Recommendation Tools:

Personalized Food Recommendations Article:

<https://pdfs.semanticscholar.org/0b1e/4850bf48699fed7b2b3ad970f211d711a1da.pdf>

Being focused more on rating-based recommendations, the system uses **Collaborative filtering** and **Content-based algorithms**.

**Features that compose a recipe are**: category, region, restaurant ID and ingredients. Context features are also considered in the moment of the recommendation, these are: temperature, period of the day, season of the year, and meal’s cost. Each feature has a specific location attributed to it in the recipe and user profile sparse vectors.

The decomposition of recipes into ingredients implemented in this experiment is simplistic: ingredient scores were computed by averaging the ratings of recipes in which they occur.

**Recommendations** are generated by comparing the restaurant’s recipes’ features with the user profile using the cosine similarity measure. The recommended recipes are ordered from most to least similar. In this case instead of referring recipes as vectors of words, recipes are represented by vectors of different features.

**Rocchio’s Algorithm** is widely used relevance feedback method that operates in the vector space model. It uses feature weights to build the prototype vectors, representing the user’s preferences. The weight attributed can be computed using the TF-IDF (Term Frequency-Inverse Document Frequency) scheme. Using relevance feedback, recipes’ feature vectors of positive and negative examples are combined into a prototype vector for each class *c*. These prototype vectors represent the learning process in this algorithm. New recipes’ features are then classified according to the similarity between the prototype vector of each class and the corresponding user’s profile vector, using for example the well-known cosine similarity metric. The algorithm returns a similarity value between the recipe features vector and the user profile vector.

**Summary:**

Recipes are broken down to a number of features with relative weights (determined by TF-IDF) and are used to build a prototype vector. Then, the prototype vector is compared to corresponding user’s profile vector to return a similarity value and suggest a new recipe.

The idea of considering ingredients in a recipe as similar to words in a document lead to the variation of TF-IDF weights. This work presented good results in retrieving the user’s favorite ingredients.

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Features from **OpenFoodFacts** database: a free, open, collaborative database of food products from around the world, with ingredients, allergens, nutrition facts and all the tidbits of information found on product labels. 5000+ contributors like you have added 600 000+ products from 150 countries using our Android, iPhone or Windows Phone app or their camera to scan barcodes and upload pictures of products and their labels

Terms and conditions for re-use: <https://world.openfoodfacts.org/terms-of-use#re-use>

How to use for GitHub: <https://github.com/openfoodfacts/openfoodfacts-python>

1. code (text)
2. url (text)
3. creator (text)
4. created\_t (text)
5. created\_datetime (text)
6. last\_modified\_t (text)
7. last\_modified\_datetime (text)
8. product\_name (text)
9. generic\_name (text)
10. quantity (text)
11. packaging (text)
12. packaging\_tags (text)
13. brands (text)
14. brands\_tags (text)
15. categories (text)
16. categories\_tags (text)
17. categories\_en (text)
18. origins (text)
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23. labels\_tags (text)
24. labels\_en (text)
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26. emb\_codes\_tags (text)
27. first\_packaging\_code\_geo (text)
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29. cities\_tags (text)
30. purchase\_places (text)
31. stores (text)
32. countries (text)
33. countries\_tags (text)
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36. allergens (text)
37. allergens\_en (text)
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