toMEto: a Networks-based Approach to Recipe Recommendation

CS145

Albert Ge
California Institute of Technology
Pasadena, CA
age@caltech.edu

Matthew Jin
California Institute of Technology
Pasadena, CA
mjin@caltech.edu

Jonathan Joo
California Institute of Technology
Pasadena, CA
jjoo@caltech.edu

Boyu (Charlie) Tong
California Institute of Technology
Pasadena, CA
bttong@caltech.edu

ABSTRACT

toMEto is a web-based application that suggests ingredients to supplement existing recipes. We develop and evaluate several network based algorithms, packaging the suggestions under an intuitive and friendly user interface.

1. INTRODUCTION

The rest of the paper is organized as follows. Section 2 contains how we scraped the data and other preprocessing steps. Section 3 describes the algorithms considered. Section 4 covers the app's web design while Section 5 covers the backend. Section 6 concludes our paper.

1.1 Related Work

There have been a select number of papers discussing analysis of food and ingredient networks. Teng et al. [?] describes the goal of being able to recommend entire recipes, using recipe suggestions made by examining communities of a co-occurrence network, to predict the success of a particular recipe's rating.

Another paper by Ahn et al. [?] compares the differences in cuisine by instead looking at a flavor-compounds network, and making general statements about the co-occurrence of ingredients by their chemical composition. They discovered that Asian recipes tend to have ingredients with different compounds, whereas Western cuisines have ingredients with like compounds.

Still other research is ongoing, some building upon the relevance of flavor compounds in regional cuisines [?], [?], and others attempt to implement these ideas to help users make suggestions about healthy food choices [?].

Within this web of research, we discovered a potential niche for recommending individual *ingredients*, as opposed to entire recipes. This combines both the practical application of current research on food networks, as well as the theory behind identifying ingredients that are compatible with each other.

2. DATA PROCESSING

2.1 Data source

Our application's source of data are the online recipe websites New York Times (NYT) Cooking and AllRecipes.com. We gained over 13,000 and 52,000 recipes by crawling and scraping these two websites respectively. This was done by a script written in `scraper.py`.

2.2 Initial parsing

Our application only requires the title, ingredients, and body of each recipe, so we extracted this data from each webpage using a simple script written in `parser.py`.

However, this extracted data was not in a clean format that our algorithms could easily use. For example, ingredients were often combined with quantifiers and other adjectives:

- *medium-size russet potato, about 10 ounces, peeled and diced*
- *shrimp, shelled and cut into bite-sized pieces*
- *kale, stemmed, rinsed and coarsely chopped to make 6 cups*

These ingredients would only occur maybe once or twice in the entire dataset, resulting in many "rare" ingredients. In the NYT dataset (12402 unique ingredients), approximately 70% of the unique ingredients occurred only once, and 90% occurred less than 10 times. We realized this resulted in suboptimal performance, as these ingredients would not be counted correctly in the co-occurrence network and many edges would not exist in the network.

2.3 Mapping

To fix this, we developed a script in `nyt_mapper.py` to find these "rare" ingredients and map them to their root ingredient. For the example ingredients from above, we generated the mappings:

- *medium-size russet potato, about 10 ounces, peeled and diced* $\rightarrow$ *potato*
- *shrimp, shelled and cut into bite-sized pieces* $\rightarrow$ *shrimps*
- *kale, stemmed, rinsed and coarsely chopped to make 6 cups* $\rightarrow$ *kale*

The script attempts to extract the root ingredient for each entry by combining several strategies. For example, some strategies that we use are:

- Removing parenthetical tokens
  - *vanilla extract (to taste)* $\rightarrow$ *vanilla extract*
- Removing comma separated descriptors
  - *honey, preferably wildflower* $\rightarrow$ *honey*
- Picking the best of two ingredients separated by 'or'
  - *sriracha or other hot sauce* $\rightarrow$ *sriracha*
- Finding a sole 'top' ingredient name
  - *coarsely grated carrot* $\rightarrow$ *carrots*

Using the mappings generated by `nyt_mapper.py`, we reduced the unique ingredient count by 75%. This resulted in a much more densely connected network, and more accuracy in recommendations.

2.4 Supplementing with AllRecipes data

We initially focused our application on the NYT dataset due to the relatively cleaner data and ingredients list. Once our basic algorithms were up and running on this dataset, we moved to supplement it with the much larger AllRecipes dataset. We reasoned that this would further improve the co-occurrence network by providing a more accurate count of ingredient frequencies. We also realized it would introduce new connections, since there may be recipes and foods that are not found in the NYT dataset.

As our application does recommendations only for NYT recipes, we modified our approach to processing the AllRecipes data accordingly. Again, we wrote a mapping script in `allrecipes_mapper.py`, but instead of mapping to only the root ingredients, the script also attempted to map to the top ingredients in the NYT dataset. This was important because our goal ultimately was to develop a co-occurrence network for the NYT dataset, and we did not want the ingredients of the AllRecipes dataset to be disjoint in any way.

The AllRecipes mapper employed many of the same techniques as the NYT mapper, with some additional strategies. The recipes from the AllRecipes websites list the ingredients with numbers and quantifiers, for example:

- *1 pound ground beef*
- *1/2 teaspoon black pepper*
- *1 (25 ounce) package frozen cheese ravioli*

Thus, we added filters that removed numerical digits from the raw ingredient name and also searched for and removed quantifiers such as "pound", "teaspoon", or "ounce". To map the ingredients to the NYT ingredients, we took a set of the most common NYT ingredients and searched for corresponding tokens in the AllRecipes ingredients. If there was a 1-to-1 matching, then we considered it a mapping.

Combining both datasets resulted in a network with 7339 unique ingredients. Of these, we selected the top 1000 which approximately corresponded to the set of ingredients with at least 10 occurrences. For several of our algorithms, we restricted the recommendations to be from within this "top set" in order to have meaningful suggestions.

3. ALGORITHM DESIGN AND ANALYSIS

The primary application of algorithm design resides in ingredient recommendation to the user. We reserve the majority of this section to understanding the different frameworks we tried for the *complement* method, which is a method that takes in a particular recipe ID, and suggests up to ten ingredients that the user could potentially add.

Before we do so, however, we first introduce some common terminology to be used throughout the text:

1. *w(x,y)* describes the weight of the edge between two ingredients. We define the weight of an edge as the co-occurrence of two ingredients; that is, how many times the two ingredients appear in the same recipe.
2. *graph* is the entire ingredient network.
3. *peripheral ingredient* describes those ingredients that are not part of a recipe, but have at least one edge (with nonzero weight) to an ingredient in the recipe (Fig. 1). Formally, this is described as
$$\{k : \text{k} \in \text{adjacent neighbors of recipe} \land k \notin \text{recipe}\}$$
4. *compatibility score* is a score computed (using different metrics) that is used to rate each ingredient suggestion. An ingredient with high c̈ompatibilityẅith another suggests that the pair are commonly used together, and therefore would be a good fit for the recipe.

There are two primary schools of thought when designing an appropriate algorithm for recipe recommendation - using degree centrality measures, versus using pointwise mutual information (PMI). Here we enumerate in detail the algorithms.

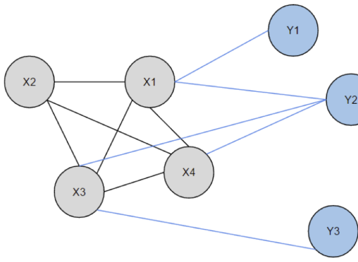


Figure 1: Peripheral ingredients. Nodes denoted in gray are part of recipe X, while ingredients in blue are peripheral ingredients with connections to some of the recipe ingredients.

First, we discuss the algorithm that uses degree centrality. We apply degree centrality toward compatibility scores of ingredients.

1. Degree Centrality (Algorithm 1). This algorithm was the first variant that we attempted on ingredient recommendation. First, we obtain a list of all peripheral ingredients of a particular recipe. Here, we exclude the top ten ingredients as part of our search. The idea was to exclude potentially obvious or very similar ingredients from our search - we wanted to suggest something that would introduce variability to our suggestions, rather than recommend the same high-frequency ingredients. Additionally, we must check if ingredients exist in the network, as our data processing eliminates certain ingredients from the graph but doesn't eliminate them from the recipes themselves.
   The key aspect of this algorithm was to compute a compatibility score of an ingredient by summing over the all its connections with ingredients in the recipe. For two ingredients (a, b), we compute the weight of its connection by $w(a, b)$ by counting the number of occurrences a, b appear together in the same recipe. Each connection is normalized by dividing by the highest weighted number of connections of the two ingredients; this helps prevent other high-frequency ingredients from dominating the recommendation. To compute the the weighted number of connections of an ingredient a, we sum the weights over all the connections with its neighbors: $\sum_{b \in N(a)} w(a, b)$.
   Formally, we write, for a pair of ingredients (i, k) with i being a recipe ingredient and k a peripheral ingredient,
   $$score = \sum_{i \in recipe} \min\left(\frac{w(i,k)}{degree(i)}, \frac{w(i,k)}{degree(k)}\right)$$

Since this algorithm takes an arbitrary standard of excluding the top ten ingredients from recommendation, this was initially seen as a naive algorithm for recipe recommendation. Hence, we turned to a much more extensive analysis of using PMI as the basis of our algorithms. The general formula of PMI, between two ingredients a, b is given by:

$$\log \frac{p(a, b)}{p(a)p(b)}$$

Algorithm 1 Degree Centrality algorithm

```
function NAIVE(recipeID)
    Let recipe = recipe with ID recipeID
    Let top10 = ten ingredients with highest weighted number of connections
    Let d = dictionary to contain all ingredients and their compatibility score
    for i in ingredients of recipe do
        if i in graph and i not in top10 then
            for peripheral ingredient k do
                d[k] = d[k] + min(w(i,k)/degree(i), w(i,k)/degree(k))
    return 10 ingredients from d with highest compatibility score
```

where $p(a)$ is defined as $\frac{\text{number of occurrences of a}}{\|graph\|}$. Intuitively, this value between two ingredients describes how likely two ingredients are to appear together in the graph. Two ingredients with very few connections could still have a high value according to this metric, if they appear together more often than they do not. Thus it was thought that this metric captures ingredient pairings much better, as now there isn't any need to remove the most frequent ingredients.

As in degree centrality, we use PMI mainly for computing compatibility scores of ingredients.

Here we enumerate the algorithms using PMI:

1. Normalized PMI. After computing a score using PMI, normalize the value by the weighted number of connections. This algorithm is the exact same as in Algorithm 1, only the weight $w(a, b)$ is subsituted for $PMI(a, b)$. This was mostly meant to compare directly with the the degree centrality algorithm.

2. Weighted PMI (Algorithm 2). This weights an ingredient's PMI score by the number of edges that exist between itself and ingredients of the recipe. Formally, for a peripheral ingredient b we describe this as
   $$\left(\sum_{a \in recipe} \mathbb{1}_{(a,b) \in graph}\right)\left(\sum_{a \in recipe} PMI(a, b)\right)$$
   Thus, for each connection to an ingredient in the recipe, we increase the weight factor by 1. Intuitively, this assigns more importance to peripheral ingredients that pairs well with many of the recipe's ingredients.

3. Generalized PMI. This is an extension to the pairwise PMI score, and generalizes it PMI between more than 2 ingredients. For an n-tuple of ingredients in the recipe, we compute sum of all their weighted connections with each other $\sum_{a,a' \in tuple} w(a, a')$. We then find the tuple whose sum of weights is the greatest - this captures the ingredients that are seen together most often in recipes, and gives us a sense of the ësssentialïngredients in the recipe. Then, using these essential ingredients, we can compute a generalized PMI score for each peripheral ingredient that has connections to all of these essential ingredients, which is given by
   $$PMI(tuple) = \log \frac{p(x \in tuple)}{\prod_{x \in tuple} p(x)}$$

In practice, we found that letting $n = 3$ for determining the size of our tuple was best, as it as large as we could get without too many division by zero errors.

4. Minimax PMI. This algorithm was meant to consider šafešuggestions; that is, recommending peripheral ingredients that would be compatible with all recipe ingredients, instead of ingredients that would work very well with some and not at all with others in the recipe. To do this, for a peripheral ingredient b we computed $\min_{a \in recipe} PMI(a, b)$, and then returned the ingredients with the highest min values. This way, we could rule out ingredients that would never pair well with at least one recipe ingredient.

Algorithm 2 Weighted PMI algorithm

function NAIVE($recipeID$)
  Let $recipe$ = recipe with ID $recipeID$
  Let $top10$ = ten ingredients with highest weighted number of connections
  Let d = dictionary to contain all ingredients and their compatibility score
  for i in ingredients of $recipe$ **do**
    if i in graph **then**
      for peripheral ingredient k **do**
        $d[k] = d[k] + \min(\frac{PMI(a,b)}{degree(b)}, \frac{PMI(a,b)}{degree(a)})$
        $count[k] = count[k] + 1$
  for ingredient in d **do** $d[k] = d[k] \cdot count[k]$
  return 10 ingredients from d with highest compatibility score

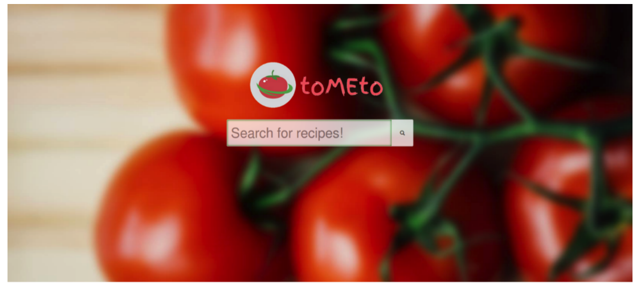
Algorithm 3 generalized PMI algorithm

function NAIVE($recipeID$)
  Let $recipe$ = recipe with ID $recipeID$
  Let $top10$ = ten ingredients with highest weighted number of connections
  Let d = dictionary to contain all ingredients and their compatibility score
  $bestMatch = \max_{(a,b,c) \in recipe} w(a,b) + w(b,c) + w(a,c)$
  $tuple = \text{argmax}_{(a,b,c) \in recipe} w(a,b) + w(b,c) + w(a,c)$
  for i in ingredients of $tuple$ **do**
    for peripheral ingredient k and $a, b, c \in N(k)$ **do**
      $d[k] = PMI(k, tuple)$
  return 10 ingredients from d with highest compatibility score

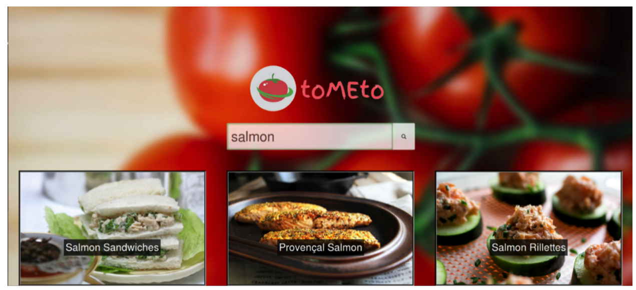
4. WEB DESIGN

Web design was done using a combination of HTML, CSS, JavaScript, and Python. HTML was used to create the content for display on the page, and CSS was used to style this content. JavaScript was also used for animations and general User Interface tweaks to make browsing the site intuitive and smooth. Finally, Python was utilized as an interface between the back-end and the front-end. Through the usage of Python's Flask framework, it was possible to integrate the back-end algorithms with displaying the relevant computed information on the front-end. In other words, our module app.py imported modules from the back-end, while also using this information to fill in the HTML templates based on search queries, etc. given by a user in the front end.

The primary focus on the front end was to develop a site that is intuitive and self-explanatory, while also featuring only the information that is needed the most. Thus, the landing page has the following design:



Upon searching for a recipe, a loading bar appears, and once recipe information ins obtained, tiles fade in. These tiles offer an image of the recipe to be prepared, with the recipe title overlaid on top. This can be seen below:

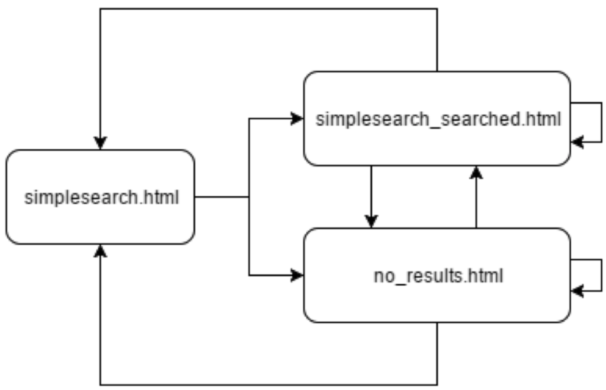


Upon clicking a recipe, a modal popup appears, which lists both the recipe itself as well as toMEto's recommended ingredients, as can be seen in the below image:

Much of the front-end was designed to be easily updated and maintained, and thus small UI tweaks, such as background images, color schemes, etc. are easily changeable by editing the HTML and/or CSS files. The front-end utilizes mainly three different HTML templates:

- simplesearch.html
- simplesearch_searched.html
- no_results.html

simplesearch.html is simply the html for the landing page, before any queries are entered. Then, once a search query is entered, app.py directs this information to the backend, which then generates information which is supplied to the simplesearch_searched.html template. The user is also redirected to this template, which includes the tiles, modal popup information, etc. Furthermore, if a search is entered into simplesearch_searched.html, this also refreshes the simplesearch_searched.html template, utilizing the new information. Finally, no_results.html is used as a template to be redirected to when the query entered into simplesearch.html or simplesearch_searched.html does not contain any results. As a note, a user will be redirected to simplesearch.html upon clicking the toMEto logo.



5. BACKEND ARCHITECTURE

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

6. CONCLUSIONS AND FUTURE WORK

The final result of our project is a web based application that suggests supplementary ingredients to existing recipes. The novel part of our application lies in our algorithms, where we use purely network metrics to rank ingredient suggestions. The generalized PMI algorithms had the most success in providing solid, consistent recommendations.

There are also several features that could be implemented to further improve toMEto. At the moment, recipes are found using a database. Allowing the user to specify his own recipe with a set of ingredients and then recommending supplementary ingredients would be a very useful feature. This would not be very difficult to implement with our current architecture. The one challenge here is restricting or preprocessing user inputs to match those in the existing ingredient network.

We could parse the dataset and classify them, allowing users to get suggestions for a certain type of recipe. For example, some classifications could be how the recipe is cooked (baked, fried, etc.) or the type of cuisune. Then, suggestions that appear will be restricted to the type of recipe the user is interested in.

Furthermore, we could allow user personalization. Allow the user to upvote or downvote suggestions, and use machine learning techniques to determine what kind of additions the user likes. This would require new algorithms to supplement our existing network algorithms.

7. REFERENCES

[1] Y.-Y. Ahn, S. E. Ahnert, J. P. Bagrow, and A.-L. Barabási. Flavor network and the principles of food pairing. *Scientific Reports*, 1, 12 2011.

[2] G. Geleijnse, P. Nachtigall, P. van Kaam, and L. Wijgergangs. A personalized recipe advice system to promote healthful choices. In *Proceedings of the 16th International Conference on Intelligent User Interfaces*, IUI '11, pages 437–438, New York, NY, USA, 2011. ACM.

[3] A. Jain, N. Rakhi, and G. Bagler. Analysis of food pairing in regional cuisines of india. *PloS one*, 10(10), 2015.

[4] C. Teng, Y. Lin, and L. A. Adamic. Recipe recommendation using ingredient networks. *CoRR*, abs/1111.3919, 2011.

[5] Y.-X. Zhu, J. Huang, Z.-K. Zhang, Q.-M. Zhang, T. Zhou, and Y.-Y. Ahn. Geography and similarity of regional cuisines in china. *PloS one*, 8(11), 2013.