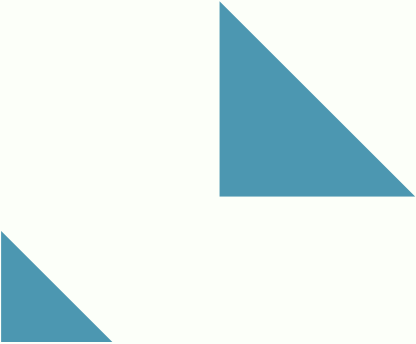


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2 Case Studies on Intelligent Recommender Systems



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Team 1

Ben Shneiderman is a pioneer of direct manipulation methods in user interfaces, his most important contribution being hyperlinks – highlighted, clickable links embedded in text and graphics. We will focus on one of the papers he has written in collaboration with a few of his Ph.D. students.

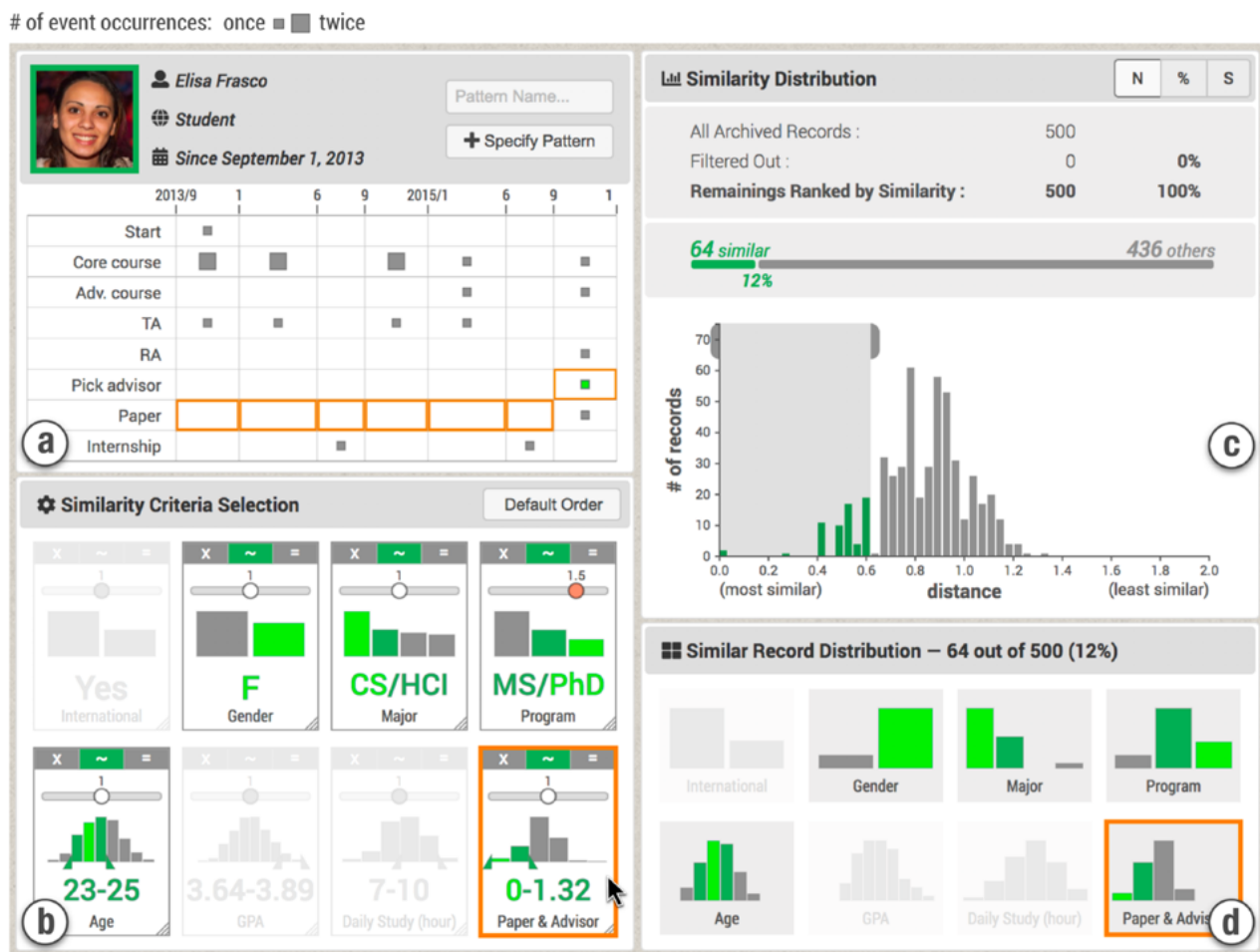
The Question

The problem they tackle is that a large no of intelligent recommender systems (systems that suggest what content to click on, watch/buy/listen, based on factors such as location, past decisions, time, what others are doing, etc), still have a lot of scope for improvement so that users can gain what they need in as less clicks as possible. **They look at a recommender system that helps students in making career decisions and corresponding educational course selections based on career trajectories of alumni.** They ask how do we give users greater control and offer more transparency? What kind of algorithmic analysis and interactive visual exploration can augment the user's ability to find better recommendations? How do these interventions cause them to act on those recommendations? (F. Du et al., 2019, 21:2)

Method

Since the question is couched in terms of “augmenting the user”, their approaches are constrained to only look for better ways to provide more data and access into the recommender systems in order to guide users to define **a personalized action plan** associated with what they want (F. Du et al., 2019, 21:4).

Fig 2, F. Du et al.,
2019, 21:9



Pros & Cons

The 'User augmented approach' leads to **designing interfaces and visualizations** (see fig above) that provide controls and context for users to interactively **find and explore records that are similar** to the stored records.

It's a great way to bring **allow the user to collaborate with the AI in the recommendation engine**, but it also increases the cognitive load that the user must now undertake. (Ashraf, 2020) Moreover, the design will always be limited by what features were provided and which ones were deemed unnecessary.

Team 2

Rosalind Picard is responsible for creating the modern branch of computer science called **'Affective Computing', the study and development of systems and devices that can recognize, interpret, process, and simulate human affects and emotions.** (Picard, 2000) A specific application of affective computing can be seen here in the scenario of online mental health services.

The Question

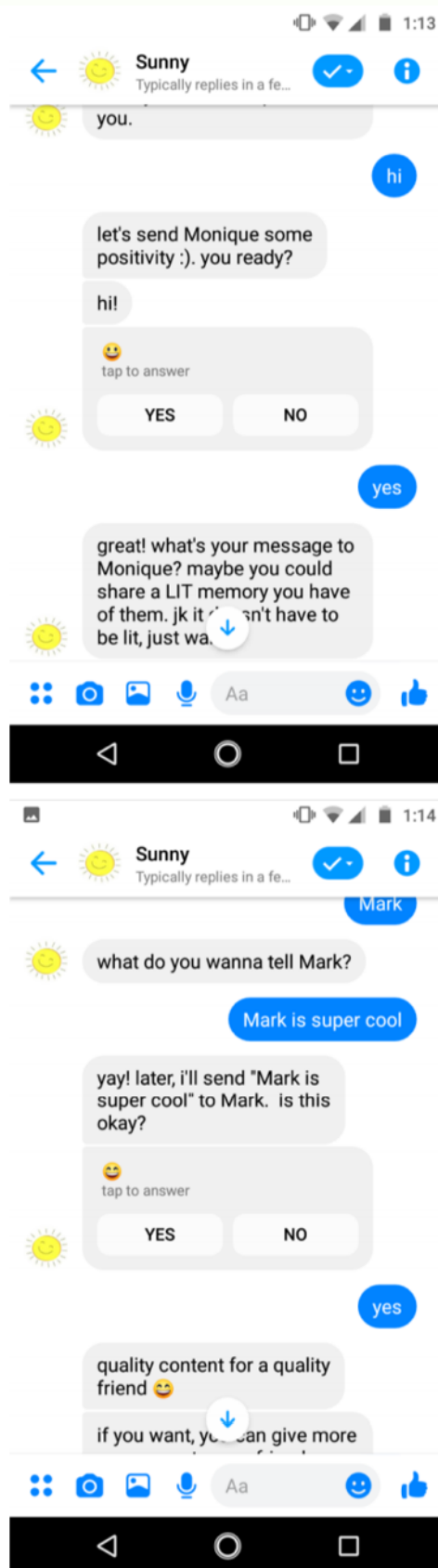
Online social networking platforms are not always positive for an individual's psychological well-being (Frost et. al. (2017). **Then how do we improve the psychological wellbeing of individuals involved in online social networking platforms?**

Specifically, Picard and her team ask -- in what ways can AI be deployed to promote positive interactions? In what ways can a chatbot facilitate good interactions between participants? (Narain et. al., 2020, 2)

Method

This question demands a user study to explore the change in experiences when engaged with a chatbot as an intermediary. This has the advantage of the data being empirical and hands-on. The research approaches this problem by performing **a 10-day study conducted with three pre-existing social groups followed by regular surveys. The chatbot was deployed to encourage sending and receiving positive messages by providing suggestions and also automated compliments** in these groups. The psychological well-being of participants was monitored using the 18-question psychological wellbeing test and the Rosenberg Self-Esteem scale. By the end of it, there was improved interaction between participants, **enhanced self-worth, and relationship depth** (See below fig for examples) (Narain et. al., 2020, 5).

FIG 1, NARAIN ET. AL., 2020, 2)



Pros & Cons

The advantage of the survey was that they could gauge the **well-being in common metrics** but this excluded the possibility of in-depth analysis of experiences when using the chatbot.

The overall limitation of the research was that the study **did not have a large enough sample size (n=12)** to generate statistically significant results.

Appendix

A few afterthoughts

Abdul, A. (2020, January 8). COGAM: Measuring and Moderating Cognitive Load in Machine Learning Model Explanations. Ashraf Abdul. <https://www.ashrafabdul.com/publication/cogam-chi20/>

Ashraf talks in detail about how XAI (Explainable AI) can overwhelm the user with cognitive overload and goes on to present a way of visualizing information in chunks with reading times mentioned and calibrated according to users.

Du, F., Plaisant, C., Spring, N., Crowley, K., & Shneiderman, B. (2019). EventAction: A visual analytics approach to explainable recommendation for event sequences. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 9(4), 1–31.

Some of these questions are mentioned explicitly in the “Problem and Approach” section of their paper. They discuss the various sorts of recommender systems that exist from temporal search queries, search based on record attributes, demographic attributes, etc.

They actually base their approach on case studies with students who are looking to get into a specific field (eg: professorship) and want to track what students in the past cohorts did in order to reach there. The recommendation engine is supposed to help out by suggesting profiles that match in terms of a sequence of events that led to the kind of job the user wants.

Frost, R. L., & Rickwood, D. J. (2017). A systematic review of the mental health outcomes associated with Facebook use. *Computers in Human Behavior*, 76, 576–600. <https://doi.org/10.1016/j.chb.2017.08.001>

Interestingly, though the use of Facebook resulted in addiction, anxiety, depression, among other issues, it also has been correlated with lower depressive symptoms when used in a way that "enabled perceived social support and connection". This lends credence to the idea that online platforms can be used in supportive ways if affective computing is considered within certain contexts.

Picard, Rosalind W. (2000). *Affective computing*. MIT press.

Affective Computing argues for integrating more emotions into our computer interactions to facilitate overall user experience. In this regard, the intermediary chat bot is a perfect example of a small scale quick application of affective computing.

References

Abdul, A. (2020, January 8). COGAM: Measuring and Moderating Cognitive Load in Machine Learning Model Explanations. Ashraf Abdul. <https://www.ashrafabdul.com/publication/cogam-chi20/>

Du, F., Plaisant, C., Spring, N., Crowley, K., & Shneiderman, B. (2019). EventAction: A visual analytics approach to explainable recommendation for event sequences. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 9(4), 1–31.

Frost, R. L., & Rickwood, D. J. (2017). A systematic review of the mental health outcomes associated with Facebook use. *Computers in Human Behavior*, 76, 576–600. <https://doi.org/10.1016/j.chb.2017.08.001>

Narain, J., Quach, T., Davey, M., Park, H. W., Breazeal, C., & Picard, R. (2020). Promoting Wellbeing with Sunny, a Chatbot that Facilitates Positive Messages within Social Groups. *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–8. <https://doi.org/10.1145/3334480.3383062>

Picard, R. W. (1995). MIT Media Laboratory; Perceptual Computing; 20 Ames St., Cambridge, MA 02139 picard@media.mit.edu, <http://www.media.mit.edu/~picard/>. 16.

Picard, Rosalind W. (2000). *Affective computing*. MIT press.