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Project Proposal for the lecture Text Analytics
Clustering and Enriching Recipes

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 Find this project on GitHub:

https://github.com/christian-heusel/ITA_WS_2020

1 Introduction

When was the last time you looked into your recipes collection and thought: *Oh, what a mess, why is there no structure in this collection?* Well, most of us tend to collect interesting recipes from various different sources – may it be old recipes from grandma or fancy modern, low-carb recipes from lifestyle magazines. Usually, we file all our recipes away in a folder or even digitalize them and throw them into virtual pile of recipes.

But wouldn't it be nice, if there was a structure in our recipes collection? All pasta recipes in one chapter, all starters in a chapter separate from deserts and even a categorization into different cultural cuisines? In our project we aim to solve this everyday-life problem by applying text analytics methods to recipe datasets. For example by clustering recipes into meaningful categories similar recipes can be detected and grouped together. One goal is to find out if recipes can be automatically separated into groups like:

- types of food: e. g. starters, mains, deserts, pastry and drinks,
- cultural origin of the cuisine: e. g. all Mediterranean dishes appear in the same cluster whereas Asian food is in another cluster far apart. Analyzing even sub-clusters would be interesting to find out how closely the different cuisines are related to each other.

Further ideas for real-world scenarios are the estimation of a healthiness score and the prediction of a dish's preparation time based on the recipe, similar to reading time estimations on websites. Additionally analyzing the comments of recipes if available with sentiment analysis methods would be interesting for automatically generating ratings. As there is barely anything more fundamental than food, all text analytics that can be performed on recipe data has real-world applications.

Could it be an idea also to do a search in the cluster over different recipes as an interpolation of them?

In the end, an intelligent recipe collection shall be offered where newly added recipes will automatically be sorted into a suitable position. Thus, one can nicely browse through all items and quickly find a suitable recipe in order to indulge oneself.

Am Schluss sollten wir einen Ueberblick über die Struktur dieses Dokumentes geben. Also kurz zwei Sätze, welche Infos man wo findet.

2 Research Topic Summary

Astonishingly, there is only a small research community which analyzes recipes, given that understanding recipes is a crucial everyday skills and their ubiquity. So far, the problems that are tackled and the issues that are tried to be solved vary a lot.

Things to cite (datasets, applications, methods):

- recipes1M+ dataset [1] with corresponding analysis [2]
- German Recipes Dataset [3]
- Recipe generation [4]
- Food.com Dataset with Interactions [5] with notebook on sentiment analysis, most/least favourite ingredients
- Cultural diffusion: [6] on the What's cooking dataset <https://www.kaggle.com/c/whats-cooking/overview>
- Recipe box dataset [7]
- Clustering Recipes [8]

definitely a more structured literature review needs to be done here

3 Project Description

Main project goals: Create a meaningful clustering/categorization of recipes and enrich plain recipes with useful additional information.

Text Analytics Tasks: Clustering, sentiment analysis, ...

Pipeline: Parsing, Tokenization, stemming, ... How to split up ingredients and instructions. Extract verbs from instructions might be useful as they are good indicators of what is happening. In Figure 1 all steps are presented in detail.

Used datasets: There are several large datasets of recipes from different websites so that we might not have to crawl our on recipe dataset. We found the following datasets:

1. recipes1M+
2. German recipes dataset
3. epirecipes

4. what's cooking dataset

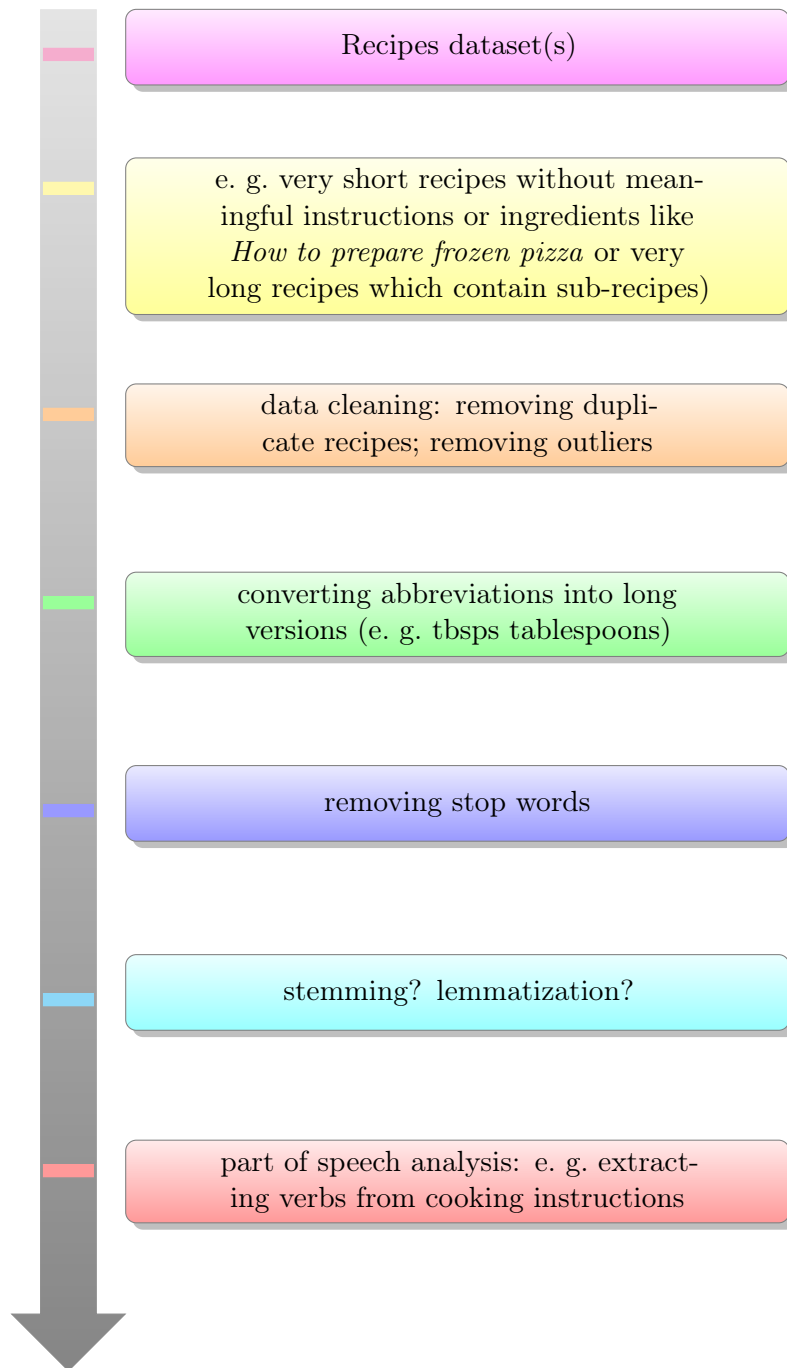


Figure 1: Pipeline: From entire recipes to features in matrices...

5. food.com recipes and interactions

All of them contain for each recipe a title, a list of ingredients with measurements and preparation instructions. Some datasets include additional information like cuisine, url to website, an image, comments on the recipe, ... We plan to compare our developed methods on several datasets to evaluate their generalization performance. So for example training on a dataset with labeled data and then evaluating on others where no labels are available makes sense. One difficulty might be that recipes are written in different languages. So generalization only works within the same language. Also the quality of the recipe data might vary a lot.

Evaluation: As there aren't many labels available a manual evaluation and qualitative analysis of the results needs to be performed. For clustering one can visually see, if it worked and how the different categories are spread.

Baselines: Do we know any baselines for our tasks?

3.1 Project roadmap

Our planned milestones are the following:

1. Data Inspection: Detailed analysis of the different datasets to get an understanding of the data quality and its distribution. Especially detecting abnormalities that need to be adjusted in consecutive work might be valuable.
2. Constructing pre-processing pipeline as outlined above.
3. Implementing different methods to cluster recipes. In parallel methods to predict additional information about the recipes like its cuisine association, its preparation time or healthiness score are developed.
4. Each method's performance will be evaluated. Ultimately all tasks will be combined into an intelligent recipes system.

References

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