# Prediction of Dynamic Preference by Using Temporal Dominance of Sensations Data

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**Abstract:** Temporal dominance of sensations (TDS) method is a method to record multiple sensory changes over time during an experience such as eating food. We recorded sensory changes and preference changes while eating strawberries by using TDS method. Dynamic sensory and preference changes were trained on a reservoir computing network model, which estimated preferences with high accuracy for untrained sensory data. Reservoir computing has attracted attention as a fast machine learning method suitable for time-series pattern recognition, and its application to the TDS method for handling multidimensional time-series data was demonstrated.
**Keywords:** *Sensory evaluation, Reservoir computing, Strawberry*

## 1. INTRODUCTION

Temporal dominance of sensations (TDS) method is a method to record multiple changes in sensory such like taste. [1]. This method is actively used in the field of food science [2, 3] and is expected to spread to other fields in the future.

TDS method records multiple sensory changes that are multi-dimensional time-series data. Temporal likings, which are changes in pleasant feeling while eating food, are also recorded in conjunction with the TDS method [4, 5]. In sensory evaluation, temporal liking is an important factor as well as taste evaluation because it leads to human satisfaction.

Recurrent neural networks (RNN) are used in pattern recognition of time-series data. Reservoir computing is one of the machine learning frameworks that use RNN [6]. In this method, the model is trained by fixing the weights of the recurrent coupling layer of RNN and adjusting only the readout layer, which makes it faster than conventional RNN. There is no attempt to use reservoir computing for TDS data.

The purpose of this study is to model the effect of sensory changes during the experience of a product on changes in preference for that product. We used the Echo state network (ESN), a typical model of reservoir computing, to estimate product preferences from sensory TDS data.

## 2. TEMPORAL DOMINANCE OF SENSATIONS METHOD

### 2.1 TDS tasks

A graphical user interface on a computer is used in TDS method experiments. Attribute words, which are adjectives that express sensations, are displayed as buttons on the screen. The experiment participant (panel) starts the task the moment he/she puts the food in his/her mouths. The panel presses the button for the attribute word that is closest to the current feeling while tasting the food. Multiple buttons cannot be selected at the same time. The panel changes the button selection each time the dominant sensation changes. There can be buttons that are never selected. When the food is swallowed, the panel ends the task.

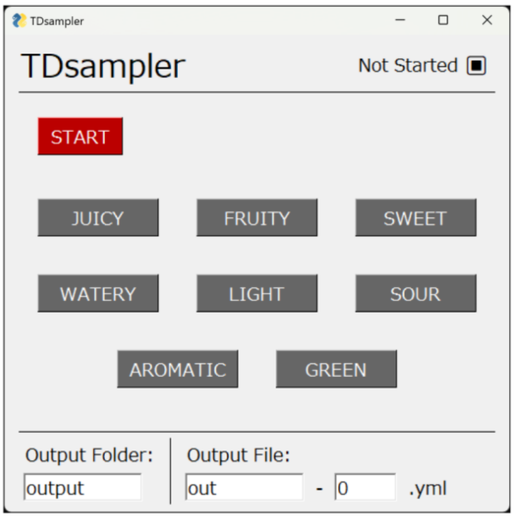


**Figure 1** Graphical user interface used for the task of Temporal Dominance of Sensations method. Adapted from [7].

In this study, we record temporal liking by using TDS method. The panel selects a button with a number from 1 to 9 written on it and answers on a 9-point scale how much he/she likes the product.

### 2.2 TDS curves

The TDS curves are used to visualize the experimental results of the TDS method. A TDS curve exists for each attribute word, which shows the changes in the dominance proportion, i.e., the proportion the attribute word selected across trials. The time axis is normalized between 0 (when the task starts) and 1 (when the task ends).

The Temporal liking curve differs from the sensory curve in that it shows the evolution over time of the average liking across trials.

## 3. PREDICTION OF TEMPORAL LIKING FROM TIME-EVOLVING SENSATIONS VIA RESERVOIR COMPUTING

### 3.1 Echo State Network

We use reservoir computing [6], a type of RNN, to estimate dynamic changes in a panel's preference for a product from TDS curves. In this study, we use the Echo State Network (ESN), a typical neural network model for reservoir computing. The ESN model consists of three units: an input layer, a reservoir, and a readout. The reservoir is a recurrent neural network that is randomly wired. Reservoirs can store inputs, making them suitable for learning contextual time series data.

### 3.2 ESN model used for predicting temporal liking

We constructed an ESN model for learning TDS curves. As a preprocessing step, the continuous TDS curve was discretized into 1000 intervals, yielding 1000 vectors with the same dimensionality as the number of attribute words. The dimension of the ESN input layer is set equal to the number of attribute words, and the readout dimension was set to 1 in order to output temporal liking values. When 1000 vectors are input to the ESN model in time-series order, the model outputs a time-series of liking.

In this study, the number of neurons in the ESN model was set to 200.

Typical ESN parameters include leakage rate, spectral radius, and input scaling. We set them to be 0.00467, 1.83838, and 3.27857, respectively. A linear learner with low computational cost was used to adjust the readout layer.

We used a bootstrap resampling method for TDS [8] to prepare for the training and test dataset. We first split all the assessors into two groups. From one group, we produced 100 sets of TDS curves and the curve of temporal liking following [8]. These curves were used for training the ESN model. From the other group of assessors, we produced 25 sets of curves, then they were used as test dataset.

## 4. TDS METHOD FOR STRAWBERRIES

We followed the protocol of Shimaoka et al [9] and recorded strawberry eating experiences using the TDS method. 31 university students in their 20s performed the sensory TDS task and temporal liking task two to three times each, yielding 92 sensory and 93 liking data. The tasks of sensory and temporal liking were conducted alternately. For example, one panel conducted a task of sensory followed by the task of liking. This process was conducted three times for him/her. Referring to [9], attribute words used in evaluation of strawberries are *aromatic, green, light, sweet, fruity, sour, watery*.

## 5. RESULTS

By using the trained ESN model, temporal liking was estimated from the TDS data on 25 validation datasets.

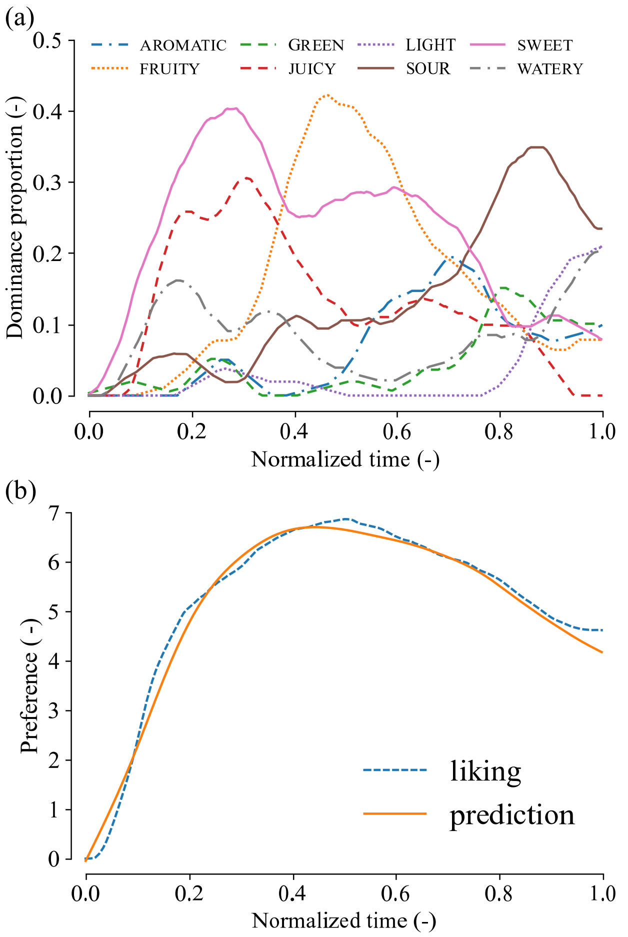


**Figure 2** TDS curve (a) and temporal liking (b) with the highest coefficient of determination ($R^2 = 0.9949$).

The resulting temporal liking curve with the largest coefficient of determination ($R^2 = 0.9949$) and the TDS curve as input are shown in Figure 2. Figure 3 shows the TDS curve and temporal liking for the case with the lowest coefficient of determination ($R^2 = 0.8848$).

## 6. CONCLUSION

Reservoir computing has never learned TDS data before. We experimentally collected TDS data and temporal likings of strawberry eating experiences and built an ESN model to estimate preferences from the sensory data. The model estimated the corresponding preference from untrained data with an accuracy of $R^2 = 0.99 - 0.88$. The model should be evaluated statistically in the future. It is hoped that reservoir computing will make it possible to estimate the results of temporal liking tasks from TDS task results alone.


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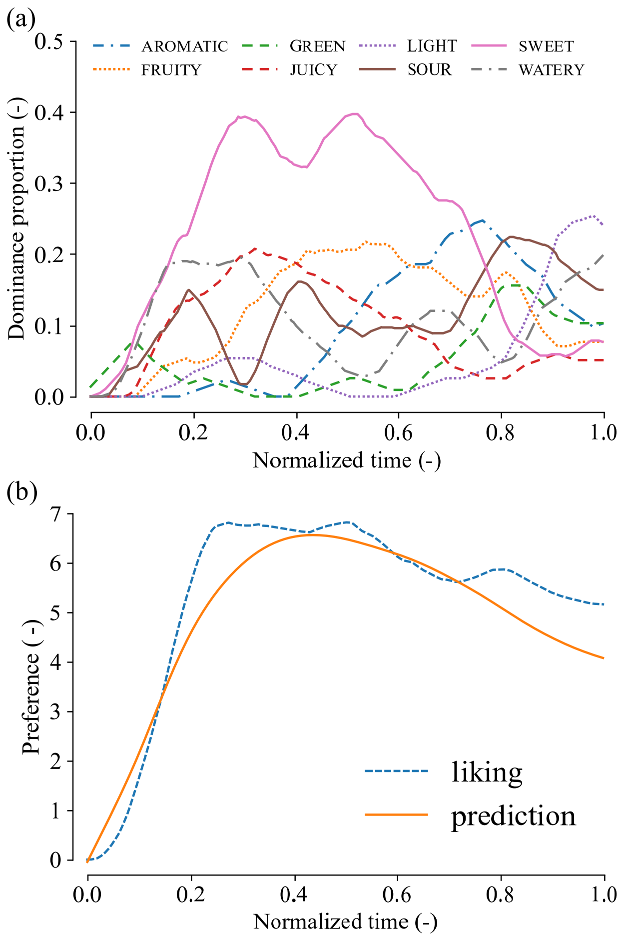


**Figure 3** TDS curve (a) and temporal liking (b) with the lowest coefficient of determination ($R^2 = 0.8848$).

## ETHICAL STATEMENT

The protocol of this study was approved by Institutional Review Board, Hino Campus, Tokyo Metropolitan University (H23-34).

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