Creative Flavor Pairing: Using RDC Metric to Generate and Assess Ingredients Combinations

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Abstract

Creating culinary recipes is one of the most creative human activities. It requires combining ingredients, performing the recipe steps, creating specific diets, and others tasks. In addition to it, the existence of publicly available repositories of recipes, as well as scientific advances in areas such as Food Chemistry and Neuro-Gastronomy, encourage the generation of *new* and *pleasurable* recipes from algorithms. Although the number of ingredients allows the generation of a huge number of recipes ($\sim 10^{15}$), only a small fraction of this potential is exploited ($\sim 10^{6}$). This paper proposes, implements and analyzes a system called *Creative Flavor Pairing* which acts cooperatively with different profiles of cooks assuming the responsibility of suggesting food ingredients that can lead to creative recipes. These ingredient combinations are generated by a genetic algorithm using the Regent-Dependent Creativity (RDC) metric as a fitness function. Our experimental results showed that the RDC metric can be applied to the culinary field as our system was able to suggest creative ingredient combinations that match the most popular ones currently published in the largest cooking social networks.

Introduction

Computational Creativity is the term used to describe a research sub-field in Artificial Intelligence, which studies how to build software that demonstrate creative behaviors (Colton 2012; Besold, Schorlemmer, and Smaill 2015). In more practical terms, this area investigates how to create algorithms to generate results that would be considered as creative as if they were produced by humans.

Unlike common approaches where a program is a mere tool to reinforce human creativity, in the Computational Creativity research field, there is an effort to create software that is independently creative, either to act as a collaborator with people or to act autonomously as an artist, musician, writer, draftsman, engineer or scientist (Besold, Schorlemmer, and Smaill 2015; Boden 2009). Although the term *creative artifact* is often used primarily for artistic artifacts such as music, painting or poetry, it also includes innovative scientific theories, mathematical concepts, and science and engineering projects.

Recently, the culinary domain has attracted attention not only from researchers in areas like Food Chemistry, Psychophysics or Neuro-Gastronomy, but also several researchers in Computational Creativity (Morris et al. 2012; Veeramachaneni et al. 2010; Sawyer 2012). The works of (Varshney, Wang, and Varshney 2016) and (Pinel, Varshney, and Bhattacharjya 2015) have become popular because they propose both a form of recipe generation and a metric of creativity that combine *Bayesian Surprise* and a human flavor perception model.

In addition to it, there is currently publicly available repository of recipes, food composition and the principles of tasty dishes (Ahn et al. 2011). On the other hand, the relatively small number of recipes in use ($\sim 10^{6}$) compared to the huge number of potential recipes ($\sim 10^{15}$) together with the frequent recurrence of particular combinations in several regional cuisines indicate that we are exploring but a small fraction of the possible combinations (Ahn et al. 2011).

A hypothesis, which in the last decade has received attention among some chefs and food scientists, claims that ingredients that share flavor compounds are more likely to generate a tasty recipe (Ahn et al. 2011). This *Food Pairing Hypothesis* has been used to find new combinations of ingredients and led, for example, some contemporary restaurants to combine white chocolate and caviar because they share certain flavors, or chocolate and cheese that share at least 73 flavor compounds.

Bearing in mind that exploring all aspects of creativity involved in generating a culinary recipe is a very hard problem, in this paper we propose, implement and analyze a creative computing system called *Creative Flavor Pairing* to act cooperatively with different profiles of cooks assuming the responsibility of selecting foods that can generate surprising and tasty ingredients combinations.

Creative Flavor Pairing uses a genetic algorithm to generate combinations of food ingredients guided by the RDC metric proposed in (França et al. 2016). This general purpose metric has been used in other domains such games and fashion, and in this work our main contribution is to verify its applicability also in the field of culinary. In order to test our proposed system, we present: i) one case study on *Allrecipes*[1] social network; ii) a quantitative evaluation of human-made recipes and recipes created by *Creative Flavor*

[1] Allrecipes is the largest social network focused on food. It can be accessed at: `http://allrecipes.com/`

Pairing; and iii) a recipe made by a chef using a combination suggested by the system.

This paper is organized as follows. In the Food Pairing Hypothesis section, the *Food Pairing Hypothesis* is explained by details. Next, in the RDC Metric section is presented the method used to assess the creativity of an artifact and its model in the culinary domain. Furthermore, the Related Work section presents a brief history of creative assessment methods and its application in the culinary domain. Next, in The Creative Flavor Pairing section, our proposed creativity system is presented. The Experimental Method section outlines the experimental setup while the Experimental Results section presents and analyses the experimental results. A discussion and conclusion are presented at the Conclusions section.

Food Pairing Hypothesis

In an attempt to combine salty foods with chocolate, chef Heston Blumenthal (Blumenthal 2008) found that the combination of white chocolate and caviar resulted in a very pleasant taste. In order to identify why this and other combinations had a good result, he made analyses on the foods involved and identified that foods that had common flavor compounds, when combined, produced pleasant and tasty results. This hypothesis became known as *Food Pairing Hypothesis*.

To validate the *Food Pairing Hypothesis*, extensive work was done on (Ahn et al. 2011), where recipes from various regions of the world were evaluated to determine whether or not the ingredients involved shared flavor compounds as determined by evaluated hypothesis.

The results obtained in (Ahn et al. 2011) have shown that North American and Western European recipes follow the *Food Pairing Hypothesis*, and that this is due to some key ingredients commonly used in recipes. For the South European and East Asian regions, a rule contrary to the hypothesis was observed. In these regions, the recipes seem to avoid ingredients that share flavor compounds. This work considers the recipes of the regions where the *Food Pairing Hypothesis* was verified.

RDC Metric

Figure 1 shows the overview of the RDC metric proposed in (França et al. 2016) to evaluate the creativity of artifacts from different domains. The metric combines *Bayesian Surprise* and *Synergy* to measure novelty and value respectively.

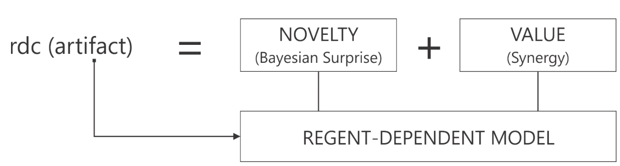

Figure 1: RDC Metric Overview.

The *Regent-Dependent* Model (RD Model) is used to assign a set of characteristics on which the creativity of an artifact is assessed in a given context. In this model, the characteristics of an artifact are represented by *pairs* p_i associated with a numerical value v_i:

$$p_i(regent, dependent) : v_i$$

Where *regent* indicates a characteristic of an artifact and *dependent* defines the state of that characteristic. The value v_i expresses the intensity of *pair* p_i when describing an artifact in a given context.

RD Model in the Culinary Domain

In the culinary domain, there is no doubt that our flavour experience is mainly made up from sensations of taste, touch (texture) and smell(aroma) (Page and Dornenburg 2008). A recipe can be characterized by its list of ingredients. Each ingredient, in turn, is modeled on the RD Model in which the taste, texture and aroma are the *regents* and the *dependents* are the various tastes, textures and aromas that a food has, as shown in Table 1.

regents	dependents
taste	..., sweet, salty, bitter, sour, umami, ...
texture	..., crispy, soft, juicy, consistent, ...
aroma	..., toasted, citric, cheesy, ...

Table 1: *Regents* and some instances of *dependents* used to describe ingredients present in a recipe.

As an example, Table 2 lists eight *Regent-Dependent pairs* used to describe the taste, texture and aroma of a strawberry (Burdock 2016).

taste	p_1(taste, sweet): 0.49 p_2(taste, sour): 0.51
texture	p_3(texture, soft): 0.38 p_4(texture, juicy): 0.62
aroma	p_5(aroma, fruit): 0.56 p_6(aroma, toasted): 0.04 p_7(aroma, cheesy 0.25 p_8(aroma, citric): 0.05

Table 2: *Pairs Regent-Dependent* used to describe a strawberry.

Novelty Metric in the Culinary Domain

Although still under discussion, some authors have adopted surprise as an emotional response that acts as a novelty detector (Grace and Maher 2016; Varshney et al. 2013; Wiggins 2006). In this article, we also use the well-known Bayesian Surprise (Baldi and Itti 2010) as a metric of novelty.

Considering an artifact as an event, the amount of information calculated by the Bayesian Surprise can be interpreted as the novelty $n(R)$ of an artifact R, as defined in Equation 1 (Baldi and Itti 2010).

$$n(R) = \delta[P(M); P(M|R)] \tag{1}$$

Where the probability distribution $P(M)$ represents the degree of belief of an observer in model M and $P(M|R)$ reflects the knowledge after a new artifact R has occurred and be inserted in the model M. Therefore, Equation 1 assumes that the novelty contained in an artifact R can be measured by considering the difference δ between probability distributions that describe how the observer's worldview changed from the occurrence of R.

The beliefs of an observer $P(M)$ define a context represented by a dataset of known artifacts. In the *Creative Flavor Pairing*, the dataset is a set of ingredients combinations represented in the RD model and arranged in rows and columns. Lines are the combinations and columns are the pairs used to describe them.

	p_1	p_2	...	p_j	...	p_{n-1}	p_n
a_1	v_{11}	v_{12}	...	v_{1j}	...	$v_{1(n-1)}$	v_{1n}
a_2	v_{21}	v_{22}	...	v_{2j}	...	$v_{2(n-1)}$	v_{2n}
...	...	...	...	...	...	...	...
a_i	v_{i1}	v_{i2}	...	v_{ij}	...	$v_{i(n-1)}$	v_{in}
...	...	...	...	...	...	...	...
a_{m-1}	$v_{(m-1)1}$	$v_{(m-1)2}$	...	$v_{(m-1)j}$	...	$v_{(m-1)(n-1)}$	$v_{(m-1)n}$
a_m	v_{m1}	v_{m2}	...	v_{mj}	...	$v_{m(n-1)}$	v_{mn}

Table 3: Dataset of known ingredients combinations. The dataset organizes in rows and columns the combinations represented in the RD model.

Table 3 shows a dataset containing m recipes described by n *pairs*. Thus a recipe R_i is placed on line i and a *pair* p_j, used to represent a characteristic of R_i, is mapped to a column j. The value v_{ij} representing the intensity of p_j in R_i, is copied to the position ij of the dataset.

Thus, the novelty of an recipe is equal to the sum of the novelties of the *pairs* used to describe it, as shown in Equation 2.

$$n(R) = \sum_{p_i \in R} n(p_i) \tag{2}$$

Mathematically, the function used to compute the novelty $n(p_i)$ of a *par* p_i used to describe a particular recipe R, is of the form as shown in Equation 3 (Baldi and Itti 2010), where σ and $\bar{m}$ are respectively the variance and mean of the *pairs* in the recipe dataset and v_i is the value associated with p_i.

$$n(p_i) = \frac{1}{2\sigma_i^2}\left[\sigma_i^2 + (v_i - \bar{m_i})^2\right] \tag{3}$$

Since there is no limit on how new an artifact can be, Equation 4 normalizes novelty in the interval $[0, 1]$ by an exponential normalization.

$$f[n(A), \lambda] = 1 - e^{-\lambda n(A)} \tag{4}$$

Where λ is a positive real number known as *smoothing factor*. The greater the *smoothing factor* λ, the more expressive are small novelties.

Value Metric in the Culinary Domain

There are plenty of information publicly available (Grace et al. 2014) that describes recipe and the elements that constitute them like in *fooDB* [2]. In particular, it is also available how these elements interact and what interactions are most valued in a given context, which is key to compose a valuable artifact.

In culinary, a recipe is valued when the combination of its ingredients produces a tasty recipe. The *Food Pairing Hypothesis* states that ingredients will work well together in a dish if they share similar flavors. These facts give evidence that the relationship between the ingredients of a recipe can be used as a measure of value.

The approximation of how a recipe is valued in a context is carried out in a *synergyset*. A *synergyset* is a way of specifying which ingredients of an recipe are synergistic. Synergistic ingredients are those described by synergistic *pairs*. And these, in turn, represent characteristics (taste, texture and aroma) that when they occur together are responsible for the value of a recipe.

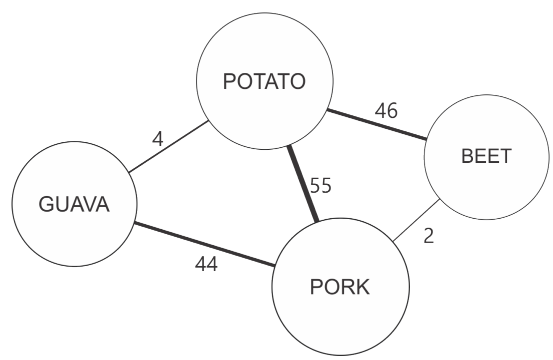

Figure 2: An example of *synergyset*.

[2]fooDB is the world's largest and most comprehensive resource on food constituents, chemistry and biology available at http://foodb.ca/

The *synergyset* structure is a graph $S(V, E)$. Figure 2 illustrates a part of the *synergyset* composed of 4 vertices representing the ingredients: pork, potato, beet and guava. The complete *synergyset* consists of 1529 vertices representing all ingredients currently available in our database to compose a recipe.

There is an edge between ingredients when they are described by synergistic *pairs*. According to the *Food Pairing Hypothesis*, a *pair* p_i is synergistic to a *pair* p_j when they have the same *regent* and same *dependent*, that is, when two ingredients share the same flavor compound. The weight w_{ij} of the edge between the ingredient i_i and i_j indicates the level of synergy between two ingredients. It is equal to the number of synergistic *pairs* between that two ingredients.

A graph G_R representing the ingredients of a recipe R is defined by the subgraph of S formed by the vertices representing the ingredients in R. From the graph G_R, the value $v(R)$ of a recipe is calculated, as defined in (França et al. 2016) by Equation 5.

$$v(R) = \frac{1}{2}kc(G_R) + \frac{1}{2}\rho(G_R) \tag{5}$$

Where $kc(G_R)$ is the Krackhardt's connectedness of G_R (Krackhardt 1994) and $\rho(G_R)$ is the density of G_R (Matta et al. 2016). The first term of the Equation 5 measures the associativity among the ingredients of a recipe. If all ingredients are synergistic, then *Krackhardt's connectedness* of G_a is maximum. If all ingredients are isolated in the recipe, then $kc(G_a)$ is minimum. The second term measures the strength of the connection among the ingredients.

The Regent-Dependent Creativity (RDC) Metric

The RDC metric for the creativity evaluation of the ingredient combination of a recipe R is defined in Equation 6 as the sum of the novelty $n(R)$ and of the value $v(R)$ together with a penalty function. This penalty is necessary to avoid that new and low-value recipe (different but useless) or valuable recipes with low novelty (useful, but already known) are considered creative.

$$rdc(R) = n(R) + v(R) - p[n(R), v(R)] \tag{6}$$

$$p[n(R), v(R)] = s(1 - e^{-kd}) \tag{7}$$

where:

s: is the sum of $n(R)$ and $v(R)$.
d: is the absolute difference between $n(R)$ and $v(R)$.

Equation 7 penalizes the creativity of an artifact depending on the difference among its novelty and its value. The greater the difference between novelty and value of an artifact, its creativity is more penalized. The penalty is more intense as the variable k is higher, however, no artifacts are penalized more than the sum of its novelty and its value. Therefore creativity is in the range [0,2].

Related Work

In Computational Creativity, an assessment method allows machines to generate and evaluate creative artifacts (Boden 2004). It was realised the importance of a consensual way to evaluate creative thinking since (Amabile 1982; Partridge 1985; Ortony and Partridge 1987) allowed machines to perform in a similar way as human beings. At that time, most of the assessment methods were based on psychology, describing it as a mental process that involves surprise, expectancy and luck (Stiensmeier-Pelster, Martini, and Reisenzein 1995). During the development of a consensual method to evaluate creativity, the surprise started to be used to create artificial agents as presented by (Macedo and Cardoso 2001; Macedo, Reisenzein, and Cardoso 2004), thus allowing to model novelty into its behavior or design. Assessment methods evolved as a set of mathematical equations that describes creative artifacts as a combination of surprise, novelty and value as shown by (Grace et al. 2014). To this date, researchers tend to agree that an artifact has to be new and valuable on a particular domain to be considered creative (França et al. 2016; Goes et al. 2016; Boden 2015; Colton et al. 2015; van der Velde et al. 2015)

Another popular approach is the use of human computation, in which artifacts' creativity is assessed by human judges (Lamb, Brown, and Clarke 2015). Human computation to assess creativity can be found in fields such as fashion, focusing on the creation of fashion styles and designs (Cheng and Liu 2008), the creation of full playable digital games (Cook and Colton 2015), and even on the development of autonomous agents (Goel and Rugaber 2015). Those systems can also utilize collaborative methods as presented by (Joyner et al. 2015), where the most creative artifact is the product of many others. Human computation can be a value estimator as pointed by (Jordanous, Allington, and Dueck 2015), where the authors show how humans evaluate music composed by others. It is important to note that the quality of a judge evaluation is highly tied to the expertise of the judge, thus this kind of system is more suitable to assist humans in tasks than to be used in automated processes. Also, the quality of the evaluation by human systems rely in sociocultural aspects as pointed and explored by (Jordanous 2012; Jordanous 2013; Jordanous, Allington, and Dueck 2015).

Theories about creative thinking vary from the incubation theory to the most recent one called the honing theory (Gabora 2010). When transformed into computational systems, those use search heuristics, evolutionary computation and AI learning systems such as artificial neural networks or knowledge-based systems. With a consensual assessment method to evaluate creative artifacts, the research conducted by (Kim and Cho 2000; Kowaliw, Dorin, and McCormack 2012; Tomasic, Znidarsic, and Papa 2014; Cook and Colton 2015) has been using genetic algorithms driven by context bounded objective functions that consider surprise or value to evaluate creative artifacts in fields such as fashion, slogan creation and artistic painting.

In culinary domain, evolutionary algorithms seems suitable to generate creative artifacts. For instance, IBM (Varshney et al. 2013) has been successful in generating creative food recipes by combining a suitable domain knowledge database (i.e. food ingredients, existing recipes etc.), genetic algorithms, novelty and pleasantness assessment metrics. Computational creativity in the culinary field was also discussed in (Morris et al. 2012), where the authors focus only on soups rather than general recipes. A genetic algorithm was implemented to generate soup recipes in which multilayer perceptron neural networks were used as fitness function. These neural networks were trained over user reviews from *Allrecipes* social network. In (Veeramachaneni et al. 2010) is demonstrated a particle multi-objective particle swarm optimization to generate a combination of ingredients capable of pleasing human evaluators. The objective function of the algorithm, in turn, was designed by genetic programming using the evaluation of flavors of different combinations of ingredients.

As an alternative to the evolutionary approach, (Varshney, Wang, and Varshney 2016) updates the proposal made in previous works (Pinel, Varshney, and Bhattacharjya 2015; Varshney et al. 2013). As well as previous studies, the new proposal maintains Bayesian Surprise and a regression model for assessing respectively, novelty and value (pleasantness of the flavors) of the recipes generated by the system. The main contribution is in how the recipes are generated, which is based on rules of association of ingredients considering factors such as: co-occurrence in recipes, shared flavor compounds, being from same region of world, and being grown in the same season of year.

The main contribution of this research in relation to those aforementioned is the employment of *RDC*, a domain independent creativity metric, in the culinary field. The *RDC* measures creativity through the *novelty* and *value* of artifacts. The *novelty* is measured by the *Bayesian Surprise*, also used in (Varshney et al. 2013; Varshney, Wang, and Varshney 2016), and the *value* is calculated through *Synergy*, presented in (França et al. 2016) for other application domains. To characterize the *value* of the artifacts in the culinary domain, the *Food Pairing Hypothesis* verified in (Ahn et al. 2011) was used. This hypothesis was the base to create the synergy graph, which characterizes ingredients that if combined, add value to a food ingredient combination.

The Creative Flavor Pairing

Figure 3 shows the overview of *Creative Flavor Pairing*. The *Pairing Builder* is a genetic algorithm (GA) that performs the recipe generation using the RDC metric as a fitness function, as established in Equation 6. The *dataset* and *synergyset* define respectively, the context for the calculation of novelty and value.

In each generation, a population of 30 candidates ingredient combinations is submitted to the operators such as: selection, crossover and mutation. The crossover operator implements *Partially Matched Crossover* (Sivanandam 2008) (crossover probability $p_C = 0.7$) and the mutation operator exchanges one ingredient from one combination for another one from the universe of the $1,530$ ingredients currently available (mutation probability $p_M = 0.05$). When evolution is no longer significant, *Pairing Builder* returns the most creative recipe found. The implementation uses the *RDC API* [3] provide in (França et al. 2016).

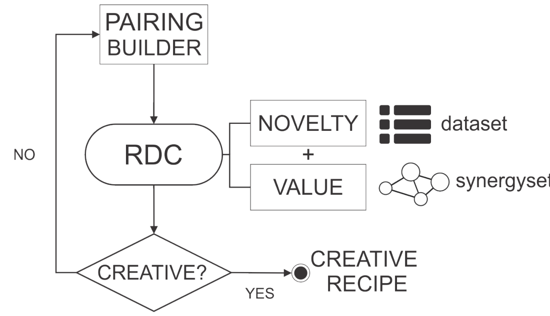

Figure 3: Overview of the Creative Flavor Pairing system.

Experimental Method

The experimental analysis was conducted in two stages. In the first stage, a case study was carried out in the *Allrecipes* culinary social network to identify the relationship between the RDC metric for combinations of ingredients and the popularity of recipes created by humans. In the second stage, the novelty, value and creativity (RDC) of the combinations generated by *Creative Flavor Pairing* were compared to the combinations of human-made recipes ingredients published in *Allrecipes*.

The *Food2Fork API*[4] was used in the case study in order to retrieved recipes with the lowest and highest *social ranking* (SR), a real number which aggregates criteria such as the number of users who reproduced and reviewed a recipe, rating (0 to 5 stars) given by the community and the number of likes and shares, from *AllRecipes*. Furthermore, the RDC of the ingredient combinations from the collected recipes was calculated to be clustered, through *K-means algorithm* (Witten, Frank, and Hall 2011), based on novelty, value and RDC of the recipe ingredient combinations, to verify if the social ranking and RDC have the same behavior.

In the second stage, we used the repository presented by (Ahn et al. 2011), that contains $41,524$ human-made recipes retrieved from *Allrecipes*. The novelty, value and RDC from all the ingredients combinations in the repository were compared with the same amount of combinations that were generated by *Creative Flavor Pairing*.

Experimental Results

The Figure 4 shows the SR normalized in the range [0,2] and the RDC of the least popular and the most popular ingredient combinations from recipes obtained by *Food2Fork API*.

All least popular combinations have SR equal to 0.698. Considering that their RDC is in the range between 0.79 and

[3]RDC API is published in Github and can be accessed at: `https://github.com/CreaPar/RDC-API/`

[4]*Food2Fork* offers an API that exposes some ingredient search functionality across multiple online recipe databases. Food2Fork documentation can be found at `http://food2fork.com/about/api`

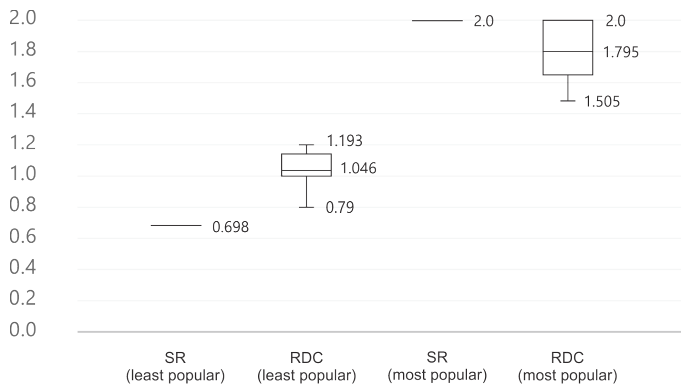

Figure 4: Comparison of SR and RDC of the least popular combinations and the most popular combinations retrivied by the Food2Fork API.

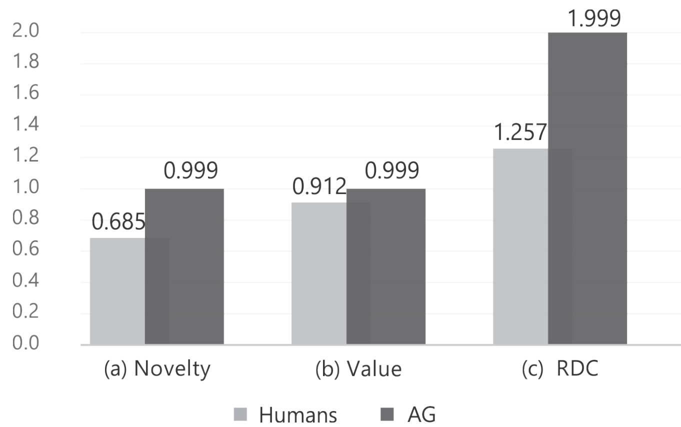

Figure 5: Average of novelty, value and creativity (RDC) of human-made recipes and recipes generated by genetic algorithm (GA) guided by the RDC metric.

1.193 with the mode being 1.046, it indicates that the less popular combinations are also the less creative ones.

On the other hand, all most popular combinations have a SR equal to 2.0. And their RDC is between $1,505$ and $2,0$ with the mode being $1,795$. That is, the most popular combinations are also the most creative.

	novelty	value	RDC
Cluster 0	0.592	0.882	1.089
Cluster 1	0.926	0.942	1.799

Table 4: Novelty, value and RDC of centroids of Cluster 0 and Cluster 1.

Table 4 shows the novelty, value and RDC of the centroids resulting from the clustered combinations. The *Cluster 0* has its centroid with RDC equals to 1.089, while the *Cluster 1* has its centroid with RDC equals to 1.799. These clusters concentrate ingredients combinations of low and high creativity, respectively. All combination of *Cluster 0* has SR equal to 0.698 while all those of *Cluster 1* has SR equal to 1.799. This fact confirms that the most creative recipes are those that are most successful among *Allrecipes* users.

As results of the second stage of experiments, Figure 5 shows that the average of novelty, value and RDC of human-made ingredient combinations and combinations created by our system. There is a relatively small number of recipes in use, ($\sim 10^6$), compared to the huge number of potential recipes, ($\sim 10^{15}$), together with the frequent recurrence of particular combinations in several regional cuisines. For this reason, the genetic algorithm in our system, in less than 30 generations, was able to find combinations with considerably greater novelties than the combinations created by humans, as shown in Figure 5(a).

In addition to it, only recently some restaurants and top chefs have started using the *Food Pairing Hypothesis*. Thus, as shown in Figure 5(b), the GA was also able to find tastier combinations than those proposed by humans.

Since it is possible to find new and valuable combinations, consequently, it is also possible to find more creative ones, which is shown in Figure 5(c). The use of the RDC metric as a fitness function allows the GA to prioritize combinations that have a balance among novelty and value.

Figure 2 shows the graph representing one of the most creative combination generated by *Creative Flavor Pairing*. It inspired the chef Otávio Mello from a restaurant in Brazil to create the recipe *Grilled Pork Loin with Guava Chutney and Beetroot and Potato Crispy*[5]. Otávio currently uses *Creative Flavor Paring* to create his restaurant's menu. He indicated that the system helps him to explore surprising and tasty dishes.

Conclusions

The results show that the *Creative Flavor Pairing* is able to generate culinary ingredient combinations as creative as those generated by humans. It was also possible to verify that through the *RDC* metric, which guides the generation of artifacts optimizing novelty and value, the proposed system contributes to the culinary domain allowing the generation of combinations of ingredients little or never explored, minimizing the scenario described in (Ahn et al. 2011), where only a small portion of the area potential is exploited.

As future works, the proposed system can be expanded to use humans to evaluate if the combinations generated are really surprising and tasty. Another possibility would be to generate the full recipe, identifying in the quantities used of each ingredient, and generate the preparation directions. Regarding the structure of the recipe, another possibility would be to identify the distribution of ingredient categories in each recipe, and generate templates to be followed in the elaboration of the ingredient combinations.

[5]The *Grilled Pork Loin with Guava Chutney and Beetroot and Potato Crispy* recipe can be acessed at: `http://allrecipes.com/personal-recipe/64632063/`

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