4YP Interim Report

Title: Multi-Objective Recommender Systems that Reconcile Sustainability
Project Number: 12500
Supervisor: Michael Osborne, Edwin Lock (co-supervisor)

Project Overview
Briefly describe the project and its background.

Recommender systems (RS) are widely used across all spaces of technology, from song suggestions on Spotify to ‘recommended products’ on Amazon. This further extends to the foodservice industry where recommending relevant and satisfying restaurant choices to the user will help user satisfaction and in turn, revenue.

Carbon Codes is a startup that aims to improve the sustainability of the foodservice industry by working with online partners and restaurant partners in Oxford, analysing their food dishes and if deemed sustainable, applying a fixed discount on the item which is passed off to users. Recommendation algorithms would be effective in sorting out the order of the partners suggested to a user on the main discounts page (https://carboncodes.co.uk/our-discounts). A primary focus of Carbon Codes isn’t just recommending relevant restaurants to users, but also ensuring that a user is eating as sustainably as possible -- these can often be conflicting objectives. Furthermore, relevance can be measured across different dimensions, namely accuracy of recommendations, diversity of recommendations and the novelty of recommendations, this forms a multi-objective optimisation (MOO) RS problem.

The scope of this project aims to explore the effectiveness of current algorithms and then potentially the implementation of a novel algorithm (which improves on any downsides of well-known MOO RS algorithms) using Bayesian Optimisation.

Key Objectives
Describe your aims and discuss whether the original project objectives need modifying.

The key objective of this project is to develop a novel algorithm for MOO in the context of RS that accounts for the carbon footprint of eating at a certain restaurant (i.e. the sustainability objective). The novelty of the project is in the development of a new algorithm using Bayesian Optimisation, whilst the application is focussed on the context of Carbon Codes: ranking restaurants based on accuracy, sustainability and discount amount. The original project objective was to explore MOO with the objective of sustainability (i.e. no exploration of a novel algorithm), this may change to exploring MOO with a novel algorithm if well-known algorithms illustrate downsides.

Progress to Date
Describe what you have achieved so far.

I have chosen to focus on collaborative filtering within the context of MOO, which uses data from a user’s past behaviour (an unsupervised problem) as opposed to content-based which is a supervised learning problem. The three objectives that I have chosen to optimise are accuracy (user-item specific), sustainability (item specific, or can be user-specific based on a monthly target) and discount amount (item specific, or user-item specific based on variable discounts).

Although I plan to use three datasets, the initial one I have selected to work from is from UCI -- 'Data from a restaurant recommender for collaborative/content-based filtering', and more specifically the collaborative dataset. The dataset contains 1161 rows of data, 138 users and 130 restaurants. The data is spread thinly so exploration would be needed initially (as well as an amount of exploitation). The dataset currently contains user-item ratings, food-ratings & service-ratings, the latter two can be repurposed and synthesised into sustainability and the discount amount.

MOO algorithms for RS can be split into two categories -- scalarization and MOEA. The two will be explored within 'well-known' algorithms:

- Scalarization: combining objectives using (e.g. weighting, epsilon greedy) and then using a normal recommender algorithm (e.g. matrix factorisation). Issues with scalarization + recommender: cold-start, harder to implement, may be ineffective.
- MOEA: selects a random group of points and keeps updating them (mating, crossover & mutation) across iterations (e.g. MOIA). Issues with MOEA: higher computation cost, may converge on a local minima.
- Pareto front approach will be used to select an optimal solution after scalarization/MOEA.

Literature review papers:

- MOO using GA: https://www.sciencedirect.com/science/article/pii/S0951832005002012
- Novel MOEA: https://www.sciencedirect.com/science/article/pii/S0743731516301423
- MOO using Bandits: https://www.sciencedirect.com/science/article/pii/S092523121730228X

Plan of Work

List the tasks remaining with estimated dates of completion.

Task	Description	Date of Completion
Problem definition	Literature review exploring the current well-known algorithms in depth and downfalls of those algorithms.	MT 7th Week
Data	Dataset selection, synthesizing & refining. Including implementation of the additional objectives.	MT 8th Week
Coding	Well-known algorithm coding, and run initial tests on the datasets.	HT -2nd Week
	Research and coding of the novel algorithm.	HT 3rd Week
Experiments	Conduct experiments of the well-known algorithm and the novel algorithm on the datasets.	HT 5th Week
Benchmarking	Benchmark and refine the novel algorithm.	HT 6th Week
Analysis	Analysis and write up, including further exploration.	HT 8th Week