

# Balancing Preferences, Popularity and Location in Context-Aware Restaurant Deal Recommendation

## A Bristol, Cardiff and Brighton Case Study

[Ercan Ezin](#), University of Bristol, [ercan.ezin@bristol.ac.uk](mailto:ercan.ezin@bristol.ac.uk)

Hugo Alcaraz-Herrera, University of Bristol, [h.alcarazherrera@bristol.ac.uk](mailto:h.alcarazherrera@bristol.ac.uk)

Iván Palomares, University of Bristol, The Alan Turing Institute, [i.palomares@bristol.ac.uk](mailto:i.palomares@bristol.ac.uk)



[dsrcs.blogs.bristol.ac.uk](https://dsrcs.blogs.bristol.ac.uk)

## HOW IT WORKS



Discover top-notch local restaurants and cafes, and get exclusive limited-quantity offers

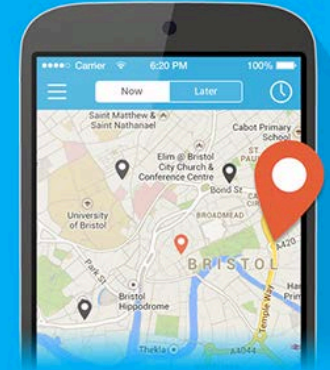


Pick something that tickles your fancy, pay via Wriggle and receive a unique code.



Head to the venue in the window of opportunity, present your Wriggle code and enjoy!

We get you **deals** at places that don't normally do them – but they don't last long so get a wriggle on!

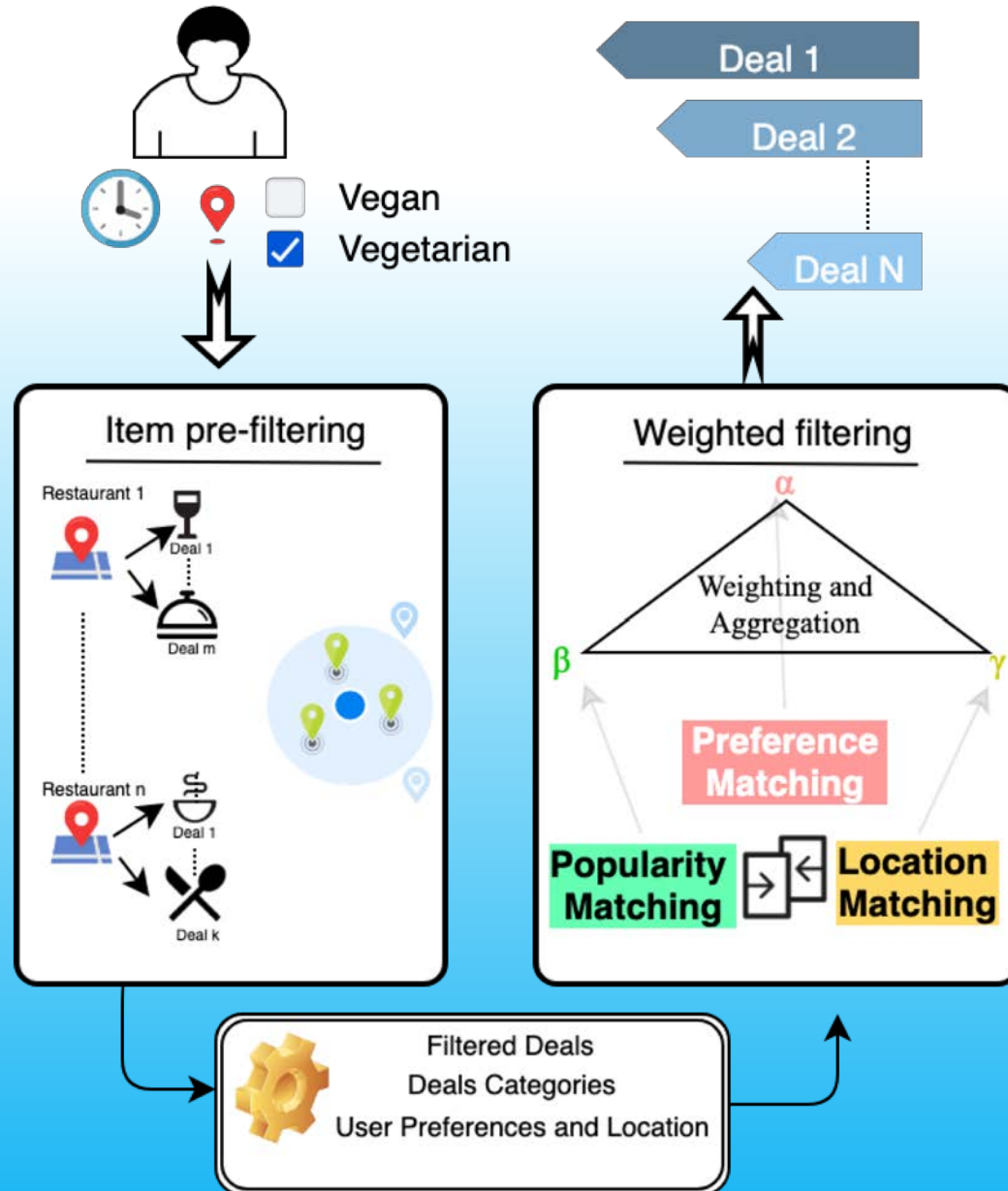


<https://www.getawriggleon.com/>

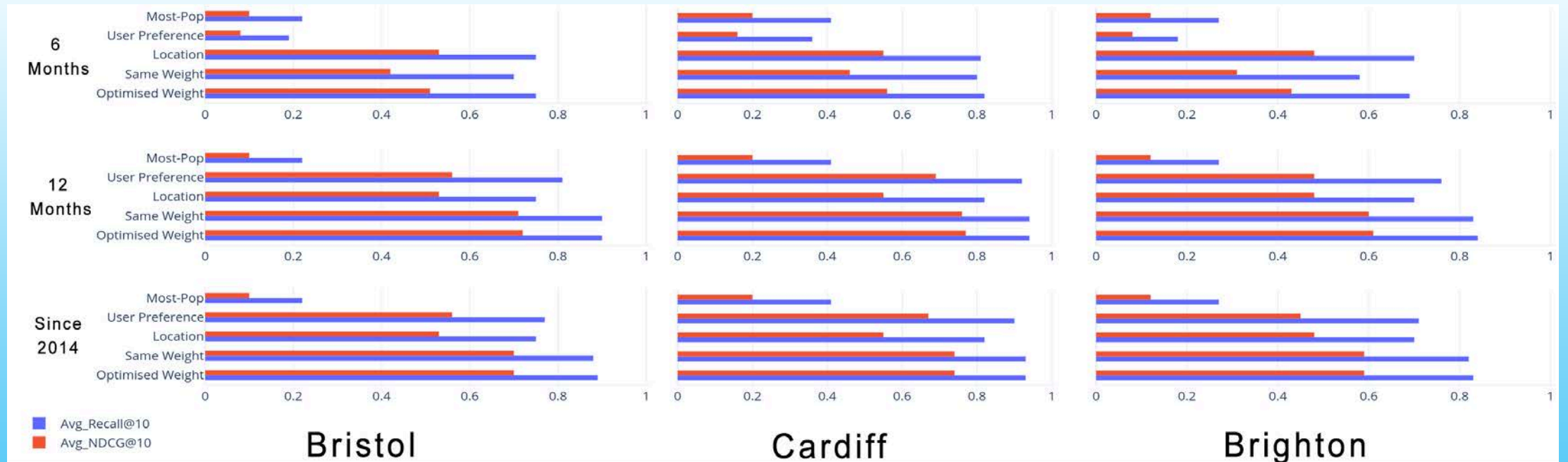
In collaboration with **Wriggle**, we developed a personalisation solution to recommend **tailored restaurant deals** for residents or visitors in a city.

Unlike previous work on recommendations in the restaurant sector where actual venues are recommended, **we focus on suggesting specific products in the form of deals** offered by such restaurants.

# The Model



# The Results



# THANK YOU

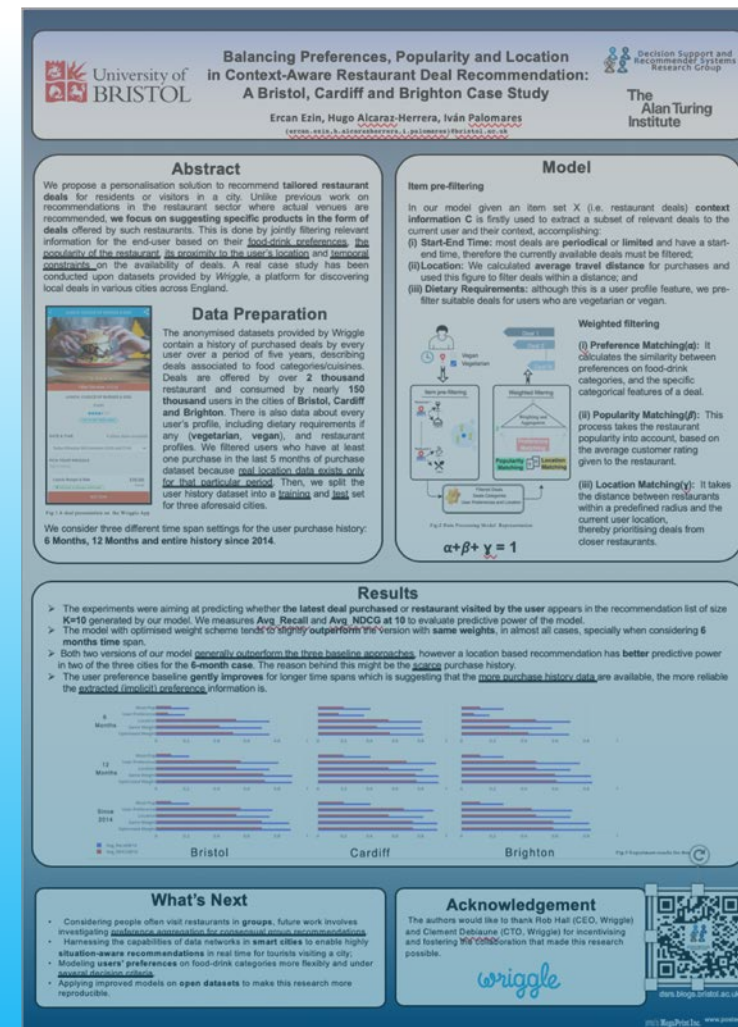
Looking forward to seeing you  
in the poster session

@15:30-16:00

[Ercan Ezin, University of Bristol, ercan.ezin@bristol.ac.uk](mailto:ercan.ezin@bristol.ac.uk)

[Hugo Alcaraz-Herrera, University of Bristol, h.alcarazherrera@bristol.ac.uk](mailto:h.alcarazherrera@bristol.ac.uk)

[Iván Palomares, University of Bristol, The Alan Turing Institute, i.palomares@bristol.ac.uk](mailto:i.palomares@bristol.ac.uk)



**Balancing Preferences, Popularity and Location in Context-Aware Restaurant Deal Recommendation: A Bristol, Cardiff and Brighton Case Study**  
Ercan Ezin, Hugo Alcaraz-Herrera, Iván Palomares  
Decision Support and Recommender Systems Research Group  
The Alan Turing Institute

**Abstract**  
We propose a personalisation solution to recommend tailored restaurant deals for residents or visitors in a city. Unlike previous work on recommendations in the restaurant sector where actual venues are recommended, we focus on suggesting specific products in the form of deals offered by such restaurants. This is done by jointly filtering relevant information for the end-user based on their food-drink preferences, the popularity of the restaurant, its proximity to the user's location, and personal preferences on the availability of deals. A real case study has been conducted upon datasets provided by Wriggle, a platform for discovering local deals in various cities across England.

**Data Preparation**  
The anonymised datasets provided by Wriggle contain a history of purchased deals by every user over a period of five years, describing deals associated to food categories/cuisines. Deals are offered by over 2 thousand restaurant and consumed by nearly 150 thousand users in the cities of Bristol, Cardiff and Brighton. There is also data about every user's profile, including dietary requirements if any (vegetarian, vegan), and restaurant profiles. We filtered users who have at least one purchase in the last 6 months of purchase dataset because deal location data exists only for that particular period. Then, we split the user history dataset into a training and test set for three addressed cities.

**Model**  
Item pre-filtering  
In our model given an item set  $X$  (i.e. restaurant deals) context information  $C$  is firstly used to extract a subset of relevant deals to the current user and their context, accomplishing:  
(i) **Start-End Time**: most deals are periodical or limited and have a start and time, therefore the currently available deals must be filtered;  
(ii) **Location**: We calculated average travel distance for purchases and used this figure to filter deals within a distance; and  
(iii) **Dietary Requirements**: although this is a user profile feature, we pre-filter suitable deals for users who are vegetarian or vegan.

**Weighted filtering**  
(i) **Preference Matching( $\alpha$ )**: It calculates the similarity between preferences on food-drink categories, and the specific categorical features of a deal.  
(ii) **Popularity Matching( $\beta$ )**: This process takes the restaurant popularity into account, based on the average customer rating given to the restaurant.  
(iii) **Location Matching( $\gamma$ )**: It takes the distance between restaurants within a predefined radius and the current user location, thereby prioritising deals from closer restaurants.

**Results**  
The experiments were aiming at predicting whether the latest deal purchased or restaurant visited by the user appears in the recommendation list of size  $K=10$  generated by our model. We measure Avg. Recall and Avg. NDCG at 10 to evaluate predictive power of the model.  
The model with optimised weight scheme tends to slightly outperform the version with same weights, in almost all cases, specially when considering 6 months time span.  
Both two versions of our model generally outperform the three baseline approaches. However a location based recommendation has better predictive power in two of the three cities for the 6-month case. The reason behind this might be the poor purchase history.  
The user preference baseline gently improves for longer time spans which is suggesting that the poor purchase history data are available, the more reliable the extracted (implicit) preference information is.

**What's Next**  
Considering people often visit restaurants in groups, future work involves investigating purchase association for personalised group recommendations.  
Harnessing the capabilities of data networks in smart cities to enable highly situation-aware recommendations in real time for tourists visiting a city.  
Modeling users' preferences on food-drink categories more flexibly and under various situation contexts.  
Applying improved models on open datasets to make this research more reproducible.

**Acknowledgement**  
The authors would like to thank Rob Hall (CEO, Wriggle) and Clement Debaune (CTO, Wriggle) for incentivising and fostering WriCollaboration that made this research possible.

**Wriggle**  
www.wriggle.com  
© 2019 WriPartners. www.wripartners.com