disciplines attempts to develop a conceptual model that begins to fill this gap by exploring constructs and variables that are likely to influence the effectiveness of Web 2.0 technologies when used as mobile learning tools in the workplace. A conceptual framework consisting of six factors which include use of Web 2.0 tools, work environment, learner’s characteristics, barriers and enablers, instructional characteristics and motivation as a moderator is developed from literature.

Keywords: Web 2.0, learning, workplace, mobile learning, effectiveness, social media.

1 INTRODUCTION

Web 2.0, a concept believed to have been officially coined in 2004 (Anderson, 2007 p. 5) refers to internet services which allows users to interact and share data (Hogsan, 2015). Although, it was initially perceived to refer to a new generation of internet-based services (Dotsika and Patrick, 2007; Cosh et al., 2008); however, these technologies have enjoyed very wide application in social communication and in the transfer of knowledge in virtual learning environments (Minocha, 2009, Chen et al, 2015). The ubiquitous characteristic of Web 2.0 technologies makes it a similar, suitable and beneficial approach for mobile learning in the workplace. Thus, when Web 2.0 technologies are employed in workplace m-learning systems, it fulfils the requirements for improving knowledge sharing capability and collaboration among employees or workers (Wang, 2011; Bing and Wei, 2015).

The emergence of Web 2.0 tools has prompted keen interest among researchers on the use of Web 2.0 technologies in education and business with the former enjoying more research. Thus in the context of education, there are studies that have empirically examined the usefulness of Web 2.0 technologies for teaching and learning. For example, Xie and Shama (2010) studied blogs, McKinney et al. (2009) examined podcasts, Parker and Chao (2007) studied wikis. Information drawn from these sources can be used to show the potential of using Web 2.0 as a mobile learning tool in the workplace.

Despite the plethora of benefits Web 2.0 presents, there are still concerns about how effective these technologies are when employed as learning tools on smart mobile devices (Boateng, Mbarika and Thomas, 2010) especially when constraints such as the device screen size and the storage or content capacity are considered. In Information Systems, effectiveness of a technology or system is measured or evaluated by using several factors. These factors are categorised into usage or usability of the IS, the user satisfaction, Performance and Self-Efficacy or knowledge gained (Gelderman, 1998; Chou and Liu, 2005; Lehner and Fteimi, 2013).

This study seeks to evaluate factors that influence the effectiveness of Web 2.0 technologies when used as mobile learning tools in the workplace. Evidence gathered from literature and the experiments could help organisations adopt Web 2.0 tools in their mobile learning programmes or projects by overcoming potential obstacles and reducing the risk of failure during implementation.

In the sections that follow a review of literature discussing the terms Web 2.0, m-learning and workplace learning is presented. Also, the development of a conceptual model, the proposed methodology that would be applied to validate the hypothesis and the future work to be done are presented.
2 WEB 2.0 EFFECTIVENESS

Web 2.0 is a conceptual framework for a web based platform where both technical and non-technical individuals are able to collaborate, publish and share content or information via the world wide web by using a number of web based software applications such as Social networks, Blogs, Wikis, Podcasting, Tagging, Multimedia sharing, Forums/bulletin boards, content communities and content aggregators (Constantinides and Fountain, 2007). Although the concept of Web 2.0 has since gained widespread interest and use especially in education and business due to its perceived benefits and potential in improving collaboration and communication within and across multiple vertical industries (Andriole, 2010), there are still concerns about the dearth in available information on the use of Web 2.0 in workplace education and training and how they can be used effectively in the workplace as an organisational learning tool for workplace education and training (Platt, 2007; Boateng, Mbarika and Thomas, 2010), the actual value of the social web for workplace learning (Zhao and Kemp, 2012), and a lack of empirical evidence on the effectiveness of Web 2.0 tools for teaching and learning (Den et al, 2012).

Researchers across disciplines such as Humanities, Psychology, Human Resources Management and Information Systems have identified important variables that are related to effectiveness or performance. Amongst these are the Model for User Acceptance of e-Collaboration Technology using TAM (Dasgupta et al., 2002), Combined Training Motivation Theory (TMT) and Input-Process-Output (IPO) Model (Klein et al., 2006), Simplified Training Transfer Model (Velada et al., 2007), Motivation Training and Performance (MTP) framework (Tabassi and Bakar, 2009). Table 1 gives a summary of these models and their dimensions. This study builds on the Simplified Training Transfer Model (Figure 1) and adapts seven dimensions from other models mentioned above to assess the factors that influence Web 2.0 effectiveness, including the Use of Web 2.0 tools, Training Design, Work Environment, Learners Characteristics, Barriers and Enablers, Instructional Characteristics and Motivation acting as a moderator.

![Figure 1: Simplified Training Transfer Model](image)

From these seven dimensions, the factors of peer/supervisor support and feedback were identified under the work environment. The instructional characteristics dimension revealed the factors of delivery mode and instructional design. Under the learner’s characteristics
dimension, the factors identified are ability (learner’s ability), self-efficacy, and learning goal orientation. These factors as revealed in literature tend to deal with nearly every area of measuring training effectiveness; however, evidence from literature shows that there is no unified framework or model for validating and determining their relationship to effectiveness. Using the factors highlighted above this study attempts to develop a model or framework as shown in Figure 2.

### Table 1: Summary of models integrated to assess factors influencing Web 2.0 effectiveness

<table>
<thead>
<tr>
<th>Author</th>
<th>Model/ Frameworks</th>
<th>Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Velada et al., (2007)</td>
<td>Simplified Training Transfer Model (STTM)</td>
<td>Transfer design, peer/organisational support, training retention, self-efficacy, feedback</td>
</tr>
<tr>
<td>Tabassi and Bakar (2009)</td>
<td>Motivation Training and performance model</td>
<td>Motivation, training and performance</td>
</tr>
<tr>
<td>Dasgupta et al., (2002)</td>
<td>Model for user acceptance of e-collaboration technology using TAM (Technology Acceptance Model)</td>
<td>Perform, use, level, perceived usefulness perceived ease of use</td>
</tr>
</tbody>
</table>

### 3 VARIABLES AND CONCEPTUAL MODEL

Based on the identified frameworks and models discussed above, a discussion of these variables, dimensions and the accompanying hypothesis for validating their relationships are presented in this section.

#### 3.1 Use of Web 2.0 tools

Learners will be more willing to use and adopt a technology if such technology possesses user friendly characteristics (Rivard, 1987; Amoroso and Cheney, 1991). The effective use of these technologies and tools by students has been reported to have a positive and significant impact on how they perceived course effectiveness (Venkatesh et al., 2014). Subsequently, the Use (U) of an Information System (IS) or technology according to Dasgupta et al. (2002) has an influence on the performance of the user. Based on a study of the adoption of an e-collaboration technology they carried out Dasgupta et al. (2002) described “Use” as the total use of the system and the use of file exchange capabilities within the system. They reported a correlation between the use of an IS to the learner's performance which they adapted from an earlier study conducted by Lucas and Spiter (1999). Lucas and Spiter (1999) tested the effect of an information technology adoption on performance; they identified two categories of users: the novice and the advanced users. The novice users are classed as those who used the system for the first time while the advanced users are those who have used the system before. Dasgupta et al. (2002) reported that there is a significant difference in actual system usage between advanced users who had used the system before and novice users who were using the system for the first time. Also they revealed that the use of an information system or technology positively affects the performance of the individual or learner.

**Hypothesis 1. There is a positive relationship between a learner's use of Web 2.0 technologies and the learner's performance or Web 2.0 effectiveness.**

#### 3.2 Instructional Characteristics

In order to gain competitive advantage it is necessary that organisations design their training to support and satisfy the needs of learners from different backgrounds and at the same time use the learning content or resources in effective ways to meet the primary goal of the training programme which, in the main, is to impart to employees a new set of KSA (knowledge, skills and abilities), behaviour or attitudes (Hong, 2008; Jayawardana and Prasanna, 2007). Leung and Tuen Mun (2006) pointed out that if training cannot be translated into both individual and organisational performance then it is useless. Learners and/or trainees are more likely to transfer the training content to the work context
when they perceive that the training program was designed and delivered in such a way that maximizes the trainee’s ability to transfer the training to the job (Holton, 1996; 2005). Consequently, Velada et al. (2007) suggested that when training instructions conform to the job requirements and trainees have a previous knowledge and practice on how to apply the newly learned knowledge and skills to the job, there is an increased likelihood of transfer. Thus, from the foregoing we hypothesize that:

_Hypothesis 2. The learner’s perception of the learning or instructional design will be positively related to the learners performance or Web 2.0 effectiveness._

The mode of delivery is an instructional characteristic that also influences the effectiveness of training. Traditionally, learning is delivered in the classroom where participants attend training in a central location where they interact face to face with the instructor and other participants (Klein et al., 2006) but in the case of mobile learning the resources or learning content is made available via electronic media. For this research we would be comparing the modes of delivery along the lines of current mobile learning which involves the delivery of read only content via the mobile device and Web 2.0 powered mobile learning which would involve both read/write content and other interactive content between the learner, the device, other learners and instructor or trainer. Klein et al., (2006) found that students in blended learning (that combines online and interactive teaching such as PowerPoint, streamed videos, self-tests, discussion boards, and chat room) were more motivated to learn as compared to the students in a traditional classroom setting (based on lectures). A search of literature returned no results on comparison made between learning delivered through mobile learning without Web 2.0 technologies and mobile learning using Web 2.0 technologies.

_Hypothesis 3. The motivation of learners using Web 2.0 technologies will be higher compared to_
those using mobile learning systems without Web 2.0 technologies.

Hypothesis 4. Learners using Web 2.0 tools will be less likely to perceive these features as enablers than learners using mobile learning systems without Web 2.0 technologies.

3.3 Work Environment

From dominant literature, researches on the influence of work environments on transfer of training have identified some notable individual factors in the work environment that influence the transfer of training. Burke and Hutchins (2007) cited the support received from peers, supervisors (management or organisation) and feedback with regards to learning as critical components of supporting the maintenance of training skills.

Support from the learner’s supervisor has been rated to be the most important and has been shown to have a positive influence on learning (Stolée et al. 2005; Burke and Hutchins, 2007). Supervisor support can be described as “the extent to which supervisors support and reinforce the use of newly learned knowledge and skills on the job” (Holton, Bates and Ruona, 2000 as cited in Velada et al., 2007, p. 286). Burke and Hutchins (2007) reported that peer support emerged as a significant relationship (B = .65, p<0.05) with skills transfer when a model of individual and organisational support for transfer was tested. Consequently, networking with peers and sharing ideas about the contents of a course helped promote skills transfer 6 months after the training (Hawley and Barnard, 2005 as cited in Burke and Hutchins, 2007). Despite the positive influence of the peers support, the lack of manager’s support back on-the-job limits this influence (Burke and Hutchins, 2007).

Hypothesis 5. Support derived from the learner’s peers and supervisors will be positively related to the learner’s performance.

Holton, Bates and Ruona (2000, p. 336) suggested that feedback “includes an indication from management about how well one is performing his or her job”. Thus, when trainees get feedback on how well they have performed by being given a chance to try out new skills that they have learnt in their work, they benefit from increased transfer of training (Boyle, 2015).

Hypothesis 6. Feedback derived from the training will be positively related to effective training.

3.4 Learners Characteristics

Research has shown that the learner’s characteristics or traits are an important factor in training and it relates to the learners’ performance (Burke and Hutchins, 2007; Cheng and Ho, 1999; Klein et al., 2006). Thus, for training to be effective the knowledge acquired from the training must be retained by the learner. Some studies have reported a positive correlation between training retention or cognitive ability and transfer of training and cited its importance in maintaining individual performance after training (Cheng and Ho, 1999; Velada et al., 2007; Burke and Hutchins, 2007). Thus training retention “is the degree to which trainees retain the content after training is completed” (Velada et al., 2007, p.285). This implies that learners who are able to retain the training content will more likely transfer their new knowledge and skills to their work. Thus we can hypothesize that:

Hypothesis 7. The learner’s retention will be positively related to workplace learning effectiveness.

An individual’s general belief that they are able to change their performance when desired is described as self-efficacy (Holton, Bates and Ruona, 2000 cited in Velada et al., 2007). Self-efficacy has been shown to influence job performance (Jayawardana and Prasanna, 2007; Liaw, 2008; Mbarek and Zaddem, 2013). Trainees with a high level of confidence in attaining anticipated performance and behaviour change will be more likely to apply what they have learned from training onto the job (Cheng and Ho, 1999).

Hypothesis 8. The learner’s self-efficacy will be positively related to workplace learning effectiveness.

Learning goal orientation is “a label used to describe the patterns of cognition and actions that result from the chronic pursuit of a mastery approach, performance-approach or performance-avoid goal over time in academic achievement settings” (DeShon and Gillespie, 2005 cited in Klein et al., 2006, p. 270). LGO has a very strong relationship with motivation to learn and course outcomes (Burke and Hutchins, 2007; Deci and Gagne, 2005). Klein et al.,
(2006) suggested that when learners have a strong LGO, they are more likely to view features as enablers rather than barriers and they focus on becoming more competent, expanding their skills, learn from experience and work toward mastery of the subject. Also Burke and Hutchins (2007) reported that when individuals were told of the training objectives in advance of training, they were more likely to transfer training to their job performance since they have a clear understanding of what knowledge is needed after training. Learners who set goals and are motivated are more likely to benefit from the training than when they are being urged to do their best.

Hypothesis 9. The LGO will be positively related to motivation.

Hypothesis 10. The LGO will be positively related to the perception of Web 2.0 tools as enablers.

3.5 Motivation

Motivation plays a very significant role in aiding learners to obtain significant benefits from a training course (Gegenfurtner et al. 2009; Tabassi and Bakar, 2009). Motivation is defined as “a trainee’s desire to learn the trained skills or technologies before and during the training and the ultimate transfer of the learned skills back to the workplace after the training” (Leung and Tuen Mun, 2006, p. 84). Motivation is a key and a critical determinant in the choices learners make to engage in, attend to and persist in learning activities (Klein et al., 2006). A low or lack of motivation can be responsible for the degree to which trainees or learners benefit from a course or training even if they have the ability to learn (Tabassi and Bakar, 2009). Past research has indicated the role of Extrinsic and Intrinsic motivational factors in predicting training or learning outcome (Deci and Gagne, 2005; Klein et al., 2006; Burke and Hutchins, 2007). Motivation has been reported to be influenced by factors such as extrinsic factors (e.g. pay and promotion), intrinsic factors (e.g. learner’s sense of recognition), individual or learner characteristics, instructional characteristics, perceived barriers and enablers (Klein et al., 2006) and work environment or transfer climate (Burke and Hutchins, 2007). Therefore,

Hypothesis 11. The effects of the use of Web 2.0 tools, the work environment, perceived barriers and enablers, learner’s characteristic and the instructional characteristics on the learner’s performance or Web 2.0 effectiveness will be mediated by motivation.

4 RESEARCH DESIGN AND METHODOLOGY

This research aims to measure the effectiveness of Web 2.0 technologies in the learning process by evaluating the individual or learner's usage of the system or technology, satisfaction and self-efficacy obtained via learning. Thus, the mixed approach would be adopted for this research since it stands to gain from either methods and will bring some rigour into the research. The strategy to be adopted would be in the main to follow the positivist paradigm by undertaking a quantitative study and using a triangulation of methods such as surveys, observations, questionnaires.

Hence, to validate the hypothesis a mobile learning environment will be developed and the adopted experimental design would be the repeated measures within-subject design (Everritt B.S., 1995; Tran Z.V, 2009; Lawal B, 2014). In this type of experimental design, the same participants are used for both the control and experimental phases of the study. This data collection process would in sum involve participants being given a pre-test and a post-test survey before and after the course respectively. An initial test would be administered during the pre-test phase of the experiment with the aim of evaluating the learners’ prior knowledge. On completion of the mobile learning course, a second test would be administered in the post-test phase of the experiment to measure the level of uptake in the course. Also this stage would involve the monitoring of the learners’ usage of the system by gathering the log files of individual users of the system.

Data collected from the experiments would be used to determine the relationships between the dependent and the independent variables in the conceptual model which would be validated using statistical techniques such as correlational analysis and parametric tests. Interviews and online surveys integrated into the mobile learning course would be employed to help answer this question. To add more rigour into the research, in-depth interviews would be conducted with policy makers and experienced practitioners in industry who are directly or indirectly involved or charged with the design and implementation of mobile learning or
learning in their respective organisations. Transcripts obtained from these interviews would aid in the development of guidelines for best practices. The survey or questionnaire would be employed to get the perception of the users on user’s satisfaction and self-efficacy. The questions on self-efficacy would be adapted from Schwarzer and Fuchs (1995) Perceived Self-Efficacy scale and Schwarzer and Jerusalem (1995) for Collective Self-Efficacy which would help in measuring the impact of the collaborative environment on the individuals in a group.

Due to the difference in the type of services and environment obtained in different industries a cross sectional study would be carried out in order to capture a snap shot of what is obtainable across different industries. Hence, industry will be categorised into two broad types: Production and Services. Recruitment from each category will consist of a minimum of 30 individuals for both the experimental and control groups, thus bringing the expected minimum total to 120 participants. The experiments should take place over three months to enable participants get used to and interact more with the technologies.

5 CONCLUSION AND FUTURE WORK

The work done in this paper is in sum a work in progress. Therefore it becomes vital that a validation by primary research of the relationships represented in the conceptual model needs to be done so that an empirically tested model which shows those factors that influence the effective use of Web 2.0 as mobile learning tools in the workplace can be presented.

The varied and dynamic nature of the work place makes it difficult to evaluate and conclude on what factors influence the effective use of Web 2.0 as mobile learning tools in the workplace. Thus using the Simplified Training Transfer model as a base, this study has attempted to discuss the potential factors that are likely to influence the effectiveness of Web 2.0 technologies as learning tools on mobile devices among workers. A future work would present the data and findings obtained from primary research.

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A Study of Devising Neural Network Based Indoor Localization Using Beacons: First Results

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Abstract: In the paper, we deal with the problem of indoor localization. There are various technologies that can generate data to be used for indoor localization. We analyze beacons, which are Bluetooth low energy transmitters. They, if installed in a building in a properly devised grid according to their characteristics, can serve as data generators for localization. We designed an artificial neural network that processes data from beacons and produces coordinates that determine the localization. Experiments show that our neural network based indoor localizator achieves accuracy comparable to other known approaches.

Keywords: Neural Network, Indoor Localization, Beacons, Bluetooth, BLE

1 INTRODUCTION

The problem of object localization and navigation has been existing for a long time. Even before the era of modern electronic devices, people used maps, compasses and starry skies. For shorter distances it was enough to remember a set of important objects in the area, due to which the orientation in space was easier. While, for the human perception system, information like "go over the brook and turn left behind a large old oak tree" is useful, it is not a suitable representation for machines (there are systems that process even image inputs. Such an approach, however, is computationally much more demanding and complicated). A common feature for people and machines remains that for localization it is necessary to know the position of any reference points. Their position has to be constant or at least calculable. These reference points may be for example satellites. Outdoor localization works thanks to them. Several satellite-based navigation systems are already deployed worldwide, for example the global positioning system (GPS), with its European variation Galileo and Russian variation GLONASS. They can operate and supply users with precise locations anywhere in the world. Provided there is an unobstructed line of sight to three or more satellites (Hofmann-Wellenhof 2012, Samper 2008). Indoor localization is however an unsolvable task with satellite-based technology due to the characteristic of the satellite signal which cannot penetrate dense objects, such as roofs, walls or terrain. Even indoor localization still needs a set of reference objects. Usually they are signal transmitting devices with a static position. This position as well as the way and the strength or time of signal transmission are fundamental and indispensable data that localization module needs in order to calculate the object position. These devices operate with different types of signals; in recent times it is usually

- Bluetooth (Wang 2011, Oksar 2014),
- GSM (LaMarca 2005) or
- other types of wireless signals (Curran 2011).

Since this is still the same problem, all types of signals (or in combination) can be processed using the same methods. Researchers have developed many different methods and approaches on how to effectively and accurately localize objects (Curran 2011, Hightower 2001, Wang 2011). Unfortunately, there is no objective way of how to compare the various algorithms of various works with each other, because the accuracy of location method depends mainly on

- the deployment of equipment (the distance between the transmitters, the coverage area of the transmitters),
- the characteristics of the transmitted signal (the signal strength, signal range, frequency of signal transmission, etc.) and
- the number of samples per location - for one run of calculation (preprocessing can also be included).

The rest of the paper is organized into 5 sections. Section 2 presents basic concepts of Bluetooth beacons. Section 3 mentions related work in the area of indoor localization. In Section 4, we report on the measurements that we conducted with beacons to analyze their properties. In Section 5, design and experiments with our neural network indoor localizator based on beacons are presented. Finally, Section 6 briefly discusses conclusions and future work.

2 BLUETOOTH BEACONS

Bluetooth beacons are in general low power consumption and low cost transmitters which notify other devices of their presence. These beacons utilize
Bluetooth protocol to periodically send short messages - advertisements to the surroundings. These messages contain the beacon identification data and can send also additional data like temperature, humidity or data from other types of sensors.

We can define three basic attributes of beacons - transmitting power, advertisement interval and battery lifetime. Transmitting power is measured in logarithmic scale dBm. The more power the transmitter gets, the stronger the signal is and the further it can reach. According to Bluetooth specification documents, there are three classes of transmitting power - class 1 (20 dBm), class 2 (4 dBm) and class 3 (0 dBm). However, in commercially available beacons the user can usually set the power according to his needs, not necessarily to the power of the mentioned classes. Transmitting power has a significant influence on battery lifetime.

Advertising interval can be set in the range from few milliseconds to few seconds. Every time this interval is met, the beacon advertises its message to the surroundings via its antenna. The advertising interval has huge influence on battery lifetime. However with shorter intervals the devices can receive beacon’s signal more often and more reliably. This means faster data gathering which leads to faster localization as a tradeoff of shorter battery lifetime.

Beacons can be powered by one of the two sources - either directly from electric grid or from built-in battery. Of course, various types of batteries exist, which do have significant influence on the lifetime of the beacon. We note that on average the manufacturers claim the beacons to have the lifetime of few months to 2-3 years of continuous interval Bluetooth signal advertising.

The beacon advertisement message is represented as a stream of bytes, which can be translated at least into the following properties:

- 6 bytes long MAC address
- 16 bytes long Universally Unique Identifier (UUID)
- 2 bytes long major value
- 2 bytes long minor value
- 1 byte of calibrated received signal strength indicator (RSSI), which the receiver should measure 1 meter from the beacon

The advertisement message can contain also additional properties, including the battery status, temperature, humidity or data from other sensors. In commercially available Bluetooth beacons the user can usually change the UUID, major and minor values. This is done purely for the ability of identification of the beacon and aligning it with the physical placement of the beacons (e.g. major value can represent the floor the beacon is on and the minor value can represent beacon ordinal number on that floor).

3 RELATED WORK

In their well-informed overview of indoor localization techniques Hightower and Borriello claim there are three main approaches to this problem (Hightower 2001).

The first one is triangulation, which utilizes the geometric properties of triangles to compute object location. This approach can be divided into two subcategories - lateration and angulation. Lateration is based on distance measurements (or estimations) from multiple reference points. Calculating the position in n dimensional space requires n+1 reference points. Angulation approach is similar to lateration, but it uses angles instead of distances to locate an object in space.

The second approach is based on scene analysis utilizing computer vision methods. Static scene analysis relies on detecting the features in the static scene and comparing them with the database, whereas the differential approach tracks the difference between successive scenes.

The final approach, which is also the topic of this paper relies on proximity location sensing. This is done either with physical contact or by making use of wireless signals.

Bahl et al. (2000) used signal from Wi-Fi access points to estimate user’s location in the building. They exploited the fact that the signal strength from the access points did not vary significantly in one location. They developed the first fingerprinting approach to in-building localization and achieved an average error of 2-3 meters by using k-nearest neighbors clustering algorithm onto the gathered data.

LaMarca et al. (2005) describe in their paper the possibility to combine the information about GSM, Wi-Fi and Bluetooth (BT) transmitters into the database. They used Bayesian particle filter on the collected data to estimate user’s location. Having created the sufficiently dense network of transmitters, by using Wi-Fi transmitter data only, they achieved a median error of 20-30 meters, whereas by using GSM data only they achieved accuracy of 100-200 meters. By combining Wi-Fi and GSM data they could localize the user with the error of 20 meters. They experimented in three different environments - urban, residential and suburban, which yielded the worst results because of low density of transmitters.

Wang et al. (Wang 2011) describe the use of particle filtering (Hightower 2004) and fingerprinting (Bahl
algorithm to combine data from Wi-Fi and BT transmitters inside of a building. The fingerprint data was gathered on a 3x3 meters grid. They could achieve an average error of 2.9 meters with maximum error of 8.9 meters. By using solely Wi-Fi data, the average error was 3 meters with maximum of 9.4 meters.

Ahmad et al. in their work (2006) on indoor localization employed Modular Multi-Layer Perceptron (MMLP) technique to provide better location estimates than other approaches. The authors collected 300 samples of Wi-Fi signal strengths for each of the reference points in their building, which were approximately 2-3 meters apart. Then the data was divided into training and testing datasets and used to train a classification neural network in various configurations. The best result they could achieve was by using a 3-8-8-1 structure, by using logsig and tan transfer functions and Levenberg-Marquardt training algorithm. Average error in this configuration was only 0.12 meters with maximum error of 2.16 meters. Although these results are extremely good for Wi-Fi signal, we cannot assume the same for Bluetooth beacon signal. Due to some inferior properties - mainly much lower transmitting power, we expect to get similar or worse results.

4 BLUETOOTH SIGNAL MEASUREMENTS

Bluetooth operates in the unlicensed 2.4 GHz band which has become useful due to the possibility of high data transfer rates. However, this part of the spectrum is used by many devices including Wi-Fi networks, car alarms, Bluetooth devices and even microwave ovens. This clearly poses a problem, because of their possible interference (Wysocki 2000).

We decided to do an experiment to find out how Bluetooth signal from different beacons behaves in different environments. At the time of the experiment we possessed two types of beacons shown in Table 1.

<table>
<thead>
<tr>
<th>Table 1. Two beacon types used in experiment.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beacon 1</td>
</tr>
<tr>
<td>Power</td>
</tr>
<tr>
<td>RSSI at 1 meter</td>
</tr>
<tr>
<td>Advertising interval</td>
</tr>
</tbody>
</table>

We placed the beacons one at the time in two different environments – an open hall and a narrow hallway. We believe that this setup is completely different in terms of signal propagation. In the open hall the signal can be radiated to the whole space, but in the corridor it will interact with walls and other possible obstacles. Before the measurement, we made sure that in the areas there are no people or any foreign objects. Then we proceeded to measure RSSI with a handheld smartphone device at 1 meter and gradually stepped up to 15 meters from the beacon. At each point of measurement we collected 100 samples. Then, according to Oksar (2014) we noted the maximum RSSI and plotted the graphs. We chose this high number of samples because we wanted to find out whether the same model of signal propagation can be used for different environments. In real user localization scenario, we would have to use lower sample count due to the time needed to collect them.

The results of the measurements are shown in Figures 1 and 2. As we can observe, the RSSI decreases with the distance. The theoretical RSSI at a given distance is calculated from the calibrated RSSI at 1 meter given by the beacon manufacturer by the use of inverse-square law which applies to electro-magnetic radiation. However, according to the measured data, the signal of USB-powered beacon fluctuates heavily and is influenced by the environment it is in.

![Fig. 1. Graph showing RSSI drop of battery-powered beacon in two environments and a theoretical RSSI decrease.](image1)

![Fig. 2. Graph showing RSSI drop of USB-powered beacon in two environments and a theoretical RSSI decrease](image2)

One more factor which may influence the strength of transmitted signal is the battery charge status. It might be possible that the beacons with almost depleted batteries will transmit less powerful signal which will influence the accuracy of localization. Unfortunately, we did not conclude any experiments so far to prove or disprove this theory.
5 NEURAL NETWORK DESIGN AND OPTIMIZATION

The goal of our work is to estimate the location of the user based on the RSSI of beacons in the vicinity by using a properly devised artificial neural network. We chose this approach because of the promising results with the Wi-Fi signal in the paper (Ahmad 2006).

The design of our neural network reflects the nature of the task. It is quite straightforward to use the architecture of a multilayered perceptron neural network. The input layer is obviously determined by the data registered from beacons. The output layer consists of two neurons determining normalized x and y coordinates in the building. We started with a single hidden layer composed of a fixed number of perceptrons. Determining that number to be optimal will be one of the objectives of the next experiments to be described subsequently.

5.1 Four beacon experiment

We decided to conclude the first experiment on the south wing of the 2nd floor of our university building with four Bluetooth beacons. Three beacons were USB-powered beacons and one battery-powered. We designed a 4x4 meters grid on which we performed fingerprinting of RSSI from all four beacons using a handheld smartphone device. This way we gathered 10 samples from each location. Each sample consisted of 10 measurements from which the maximum value of RSSI was taken. We chose 10 measurements because of the similarity to the real user scenario. Ten measurements take about 1-2 seconds to collect and process, which means we can use this approach to localize semi-static target in a real environment.

The beacon locations and the associated heat maps are shown in the Fig. 3. The gathered data was preprocessed for the use of neural network training. We used Encog Machine Learning Framework for the learning phase.

The input data consisted of four real RSSI values from all of the beacons, and the output data represented x and y coordinates on the building floor. Point zero was set in the middle of the hall opening. All values were linearly normalized to the interval from 0 to 1, which means that upon receiving the results from output neurons, we will have to denormalize them to find out the actual x and y coordinates. The whole dataset was divided into the training set (75%) and the testing set (25%).

We trained more neural network configurations. The training algorithm was resilient backpropagation in all cases and the target error goal was set to 0.1 %, which was reached in all the cases. We primarily used two transfer functions inspired by Ahmad (2006). The number of neurons in the hidden layer was recommended by the Encog Framework, but we plan to conclude more testing in this aspect according to the best practices. The results are shown in Table 2.
The average error in all the configurations is in the interval of 2-3 meters. One of the possible reasons for this result may be the characteristic of the three USB-powered beacons.

In the next experiment we wanted to simplify the experiment area, use more and better quality beacons from a well-known manufacturer, increase their transmitting power and advertising intervals.

5.2 Nine beacon experiment

The second experiment was held in a 36 meters long corridor. The y coordinate was set to zero. This time, we used 9 battery-powered beacons from a well-known manufacturer kontakt.io which were placed approximately 4 meters aside behind glass panels over the doors. The beacons were set to the highest possible transmission power level of 4 dBm and according to the datasheet, the calibrated RSSI at 1 meter from the beacon is -59 dBm. The advertising interval was set to 100 milliseconds.

This time we gathered 20 samples from each of the 36 locations 1 meter aside. Each sample, as in the previous experiment, consisted of 10 measurements of RSSI of all 9 beacons, from which only the maximum RSSI values were noted.

As in the previous experiment, the data was preprocessed - normalized and segregated. The training algorithm was resilient backpropagation in all the cases and target error goal of 0.1% which was reached. The results are shown in Table 3.

Table 3. Results of various configurations of neural networks in the second experiment.

<table>
<thead>
<tr>
<th>Network structure</th>
<th>Transfer function</th>
<th>Average error</th>
<th>Maximal error</th>
</tr>
</thead>
<tbody>
<tr>
<td>9-15-2</td>
<td>Log</td>
<td>1.42 m</td>
<td>7.41 m</td>
</tr>
<tr>
<td>9-15-2</td>
<td>Tanh</td>
<td>1.37 m</td>
<td>14.60 m</td>
</tr>
<tr>
<td>9-15-15-2</td>
<td>Log</td>
<td>1.21 m</td>
<td>5.98 m</td>
</tr>
<tr>
<td>9-15-15-2</td>
<td>Tanh</td>
<td>1.25 m</td>
<td>6.52 m</td>
</tr>
</tbody>
</table>

We also tried to reduce the dataset by one half - we selected only those even coordinated. Results of reduced dataset are shown in Table 4, which are very similar to the results of non-reduced dataset.

In this experiment we could achieve the average error of 1.2 to 1.5 meters across all the configurations. However, as we can observe, the hyperbolic tangent (tanh) transfer function performed much worse in terms of the maximal error - up to 14 meters.

Table 4. Results of various configurations of neural networks in the second experiment using reduced dataset.

<table>
<thead>
<tr>
<th>Network structure</th>
<th>Transfer function</th>
<th>Average error</th>
<th>Maximal error</th>
</tr>
</thead>
<tbody>
<tr>
<td>9-15-2</td>
<td>Log</td>
<td>1.24 m</td>
<td>4.24 m</td>
</tr>
<tr>
<td>9-15-2</td>
<td>Tanh</td>
<td>1.52 m</td>
<td>9.66 m</td>
</tr>
<tr>
<td>9-15-15-2</td>
<td>Log</td>
<td>1.48 m</td>
<td>5.71 m</td>
</tr>
<tr>
<td>9-15-15-2</td>
<td>Tanh</td>
<td>1.53 m</td>
<td>6.15 m</td>
</tr>
</tbody>
</table>

However, if our approach would be used in a real life situation of a semi-static object, the accuracy could be slightly worse due to the movement of the object, which would cause signal variance in the samples. We cannot evaluate this situation yet because we do not possess a device capable of accurately showing the actual position of it in time and that way we cannot compare our results with real ones.

6 CONCLUSION

We defined the problem of accurate indoor localization and analyzed the possibilities of using Bluetooth beacons. We performed basic Bluetooth beacon signal analysis and compared it to the theoretical model. We devised a neural network to yield coordinates for indoor localization. As a part of our design methodology, we performed two experiments to determine suitable neural network parameters and to evaluate its performance. First results of our experiments show that our approach has an acceptable localization accuracy compared to the other Bluetooth based solutions. We will continue with further research of this topic and try to achieve even more accurate localization.

Table 5. Comparison of localization accuracy.

<table>
<thead>
<tr>
<th>Solution</th>
<th>Transmitter type</th>
<th>Number of neighbors</th>
<th>Algorithm</th>
<th>Samples per location</th>
<th>Average error (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RADAR (Bahl 2000)</td>
<td>Wi-Fi</td>
<td>3</td>
<td>k-nearest neighbors</td>
<td>40</td>
<td>2.65</td>
</tr>
<tr>
<td>Rice University (Ladd 2002)</td>
<td>Wi-Fi</td>
<td>9</td>
<td>Bayesian inference</td>
<td>100</td>
<td>1.50</td>
</tr>
<tr>
<td>Kyung Hee University (Ahmad 2006)</td>
<td>Wi-Fi</td>
<td>3</td>
<td>Classification neural network</td>
<td>300</td>
<td>0.13</td>
</tr>
<tr>
<td>Fusion (Wang 2011)</td>
<td>Wi-Fi</td>
<td>?</td>
<td>Bayesian filtering</td>
<td>700</td>
<td>3.03</td>
</tr>
<tr>
<td>Fusion (Wang 2011)</td>
<td>Wi-Fi + BT</td>
<td>?</td>
<td>Bayesian filtering</td>
<td>700</td>
<td>2.91</td>
</tr>
<tr>
<td>ASELSAN (Oksar 2014)</td>
<td>BT</td>
<td>6</td>
<td>RMSE</td>
<td>?</td>
<td>2.31</td>
</tr>
<tr>
<td>our best attempt</td>
<td>BT</td>
<td>9</td>
<td>Regression neural network</td>
<td>20</td>
<td>1.21</td>
</tr>
</tbody>
</table>

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