

Learning to Taste 🍷 : A Multimodal Wine Dataset

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Abstract

We present *WineSensed*, a large multimodal wine dataset for studying the relations between visual perception, language, and flavor. The dataset encompasses 897k images of wine labels and 824k reviews of wines curated from the Vivino platform. It has over 350k unique bottlings, annotated with year, region, rating, alcohol percentage, price, and grape composition. We obtained fine-grained flavor annotations on a subset by conducting a wine-tasting experiment with 256 participants who were asked to rank wines based on their similarity in flavor, resulting in more than 5k pairwise flavor distances. We propose a low-dimensional concept embedding algorithm that combines human experience with automatic machine similarity kernels. We demonstrate that this shared concept embedding space improves upon separate embedding spaces for coarse flavor classification (alcohol percentage, country, grape, price, rating) and aligns with the intricate human perception of flavor.

1 Introduction

Vision, language, audio, touch, smell, and taste are sensory inputs that ground humans in a shared representation, which enables us to interact, converse, and create. Recent advances in multimodal learning have shown that combining diverse modalities in a shared representation leads to useful and better-grounded models [Girdhar et al., 2023, Chen et al., 2023]. Inspired by recent progress, we propose to add flavor to the list of modalities used to learn shared representations.

As a first step towards modeling flavor, we focus on wine since (1) wines have been studied for centuries, (2) their flavors have been carefully categorized, and (3) classification systems exist to ensure that flavor is near-consistent across bottles of the same unique bottling.

We bridge the gap between the machine learning and food science communities by presenting WineSensed, a multimodal wine dataset that consists of images, user reviews, and flavor annotations. Our motivation is twofold. On one hand, internet photos and user reviews are a scalable source of data, offering abundant, diverse, and easily accessible insights into wine qualities. On the other hand, human flavor annotations, while not as scalable, provide a more direct and granular understanding of the wines’ flavor profile. By combining these resources, we aim to capture the best of both worlds, yielding a richer, more intricate dataset.

We organized a large sensory study to obtain human-annotated flavor profiles of the wines. The study applies the “Napping” methodology [Pagès, 2005], which is commonly used to conduct consumer surveys [Kim et al., 2013, Ribeiro et al., 2020]. In this study, 256 participants annotated their perceived taste similarities of various wines. In Fig. 1, the “human kernel” illustrates how participants were instructed to place wines on a sheet of paper based on how similar they perceived their flavor to be. The Napping method enabled us to annotate wine flavors with a high level of detail and harness the perception of a broad spectrum of individuals. It scales well, as asking a participant to annotate

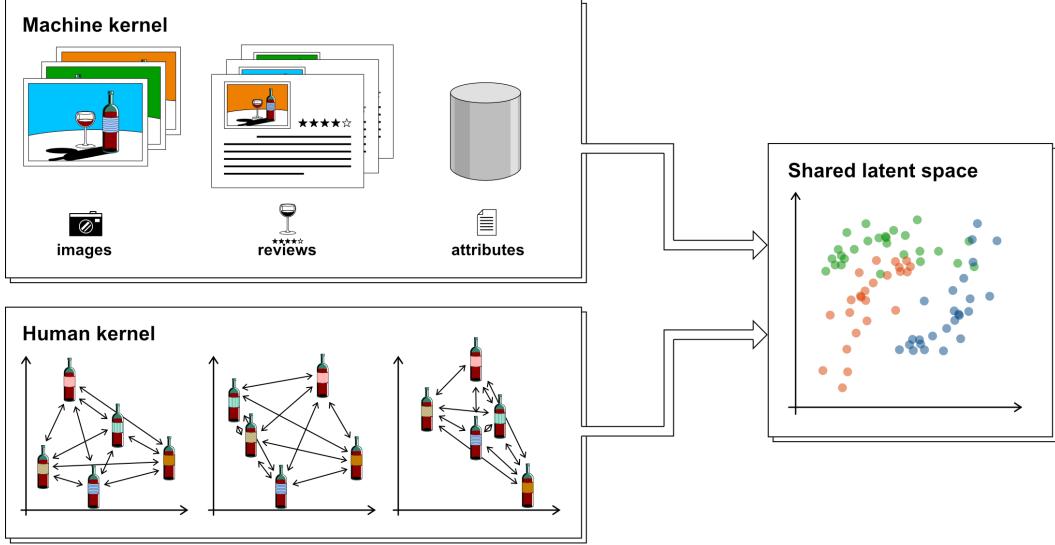


Figure 1: Flavor as an additional data modality. The WineSensed dataset consists of a large collection of images, user reviews, and metadata about unique bottlings (upper left). In a large user study, we collected flavor annotations of over 100 wines using the “Napping” method [Pagès, 2005], where participants were asked to place wines on a sheet of paper based on their perceived taste similarity (lower left). We propose an algorithm to combine these data modalities into a shared representation (right) and find that using taste annotations as an additional modality improves performance in downstream tasks.

five wines yields 10 pairwise annotations. All participants combined annotated more than 5k flavor distances.

To complement these annotations, we curate images of wine labels, user reviews, and wine attributes (country of origin, alcohol percentage, price, and grape composition) from the Vivino platform, a popular online social network for wine enthusiasts.¹ WineSensed, therefore, represents a large, multimodal dataset that merges user-generated content with sensory assessments, bridging the gap between subjective consumer perception and objective flavor profiles.

Along with the dataset, we propose *Flavor Embeddings from Annotated Similarity & Text-Image* (FEAST) that leverages recent developments in large multimodal models to embed user reviews and images of wine labels into a low-dimensional, latent representation that contains semantic and structural information that correlates with taste. Our model aligns this representation with the flavor annotations from our user study. We find that this combined representation yields a “flavor space” that models coarse flavor concepts like alcohol percentage, country, grape, and the year of production, while also being aligned with more intricate human perception of flavor.

Experimentally, we find (1) that using the pairwise distances (rather than ordering) of the annotated wines improves the flavor representation, which confirms the established methodology in food science, and validates our annotation process. (2) We discover that using multiple data modalities (images, text, and flavor annotations) boosts the flavor representations, highlighting the usefulness of our multimodal dataset. (3) Finally, we show that the proposed multimodal model produces a flavor space with a high alignment with humans’ perception of flavor.

2 Background and related work

Multimodal representations. Learning a shared representation between modalities can reveal useful representations that generalize well and appear grounded in reality. Pioneering work [de Sa, 1994] proposes to learn the correlation between vision and audio. A number of deep learning methods propose to use large collections of weakly annotated data to learn shared vision-language representa-

¹<https://vivino.com>

Images	User reviews	Attributes
	<p>Classy Sangiovese. Complex, velvety, berries, liquorice, peppery bearing on spice...gets better with every sip!</p> <p>Dark ripe fruity notes, medium bodied one and really nice smooth and full taste in the mouth. I love it 🍷</p> <p>Great wine. Rich flavour, yet still smooth with a "sweet" finish. Would go well with Italian dishes, but also roasted meats. 5 out of 5 !</p> <p>A superb wine, bursting of fruity tones of cherries, blue berries and black current. Well balanced tannins and acid.</p>	<p>Country: Italy Grape: Sangiovese Region: Abruzzo Alc%: 14.5 Rating: 4.3 Price: \$9.47</p>
	<p>More of food wine... Unbalanced with too much emphasis on the fruit and lacking in acidity. Too rich on its own!</p> <p>Heavy wine but still round and soft tannin. Great with heavy autumn stews 🍷</p> <p>Great wine, really round and soft in the mouth, chocolate, plum, vanilla, leather in the end</p> <p>A nice Zinfandel, and I'm not a fan! Good balance of acidity and sweetness, medium body, slightly dry.</p>	<p>Country: United States Grape: Zinfandel Region: Lodi Alc%: 14.5 Rating: 3.8 Price: \$23.85</p>
	<p>Cherry, taste a bit like liquor, hint of spices, I bit steel barrel aroma that I don't like, a strong body.</p> <p>It shows intense notes to black fruits with fine hints to clove and vanilla. It's also full bodied with silky tannins.</p> <p>was not my type of wine. Very distinct and sweet taste. Airing an hour or two later the sweeteness really comes out but</p> <p>Great wine!!! Uhhhhh! Thanks Daniel & Babette!!! I ❤️ it</p>	<p>Country: Italy Grape: Aglianico Region: Irpinia Campi Taurasini Alc%: 15 Rating: 4.2 Price: \$20.99</p>

Figure 2: **Examples from WineSensed.** The dataset consists of images of wine labels, user-generated reviews, per-wine attributes (country, grape, region, alcohol percentage, rating, price), and flavor annotations. Here are examples of the images, reviews, and attributes.

tions [Joulin et al., 2016, Desai and Johnson, 2021, Radford et al., 2021b, Mahajan et al., 2018], shared audio-text representations [Agostinelli et al., 2023], shared vision-audio representations [Ngiam et al., 2011, Owens et al., 2016, Arandjelovic and Zisserman, 2017, Narasimhan et al., 2022, Hu et al., 2022], shared vision-touch [Yang et al., 2022] representations, or shared sound and Inertial Measurement Unit (IMU) representations [Chen et al., 2023]. Recently, ImageBind [Girdhar et al., 2023] showed that images can bind multiple modalities (images, text, audio, depth, thermal, IMU) into a shared representation. While recent advances in other areas of multimodal learning have been fueled by large datasets, the difficulty of quantifying and collecting high-quality flavor data has made it challenging for the machine learning community to develop similar representations for flavor.

Quantifying flavor. Understanding and engineering *flavor* is a central part of food science and essential in the quest towards healthy and sustainable food production [Savage, 2012], but the use of machine learning methods to this end is still in its infancy. Fuentes et al. [2019] found a correlation between seasonal weather characteristics, and wine quality and aroma profiles, thereby verifying what wine producers have long held to be true. Similarly, Gupta [2018] found that sulfur dioxide, pH, and alcohol levels are useful for predicting wine quality. Due to the difficulty of gathering quality perception data, much work focuses on how ‘low-level’ chemical aspects related to ‘high-level’ taste properties, e.g. in assessing the quality of chocolate and beer [Gunaratne et al., 2019, Gonzalez Viejo et al., 2018].

Analyzing a person’s perception of wine is challenging due to the complex nature of flavor, which remains ill-understood, and the difficulty in obtaining consistent verbal descriptions of taste across individuals. Napping [Pagès, 2005] is the *de facto* method to analyze perceived taste in consumer surveys. Participants receive taste samples and are instructed to place them on a sheet of paper based on how similar they perceive their taste to be, with closer meaning more similar. Such experiments are usually conducted with 10-25 participants and less than 20 variants of a product [Giacalone et al., 2013, Pagès et al., 2010, Mayhew et al., 2016]. In this study, we scale this data collection process to 256 participants and 108 unique bottlings of red wine, resulting in over 400 napping papers collected and more than 5k annotated flavor distances. In contrast to previous works [Giacalone et al., 2013, Pagès et al., 2010, Mayhew et al., 2016] our objective is to incorporate taste as one of the modalities that contribute to the shared representations for improved grounding of machine learning models.

Human kernel learning. Annotating flavor with Napping [Pagès, 2005] does not provide image-flavor or text-flavor correspondences but rather relative flavor similarities between sampled products. According to [Miller, 2019] humans are better at describing abstract concepts such as taste with contrastive questions, such as “*does wine X taste more similar to wine Y or Z?*” For this reason, the machine learning community has used contrastive questions in multiple settings, e.g., for understanding how humans perceive light reflection from surfaces by presenting annotators with image triplets depicting the Stanford Bunny with varying material properties [Agarwal et al., 2007], to produce a genre embedding of musical artists [Van Der Maaten and Weinberger, 2012], and for discovering underlying narratives in online discussions [Christensen et al., 2022]. Most relevant to our work is SNaCK [Wilber et al., 2015], which presents annotators with image triplets depicting foods and asked which two of them taste more similar, to obtain flavor triplets. They proposed to combine this high-level human flavor understanding with low-level image statistics to learn food concepts, e.g., that even though guacamole and wasabi look similar, their taste is not. Having humans annotate image triplets of foods works well for coarse concepts, but does not encompass nuanced differences in taste. In this work, we focus on the much finer-grained taste difference found in wines. These nuances and the complex nature of wine tasting, which involves taste *and* smell, are not easily conveyed through text or images.

Flavor datasets. The machine learning community has produced numerous food datasets for classifying which meal is in an image [Bossard et al., 2014, Min et al., 2020], retrieving a recipe given an image [Salvador et al., 2017, Li et al., 2022], or predicting the origin of wines [Dua and Graff, 2017]. While it is possible to extract coarse information about taste from such datasets [Wilber et al., 2015], they do not encompass higher resolution details of taste, such as the differences between a Cabernet Sauvignon and Pinot Noir.

Similarly, the food science community has developed many datasets for understanding and predicting food flavors, nutrient content, and chemistry. Flavornet [Arn and Acree, 1998], a dataset on human-perceived aroma compounds, explores partly how smells relate to perceived bitterness or fruitiness in a wine. However, its limitation is its lack of context linking these odors to specific wine varieties and its limited focus on flavor aspects. FoodDB [Harrington et al., 2019] offers comprehensive information on a wide variety of food, its nutrient contents, potential health effects, and macro and micro constituents. However, it lacks user-generated reviews and sensory data, which are crucial for understanding the subjective human perception of food and wine. The Wine Data Set [Dua and Graff, 2017] focuses on wines, but only contains wines originating from one region in Italy, limiting the dataset’s ability to capture the broader diversity of flavor profiles of wines from various regions worldwide. Furthermore, Dua and Graff [2017] solely incorporate the chemical compounds present in each wine, without annotations of flavors and information associating specific wines with each chemical compound. In contrast to previous work, we present a multimodal dataset that contains a large corpus of images and reviews, as well as human-annotated flavor similarities.

3 The WineSensed dataset

We present WineSensed, a large, multimodal wine dataset that combines human flavor annotations, images, and reviews. In this section, we provide an overview of the curation process for each of these modalities.

Annotated flavors. The flavor data consists of over 5k human-annotated pairwise similarities between 108 unique bottlings. Each annotated pair is annotated at least five times to reduce noise.

These annotations are collected through a series of wine-tasting events attended by a total of 256 non-expert wine drinkers. Most participants were between 21-25 years old, and more than half of them were from Denmark. Each participant volunteered their time, dedicating a maximum of two hours to complete the annotations. The experiment was conducted in accordance with the ”De Videnskabsetiske Komiteer” (e. the Danish ethics committee for science) (see Appendix I).

We randomly selected 5 wines for the participants to taste. The participants did not have access to any information regarding the individual wines. The wine was poured into non-transparent shot glasses and the labels of the wines were covered during the entire experiment. The participants were instructed to put colored stickers (representing each of the five wines) on a sheet of paper based on their taste similarity, closer meaning more similar. The participants could repeat the process up



Figure 3: **Examples of images.** The viewpoint, lighting, and composition vary across images.

to three times, ensuring they did not consume more than 225 ml of wine. The average participant repeated the experiment two times.

We automatically digitized the participants’ annotations by taking a photo of each filled-out sheet. We used the Harris corner detector [Harris et al., 1988] to find the corners of the paper and a homographic projection to obtain an aligned top-down view of the paper. The images were mapped into HSV color space and a threshold filter applied to find the different colored stickers that the participant used to represent the wines. Having identified the location, we computed the Euclidean pixel-wise distance between all pairs of points, resulting in a distance matrix of wine similarities. A more detailed description of the collection and digitization of the napping papers can be found in D.

User-reviews. We curated 824k text reviews from the Vivino platform. The reviews were filtered to contain at least 10 characters to avoid non-informative reviews such as ‘good’ and ‘bad.’ Fig. 2 shows examples of user-reviews. The reviews are free text and can contain special tokens such as emojis. The reviews tend to describe price, pairing, and general terms of wine. Some also describe which flavors the reviewer tastes. These reviews are subjective and can vary based on personal factors and context, leading to inconsistent flavor profiles. Moreover, they only contain coarse flavor descriptions and focus more on aspects like preference, price, occasion, and so forth. Fig. 4 shows the distribution of word count per review, number of reviews per unique bottling, and the most common keywords.

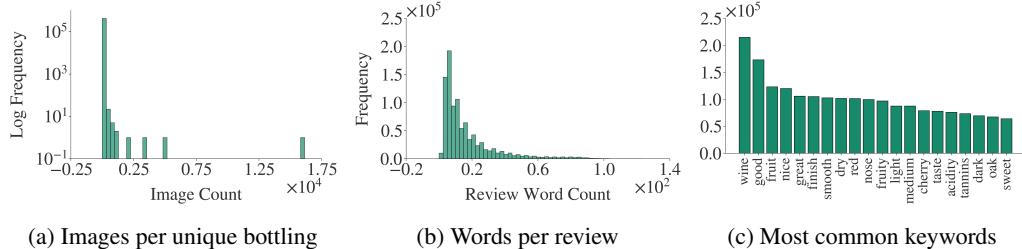


Figure 4: **Summary statistics of user reviews and images.** Most unique bottlings have less than 10 images. The average review length is 16 words. Common keywords in the reviews include ‘fruit’, ‘dry’, and ‘smooth’ revealing coarse semantic information about the flavor of the wines while other keywords such as ‘good’ and ‘great’ do not reveal flavor information.

Images. The dataset has 897k images of wine labels. Wine labels are known to play a major role in a consumer’s decision to purchase a particular wine, so it is reasonable to believe that label design

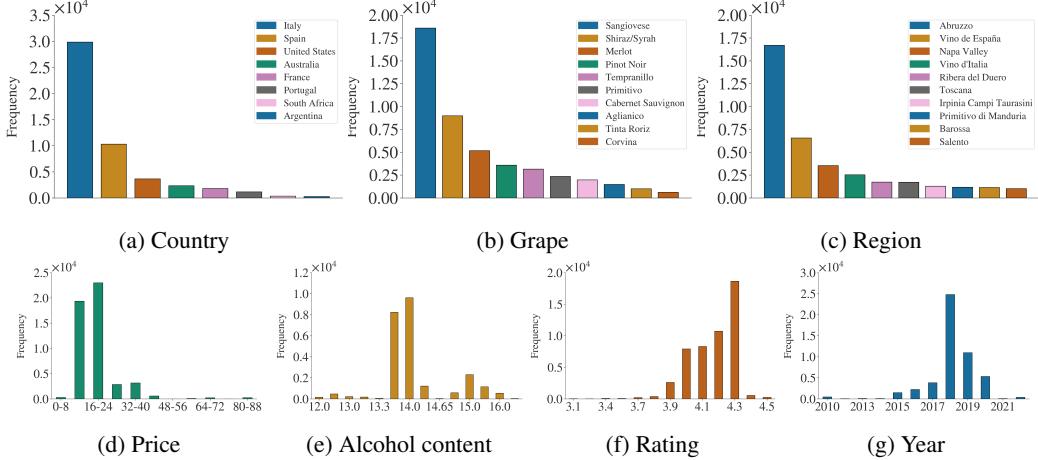


Figure 5: **Wine attributes.** WineSensed contains attributes about the geolocation of production (country, region) and the grape composition of each wine. Furthermore, the dataset includes information on the average price of the wine, alcohol percentage, average rating on the Vivino platform, and the year of production. The histograms show the distribution of these attributes.

carries information regarding the taste of the wine [Talbot, 2019]. Fig. 3 shows examples of images from the dataset. The images vary in their viewing angle, illumination, and image composition.

Attributes. Each wine is associated with the geographical location of the vineyard (both country and region), grape varietal composition, vintage, alcohol content, pricing, and average user rating. Fig. 5 shows the distribution of these attributes. Most wines originate from Italy, with Sangiovese being the most commonly used grape. The wines occupy the lower range of the price spectrum, with the most expensive ones priced at around 40 USD. The attributes are available for 5% of the dataset entries.

4 Flavor Embeddings from Annotated Similarity & Text-Image (FEAST)

The embeddings of recent large image and text networks contain structural and semantic information, however, they do not model the intricacies of human flavor. We propose FEAST, a method to align these embeddings to the human perception of flavor using a small set of human-annotated flavor similarities. FEAST takes text and/or images as input, as well as human-annotated flavor similarities. It outputs a unified embedding that aligns with human sensory perception. Fig. 6 provides an overview of the proposed method.

We first embed the text and/or images into a latent space with CLIP [Radford et al., 2021a]. We use CLIP because of its large training corpus and its image-text aligned latent space, however, highlights that other pretrained networks can be used. We use t-SNE [Van der Maaten and Hinton, 2008] to reduce the dimensionality of the latent space to 2, which simplifies and constrain the later alignment with the pairwise flavor annotations.

The pairwise distances are embedded into a 2D representation using Non-metric multidimensional scaling (NMDS) with the SMACOF strategy [de Leeuw and Mair, 2009]. NMDS allows us to preserve the original flavor distances provided by humans in a shared space, where each unique bottling is represented with point location, rather than pairwise distances. MDS is commonly used in food science to analyze sensory annotations from Napping studies [Pineau et al., 2022, Varela and Ares, 2012, Nestrud and Lawless, 2010].

We then align these two 2D representations to get a joint representation that benefits from the structural and semantic information of the image and/or text representations, scales to unobserved unique bottlings, and is aligned with the human perception of flavor. We use Canonical Correlation Analysis (CCA) [Harold, 1936] to align the two representations. CCA identifies and connects common patterns between these representation spaces, ensuring that the final representation is consistent across all input modalities.

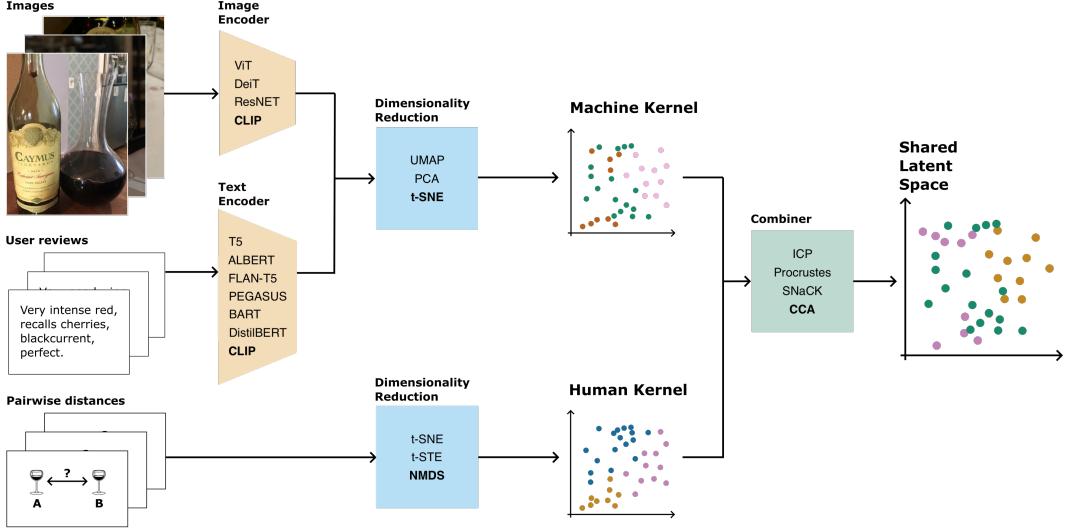


Figure 6: Model overview. FEAST takes text and/or images as input as well as human-annotated flavor similarities. The text and/or images are embedded into a latent representation with CLIP. We use NMDS to embed the flavor similarities. The two representations are aligned with CCA to produce a latent space that uses the structural information in CLIP embeddings and the intricacies of human annotations. The bolded methods in the orange, blue, and green boxes indicate choices for our best model, and their remaining combinations serve as an overview of the evaluated baselines.

5 Experiments

We conduct two experiments on the WineSensed dataset. First, we explore how well recent large pretrained language and image models explain wine attributes that correlate with the flavor of a wine. Second, we explore multimodal models’ capabilities to represent more intricate flavors.

Experimental setup. We explore several configurations of human kernels, machine kernels, and “combiners” that align the two representations. Fig. 6 provides an overview of our baselines. The **human kernel** is formed with t-STE [Van Der Maaten and Weinberger, 2012], a low dimensional graph representation reduced with t-SNE or NMDS, where the notable difference is that t-STE discards the flavor distances, and solely optimizes for triplet orderings. The **machine kernel** consists of two steps: (1) we use a pretrained model to embed text and/or images into a low dimensional space, (2) which is then compressed into a two-dimensional space. For (1), we explore DistilBert [Sanh et al., 2019], T5 [Raffel et al., 2020], ALBERT [Lan et al., 2019], BART [Lewis et al., 2019], PEGASUS [Zhang et al., 2020], FLAN-T5 [Chung et al., 2022] and CLIP for embedding text and ViT [Dosovitskiy et al., 2020], ResNet [He et al., 2016], DeiT [Touvron et al., 2021], and CLIP for embedding images. For (2), we explore t-SNE, UMAP [McInnes et al., 2018], and PCA [Pearson, 1901]. For the **combiners**, we experiment with CCA, Iterative Closest Point (ICP) [Chen and Medioni, 1992], Procrustes [Gower, 1975] and SNaCK. For a more detailed description of the implementation and software packages used, please refer to E the Appendix.

5.1 Coarse flavor predictions

We first explore how well pretrained language and vision models explain wine attributes that correlate with flavor. We then investigate if using FEAST to align the machine and human kernels improves the representation.

Implementation details. We use a balanced SVM classifier with an RBF kernel as well as a Multi-layer Perceptron [] neural network to predict wine attributes of the flavor embeddings. We predict price, alcohol percentage, rating, region, country, and grape variety as these attributes are known to correlate with the perceived wine flavor. We mitigate imbalanced class distributions with class weight balancing and oversampling of the minority classes. We report the accuracy averaged over the seven attributes computed through 5-fold cross-validation. The accuracy measures how coherent the

Table 1: Ablation of machine kernels. Accuracy of machine kernels across image and text modalities. Image models perform worse than text models. ALBERT, BART and CLIP perform the best, all models perform better than random using at least one classification method.

Machine kernel	Modality	Acc ↑	
		SVM	NN
Random		0.11	0.11
ViT	Image	0.09	0.13
DeiT	Image	0.14	0.15
ResNET	Image	0.15	0.16
CLIP	Image	0.11	0.15
T5	Text	0.15	0.16
ALBERT	Text	0.15	0.18
BART	Text	0.16	0.15
DistilBERT	Text	0.15	0.17
CLIP	Text	0.16	0.18
FLAN-T5	Text	0.15	0.17
PEGASUS	Text	0.13	0.13
BART	Text	0.11	0.15

Table 2: Ablation of Modalities. Accuracy of single and combined modalities. Using multiple modalities improves performance. We find that combining image, text, and flavor yields much better accuracy than modeling each modality separately.

Modality	Acc ↑	
	SVM	NN
Flavor	0.16	0.11
Image	0.11	0.15
Text	0.16	0.18
Text+Flavor	0.23	0.18
Image+Text	0.22	0.25
Image+Flavor	0.23	0.18
Image+Text+Flavor	0.28	0.26

Table 3: Ablation of human kernels, reducers, and combiners.

Reducer	Acc ↑	
	SVM	NN
Human Kernel		
Random	0.11	0.11
t-STE	0.13	0.10
t-SNE	0.15	0.13
NMDS	0.16	0.13

Reducer	Acc ↑	
	SVM	NN
Machine Kernel		
UMAP	0.15	0.18
PCA	0.20	0.21
t-SNE	0.22	0.25

Combiner	Acc ↑	
	SVM	NN
ICP	0.21	0.24
Procrustes	0.19	0.23
SNaCK	0.23	0.24
CCA	0.28	0.26

embeddings are with the flavor attributes. A more detailed description of the implementation can be found in J.2.

Results. Tables 1 to 3 ablates our proposed method and summarizes our main conclusions. Please see Appendix J.2 for per attribute classification accuracy for all combinations of machine kernels, human kernels, modalities, reduces, and combiners.

Table 1 shows that most pretrained image and text models yield slightly higher performance than the random baseline. The text encoders are slightly better than the image encoders. BART and CLIP perform the best. All encoders in the table use t-SNE to reduce the embedding to 2D. Table 3 (middle) shows t-SNE yields better accuracy than UMAP and PCA when using a CLIP encoder.

Table 3 (top) shows that NMDS performs better than t-STE. NMDS uses the relative distances between annotations, whereas t-STE discretizes the annotations and considers only the ordering within each triplet. The results suggest that the pairwise distances are useful to model the flavor space. Table 3 (bottom) shows that using CCA to align the two representations yields higher accuracy than SNaCK or ICP.

Table 2 shows that including flavor as a modality increases the accuracy, *e.g.* using flavor to align the image or text embeddings lead to higher accuracy. Using CLIP followed by t-SNE, NMDS, and CCA to combine language, vision, and flavor into a single representation leads to the best configurations, illustrating that the human annotations are useful for learning a flavor representation. Maybe most surprisingly, we show that each modality by itself is on par with the random baseline, but their combination produces a latent space that much better describes the flavor attributes.

5.2 Fine-grained flavor predictions

We now proceed to evaluate more intricate flavor predictions by using human-annotated flavor similarities as ground truth.

Implementation details. To evaluate our representation, we measure the Triplet Agreement Ratio (TAR) [van der Maaten and Weinberger, 2012] between our predicted flavor embeddings and the human-annotated flavors. TAR measures the agreement between a triplet derived from the latent space and the ground truth triplets from the flavor annotations. Higher TAR means that the ordering of distances in the latent space corresponds to the human perception of flavor. This measure indicates how aligned the two representations are, and provides a higher granularity of flavor prediction than flavor attributes. A more detailed description of the implementation can be found in F.

Table 4: Fine-grained flavor predictions. Triplet Agreement Ratio (TAR) between text, image, and multi-modal encoders and human annotated flavor similarities. A higher TAR indicates that the model’s representation space is more aligned with humans’ perception of flavor.

Machine Kernel	Human Kernel	Combiner	Modality	TAR \uparrow
Random				0.5
CLIP + t-SNE			Text	0.82
CLIP + t-SNE			Image	0.82
CLIP + t-SNE			Image + Text	0.81
CLIP + t-SNE			Image + Flavor	0.89
CLIP + t-SNE			Text + Flavor	0.88
CLIP + t-SNE	NMDS	CCA	Image + Text + Flavor	0.91

Results. Table 4 ablates FEAST and shows that for the higher granularity predictions both the pretrained text and image encoders improve upon the random baseline. We show that including the human kernel with NMDS further improves the TAR scores. This highlights the usefulness of the flavor distances recorded by the human annotators. In Appendix F, we show results from all configurations of human kernels, machine kernels, reducers, and combiners. We find that NMDS consistently yields better performance than t-STE, and that combining human and machine kernels improves the TAR scores across multiple model configurations.

6 Discussion & Conclusion

In this paper, we introduce WineSensed, an extensive multimodal dataset curated for flavor modeling. The dataset comprises over 897k images and 824k reviews, and has over 5k human-annotated pairwise flavor similarities, obtained via a sensory study involving 256 participants. We propose a simple algorithm, FEAST, to align semantic information from machine kernels with flavor similarities from human annotators in a shared flavor representation. We find that combining these modalities improves both coarse and fine-grained flavor predictions.

WineSensed further strengthens the collaboration between the food science and machine learning communities, introduces flavor as a modality in multimodal models, and serves as an entry point for the development of machine learning models for flavor analysis and potentially deepening our comprehension of wine flavors. The dataset and the proposed procedures open many interesting possibilities, such as using flavor to ground foundation models or extending the dataset with other modalities, such as chemical composition, or other food categories.

Constraints and considerations. The dataset serves as a novel first step to including human-annotated flavor in the array of modalities in multimodal models. Its current scope is constrained to a selected group of red wines, predominantly Italian ones. While this enables a more nuanced understanding of flavors within Italian wines, it may not represent the broader spectrum of red wines globally. Furthermore, the dataset’s emphasis on wines prevalent in Western cultures highlights a geo-cultural bias. Expanding the dataset to encompass more diverse drink types from different cultures could provide a more comprehensive understanding of global flavor perception. Lastly, the Napping methodology is not immune to the influences of participants’ backgrounds and experiences. Individual perceptions, shaped by personal histories, can introduce nuances in the data. Though leveraging non-expert wine drinkers for flavor annotations introduces subjectivity, this approach, inspired by common sensory study practices, broadens taste perspectives, enhances study accessibility, and offers commercial value, with multiple annotations per entry mitigating individual biases. Exploring a broader range of foods and beverages remains a valuable direction for future work.

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A Project webpage

We provide a project webpage for the dataset that can be found here: https://thoranna.github.io/learning_to_taste/, which contains a link to the dataset and the code to reproduce our experiments. Additionally, we provide more examples from our dataset and images from the data collection.

B License

The WineSensed dataset is licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License. Details can be found here: <https://creativecommons.org/licenses/by-nc-nd/4.0/>.

C The WineSensed file structure

Our dataset is currently available here: https://data.dtu.dk/articles/dataset/WineSensed_Learning_to_Taste_A_Multimodal_Wine_Dataset/23376560. The dataset will be maintained on this site, which is hosted on a server run by the Technical University of Denmark.

WineSensed contains a `metadata.zip` file consisting of the files `participants.csv`, which contains information connecting participants to annotations in the experiment, `images_reviews_attributes.csv`, which contains reviews, links to images, and wine attributes, and `napping.csv`, which contains the coordinates of each wine on the napping paper, alongside information connecting each coordinate pair to the wines being annotated and the participant that annotated them. The `chunk_<chunk num>.zip` folders contain the images of the wines in the dataset in `.jpg` format.

`napping.csv` contains the following fields:

- `session_round_name`: session number during the `event_name`, at most three sessions per event (maps to `experiment_round` in `participants.csv`)
- `event_name`: name of the data collection event (maps to the same attribute in `participants.csv`)
- `experiment_no`: the serial number of the napping paper in the `session_round_name` in which it was collected (maps to `experiment_no` in `participants.csv`)
- `experiment_id`: id of the wine annotated
- `coor1`: x-axis coordinate on the napping paper
- `coor2`: y-axis coordinate on the napping paper
- `color`: color of the sticker used

`participants.csv` contains the following fields:

- `session_round_name`: session number during the `event_name`, at most three sessions per event (maps to `experiment_round` in `napping.csv`)
- `event_name`: name of data-collection event (maps to `event_name` in `napping.csv`)
- `experiment_no`: the serial number of the napping paper in the `session_round_name` in which it was collected (maps to `experiment_no` in `napping.csv`)
- `round_id`: round number (from 1-3)
- `participant_id`: id the participant was given in the experiment

`images_reviews_attributes.csv` contains the following fields:

- `vintage_id`: vintage id of the wine
- `image`: image link (each `<image name>.jpg` in `chunk_<chunk num>.zip` can be mapped to a corresponding image link in this column by removing the `/p` prefix from the link).

- **review:** user review of the wine
- **experiment_id:** id the wine got during data collection (each `experiment_id` can be mapped to the same column in `napping.csv`)
- **year:** year the wine was produced
- **winery_id:** id of the winery that produced the wine
- **wine:** name of the wine
- **alcohol:** the wine’s alcohol percentage
- **country:** the country where the wine was produced
- **region:** the region where the wine was produced
- **price:** price of the wine in USD (collected 05/2023)
- **rating:** average rating of the wine (collected 05/2023)
- **grape:** the wine’s grape composition, represented as a comma-separated list ordered in descending sequence of the percentage contribution of each grape variety to the overall blend.

D Data collection details

The annotations in WineSensed were collected through a series of wine-tasting events attended by a total of 256 non-expert wine drinkers. Most participants were between 21-25 years old, and more than half of them were from Denmark. The experiment was conducted in accordance with the "De Videnskabsetiske Komiteer" (e. the Danish ethics committee for science).

Five wines were selected at random for the participants to taste. The participants did not have access to any information regarding the individual wines. The wine was poured into non-transparent shot glasses and the labels of the wines were covered during the entire experiment. The participants were instructed to put colored stickers (representing each of the five wines) on a sheet of paper based on their taste similarity, closer meaning more similar. The participants could repeat the process up to three times, ensuring they did not consume more than 225 ml of wine. The average participant repeated the experiment two times. Figure 7 provides a visual representation of the data collection events.

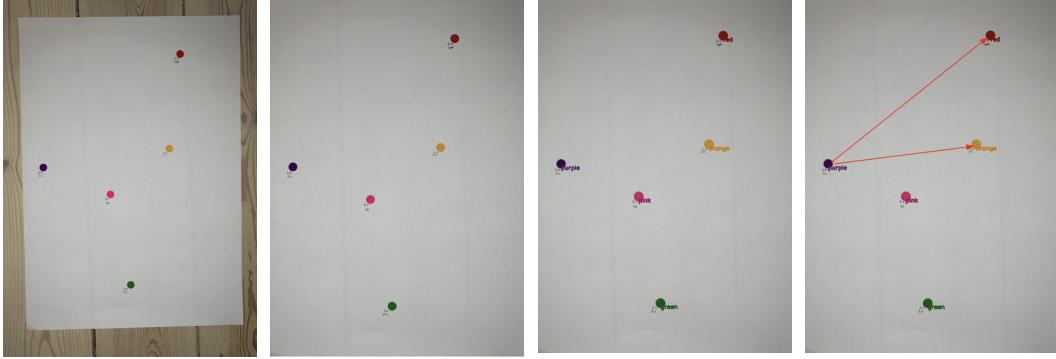


- (a) The participants were given instructions as to how to conduct the wine tasting, and palate cleansers were available.
- (b) Each wine was labelled with a color and a number to how the ber, and each participant was given a combination of wines to taste. In total, 108 different wines were used in the wine tastings.
- (c) The portions were 15 ml each, such that each participant could taste five different wines up to three times, and still consume less than two glasses of wine.
- (d) Anonymized wines, set up for a Napping-type data collection.

Figure 7: Data collection events.

The participants’ annotations were automatically digitized by taking a photo of each filled-out sheet. We used the Harris corner detector to find the corners of the paper and a homographic projection to

obtain an aligned top-down view of the paper. The images were mapped into HSV color space and a threshold filter applied to find the different colored stickers that the participant used to represent the wines. Having identified the location, we computed the Euclidean pixel-wise distance between all pairs of points, resulting in a distance matrix of wine similarities. Figure 8 provides a visual representation of the procedure used to process the napping papers.



(a) An unprocessed sample sheet with colored stick-
ers representing the relative positions of the five
different wines in the sample.
(b) The corners of the sample sheet have been detected and used to perform perspective warping in order to correct for the angle and distance of the camera.
(c) Blob detection has been performed on the perspective-corrected sample and the color of each blob classified.
(d) The Euclidean distance between each pair of labels is calculated.

Figure 8: Napping paper analysis.

E Implementation details for flavor space generation

Preprocessing. For the image data, we resized images to a 256x256 pixel format, applied a central crop to bring the images down to 224x224 pixels. Subsequently, we converted them into a tensor format, followed by normalization using mean and standard deviation values for each color channel (RGB).

For the user reviews, we first converted the text to lowercase to maintain consistency. Then, we removed punctuation marks to minimize noise. We further eliminated stopwords using the nltk library’s English stopword list since these words usually do not contribute significantly to the overall meaning of the reviews. After these preprocessing steps, the data was tokenized and reassembled into a clean text string.

The preprocessing of human-annotated data varied based on its intended use, either as a distance matrix, triplets or graph. In the first case, we calculated the Euclidean distances between each data point and arranged these distances into an $N \times N$ matrix, where N is the total number of annotated wines. The matrix element $m[i][j]$ had a value of 0 if there were no annotated distances between wines i and j . For triplets, we constructed a list of triplets derived from the computed Euclidean distances. We generated triplets (i, j, k) based on the Euclidean distances, such that i is closer to j than to k ; i.e. $\|i - j\|_2 < \|i - k\|_2$. In order to make a graph representation, we used the euclidean distance matrix to form a graph where the similarities between wines form the weights on the edges and the nodes represent the wines.

Dimensionality reduction. In our experiments, we used several dimensionality reduction methods such as NMDS, t-STE, t-SNE, PCA, and UMAP. For these methods, we prepared two embedding pipelines, one to reduce the dimensionality of machine kernel, and another to reduce the dimensionality of the human kernel.

For the human kernel, NMDS, t-STE, t-SNE and node2vec [Grover and Leskovec, 2016] were used, depending on the form of the input data. The NMDS method was optimized through a series of hyperparameter tunings, including number of initial positions (`n_inits`), maximum number of

iterations (`max_iters`), and tolerance to stress convergence (`eps_values`). These hyperparameters were evaluated using a range of values with the number of initial positions set to 5, 7, 10, the maximum number of iterations set to 300, 400, 500, 600, and the tolerance for stress convergence set to 1e-3, 1e-4, 1e-5.

The optimal hyperparameters for NMDS were selected by applying 5-fold cross validation (`cross_val_score`) using a K-nearest neighbors classifier model (`KNeighborsClassifier`) and oversampling to handle class imbalances in the data. In NMDS, The parameter `metric` was set to `False` to handle dissimilarities missing values represented by zeroes, and `dissimilarity` to precomputed as the input data was a distance matrix. Classification improvements during grid-search were not significant.

For the machine kernel pipeline, t-SNE, PCA, and UMAP, were used with a set seed to ensure the results' reproducibility. These methods were called using their default hyperparameters in the respective libraries (see External packages).

Pre-trained models. The machine kernel embeddings were obtained using a collection of pre-trained text, image, and combined image-text models. All models were obtained from the HuggingFace [hug] library. The chosen models for the text were T5 (60.5M params), ALBERT (11.8M params), BART (406MM params), DistilBERT (67M params), FLAN-T5 (60M params), PEGASUS (568M params) and CLIP text model. For images, we chose ViT, DeiT, ResNET-50 and the CLIP image encoder. Lastly, we used CLIP for the combined image-text model. All embeddings were obtained from the models' last hidden state.

Combiners. We leveraged four methods to combine the human kernel and the machine kernel: CCA, ICP, Procrustes and SNaCK. These three methods were employed using their default hyperparameters in their respective libraries (see External packages). In the case of CCA, Procrustes and ICP, we found common experiment identifiers across the two datasets and used them to align corresponding data points from the two datasets. Once the matrices were aligned, we subsequently applied CCA, Procrustes and ICP, respectively, and generated the combined embeddings.

SNaCK follows a slightly different process as it uses triplets from the human kernel and an embedding matrix from the machine kernel. We passed the triplet list (human kernel) and scaled embeddings (machine kernel) into SNaCK, which output the combined embedding.

External packages. We used several external packages: `scikit-learn` (v1.2.2) [sci], for dimensionality reduction, hyperparameter optimization, classification and human-and machine kernel combination; `umap-learn` (v0.5.3) [uma], for dimensionality reduction of the machine kernel; `imblearn` (v0.10.1) [imbl], to address the problem of imbalanced datasets; `snack` sna, an implementation of SNaCK for human-and machine kernel combination; `icp` [icp], implementing the Iterative Closest Point algorithm for human-and machine kernel combination; `tste` [tst], an implementation of the t-Distributed Stochastic Triplet Embedding algorithm for the dimensionality reduction of human-kernel triplets; `node2vec` [Grover and Leskovec, 2016] for dimensionality reduction of the human kernel in graph form and `procrustes` [Virtanen et al., 2020], an implementation of the Procrustes algorithm for combining the human and machine kernel. Additionally, our project employed these Python packages: `torchmetrics` (v0.11.4) tor, `ftfy` (v6.1.1) [ftf], `open-clip-torch` (v2.19.0) [ope], `transformers` (v4.28.1) tra, `pandas` (v2.0.1) [pan], `nltk` (v3.8.1) [nlt], `psutil` (v5.9.5) [psu], `urllib3` (v1.26.15) [url], `matplotlib` (v3.5.1) mat, `seaborn` (v0.11.2) [sea], and `h5py` (v3.8.0) [h5p].

F Details for fine-grained flavor predictions

Implementation details. The combination of dimensionality reduction methods, pre-trained models, and combiners described in F were used to generate multiple flavor spaces (using images, text and flavor). Additionally, to compare TAR across modalities, embeddings were produced for all combinations of modalities (text, image and flavor) using the relevant methods from F.

The human kernel was split into a training and a testing set. We made sure that for any given triplet (i, j, k) in the testing set, none of the wines i, j or k were present in the training set. The training set was processed and combined with the machine kernel using the reduction methods and combiners from F. The triplet agreement ratio was calculated using the level of agreement between the testing set and the triplets in the embeddings, by dividing agreements with disagreements. The triplet agreement

ratio’s random baseline was set at 0.5, because when comparing triplets, either (i, j, k) or (j, i, k) could be chosen, which makes the ratio 0.5/1.0, similar to a random guess.

Results. All results produced in this experiment can be found in tables 5, 6 and 7.

Table 5: **Fine-grained flavor predictions: Text encoders.** Triplet Agreement Ratio (TAR) between text encoders and human annotated flavor similarities.

Machine Kernel	Human Kernel	Combiner	Modality	TAR \uparrow
DistilBeRT + UMAP			Text only	0.81
DistilBeRT + t-SNE			Text only	0.81
DistilBeRT + UMAP	MDS	CCA	Text + flavor	0.91
DistilBeRT + t-SNE	MDS	ICP	Text + flavor	0.90
DistilBeRT + t-SNE	MDS	CCA	Text + flavor	0.90
DistilBeRT + UMAP	t-STE	CCA	Text + flavor	0.76
DistilBeRT + t-SNE	t-STE	ICP	Text + flavor	0.78
DistilBeRT + t-SNE	t-STE	SNaCK	Text + flavor	0.75
T5 + UMAP			Text only	0.82
T5 + t-SNE			Text only	0.82
T5 + UMAP	MDS	CCA	Text + flavor	0.89
T5 + t-SNE	MDS	ICP	Text + flavor	0.90
T5 + t-SNE	MDS	CCA	Text + flavor	0.90
T5 + UMAP	t-STE	CCA	Text + flavor	0.83
T5 + t-SNE	t-STE	ICP	Text + flavor	0.78
T5 + t-SNE	t-STE	SNaCK	Text + flavor	0.84
ALBERT + UMAP			Text only	0.80
ALBERT + t-SNE			Text only	0.81
ALBERT + UMAP	MDS	CCA	Text + flavor	0.89
ALBERT + t-SNE	MDS	ICP	Text + flavor	0.90
ALBERT + t-SNE	MDS	CCA	Text + flavor	0.90
ALBERT + UMAP	t-STE	CCA	Text + flavor	0.74
ALBERT + t-SNE	t-STE	ICP	Text + flavor	0.78
ALBERT + t-SNE	t-STE	SNaCK	Text + flavor	0.78
BART + UMAP			Text only	0.81
BART + t-SNE			Text only	0.82
BART + UMAP	MDS	CCA	Text + flavor	0.89
BART + t-SNE	MDS	ICP	Text + flavor	0.90
BART + t-SNE	MDS	CCA	Text + flavor	0.89
BART + UMAP	t-STE	CCA	Text + flavor	0.78
BART + t-SNE	t-STE	ICP	Text + flavor	0.79
BART + t-SNE	t-STE	SNaCK	Text + flavor	0.72

G Details for coarse-grained flavor predictions.

H Implementation Details

We utilize a SVM classifier with parameter `class_weight` set to balanced and and K-fold cross-validation with `n_splits` set to 5 and `shuffle` set to True using the classifier SVC and the method KFold as well as a Multi-Layer Perceptron (MLP) neural network from the Scikit-Learn library [sci]. Additionally we utilize RandomOverSampler from the imblearn library with `sampling_strategy` set to 'not majority'. When dealing with non-numerical attributes, a LabelEncoder (using the default values) from Scikit-Learn [sci] was used to create numerical features. The random baseline value was calculated by dividing 1 by the number of classes to predict.

Results. All results produced in this experiment can be found in tables 8, 15, 16, 17, 18, 13, 10, 9, 11, 12, 14 and 20.

Table 6: **Fine-grained flavor predictions: Image encoders.** Triplet Agreement Ratio (TAR) between image encoders and human annotated flavor similarities.

Machine Kernel	Human Kernel	Combiner	Modality	TAR ↑
ViT + UMAP			Image only	0.83
ViT + t-SNE			Image only	0.82
ViT + UMAP	MDS	CCA	Image + flavor	0.90
ViT + t-SNE	MDS	ICP	Image + flavor	0.90
ViT + t-SNE	MDS	CCA	Image + flavor	0.90
ViT + UMAP	t-STE	CCA	Image + flavor	0.82
ViT + t-SNE	t-STE	ICP	Image + flavor	0.78
ViT + t-SNE	t-STE	SNaCK	Image + flavor	0.75
ResNET + UMAP			Image only	0.82
ResNET + t-SNE			Image only	0.82
ResNET + UMAP	MDS	CCA	Image + flavor	0.89
ResNET + t-SNE	MDS	ICP	Image + flavor	0.90
ResNET + t-SNE	MDS	CCA	Image + flavor	0.88
ResNET + UMAP	t-STE	CCA	Image + flavor	0.79
ResNET + t-SNE	t-STE	ICP	Image + flavor	0.78
ResNET + t-SNE	t-STE	SNaCK	Image + flavor	0.76
DeiT + UMAP			Image only	0.82
DeiT + t-SNE			Image only	0.83
DeiT + UMAP	MDS	CCA	Image + flavor	0.91
DeiT + t-SNE	MDS	ICP	Image + flavor	0.90
DeiT + t-SNE	MDS	CCA	Image + flavor	0.92
DeiT + UMAP	t-STE	CCA	Image + flavor	0.82
DeiT + t-SNE	t-STE	ICP	Image + flavor	0.78
DeiT + t-SNE	t-STE	SNaCK	Image + flavor	0.86
CLIP + UMAP			Image only	0.82
CLIP + t-SNE			Image only	0.82
CLIP + UMAP	MDS	CCA	Image + flavor	0.89
CLIP + t-SNE	MDS	ICP	Image + flavor	0.90
CLIP + t-SNE	MDS	CCA	Image + flavor	0.90
CLIP + UMAP	t-STE	CCA	Image + flavor	0.81
CLIP + t-SNE	t-STE	ICP	Image + flavor	0.78
CLIP + t-SNE	t-STE	SNaCK	Image + flavor	0.81

Table 7: **Fine-grained flavor predictions: Text-Image encoder.** Triplet Agreement Ratio (TAR) between CLIP and human annotated flavor similarities.

Machine Kernel	Human Kernel	Combiner	TAR Machine Kernel ↑	TAR ↑
CLIP + UMAP			Image + text	0.82
CLIP + t-SNE			Image + text	0.81
CLIP + UMAP	MDS	CCA	Image + text + flavor	0.91
CLIP + t-SNE	MDS	ICP	Image + text + flavor	0.90
CLIP + t-SNE	MDS	CCA	Image + text + flavor	0.91
CLIP + UMAP	t-STE	CCA	Image + text + flavor	0.84
CLIP + t-SNE	t-STE	ICP	Image + text + flavor	0.78
CLIP + t-SNE	t-STE	SNaCK	Image + text + flavor	0.79

Table 8: ViT: Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Image	0.17	0.17
ViT + Umap			Alc %	Image	0.03	0.06
ViT + t-SNE			Alc %	Image	0.07	0.06
ViT + Umap			Alc %	Image + flavor	0.02	0.04
ViT + t-SNE			Alc %	Image + flavor	0.39	0.40
ViT + t-SNE			Alc %	Image + flavor	0.04	0.13
ViT + Umap			Alc %	Image + flavor	0.03	0.07
Random	t-SNE	ICP	Country	Image	0.13	0.13
ViT + Umap			Country	Image	0.11	0.13
ViT + t-SNE			Country	Image	0.09	0.09
ViT + Umap			Country	Image + flavor	0.08	0.09
ViT + t-SNE			Country	Image + flavor	0.13	0.20
ViT + t-SNE			Country	Image + flavor	0.15	0.16
ViT + Umap			Country	Image + flavor	0.09	0.13
Random	t-SNE	ICP	Grape	Image	0.03	0.03
ViT + Umap			Grape	Image	0.00	0.00
ViT + t-SNE			Grape	Image	0.00	0.00
ViT + Umap			Grape	Image + flavor	0.00	0.00
ViT + t-SNE			Grape	Image + flavor	0.04	0.05
ViT + t-SNE			Grape	Image + flavor	0.01	0.02
ViT + Umap			Grape	Image + flavor	0.00	0.00
Random	t-SNE	ICP	Price	Image	0.10	0.10
ViT + Umap			Price	Image	0.21	0.23
ViT + t-SNE			Price	Image	0.23	0.18
ViT + Umap			Price	Image + flavor	0.20	0.14
ViT + t-SNE			Price	Image + flavor	0.33	0.26
ViT + t-SNE			Price	Image + flavor	0.17	0.22
ViT + Umap			Price	Image + flavor	0.17	0.22
Random	t-SNE	ICP	Rating	Image	0.25	0.25
ViT + Umap			Rating	Image	0.35	0.09
ViT + t-SNE			Rating	Image	0.32	0.41
ViT + Umap			Rating	Image + flavor	0.32	0.17
ViT + t-SNE			Rating	Image + flavor	0.42	0.41
ViT + t-SNE			Rating	Image + flavor	0.38	0.34
ViT + Umap			Rating	Image + flavor	0.41	0.13
Random	t-SNE	ICP	Region	Image	0.02	0.02
ViT + Umap			Region	Image	0.00	0.01
ViT + t-SNE			Region	Image	0.00	0.00
ViT + Umap			Region	Image + flavor	0.00	0.00
ViT + t-SNE			Region	Image + flavor	0.03	0.02
ViT + t-SNE			Region	Image + flavor	0.00	0.00
ViT + Umap			Region	Image + flavor	0.00	0.00
Random	t-SNE	ICP	Year	Image	0.08	0.08
ViT + Umap			Year	Image	0.04	0.05
ViT + t-SNE			Year	Image	0.07	0.07
ViT + Umap			Year	Image + flavor	0.08	0.04
ViT + t-SNE			Year	Image + flavor	0.08	0.06
ViT + t-SNE			Year	Image + flavor	0.10	0.11
ViT + Umap			Year	Image + flavor	0.05	0.08

Table 9: **DeiT**: Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Image	0.17	0.17
DeiT + Umap			Alc %	Image	0.17	0.08
DeiT + t-SNE			Alc %	Image	0.18	0.08
DeiT + Umap			Alc %	Image + flavor	0.13	0.10
DeiT + t-SNE			Alc %	Image + flavor	0.33	0.38
DeiT + t-SNE			Alc %	Image + flavor	0.18	0.17
DeiT + Umap			Alc %	Image + flavor	0.13	0.04
Random	t-SNE	ICP	Country	Image	0.13	0.13
DeiT + Umap			Country	Image	0.08	0.13
DeiT + t-SNE			Country	Image	0.19	0.18
DeiT + Umap			Country	Image + flavor	0.01	0.05
DeiT + t-SNE			Country	Image + flavor	0.18	0.11
DeiT + t-SNE			Country	Image + flavor	0.18	0.10
DeiT + Umap			Country	Image + flavor	0.04	0.04
Random	t-SNE	ICP	Grape	Image	0.03	0.03
DeiT + Umap			Grape	Image	0.00	0.00
DeiT + t-SNE			Grape	Image	0.01	0.03
DeiT + Umap			Grape	Image + flavor	0.00	0.00
DeiT + t-SNE			Grape	Image + flavor	0.05	0.04
DeiT + t-SNE			Grape	Image + flavor	0.01	0.02
DeiT + Umap			Grape	Image + flavor	0.00	0.01
Random	t-SNE	ICP	Price	Image	0.10	0.10
DeiT + Umap			Price	Image	0.25	0.08
DeiT + t-SNE			Price	Image	0.20	0.15
DeiT + Umap			Price	Image + flavor	0.19	0.19
DeiT + t-SNE			Price	Image + flavor	0.34	0.30
DeiT + t-SNE			Price	Image + flavor	0.19	0.18
DeiT + Umap			Price	Image + flavor	0.22	0.16
Random	t-SNE	ICP	Rating	Image	0.25	0.25
DeiT + Umap			Rating	Image	0.23	0.26
DeiT + t-SNE			Rating	Image	0.29	0.37
DeiT + Umap			Rating	Image + flavor	0.28	0.34
DeiT + t-SNE			Rating	Image + flavor	0.50	0.44
DeiT + t-SNE			Rating	Image + flavor	0.38	0.42
DeiT + Umap			Rating	Image + flavor	0.20	0.26
Random	t-SNE	ICP	Region	Image	0.02	0.02
DeiT + Umap			Region	Image	0.01	0.01
DeiT + t-SNE			Region	Image	0.01	0.02
DeiT + Umap			Region	Image + flavor	0.00	0.01
DeiT + t-SNE			Region	Image + flavor	0.04	0.05
DeiT + t-SNE			Region	Image + flavor	0.00	0.01
DeiT + Umap			Region	Image + flavor	0.00	0.00
Random	t-SNE	ICP	Year	Image	0.08	0.08
DeiT + Umap			Year	Image	0.07	0.06
DeiT + t-SNE			Year	Image	0.13	0.14
DeiT + Umap			Year	Image + flavor	0.07	0.09
DeiT + t-SNE			Year	Image + flavor	0.14	0.08
DeiT + t-SNE			Year	Image + flavor	0.10	0.11
DeiT + Umap			Year	Image + flavor	0.08	0.05

Table 10: **ResNET**: Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Image	0.17	0.17
ResNET + Umap			Alc %	Image	0.07	0.06
ResNET + t-SNE			Alc %	Image	0.13	0.06
ResNET + Umap			Alc %	Image + flavor	0.08	0.05
ResNET + t-SNE			Alc %	Image + flavor	0.36	0.37
ResNET + t-SNE		SNaCK	Alc %	Image + flavor	0.21	0.21
ResNET + Umap			Alc %	Image + flavor	0.09	0.06
Random	t-SNE	ICP	Country	Image	0.13	0.13
ResNET + Umap			Country	Image	0.15	0.13
ResNET + t-SNE			Country	Image	0.19	0.21
ResNET + Umap			Country	Image + flavor	0.18	0.14
ResNET + t-SNE			Country	Image + flavor	0.19	0.18
ResNET + t-SNE		SNaCK	Country	Image + flavor	0.12	0.13
ResNET + Umap			Country	Image + flavor	0.14	0.10
Random	t-SNE	ICP	Grape	Image	0.03	0.03
ResNET + Umap			Grape	Image	0.00	0.00
ResNET + t-SNE			Grape	Image	0.00	0.01
ResNET + Umap			Grape	Image + flavor	0.00	0.01
ResNET + t-SNE			Grape	Image + flavor	0.02	0.00
ResNET + t-SNE		SNaCK	Grape	Image + flavor	0.00	0.00
ResNET + Umap			Grape	Image + flavor	0.00	0.00
Random	t-SNE	ICP	Price	Image	0.10	0.10
ResNET + Umap			Price	Image	0.20	0.15
ResNET + t-SNE			Price	Image	0.27	0.25
ResNET + Umap			Price	Image + flavor	0.28	0.11
ResNET + t-SNE			Price	Image + flavor	0.27	0.23
ResNET + t-SNE		SNaCK	Price	Image + flavor	0.28	0.22
ResNET + Umap			Price	Image + flavor	0.27	0.12
Random	t-SNE	ICP	Rating	Image	0.25	0.25
ResNET + Umap			Rating	Image	0.21	0.12
ResNET + t-SNE			Rating	Image	0.25	0.29
ResNET + Umap			Rating	Image + flavor	0.37	0.17
ResNET + t-SNE			Rating	Image + flavor	0.39	0.43
ResNET + t-SNE		SNaCK	Rating	Image + flavor	0.26	0.25
ResNET + Umap			Rating	Image + flavor	0.28	0.20
Random	t-SNE	ICP	Region	Image	0.02	0.02
ResNET + Umap			Region	Image	0.00	0.00
ResNET + t-SNE			Region	Image	0.00	0.00
ResNET + Umap			Region	Image + flavor	0.00	0.02
ResNET + t-SNE			Region	Image + flavor	0.00	0.00
ResNET + t-SNE		SNaCK	Region	Image + flavor	0.00	0.00
ResNET + Umap			Region	Image + flavor	0.00	0.01
Random	t-SNE	ICP	Year	Image	0.08	0.08
ResNET + Umap			Year	Image	0.08	0.08
ResNET + t-SNE			Year	Image	0.08	0.08
ResNET + Umap			Year	Image + flavor	0.06	0.05
ResNET + t-SNE			Year	Image + flavor	0.09	0.06
ResNET + t-SNE		SNaCK	Year	Image + flavor	0.08	0.07
ResNET + Umap			Year	Image + flavor	0.08	0.05

Table 11: **CLIP (image):** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %		0.17	0.17
CLIP (image) + Umap			Alc %	Image	0.10	0.26
CLIP (image) + t-SNE			Alc %	Image	0.22	0.23
CLIP (image) + Umap			Alc %	Image + flavor	0.13	0.14
CLIP (image) + t-SNE			Alc %	Image + flavor	0.38	0.39
CLIP (image) + t-SNE		SNaCK	Alc %	Image + flavor	0.14	0.15
CLIP (image) + Umap			Alc %	Image + flavor	0.17	0.28
Random	t-SNE	ICP	Country		0.13	0.13
CLIP (image) + Umap			Country	Image	0.06	0.06
CLIP (image) + t-SNE			Country	Image	0.04	0.04
CLIP (image) + Umap			Country	Image + flavor	0.07	0.04
CLIP (image) + t-SNE			Country	Image + flavor	0.25	0.19
CLIP (image) + t-SNE		SNaCK	Country	Image + flavor	0.12	0.12
CLIP (image) + Umap			Country	Image + flavor	0.07	0.07
Random	t-SNE	ICP	Grape		0.03	0.03
CLIP (image) + Umap			Grape	Image	0.00	0.01
CLIP (image) + t-SNE			Grape	Image	0.00	0.00
CLIP (image) + Umap			Grape	Image + flavor	0.00	0.00
CLIP (image) + t-SNE			Grape	Image + flavor	0.05	0.02
CLIP (image) + t-SNE		SNaCK	Grape	Image + flavor	0.00	0.01
CLIP (image) + Umap			Grape	Image + flavor	0.00	0.00
Random	t-SNE	ICP	Price		0.10	0.10
CLIP (image) + Umap			Price	Image	0.13	0.05
CLIP (image) + t-SNE			Price	Image	0.18	0.19
CLIP (image) + Umap			Price	Image + flavor	0.12	0.19
CLIP (image) + t-SNE			Price	Image + flavor	0.22	0.21
CLIP (image) + t-SNE		SNaCK	Price	Image + flavor	0.19	0.26
CLIP (image) + Umap			Price	Image + flavor	0.15	0.07
Random	t-SNE	ICP	Rating		0.25	0.25
CLIP (image) + Umap			Rating	Image	0.08	0.21
CLIP (image) + t-SNE			Rating	Image	0.11	0.18
CLIP (image) + Umap			Rating	Image + flavor	0.06	0.10
CLIP (image) + t-SNE			Rating	Image + flavor	0.39	0.35
CLIP (image) + t-SNE		SNaCK	Rating	Image + flavor	0.30	0.26
CLIP (image) + Umap			Rating	Image + flavor	0.07	0.18
Random	t-SNE	ICP	Region		0.02	0.02
CLIP (image) + Umap			Region	Image	0.00	0.00
CLIP (image) + t-SNE			Region	Image	0.00	0.00
CLIP (image) + Umap			Region	Image + flavor	0.00	0.00
CLIP (image) + t-SNE			Region	Image + flavor	0.00	0.00
CLIP (image) + t-SNE		SNaCK	Region	Image + flavor	0.01	0.00
CLIP (image) + Umap			Region	Image + flavor	0.00	0.00
Random	t-SNE	ICP	Year		0.08	0.08
CLIP (image) + Umap			Year	Image	0.19	0.34
CLIP (image) + t-SNE			Year	Image	0.26	0.38
CLIP (image) + Umap			Year	Image + flavor	0.18	0.29
CLIP (image) + t-SNE			Year	Image + flavor	0.16	0.15
CLIP (image) + t-SNE		SNaCK	Year	Image + flavor	0.41	0.39
CLIP (image) + Umap			Year	Image + flavor	0.21	0.29

Table 12: **PEGASUS:** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %		0.17	0.17
PEGASUS + Umap			Alc %	Text	0.25	0.15
PEGASUS + t-SNE			Alc %	Text	0.23	0.19
PEGASUS + Umap			Alc %	Text + flavor	0.21	0.21
PEGASUS + t-SNE			Alc %	Text + flavor	0.41	0.42
PEGASUS + t-SNE			Alc %	Text + flavor	0.28	0.29
PEGASUS + Umap			Alc %	Text + flavor	0.07	0.20
Random	t-SNE	ICP	Country		0.13	0.13
PEGASUS + Umap			Country	Text	0.09	0.16
PEGASUS + t-SNE			Country	Text	0.15	0.20
PEGASUS + Umap			Country	Text + flavor	0.07	0.05
PEGASUS + t-SNE			Country	Text + flavor	0.23	0.19
PEGASUS + t-SNE			Country	Text + flavor	0.15	0.13
PEGASUS + Umap			Country	Text + flavor	0.15	0.19
Random	t-SNE	ICP	Grape		0.03	0.03
PEGASUS + Umap			Grape	Text	0.00	0.00
PEGASUS + t-SNE			Grape	Text	0.02	0.03
PEGASUS + Umap			Grape	Text + flavor	0.02	0.01
PEGASUS + t-SNE			Grape	Text + flavor	0.04	0.03
PEGASUS + t-SNE			Grape	Text + flavor	0.05	0.02
PEGASUS + Umap			Grape	Text + flavor	0.00	0.01
Random	t-SNE	ICP	Price		0.10	0.10
PEGASUS + Umap			Price	Text	0.07	0.11
PEGASUS + t-SNE			Price	Text	0.17	0.15
PEGASUS + Umap			Price	Text + flavor	0.18	0.07
PEGASUS + t-SNE			Price	Text + flavor	0.30	0.34
PEGASUS + t-SNE			Price	Text + flavor	0.22	0.24
PEGASUS + Umap			Price	Text + flavor	0.05	0.06
Random	t-SNE	ICP	Rating		0.25	0.25
PEGASUS + Umap			Rating	Text	0.16	0.20
PEGASUS + t-SNE			Rating	Text	0.26	0.20
PEGASUS + Umap			Rating	Text + flavor	0.34	0.26
PEGASUS + t-SNE			Rating	Text + flavor	0.47	0.43
PEGASUS + t-SNE			Rating	Text + flavor	0.37	0.41
PEGASUS + Umap			Rating	Text + flavor	0.27	0.27
Random	t-SNE	ICP	Region		0.02	0.02
PEGASUS + Umap			Region	Text	0.01	0.00
PEGASUS + t-SNE			Region	Text	0.00	0.01
PEGASUS + Umap			Region	Text + flavor	0.01	0.01
PEGASUS + t-SNE			Region	Text + flavor	0.03	0.01
PEGASUS + t-SNE			Region	Text + flavor	0.01	0.02
PEGASUS + Umap			Region	Text + flavor	0.01	0.02
Random	t-SNE	ICP	Year		0.08	0.08
PEGASUS + Umap			Year	Text	0.03	0.08
PEGASUS + t-SNE			Year	Text	0.10	0.07
PEGASUS + Umap			Year	Text + flavor	0.07	0.03
PEGASUS + t-SNE			Year	Text + flavor	0.14	0.11
PEGASUS + t-SNE			Year	Text + flavor	0.11	0.14
PEGASUS + Umap			Year	Text + flavor	0.04	0.05

Table 13: **BART (large):** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Text	0.17	0.17
BART (large) + Umap			Alc %	Text	0.21	0.30
BART (large) + t-SNE			Alc %	Text	0.13	0.28
BART (large) + Umap			Alc %	Text + flavor	0.15	0.08
BART (large) + t-SNE			Alc %	Text + flavor	0.40	0.39
BART (large) + t-SNE			Alc %	Text + flavor	0.25	0.17
BART (large) + Umap			Alc %	Text + flavor	0.18	0.26
Random	t-SNE	ICP	Country	Text	0.13	0.13
BART (large) + Umap			Country	Text	0.10	0.13
BART (large) + t-SNE			Country	Text	0.14	0.17
BART (large) + Umap			Country	Text + flavor	0.07	0.11
BART (large) + t-SNE			Country	Text + flavor	0.19	0.15
BART (large) + t-SNE			Country	Text + flavor	0.07	0.15
BART (large) + Umap			Country	Text + flavor	0.07	0.06
Random	t-SNE	ICP	Grape	Text	0.03	0.03
BART (large) + Umap			Grape	Text	0.01	0.00
BART (large) + t-SNE			Grape	Text	0.01	0.05
BART (large) + Umap			Grape	Text + flavor	0.04	0.02
BART (large) + t-SNE			Grape	Text + flavor	0.01	0.02
BART (large) + t-SNE			Grape	Text + flavor	0.03	0.02
BART (large) + Umap			Grape	Text + flavor	0.01	0.02
Random	t-SNE	ICP	Price	Text	0.10	0.10
BART (large) + Umap			Price	Text	0.14	0.09
BART (large) + t-SNE			Price	Text	0.18	0.19
BART (large) + Umap			Price	Text + flavor	0.11	0.03
BART (large) + t-SNE			Price	Text + flavor	0.36	0.28
BART (large) + t-SNE			Price	Text + flavor	0.12	0.17
BART (large) + Umap			Price	Text + flavor	0.17	0.06
Random	t-SNE	ICP	Rating	Text	0.25	0.25
BART (large) + Umap			Rating	Text	0.33	0.27
BART (large) + t-SNE			Rating	Text	0.25	0.37
BART (large) + Umap			Rating	Text + flavor	0.40	0.37
BART (large) + t-SNE			Rating	Text + flavor	0.43	0.47
BART (large) + t-SNE			Rating	Text + flavor	0.37	0.38
BART (large) + Umap			Rating	Text + flavor	0.46	0.29
Random	t-SNE	ICP	Region	Text	0.02	0.02
BART (large) + Umap			Region	Text	0.00	0.00
BART (large) + t-SNE			Region	Text	0.00	0.01
BART (large) + Umap			Region	Text + flavor	0.00	0.02
BART (large) + t-SNE			Region	Text + flavor	0.00	0.02
BART (large) + t-SNE			Region	Text + flavor	0.00	0.01
BART (large) + Umap			Region	Text + flavor	0.00	0.01
Random	t-SNE	ICP	Year	Text	0.08	0.08
BART (large) + Umap			Year	Text	0.02	0.01
BART (large) + t-SNE			Year	Text	0.09	0.10
BART (large) + Umap			Year	Text + flavor	0.05	0.01
BART (large) + t-SNE			Year	Text + flavor	0.12	0.09
BART (large) + t-SNE			Year	Text + flavor	0.08	0.05
BART (large) + Umap			Year	Text + flavor	0.05	0.02

Table 14: **FLAN-T5:** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %		0.17	0.17
FLAN-T5 + Umap			Alc %	Text	0.10	0.13
FLAN-T5 + t-SNE			Alc %	Text	0.47	0.40
FLAN-T5 + Umap			Alc %	Text + flavor	0.22	0.27
FLAN-T5 + t-SNE			Alc %	Text + flavor	0.46	0.51
FLAN-T5 + t-SNE		SNaCK	Alc %	Text + flavor	0.39	0.41
FLAN-T5 + Umap			Alc %	Text + flavor	0.19	0.24
Random	t-SNE	ICP	Country		0.13	0.13
FLAN-T5 + Umap			Country	Text	0.04	0.08
FLAN-T5 + t-SNE			Country	Text	0.12	0.05
FLAN-T5 + Umap			Country	Text + flavor	0.08	0.11
FLAN-T5 + t-SNE			Country	Text + flavor	0.08	0.10
FLAN-T5 + t-SNE		SNaCK	Country	Text + flavor	0.11	0.14
FLAN-T5 + Umap			Country	Text + flavor	0.04	0.06
Random	t-SNE	ICP	Grape		0.03	0.03
FLAN-T5 + Umap			Grape	Text	0.00	0.00
FLAN-T5 + t-SNE			Grape	Text	0.00	0.01
FLAN-T5 + Umap			Grape	Text + flavor	0.00	0.00
FLAN-T5 + t-SNE			Grape	Text + flavor	0.02	0.02
FLAN-T5 + t-SNE		SNaCK	Grape	Text + flavor	0.02	0.02
FLAN-T5 + Umap			Grape	Text + flavor	0.00	0.00
Random	t-SNE	ICP	Price		0.10	0.10
FLAN-T5 + Umap			Price	Text	0.00	0.04
FLAN-T5 + t-SNE			Price	Text	0.13	0.08
FLAN-T5 + Umap			Price	Text + flavor	0.17	0.08
FLAN-T5 + t-SNE			Price	Text + flavor	0.26	0.16
FLAN-T5 + t-SNE		SNaCK	Price	Text + flavor	0.23	0.16
FLAN-T5 + Umap			Price	Text + flavor	0.00	0.01
Random	t-SNE	ICP	Rating		0.25	0.25
FLAN-T5 + Umap			Rating	Text	0.10	0.20
FLAN-T5 + t-SNE			Rating	Text	0.22	0.31
FLAN-T5 + Umap			Rating	Text + flavor	0.20	0.22
FLAN-T5 + t-SNE			Rating	Text + flavor	0.43	0.45
FLAN-T5 + t-SNE		SNaCK	Rating	Text + flavor	0.24	0.28
FLAN-T5 + Umap			Rating	Text + flavor	0.06	0.17
Random	t-SNE	ICP	Region		0.02	0.02
FLAN-T5 + Umap			Region	Text	0.00	0.03
FLAN-T5 + t-SNE			Region	Text	0.00	0.01
FLAN-T5 + Umap			Region	Text + flavor	0.00	0.03
FLAN-T5 + t-SNE			Region	Text + flavor	0.03	0.03
FLAN-T5 + t-SNE		SNaCK	Region	Text + flavor	0.01	0.04
FLAN-T5 + Umap			Region	Text + flavor	0.00	0.03
Random	t-SNE	ICP	Year		0.08	0.08
FLAN-T5 + Umap			Year	Text	0.04	0.04
FLAN-T5 + t-SNE			Year	Text	0.13	0.12
FLAN-T5 + Umap			Year	Text + flavor	0.08	0.08
FLAN-T5 + t-SNE			Year	Text + flavor	0.16	0.20
FLAN-T5 + t-SNE		SNaCK	Year	Text + flavor	0.13	0.10
FLAN-T5 + Umap			Year	Text + flavor	0.05	0.06

Table 15: **DistilBERT**: Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Text	0.17	0.17
DistilBERT + Umap			Alc %	Text	0.27	0.31
DistilBERT + t-SNE			Alc %	Text	0.25	0.24
DistilBERT + Umap			Alc %	Text + flavor	0.24	0.25
DistilBERT + t-SNE			Alc %	Text + flavor	0.46	0.39
DistilBERT + t-SNE			Alc %	Text + flavor	0.33	0.29
DistilBERT + Umap			Alc %	Text + flavor	0.27	0.32
Random	t-SNE	ICP	Country	Text	0.13	0.13
DistilBERT + Umap			Country	Text	0.27	0.28
DistilBERT + t-SNE			Country	Text	0.34	0.26
DistilBERT + Umap			Country	Text + flavor	0.06	0.18
DistilBERT + t-SNE			Country	Text + flavor	0.28	0.23
DistilBERT + t-SNE			Country	Text + flavor	0.28	0.27
DistilBERT + Umap			Country	Text + flavor	0.26	0.30
Random	t-SNE	ICP	Grape	Text	0.03	0.03
DistilBERT + Umap			Grape	Text	0.08	0.05
DistilBERT + t-SNE			Grape	Text	0.13	0.11
DistilBERT + Umap			Grape	Text + flavor	0.02	0.03
DistilBERT + t-SNE			Grape	Text + flavor	0.01	0.06
DistilBERT + t-SNE			Grape	Text + flavor	0.07	0.07
DistilBERT + Umap			Grape	Text + flavor	0.06	0.08
Random	t-SNE	ICP	Price	Text	0.10	0.10
DistilBERT + Umap			Price	Text	0.25	0.15
DistilBERT + t-SNE			Price	Text	0.20	0.15
DistilBERT + Umap			Price	Text + flavor	0.08	0.04
DistilBERT + t-SNE			Price	Text + flavor	0.28	0.21
DistilBERT + t-SNE			Price	Text + flavor	0.26	0.13
DistilBERT + Umap			Price	Text + flavor	0.26	0.14
Random	t-SNE	ICP	Rating	Text	0.25	0.25
DistilBERT + Umap			Rating	Text	0.35	0.41
DistilBERT + t-SNE			Rating	Text	0.30	0.35
DistilBERT + Umap			Rating	Text + flavor	0.04	0.12
DistilBERT + t-SNE			Rating	Text + flavor	0.42	0.47
DistilBERT + t-SNE			Rating	Text + flavor	0.41	0.42
DistilBERT + Umap			Rating	Text + flavor	0.40	0.48
Random	t-SNE	ICP	Region	Text	0.02	0.02
DistilBERT + Umap			Region	Text	0.00	0.00
DistilBERT + t-SNE			Region	Text	0.00	0.00
DistilBERT + Umap			Region	Text + flavor	0.00	0.01
DistilBERT + t-SNE			Region	Text + flavor	0.02	0.02
DistilBERT + t-SNE			Region	Text + flavor	0.00	0.00
DistilBERT + Umap			Region	Text + flavor	0.00	0.01
Random	t-SNE	ICP	Year	Text	0.08	0.08
DistilBERT + Umap			Year	Text	0.15	0.10
DistilBERT + t-SNE			Year	Text	0.07	0.08
DistilBERT + Umap			Year	Text + flavor	0.04	0.05
DistilBERT + t-SNE			Year	Text + flavor	0.13	0.13
DistilBERT + t-SNE			Year	Text + flavor	0.12	0.12
DistilBERT + Umap			Year	Text + flavor	0.07	0.07

Table 16: **T5:** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Text	0.17	0.17
T5 + Umap			Alc %		0.24	0.14
T5 + t-SNE			Alc %		0.30	0.34
T5 + Umap			Alc %		0.19	0.17
T5 + t-SNE			Alc %		0.47	0.46
T5 + t-SNE			Alc %		0.31	0.32
T5 + Umap			Alc %		0.19	0.13
Random	t-SNE	ICP	Country	Text	0.13	0.13
T5 + Umap			Country		0.14	0.09
T5 + t-SNE			Country		0.16	0.19
T5 + Umap			Country		0.09	0.14
T5 + t-SNE			Country		0.19	0.12
T5 + t-SNE			Country		0.21	0.25
T5 + Umap			Country		0.16	0.07
Random	t-SNE	ICP	Grape	Text	0.03	0.03
T5 + Umap			Grape		0.01	0.00
T5 + t-SNE			Grape		0.03	0.03
T5 + Umap			Grape		0.00	0.01
T5 + t-SNE			Grape		0.03	0.03
T5 + t-SNE			Grape		0.02	0.01
T5 + Umap			Grape		0.00	0.00
Random	t-SNE	ICP	Price	Text	0.10	0.10
T5 + Umap			Price		0.10	0.07
T5 + t-SNE			Price		0.10	0.15
T5 + Umap			Price		0.08	0.06
T5 + t-SNE			Price		0.33	0.24
T5 + t-SNE			Price		0.20	0.20
T5 + Umap			Price		0.08	0.12
Random	t-SNE	ICP	Rating	Text	0.25	0.25
T5 + Umap			Rating		0.22	0.24
T5 + t-SNE			Rating		0.29	0.30
T5 + Umap			Rating		0.17	0.26
T5 + t-SNE			Rating		0.40	0.35
T5 + t-SNE			Rating		0.19	0.30
T5 + Umap			Rating		0.24	0.15
Random	t-SNE	ICP	Region	Text	0.02	0.02
T5 + Umap			Region		0.00	0.01
T5 + t-SNE			Region		0.02	0.01
T5 + Umap			Region		0.00	0.00
T5 + t-SNE			Region		0.03	0.03
T5 + t-SNE			Region		0.00	0.00
T5 + Umap			Region		0.00	0.02
Random	t-SNE	ICP	Year	Text	0.08	0.08
T5 + Umap			Year		0.07	0.01
T5 + t-SNE			Year		0.09	0.08
T5 + Umap			Year		0.03	0.04
T5 + t-SNE			Year		0.11	0.11
T5 + t-SNE			Year		0.12	0.08
T5 + Umap			Year		0.09	0.01

Table 17: **ALBERT**: Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Text	0.17	0.17
ALBERT + Umap			Alc %	Text	0.24	0.17
ALBERT + t-SNE			Alc %	Text	0.23	0.28
ALBERT + Umap			Alc %	Text + flavor	0.10	0.25
ALBERT + t-SNE			Alc %	Text + flavor	0.46	0.51
ALBERT + t-SNE			Alc %	Text + flavor	0.20	0.15
ALBERT + Umap			Alc %	Text + flavor	0.10	0.15
Random	t-SNE	ICP	Country	Text	0.13	0.13
ALBERT + Umap			Country	Text	0.13	0.12
ALBERT + t-SNE			Country	Text	0.20	0.20
ALBERT + Umap			Country	Text + flavor	0.19	0.15
ALBERT + t-SNE			Country	Text + flavor	0.20	0.17
ALBERT + t-SNE			Country	Text + flavor	0.24	0.21
ALBERT + Umap			Country	Text + flavor	0.10	0.16
Random	t-SNE	ICP	Grape	Text	0.03	0.03
ALBERT + Umap			Grape	Text	0.01	0.03
ALBERT + t-SNE			Grape	Text	0.06	0.04
ALBERT + Umap			Grape	Text + flavor	0.03	0.05
ALBERT + t-SNE			Grape	Text + flavor	0.06	0.03
ALBERT + t-SNE			Grape	Text + flavor	0.07	0.05
ALBERT + Umap			Grape	Text + flavor	0.01	0.01
Random	t-SNE	ICP	Price	Text	0.10	0.10
ALBERT + Umap			Price	Text	0.08	0.07
ALBERT + t-SNE			Price	Text	0.25	0.16
ALBERT + Umap			Price	Text + flavor	0.20	0.02
ALBERT + t-SNE			Price	Text + flavor	0.36	0.24
ALBERT + t-SNE			Price	Text + flavor	0.28	0.18
ALBERT + Umap			Price	Text + flavor	0.10	0.06
Random	t-SNE	ICP	Rating	Text	0.25	0.25
ALBERT + Umap			Rating	Text	0.34	0.28
ALBERT + t-SNE			Rating	Text	0.30	0.35
ALBERT + Umap			Rating	Text + flavor	0.43	0.35
ALBERT + t-SNE			Rating	Text + flavor	0.47	0.51
ALBERT + t-SNE			Rating	Text + flavor	0.42	0.32
ALBERT + Umap			Rating	Text + flavor	0.39	0.28
Random	t-SNE	ICP	Region	Text	0.02	0.02
ALBERT + Umap			Region	Text	0.01	0.02
ALBERT + t-SNE			Region	Text	0.00	0.00
ALBERT + Umap			Region	Text + flavor	0.02	0.00
ALBERT + t-SNE			Region	Text + flavor	0.00	0.01
ALBERT + t-SNE			Region	Text + flavor	0.01	0.00
ALBERT + Umap			Region	Text + flavor	0.00	0.02
Random	t-SNE	ICP	Year	Text	0.08	0.08
ALBERT + Umap			Year	Text	0.01	0.03
ALBERT + t-SNE			Year	Text	0.11	0.10
ALBERT + Umap			Year	Text + flavor	0.04	0.08
ALBERT + t-SNE			Year	Text + flavor	0.08	0.12
ALBERT + t-SNE			Year	Text + flavor	0.06	0.08
ALBERT + Umap			Year	Text + flavor	0.01	0.04

Table 18: **BART (small):** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Text	0.17	0.17
BART + Umap			Alc %	Text	0.14	0.15
BART + t-SNE			Alc %	Text	0.27	0.33
BART + Umap			Alc %	Text + flavor	0.30	0.19
BART + t-SNE			Alc %	Text + flavor	0.47	0.44
BART + t-SNE		SNaCK	Alc %	Text + flavor	0.21	0.14
BART + Umap			Alc %	Text + flavor	0.14	0.15
Random	t-SNE	ICP	Country	Text	0.13	0.13
BART + Umap			Country	Text	0.08	0.05
BART + t-SNE			Country	Text	0.15	0.12
BART + Umap			Country	Text + flavor	0.06	0.07
BART + t-SNE			Country	Text + flavor	0.21	0.15
BART + t-SNE		SNaCK	Country	Text + flavor	0.13	0.09
BART + Umap			Country	Text + flavor	0.07	0.03
Random	t-SNE	ICP	Grape	Text	0.03	0.03
BART + Umap			Grape	Text	0.02	0.02
BART + t-SNE			Grape	Text	0.01	0.02
BART + Umap			Grape	Text + flavor	0.02	0.00
BART + t-SNE			Grape	Text + flavor	0.01	0.04
BART + t-SNE		SNaCK	Grape	Text + flavor	0.03	0.00
BART + Umap			Grape	Text + flavor	0.02	0.01
Random	t-SNE	ICP	Price	Text	0.10	0.10
BART + Umap			Price	Text	0.06	0.01
BART + t-SNE			Price	Text	0.17	0.18
BART + Umap			Price	Text + flavor	0.04	0.03
BART + t-SNE			Price	Text + flavor	0.36	0.29
BART + t-SNE		SNaCK	Price	Text + flavor	0.17	0.11
BART + Umap			Price	Text + flavor	0.08	0.00
Random	t-SNE	ICP	Rating	Text	0.25	0.25
BART + Umap			Rating	Text	0.34	0.27
BART + t-SNE			Rating	Text	0.34	0.44
BART + Umap			Rating	Text + flavor	0.40	0.27
BART + t-SNE			Rating	Text + flavor	0.44	0.45
BART + t-SNE		SNaCK	Rating	Text + flavor	0.24	0.21
BART + Umap			Rating	Text + flavor	0.27	0.22
Random	t-SNE	ICP	Region	Text	0.02	0.02
BART + Umap			Region	Text	0.00	0.00
BART + t-SNE			Region	Text	0.00	0.00
BART + Umap			Region	Text + flavor	0.00	0.01
BART + t-SNE			Region	Text + flavor	0.01	0.01
BART + t-SNE		SNaCK	Region	Text + flavor	0.00	0.00
BART + Umap			Region	Text + flavor	0.00	0.00
Random	t-SNE	ICP	Year	Text	0.08	0.08
BART + Umap			Year	Text	0.03	0.07
BART + t-SNE			Year	Text	0.16	0.18
BART + Umap			Year	Text + flavor	0.04	0.06
BART + t-SNE			Year	Text + flavor	0.10	0.08
BART + t-SNE		SNaCK	Year	Text + flavor	0.10	0.05
BART + Umap			Year	Text + flavor	0.04	0.05

Table 19: **CLIP (text):** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random	t-SNE	ICP	Alc %	Text	0.17	0.17
CLIP (text) + Umap			Alc %	Text	0.16	0.06
CLIP (text) + t-SNE			Alc %	Text	0.23	0.24
CLIP (text) + Umap			Alc %	Text + flavor	0.15	0.10
CLIP (text) + t-SNE			Alc %	Text + flavor	0.51	0.45
CLIP (text) + t-SNE			Alc %	Text + flavor	0.19	0.20
CLIP (text) + Umap			Alc %	Text + flavor	0.08	0.05
Random	t-SNE	ICP	Country	Text	0.13	0.13
CLIP (text) + Umap			Country	Text	0.12	0.11
CLIP (text) + t-SNE			Country	Text	0.15	0.21
CLIP (text) + Umap			Country	Text + flavor	0.15	0.19
CLIP (text) + t-SNE			Country	Text + flavor	0.12	0.17
CLIP (text) + t-SNE			Country	Text + flavor	0.12	0.15
CLIP (text) + Umap			Country	Text + flavor	0.17	0.03
Random	t-SNE	ICP	Grape	Text	0.03	0.03
CLIP (text) + Umap			Grape	Text	0.04	0.00
CLIP (text) + t-SNE			Grape	Text	0.01	0.03
CLIP (text) + Umap			Grape	Text + flavor	0.02	0.02
CLIP (text) + t-SNE			Grape	Text + flavor	0.04	0.01
CLIP (text) + t-SNE			Grape	Text + flavor	0.03	0.01
CLIP (text) + Umap			Grape	Text + flavor	0.02	0.00
Random	t-SNE	ICP	Price	Text	0.10	0.10
CLIP (text) + Umap			Price	Text	0.22	0.16
CLIP (text) + t-SNE			Price	Text	0.16	0.09
CLIP (text) + Umap			Price	Text + flavor	0.15	0.23
CLIP (text) + t-SNE			Price	Text + flavor	0.28	0.23
CLIP (text) + t-SNE			Price	Text + flavor	0.17	0.13
CLIP (text) + Umap			Price	Text + flavor	0.17	0.13
Random	t-SNE	ICP	Rating	Text	0.25	0.25
CLIP (text) + Umap			Rating	Text	0.35	0.12
CLIP (text) + t-SNE			Rating	Text	0.22	0.25
CLIP (text) + Umap			Rating	Text + flavor	0.36	0.26
CLIP (text) + t-SNE			Rating	Text + flavor	0.46	0.42
CLIP (text) + t-SNE			Rating	Text + flavor	0.33	0.40
CLIP (text) + Umap			Rating	Text + flavor	0.37	0.06
Random	t-SNE	ICP	Region	Text	0.02	0.02
CLIP (text) + Umap			Region	Text	0.02	0.00
CLIP (text) + t-SNE			Region	Text	0.02	0.00
CLIP (text) + Umap			Region	Text + flavor	0.01	0.02
CLIP (text) + t-SNE			Region	Text + flavor	0.01	0.01
CLIP (text) + t-SNE			Region	Text + flavor	0.00	0.00
CLIP (text) + Umap			Region	Text + flavor	0.02	0.03
Random	t-SNE	ICP	Year	Text	0.08	0.08
CLIP (text) + Umap			Year	Text	0.03	0.06
CLIP (text) + t-SNE			Year	Text	0.08	0.07
CLIP (text) + Umap			Year	Text + flavor	0.04	0.04
CLIP (text) + t-SNE			Year	Text + flavor	0.06	0.06
CLIP (text) + t-SNE			Year	Text + flavor	0.05	0.05
CLIP (text) + Umap			Year	Text + flavor	0.03	0.08

Table 20: **CLIP (image and text):** Classification results.

Machine Kernel	Human Kernel	Combiner	Class	Modality	Acc ↑	
					SVM	NN
Random			Alc %	Image + text	0.17	0.17
CLIP + Umap			Alc %	Image + text	0.27	0.06
CLIP + t-SNE			Alc %	Image + text	0.34	0.36
CLIP + Umap	t-SNE	ICP	Alc %	Image + text + flavor	0.05	0.13
CLIP + t-SNE	NMDS	CCA	Alc %	Image + text + flavor	0.54	0.53
CLIP + t-SNE	t-STE	SNaCK	Alc %	Image + text + flavor	0.24	0.24
CLIP + Umap	t-STE	ICP	Alc %	Image + text + flavor	0.30	0.08
Random			Country		0.13	0.13
CLIP + Umap			Country	Image + text	0.47	0.25
CLIP + t-SNE			Country	Image + text	0.51	0.48
CLIP + Umap	t-SNE	ICP	Country	Image + text + flavor	0.34	0.45
CLIP + t-SNE	NMDS	CCA	Country	Image + text + flavor	0.43	0.41
CLIP + t-SNE	t-STE	SNaCK	Country	Image + text + flavor	0.51	0.48
CLIP + Umap	t-STE	ICP	Country	Image + text + flavor	0.44	0.26
Random			Grape		0.03	0.03
CLIP + Umap			Grape	Image + text	0.12	0.03
CLIP + t-SNE			Grape	Image + text	0.11	0.13
CLIP + Umap	t-SNE	ICP	Grape	Image + text + flavor	0.09	0.08
CLIP + t-SNE	NMDS	CCA	Grape	Image + text + flavor	0.05	0.05
CLIP + t-SNE	t-STE	SNaCK	Grape	Image + text + flavor	0.08	0.08
CLIP + Umap	t-STE	ICP	Grape	Image + text + flavor	0.09	0.08
Random			Price		0.10	0.10
CLIP + Umap			Price	Image + text	0.23	0.19
CLIP + t-SNE			Price	Image + text	0.08	0.13
CLIP + Umap	t-SNE	ICP	Price	Image + text + flavor	0.19	0.17
CLIP + t-SNE	NMDS	CCA	Price	Image + text + flavor	0.34	0.25
CLIP + t-SNE	t-STE	SNaCK	Price	Image + text + flavor	0.13	0.15
CLIP + Umap	t-STE	ICP	Price	Image + text + flavor	0.26	0.13
Random			Rating		0.25	0.25
CLIP + Umap			Rating	Image + text	0.26	0.44
CLIP + t-SNE			Rating	Image + text	0.28	0.36
CLIP + Umap	t-SNE	ICP	Rating	Image + text + flavor	0.23	0.28
CLIP + t-SNE	NMDS	CCA	Rating	Image + text + flavor	0.43	0.46
CLIP + t-SNE	t-STE	SNaCK	Rating	Image + text + flavor	0.41	0.47
CLIP + Umap	t-STE	ICP	Rating	Image + text + flavor	0.32	0.45
Random			Region		0.02	0.02
CLIP + Umap			Region	Image + text	0.04	0.03
CLIP + t-SNE			Region	Image + text	0.03	0.03
CLIP + Umap	t-SNE	ICP	Region	Image + text + flavor	0.02	0.06
CLIP + t-SNE	NMDS	CCA	Region	Image + text + flavor	0.04	0.04
CLIP + t-SNE	t-STE	SNaCK	Region	Image + text + flavor	0.03	0.03
CLIP + Umap	t-STE	ICP	Region	Image + text + flavor	0.04	0.04
Random			Year		0.08	0.08
CLIP + Umap			Year	Image + text	0.12	0.09
CLIP + t-SNE			Year	Image + text	0.11	0.10
CLIP + Umap	t-SNE	ICP	Year	Image + text + flavor	0.08	0.05
CLIP + t-SNE	NMDS	CCA	Year	Image + text + flavor	0.08	0.09
CLIP + t-SNE	t-STE	SNaCK	Year	Image + text + flavor	0.13	0.11
CLIP + Umap	t-STE	ICP	Year	Image + text + flavor	0.13	0.10

I Ethical approval

The original ethical approval is shown in Figure 9 English translation of the ethical approval can be found in section I.1.

Figure 9: Ethical Approval (in Danish)

I.1 English translation

F-22052371 Inquiry Regarding Reporting Obligations to the Ethical Scientific Committee

Project: Learning to Taste

You have asked via email on September 16, 2022, if the above-mentioned project must be reported to the Ethical Scientific Committee. The project involves evaluating an artificial intelligence developed to mimic the human ability to taste, comparing it with the way humans experience flavors. The model should function as a "low-dimensional taste space", which can determine whether something is close to or far from each other in terms of taste.

The aim is to better understand taste and conduct basic research in machine learning. Near-future applications include market analysis for wine producers and improved recommendation systems for consumers (e.g., these wines taste very similar, but this one costs half as much).

In the project, taste impressions from humans are collected by conducting a wine tasting at DTU, where students are given three small glasses of wine to taste whether wine A is more similar to wine B or C. All participants are over 18 and receive no more than a maximum of 6 cl of wine in total. No sensitive personal data is collected.

The committee has assessed that this is not a health science research project as defined in the committee law's section 21, as it does not create new knowledge or test existing knowledge about disease onset or treatment, diagnostics, prevention, and rehabilitation of humans.

Therefore, the project is not subject to reporting according to the committee law's section 1, paragraph 4 and can be implemented without permission from the Ethical Scientific Committees for the Capital Region of Denmark.

In Denmark, the task of the Ethical Scientific Committee system is to assess health science and health data science research projects.

Health science research projects refer to experiments involving live-born human individuals, human gametes intended for fertilization, human fertilized eggs, embryonic and fetal tissues, cells, and hereditary components from humans, fetuses, and the like, or deceased individuals. This includes clinical trials with drugs on humans and clinical testing of medical equipment.

Health science research primarily covers research in the field of medical science, clinical, and social-medical epidemiological research. In addition to research on somatic diseases, the term also

encompasses psychiatric and clinical-psychological diseases and conditions. Correspondingly, dental and pharmaceutical research are included under the term.

Registered research projects (except for health data science projects), interviews, and questionnaire surveys only need to be reported if human biological material is included in the project. However, investigations of anonymous biological human material do not need to be reported to an ethical scientific committee unless the research project relates to fertilized human eggs and sex cells, cf. sections 25 and 27, paragraph 2 in the Act on Artificial Fertilization in connection with medical treatment, diagnosis, and research. It is a requirement that the material is completely anonymous (there must not be an identification code for data), and that the material is collected in accordance with the law at the collection site.

Experiments on cell lines or similar originating from an experiment collecting cells or tissue, which has received the necessary approval, also do not need to be reported. Experiments that aim solely to determine a chemical's toxicological limit in humans do not need to be reported. In this context, a chemical is understood to mean a substance that does not find therapeutic use.

The rejection to review the project does not imply an ethical stance or negative assessment of its content.

Health data science research projects refer to research concerning particular complex areas of derived sensitive bio-information data produced by comprehensive mapping of the genetic mass or imaging diagnostics in connection with experiments or clinical diagnostics of patients.

We note that in certain cases, the regions must approve the disclosure of information from patient records. The region in which the researcher is employed must be applied to for this. More information can be found on the relevant region's website.

The processing of identifiable personal information is subject to the Data Protection Act/Data Protection Regulation. More information about this can be found on the Danish Data Protection Agency's website.

According to section 26, paragraph 1 of the Committee Act, the decision can be appealed to the National Ethical Scientific Committee no later than 30 days after the decision has been received. The National Ethical Scientific Committee may, for the sake of safeguarding the rights of the test subjects, handle aspects of the project not covered by the appeal itself.

Appeals must be filed electronically and using a digital signature and encryption if the protocol contains confidential information. This can be done at the address: dketik@dke-tik.dk.

The appeal must be justified and accompanied by a copy of the decision of the Regional Ethical Scientific Committee and the case documents on which the Regional Ethical Scientific Committee has made its decision.

Note: No changes should be made to the documents that have been reviewed by the committee, otherwise, the case will be returned to the committee.

Data Protection - Registry Requirement

Please note that you may be required to register the research project.

If you are a researcher employed in the Capital Region, you do this by contacting the Knowledge Center for Data Reviews in the Capital Region, which is the regional unit that administers the research registry. You can read more about the registry and find contact information on the knowledge center's website.

If you are not employed in the Capital Region, you can learn about the registry requirement in the Guide to the Registry on the Data Inspectorate's website.

Best regards,
René Mathiasen
Chairman of Committee C

J Datasheet

J.1 Motivation

For what purpose was the dataset created?

Answer: The dataset was created to bridge the gap between food science and machine learning communities and introduce flavor as a modality in multimodal models.

Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

Answer: Eight researchers at the Technical University of Denmark, University of Copenhagen, Vivino and California Institute of Technology have created the dataset: Thoranna Bender, Simon Moe Søresen, Alireza Kashani, Kristjan Eldjarn Hjorleifsson, Grethe Hyldig, Søren Hauberg and Frederik Warburg.

Who funded the creation of the dataset?

Answer: The dataset is funded in part by The Danish Data Science Academy (DDSA) and the Pioneer Centre for AI (DNRF grant number P1).

Any other comments?

Answer: No.

J.2 Composition

What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?

Answer: Each instance is an image of a wine bottle, a review about the wine, position of the wines on napping papers and attributes (grape, country, region, alcohol %, price and rating).

How many instances are there in total (of each type, if appropriate)?

Answer: 897k images, 824k reviews of 350k vintages, around 5% of which are also associated with year, region, rating, alcohol percentage, and grape composition. In addition there are over 5k annotated pairwise flavor distances for 108 of the wines.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set?

Answer: The provided images, reviews and attributes are sampled from Vivino's database. The provided flavor annotations are provided in full for the 108 wines they exist for.

What data does each instance consist of?

Answer: The images are .jpg files, the reviews are unprocessed text, the attributes are either numerical or categorical fields and the flavor annotations are numerical x-axis and y-axis position annotations.

Is there a label or target associated with each instance?

Answer: No, but attributes can be used as targets as shown in section .

Is any information missing from individual instances?

Answer: Yes, the attributes are available for approximately 5% of the dataset and the flavor annotations are available for 108 vintages in the dataset.

Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)?

Answer: Yes, participant ID's are mappable to flavor annotations by using the values in the session_round_name, experiment_round and experiment_no fields in participants.csv and napping.csv.

Are there recommended data splits (e.g., training, development/validation, testing)?

Answer: No.

Are there any errors, sources of noise, or redundancies in the dataset?

Answer: No.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?

Answer: The data is self-contained.

Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)?

Answer: No.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?

Answer: No.

Does the dataset relate to people?

Answer: Yes, but indirectly. Reviews, images and flavor annotations could provide some indirect information about the people annotating them (such as language used in reviews or background in images) but no attributes containing specific information about the people (such as gender, country, age etc.) exists in the dataset.

Does the dataset identify any subpopulations (e.g., by age, gender)?

Answer: No.

Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset?

Answer: No.

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)?

Answer: No.

Any other comments?

Answer: No.

J.3 Collection process

How was the data associated with each instance acquired?

Answer: The flavor data was reported by subjects using the Napping method. The images, reviews and attributes were fetched from the Vivino platform. The flavor data was verified by a human manually checking the correctness of the algorithms annotating the napping papers. The attributes have been verified by a human to correctly represent the information about individual vintages available on the Vivino platform.

What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)?

Answer: Manual human curation and information fetched from Vivino's databases.

If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?

Answer: Not applicable.

Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?

Answer: Crowd-workers that volunteered their time annotated the flavor distances. Alireza Kashani provided the image- and review data on behalf of Vivino. Attributes for the wines were collected from the Vivino platform.

Over what timeframe was the data collected?

Answer: The data was collected over the timeframe of June 2022 to May 2023.

Were any ethical review processes conducted (e.g., by an institutional review board)?

Answer: Yes, the ethical approval is provided in I.

Does the dataset relate to people?

Answer: Yes.

Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?

Answer: Obtained from the individuals directly.

Were the individuals in question notified about the data collection?

Answer: Yes.

Did the individuals in question consent to the collection and use of their data?

Answer: Yes.

If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses?

Answer: No, this was not considered necessary, as the data can not be traced back to individuals.

Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted?

Answer: No.

Any other comments?

Answer: No.

J.4 Preprocessing/cleaning/labeling

Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)?

Answer: Yes, flavor annotation sample sheets from crowd-workers were digitized, by using the Harris corner detector [Harris et al., 1988] to find the corners of the paper and a homographic projection to obtain an aligned top-down view of the paper. The images were mapped into HSV color space and a threshold filter applied to find the different colored stickers that the participant used to represent the wines. Having identified the location, we provide the Euclidean pixel-wise distance between all pairs of points in the dataset.

Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)?

Answer: No, the sample sheets themselves were deemed to contain no information in addition to the pairwise distances provided.

Is the software used to preprocess/clean/label the instances available?

Answer: Yes, the preprocessing software is available at https://github.com/thoranna/learning_to_taste.

Any other comments?

Answer: No.

J.5 Uses

Has the dataset been used for any tasks already?

Answer: Yes, the dataset has been used to classify different wines according to the attributes provided in the dataset.

Is there a repository that links to any or all papers or systems that use the dataset?

Answer: Yes, the analysis performed is available at https://github.com/thoranna/learning_to_taste.

What (other) tasks could the dataset be used for?

Answer: The dataset could be used for analyzing how similar different peoples' sense of taste is. It could also be used to identify wines that taste similar, but are available at different price points.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses?

Answer: Not to the authors' knowledge.

Are there tasks for which the dataset should not be used?

Answer: No.

Any other comments?

Answer: No.

J.6 Distribution

Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created?

Answer: Yes, the dataset will be freely available to everyone.

How will the dataset will be distributed (e.g., tarball on website, API, GitHub)?

Answer: Tarball on website.

When will the dataset be distributed?

Answer: The dataset is freely available as of June 12, 2023.

Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?

Answer: The dataset is available under Creative Commons Attribution 4.0 International License.

Have any third parties imposed IP-based or other restrictions on the data associated with the instances?

Answer: No.

Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?

Answer: No.

Any other comments?

Answer: No.

J.7 Maintenance

Who is supporting/hosting/maintaining the dataset? How can the owner/curator/manager of the dataset be contacted (e.g., email address)?

Answer: The maintainer of the dataset is Frederik Warburg (frewar1905@gmail.com)

Is there an erratum?

Answer: No.

Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?

Answer: No.

If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)?

Answer: No.

Will older versions of the dataset continue to be supported/hosted/maintained?

Answer: Yes.

If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?

Answer: No, this will be resolved on a case-by-case basis, as the nature of the dataset requires data collection events for expansion.

Any other comments?

Answer: No.