Final Report by Jarvis

The following report was completed by the project team members in the end of October 2017 as a final report for the first incubation phase. This does not mean that the incubation nor the project are at a final stage.

What was your Vision?

Chatbots are a new way to interact with companies, products and services. The product is the same, but the interface between the product and the user is different.

Access to information has changed in the recent years thanks to the huge advances in predictive algorithms. The relevant information is displayed to the user even before he requests it. Everything is based on the tastes and preferences of the user.

Our project is the create a personalized recommender system for cooking recipes available through a friendly conversational interface.

What goals did you set for the incubation time frame?

- Build a recommender system based on a dataset of recipes and user interactions
- Build a chatbot interface that will guide the user through the recommendation process

What open data did you use or generate?

- we use the Swiss Food Composition Database: http://www.naehrwertdaten.ch
- we'll generate data about people's food consumption

What did you accomplish?

- Scrap all the recipes from the allrecipes website (45k recipes, ~4.5M interactions with ~1M users)
- Build a chatbot prototype of Jarvis with Dialogflow (our first ideas, but the final goal changed since then)
- Gather information about chatbot design and recommender systems

How did Open Data support you?

- With financing
- A meeting with Hannes Gassert (29.07.2017): brainstorming, strategies, ideation
- A meeting with Thomas Rippel (10.08.2017): brainstorming, knowledge sharing

Feedback for OpenData

- The strategic meeting with Hannes was really interesting and helpful in the way that he knows what he says and has a lot of experience in the domain.

- The way you adapt to each team is really good (eg. we do not need offices so the money is used for something more useful for the success of the project, and so on)

What are the next steps?

- Design, development and validation of the recipe recommender system model using collected data. ~15 hours*person/week for the next 10 weeks, with the assistance of LSIR lab at EPFL. The collected data contains both implicit (made it / reviews) and explicit feedback (ratings) from user to recipes.

  The recommender model will be based on Bayesian Personalized Ranking, using implicit feedback, which is expected to outperform standard learning techniques [1]. The current development seems to lead to a Matrix-factorization [2] based model.

  A model using the explicit rankings data might be developed in parallel in order to evaluate and compare their respective performances and validate the choice of using implicit data. Other ways of evaluation the model will be explored [3].

  Rendle [4] [5] introduces the factorization machines, an approach combining the power of factorization models with the generality of standard features engineering. Since the collected data contains lots of features for recipes it would be interesting to implement it in our model and compare the results.

  Latest researches on Neural Networks suggest that the use of an underlying (deep) neural networks outperforms standard factorization methods for recommender system [6]. On the long-term it might be interesting to try something and see if it is actually of any help to enhance the performance of our model, but at such an early stage beginning with a factorization based model is best.

- Integrate constraint in the recommender system, allowing for example to propose a set of recipes that comply with specific nutrition goals. (Vegan, Low-meat, WHO's nutritional guidelines)
- Adapt the recommender system to legally available data (TBD).
- Creation of the personality of the chatbot
- Design of the conversational flow
- Integration of the recommender in the chatbot. Since we will have no information about the users and recipes at the beginning, we will need to implement a smart cold-start recommendations strategy. [7] proposes such a strategy that basically consist in mapping users or items features to the latent factors of our model. We need to design a smart strategy to ask users for their preference, for example by proposing them recipes/ingredients and let them swipe left/right according to their preferences and use it to build a profile. With a sufficient amount of user we could then use the profile to map them to the latent factors of our model and be able to recommend recipes to a new user.
- Find a new name and brand image for the Jarvis project
- Regarding open data, we'll be releasing aggregated and anonymized data generated by our platform containing users interactions, behaviours and evolutions. This data will be freely available online, and would provide an interesting dataset for scientist trying to find patterns in people's food consumption.

- Expected time frame:
  January 2018:
  - end of the recommender system prototype
  - end of the basic chatbot

  February 2018:
  - adapting the recommender system to new recipes (legally available)
  - integrating the recommender system to the chatbot

  March 2018:
  - first test of the bot with real users
  - creation of branding & launch strategy)

Team Members & Contact

- Jacky Casas, casas.jacky@gmail.com, @jackycasas_
- Nathan Quinteiro, nathan.quinteiro@gmail.com, @nathan_quint

OpenData Contact

Nikki Böhler, Project Leader OpenData.ch, nikki.boehler@opendata.ch

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