Wu, Y.-T., Chang, M., Li, B., Chan, T.-W., Kong, S. C., Lin, H.-C.-K., Chu, H.-C., Jan, M., Lee, M.-H., Dong, Y., Tse, K. H., Wong, T. L., & Li, P. (Eds.). (2016). *Conference Proceedings of the 20th Global Chinese Conference on Computers in Education 2016*. Hong Kong: The Hong Kong Institute of Education.

A Versatile Learning Context Framework for Heterogeneous E-learning Applications

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Abstract: *Contextual data of learners play a vital role in various e-learning applications in recent years, as learning contexts not only provide learners with context-aware services but also enhance effectiveness. However, various e-learning systems adopt different contextual models (i.e., application-dependent contextual model), and consequently data sharing and system integration are challenging. In this article, we propose a unified learning context framework to support heterogeneous e-learning applications. This context framework, being versatile and flexible to various e-learning applications, can address the shortcoming of application-dependent models. Within the framework, we define a set of contextual operations to manipulate and customize the learning context data. The proposed context framework can support various context-aware e-learning applications. Through the case studies, we also verify that the proposed framework is very flexible and powerful in different scales.*

Keywords: context model, e-learning systems, semantic operations, learning context, conceptual framework

1. Introduction

Contextual data of learners play a vital role in various e-learning applications in recent years, as learning contexts not only provide learners with context-aware services but also enhance effectiveness. Recently, there have been many studies in context models for recommender and personalized systems (Jin, Xie, Lei, Li, Li, Mao, & Rao, 2013; Xie, Li, & Mao, 2012; Derntl & Hummel, 2005). However, a main flaw of these context models is the application-dependence. That is, various e-learning systems adopt different contextual models so that it is quite difficult for the following issues.

Data Sharing. Contextual data are challenging to share and communicate in various systems, as the application-dependent context models employ different formats for contextual data storage. Also, there is no explicit well-defined mechanism for context manipulation and customization, so that even contextual data shared with similar formats (e.g., the subset relation) need to be re-defined.

System Integration. If the system needs to be integrated with an existing sub-system, it will encounter the similar problem that contextual data should be re-defined due to the format variety of the application-dependent context models. Since system integration is common, the unified contextual framework and the well-defined mechanism for context manipulation are indispensable.

In this article, we propose a unified learning context framework to support heterogeneous e-learning applications. In other words, the proposed context framework is versatile and flexible to various e-learning applications such that the shortcoming of application-dependent models can be addressed. Within the framework, we define a set of contextual operations to manipulate and customize the learning context data. The proposed context framework can be easily integrated with the existing framework such as the augmented hybrid graph (Xie, Li, Mao, Li, Cai, & Rao, 2014) and the learner profile (Zou, Xie, Li, Wang, & Chen, 2014) to support various context-aware e-learning applications.

2. Related Work

The context model has been widely and extensively studied and applied in various areas, including web information retrieval, location-based services and social media. In particular, the context modeling in e-learning systems primarily aims to capture and depict the current learning context of a learner (Schmidt & Winterhalter, 2004). Derntl and Hummel (2005) introduced a UML-based modeling extension to explicitly include relationships between contexts and learning activities in learning design models. Yu, Nakamura, Jang, Kajita, & Mase (2007) depicted learning contexts by making use of ontology-based concepts so as to facilitate the context-aware semantic recommendations in the e-learning systems. Moreover, a knowledge engineering approach was proposed to develop Mindtools for modeling innovative learning scenarios into the context (Chu, Hwang, & Tsai, 2010), which not only boosted learning motivation, but also increased the learning achievement of students in the empirical studies. Wang and Wu (2011) proposed a life-long context modeling for ubiquitous e-learning systems (u-learning), which assisted learners to engage in learning activities by incorporating relevant contextual information such as locations, time and learner state obtained from mobile devices. Verbert, Manouselis, Ochoa, Wolpers, Drachsler, Bosnic, and Duval (2012) further investigated various kinds of contextual sources (e.g., spatial-temporal contexts, computing contexts, physical conditions, activity contexts, resource contexts and learner contexts) and compared a range of context-aware e-learning applications in terms of their contextual dimensions, frameworks and evaluation methods. In addition, Dwivedi and Bharadwaj (2013) presented a fuzzy approach to handling multi-dimension contexts (e.g., learning duration, learner moods) and assisting the learning material recommendations in e-learning systems.

3. The Proposed Framework

Contextual level	Contextual attribute	Contextual values
Individual	weather time place motivation ...	sunny, rainy, snowy, cloudy, stormy,... morning, afternoon, evening, night,... school, company, home... exam, skill, interest... ...
Group	task size ...	project, presentation, survey report... small, medium, large... ...
Class	medium duration ...	English, Mandarin, Cantonese ... short, long ... ...

Figure 1. The illustration of contextual factors at three levels.

3.1. Context Model

As shown in Figure 1, the contextual factors to be considered and modeled are enumerated and classified into individual context, group context and class context. Each contextual factor contains a pair of contextual attributes and corresponding values (e.g., place is the contextual attribute, while school, company and home are contextual values). Formally, an individual (personal) context for a learner *i* can be defined by a vector of contextual attribute-value pairs.

$$PC_a^i = (c_1: w_{1,a}^i; c_2: w_{2,a}^i \dots c_n: w_{n,a}^i) \quad (1)$$

where $c_1, c_2, \dots c_n$ are the contextual attributes included in the context modeling, $w_{1,a}^i, w_{2,a}^i \dots w_{n,a}^i$ are the corresponding contextual values for the attributes (e.g., the contextual value 'rain' for the attribute 'weather') for learner *i* under individual context *a*. The group context *a* for group *k*, which is formed by the individual context of each group member, can be formalized as follows.

$$GC_a^k = (c'_1: w_{1,a}^k; c'_2: w_{2,a}^k \dots c'_m: w_{m,a}^k) \cup_{i \in k} PC_a^i \quad (2)$$

where $c'_1, c'_2, \dots c'_m$ are the contextual attributes only at the group level, $w_{1,a}^k, w_{2,a}^k \dots w_{n,a}^k$ are the contextual values for these attributes (e.g., the contextual value 'project' for the attribute 'task') and $\cup_{l_i \in k} PC_a^i$ is the union set of all group members' personal contexts. Similarly, the class context for class x, which is also the union of all group contexts and unique contextual factors in class level, is defined as

$$DC_a^x = (c_1^*: w_{1,a}^x; c_2^*: w_{2,a}^x \dots c_q^*: w_{q,a}^x) \cup_{k \in x} GC_a^k \quad (3)$$

where $c_1^*, c_2^*, \dots c_q^*$ are the unique contextual attributes at the class level, $w_{1,a}^x, w_{2,a}^x \dots w_{n,a}^x$ are the contextual values, and $\cup_{k \in x} GC_a^k$ is the union set of all group contexts in the class.

3.2. Contextual Operations

To provide a very flexible way to manipulate context data, a set of contextual operations will be defined and given by following the same spirit in algebraic operations.

- Projection based on unique contextual attributes at the group level, denoted by $\pi_{gc=c_i'}$, for example:

$$\pi_{gc=c_1',c_2'}(GC_a^k) = (c_1': w_{1,a}^k; c_2': w_{2,a}^k) \quad (4)$$

where GC_a^k is given in definition (2), and this operation $\pi_{gc=c_i'}$ enables us to focus on some unique group-level contextual factors. For example, a learner wants to search some learning materials which are relevant to the content of project by ignoring group members' contextual information. Obviously, this projection operation can help in this case.

- Projection based on personal-level contextual attributes, denoted by $\pi_{pc=c_i}$, for example:

$$\pi_{pc=c_1,c_2}(GC_a^k) = \cup_{i \in k}(\pi_{pc=c_1,c_2}(PC_a^i)) = \cup_{i \in k}(c_1: w_{1,a}^i; c_2: w_{2,a}^i) \quad (5)$$

where GC_a^k and PC_a^i are given in definition (2) and (1), respectively. $\pi_{pc=c_i}$ enables us to focus on the personal contextual factors of the group members. For example, we would like to find out all group members' available time in order to find out common time slots for group meetings.

- Zoom-In, which is to focus on a particular member's personal context, denoted by θ, for example:

$$\theta_i(GC_a^k) = PC_a^i = (c_1: w_{1,a}^i; c_2: w_{2,a}^i \dots c_n: w_{n,a}^i) \quad (6)$$

where PC_a^i is the personal context as given in (7), ϑ_i means to zoom in to the context of group member i in the group.

- Zoom-Out, which is the reverse of the Zoom-In operator, denoted by ϑ, for example:

$$\vartheta_x(GC_a^k) = DC_a^x(k \in x) \quad (7)$$

where ϑ_x means to zoom out to the context of class x which contains group k. This operation is useful to move one level up so as to get more global pictures.

4. Facilitating E-learning Applications

In this section, we illustrate how the proposed framework to facilitate various e-learning applications in different scales. Specifically speaking, two applications which are at the personalized and group levels are discussed.

Recommendation customization: Given a user *i*, a personal context PC_a^i, a courseware set R and user learning logs L (in the form of *l* = (k, PC_b^k, r), where *l* is a specific record, and *r* is the courseware which is learnt by a user k under a context PC_b^k), the recommendation can be given by adopting some conventional approaches like collaborative filtering, a critical step of which is to measure the similarities between other contexts and the current context PC_a^i (e.g., $Sim(PC_a^i, PC_b^k)$). Before the measurement, the user can tail the context PC_a^i by specifying interested contextual attributes through using the projection operation (i.e., $Sim(\pi_{pc=c_1,c_2}(PC_a^i), \pi_{pc=c_1,c_2}(PC_b^k))$.

Group formation: The group formation is a typical issue in both e-learning systems and classroom teaching. To support group formation, an instructor of a course can define a group context GC_a^k by specifying related contextual attributes and conditions. For example, "the average grade of course A" is defined as the group-level contextual attribute and "average grade > 70" is a condition. The conditions can be examined during the context formation stage as defined in (2), i.e., calculating the average values of the attribute "grade of course A" for all group members. The projection can also be adopted in this step. Additionally, if we want to exclude a personal context of a group member who quits the project halfway, the "zoom in" could be helpful by combining it with the set operation minus, which is $\mathrm{GC}_a^k - \theta_i(\mathrm{GC}_a^k)$.

5. Conclusion & Future Work

In this paper, we have proposed a unified context framework with a set of contextual operations to address the problems in the application-dependent context models. Furthermore, the proposed framework can provide powerful manipulation and customization for the context models. Additionally, various e-learning applications in different scales can be also supported by the framework. In the future, we plan to apply the framework in some real e-learning systems, so that the performance of the proposed framework can be further investigated and verified.

Acknowledgements

The work described in this paper was fully supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (UGC/FDS11/E06/14) and the Internal Research Grant (RG 30/2014-2015) of the Hong Kong Institute of Education.

References

Anderson, A., Huttenlocher, D., Kleinberg, J., & Leskovec, J. (2012). Effects of user similarity in social media. In *Proceedings of the Fifth ACM International Conference on Web Search and Data Mining* (pp. 703-712). ACM.

Chu, H. C., Hwang, G. J., & Tsai, C. C. (2010). A knowledge engineering approach to developing mindtools for context-aware ubiquitous learning. *Computers & Education*, *54*(1), 289-297.

Derntl, M., & Hummel, K. (2005, March). Modeling context-aware e-learning scenarios. In *Third IEEE International Conference on Pervasive Computing and Communications Workshops, 2005*. (pp. 337-342). IEEE.

Dwivedi, P., & Bharadwaj, K. K. (2013). A fuzzy approach to multidimensional context aware e-learning recommender system. In *Mining Intelligence and Knowledge Exploration* (pp. 600-610). Springer.

Jin, T., Xie, H., Lei, J., Li, Q., Li, X., Mao, X., & Rao, Y. (2013, November). Finding dominating set from verbal contextual graph for personalized search in folksonomy. In *Web Intelligence (WI) and Intelligent Agent Technologies (IAT), 2013 IEEE/WIC/ACM International Joint Conferences* on (Vol. 1, pp. 367-372). IEEE.

Schmidt, A., & Winterhalter, C. (2004). User context aware delivery of e-learning material: approach and architecture. *Journal of Universal Computer Science*, *10*(1), 28-36.

Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I., & Duval, E. (2012). Context-aware recommender systems for learning: a survey and future challenges. IEEE Trans. *Learning Technologies*, *5*(4), 318-335.

Wang, S. L., & Wu, C. Y. (2011). Application of context-aware and personalized recommendation to implement an adaptive ubiquitous learning system. *Expert Systems with Applications*, *38*(9), 10831-10838.

Xie, H., Li, Q., & Mao, X. (2012). Context-aware personalized search based on user and resource profiles in folksonomies. In *Web Technologies and Applications* (pp. 97-108). Springer Berlin Heidelberg.

Xie, H., Li, Q., Mao, X., Li, X., Cai, Y., & Rao, Y. (2014). Community-aware user profile enrichment in folksonomy. *Neural Networks*, *58*, 111-121.

Yu, Z., Nakamura, Y., Jang, S., Kajita, S., & Mase, K. (2007). Ontology-based semantic recommendation for context-aware e-learning. In *Ubiquitous Intelligence and Computing* (pp. 898-907). Springer Berlin Heidelberg.

Zou, D., Xie, H., Li, Q., Wang, F. L., & Chen, W. (2014). The load-based learner profile for incidental word learning task generation. In *Advances in Web-Based Learning–ICWL 2014* (pp. 190-200). Springer.