On food, bias and seasons: A recipe for sustainability

Michel Deudon

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Abstract

Food is a common thread, linking all seventeen Sustainable Development Goals set by the United Nations (2016) for 2030. In this paper, we consider local-seasonal food as a proxy for social and environmental impact. We present a static and a dynamic generative model to resample ingredients from a dataset of 10k vegan recipes, in various context (location, season). We compare the static and dynamic behaviors in terms of greenhouse gas emissions and our results suggest that eating local-seasonal could save 0.25 to 1.5 kg CO2 per kg of product compared to randomly picked recipes, in Paris. We introduce a label, local-seasonal, to inform Human and Machine decisions for food and to protect/celebrate (bio)diversity. We propose an application to gather and share knowledge on local-seasonal food, worldwide, with professional and amateur cooks, farmers or markets, accessible at https://www.local-seasonal.org. We encourage initiatives to grow and support local communities as part of our recipe for sustainability.

1 Introduction

Food has a language, a story (Jurafsky, 2014), a vocabulary and a syntax (Daguin, 2015). Similar to other languages, the language of food has evolved, from the first agricultural revolution in the Neolithic, 12,000 years ago, to our modern and connected digital age. In particular, its vocabulary (Kicherer et al., 2017) has profoundly been transformed with new forms of life appearing, but many more disappearing and going extinct. In the past 40 to 50 years, we lost 60% of the world's biodiversity (WWF, 2018).

The language of food became highly standardized. We find the same tomatoes from Almeria (Spain) or asparagus from Peru, *all year*, in supermarkets across Europe. Humans and machines forgot, if not lost, the origins and seasons of food. And as a consequence, by buying, eating, ordering or cooking imported/*out-of-season* fruits and vegetables, we accelerate climate change and widen social inequalities in the world. Our options are getting limited as we sacrifice (bio)diversity for availability, despite healthy, social and environmental considerations.

In this paper, we attempt to quantify food bias and the relative carbon impact of different food behaviors in different context (location, season), using a simple generative model to explain static and dynamic behaviors. Our work tries to automate the process of resampling local-seasonal baskets of food from vegan recipes. More importantly, our work attempts to understand and help individuals eat/cook healthier, better, with a lower carbon footprint. We propose a label, local-seasonal, to reconnect with the dynamic language of food, overcome our biases and mitigate the negative impact of imported/*out-of-season* food.

In section 2 we will motivate the use of a local-seasonal metric for social and environmental impact. We discuss related work in section 3. Then in section 4, we will present Vegan10K, the dataset curated for this study. In section 5, we present Recipe2BetterRecipe, a generative model (Smolensky, 1986; Hinton, 1999) to resample ingredients from recipes, and we introduce context-specific biases to generate local-seasonal recipes on the fly. We present our results, limits and future work in section 6. We discuss human bias and motivate the benefits of a local-seasonal API and label in section 7 before concluding.

2 Background

2.1 Food, a common thread for sustainability

One third of the food in the world is wasted with the highest rates (40-50%) for fruits, vegetables, roots and tubers (FAO, 2013). See Figure 1 for an example. This waste generates unnecessary emissions for production, storage and transportation of food, in particular when imported and *out-of season*. Indeed, such fruits and vegetables emit 20 times more greenhouse gas emissions than their local and seasonal counterparts, due to the use of pesticides, green houses and increased traveled distances (Bon Pour Le Climat, 2014). Yet, we import and ship *fresh food*, worldwide, in particular our fruits and vegetables.

Figure 1: *[A tomato] is not truly one, but truly two* - Paris, December 2018. Adapted from the Strange Case of Dr. Jekyll and Mr. Hyde (Stephenson, 1886): "Man is not truly one but two". Tomatoes can be local-seasonal or imported/out-season.

Our intensive and conventional food system threatens the environment but also undermines our health and widens social inequalities across the world. We refer the reader to Oxfam's "Good Enough to Eat" index (Oxfam, 2014b) which ranks 125 countries according to whether people have enough to eat, food quality, affordability, and dietary health. "[This index] reveals how the world is failing to ensure that everyone is able to eat healthily, despite there being enough to go around." - Oxfam International Executive Director Winnie Byanyima (Oxfam, 2014a). In developing countries, nutritive ingredients are missing. Meanwhile, populations in developed countries suffer from increased diabetes and obesity (Dufumier, 2012). Migrants and women, forced to harvest fruits and vegetables, are smuggled, exploited, harassed and sexually abused (Sciurba and Palumbo, 2018). Human rights are violated.

2.2 The strange case of tomatoes

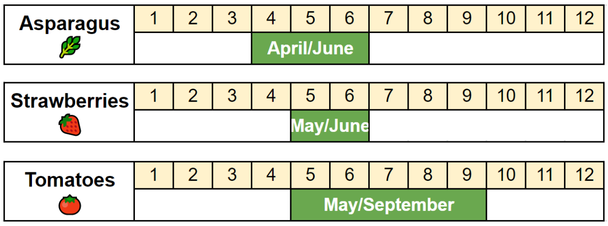

Figure 2: Local-seasonal calendar of asparagus (top), strawberries (middle) and tomatoes (bottom) in Paris, France. From Leers and Fessard (2017).

All-year, industrial tomatoes were selected to be productive. Grown in a conventional and intensive way, with chemicals, plastic and pesticides, they are harvested in greenhouses and shipped across countries and continents to supply super and hypermarkets *all-year* long. First prices are cheap, but disrespectful of the environment and society. Strawberries from Morroco, asparagus from Peru are other examples. On average this type of food travels 3000 km, is standardized, calibrated, identical in an utopical way (French Grandes Ecoles, 2018). Available *all-year*, these products disrespect seasonality and contradict our long-term efforts.

Local-seasonal friendly tomatoes, those cooked by responsible cooks, are seasonal. They don't grow all year long. The harvest is from May to September in the Northern Hemisphere and they are used to cook delicious gazpacho or salmorejo in summer. These tasty and nutritive tomatoes are grown "slowly" via a reasonable or organic agriculture that respects the environment and society. The use of chemicals and pesticides is limited or banned. The product is respected. Freshly harvested, produced within 250 km, seasonal fruits/vegetables change with seasons and can be bought from local producers, permacultures and communities. Producers and consumers are connected. Mode of production, food composition and other information are known. Prices cover the producer's expenses and supports a sustainable economic development (French Grandes Ecoles, 2018).

All-year ingredients dominate our shelves, while friendly tomatoes and asparagus have seasons and are misrepresented. We don't dress the same way in winter and summer. Why would we eat the same food? Life has periodic patterns (revolution of planets, seasons, tides, blossom) and we, humans, celebrate periodicity. We celebrate the cycles of life. We gather together for birthdays, religious, social and cultural events. Friendly fruits and vegetables are available during a limited time window, known as a season, as shown in Figure 2 in the case of Paris, France. Seasonal food comes with healthy, nutritive, tasty meals. Better for the planet, better for our health, better for our economy and society, eating local and seasonal is a simple, inclusive and scalable solution to address the UN Sustainable Development Goals (United Nations, 2016) together.

2.3 Meal carbon footprint

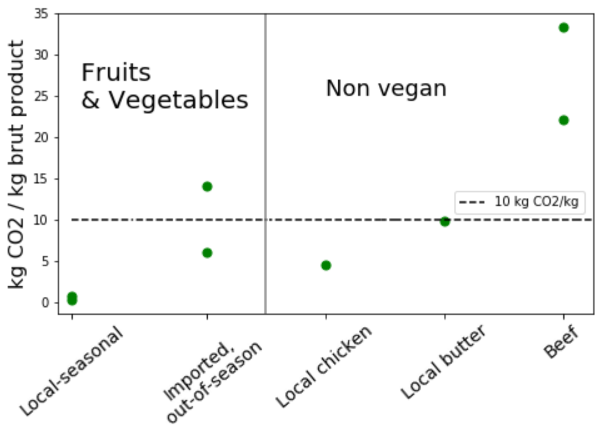

Figure 3: Food individual contributions (intervals) to Green House Gas emissions, and vegan subset for this study (left). *Local* means produced within 250 km. From Bon Pour Le Climat (2014).

How much could we save by eating **local-seasonal**? This paper attempts to quantify the potential impact of such behavior from an analysis of 10K vegan recipes, presented in section 4. To calculate a recipe's carbon impact, we employ the estimates of greenhouse gas emissions given by Bon Pour Le Climat (2014) and validated by the French Environment & Energy Management Agency Ademe. In this setting, local-seasonal fruits and vegetables emit 0.3-0.7 kg CO2 per kg of product, while the same imported, *out-of-season* fruits and vegetables emit 20 times more. The greenhouse gas emissions of different ingredients are shown in Figure 3 for comparison. Beef and imported/out-of-season fruits or vegetables both have emissions that exceed 10 kg of CO2 per kg of product. In this paper, we consider vegan recipes for which the emissions are significantly lower, when local-seasonal, than recipes with meat or fish. We focus on fruits and vegetables for which attributes vary with time and space, and for which food waste is the highest (40%-50%).

3 Related work

Generating, planning or optimizing discrete combinatorial structures such as recipes has recently received attention. Kochanski et al. (2017) proposed a Bayesian framework to optimize a single recipe via a trial-and-error process (144 experiments). However, most optimization methods look into static attributes of recipes: proportions, category, nutrition or ratings (Pagnutti and Whitehead, 2017; Yang et al., 2017; Nezis et al., 2018).[1]

The study proposed by De Laurentiis et al. (2019) looked into the carbon and water footprint of different meals in a US cafeteria. The authors showed that "the highest value of [carbon footprint] is obtained when the horticultural products are out of season and produced in heated greenhouses, while the highest value of [water footprint] is obtained when the origin of the ingredients is unknown". To our best knowledge no vegan/vegetarian datasets and automated approach exist or have been published to study food, bias, seasons and their implications on the environment and society.

4 Vegan10k

In this section we present our curated dataset for analysis and generation of friendly recipes in various context (location, season). Our schema for data is illustrated in Figure 4.

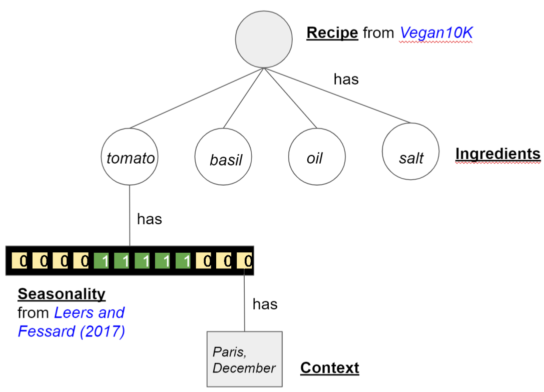

Figure 4: Schema used in this study. Recipes are made of ingredients with different seasonality for a specific context.

[1]Nutrition and ratings are not static attributes in reality since they vary with locations and seasons.

4.1 Dataset

Vegan10K consists of 12436 vegan recipes from the Kaggle dataset *What's cooking?*. The original dataset contains 49718 recipes in English from which we extracted vegan recipes, using substring matching. For example "chicken wings" is not vegan because it contains the word chicken. Essentially, for each ingredient in a recipe, we checked if it contained a non-vegan substring from a curated list of 139 substrings (e.g. beef, pork, duck), and discarded recipes not considered vegan.

Recipes from the vegan subset have on average 8-9 ingredients per recipes. Many words represent the same ingredient, e.g. tomatoes and tomato. We thus preprocessed and remapped the vegan dataset, as illustrated in Table 1, resulting in a corpus of size $n = 12436$ vegan recipes (25.80% of original) and $d = 843$ words (17.07% of original).

- Preprocess: We lower case words, remove parenthesis and non alpha characters (alphabet: a-z). We further lemmatize words using NLTK, removed adjectives from a curated list of 47 words (e.g. fresh, fried, free). We stripped white space, keep ingredients with 3 or more characters and removed recipes with one or less ingredient.

- Remap: We rename our noisy ingredients in an unsupervised way. First, we define a parent-child relationship among ingredients, using substring matching. We then map each child (long string) to one of its parents (substring in vocabulary).

Step	Recipe example
Original	Tomatoes, fresh basil, 2cs Olive oil
Preprocess	tomato, basil, cs olive oil
Is vegan?	True
Remap	tomato, basil, olive oil

Table 1: Data pipeline (original, is vegan, preprocess, remap)

4.2 On food, bias and seasons

The distribution of word frequencies in a coherent linguistic corpus typically follows a Zipf law (Zipf, 1949; Manning et al., 1999), i.e. a power distribution of the word counts. Food, as a language, exhibits similar properties. For instance, the word tomato appears in 18% of recipes, while hazelnut, artichoke, pear and turnip appear in less than 0.5% of recipes. We refer to the frequency of an ingredient in a recipe as food bias.

We report in Figure 5 fruits and vegetables ranked by their food bias and colored/marked according to their seasonality in Paris, in December.

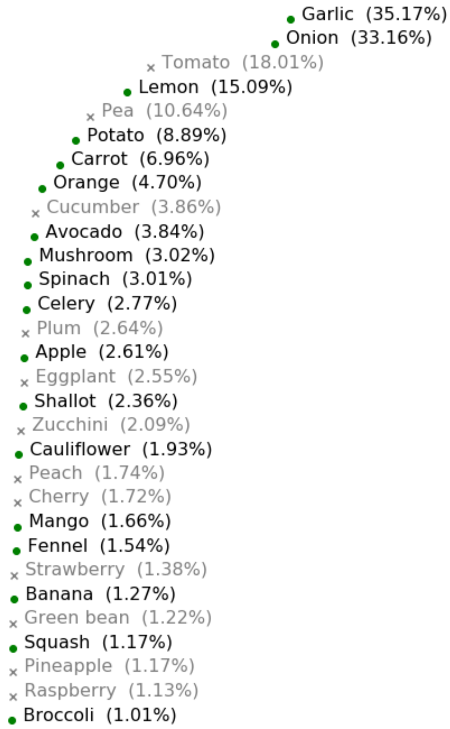

Figure 5: Food, bias and seasonality: Fruits and vegetables from Leers and Fessard (2017) are ranked, top to bottom, according to their bias in Vegan10K (top 30) and colored depending on their seasonality. o: local-seasonal in Paris, in December. x: *Out-of-season*.

Garlic, onion, tomato and lemon accounts for more than 50% of the fruits/vegetables used in Vegan10K, as shown in the pie representation in Figure 6. In reality, the bias of an ingredient is dynamic, i.e. varies with locations and seasons, in a cyclic way. The probability of an ingredient in a recipe depends on available local resources and cultures. In this paper we set the context to Paris, France and consider the seasonal calendar curated by Leers and Fessard (2017), for which 61 out of 63 fruits/vegetables intersect with the extracted vocab from Vegan10K.

5 Recipe2BetterRecipe

Recipes are made of ingredients (visible states). We thus represent a recipe as a basket of food, the equivalent of bag of words in linguistics, similar to Kicherer et al. (2017). Our vegan, prepro-

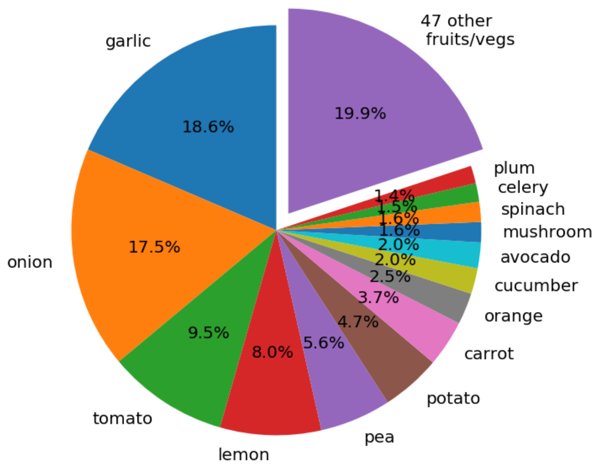

Figure 6: Fruits and vegetables representation in Vegan10K. Four ingredients account for more than 50% of representations. Conversely, 47 ingredients appear in less than 20% of the cases.

cessed and remapped corpus consists in a sparse matrix $X \in \mathbb{N}^{nd}$ with $n = 12436$ vegan recipes and $d = 843$ words. We infer hidden states h of dimension $k = 150$, such as diets or cuisine, with a Restricted Boltzman Machine (RBM) which we detail below. A trained RBM on Vegan10k can be used to resample ingredients for vegan recipes.

Restricted Boltzmann Machines are a class of undirected probabilistic graphical models containing a layer of observable variables and a single layer of latent variables (Smolensky, 1986; Hinton, 1999, 2002; Hinton and Salakhutdinov, 2006; Salakhutdinov et al., 2007). The observed states v could be words or food and the hidden states h co-occurences, topics or diets. The whole system, hidden and visible states, is described by an energy function, with high-energy configurations being less probable:

$E(v, h) = -v^T W h - v^T b - h^T c$ where the weights $W \in \mathbb{R}^{dk}$, visible bias $b \in \mathbb{R}^d$ and hidden bias $c \in \mathbb{R}^k$ are the parameters of our model. The probability of a given configuration (v,h) is given by $p(v, h) = \frac{1}{Z} e^{-E(v,h)}$ where Z is the partition function.

Inference Since there are no connections within a layer, the conditional distribution factorizes. This means that one can easily sample hidden states h, given visible states v and vice versa to resample ingredients.

$$p(h_j = 1|v) = sigmoid(c_j + v^T W_{:j})$$
$$p(v_i = 1|h) = sigmoid(b_i + W_{i:} h)$$

Learning Our goal is to fit the best parameters W, b and c that maximize the probability over the data, also known as likelihood. Maximizing the exact log-likelihood is impractical due to the intractable partition function Z. The idea behind contrastive divergence is to replace the intractable expectation by a point estimate v' obtained by Gibbs sampling. The training aims to lower the energy of true data samples v, h(v), relative to reconstructed samples v', h(v'), by stochastic gradient descent:

$$W_{new} = W_{old} + \eta(h(v)v^T - h(v')v'^T)$$
$$b_{new} = b_{old} + \eta(v - v')$$
$$c_{new} = c_{old} + \eta(h(v) - h(v'))$$

Dynamic, context-specific bias We trained a Bernoulli RBM, using scikit-learn, for 100 epochs, with batch_size 32 and learning_rate $\eta = 0.1$. Nothing in this model captures seasonality or the dynamic and cyclic nature of visible states. A default RBM is static: it's energy function is independent of the spatial or temporal context (region, season).

However, an RBM's visible bias b could easily be modified on the fly, depending on spatial and temporal context. For a given location L and month t, we define a context-specific bias $b_{L,t}$, with $b_{L,t}[i]$ = $b[i]$ if ingredient i is local-seasonal and $b_{L,t}[i]$ = $-\infty$ otherwise. By setting an RBM's bias to $b_{L,t}$, our model significantly lowers the probability of imported/*out-of-season* recipes for the context L, t (cf. section results).

6 Experiments and results

6.1 Experiments

We considered two behaviors to revisit recipes (resample ingredients) from Vegan10k, using a static and a dynamic model (see section 4. Recipe2BetterRecipe). We also considered a behavior consisting in never resampling ingredients.

Reporting the absolute value of greenhouse gas emissions of Vegan10K recipes, for each month t, in Paris, $G^{Paris,t}$ would require to know emissions of all $d = 843$ ingredients, for each month, in Paris, which is beyond the scope of this paper. Instead, we report in figure 7 the excess of greenhouse gas emissions due to out-of-season fruits and vegetables in sampled baskets of food, averaged across all recipes from Vegan10K, for each month t, in Paris: $\Delta_{outofseason} G^{Paris,t}$, noted $\Delta G^t = \frac{1}{n} \sum_{i=1}^{n} \Delta G_i^t$ for simplicity.

Formally, for a month t, we decompose the emissions of a recipe i into those related to local-seasonal fruits/vegetable s_i^t, imported/out-of-season ones hs_i^t and the rest r_i (e.g. rice, salt) considered season agnostic. In absolute terms, the carbon impact is given by

$$G_i^t = q(s_i^t)g(s_i^t) + q(hs_i^t)g(hs_i^t) + q(r_i)g(r_i) \quad (1)$$

where q denotes quantities and g denotes emissions. In relative terms, the excess of greenhouse gas emissions due to out-of-season fruits and vegetables is approximated by

$$\Delta G_i^t = \frac{q(hs_i^t)}{q(s_i^t) + q(hs_i^t) + q(r_i^t)} \Delta g_{s \to hs} \quad (2)$$

where the first term is the ratio of out-of-season fruits/vegetables and the second term $\Delta g_{s \to hs}$ is derived from (Bon Pour Le Climat, 2014) and Figure 3. $\Delta g_{s \to hs} \in [5.7, 13.3]$ kg CO2/kg product.

In addition to reporting the average excess of greenhouse gases emissions (always zero for the model with the dynamic bias by design), we report in table 2 examples of food substitution with our dynamic model, for different baskets of ingredients, not seasonal in Paris, in December.

6.2 Results

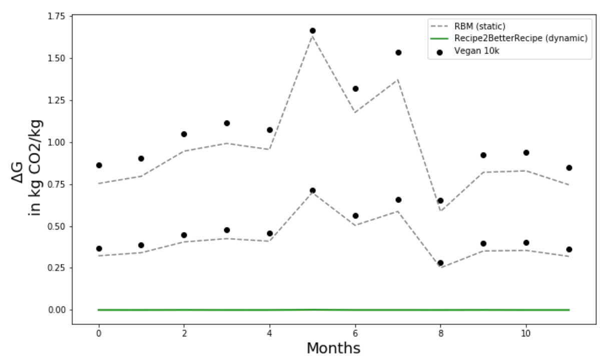

Figure 7: Excess of greenhouse gas emissions on Vegan10k due to imported/out-of-season fruits and vegetables (lower and upper bound). Black dots: Without resampling ingredients. Gray dashes: Our static behavior to resample ingredients. Green line: Our dynamic behavior.

35-70% of recipes in Vegan10K are local-seasonal each month in Paris. May is the month with the least local-seasonal recipes and September the month with the most. On average, 4-12% of ingredients in Vegan10K recipes are out-of-season. (depending on each month) and, as a consequence, randomly picking such recipes generates an excess of 0.25 to 1.5 kg CO2 per kg of product, due to

In-season	May, July, September
Recipe	**basil, garlic, oil, parsley, salt**, *tomato*
December	*tomato* → **onion**
In-season	June - August
Recipe	**lemon**, *raspberry*, **sugar, yogurt**
December	*raspberry* → **mango**
In-season	September
Recipe	**cilantro, lime, onion, salt**, *tomato*
December	*tomato* → **garlic**
In-season	May - June
Recipe	**lemon, lime**, *strawberry*
December	*strawberry* → **orange**

Table 2: Recipe2BetterRecipe for different baskets of food. *Italic*: Out-of-season ingredients, in Paris, in December.

imported/*out-of-season* fruits and vegetables (black dots in Figure 7).

Our static model slightly lowers the excess of emissions (gray dashes in Figure 7), although there is nothing built into this model that would cause it to specifically optimize for low greenhouse gas emissions. It is possible that, because the model is maximizing the probability of the overall dataset, it is avoiding the rarest ingredients, which also happen to be season specific ingredients, such as nectarine or clementine. Our dynamic model generates local and seasonal recipes, thanks to the context-specific bias set on the fly, resulting in $q(hs_i^t) = 0$ and $\Delta G_i^t = 0$ (green line in Figure 7).

Recipe2BetterRecipe could help resample recipes' ingredients, in a given context such as Paris, December, taking sustainability and (bio)diversity into account. We report in table 2 concrete examples from Vegan10K. Considering different baskets of food not seasonal in Paris, in December, we sample alternatives to out-of-season ingredients, with our dynamic model. For instance, *lemon, lime, strawberry* is replaced by *lemon, lime, orange*, resulting in a local-seasonal recipe for the given context (Paris, December).

Our code is available at https://github.com/MichelDeudon/r2br. We hope the proposed label and code will be useful to communities interested in food and sustainability. We refer the reader to more comprehensive frameworks, e.g LESSAJ or Riches Terres (Dallaire and

Emond, 2012; Daguin, 2015), which both include local-seasonal food as a metric.

6.3 Limits and future work

Our model suggests alternatives, following the idea that ingredients that appear together, marry well with each other. However, alternative ingredients are not always good substitutes. Replacing tomatoes in pasta with lemon could result in a totally different dish and be undesirable. Our approach could potentially benefit from additional constraints (e.g. nutrition, cost) and a deeper qualitative analysis to preserve the semantics of revisited recipes (resampled ingredients).

Our analysis could be improved with further preprocessing, extended to weighted words and instructions to take quantities and food proportions into account. A deeper analysis would likely yield higher estimates, in particular if considering recipes with meat or fish.

Despite the above limits, the conclusion of our study is the same as De Laurentiis et al. (2019): "careful menu planning and procurement choices can considerably reduce the overall environmental impact of the service provided without compromising quality or variety".

Our *rule-based method* (don't sample imported/out-of-season ingredients to generate local, seasonal baskets) and our evaluation of local-seasonal recipes are relatively simple. Yet they require knowing what is local-seasonal, in various locations, for different months, and this information is not widely available today, in a transparent way and standard format, which is the purpose of a label motivated in the next section, intended for both Human and Machines.

7 From machine to Human bias

In this section, we motivate the benefit of a local-seasonal label to overcome food bias in society, reconnect with the language of food and create more sustainable communities (Davies et al., 2019).

Our insights suggest that a model with dynamic bias could cut the excess of greenhouse gas emissions related to imported/*out-of-season* fruits and vegetables, in various context (time and location). So why do Humans behave differently? "[We eat seasonal. It's fundamental, but faced with shelves full of exotic fruits, tomatoes, avocados, citrus, strawberries *all-year*, we are confused]". - translated from Qu'est ce qu'on fait? French Grandes Ecoles (2018). Eating seasonal is challenging. Seasonal knowledge is diffused, spread across websites, blogs and social networks, changes with geographic locations, with climate change, and is often contradictory with what can be found online or in supermarkets.

7.1 Towards a local-seasonal label

We propose an API and website, local-seasonal.org, to gather and share knowledge on local-seasonal fruits and vegetables with professional and amateur cooks, farmers or markets. The first aim of the API is to communicate knowledge of what is local-seasonal in various locations. As illustrated in this paper, this could help cooking websites, blogs and recommendation systems to suggest local-seasonal recipes. The API could potentially help coordinate and promote sustainable labels to help citizens identify and choose local-seasonal products. We wish to extend the API, in partnerships with local farmers, cooks and markets, to map available resources and release features such as Recipe2BetterRecipe.

7.2 Growing local communities

A large number of experts proposed alternatives to our intensive and unsustainable monocultures. Dufumier (2018) proposed a scientific agroecology to achieve a sustainable agriculture. Poux and Aubert (2018) proposed a ten years transition plan for an agroecological Europe, with permacultures, for instance, playing an increasing role.

Food is the problem, and food is the solution. Eating, growing, cooking **local-seasonal** food is an opportunity for education, social reinsertion, social inclusion and sustainable development (Finley, 2013). Slow Food started in Italy to counter balance Fast Food and raise awareness on food, cultures and (bio)diversity. Community kitchen such as Food for Soul and Food Cycle promote social inclusion by feeding souls with delicious recipes from ingredients that would otherwise be wasted. The Refugee Food Festival integrates refugees in society through social and cultural events. Labels, such as Ecotable, identify and promote sustainable restauration services. We encourage inclusive initiatives (Davies et al., 2019) to grow and support local and sustainable communities.

8 Conclusion

Food has multiple dimensions and share properties similar to other languages, in particular a natural bias in word frequencies, regardless of context. Our results suggest that a dynamic generative model could revisit recipes (resample ingredients) and make them local-seasonal, using context-specific biases. We illustrated our experiments in the context of Paris, using the seasonal calendar from Leers and Fessard (2017) and showed that local-seasonal vegan recipes could save 0.25 to 1.5 kg CO_2 (greenhouse gas emissions) per kg of product on average compared to randomly chosen vegan recipes.

AI could help fight climate change (Rolnick et al., 2019) and positively contribute to the environment and society if we change and optimize the right metrics together (Dallaire and Emond, 2012; Daguin, 2015). Eating/cooking local and seasonal is a simple way to celebrate and defend (bio)diversity. We propose a local-seasonal API for cooks, farmers, markets and sustainable citizens, accessible through `local-seasonal.org`. We welcome initiatives to grow and support local communities aiming for a sustainable agroecology.

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