Human-Technology relations in a machine learning based commuter app.*

Lars Holmberg[1]

Faculty of Technology and Society, Malmö University, Sweden
Internet of Things and People Research Center, Malmö University, Sweden
Lars.Holmberg@mau.se

1 Introduction

Artifacts that take advantage of Machine Learning (ML) influence our daily life to an increasing extent. The development and use of these artifacts often leaves out the human actors and the context and thus risks to become technocentric [6].

Many ML techniques, for example active learning, interactive learning or machine teaching, calls for user involvement [3, 10, 12, 13, 15]. To our knowledge there is a lack of research concerning relations between humans and ML-based artifacts, the attention is instead often on the desired outcome [4, 11], for example trust.

If we are to understand how ML can support humans, we need to turn attention to the human-technology relations. In this work we will use a postphenomenological lens and focus on how different ML techniques can create, build and maintain relations between humans and technology [5, 14].

Our work is explorative and use material sketching to produce artifactual knowledge [7], methodologically this fits into a Research Through Design approach [16].

In this work, our artifact and the relevance of a postphenomenological approach is the main contribution. In the work presented here the focus is on adaptive learning in a background relation [5] and identifying situations where the background relation can promote a transition to another type of relation (embodied, hermeneutic, alterity). We hope to initiate a discussion on this approach and inspire further work by our contribution.

In this extended abstract, we will focus on the artifact and its relevance for human-technology relations and only briefly expand on application context, theory and methodology.

2 Related research and Methodology

As a blueprint for this work we have followed the directions of Ohlin et al. [9] and we aim at promoting transitions between relations initiated either by the

* This work partially financed by the Knowledge Foundation through the Internet of Things and People research profile. I would also like to thank Paul Davidsson and Carl Magnus Olsson for invaluable support during the work.

artifact or the user. We start by creating an adaptive ML-backend for an existing commuter app [1] [2]. The ML-backend predicts and presents the users next journey when the app is started, the prediction is based on historical individual travel patterns and the users ML-model is trained online. To create a baseline for our predictions, personas based on a local transportation company are used [8].

3 Result and discussion

In our process to create an artifact that meets our initial design goals regarding: prediction accuracy, cloud service cost and performance, we have iterated and re-framed our artifact multiple times. The users trust in the predictions is central to be able to build relations, but trust doesn't automatically follow prediction accuracy [4]. This implies an adaptive backend in the background that delivers reasonable accurate predictions for data sets that reflects use over weeks, months and year.

The current artifact iteration is a solution that extends the Android commuter app and adds a backend based on Google Cloud services (Firebase, BigQuery, compute engine), TensorFlow estimators [1, 2] and Node.js [3]. With our personas in focus we created one travel pattern that is periodic, one that drifts over time and one more random. Based on this data an adaptive ML-backend was created that uses different ML-Algorithms depending on amount of labeled data and noise in input data. The resulting system delivers journey predictions to the app in an acceptable time-frame (less than 2 seconds) and identifies situations were transition to another type of relation is appropriate.

The main contribution in this work is identifying situations where there is a need for a transition to a new type of human-technology relation. Since the work presented here builds a background relation the transitions calls for an ML-technology that allows or invites users to get involved.

4 Conclusion

This extended abstract set out to turn attention to the human-technology relations ML-artifacts promote. We have done that by using the vocabulary of post-phenomenology and by exploring the design space created by a commuter app. By specifically focusing on adaptive learning in a background relation and identifying situations that calls for a shift in type of relation (embodied, hermeneutic, alterity) we have laid a base for future research.

In terms of future research we particularly suggest to include active learning, interactive learning and machine teaching to explore the relations these techniques promote.

---

[1] https://skanependlaren.firebaseapp.com
[2] https://play.google.com/store/apps/details?id=se.k3larra.alvebuss
[3] https://github.com/k3larra/commuter/

References

1. Cheng, H.T., Haque, Z., Hong, L., Ispir, M., Mewald, C., Roumpos, G., Sculley, D., Smith, J., Soergel, D., Tang, Y., Tucker, P., Wicke, M., Xia, C., Xie, J.: TensorFlow Estimators: Managing Simplicity vs. Flexibility in High-Level Machine Learning Frameworks. In: Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 1763–1771 (2017). https://doi.org/10.1145/3097983.3098171, https://terrytangyuan.github.io/data/papers/tf-estimators-kdd-paper.pdf
2. Cheng, H.T., Koc, L., Harmsen, J., Shaked, T., Chandra, T., Aradhye, H., Anderson, G., Corrado, G., Chai, W., Ispir, M., Anil, R., Haque, Z., Hong, L., Jain, V., Liu, X., Shah, H.: Wide & Deep Learning for Recommender Systems. In: Proceedings of the 1st Workshop on Deep Learning for Recommender Systems. pp. 7–10 (2016). https://doi.org/10.1145/2988450.2988454, http://arxiv.org/abs/1606.07792
3. Fails, J.A., Olsen, D.R.: Interactive machine learning. Proceedings of the 8th international conference on Intelligent user interfaces - IUI '03 p. 39 (2003). https://doi.org/10.1145/604045.604056, http://dl.acm.org/citation.cfm?doid=604045.604056
4. Glass, A., McGuinness, D.L., Wolverton, M.: Toward establishing trust in adaptive agents. Proceedings of the international conference on Intelligent user interfaces (IUI '08) pp. 227–236 (2008). https://doi.org/10.1145/1378773.1378804
5. Ihde, D.: Technology and the Lifeworld, vol. 1 (1990). https://doi.org/10.1049/et:20060114
6. Johnson, D.G., Verdicchio, M.: Reframing AI Discourse. Minds and Machines **27**, 575–590 (2017). https://doi.org/10.1007/s11023-017-9417-6
7. Löwgren, J.: On the significance of making in interaction design research. Interactions **23**(3), 26–33 (2016). https://doi.org/10.1145/2904376
8. Nielsen, L.: Personas - User Focused Design. Springer (2013). https://doi.org/10.1007/978-1-4471-4084-9, http://link.springer.com/10.1007/978-1-4471-4084-9
9. Ohlin, F., Olsson, C.M.: Beyond a utility view of personal informatics. Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers - UbiComp '15 pp. 1087–1092 (2015). https://doi.org/10.1145/2800835.2800965
10. Porter, R., Theiler, J., Hush, D.: Interactive machine learning in data exploitation. Computing in Science and Engineering **15**(5), 12–20 (2013). https://doi.org/10.1109/MCSE.2013.74
11. Ribeiro, M.T., Singh, S., Guestrin, C.: "Why Should I Trust You?": Explaining the Predictions of Any Classifier (feb 2016). https://doi.org/10.1145/2939672.2939778, http://arxiv.org/abs/1602.04938
12. Simard, P.Y., Amershi, S., Chickering, D.M., Pelton, A.E., Ghorashi, S., Meek, C., Ramos, G., Suh, J., Verwey, J., Wang, M., Wernsing, J.: Machine Teaching: A New Paradigm for Building Machine Learning Systems. Tech. rep., Microsoft Research (2017), http://arxiv.org/abs/1707.06742
13. Smith, A., Kumar, V., Boyd-Graber, J., Seppi, K., Findlater, L.: Closing the loop: User-centered design and evaluation of a human-in-the-loop topic modeling system. In: International Conference on Intelligent User Interfaces, Proceedings IUI. pp. 293–304 (2018). https://doi.org/10.1145/3172944.3172965, http://cs.colorado.edu/

14. Verbeek, P.P.: What things do. No. 9 (2013). https://doi.org/10.1017/CBO9781107415324.004
15. Zhu, X., Singla, A., Zilles, S., Rafferty, A.N.: An Overview of Machine Teaching (2018), http://arxiv.org/abs/1801.05927
16. Zimmerman, J., Forlizzi, J., Evenson, S.: Research Through Design as a Method for Interaction Design Research in HCI design research in HCI. Proceedings of the SIGCHI conference on Human factors in computing systems pp. 493–502 (2007). https://doi.org/http://doi.acm.org/10.1145/1240624.1240704, http://repository.cmu.edu/hcii