Towards Context Clarity in Personal Informatics Applications

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What kinds of explanations and interactions are the most valuable to users of personal informatics systems depends on the context. However, in AI research context tends to be vaguely defined and difficult to reuse across different domains and applications. We propose the need for a generalizable method to define and capture context, using a semantically rich representation, to help users better understand AI systems and their results. By developing such a context model, personal informatics applications may benefit from greater explainability capabilities and interoperability among varying views of context.

Additional Key Words and Phrases: Context, Personal Informatics, Semantic Web, Explainable AI

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1 Introduction

In recent years, AI systems become increasingly capable of using personal data for tasks such as personalized recommendation or decision making support. One of the key challenges in utilizing such data is that of **forms of support and interaction paradigms**: in particular, supporting users through explanations is important to help them understand the results and develop trust in the AI systems. How to best explain a system, in turn, depends on the context – for example, a user might find different explanations for a food recommendation more valuable if they're celebrating with friends or if they're trying to use up the ingredients in their pantry.

Context plays an important role in understanding what the data actually means, and it can help to give more meaningful explanations to users. But what do we actually mean by ***context***? While we may have an intuitive sense of what context means, AI research seldom provides a clear, holistic definition of it in their work. Existing works typically use very narrow definitions that only suit their specific application to label input features as being "context" or not. However, such definitions are lacking in flexibility and extensibility when considering the scope of what constitutes context in a broader range of personal informatics applications. Indeed, it is difficult to arrive at a satisfactory definition of context because *what context* ***is*** *depends on the context.*

We argue that computationally accessible definitions of context are needed to enable effective usage and interoperability among "context-aware" applications. Our vision for this includes the use of an ontology to support semantically rich representations of context, as well as methods to compute context information that is "interesting" and "useful" to users. A common understanding of context can enable reuse of context-related data and methods among personal informatics applications, and further support users through explanations about various levels of context involved in the underlying AI systems.

2 Related Work

Commonly cited definitions of context, such as "Any information that can be used to characterize an entity or situation." [7], tend to lack any distinction between what is and is not context. Some also argue that context goes beyond a problem of just representation, but rather view contextuality as a property of information that arises from the activity at hand [8]. As it stands, such definitions are too broad to serve as a grounding for a common understanding of context among different works. Nonetheless, efforts have been made towards a high-level categorize a variety of context elements such as social, physical, technological, and domain-specific contexts [4].

Within specific applications like context-aware recommender systems [1], context is commonly understood as any information besides users, items, and ratings. Examples of such context include time, location, weather, and social situations (alone, with friends, etc) [2, 6]. While this type of research has a clear delineation of what context is, they are often limited to physical contexts and tend to simply use it as yet another input feature.

There have also been investigations in recent years to use knowledge graphs as a form of background knowledge to serve as context, such as applying them to improve language models [11, 12]. In such works, context is framed as the neighboring entities or paths between entities in the graph [10, 13]. The definition of context in this area mainly captures structural information about the graph and does not easily integrate with broader notions of context that we may wish to consider in personal informatics systems.

Although it might be appropriate for different works to define context differently to suit their work, a key shortcoming is that there is no common understanding of *how* to clearly define and capture different definitions. This leads to challenges in interoperability and reusability among context-aware systems, which our work aims to address.

3 Representing and Using Context

To adequately define and capture context, a flexible representation scheme is necessary to encompass a variety of applications, domains, and knowledge sources. Our approach is to use semantic technologies, such as RDF and OWL [3], to capture the following three components of information:

Background Knowledge, which captures the knowledge sources used and describes the environment in which the AI system is developed. This may include resources like knowledge graphs, domain-specific ontologies, and other heterogeneous data sources and their links to knowledge graph entities. Background knowledge remains unchanged across different runs of a system, and serves as a source of provenance for AI system.

Activity, which captures information about the user's current interaction with the AI system that sheds light on the larger picture of what they are doing and trying to accomplish. This can include inputs such as personal data, goals, constraints, the operating environment, and any other features that are necessary to perform a particular task.

Connective Knowledge,[1] which encompasses relevant information based on connections between the background knowledge, the activity, and the results produced by the AI system. Additionally, new knowledge produced by reasoning systems based on activity information (e.g., inferring prohibited foods based on input about a user's allergies) is also captured in connective knowledge. Connections between entities in structured background knowledge sources, such as knowledge graphs, can be used to compute the relevance of information.

[1]We note the similarity of our use of "connective knowledge" with that of work such as [9], where the term is applied in the domain of education.

We believe that these components can serve to provide sufficient coverage of the main concepts of "context" that AI systems would wish to utilize. The connective knowledge in particular aims to support personal informatics systems by framing context as it relates to a user's interactions with the system. As the connective portion of context is inherently tied to the activity, what background information is "relevant" or "useful" depends on how the user is currently interacting with the AI system – this in turn can inform the system of how to best explain itself to the user.

4 Context to Support Personal Informatics

By developing a method to more holistically define and represent of context, we believe that we can make progress on addressing the challenge of user support and interaction with personal informatics systems. This can be done by leveraging context to provide greater levels of explainability, both about the underlying AI system and the results it produces. In our own work, for example, we seen examples of context playing an important role in explanations. When providing a clinician with explanations about the results produced by a disease risk-prediction model, they often asked for further elaboration on context surrounding the prediction [5]. Contextualizing the results in terms of the patient's information, medical guidelines used to develop the model, and feature weights in the neural network model helped clinicians to better understand why the system indicated that certain features were more important than others.

More broadly, explanations that can be generated by personal informatics systems can benefit from context by (1) providing users with a greater level of understanding about the system itself and (2) identifying information that is most valuable to explain to users based on different contexts. Understanding the context, in terms of background knowledge and data provenance, can help users critically assess the limitations of a system. Explaining how the system processes personal data and how it infers new knowledge will allow users to develop trust in the system (or alternatively understand when *not* to follow a system's recommendations). Explaining the context in which the system operates, as well as identifying what aspects of that context are valuable to users, may be a powerful tool in interactions with personal informatics systems.

Lastly, following a common method to define and capture context more precisely will facilitate reuse of context-related methods among different AI systems. While the current standard of using "context" loosely may be sufficient for disparate one-off systems, it becomes increasingly difficult to integrate new ideas and methods surrounding context as new applications and domains are explored. We hope that a declarative, semantically rich representation of context such as we envision can help to bring together research involving context and support more effective interactions between users and AI systems.

5 Conclusion

Context is an important concept to consider for personal informatics systems, but its usage remains vague and difficult to interpret across different applications. Developing a semantically rich representation of context, both as a description of the environment as well as the result of activities involving the system, will allow us to provide users with a better understanding of how systems are using their personal data and explanations about how the context shapes the results of such systems. Further, clearer usage of context will enable greater reuse of data and methods as AI systems are applied to new domains and applications.

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References

[1] Gediminas Adomavicius, Bamshad Mobasher, Francesco Ricci, and Alexander Tuzhilin. 2011. Context-Aware Recommender Systems. *AI Magazine* 32, 3 (2011), 67–80. https://doi.org/10.1609/aimag.v32i3.2364 Number: 3.

[2] Mohammad Aliannejadi and Fabio Crestani. 2018. Personalized Context-Aware Point of Interest Recommendation. *ACM Transactions on Information Systems* 36, 4 (Oct. 2018), 45:1–45:28. https://doi.org/10.1145/3231933

[3] Grigoris Antoniou and Frank van Harmelen. 2004. *Web Ontology Language: OWL*. Springer Berlin Heidelberg, Berlin, Heidelberg, 67–92. https://doi.org/10.1007/978-3-540-24750-0_4

[4] Christine Bauer and Alexander Novotny. 2017. A consolidated view of context for intelligent systems. *Journal of Ambient Intelligence and Smart Environments* 9 (06 2017), 377–393. https://doi.org/10.3233/AIS-170445

[5] Shruthi Chari, Prithwish Chakraborty, Mohamed Ghalwash, Oshani Seneviratne, Elif K. Eyigoz, Daniel M. Gruen, Fernando Suarez Saiz, Ching-Hua Chen, Pablo Meyer Rojas, and Deborah L. McGuinness. 2021. Leveraging Clinical Context for User-Centered Explainability: A Diabetes Use Case. arXiv:2107.02359 [cs.LG]

[6] Víctor Codina, Francesco Ricci, and Luigi Ceccaroni. 2015. Distributional semantic pre-filtering in context-aware recommender systems. *User Modeling and User-Adapted Interaction* 25 (March 2015). https://doi.org/10.1007/s11257-015-9158-2

[7] Anind Dey. 2001. Understanding and Using Context. *Personal and Ubiquitous Computing* 5 (02 2001), 4–7. https://doi.org/10.1007/s007790170019

[8] Paul Dourish. 2004. What we talk about when we talk about context. *Personal and Ubiquitous Computing* 8, 1 (Feb. 2004), 19–30. https://doi.org/10.1007/s00779-003-0253-8

[9] Stephen M. Downes. 2020. An Introduction to Connective Knowledge.

[10] Huan Gao, Jun Shi, Guilin Qi, and Meng Wang. 2018. Triple Context-Based Knowledge Graph Embedding. *IEEE Access* 6 (2018), 58978–58989. https://doi.org/10.1109/ACCESS.2018.2875066

[11] Qizhen He, Liang Wu, Yida Yin, and Heming Cai. 2020. Knowledge-Graph Augmented Word Representations for Named Entity Recognition. *Proceedings of the AAAI Conference on Artificial Intelligence* 34 (Apr. 2020), 7919–7926. https://doi.org/10.1609/aaai.v34i05.6299

[12] Isaiah Onando Mulang', Kuldeep Singh, Chaitali Prabhu, Abhishek Nadgeri, Johannes Hoffart, and Jens Lehmann. 2020. Evaluating the Impact of Knowledge Graph Context on Entity Disambiguation Models. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management* (Virtual Event, Ireland) *(CIKM '20)*. Association for Computing Machinery, New York, NY, USA, 2157–2160. https://doi.org/10.1145/3340531.3412159

[13] Haoyu Wang, Vivek Kulkarni, and William Yang Wang. 2020. DOLORES: Deep Contextualized Knowledge Graph Embeddings. *ArXiv* abs/1811.00147 (2020).