Enhancing the Affective Sensitivity of Location Based Services Using Situation-Person-Dependent Semantic Similarity

Antonios Karatzoglou[1,2], Michael Beigl[2]

[1]Robert Bosch GmbH
Corporate Sector Research and Advance Engineering, and
[2]Karlsruhe Institute of Technology
Germany
Email: antonios.karatzoglou@de.bosch.com, antonios.karatzoglou@kit.edu
Email: michael.beigl@kit.edu

***Abstract*—Location prediction plays a steadily growing role in Location Based Services (LBS), as these try to be more proactive and improve in this way the quality of service provided. Although recent location prediction systems go beyond just location data and build upon a wide range of models that describe semantic locations and personal preferences, none of them considers locations from the view of the user. Moreover, none takes into account the variance in people's way of perceiving and understanding concepts (locations in our case) depending on the situation. Minsky referred to this as (cognitive) *frames*. This paper posits that a dynamic semantic-similarity-based clustering of locations can be used for mining such location-specific frames, e.g. the varying meanings that people give to locations over time depending on the situation, their personality and their emotional state. The resulting situation-person-specific frames can in turn be used to enhance the location prediction.**

***Keywords*–LBS; Location Prediction, Ontologies, Dynamic Semantic Similarity, Personality Traits, Emotional State, Personalization, Cognitive Frames.**

I. Introduction

Emerging context-aware systems and applications are capable of offering intelligent and personalized services that are tailored to the users and their current environment. Recently, in order for such systems to provide an even better quality of service to the users, developers aim at making them more *proactive* by giving them the ability to take the initiative, instead of just reacting. This is attempted by applying various context prediction techniques. Location represents a particularly important context information type. There exist numerous applications and services by now, so called *Location Based Services (LBS)*, that are premised on the users' current or future location, like location-based advertising and marketing. Social networks experience nowadays a significant upgrade as well through utilizing the current location of their users. In this case these are referred to as *Location-Based Social Networks (LBSNs)*. The location information is provided either manually by the users (e.g. Foursquare [1]) or sensed automatically from the users' personal devices. Furthermore, predictive location awareness can also contribute to a more efficient resource management, e.g. in intelligent navigation and traffic management scenarios or in communication networks.

Location reveals not only the *whereabouts*, but also the *what*, the *when* and eventually the *who* you are. By knowing the location, we humans are able to extract even more information than just the location itself; information that can be used to model and identify behavioral patterns. So, we could, for instance, derive a certain activity (*what*) related to a particular location, or the time of visit (*when*). Moreover, we humans could even draw conclusions regarding the users' temporary mental state and their overall personality profile (*who*) from *knowing their locations* and how they move between them. Vice versa, by knowing all this "metadata" about a person, we could assume to be able to provide an at least rough estimation about her current or future location. Nathan et al. support this theory by interpreting movement as the outcome of the synergy of four components [2]: the internal state of the individual, its motion capacity, its navigation capacity and potential external factors, whereby *internal state* addresses the reason and the motive for the individual to move and visit a certain location, which in turn reflects his/her needs, preferences and personality.

The key phrase here is *knowing the location*. Knowledge is defined as [3]:

> Facts, information and skills acquired through experience or education; the theoretical or practical understanding of a subject

So, each and every type of knowledge acquired by a person refers to the result of personal experience and interpretation. In the special case of location information, this can be interpreted as follows:

> The same place or location has potentially a different meaning to different people

For example, while a guest normally sees in a *restaurant* a place to eat, the same restaurant stands for a working place to the cook working there. Moreover,

> A place may even have many different meanings to the same person depending on the situation and/or her mental and emotional state

People tend to employ *cognitive frames* in order to interpret their experiences [4]. Minsky introduced first in [5] the concept *frame* in the 1970s' as a dynamic structure to be used when *"one encounters a new situation or makes a substantial change in one's view of the present problem"* underpinning our statement. For example, a *company building*, which is usually sensed as a working location, turns into a space of leisure and entertainment during the firm's Christmas party. Similarly, the location *hotel* is usually strongly correlated with a stay over the holidays by a tourist, while it is perceived as a place of work for someone working there as a bellboy or for someone who often visits conferences and/or has business lunches there. Furthermore, a person that enjoys having a drink at the bar of a particular hotel in his hometown (without necessarily being a guest) and a person that makes use of the hotel's Sunday's brunch offer, would associate a hotel on one hand more with night life locations, like a bar or a club, and on the other hand more with a cafe or a restaurant, respectively. A preliminary user study in which we asked 20 people to interpret various locations on their daily routes confirmed the dynamic nature of how people perceive locations. This varying perception of locations could be used to enhance location prediction.

The majority of the existing location prediction systems rely on statistical and machine learning based algorithms in order to estimate the current or predict the future location of a user. These systems recognize and model regularities in the movement patterns of one or more users to provide their estimations. Some use solely recorded trajectories (sequences of locations in form of Global Positioning System (GPS) coordinates or cell IDs and time), while other utilize further information, such as transportation mode and proximity of social contacts among others. However, these systems come with two major drawbacks; first, they are a black box to the user. The users don't really have insight into the estimation mechanism. Second, they work only at that particular regions well, for which they have been trained for. Recently, a new generation of location prediction systems tries to overcome these shortcomings through the use of semantics and so called *semantic trajectories*. The corresponding algorithms yield good results even in regions or cities that users have never visited before and offer (human-understandable) transparency at the same time. Under normal circumstances both approaches are capable of providing good, yet perfectible results. This is principally due to both their incapability of handling irregular human behavior and exceptional situations, as well as to the lack of flexibility and dynamics in their semantic knowledge representation of locations in their models, which makes them incapable of covering the varying perception of locations mentioned before.

We hypothesize that a *dynamic and stochastic semantic-similarity-based clustering* that takes both the person herself, as well as the current situation into consideration when grouping locations, instead of just categorizing them into fixed hierarchies, can lead to capturing the *person-situation-dependent varying perception of locations*, and consequently to a more accurate estimation of the users' intention to visit a certain region or location. Here, *person* refers, on one hand, to the users? preferences and interests, and, on the other hand to their personality traits, while *situation* includes both context information (time, certain event, purpose of visit, activity, etc.) and mental state of the users. Our hypothesis could also be expressed by the following two propositions:

- *Dynamic semantic similarity can be used for mining location-specific (Minsky's) cognitive frames from the user's semantically enriched and ontology-structured context & tracking data,* and
- *A (cognitive) frame-based location prediction yields higher prediction accuracy*

We aim at modeling the variety in people's way of seeing and understanding things (locations in a first case) in order to achieve a higher adaptivity and personalization on the part of the application. After all, what is more personal and human, than the trait of changing our point of view about things, sometimes more and sometimes less, depending on the moods and the events of the day?

This paper is structured as follows. Section II gives a brief summary of the related work. Next, in Section III we describe in detail our approach. Finally Section IV and Section V provide a preliminary evaluation and our conclusions respectively.

II. State of the Art

According to Glassey and Ferguson [6], there exist four representation model types for describing locations: The *geometric*, the *symbolic* the *hybrid* and the *semantic* model that considers the relationship of entities in space among others. Our work concentrates on the *semantic-enhanced location prediction*. Usually, systematic approaches that leverage semantic information for destination prediction base on trajectory mining and analysis, but there exist also other ways for incorporating semantics as we shall see next.

Ying et al. [7] introduced one of the first semantic trajectory mining based approaches, which is based on a Geographic Semantic Information Database (GSID) in order to have the recorded GPS or Cell-ID trajectories semantically enriched. Patterns mined in the resulting trajectory data base are in turn converted into *Semantic Pattern Trees* to finally provide the next place prediction. In [8], they extend their approach by taking temporal information into account as well. Samaan et al. describe buildings and road network elements semantically by using *spatial conceptual maps* in [9]. Furthermore, they utilize a context knowledge base formulated in XML, which contains the users' preferences, schedule, tasks and goals among others, to leverage their system's performance. The underlying algorithm is probabilistic, based on the Dempster-Shafer Theory (DS-Theory). In [10] and [11] they illustrate the same algorithm, only that now, the locations are represented by Cell-IDs assigned by the corresponding cell towers. Ridhawi et al. follow in their work, [12] and [13], a similar direction for improving their indoor tracking and prediction algorithm. Their system uses the Dempster-Shafer Theory as well, but, in contrast with Samaan et al., the knowledge is structured and stored by means of *ontologies*. These include profiles of users, their location history and some activities. Wannous et al. base their framework also on an *ensemble of ontologies*, as well as on a set of *rules* in order to represent and estimate future movement and activity patterns of marine mammals [14]. They defined their rule base with the help of a group of experts and subdivided it into a spatial, a domain-specific and a temporal set of rules, respective each time to the applied ontologies.

Long et al. base their work, [15], on a probabilistic model called Latent Dirichlet Allocation (DLA). DLA is used in text mining and takes the documents' topics into account in order to cluster these accordingly. Long et al. use DLA to extract so called *geographic topics* from the text entered by Foursquare users in their check-ins based on their popularity. By using these geographic topics, their system becomes more adjustable, since in this way, they move away from a static location categorization, like the one provided by Foursquare. Krishnamurthy et al. rely their work on a social network as well [16]. They analyze the Tweets of Twitter [17] users to predict their locations. Specifically, they define a metric (*localness*) to formulate the vicinity of special terms (*local entities*), which appear in Tweets, to particular geographic regions or towns. Various measures including two semantic relatedness measures, the *Jaccard* and the *Tversky Indices* were examined for this purpose. By determining all localness scores between geographic regions and the corresponding local entities in the Tweets of a user, they are finally able to provide an estimation of the location of the users.

Mabroukeh et al. explore a semantic-enhanced method in order to mine Web usage patterns and to be able to predict the next visited Web page at the same time [18]. They use *semantic relatedness* to adjust their probabilistic model accordingly in order to raise the prediction performance. In [19], a *time-dependent semantic similarity measure* is introduced by Zhao et al. for describing the dynamic nature of Web search queries over the time. In addition, they place their trust in a probabilistic similarity measure that reflects the Web queries' frequency distribution.

The person-situation debate addresses the challenging question of what influences the humans' behavior at most; is it their personality or the situation in which they find themselves? While *personality trait theorists* believe that people's behavior is guided by consistent and stable in time traits (habitual patterns of behavior, thought, and emotion [20]), *situationists* argue that people are rather inconsistent in their behavior depending on the situation [21]. Meanwhile, current behavior researchers accept that both of them contribute to a person's behavior [22]. Buss states further that the effect of personality on behavior depends on the situation and vice versa [23]. Numerous works exist, which pursuit and substantiate this subject like Jacquard's [24] and Borkenau's [25]. Therefore, one could easily assume that knowledge of both personality and situation, as well as their interrelation, builds a solid prerequisite to predict one's behavior and intentions. *In this paper, we claim that this fact could be further exploited for raising the location prediction accuracy.* On the other hand, there exists research that goes in the opposite direction as well. Adali et al. and Staiano et al. attempt for instance to infer the personality from the behavior [26] and the social network structure [27], respectively.

All existing location prediction approaches constrain themselves to static location definitions and hierarchies without considering the users' varying perception of locations over time and situation. This leads to non-adaptive and thus perfectible location modelling and prediction algorithms.

III. PROPOSED APPROACH

The location prediction framework that we propose in this paper is illustrated in Fig. 1. Our approach is hybrid and consists of two parts. One part takes over the semantical processing of the input stream (top branch), while the other one takes charge of the actual users' future location prediction (bottom branch).

Recorded data like location and time (e.g., GPS readings), low level activity (e.g., through accelerometer and gyroscope measurements) and biometric data (e.g., pulse, perspiration), together with user-specific high level data retrieved either directly through the users' feedback or indirectly from their calendar, e-mail and social media communication data, are being fed to two separate paths simultaneously (top and bottom branch respectively). On one hand, these are being semantically annotated and stored in our so called Semantically Annotated Database (SADB). The annotation takes place semi-supervised partly by the user (through an Android app running on the smartphone or the smartwatch), partly by utilizing a (geographic) Linked Open Database (LODB), like the OSMonto [28], and partly through an internal loop considering the existing ontology so far, as well as the similarity analysis taking place in a next step. The annotated data are then used to propagate our Ontology-Suite-based Knowledge Base (OSKB) described in III-A. The reasoner attempts to derive the current mental state and the overall personality of the user from the available data among others and plays therefore a significant role (see III-C) in order to achieve our goal of correlating locations with the users' experience and building that way location-specific cognitive frames. PSSSA is the core component of our approach and refers to the *Person-Situation Semantic Similarity Analysis* component. It is responsible for awarding our approach with a highly personal and human-like dynamic view of locations at anytime. Details about PSSSA can be found in Section III-B. The bottom branch of our framework includes the actual location prediction model. This could be for instance a probabilistic graph, as the Markov model we use at this phase. But other machine learning based prediction models like Artificial Neural Networks (ANNs) are also to be considered and shall be explored in the future. The prediction model is first being trained with the available data. In a next step, the trained model is being optimized through the customization of its (previously learned) parameters by taking the current semantic similarity scores of the locations into account. Section IV provides a brief description of the customization process based on a Markov Chain model. Finally, the customized PSSSA prediction model estimates the users' future location.

A. Ontology suite

We propose a modular ontology that consists of following five major ontologies:

1) Spatial ontology
2) Location ontology
3) Activities & Actions ontology
4) Person, Personality & Mood ontology
5) Temporal & Event ontology

The Spatial ontology describes core geospatial concepts and properties, like *building, park, street, etc.* and *close to, near, etc.*, respectively. The Location ontology represents a taxonomy of various location types, like *night life locations, club, bar, restaurant, dinner, fast food restaurant, etc.* The Activities & Actions ontology includes both complex activities, as well as elementary actions of which they are composed. A complex activity represents in our case a high level purpose of visiting a certain location. For instance, the activity *celebrate a birthday* covers the actions *meet friends, meet family, eat, drink, etc.* Person, Personality & Mood ontology profiles the user. This ontology models the user from both a "shallow", as well as a "deeper" point of view and comprises demographic information (*age, sex, profession, etc.*), hobbies and interests up to personality traits (*extroversion, openness, etc.*) and mental states (*emotions, moods, ...*) respectively. In both last two cases, our focus lies on features that can affect the social and particularly the movement behavior of the user. Our personality and mental state models build upon the work of Vidacek-

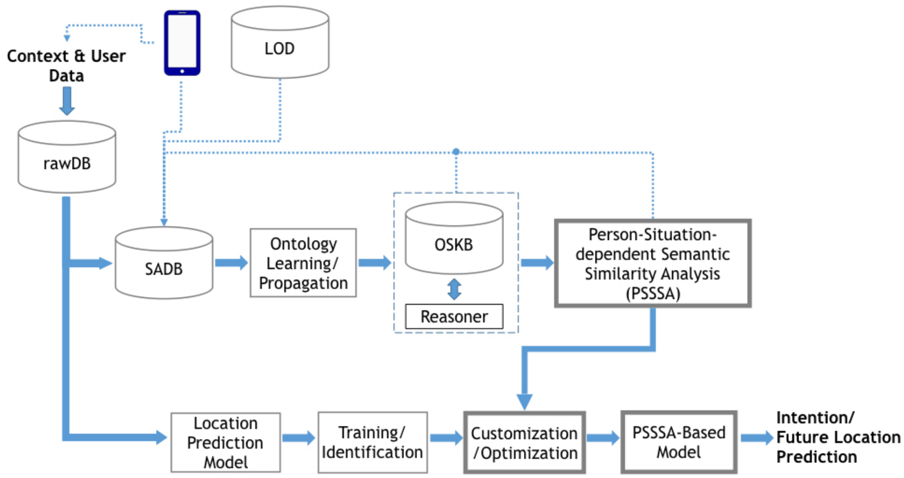

Figure 1. Situation-person-dependent semantic-similarity-based location prediction framework, whereby SADB refers to Semantically Annotated Database, OSKB to Ontology suite Database and PSSSA to Person-Situation Semantic Clustering of Locations respectively.

Hains et al. [29] and Hastings [30] respectively. Finally, the Temporal & Event ontology describes time from a human point of view, considering a human-like time granularity. Beside time in general, a particular attention is paid to the temporal entity event, which refers to special events like *anniversaries, birthdays, public holidays, etc.* that are strongly related to irregular behavior.

The ontology ensemble is instantiated by the users data. For the moment, changes in their lives, like moving to another town or streets, must be stated explicitly by the users. However, we plan to use online pattern mining algorithms to detect such kind of changes in the users' regular movement patterns and update our ontology base automatically.

B. Semantic similarity & probabilistic approach

Our goal is to capture and encapsulate the varying human perception of locations in order to cluster them in a more personalized manner based on the users' current experience. The general idea is to build *location-specific cognitive frames* by tying together situation, purpose of visit, activity, mental state of the user, his/her personality traits and locations using semantic similarity measures. These resulting location-specific frames will engender a dynamic and highly personalized method of modeling and storing location information. Beyond that, the usage of such location-specific frames complies to the Ontology Design Pattern (ODP) method [31], whereby such objects are used to encapsulate complex knowledge and/or to overcome the *n-ary relation* representation issue in the Web Ontology Language (OWL).

There are two different ways of specifying to what degree one term associates with another. On one hand *semantic relatedness* determines the relation between two concepts. On the other hand, *semantic similarity* refers to how similar, how likely two concepts are. For instance, a car is *related* to its driver but rather *similar* to another vehicle like a truck. The Person-Situation Semantic Similarity Analysis attempts to mine dynamic similarities between locations that vary in relation to the current situation, the personality and the mental state of a user. To this end, it mines and makes use of the interconceptual semantic relatedness between the respective locations and other classes/concepts in the ontology suite (like the activities and time). Even locations, which normally do not belong to the same type, can find their way in such situation-person-depended groups. For instance for a user that is jogging in a park, the *park* gets semantically closer to a *gym* than usual. We propose a hybrid and stochastic semantic similarity measure that takes both the topology, as well as the eventual underlying uncertainty into consideration. Thus, our proposed similarity metric consists of the following four parts:

1) *Topological similarity measures* are applied on ontologies and consider on one hand the relations between locations and the type of relation itself (edge-based measures) and on the other hand the surroundings of the locations (node-based measures). Wu & Palmer in [32] propose with the formula (1) an edge-based similarity measure that takes depth into account as well, providing by this means better results. The fact that it is already normalized and can never be zero serves additionally our overall framework because the similarity scores are used to adapt the parameters of the location prediction model. A zero could lead to "broken" inference chains.

$$S_{W\&P} = \frac{2 * depth(LCS(l_1, l_2))}{length(l_1, l_2) + 2 * depth(LCS(l_1, l_2))} \quad (1)$$

- *LCS*: Least Common Subsumer
- *depth*: Length from a node up to the root
- *l1, l2*: 2 locations

Lin [33], on the other hand introduced a similarity measure based on the information content:

$$S_{Lin} = \frac{2 * logP(LCS(l_1, l_2))}{logP(l_1) + logP(l_2)} \quad (2)$$

- $-logP(l) = IC(l)$: *Information Content* of location l in the corresponding ontology

2) A particularly important type of similarity measures for our work are the so called *feature-based similarity measures*. These measures define similarity based on the set of common features between two objects (locations in our case). The Jaccard Coefficient, adapted

for our case in (3), is such a measure:

$$S_{Jaccard} = \frac{|l_1 \cap l_2|}{|l_1 \cup l_2|} \quad (3)$$

- $|l_1|$ and $|l_2|$: Feature sets of locations l_1 and l_2 respectively

The features are in our case both user-dependent, such as purpose of visit and correlated emotions (among others), and user-independent, like time of day.

3) At the same time, we plan to treat the available sensor input data as text and the daily semantic enriched trajectories of the user as sentences about locations and project them onto a *vector-space model*. This can help us to learn and to determine non-predefined similarities from the data in an unsupervised manner by analyzing the frequency distribution of locations and their properties in the ontology (statistical similarity). Latent semantic analysis and cosine similarity in combination with term-frequency-inverse document frequency (tf-idf) adjusted to our case would be a solid basis to begin with.
4) Finally, a conditional probabilistic kernel, such as the marginalized kernel from Tsuda [34], will be employed to counteract on one hand the "soft" categorization of locations mentioned in Section I and on the other hand the general underlying uncertainty in humans' behavior. Kernels represent principally the similarity between two objects (in our case locations) and is defined as the dot product in the feature space. Tsuda's kernel employs both visible and hidden information for its calculation.

By fusing the above four types of similarity measures, we expect to overcome the single drawbacks that come when each of them is used alone. In tangible terms, our plan is to implement and evaluate each of them separately first. Then, the best of them will be selected and incorporated into our algorithm. Majority voting and/or a hierarchical decision making process shall be considered and investigated for determining the final similarity score.

C. Social behavior from personality and mental state and vice versa

Our focus rests on the group of personality traits and mental states that correlate stronger with the disposition for changing between locations. There are two directions one can go and we plan to consider both. On one hand, we want to derive movement behavior and consequently locations from them. This is done indirectly by taking them into consideration at the semantic clustering process mentioned in the previous Section. On the other hand, we want to use the available data to infer these automatically in the first place. Here comes axiomatic or rule-based reasoning into play. The rules shall regard all available information and knowledge at the time of the inference process. Two simplified Semantic Web Rule Language (SWRL) [35] rule examples in a human readable syntax are shown below:

$$Person(?p) \wedge hasHighWorkload(?p) \implies hasStress(?p)$$

and

$$\begin{aligned}&Person(?p) \wedge PersonalityTrait(?t) \wedge introversion(?t)\\ &\wedge hasPersonalityTrait(?p, ?t) \wedge Situation(?s)\\ &\wedge hasCurrentLocation(?p, ?l) \wedge isPArk(?l) \wedge isAlone(?p)\\ &\implies hasStress(?p)\end{aligned}$$

The second rule describes implicitly the assertion that an introvert person, in contrast to an extrovert one, seeks more probably space and distance when he feels he is stressed, rather than company.

IV. First Results

A first light draft of our ontology suite has already been implemented in OWL2 with Protege [36]. At this stage, it consists of four of the overall five aforementioned major ontologies; the Location, the Person, Personality & Mood, the Activity & Actions and the Temporal & Event ontology. Right now, we use a hybrid semantic similarity metric, which takes both the common features of locations, as well as the topology into account to cluster the available locations and create our corresponding location-specific frames with regard to time, activity, action and/or a certain event. Then, we employ the measured semantic similarity scores to update a 1st Order Markov Chain model by applying the following formula:

$$p(l_{cur})_{i,new} = p(l_{maxSim}) \times Sim + \alpha \times p(l_{cur})_{i,old} \quad (4)$$

- p: Transition probability of the Markov Model
- l_{cur}: Current location
- l_{maxSim}: Most similar location to l_{cur}
- Sim: Semantic similarity score
- α: Offset parameter

Since, to the best of our our knowledge, there is no open dataset containing the semantic information, we need to evaluate our approach, we preliminary tested it on a 5-week long real life dataset, which consists of semantically annotated locations and the respective purpose of visit and activities of 4 users. The data were collected during a user study by using an Android tracking and annotation App we designed. Table I illustrates the performance of our first draft approach compared to the standalone Markov model and the semantic trajectory based approach of Ying discussed in Section II.

TABLE I. EVALUATION TABLE. PSSSA vs. 1st ORDER MARKOV MODEL vs.YING'S APPROACH (min. support=0,01, a=0,2 and b=0,8).

Metrics	ACC	F-measure	Precision	Recall
U1 (1), Markov	0,32	0,46	0,38	0,75
U1(1), PSSSA	0,29	0,42	0,33	0,79
U1 (1), Ying	0,27	0,29	0,29	0,36
U5 (2), Markov	0,23	0,37	0,33	0,56
U5 (2), PSSSA	0,28	0,45	0,40	0,66
U5 (2), Ying	0,2	0,2	0,2	0,53
U2 (3), Markov	0,39	0,55	0,43	0,87
U2 (3), PSSSA	0,37	0,52	0,42	0,87
U2 (3), Ying	0,2	0,2	0,2	0,2
U4 (4), Markov	0,20	0,24	0,23	0,60
U4 (4), PSSSA	0,21	0,24	0,23	0,6 1
U4 (4), Ying	0,0	0,0	0,0	0,0

As we can see, our approach clearly outperforms Ying's framework, which performs extremely weak, especially in the sparse data case. Our approach achieves a f-score of 0.52, the overall second highest score behind the Markov with 0.55. At the same time, it outperforms all other approaches with respect to recall. This reflects the fact that our approach can handle extremely good sparse data sets. However, table I also points out that in two of the cases, the Markov can provide slightly better results than our approach. This can be in part attributed to the similarity threshold we used (0.5%) and in part to the small and unfortunately incomplete semantically annotated data set due to recording inconsistencies during the user study.

V. Conclusions and Future work

This research is centered around the following research question: *Does Semantic Similarity Analysis lead to a more human-like representation of locations? Moreover, does this approach provide us with a solid basis for predicting locations more accurately?* Some first fundamental steps towards answering the above two questions have already been made. Promising preliminary results underpin our hypothesis and point the way to a clearly structured future work to come.

First of all, we plan to refine and finish up our ontology suite. After that, we want to investigate various similarity metrics, such as the marginalized kernel discussed in Section III-B. Then we plan to focus further on the personality-situation debate, because we believe it is a "cherry on the top" feature on the way to reaching personalization and building a preferably human-like Human-Machine Interface. For this purpose we collaborate with a team of psychologists in order to extend our ontological model accordingly. At last, we plan to work on an automated method of propagating our ontology suite with the available data. Various ontology learning methods shall be investigated and tested. Calendar entries, Email content and Reminders or Todo Check List apps shall be used to support this attempt.

References

[1] "Foursquare," 2017. [Online]. Available: https://www.foursquare.com/

[2] R. Nathan et al., "A movement ecology paradigm for unifying organismal movement research," vol. 105, no. 49, 2008, pp. 19 052–19 059.

[3] "Oxford english dictionary," September, 2017. [Online]. Available: https://en.oxforddictionaries.com/definition/knowledge

[4] C. J. Fillmore and C. Baker, "A frames approach to semantic analysis," in The Oxford handbook of linguistic analysis, 2010.

[5] M. Minsky, "A framework for representing knowledge." Cambridge, MA, USA: Massachusetts Institute of Technology, 1974.

[6] R. Glassey and R. Ferguson, "Modeling location for pervasive environments," in 1st UK-UbiNet Workshop, 2003.

[7] J. J.-C. Ying, W.-C. Lee, T.-C. Weng, and V. S. Tseng, "Semantic trajectory mining for location prediction," in Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, ser. GIS '11. New York, NY, USA: ACM, 2011, pp. 34–43.

[8] J. J.-C. Ying, W.-C. Lee, and V. S. Tseng, "Mining geographic-temporal-semantic patterns in trajectories for location prediction," vol. 5, no. 1. New York, NY, USA: ACM, Jan. 2014, pp. 2:1–2:33.

[9] N. Samaan and A. Karmouch, "A mobility prediction architecture based on contextual knowledge and spatial conceptual maps," vol. 4, no. 6. Piscataway, NJ, USA: IEEE Educational Activities Department, Nov. 2005, pp. 537–551.

[10] N. Samaan, A. Karmouch, and H. Kheddouci, "Mobility prediction based service location and delivery," in Canadian Conference on Electrical and Computer Engineering 2004 (IEEE Cat. No.04CH37513), vol. 4, May 2004, pp. 2307–2310 Vol.4.

[11] N. Samaan, B. Benmammar, F. Krief, and A. Karmouch, "Prediction-based advanced resource reservation in mobile environments," in Canadian Conference on Electrical and Computer Engineering, 2005., May 2005, pp. 1411–1414.

[12] Y. A. Ridhawi, I. A. Ridhawi, A. Karmouch, and A. Nayak, "A context-aware and location prediction framework for dynamic environments," in 2011 IEEE 7th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), Oct 2011, pp. 172–179.

[13] I. A. Ridhawi, M. Aloqaily, A. Karmouch, and N. Agoulmine, "A location-aware user tracking and prediction system," in 2009 Global Information Infrastructure Symposium, June 2009, pp. 1–8.

[14] R. Wannous, J. Malki, A. Bouju, and C. Vincent, "Trajectory ontology inference considering domain and temporal dimensions: Application to marine mammals." Elsevier, 2016.

[15] X. Long, L. Jin, and J. Joshi, "Exploring trajectory-driven local geographic topics in foursquare," in Proceedings of the 2012 ACM Conference on Ubiquitous Computing, ser. UbiComp '12. New York, NY, USA: ACM, 2012, pp. 927–934.

[16] R. Krishnamurthy, P. Kapanipathi, A. P. Sheth, and K. Thirunarayan, "Knowledge enabled approach to predict the location of twitter users," in The Semantic Web. Latest Advances and New Domains: 12th European Semantic Web Conference, ESWC 2015, Portoroz, Slovenia, May 31 – June 4, 2015. Proceedings. Springer International Publishing, 2015, pp. 187–201.

[17] "Twitter," 2017. [Online]. Available: https://www.twitter.com

[18] N. R. Mabroukeh and C. I. Ezeife, "Using domain ontology for semantic web usage mining and next page prediction," in Proceedings of the 18th ACM Conference on Information and Knowledge Management, CIKM 2009, Hong Kong, China, November 2-6, 2009, 2009, pp. 1677–1680.

[19] Q. Zhao et al., "Time-dependent semantic similarity measure of queries using historical click-through data," in Proceedings of the 15th international conference on World Wide Web. ACM, 2006, pp. 543–552.

[20] S. Kassin, "Psychology." Pearson/Prentice Hall, 2004.

[21] D. Funder, "The personality puzzle." W. W. NORTON & Company Incorporated, 2015.

[22] W. Fleeson, "Toward a structure-and process-integrated view of personality: Traits as density distributions of states." vol. 80, no. 6. American Psychological Association, 2001, p. 1011.

[23] A. R. Buss, "The trait-situation controversy and the concept of interaction," vol. 3, no. 2. Sage Publications, 1977, pp. 196–201.

[24] J. J. Jaccard, "Predicting social behavior from personality traits," vol. 7, no. 4. Elsevier, 1974, pp. 358–367.

[25] P. Borkenau, "To predict some of the people more of the time," in Fifty Years of Personality Psychology. Springer US, 1993, pp. 237–249.

[26] S. Adali and J. Golbeck, "Predicting personality with social behavior: a comparative study," vol. 4, no. 1, 2014, p. 159.

[27] J. Staiano, B. Lepri, N. Aharony, F. Pianesi, N. Sebe, and A. Pentland, "Friends don't lie: Inferring personality traits from social network structure," in Proceedings of the 2012 ACM Conference on Ubiquitous Computing. New York, NY, USA: ACM, 2012, pp. 321–330.

[28] M. Codescu, G. Horsinka, O. Kutz, T. Mossakowski, and R. Rau, "Osmonto – an ontology of openstreetmap tags," 2014.

[29] V. V. Hainš, S. Lovrenčić, and V. Kirinić, "Personality model representation using ontology."

[30] J. Hastings, W. Ceusters, B. Smith, and K. Mulligan, "Dispositions and processes in the emotion ontology," in Proceedings of the 2nd International Conference on Biomedical Ontology, 2011, pp. 71–78.

[31] A. Gangemi and V. Presutti, "Ontology design patterns," 2009.

[32] Z. Wu and M. Palmer, "Verbs semantics and lexical selection," in Proceedings of the 32Nd Annual Meeting on Association for Computational Linguistics, ser. ACL '94. Stroudsburg, PA, USA: Association for Computational Linguistics, 1994, pp. 133–138.

[33] D. Lin, "An information-theoretic definition of similarity," in Proceedings of the Fifteenth International Conference on Machine Learning. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1998, pp. 296–304.

[34] K. Tsuda, T. Kin, and K. Asai, "Marginalized kernels for biological sequences," vol. 18, no. 1, 2002, pp. S268–S275.

[35] "Swrl: A semantic web rule language," 2017. [Online]. Available: https://www.w3.org/Submission/SWRL/

[36] "Protege," 2017. [Online]. Available: http://protege.stanford.edu