RESERVOIR NETWORK FOR TIME-SERIES PREDICTION OF PREFERENCE TOWARDS COFFEE PRODUCTS

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ABSTRACT

The temporal dominance of sensations (TDS) method involves recording the various sensory fluctuations experienced during activities such as eating food. We applied this method to collect TDS data on sensory changes while tasting coffee. Our aim is to predict temporal changes in preferences based on sensory changes using a reservoir network, a neural network designed to learn time-series data. The reservoir model we developed showed practical accuracy in prediction. We believe that predicting food and beverage preferences over time can provide valuable insights for product analysis and design, and we propose to employ reservoir computing in this use.

Keywords: temporal dominance of sensations, reservoir computing, sensory evaluation, coffee

1 INTRODUCTION

The temporal dominance of sensations (TDS) method is used to record multiple sensory changes during food and beverage consumption (ISO, 2016). This method is widely recognized in the food science field and is becoming popular in other domains as well. The temporal liking method is a technique to monitor changes in consumer preferences for food products (Thomas, 2015). Reservoir networks, a subtype of recurrent neural networks, are utilized to predict and generate time series data and have attracted attention as a simple and lightweight machine learning approach (Tanaka, 2019). Experimental results obtained from the TDS method are often represented as TDS curves. In this study, we train reservoir models with TDS curves to infer changes in preference. In a previous study, we estimated temporal preference for

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strawberries using a reservoir network (Natsume & Okamoto, 2024), however, this has not yet been addressed for other products.

2 TEMPORAL DOMINANCE OF SENSATIONS AND TEMPORAL LIKING METHOD

The experiment of the TDS method is performed by using a user interface (Figure 1(a)) on a computer screen with buttons of attribute words that explains sensations. Experimental participant (panel) starts the task when he/she takes a sip of coffee. For ten seconds, the panel presses a button of attribute that most describes his/her current sensation every time it changes. Multiple buttons cannot be selected at once. The panel finishes the task five seconds after swallowing the coffee in the mouth. The temporal liking tasks are performed in a similar manner, but instead of sensations, buttons with numbers from 1 to 9 are used for scoring.

The TDS curves are used to visualize the results of TDS tasks. TDS curves show the evolution of the percentage of trials in which the attribute is chosen at a particular time. They are smoothed by a moving average for ease of viewing. Figure 1(b) shows the TDS curves of a coffee product. The normalized time 0 means the start of the task and 1 means the end of the task.

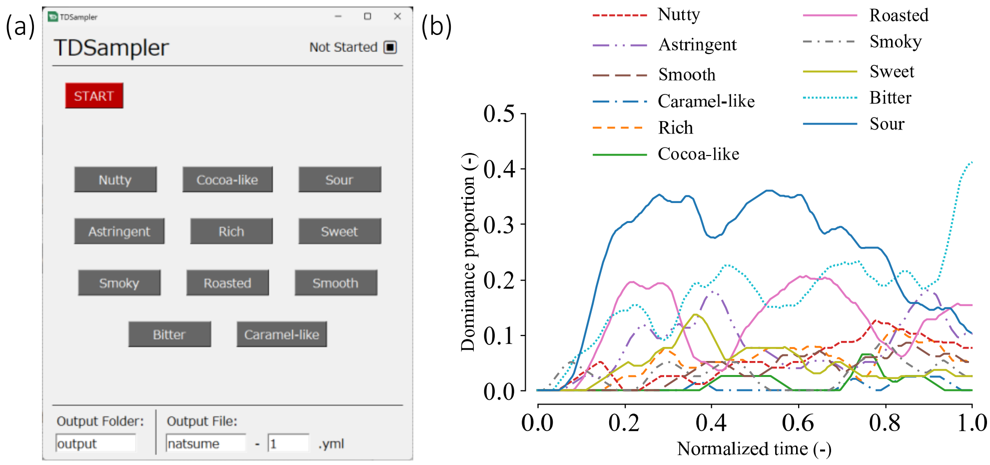

Figure 1. Temporal dominance of sensations method. (a) User interface used in the task. Adapted from (Natsume et al., 2023). (b) Example of TDS curves of sensations during tasting coffee.

We collected the TDS and liking data of four coffee products. We used 11 attributes for TDS: *caramel-like*, *nutty*, *roasted*, *bitter*, *rich*, *astringent*, *smoky*, *sour*, *cocoa-like*, *smooth*, and *sweet*.

3 RESERVOIR NETWORK FOR ESTIMATION OF COFFEE PREFERENCE

Echo state network is the typical reservoir network model. It consists of three layers: input, reservoir, and output. The reservoir layer forms a recurrent neural network characterized by randomly interconnected nodes with predetermined weights. During the training process, solely the weights linking the reservoir to the output layer are modified.

We constructed echo state network models to predict preference changes from TDS curves. Continuous TDS curves are discretized into 1000 vectors with the same number of dimensions of the input layer as the number of sensory attributes. The dimension of the output layer is one.

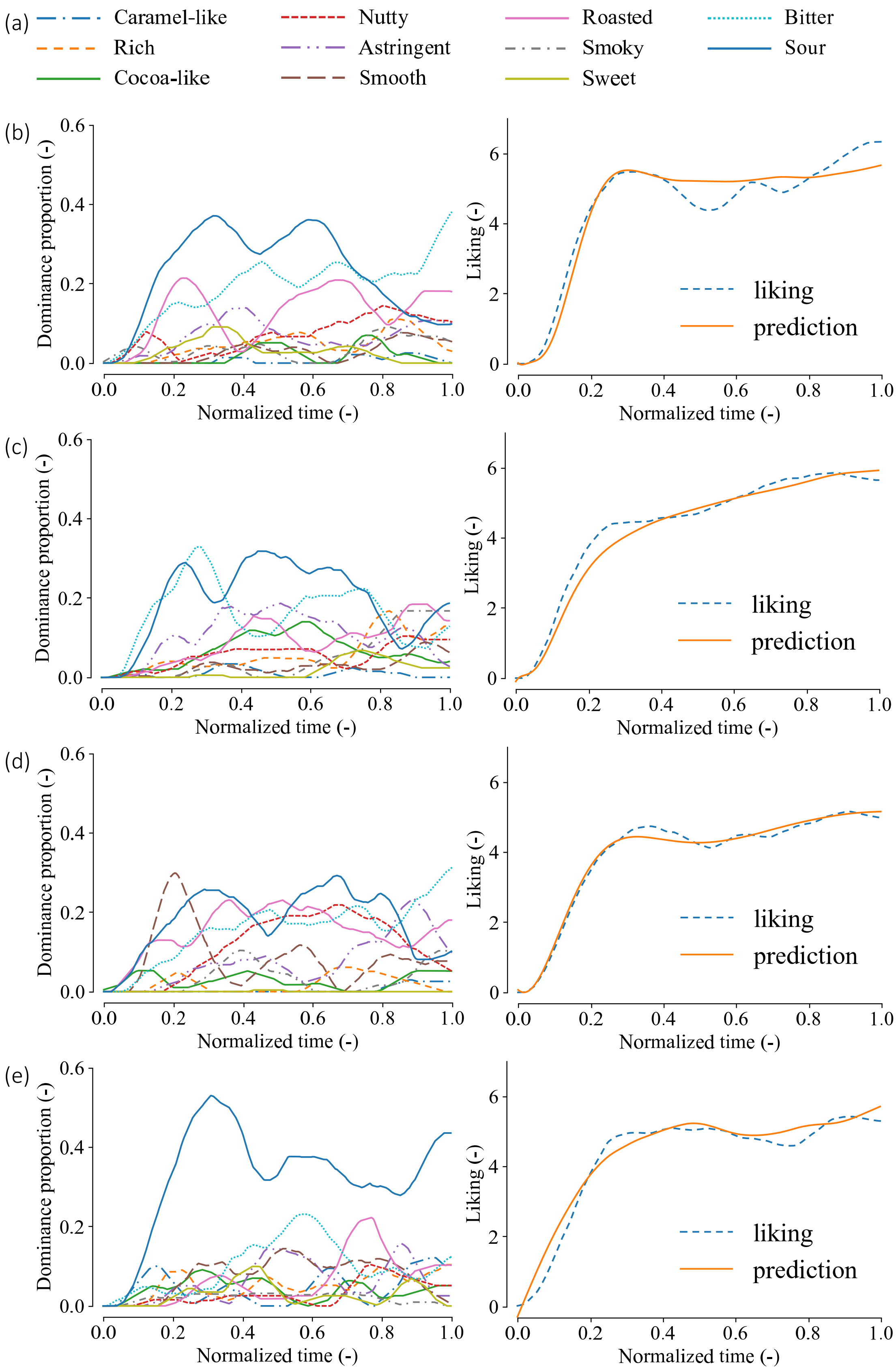

Figure 2. Pairs of TDS curves and liking curves with the highest estimating accuracy.
(a) Legends of TDS curves attributes.
(b) Coffee A ($R^2 = 0.9401$, $RMSE = 0.4025$). (c) Coffee B ($R^2 = 0.9678$, $RMSE = 0.2877$).
(d) Coffee C ($R^2 = 0.9908$, $RMSE = 0.1348$). (e) Coffee D ($R^2 = 0.9620$, $RMSE = 0.2915$).

To generate dataset for learning, we used a bootstrap resampling method (Okamoto, 2021). For each product, we produced 100 sets of TDS curves for model training and 16 sets for the validation. The number of reservoir neurons was set to 128. Other principal parameters are shown in Table 1.

Table 1. Parameters of reservoir models

	Coffee A	Coffee B	Coffee C	Coffee D
Leaking rate	0.0265	0.0195	0.0139	0.0003
Spectral radius	0.9000	0.9000	0.9000	0.9000
Input scaling	0.0231	0.0118	0.0100	0.8688

4 RESULTS

The model predicted preference changes for four coffee products. The range of coefficients of determination was $0.6307 \leq R^2 \leq 0.9908$, and the range of root mean squared errors was $0.1348 \leq RMSE \leq 0.8514$. Figure 2 shows TDS curves and temporal liking curves with the highest estimating accuracy for each product.

5 DISCUSSION AND CONCLUSION

In our previous study, we performed time-series estimation of strawberry preferences by using reservoir network (Natsume & OKamoto, 2024). In the current study, coffee was used, and the estimation was made with a certain degree of accuracy as well as for strawberries. The results showed that time-series estimation of preferences by reservoir computing could be applied to a wide variety of food products.

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