A Cross-lingual Analysis on Culinary Perceptions to Understand the Cross-cultural Difference

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Abstract

Native cuisines are usually acquired tastes for local people but often appear to be unpalatable choices for foreign travelers. This is attributable not only to taste preferences, but also to the different dish perceptions between cultures. Understanding culinary cultures is of great interest these days, with many studies investigating the ingredient uses and tastes among dishes, while little is known about the subjective perceptions people have toward them. In this paper, we introduce a new dimension to the understanding of culinary cultures. We specifically assess 'cross-cultural perceptions of food', and develop a model to compare culinary perceptions between cultures, especially different linguistic areas, using descriptions acquired from social media. To evaluate the validity of the proposed model, we conducted a series of experimental assessments using beverages as targets. We analyzed the perceptual differences between drinks in Japanese culture and US culture. Results revealed social trends of culinary cultures. For instance, the results show US residents' preferences for colorful foods, Japanese people's general recognition of 'bitter' for coffee, US residents' frequent mention of smoothie thickness, and the unique latte art culture in Japan. Such perceptual differences are expected to be useful for strategies of localization, and for recipe recommendation.

Introduction

Food is an integral part of our life and culture. Cuisines reflect culinary habits, lifestyles, and the regional cultures of ethnic groups. Native cuisines are usually acquired tastes for local people but often appear to be unpalatable choices for foreign travelers. This difference of preferences is attributable not only to the tastes but also to a sense of discomfort that arises from unfamiliar dish perceptions and environments in which the dishes are offered. People from different areas differ in their sensitivities, perceptions of things, and preferences and values. Even a cup of coffee made from the same materials can elicit widely diverse comments depending on the area in which it is tasted. Understanding such cross-cultural culinary perceptions and preferences is of great interest these days. Food companies trying to expand their businesses overseas expend vast amounts of money and time to investigate the culinary habits of different areas, which are usually based on communications or questionnaires administered to local people; a time-consuming and expensive processes. Social media are attracting attention as a possible substitute for traditional laborious investigations, and many works proposed the framework for analyzing food culture fusing data acquired from social media (Silva et al. 2014; Sajadmanesh et al. 2017). These works succeed in comparing cuisines from a worldwide perspective, but they are still inadequate for providing detailed information about experiences aside from those involving food. Some framework is needed for comparing culinary cultures for dishes among local communities.

As described in this paper, we introduce a new dimension to the understanding of culinary cultures. We specifically assess 'cross-cultural perceptions of food', and develop a model to compare culinary perceptions between cultures, especially different linguistic areas, using descriptions acquired from social media. For example, an English-language tweet says that the poster does not like ramen but desires to eat a hot and spicy noodle, while a Japanese tweet says that the poster wants to eat ramen with 'umami' at night in midwinter. What can be said from these posts? At least, the poster of the English tweet prefers hot and spicy noodles, and the poster of the Japanese tweet imagines 'midwinter' and 'umami' from ramen.

These descriptions used unconsciously on social media reflect the preferences and values of a particular culture. In the proposed framework, the cross-cultural attitude about a specific food is understood by analyzing the description patterns used in a specific cultural area. We first gather descriptions related to the targets of the analysis from Social Media. Next, descriptions with close meanings are categorized as the same concept, so that descriptions can be compared in a unified scale between languages. By comparing the frequency of concepts used in each linguistic area, it is possible to analyze the perceptual differences of food between cultures.

To evaluate the validity of the proposed model, we conducted a series of experimental assessments using beverages as targets. We analyzed the perceptual differences between drinks in Japanese culture and US culture with three experiments. Results revealed social trends of culinary cultures. For instance, the results show US residents' preferences for colorful foods, Japanese people's general recognition of 'bitter' for coffee, US residents' frequent mention of smoothie thickness, and the unique latte art culture in Japan. Such perceptual differences are expected to be useful for strategies of localization, and for recipe recommendation.

The contributions of this paper can be summarized as presented below.

- We introduce a model to compare culinary perceptions between languages using descriptions on social media.
- We introduce 'perception' as a criterion for analyzing the distance of culinary habits.
- We suggest the possibility of applying the model to recipe analysis and retrieval, and food and restaurant recommendation.

Related Work

Our work is closely related to two research fields: culinary habits and social media, and recipe recommendation.

Culinary Habits and Social Media

With the spread of social media and review services, data related to people's food preferences and recipe information are becoming easier to access. Many studies use these data to analyze the culinary habits of people. Wagner et al. used server log data to understand online food preferences and suggested the influence ingredients have on recipe preferences(Wagner, Singer, and Strohmaier 2014). Abbar et al. examined the potential of Twitter to lend insight into US-wide dietary choices (Abbar, Mejova, and Weber 2015). Location data from the social app 'Untapped' revealed the drinking habits of numerous users and helped highlight important behavioral trends (Chorley et al. 2016). Laufer et al. conducted cross-cultural analysis of food cultures by exploring descriptions on Wikipedia (Laufer et al. 2015).

Some studies have specifically examined cross-cultural analysis. Kular et al. used network analysis to elucidate the relation between cuisine and culture (Kular, Menezes, and Ribeiro 2011). They demonstrated that cultures can be defined by similarities in how people prepare food. Sajadmanesh et al. analyzed ingredients, flavors, and nutritional values that distinguish dishes from different regions (Sajadmanesh et al. 2017). Silva et al. identified cultural boundaries by analyzing food and drink habits in Foursquare (Silva et al. 2014). Min et al. performed cross-region recipe analysis by jointly using the recipe ingredients, food images, and attributes such as the cuisine and course(Min et al. 2018). Silva et al. proposed a methodology to identify cultural boundaries and similarities across populations at different scales (Silva et al. 2017). On a smaller scale, city size can indicate the influence of dietary choices (Cheng, Rokicki, and Herder 2017).

These works compared cuisines from a worldwide perspective, but they are inadequate for providing detailed information related to what experience people have aside from those related to food. A framework is needed for comparing culinary cultures for each dish among local communities.

Our work differs from those in that we specifically examine the 'perception' of food. We introduce 'perception' as a new criterion for analyzing the distance of culinary habits. We also propose a framework to discuss detailed culinary differences of specific dishes.

Recipe Recommendation

Many efforts have been undertaken for developing recipe recommendation algorithms. User ratings of recipes are thought to be fundamentally important for recipe recommendation (Freyne, Berkovsky, and Smith 2011; Kotonya, De Cristofaro, and De Cristofaro 2018). Most recipe recommendation algorithms are based on recipe similarities. Information related to ingredients is a popular elements used for calculating similarity (Teng, Lin, and Adamic 2012; Kuo et al. 2012; Ueda et al. 2014). Other recipe attributes such as flavors and nutrients are attracting attention these days (Min et al. 2017; Ahn et al. 2011). Furthermore, visual information can be a source for recipe recommendation (Maruyama, Kawano, and Yanai 2012; Herranz, Min, and Jiang 2018).

Some studies evaluate the most suitable algorithms for certain environments (Berkovsky and Freyne 2010). A personalized recipe suggestion system can support its users in considering the balance of nourishment (Mino and Kobayashi 2009), and in making health-aware meal choices (Geleijnse et al. 2011; Ge, Ricci, and Massimo 2015; van Pinxteren, Geleijnse, and Kamsteeg 2011).

Our research provides a new dimension for recipe recommendation: people's subjective perceptions of food. By consideration of objective aspects of food, and subjective perceptions of food, it is highly probable that the recommendation accuracy and generalization capability can be increased.

Proposal Method

This section proposes a framework to detect cross-cultural differences on culinary perceptions between languages. First, we gather descriptions related to the targets of the analysis from social media. To compare the descriptions in a scale beyond languages, descriptions with close meanings are treated as the same concept. When defining concepts, we use a database showing correspondence between words of multiple languages, construct a network with edges representing the closeness of meaning, and regard expressions gathered at close positions on the network as one concept. Finally, by comparing the frequency of concepts used in each linguistic area, it is possible to analyze the perceptual differences of food between cultures.

Gathering Descriptions. The first task is formulating a target list and gathering descriptions about them from the internet. Microblogs such as Twitter and review sites such as Yelp are suitable for the source. Then one gathers posts that describe each target, and obtains as many descriptions as possible. Because the purpose is to extract personal remarks, one must exclude posts that are not user's utterances (e.g., re-tweets and bot) before processing data.

Then, descriptive expressions must be extracted from these data. Descriptive expressions include expressions about the state of the subject, the poster's emotional expressions about the subject, and the environmental characteristics in which the object exists. For our research, we regard adjectives as descriptive expressions. For example, what is 'pretty' and what is 'beautiful' depend on the speaker's perception. Adjectives are the easiest way to describe something. Therefore, we think that a frequency distribution of adjectives can represent the tendencies of cross-cultural perceptions.

Constructing Description Network. In this procedure, a description network is created by attaching weighted connections to expression pairs that have close meanings. To incorporate consideration of the cross-lingual word relation, a database giving the relation of words of multiple languages is used as an input.

Here, we used ConceptNet 5.5 (Speer, Chin, and Havasi 2017) as the multilingual database. For all adjective pairs including English–English, Japanese–Japanese, and English–Japanese combinations, we assigned weighted links to expression pairs with close meanings. There are several reasons for adopting ConceptNet. First, ConceptNet has sufficient data volume and reliability for both English and Japanese terms, which are the subjects of our research. In addition, information related to the word relation can be acquired easily using API. Simultaneously, information related to closeness (weights of 0–1) can be acquired.

Figure 1 presents an example of description network with English and Japanese adjectives. Adjectives with similar meanings are located in a near place irrespective of the language. In the figure, colors are displayed separately for respective clusters. We visualized the graph using the Gephi software [1].

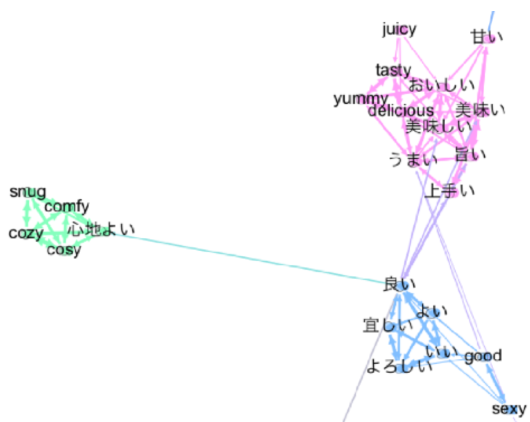


Figure 1: Example of a description network.

Defining Concepts. For the description network, one must then conduct clustering and categorize descriptions into several clusters. Because the edge represents closeness in meaning, each cluster is a set of terms with similar meanings. Because some edges connect different languages, terms from different languages with close meanings also belong to the same cluster. Defining each cluster as a 'concept cluster' that represents a concept which exceeds language, then similarity measurements and other analysis are performed using this concept cluster classification.

Modularity maximization (Newman and Girvan 2004) is used for network clustering. For our research, we used Louvain method (Blondel et al. 2008) to calculate the modularity maximization. $C_0 = \{cozy, cosy, snug, comfy, comfortable(ja)\}$ is an example of a concept cluster, which is a subset of adjectives with green color in Figure 1.

Calculating the Concept Frequency Distribution. In this procedure, sum up the co-occurrence frequency by each concept. Calculate the 'concept frequency distribution'. Details of processes are explained in the following text using relevant formulae. Presuming that the number of co-occurrences between target t_i and description d_j is $n(t_i, d_j)$, the number of co-occurrence between target t_i and concept c_k is calculated using the sum of co-occurrence between target and descriptions that belong to the concept cluster.

$$N(t_i, c_k) = \sum_{d_j \in C_k} n(t_i, d_j) \tag{1}$$

About target t_i, define the co-occurrence probability of concept c_k as P_{t_i,c_k}. Here, P_{t_i,c_k} is described using the following formula.

$$P_{t_i,c_k} = \frac{N(t_i, c_k)}{\sum_{k=1}^{k_{max}} N(t_i, c_k)} \tag{2}$$

For target t_i, the frequency distribution of the target's co-occurrence with concept c_k is calculable with the following formula. We define this distribution as P_{t_i} and designate it as the concept frequency distribution.

$$\begin{cases} P_{t_i} = \{P_{t_i,c_k}, \forall c_k \in \mathbb{C}\} \\ \sum_{c_k} P_{t_i,c_k} = 1 \end{cases} \tag{3}$$

Analyzing Cross-cultural perceptions using Concept Frequency Distribution. In this procedure, we introduce two methods that can be used to analyze cross-cultural perceptions using the concept frequency distribution.

- **JS Divergence of Concept Frequency Distribution:** Calculate the JS divergence of the concept frequency distribution. This figure is regarded as a barometer of the closeness between targets. JS divergence approaches zero if the two probability distributions are similar. In fact, it gets closer to one for different shapes. Using this condition, JS divergence of two concept frequency distributions can represent the distance between two targets. A small value of the JS divergence between two concept frequency distributions indicates that two targets are close in their perceptions, and vice versa.
- **Content of Concept Frequency Distribution:** To see details of the difference, one must look into the content of the concept frequency distribution. One must then check the concept clusters with a large gap in their frequencies between languages, which can suggest perceptual differences related to food. For example, assuming that you want to compare the perceptual differences toward 'dog' between English-speakers and Japanese-speakers. You will find English-speakers are more familiar to 'handsome' dogs than Japanese-speakers if descriptions belonging to 'handsome' cluster appear more in English context than in Japanese context. From here, the differences of general impressions toward dogs between English and Japanese cultures can be inferred.

[1] https://gephi.org/

Experimental Evaluation

Based on the method of detecting differences in culinary perceptions between languages introduced in the preceding section, we conducted an experimental evaluation.

Datasets

We used Twitter to gather descriptions. There are several reasons for this. First, Twitter is extremely popular as private media to deliver opinions and feelings every day. Secondly, posts are mainly given by a short text that delivers the poster's opinion directly. These characteristics suit our purpose of gathering descriptions. We chose targets of analysis based on the categories of online recipe service. English targets are consulted from 'Drinks Recipes' category of allrecipes[2]. Japanese targets are consulted from the 'Drinks' category of Rakuten Recipe[3]. Each target is used as the query for gathering descriptions. They are presented in Table 1.

Table 1: English and Japanese targets for the experiment. Queries with a too small number of data acquired is excluded from the list.

language	targets
English	cider, cocktail, coffee, eggnog, juice, lemonade, liqueur, mulled wine, punch, shot, shake, float, smoothie, tea
Japanese	coffee, hot chocolate, tea, matcha, soy milk, yogurt, honey drink, mixed juice, shake, smoothie, chai, beer, Japanese distilled spirit, plum wine, amazake, cocktail, Mojito, healthy liquor

We acquired 1.04 million tweets and 34,000 tweets, respectively, for English and Japanese. As a preprocessing step, we excluded those tweets that include 'RT' at the beginning of the content in the process of morphological analysis. Additionally, we limited the users to 'Twitter for iPhone' and 'Twitter for Android' because the data needed are raw descriptions by individuals. After preprocessing, 256,000 tweets for English and 12,000 tweets for Japanese remained. These were used for subsequent analyses.

For the adjectives acquired after morphological analysis, we limited their number to create description network so that the calculation can be finished in time. After defining concepts, we also limited the concept clusters used for the calculation of concept frequency distribution so that the subsequent analyses do not become too confusing. As a result, 30 concept clusters are acquired. Table 2 presents the representative adjectives belonging to each concept cluster. For the figures in the following sections, we will specify concept clusters using the index shown in Table 2.

Evaluation Methods

To check the validity of the framework for detecting cross-cultural differences on culinary perceptions, we conducted three analyses.

(1) Comparing the general perceptions of beverages. Is it possible to extract cultural culinary perception differences from descriptions? Is it appropriate to use adjectives as descriptions? To address these questions, we used all English and Japanese tweets to evaluate the extractability of general perception differences. We analyzed the contents of concepts with a wide gap separating English and Japanese in the concept frequency distribution. Because most English-speaking users on Twitter are from the US, we compared our results with generally known differences between Japanese and US residents.

(2) Comparing networks of beverage perceptions. In our research, the JS divergence of concept frequency distribution is regarded as a barometer of the closeness between targets. To evaluate the validity, we draw a network based on JS divergence, for English and Japanese target list respectively, and assess whether it can represent the relation of targets, or not. When drawing a beverage network, each target is regarded as a node. Edges are provided to target pairs with JS divergence under a certain threshold. As the weight w_{ij} added on the edge e_{ij} linking node t_i and t_j, we used the following value.

$$w_{ij} = 1 - D_{JS}(P_{t_i} \parallel P_{t_j}) \tag{4}$$

Here, P_{t_i} and P_{t_j} respectively denote the concept frequency distribution of target t_i or target t_j.

(3) Cross-lingual analysis of specific targets. In this paper, we introduce that by looking into the concept frequency distribution, perceptual differences can be extracted. To evaluate the validity, we compared the concept frequency distributions of specific drinks. Among the target list items, English and Japanese share some targets: coffee, tea, smoothies, and juice. We used them for the experiment, and by comparing the results with social and cultural environments around us, evaluated the method's validity.

Results and Discussion

Comparing the General Perception of Beverages

Results of comparisons of general perceptions of beverages are presented in Figure 2. The value in the graph shows the co-occurrence frequency in English minus the co-occurrence frequency in Japanese for each concept cluster. Concept clusters with positive values appear more in the English context. Concept clusters with negative values appear more in the Japanese context.

In English, Concept 13 (white, young, blue), Concept 17 (refreshing, cool, icy), Concept 18 (thick, giant, massive), and Concept 26 (much, few, many) show higher frequency than in Japanese. Among these, the high frequency of Concept 26 (much, few, many) can be attributed to the English language system.

Concept 13 (white, young, blue) is a cluster of colors. **The result demonstrating that English-speakers mention color more agrees with the fact that the US has more colorful foods.** From long ago, edible dyes have been used in the US to prevent food from bruising and to make food eye-catching, which also facilitates coloration of products by US

[2] http://allrecipes.com/

[3] https://recipe.rakuten.co.jp/

Table 2: Concept clusters and representative adjectives that belong to each cluster

index	representative adjectives	index	representative adjectives
1	fast, snap, quick, quick(ja), early(ja)	16	spicy, bloody, bad-smelling(ja), acrid(ja)
2	salted, salty, salty(ja)	17	refreshing, cool, chilly, cold(ja), new(ja)
3	difficult, strong, bitter, sour, strong(ja), heavy(ja), bitter(ja)	18	thick, massive, fat, great, deep, thick(ja), greasy(ja), deep(ja)
4	weak, soft, cheap, simple, light, soft(ja), light(ja), brittle(ja), cheap(ja)	19	like, -like(ja)
5	little, poor, slight, thin(ja), poor(ja)	20	old, old(ja)
6	nervous, excited, warm, hot, hot(ja), affable(ja), warm(ja)	21	proper, decent, modest(ja)
7	interesting, hilarious, curious, exciting, interesting(ja), pleasant(ja), fun(ja)	22	clean, refreshing(ja)
8	asleep, sleepy, sleepy(ja)	23	brown, brown(ja)
9	fantastic, dangerous, awful, scary, dangerous(ja), great(ja), amazing(ja)	24	mad, crazy, insane, crazy(ja)
10	bad, evil, tired, ugly, awkward, bad(ja), not delicious(ja), annoying(ja)	25	rare, rare(ja)
11	blunt, boring, late, obtuse, late(ja), boring(ja), lax(ja), blunt(ja)	26	much, few, many, multiple, several, few(ja), many(ja)
12	high, expensive, long, tall, short, short(ja), low(ja), venerable(ja), shallow(ja), long(ja)	27	relaxing, comfy, soothing, friendly, cozy, comfortable(ja), agreeable(ja)
13	white, young, blue, yellow, dark, black(ja), white(ja), young(ja), dark(ja), yellow(ja)	28	busy, busy(ja)
14	near, close, near(ja)	29	sorry, sorry(ja)
15	pretty, adorable, cute, beautiful, lovely, pretty(ja), nostalgic(ja), beautiful(ja)	30	flat, flat(ja)

food companies. US residents tend to regard colorful food as tempting. For example, Gatorade, which is a US brand and which boasts the world's top share among sports drinks, are colored with different colors for each type. Despite being drunk in more than 70 countries worldwide, Gatorade is not currently produced in Japan. In Japan, loud colors from edible dyes give a strong unhealthy and even harmful impression. Loud coloring of food is not preferred.

In Japanese, Concept 3 (hard, strong, bitter), Concept 4 (soft, light, cheap), Concept 7 (interesting, fun), and Concept 9 (fantastic, great) show higher frequency than English.

The high frequencies of Concept 3 (hard, strong, bitter), Concept 7 (interesting, fun), and Concept 9 (fantastic, great) suggest that **Japanese people post more negative opinions and emotions related to themselves.** This result corresponds with those of earlier research. Vidal et al. analyzed English-written Twitter data for breakfast, lunch, dinner and snack occasions, and performed manual content analyses of tweets for deeper insights. They found contextual characteristics of eating occasions that were frequently described in tweets, whereas emotions were rarely described in tweets(Vidal et al. 2015). Acar et al. reported that Japanese university students post mainly about themselves, whereas many US students' posts include questions (Acar and Deguchi 2013). Our results indicate a similar tendency for characteristics of social media usage for Japanese and US residents.

The high frequency of Concept 4 (soft, light, cheap) might represent **Japanese people's interest in everyday drinks** (e.g., 'cheap' drinks and 'light' drinks). In Japan, more options are presented in beverage vending machines than in the US. A greater variety of beverages are available at convenience stores. Although further investigation is needed, one might infer that Japanese people are more sensitive about daily drinks because of the wide variety of beverages in their everyday environment.

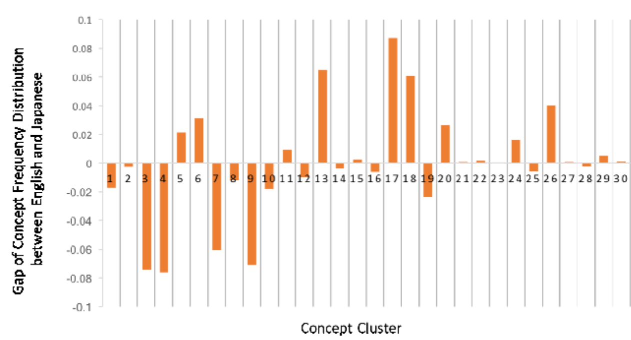
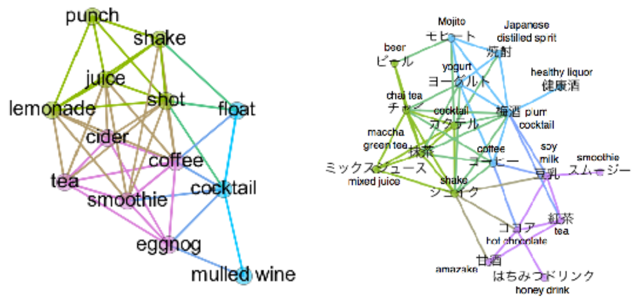


Figure 2: Gap of the concept frequency distribution between English and Japanese tweets. Concept clusters with positive values appear more in the English context; negative in the Japanese context.



(a) English (b) Japanese

Figure 3: Beverage networks.

Comparing Networks of Beverage Perceptions

Results of beverage networks of perception comparisons are shown in Figure 3. We visualized these networks using the Gephi software.

In the English beverage network, juice, lemonade, and tea appear in adjacent positions, reflecting the fact that these three beverages often have fruit among their ingredients. In the Japanese beverage network, hot chocolate, Amazake, tea and honey drinks appear in proximate positions, all of which share the commonality of being warm drinks. In addition, alcohol drinks including Mojito, Japanese distilled spirits, plum wine, and cocktails are proximate in the network. Soy milk and smoothies are both perceived as healthy drinks. Both use milk as an ingredient. Therefore, it is not surprising that they share a close perception in Japan.

Comparison of these two networks reveals apparent differences of positions among beverages. As an example, one can specifically examine the smoothie. In the English network, a smoothie has edges with tea, cider, and coffee. Its position is in the center of the network. However, in the Japanese network, the only edge smoothie shares is that with soy milk: its position is at the network edge.

This beverage network is based on the proximity of peoples' perceptions. The network represents a relation to our perceptions. Therefore, using JS divergence of the concept frequency distribution to describe the distance of perception on the target is regarded as reasonable.

Cross-lingual Analysis on Specific Targets

The results of cross-lingual analysis of specific targets are presented in Figure 4. When comparing the contents of the concept frequency distribution for specific targets, we used the result of Figure 2, and selected concept clusters with larger gaps than the general perception because concepts that have large gaps after eliminating the influence of the general tendency (e.g. usage of social media) are highly likely to differ in their perception by cultures.

coffee In the English context, Concept 6 (warm, excited, nervous) appears more than in Japanese. Iced coffee originated in Japan. **Because US residents are not familiar with iced coffee, the impression of 'hot' or 'warm' might be stronger in the US than in Japan.** However, Concept 17 (refreshing, cool) also appears more frequently in the English context. This frequent appearance is presumably because 'refreshing' and 'cool' belong to the same concept. Further investigation separating these two concepts might be needed. Higher frequency of Concept 11 (blunt, boring, sharp) in English implies that **US residents often see coffee in a 'boring' context, and desire 'exciting' coffee.** In fact, many articles on the internet introduce how to make coffee not boring.

In Japanese posts, however, Concept 3 (hard, strong, bitter) and Concept 15 (dear, pretty, nostalgic) appear more frequently than in English. From the high appearance of Concept 3 (hard, strong, bitter), one can infer the general perception of 'bitter' related to coffee in Japan. Concept 15 (dear, pretty, nostalgic) presumably reflects **the Japanese unique latte art culture.** Latte art is not rare in the US, but no custom of drawing animals and characters exists as in Japan. One can infer that there is no general recognition of 'cute' for coffee and latte art in the US.

tea In the English context, Concept 13 (white, young, blue) and Concept 15 (pretty, very, adorable) appears more than in Japanese. In the US, fruit tea is popular. Specialty tea shops sell widely diverse kinds of tea, for which color also varies greatly. The color of tea leaves and the color of water when tea is poured are enjoyed. **US residents have a culture of enjoying tea with their eyes.** Given the high frequency of Concept 15 (pretty, very, adorable) together, one can assume more aspects of the US tea market. **In the US, women commonly give tea to their friends as a present.** Colorful and cute package decorations on tea caddies and bags are made. Pretty tea cutlery or accessories are manufactured and sold.

smoothie In the English context, Concept 5 (little, poor, mini), Concept 13 (white, young, blue), Concept 15 (pretty, very, adorable), and Concept 18 (thick, giant, massive) appear more frequently than in Japanese. The high frequency of Concept 13 (white, young, blue) and Concept 15 (pretty, very, adorable) shows the same tendencies as those for tea and are presumably more affected by **the colorful and fruitful perception of smoothie in the US.** According to the high frequency of Concept 18 (thick, giant, massive), one can infer that **US residents use thickness to evaluate smoothies.** In fact, ways to make thick smoothies are introduced on the Internet.

In the Japanese context, however, Concept 8 (sleepy), Concept 9 (fantastic, great), Concept 10 (bad, not delicious, troublesome), and Concept 19 (-like) appear more than in English. The high frequency of Concept 10 (bad, not delicious, troublesome) implies **a general recognition of 'not delicious' in Japan.** Using Concept 19 (-like) frequently might mean **a tendency to evaluate smoothies in the comparison with other beverages in Japan.** This result suggests the possibility that smoothies are not so common and popular in Japan, and that they are recognized as a substitute for other drinks in Japan.

juice In the English context, Concept 5 (little, poor, mini) Concept 17 (refreshing, cool, icy) and Concept 26 (much, few, many) appear more frequently than in Japanese. High

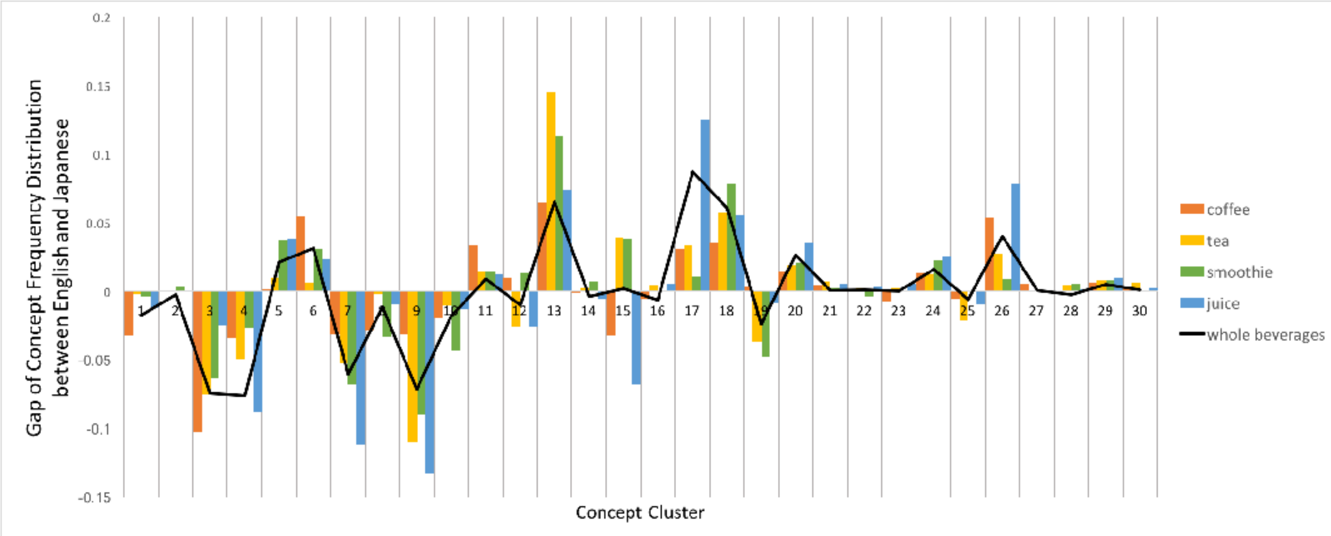


Figure 4: Results of cross-lingual analysis of specific targets. The black line shows the gap of the concept frequency distribution between English and Japanese tweets related to beverages, which reveals the same result as that portrayed Figure 2. Each bar shows the gap of Concept Frequent Distribution between English and Japanese for each target. For each target, concept clusters with larger absolute values than the whole beverages shown in the black line are selected for deeper investigation.

appearance of Concept 5 (little, poor, mini)and Concept 26 (much, few, many) implies that **US residents are concerned about the amount of juice.** High appearance of Concept 17 (refreshing, cool, icy) might indicate that **US residents generally regard juice as a cold drink.**

In the Japanese context, on the other hand, Concept 7 (interesting, fun), Concept 9 (fantastic, great), and Concept 15 (pretty, very, adorable) co-occur more frequently than in English. One can assume that **there for Japanese people, juice is a drink appearing in scenes that evoke positive emotions.**

Conclusion

In this work, we propose a framework to compare cross-cultural culinary perceptions by grouping descriptions with the meanings of words. To evaluate the validity of the proposed method, we conducted a series of experimental evaluations using beverages as targets. We analyzed the perceptual differences of drinks in Japanese culture and US culture using three experiments. The results revealed social trends of culinary cultures. Cultural differences that can be acquired with the proposed framework can be categorized into the following four groups.

general recognition
This is the general recognition of targets in a cultural area. Japanese popular impressions of ‘not delicious’ assigned to smoothies and ‘bitter’ for coffee, and US residents’ impressions of ‘cold’ for juice are salient examples.

values and standards
These are values regarded as important in a cultural area and as standards for evaluating the target in a cultural area. US residents’ frequent mention of smoothie thickness, juice amount, and tea color are salient examples.

context and environment
These are the context in which a target appears in a cultural area. US residents’ mention of ‘boring’ for coffee and Japanese people’s mention of ‘fun’ for mixed juice are salient examples.

unique genre
This is a genre unique to a culture. Latte art in Japan and hot cider in the US (not described in the results) are noteworthy examples.

These perceptual differences can be useful for localization strategies of food companies. Localization strategies are processes of understanding local culture, habits and preferences used to assess what changes are necessary to spread a company’s products. Our model can at least perform well as a cost-effective and time-effective way to clarify cross-cultural characteristics of food culture, and give advice for strategies.

In the context of recipe recommendation, we suggest a new criterion: culinary perception. With cultural bias regarded together with objective attributes such as ingredients, flavors, and visual appearance, the recommendation algorithm would move on to the next stage. This progression is not merely for recipe recommendation; it applies widely to a recommendation of any kind. Methods to detect and manipulate within-group biases properly are needed.

As future work, we plan to build a recipe recommendation algorithm based on culinary perceptions. We also wish to investigate how elements of food (ingredients, flavors, nutrients, visual appearance, and perceptions) are mutually related and how they influence our culinary preferences. Finding the answer to this question is expected to provide a better recommendation system with high generalization capability, which can suggest a choice with healthier, more satisfactory and more diverse experience for any person in the world.

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