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Abstract. Food trucks are vehicles with which fast food, from various cuisines, is cooked and sold. They have been popular in several countries and usually offer food in different locations of a city. Frequently, several food trucks offer their dishes in music concerts, festivals and other events. When several food trucks are present in a place, the variety of possible cuisines and food dishes makes their choice by the public a challenging task. This paper describes the task of recommending food trucks using a multi-label classification approach, where more than one option can be suggested. The recommendation is made using customers' personal information and preferences. Six multi-label transformation strategies were used to induce learning models from real data obtained via a market research, where hundreds of participants provided their food preferences. The experimental results show that the strategies overcame the adopted baseline in almost all cases, with RAndom k-labELsets (RAkEL) and Binary Relevance (BR) in specific, were the ones who had the best overall result, respectively. On the other hand, it is required to investigate the matter furthermore to improve the predictive outcome of the task. From a machine learning perspective, a new way to analyze multi-label results, called confusion matrix plot, is discussed and the food truck dataset is released as a new multi-label benchmark.

Keywords: Food truck recommendation, Recommendation system, Multi-label classification, Multi-label dataset

1 Introduction

From the beginning of the 21st century, food trucks started to spread throughout the world [21]. Generally, they sell food that belongs to a wide range of cuisines, moving from one location to another, in any given region of a city, without having to settle in a specific place. In festivals, music concerts and large-scale events, it is common to have more than one of them. The large number of possibilities can make the food choice by the public a challenging task. Recommender systems, like personalized event app and iterative totems, can be used to suggest options to the public and help them select one or more options among the available alternatives.

Motivated by this emerging business, a food truck recommendation task, using data related to socioeconomic profiles and the personal information of customers like their habits and preferences, is investigated in this paper. While related works [15, 9, 23] recommend specific places (restaurants), in this work, the food truck recommendation is performed considering the different types of menus offered by a set of food trucks, allowing the suggestion of more than one option. The hypothesis assumed in this study is that it is possible to use machine learning (ML) techniques to recommend, with a good predictive accuracy, one or more different food truck options.

The problem is addressed using a multi-label classification (MLC) approach, a supervised ML task where each instance is related to one or more class labels [5]. In this approach, each different type of food truck is mapped to a class label and more than one class labels can be recommended to any given user. Thus, each recommendation can suggest one or more options. The data used in the learning process was obtained from a market research regarding food truck preferences conducted by one of the authors. The research was carried out in Natal, a Brazilian city, using a social media app. Overall, 407 users, who have bought from food trucks, participated in this survey. They anonymously filled-out a questionnaire describing their food truck preferences along with personal information, such as their age, address, gender, etc.

The aim of this work is to explore the task of food truck recommendation as a MLC task. Experiments were performed comparing six different MLC transformation strategies when applied to the collected food truck data. Some business opportunities that can benefit from this study are: food truck market research, discovery of trends in food truck preferences, food truck advertising and food truck recommendation apps.

Regarding ML contributions, this paper investigates, for the first time, ML for food truck/restaurant recommendation, use of MLC strategies to deal with the possibility of more than one recommendation and proposes a new alternative to analyze MLC results: the *confusion matrix plot*. This plot provides support to compare results among different MLC strategies, considering all of the labels' confusion matrices at the same time.

The rest of this paper is organized as follows: In Section 2, the main aspects and previous works on restaurant and food recommendation are briefly presented. Next, Section 3, multi-label classification is defined. Section 4 describes the food truck multi-label dataset. Then, Section 5 presents and analyzes the experimental results. The paper ends with a highlight of the relevant points (Section 6).

2 Related Works

To the best of the authors' knowledge, the use of ML for food truck recommendation has not been explored in the literature. However, restaurant recommendation has been the subject of several studies, some of them recent [9, 24, 18, 23]. This problem has been studied in the recommender system scientific community as a specialization of the location prediction problem [15].

Restaurant recommender systems usually base their recommendation on a broad range of attributes, including user's feedback (restaurant visit via check-ins, reviews and ratings), geolocation information, demographic data (age, gender, etc.), friends' preferences and restaurant features. In some cases, the prediction is a ranking of restaurants [9] or the top-k most relevant restaurants [24]. However, neither authors modeled their tasks as a MLC problem, which supports both scenarios intrinsically.

The main approaches used for restaurant recommender systems are designed to predict specific places and their solutions are developed in a dynamic and ubiquitous environment. This work follows a different, more generic approach, addressing food truck recommendation through the recommendation of cuisine categories.

3 Multi-label Classification

In MLC tasks, an instance can be simultaneously classified in more than one of the existing class labels. Binary and multi-class classification tasks can be seen as special cases of MLC tasks [5] where a single class is predicted. To formally define MLC, let $\mathcal{L} = \{\lambda_1, \lambda_2, ..., \lambda_q\}$ be the set of q labels λ_j related to a particular problem $\mathcal{X}$, where $\mathcal{X}$ is the instance space with d attributes. The learning process results in a hypothesis $h : \mathcal{X} \rightarrow 2^{\mathcal{L}}$ that associates new instances with a subset of labels contained in $\mathcal{L}$. It is done using an inductive process that learns from available data [1].

MLC tasks are often treated by transformation strategies, which transforms the original multi-label data set into a set of single-label data sets, where conventional ML algorithms can be used [19]. Several transformation-based strategies have been proposed in the literature. This study evaluates the predictive performance obtained by six of them when applied to the the food truck recommendation tasks: Binary Relevance (BR) [3]; Calibrated Label Ranking (CLR) [10]; Dependent Binary Relevance (DBR) [14]; Ensemble of Classifier Chains (ECC) [16]; multi-label learning with Label specIfic FeaTures (LIFT) [25]; and, RAndom k-LabELsets (RAkEL) [20]. These strategies were selected due to their popularity and different approaches used.

BR is the simplest and most common multi-label strategy [12]. It uses the one-versus-all approach [5] to generate q binary datasets and induce a binary model for each dataset. The final MLC prediction is the combination of all binary predictions. Similarly, LIFT creates a binary model for each label, but uses an unsupervised approach to transform the input space for each subtask. The DBR strategy is based on stacking generalization [22], thus the label values are used to increase the feature space, to model the label dependencies in the learning process. The ECC strategy is an ensemble of distinct Classifier Chains (CC) models. It organizes the binary classifiers in a chain and increment the input space with the results obtained by the previous classifiers in the chain. The CLR strategy uses a pairwise transformation where each pair of labels generates a binary dataset. The prediction is defined using a voting scheme. RAkEL is an ensemble of multi-class models. Each model is induced using a subset of labels, named labelset, and each labelset is mapped to a class.

The evaluation of the predictive performance of MLC strategies and ML techniques for MLC tasks requires the use of specific measures that are able to explore their particularities [19]. In this work, measures that evaluate different perspectives of the learning process were considered. *Accuracy* and *subset accuracy* measure the predictive quality. The first is lenient when considering the partial successes, while the second is rigid and considers only complete arrangements. *Macro-F1* and *micro-F1* are label-based measures and they are computed considering each individual labels. In practice, a macro measure gives equal weight to all labels whereas a micro measure focuses on the most common labels [11]. Finally, *hamming-loss* and *one-error* are error measures. The former computes the proportion of misclassified instance-label pairs while the later is a ranking measure that indicates whether or not the most relevant label predicted should be really predicted. A complete list of measures, definitions and formulation can be found in [26].

4 Data Description

The food truck dataset was created from the answers provided by the 407 survey participants. They either were approached in fast food festivals and popular events or anonymously received a request to fill out a questionnaire, in Portuguese, describing their personal information and preferences when it comes to their selection from food trucks[4]. This section describes the questionnaire used and analyzes the multi-label dataset.

4.1 The survey

The form used for the survey had 15 objective questions about the habits and preferences related to food trucks and 6 objective questions about users' profile. These 21 questions were considered predictive attributes, as summarized in Table 1. Some attributes were inherently organized in categories, like `gender` and `marital.status`, however those that have some intrinsic order were converted to numeric, like `scholarity` and `age.group`. In the table, the questions and options are reduced due to space limitation. The types *num*, *categ* and *bin* are respectively abbreviations for numeric, categorical and binary.

The target attribute, the labels, was associated with food preferences and multiple alternatives could be simultaneously assigned, making the target prediction a MLC task. The form provided 12 alternatives:

[4] The survey was conducted between November 15th and 20th, 2015. The Google Form tool was used to collect the responses.

Table 1. Summary of dataset attributes. The questions and options used in the survey and their respective values mapped in the dataset.

Attribute	Type	Question - Options
Habits and preferences questions		
`frequency`	num	Often eating out 0 - rarely, 1 - monthly, 2 - weekly, 3 - twice a week, 4 - almost daily or daily
`time`	categ	Day period of preference afternoon, dawn, dinner, happy hour, lunch
`expenses`	num	How much to spend 15 - until R$15,00, 20 - until R$20,00, 30 - until R$30,00, 40 - until R$40,00, 50 - without limit
`motivation`	categ	What is the motivation ads, by chance, friend, social network, web
`taste`	num	Importance of food taste 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`hygiene`	num	Importance of hygiene 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`menu`	num	Importance of menu diversity 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`presentation`	num	Importance of food presentation 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`attendance`	num	Importance of service quality 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`ingredients`	num	Importance of ingredients quality 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`place.to.sit`	num	Importance of a place to sit 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`takeout`	num	Importance of takeout option 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`variation`	num	Importance of varying the choices 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`stop.strucks`	num	Importance of food truck meetings 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
`schedule`	num	Importance of food truck schedule 1 - very low, 2 - low, 3 - medium, 4 - high, 5- very high
Profile questions		
`gender`	categ	Gender F - Female, M - Male
`age.group`	num	Age group 1 - <19, 2 - 20-25, 3 - 26-30, 4 - 31-35, 5 - 36-40, 6 - 41-45, 7 - 46-50, 8 - >50
`scholarity`	num	Scholarity 0 - no study, 1 - high school, 1.5 - in graduation, 2 - graduation, 3 - specialization, 4 - master degree, 5 - phd
`average.income`	num	Average income 1 - <2 salaries, 2 - 2-3 salaries, 3 - 3-5 salaries, 4 - 5-10 salaries, 5 - 10-20 salaries, 6 - >20 salaries
`has.work`	bin	Has a work 0 - No, 1 - Yes
`marital.status`	categ	Marital status divorced, married, single

Table 2. Multi-label statistics of the food truck dataset

Characteristic	Value	Characteristic	Value
Attributes	21	Labelsets	117
Instances	407	Single labelsets	74
Labels	12	Labels dependency	0.13
Cardinality	2.28	Density	0.19

`arabic_food`	`brazilian_food`	`chinese_food`	`street_food`
`fitness_food`	`gourmet`	`healthy_food`	`italian_food`
`japanese_food`	`mexican_food`	`snacks`	`sweets_desserts`

4.2 Dataset Analysis

Table 2 shows the main aspects of the food truck dataset. The 21 attributes are composed of 16 numeric attributes, 4 categorical attributes and 1 binary attribute. The 12 labels are combined in 117 distinct ways (labelsets), where 74 of these combinations occur only once (single labelsets). Labels dependency [12] measures the averaged correlation among the labels, where the value 0.13 indicates a low correlation. The cardinality 2.28 means that each instance is tagged with two labels, on average, and a 0.19 density, averaged labels' frequency, is a value larger than is often found on the literature [12][5].

Figure 1 illustrates the frequency of each label in the dataset, which measures the number of instances that receives each label. Most labels appear in more than 10% of the instances and the 3 most frequent labels appear in, at least, 30% of the instances. Particularly, the `street_food` appears in more than 70% of the instances, which is not very common in multi-label datasets[6]. Regarding the co-occurrences of the labels, shown in Figure 2, it is possible to notice that, given their high frequency, the 4 most popular labels are highly related to the others. Other frequent pairs of labels were observed, such as:

`chinese_food` ⇔ `japanese_food`	`arabic_food` ⇔ `japanese_food`
`arabic_food` ⇔ `mexican_food`	`fitness_food` ⇔ `healthy_food`
`japanese_food` ⇔ `mexican_food`	`italian_food` ⇔ `brazilian_food`

The food items in each pair are somewhat related, like spicy food (Arabic and Mexican), oriental cuisine (Chinese and Japanese), with many pasta dishes (Italian and Brazilian), and health-related (fitness and healthy).

Figure 3 shows the Pearson correlation coefficient between each predictive attribute and each label. The most relevant attributes, with regards to correlation, is the `average.income`, followed by `scholarity`, both of which are considered part of an individual's personal information. `Gourmet` is the label mostly related to the attributes and `snacks` is the second, although it is inversely correlated with most of the attributes. All other pairs of labels and attributes have some occurrences, however it was not possible to see a clear pattern.

[5] 0.03 is the average density of the ML datasets available in the MULAN repository.
[6] Usually, a label is associated with less than 50% of the instances.

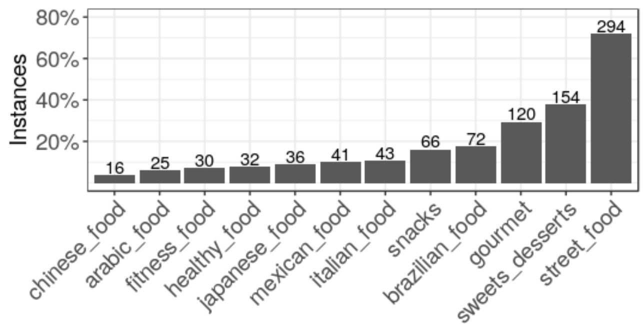

Fig. 1. Frequency of the labels present in the food truck dataset.

5 Food Truck Recommendation

This section describes the MLC experiments carried out using the food truck dataset. It starts with the methodology and the tools used and next reports the experimental results and their analysis.

5.1 Methodology

The experiments were carried out using the R environment. The implementations of the MLC strategies used in the experiments are available in the `utiml` package[7] and the MLC dataset support was provided by `mldr` package [6]. The Random Forest [4] implementation is available in the `randomForest` package[8] and it was used as base algorithm for the MLC strategies.

As mentioned in Section 3, six distinct strategies were selected to induce MLC models for food truck recommendation. These strategies were chosen because they cover different MLC approaches. Table 3 shows the parameters used for each strategy. These are the default values specified in their original papers. The Random Forest was used as base algorithm due to its high predictive performance in several classification tasks, even without hyper-parameter tuning [8]. Thus, the Random Forest hyper-parameters used the default values defined in the `randomForest` package.

All of the reported results were obtained using 10-fold cross validation. The same training and testing partitions were used to obtain the average of the measures for all strategies. To ensure the same proportion of each label in each fold, the split between train and test followed the label stratification algorithm [17].

Additionally, the multi-label baseline General$_B$ [13] was considered. The idea behind this baseline consists of predicting the top most frequent labels based on the cardinality of the train data. In this case, just the 2 most frequent labels (`street_food` and `sweets_desserts`) were predicted as relevant.

[7] https://cran.r-project.org/package=utiml
[8] https://cran.r-project.org/package=randomForest

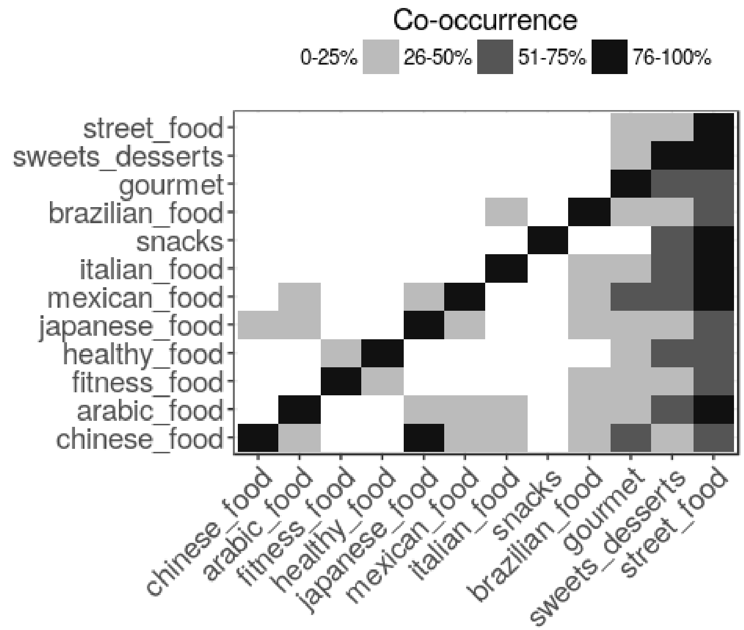

Fig. 2. Co-occurrence of the labels in the food truck dataset. The rows indicate the presence of each label and the columns reflect the co-occurrence.

5.2 Analysis of the Experimental Results

Table 4 shows the MLC results obtained for each strategy, including the baseline. The bold markup indicates the best value obtained for each measure. The strategies BR and RAkEL obtained the best result for 2 measures, while the strategies CLR and ECC for one measure. The strategies BR, DBR, ECC and RAkEL outperformed the baseline for all considered measures. On average, RAkEL followed by BR obtained the best results for the measures considered in this work, as reported in the column *Averaged Ranking*.

All of the strategies, with the exception of one (the CLR strategy), presented similar results. For the measures hamming loss, micro-F1 and one-error the differences against the baseline were also small. The biggest differences between the baseline and the evaluated strategies were observed in the macro-F1 and the subset accuracy measures. The best predictive performance for the macro-F1 was obtained by the CLR strategy. Regarding the subset accuracy, the high range observed was due to the poor result obtained by the baseline.

Figure 4 shows the confusion matrix plot, where the performance of each label (x-axis) and strategy can be comparatively analyzed. The colors in each column indicate the amount of false negative (FN), false positive (FP), true negative (TN) and true positive (TP). An optimal prediction should have only two colors (TP and TN) and the black line shows where this division should be. The labels

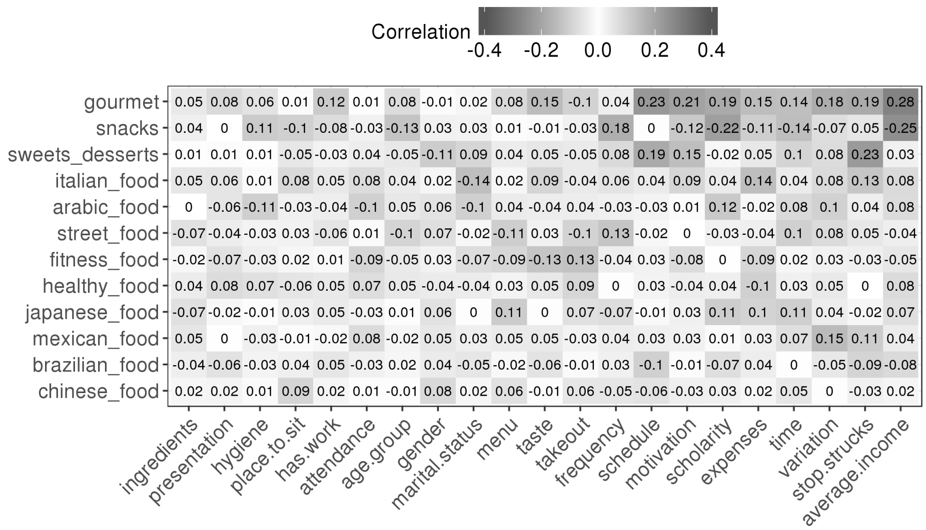

Fig. 3. Correlation coefficient among the attributes (x-axis) and the labels (y-axis). The attributes are ordered from left to right by the absolute average of the correlations. Similarly, the labels are ordered from the bottom to the top.

are sorted by their frequency and the strategies arranged in alphabetical order. Based on the plot, the strategies BR, DBR, ECC, LIFT and RAkEL presented similar confusion matrices.

Surprisingly, most of the strategies did not predict the presence of the labels `arabic_food`, `brazilian_food`, `chinese_food`, `fitness_food`, `healthy_food`, `italian_food`, `japanese_food` and `mexican_food`, even as false positive. Just the CLR strategy was able to overcome this limitation, at the cost of a higher number of false positive rate. Consequently, CLR obtained the best result for the macro-F1 measure and the worst results for the other measures.

It was assumed that the predictive performance was harmed by the class imbalance in the dataset. To deal with this problem, two techniques were applied: *i)* the SMOTE [7] oversampling technique to mitigate the imbalance caused by the transformations; *ii)* different threshold values for each label. The threshold value was selected using the SCUT algorithm [2]. Both alternatives resulted in a decrease of the MLC performance for some strategies, so these results are not reported here. Their thorough investigation are suggested as future work, especially the first option and the use of other MLC imbalance techniques.

The correlation between attributes and labels was not sufficient for the induction of models with high predictive performance. Even for the strategies capable of incorporating the label's dependencies in the learning process (DBR, ECC, LIFT and RAkEL), the results were not improved, suggesting that this MLC task is not easy to model with the currently used predictive attributes.

Table 3. Parameters of the MLC strategies used in the experiments

Strategy	**P**arameters	**S**trategy	**P**arameters
BR	-	CLR	-

DBR	-	ECC	`m=10`
			`subsample = 1`
			`attr.space = 1`
			`vote.schema = "maj"`

LIFT	`ratio = 0.1`	RAkEL	`k = 3` `m = 24`

Table 4. Results obtained from the evaluation of distinct MLC strategies.

Strategy	Accuracy↑	Macro-F1↑	Micro-F1↑	Subset Accuracy↑	Hamming Loss↓	One Error↓	Averaged Ranking
BR	0.479	0.194	**0.540**	0.255	**0.144**	0.265	2.7
CLR	0.293	**0.290**	0.455	0.002	0.375	0.260	4.8
DBR	0.467	0.173	0.516	**0.280**	0.146	0.260	3.7
ECC	0.473	0.174	0.516	0.277	0.147	**0.255**	3.3
LIFT	0.444	0.198	0.516	0.213	0.157	0.287	4.5
RAkEL	**0.483**	0.188	0.530	**0.280**	0.145	0.257	**2.1**
Baseline	0.386	0.116	0.516	0.040	0.173	0.272	-

6 Conclusions

This paper investigated food truck recommendation using a MLC approach. The food truck options were used as class labels and the predictive attributes were personal information and user preferences. Popular multi-label strategies were applied to the food truck data set and they obtained a similar predictive performance. Although the obtained results were superior to a baseline, most of them were not able to estimate correctly the least common labels. Additionally, a confusion matrix plot was used to analyze the multi-label result, providing an overview of the performance of the investigated strategies for the different class labels.

Alternatives like increasing the number of instances and exploring new predictive attributes can improve the performance obtained. Nevertheless, the authors did not find other works investigating the use of MLC for food truck recommendation based on users' preferences.

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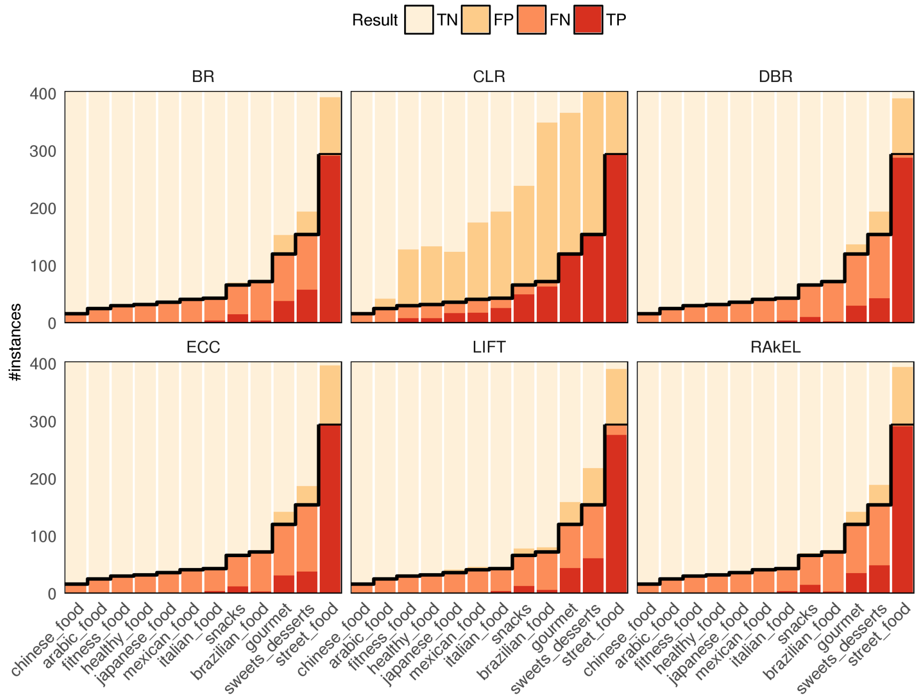

Fig. 4. Confusion matrix of each label obtained for the evaluated strategy. The colors indicate the values False Negative (FV); False Positive (FP); True Negative (TN); and, True Positive (TP). The line indicates the expected values to divide the TP from TN values considering an optimal prediction.

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