**TASTEset - RECIPE DATASET AND FOOD ENTITIES RECOGNITION BENCHMARK**

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**ABSTRACT**

Food Computing is currently a fast-growing field of research. Natural language processing (NLP) is also increasingly essential in this field, especially for recognising food entities.

However, there are still only a few well-defined tasks that serve as benchmarks for solutions in this area. We introduce a new dataset – called TASTEset – to bridge this gap. In this dataset, Named Entity Recognition (NER) models are expected to find or infer various types of entities helpful in processing recipes, e.g. food products, quantities and their units, names of cooking processes, physical quality of ingredients, their purpose, taste.

The dataset consists of 700 recipes with more than 13,000 entities to extract. We provide a few state-of-the-art baselines of named entity recognition models, which show that our dataset poses a solid challenge to existing models. The best model achieved, on average, 0.95 $F_1$ score, depending on the entity type – from 0.781 to 0.982. We share the dataset and the task to encourage progress on more in-depth and complex information extraction from recipes.

**Keywords** BioNLP Application · Food Computing · Named Entity Recognition

**1 Introduction**

Food computing is a multidisciplinary field as it integrates food, nutritional, and computer sciences, as well as gastronomy [Min et al. 2019]. Preparing a health-aware food management system requires a vast amount of domain knowledge and a deep understanding of recipes, especially extracting crucial information. This research is a step toward deeper analysing and extracting vital information from recipes.

The main contributions of this study are:

1. *TASTEset* – our novel dataset of 700 text recipes with 3,788 ingredients and above 13,000 entities of different types (helpful in food computing);
2. Our method of collecting and annotating the dataset (see Section 3);
3. Evaluation of several state-of-the-art Named Entity Recognition (NER) baselines (see Sections 4 and 5);

In the following, Section 2 describes our motivation and related work. Then, we describe our approach to preparing the dataset and perform exploratory dataset analysis in Section 3. We also present experiments with the state-of-the-art baselines (Section 4) and their results (Section 5). Finally, we conclude our paper in Section 6.
2 Related Work

Our main reason for preparing a new dataset was to develop a strategy to deal with challenges faced by food computing, especially concerning a deeper understanding of information about ingredients in recipes, e.g., their quantities, processing, and various aspects regarding different dietary needs. This comprehensive information then can advise proper nutrition, e.g., it can be utilized to build health-aware recommendation systems.

According to the survey in [Min et al., 2019], existing datasets and methods are not well prepared for health-aware and lifestyle preferences or constraints. In order to design health-aware systems for recipe recognition and recommendations, we need to understand recipes deeply, e.g., recognizing specific ingredients, their groups, understanding their relations and functions, quantities, or other dietary issues. For example, different degrees of food or ingredient processing show whether something is healthy or not [Menichetti et al., 2021]. In order to prepare more advanced analysis or recommendations considering all food processing aspects, ingredient quantities, etc., we need fine-grained as well as very precise entity extraction and analysis.

However, these knowledge and notation is scarce in currently available datasets to train machine learning models. Available recipe datasets are mainly focused on information retrieval (mainly visual or cross-modal), image-text recipe generation, or extracting general information about cooking and ingredients. [Min et al., 2019] survey existing benchmark food datasets and challenges. The most extensive recipe datasets are Recipe1M+ [Marín et al., 2021] and RecipeNLG [Bien et al., 2020]. However, they lack specific fine-grained tags related to ingredients.

Though there is a substantial number of available annotated datasets with entities from the biomedical domain, such resources are still insufficient in the food domain. The available corpora include r-FG (recipe flow graph) [Mori et al., 2014], CURD (Carnegie Mellon University Recipe Database) [De la Torre et al., 2008], and FoodBase [Popovski et al., 2019]. The r-FG dataset is composed of 266 Japanese recipes, annotated with eight tags, associated with food, tool, duration, quantity, chef’s action, action by foods, food state, and tool state. CURD consists of 300 annotated and 350 unannotated recipes, for which the Minimal Instruction Language for the Kitchen Language (MILK) is used. FoodBase [Popovski et al., 2019] comprises of 12,844 food entity annotations describing 2,105 food entities, which are later linked to the Hansard corpus (https://www.hansard-corpus.org). All the above-mentioned corpora are limited. The r-FG dataset consists of only Japanese food recipes. All the state-of-art corpora use annotations schemes that have limitations, in particular they are too coarse-grained, mostly providing only general food entities.

The goal of making entities recognition automatic can be achieved by applying natural language processing methods (i.e., Named Entity Recognition (NER) [Nasar et al., 2021]). Classical approaches for Named Entity Recognition frequently involved Conditional Random Fields (CRFs) proposed by Lafferty et al. [Lafferty et al., 2001]. Currently, most of the methods solving NER problems use deep neural networks to capture context information about a given token. Huang et al. [Huang et al., 2015] proposed a bidirectional recurrent neural network using long short-term memory (LSTM) cells [Hochreiter and Schmidhuber, 1997] enriched with a CRF layer to tag sequences with predefined labels. In recent years, the focus shifted from recurrent neural networks to attention-based models that allow large-scale parallel training and overcome problems with long dependencies observed among recurrent architectures. Devlin et al. [Devlin et al., 2019] proposed BERT, a bidirectional encoder representation based on the Transformer architecture [Vaswani et al., 2017]. BERT was shown as an efficient model that may be used to recognize named entities. Yamada et al. [Yamada et al., 2020], a method based on Transformer architecture that is trained using a new pretraining task based on BERT. Akbik et al. [Akbik et al., 2018] proposed contextual string embeddings based on character-level language models that provide information to bidirectional LSTM with CRF layers.

In [Perera et al., 2022], the authors indicate biomedical named entity recognition (bioNER) as a sub-field of NER approaches. The bioNER field copes with biological entities, such as genes, diseases, or names of biological substances, e.g., food names. This survey divides bioNER techniques into rule-based models, dictionary-based models, machine learning-based models, and hybrid models. The authors identified food dedicated solutions: BuTTER method based on a bidirectional long-short term memory (LSTM) [Cenikj et al., 2020], FoodIE rule-based detector [Popovski et al., 2019b], and ontolgy-based NCBO annotator. This NCBO annotator can be used with any ontology, particularly also with ontology containing concepts associated with food and dietary entities [Jonquet et al., 2009]. It works as a dictionary-based technique limited to only simple data preprocessing, so it can only recognize entities its dictionaries/ontologies contain [Popovski et al., 2020]. The authors of [Perera et al., 2022] also provided extensive tests and compared their hybrid dictionary and CRF-based model, FoodCoNER, that outperforms the other bioNER models and four deep language models: BERT, BioBERT, RoBERTa, and ELECTRA. The results, yet promising, were made on the FoodBase dataset containing only food product entities.
3 Dataset

A total of 700 sets of ingredients from recipes were manually annotated using BRAT annotation tool [Stenetorp et al. 2012]. The recipes were scraped from the websites https://www.allrecipes.com/, https://tasty.co/ and https://www.yummly.com/, using the tool https://github.com/hhursev/recipe-scrapers. In this paper, we discuss 9 entity types.

3.1 Tagset Description

The manual annotation covered 3,788 ingredients of varying complexity. These ranged from relatively simple ingredients (e.g. 2 eggs) to much more complex ones (e.g. 2 lbs sweet potatoes, peeled and cut into 1/8 inch thick slices), which revealed that the name of an ingredient is often accompanied by a variety of its attributes. On this basis, we identified entities such as:

- **FOOD** as the name of an ingredient (e.g. bread, mayonnaise, salt, tomato),
- **QUANTITY** as a quantity (usually expressed by digits or a float),
- **UNIT** as a unit of measurement (e.g. bunch, cup, grams, jar, millimeters, slices, stalks, tablespoon, teaspoon, ounces, package, pinch)
- **PROCESS** as the attribute of the ingredient, usually referring to an action to be taken to prepare the ingredient (e.g. chopped for parsley, crushed for garlic, grated for ginger, ground for black pepper, minced for garlic, quartered for onion, softened for butter, shredded for cheese),
- **PHYSICAL QUALITY** as the characteristic of the ingredient (e.g. boneless for chicken breast, frozen for spinach, fresh or dried for basil, powdered for sugar),
- **COLOR** as the color of the ingredient (e.g. brown for rice, green for apples, white for bread),
- **TASTE** as the flavour (e.g. bittersweet, butter-flavoured, sweet, semi-sweet),
- **PURPOSE** as the purpose of using the ingredient in the recipe (e.g. for dusting about flour, for garnish about sunflower seeds, for frying about canola oil, and as topping about sour cream),
- **PART** as a part of the ingredient required by the recipe (e.g. breast and wing as parts of the chicken, heart as part of the artichoke, yolks and whites as parts of the eggs).

As one can easily guess, some entities appear in the corpus more frequently (e.g. UNIT and QUANTITY), while others are less frequent (e.g. COLOR and TASTE). And within each category, there will be both very frequent and very rare entities - see Figure 1 for the percentage ratios of the ten most frequent attributes of the PROCESS and PHYSICAL QUALITY entity types as an example.

3.2 Tags and Values: Common and Less Common Entity Examples

While it was possible to assume, for example, that entities of the PROCESS type would be typical past participles ending in -ed, it soon turned out that either not every participle should be treated as a process name (e.g. salted is a TASTE in the case of butter and granulated is a PHYSICAL QUALITY in the case of sugar), or the PROCESS tag took on more complex values – cf. e.g. thinly sliced in the example 3 cups onion (thinly sliced), cooked al dente in 2 cups pasta cooked al dente, cut in small wedges in 1 head cabbage cut in small wedges and cut lengthwise in half (about peppers).

Almost every entity listed above has taken on quite unusual, context-dependent values in addition to the expected ones, e.g. regular is a COLOR in the example 15 ounces oreos (white or regular), bone-in and with skin are PHYSICAL QUALITIES of the chicken, and 1 per person indicates the QUANTITY of tomatoes - the entity is discontinuous - see Figure 2.

3.3 Proper Names

The names of ingredients are mostly simple *apellativa*. However, in the corpus we found quite a few examples of proper names written with a capital letter, naming products of specific brands or producers (e.g. Jello for a gelatine producer, Splenda for a sweetener producer, as well as more complex product names, e.g. NESTLÉ TOLL HOUSE Refrigerated Sugar Cookie Bar Dough), and besides them quite a few examples of proper names written with a lower case letter (e.g. breyers for a producer of chocolate ice-cream, truvia for a producer of sweeteners). There are also quite a few examples of names written with a capital letter, which in a way are proper names, but they do not really refer to brand
names, but to various kinds of products produced today in different parts of the world (e.g. *Dijon* for mustard, *Gouda*, *Grayère*, *Monterey Jack* and *Parmesan* for cheese types, *Tabasco* and *Worcestershire* for sauces, *Bourbon*, *Cointreau*, *Kahlua* and *Triple Sec* for alcohols and liqueurs).

### 3.4 Distribution of Ingredients

While generally one ingredient is indicated on a single line in the ingredient set, it is quite common for another ingredient, additional or alternative, to be indicated explicitly or implicitly in the same line, next to the main ingredient (e.g. *salt and pepper* vs. 2 tablespoons sunflower butter, or nut vs. 1 1/2 cups heavy cream, plus additional, lightly whipped, for serving). Of these three examples, *nut butter* and (additional) *heavy cream* are discontinuous. Manual annotation was done in BRAT, which allows for the annotation of such cases. The colors below refer to different entities. As can be seen in the Figure 3, Figure 4 and Figure 5, where two ingredients were indicated on one line, usually the quantity and measure were indicated only once, referring to both the first indicated ingredient and the second indicated ingredient, which was then some distance away from the quantity and/or measure.

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1[https://brat.nlplab.org](https://brat.nlplab.org)
Figure 3: Two ingredients on one line without indication of measures and quantities (simple case).

Figure 4: Two ingredients on one line with common measure and quantity (complex case).

Figure 5: Two ingredients on one line with common measure and quantity (alternative ingredients).

It is worth pointing out, in addition to the above-mentioned characteristics, that the corpus we manually annotated was rather noisy, containing repetitions and spelling errors and, besides the names of ingredients, their quantities and measures, also additional comments (e.g. on the availability of a given product in such and such a shop for such and such a price). These features occurred irregularly in the corpus, with varying degrees of intensity, making it at the same time very challenging.

3.5 Exploratory Analysis

The TASTEset comprises 700 recipes with an average number of ingredients of 5.41 (from 1 to 7 ingredients). Table 1 lists the detailed statistics of the entities in the dataset.

| Entity                  | Total count | Unique values | Avg. entity count/recipe | % in the set | Example gold value | Avg. token count/entity |
|-------------------------|-------------|---------------|--------------------------|--------------|--------------------|-------------------------|
| FOOD                    | 4,020       | 1,123         | 5.74                     | 30.08        | salt               | 1.52                    |
| QUANTITY                | 3,780       | 206           | 5.4                      | 28.29        | 1/2                | 1.10                    |
| UNIT                    | 3,172       | 127           | 4.53                     | 23.74        | teaspoon           | 1.01                    |
| PROCESS                 | 1,091       | 254           | 1.56                     | 8.16         | chopped            | 1.44                    |
| PHYSICAL QUALITY        | 793         | 202           | 1.13                     | 5.93         | fresh              | 1.24                    |
| COLOR                   | 231         | 24            | 0.33                     | 1.73         | white              | 1.02                    |
| TASTE                   | 126         | 31            | 0.18                     | 0.94         | sweet              | 1.06                    |
| PURPOSE                 | 94          | 33            | 0.13                     | 0.70         | garnish            | 2.23                    |
| PART                    | 55          | 18            | 0.08                     | 0.41         | whites             | 1.16                    |
| all                     | 13,362      | 1,969         | 19.09                    | 100          | –                  | 1.25                    |

Table 1: Summary of the entities in the TASTEset dataset

The majority of the entities in the dataset belong to FOOD, QUANTITY and UNIT while the least represented entities are TASTE, PURPOSE and PART. Although such an imbalance of entities in a dataset seems natural in the field of recipes, it must be taken into account when building machine learning models. Figure 6 shows the entity distribution.

4 Experiments

The TASTEset dataset is also challenging because of the fine-grained structure of entities and, from time to time, different semantic meanings of the same tokens, e.g. garlic can be a taste or a food entity, hot can be a taste (e.g. hot sauce), a physical quality (e.g. hot water) or a part of a food name (e.g. hot dog). The annotation of some elements describing ingredients is problematic. It may be a matter of interpretation, e.g. egg noodles can be interpreted as a part of the food entity in the list of ingredients or as a physical quality of it: 8 ounces dried pasta (egg noodles or fettuccine). Although in most cases, the interpretation seems obvious as in example 8 ounces fine egg noodles where egg noodles is a food name.
The goal of the experiments was to establish baselines for properly indicating entities in a recipe text (i.e., in its list of ingredients) and recognizing its semantic meaning as one from the tag list: FOOD, UNIT, QUANTITY, PHYSICAL QUALITY, PROCESS, COLOR, TASTE, PURPOSE, PART. Figure 7 presents an example of predictions achieved by one of our baselines.

We trained a set of NER models using one of the state-of-the-art architectures working on plain texts. We focused on BERT [Devlin et al. 2019a] and LUKE [Yamada et al. 2020].

As for the BERT, we tested three models: BERT-base-cased, BERT-large-cased, FoodNER. The first two were released by BERT’s authors [Devlin et al. 2019b]. FoodNER [Stojanov et al. 2021] is a BERT with token classification layer, and is already fine-tuned on the food entity recognition problem, on the FoodBase dataset [Popovski et al. 2019a], and might contain domain-specific knowledge. However, TASTEset has more entities, therefore only the BERT part from FoodNER could be used. The classification layer was trained once again from the beginning.

We tested two types of architectures that utilized BERT. Namely, BERT with a dropout and a classification layer, and the second which additionally had a CRF layer on top of it. The CRF layer exploits the dependencies between consecutive entities while inference. In TASTEset, the entities are naturally highly codependent, for example the QUANTITY entity is usually followed by UNIT (e.g., 1 teaspoon), or COLOR and PHYSICAL QUALITY usually directly precede or follow the FOOD entity (e.g., brown sugar). For the BERT with CRF model implementation we closely followed Souza et al. [2020].

For all BERT-related models, the single input consisted of at most 128 tokens. We used the AdamW optimizer with linear scheduler, and weight decay equal to 0.01. The mini batch size was set to 16. We used 0.2 as the dropout rate in the classification layer. The following parameters were optimized with the grid search: number of training epochs – \{10, 15, 20, 25, 30\}, the learning rate – \{2 \cdot 10^{-5}, 5 \cdot 10^{-6}\}. Table 3 presents the hyperparameters that yielded the best results during the cross-validation. For the BERT + CRF results, we depicted only the ones associated with BERT-large-cased, as this model was the best in the basic scenario.

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1. [https://huggingface.co/docs/transformers/main/en/model_doc/bert#transformers.BertForTokenClassification](https://huggingface.co/docs/transformers/main/en/model_doc/bert#transformers.BertForTokenClassification)
2. [https://github.com/neuralmind-ai/portuguese-bert/tree/master/ner_evaluation](https://github.com/neuralmind-ai/portuguese-bert/tree/master/ner_evaluation)
We tested LUKE model from huggingface library fine-tuned according to the official huggingface script based on the pre-trained model "studio-ousia/luke-base" by Yamada et al. (2020). Luke-base is pretrained on RoBERTa-base which is case-sensitive. In our experiment, the LUKE head used for the testing was LukeForEntitySpanClassification. We used the AdamW optimizer with linear scheduler, and weight decay equal to 0.0. The best hyperparameters set was obtained during 5-fold cross-validation. The following parameters were optimized: number of training epochs – \{10, 15, 20, 25, 30\}, mini_batch_size – \{8, 16\}, and LUKE-specific parameters: max_mention_length (the maximum number of tokens inside an entity span) – \{3, 5, 30\} (see Figure 8), max_entity_length (the maximum total input entity length after tokenization) – \{32, 128, 512\}.

At the evaluation stage, we used the NER model to detect all entity occurrences in the text. We utilized F1-score, with exact-boundary and type matching Segura-Bedmar et al. (2013).

In our experiments, we used 5-fold cross-validation. All the results are reproducible with the seed 42. We have not applied any additional preprocessing to the inputs, especially, we preserved the newline character, as it separates different ingredients and their attributes from one another (see Figure 7).

5 Results

Table 2 shows the results of baseline models for our TASTEset datasets. The baselines we utilized were models being one of the best, or even state-of-the-art in standard NER tasks. For the BERT with CRF model, we presented only the best results, which were achieved with the BERT\textsubscript{base-cased} model. The results are obtained through 5-folds cross-validation, we provided the mean score along with standard deviations of all runs.

Based on the achieved results, we see that BERT-based models are better for the food entity recognition task on the TASTEset. LUKE achieved higher scores only for the FOOD entity, with average F1-score over 0.9. For QUANTITY, UNIT, PROCESS and PHYSICAL QUALITY, the difference between BERT models and LUKE is negligible. However, for the less frequent entities, LUKE performs significantly worse.

All BERT models obtained similar performance on most of the entities. However, the BERT\textsubscript{large-cased} handles the rarest entities: PURPOSE and PART much better than all other models. For that particular reason, we believe that this is the best model out of all that we have tested in this work. We did not find adding CRF layer to the BERT\textsubscript{large-cased} to improve the model’s performance.

Table 3 depicts our baselines’ customized hyperparameters to reproduce the results. All the parameters that are not mentioned were left as default, and can be derived from the models’ default library settings.

For the BERT models, we tested the impact of two hyperparameters: the learning rate and the number of training epochs. Regarding the first one, we found $2 \cdot 10^{-5}$ to be the optimal value. The optimal value for the second hyperparameter differed per model. Interestingly, the number of training epochs was a crucial hyperparameter for less frequent entities – COLOR, TASTE, PURPOSE and PART.
Table 2: The detailed results (average $F_1$-scores over 5 runs in 5-fold cross-validation) of our baselines for TASTEset dataset.

| Training technique | Evaluated on 5-fold cross-validation using seed 42 (models' weights also initialized with seed 42). |
|-------------------|------------------------------------------------------------------------------------------------------|
| Training data     | TASTEset                                                                                            |
| Tag dictionary    | FOOD, UNIT, QUANTITY, PHYSICAL QUALITY, PROCESS, COLOR, TASTE, PURPOSE, PART, O (not an entity), BERT-based models trained in BIO format, LUKE according to its own procedure: text + potential entity spans to classify |

Table 3: Our baselines’ information and customized parameters.

Table 4: The impact on the training time on the BERT large-cased results (average $F_1$-scores over 5 runs in 5-fold cross-validation)
Table 4 illustrates the impact of the longer training on BERTlarge-cased performance. While increasing the training time had subtle effect on the most popular entities, it substantially improved the performance on the rarest entities.

6 Conclusions

We collected a novel dataset with a rich set of entities with crucial information about ingredients. We also tested several benchmarks based on Named Entity Recognition approaches to extract the critical information from recipes.

Our datasets and benchmarks have the potential to be helpful in, e.g., determining similarity between recipes, understanding and recommending new recipes or ingredients based on deep knowledge of food products as ingredients and their dietary and functional effects, translating recipes between languages, generating new recipes and estimating nutrition values of ingredients in recipes.

Moreover, our dataset contains non-trivial challenges, such as rare cases of discontinuous annotations that may be challenging for NERs.

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A Detailed Dataset Analysis

Analysis of the distribution of the number of ingredients in the dataset reveal the recipes’ diversity – see Figure 9.

![Figure 9: The distribution of the number of ingredients](image)

The most common non-stop words are shown in Figure 10.

![Figure 10: Most frequent non-stop words](image)

The most frequent bigrams are shown in Figure 11.

The most frequent words from the entity food are shown in Figure 12.

The most frequent words from the entity unit are shown in Figure 13.

The most frequent words from the entity quality are shown in Figure 14.

The most frequent words from the entity part are shown in Figure 15.

The most frequent words from the entity color are shown in Figure 16.
The most frequent words from the entity taste are shown in Figure 17.
The most frequent words from the entity purpose are shown in Figure 18.
Figure 14: Most frequent words in the quality entity

Figure 15: Most frequent words in the part entity

Figure 16: Most frequent words in the color entity
Figure 17: Most frequent words in the taste entity

Figure 18: Most frequent words in the purpose entity