CSC366

Project Part 4

The problem that we have chosen is a system that helps the user to make a decision on where to eat based on facts they provide to the system. This problem fits into the broad topic of recommendation systems in cognitive science. This problem has had many proposed solutions in the form of various approaches based largely on your knowledge source and how it relates to the domain of the recommendations. Some of the approaches taken include classical, sequential, and cognitive recommendation systems.

Classical recommendation systems are systems that typically have a single source that is exploited for a knowledge base. These systems include recommendations on Netflix, Spotify and Facebook. These systems are generally broken into two types. The first type is a single domain where the material is gathered from the same domain that it is making a recommendation on. One example is when Spotify recommends artists based on a user's listening history. These systems can use key features along with weights to make a recommendation. There are also cross domain systems where knowledge from one domain is used to make a decision on another. These systems seek to build a profile from one domain such as your Facebook profile to make recommendations such as what you might want to watch at the movies. The system that we will be building classifies as a single domain system since we will be collecting information from the user about their food preferences as well as past restaurants they have visited to create a recommendation in the same domain. We will also be employing the weights mentioned above to generate a better understanding of the users' input.

Another type of recommendation system is a sequential recommendation system. This system uses a pattern of user-item interactions to determine the next likely decision a user will make (Behesti et al., 2020). These systems can use either a model approach where a computational model is used alongside data to build a prediction or a model-free approach where only past patterns are used to predict. The model-free system offers a simpler solution that does not require the computation needed to build a model; however it is limited since it needs a large collection of data to handle cases. These systems can run into problems if a provided sequence or item has never or rarely been seen. The model-based approach handles cases with complex chains of events since these models use machine learning to build a model that can be applied to many different sequences (Behesti et al., 2020). However, neither system works for our given problem as they require a massive amount of data that would be difficult for the user to provide. Additionally, the system would have trouble adapting quickly to negative feedback from the user. Therefore, the system we are building will need to be able to make decisions and handle revisions to its knowledge base.

The final recommendation system that we found is a cognitive recommendation system. This system attempts to act like a human brain to reach a conclusion using a combination of implicit and explicit behaviors (Behesti et al., 2020). This type of system fits what we need to build for our system; it will utilize explicit information through a user's statement about what food they want as well as implicit information in the form of background information both collected from users and pre-programmed into the knowledge base. The benefit to modeling a system after this system is that, rather than operating solely on data and probabilities, our model can map the cognitive similarities between cases to make a recommendation (Nguyen et al., 2020). This model allows us to collect claims made by the user to attempt to build their cognitive state. This allows us to make better predictions on an individual level since the system will be based mostly on the users' past decisions. This system also allows for the revision of beliefs since it can easily use the refined beliefs to expand or modify the user's mental state in the system.

The system we are building will have elements of single domain classical recommendations systems and cognitive recommendations systems. Our system will use weights and elements from a single domain system to build the meaning of the user's input. Furthermore, we will use a cognitive recommendation system to build a recommendation as well as to correct for any mistakes in the recommendation. We believe this will result in the most accurate recommendation system.

Works Cited

Behesti, Amin, et al. "Towards Cognitive Recommender Systems." Algorithms, vol. 13, no. 8, July 2020, p. 176. doi.org/10.3390/a13080176

Nguyen, Luong Vuong, et al. "Cognitive Similarity-Based Collaborative Filtering Recommendation System." Applied Sciences, vol. 10, no. 12, June 2020, p. 4183. doi.org/10.3390/app10124183