Deep Neural Networks for New Product Form Design

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Abstract: Neural Networks (NNs) are non-linear models and are widely used to model complex relationships, thus being well suited to formulate the product design process for matching design form elements to consumers' affective preferences. In this paper, we construct 36 deep NN models, using one to four hidden layers with three different dropout ratios and three widely used rules for determining the number of neurons in the hidden layer(s). As a result of extensive experiments, the NN model using one hidden layer with 140 hidden neurons has the highest predicting accuracy rate (80%) and is used to help product designers determine the optimal form combination for new fragrance bottle design.

1 INTRODUCTION

Artificial intelligence (AI) is a technique which enables machines to mimic human behavior, and is defined as an innovative approach to reasoning and learning the human mind in an uncertainty and imprecision environment (Lin and Yeh, 2015). The aim of AI is to exploit the tolerance for imprecision, uncertainty, approximate reasoning to achieve tractability, low solution cost, and close resemblance with humanlike decision-making (Zheng et al., 2017). Deep learning is a subfield of machine learning, which both fall under the broad category of AI. Moreover, deep learning is usually used behind the most humanlike AI as it structures algorithms in layers to create an artificial neural network that can learn and make intelligent decisions on its own (Deep Learning Studio, 2019; Azure Machine Learning Studio, 2019).

Chan et al. (2018) have revealed that consumers are not only concerned with the functionality and reliability of products, but are also concerned with product affections (e.g. texture, shape, color, style, etc.) that are related to the emotional feelings and impressions of the products (Chan et al., 2018). Affect is defined as consumers' psychological responses (or emotional feelings) to the perceptual design details of the products (Lin and Wei, 2017). In order to be successful in a competitive market, products need to appeal to consumers on an affective level, and further capture their affective preferences (Chan et al., 2018; Lin and Wei, 2017). However, consumers' affective preferences are often a black box and cannot be precisely described (Lin and Wei, 2017; Lai et al., 2005; Lin et al., 2014). How to accurately capture consumers' affective preferences and then transforms them into design elements is thus a major challenge for product designers (Wang, 2011). What specific techniques can be used to help product designers achieve this goal and design products that match consumers' affective preferences?

To address this challenging design research issue, we develop a consumer-oriented expert system based on deep neural networks (DNNs) for new product form design (Negnevitsky, 2002). To collect data required for training and testing DNNs, we conduct a consumer-oriented experiment on fragrance bottle form design due to its wide variety of appearances and appropriate for verifying the consumer-oriented expert system (Lin and Wei, 2017; Lin and Chen, 2016; Zheng and Lin, 2017; Lin et al., 2018). The expert system can be used to help product designers determine the optimal form

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combination of a new product design that best matches consumers' affective preferences.

2 A CONSUMER-ORIENTED EXPERIMENT ON FRAGRANCE BOTTLE FORM DESIGN

In our previous studies (Lin and Wei, 2017; Lin and Chen, 2016; Zheng and Lin, 2016; Lin et al., 2018; Chen, 2015), we investigated 617 various world-famous fragrances and their own fragrance bottle forms with 75 different brands. After performing a preliminary assessment by a focus expert group, the multidimensional scaling analysis and the cluster analysis were used to choose the representative experimental samples. Finally, 28 fragrance bottle forms were selected to conduct the morphological analysis which was used to identify the product form elements, as shown in Figure 1. As a result of the morphological analysis, nine product form elements and 30 associated product form types were identified, as shown in Table 1. The nine product form elements are "Shape of bottle top *(x_1)*", "Connection of bottle top and body *(x_2)*", "Shape of bottle shoulder *(x_3)*", "Shape of bottle body *(x_4)*", "Shape of bottle bottom *(x_5)*", "Ratio of bottle width and length *(x_6)*", "Transparency of bottle top *(x_7)*", "Transparency of bottle body (x_8)", and "Texture of bottle body *(x_9)*". Please refer to our previous studies for details (Lin and Wei, 2017; Lin and Chen, 2016; Zheng and Lin, 2016; Lin et al., 2018).

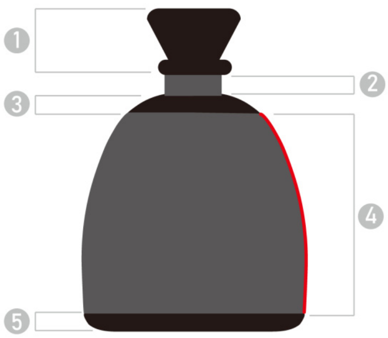

Figure 1: The product form elements of fragrance bottle.

("1" indicating "Bottle Top", "2" meaning "Connection of Bottle Top and Body", "3" showing "Bottle Shoulder", "4" representing "Bottle Body", and "5" being "Bottle Bottom", respectively).

Table 1: The morphological analysis.

Product Form Element	Product Form Type					
	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6
Shape of bottle top (x_1)	Arch	T-shape	Rectangle	Extraordi-nary-shape	Cylinder	None
Connection of bottle top and body (x_2)	With-connection	None				
Shape of bottle shoulder (x_3)	0-40^0	40^0-70^0	Above 70^0	Others		
Shape of bottle body (x_4)	Symmetric-al curves	Symmet-rical lines	Parallels	Irregular-lines		
Shape of bottle bottom (x_5)	Obtuse-angled ($> 90^0$)	Acute-angled ($< 90^0$)	Right-angled ($= 90^0$)			
Ratio of width and length (x_6)	1:1	1:1-1:3	Above 1:3			
Transparency of bottle top (x_7)	Transpar-ent	Opaque				
Transparency of bottle body (x_8)	Transpar-ent	Opaque				
Texture of bottle body (x_9)	Patterned	Geomet-ric	Streaked	None		

According to the morphological analysis, the fragrance bottle sample can be coded using the value of 1, 2, 3, 4, 5, or 6, if it has a particular design form type for each of its nine product form elements, as shown in Table 2. For each selected fragrance bottle sample, the first column of Table 2 shows the fragrance bottle sample number and Columns 2-10 show the corresponding type number for each of its nine product form elements. Table 2 provides a data set for training and testing DNNs to develop the consumer-oriented expert system described in the following sections.

3 DEEP NEURAL NETWORKS (DNNs)

Machine learning uses algorithms to parse data, learn from that data, and make informed decisions based on what it has learned, while deep learning is a particular kind of machine learning that is inspired by the functionality of our brain cells called neurons which led to the concept of neural networks (NNs) (Deep Learning Studio, 2019; Azure Machine Learning Studio, 2019). NNs are non-linear models and are widely used to examine the complex relationship between input variables (features) and output variables (labels) (Negnevitsky, 2002).

Table 2: Data for training and testing deep neural networks.

No.	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
1	1	2	4	1	1	1	2	1	4
2	4	1	4	1	1	1	2	2	4
3	6	2	4	3	3	1	2	1	4
4	4	1	4	1	1	1	2	1	1
5	4	1	1	3	1	1	1	1	1
6	3	1	4	3	3	2	2	1	4
7	4	2	2	1	2	2	1	1	3
8	4	1	2	1	1	2	2	1	4
9	1	2	3	1	1	2	2	1	4
10	3	2	3	3	3	3	2	1	4
11	4	1	1	2	1	2	2	2	4
12	5	2	4	4	2	3	1	1	4
13	3	1	1	3	3	2	2	1	2
14	2	1	1	3	3	2	2	1	4
15	1	2	3	1	2	2	2	2	3
16	4	2	4	4	1	2	2	2	4
17	5	1	4	1	1	2	1	1	4
18	2	1	1	3	3	2	1	1	4
19	1	1	4	1	2	2	1	1	2
20	4	1	1	3	3	2	1	1	4
21	3	2	3	3	3	2	2	1	1
22	3	2	3	2	3	2	2	1	4
23	5	2	4	2	1	2	2	1	4
24	5	2	1	3	3	2	2	1	4
25	4	1	1	3	3	2	2	1	4
26	5	2	2	3	1	2	2	1	4
27	1	1	4	1	1	2	2	1	1
28	4	2	1	4	2	2	2	1	1

NNs are thus well suited to formulate the product design process for matching design form elements (modelled as features) to consumers' affective preferences (modelled as labels) (Cross, 2000; Nelson and Illingworth, 1991). For example, Lai et al. (2005) used an NN model and a grey prediction (GP) model in conjunction with a grey relational analysis (GRA) model to help product designers determine the best combination of form elements for achieving a desirable product image (Lai et al., 2005).

However, most studies in relation to affective design use NN models, while only few studies pay attention to DNNs (Chan et al., 2018; Lin et al., 2007; Lin et al., 2012). In other words, most studies use a three-layer NN that includes one input layer, one output layer, and one single hidden layer. Although this three-layer NN may produce a good outcome, it cannot effectively model the complex consumers' affective preferences as a black box. In addition, the availability of social big data is valuable to support product design decision-making and to fulfill consumer requirements in developing new products (Chan et al., 2018; Jin et al., 2016). As such, it is desirable for researchers or product designers to consider using DNNs with multiple hidden layers to develop a consumer-oriented expert system for new product form design.

In this paper, we use the Deep Learning Studio (DLS) software developed by Deep Cognition Inc. for its powerful utility and convenient implementation (Deep Learning Studio, 2019). There are three main parts to develop a model or system in the DLS, including (1) Create a DNN model (e.g. get data, prepare the data, and define features), (2) Train the model (e.g. choose and apply a learning algorithm, transfer function, loss function, and parameters tuning), and (3) Predict (e.g. evaluate or track performance).

In this paper, we use the multilayered feedforward DNNs trained with the backpropagation learning algorithm, as it is an effective and the most popular supervised learning algorithm (Negnevitsky, 2002; Nelson and Illingworth, 1991). As mentioned above, the 30 product form types of nine product form elements are used as the input variables (features). Therefore, there are 30 neurons in the input layer. In the output layer, we use the "Sexy" image word to represent the consumers' affective preference as the output variable (label). 250 participants (with ages ranging from 25 to 50) are recruited to assess the form (look) of the 28 fragrance bottle samples on the "Sexy" image scale (Lin and Wei, 2017; Lin et al., 2018). A 5-point Likert scale is used, ranging from 1 (the lowest) to 5 (the highest), so there are five neurons in the output layer. As a pilot study for using DNNs, 36 (=4*3*3) DNN models are developed with one to four hidden layers with three different hidden neurons and dropout ratios. We use three widely used rules for determining the number of neurons in the hidden layer(s), as follows:

HN1: (The number of input neurons + the number of output neurons) (a)

HN2: (The number of input neurons + the number of output neurons)*2 (b)

HN3: (The number of input neurons + the number of output neurons)*4 (c)

In this paper, the number of the total input data is randomly divided into two sets for the training data and the testing data with the ratio of 8:2. The transfer function is Relu for all layers, except the Softmax function (Deep Learning Studio, 2019; Azure Machine Learning Studio, 2019) is adopted between the last one hidden layer and the output layer. The loss function used is Crossentropy, while the optimizer used is Adadelta (Deep Learning Studio, 2019). Moreover, the default values of DLS are used for other parameters such as learning rate and momentum. Figure 2 shows a DNN model with two hidden layers as an illustration.

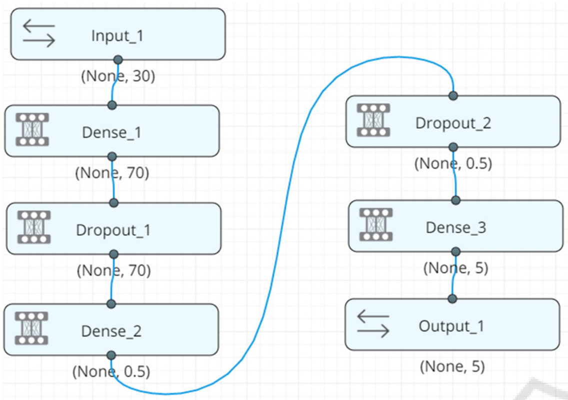

Figure 2: The DNN model with two hidden layers.

4 RESULTS AND DISCUSSION

To evaluate the performance of the 36 DNN models developed in terms of their prediction ability, Table 3 shows their loss and accuracy values. As shown in Table 3, two DNN models out of these 36 DNN models have the highest test accuracy (0.8), i.e. the Den1_Dp1_HN3 model and the Den3_Dp2_HN1 model. This result indicates that these two models have an accuracy rate of 80% for predicting the value of the Sexy image about fragrance bottles. That is, they are more suitable for modeling the consumers' preference about fragrance bottles.

According to the experimental result, these two models have the same accuracy rate for predicting the consumers' preference. For further analysis, the Den1_Dp1_HN3 model is a three-layer model (one hidden layer) with the dropout ratio of 0.10 and 140 hidden layer's neurons, while the Den3_Dp2_HN1 model is a five-layer model (three hidden layers) with the dropout ratio of 0.25 and 35 hidden layer's neurons. It is evident that the Den3_Dp2_HN1 model is deep (in terms of hidden layers), whereas the Den1_Dp1_HN3 model is wide (in terms of hidden neurons on the hidden layer). As such, a "deep" neural network architecture is not always performing better. In other words, in some design settings, a "wide" neural network architecture may have a better performance.

Table 3: The loss and accuracy values of 36 dnn models.

			HN1		HN2		HN3	
	Drop		Train	Test	Train	Test	Train	Test
Den1	Dp1	Loss	0.82	1.03	0.16	1.01	0.17	0.96
		Accu.	0.80	*0.50*	1.00	*0.50*	1.00	***0.80***
	Dp2	Loss	0.65	1.00	0.41	0.98	0.30	0.93
		Accu.	0.90	*0.70*	1.00	*0.70*	1.00	*0.50*
	Dp3	Loss	0.88	1.27	0.92	1.13	0.75	0.97
		Accu.	0.80	*0.50*	0.70	*0.60*	0.90	*0.60*
			HN1		HN2		HN3	
	Drop		Train	Test	Train	Test	Train	Test
Den2	Dp1	Loss	0.62	1.22	0.10	1.06	0.02	1.25
		Accu.	0.80	*0.50*	1.00	*0.60*	1.00	***0.70***
	Dp2	Loss	1.08	1.11	0.57	1.04	0.12	0.90
		Accu.	0.40	***0.70***	0.90	*0.50*	1.00	***0.70***
	Dp3	Loss	1.60	1.35	0.99	1.20	0.52	0.95
		Accu.	0.30	*0.50*	0.70	*0.50*	0.80	*0.60*
			HN1		HN2		HN3	
	Drop		Train	Test	Train	Test	Train	Test
Den3	Dp1	Loss	0.44	1.28	0.03	1.21	0.00	1.41
		Accu.	0.90	*0.60*	1.00	*0.60*	1.00	*0.70*
	Dp2	Loss	1.39	0.83	0.28	1.01	0.08	1.41
		Accu.	0.40	***0.80***	1.00	*0.70*	1.00	*0.60*
	Dp3	Loss	1.61	1.51	1.38	1.35	0.36	1.01
		Accu.	0.20	*0.30*	0.20	*0.40*	0.90	*0.50*
			HN1		HN2		HN3	
	Drop		Train	Test	Train	Test	Train	Test
Den4	Dp1	Loss	0.35	1.39	0.03	1.52	0.01	1.95
		Accu.	1.00	*0.50*	1.00	*0.50*	1.00	*0.60*
	Dp2	Loss	1.45	1.54	0.27	1.14	0.14	2.27
		Accu.	0.50	***0.70***	1.00	***0.70***	0.90	*0.60*
	Dp3	Loss	1.47	1.56	1.60	1.37	1.46	1.14
		Accu.	0.30	*0.40*	0.30	*0.60*	0.40	*0.50*

Note: "Den1" indicates one hidden layer in the architecture of the DDN model, and "Den2" indicates two hidden layers, and so on. In addition, "Drop." means "dropout", and Dp1 has the dropout ratio of 0.10, Dp2 is 0.25, and Dp3 is 0.50. "Accu." means "accuracy".

With its highest predicting accuracy rate, the Den1_Dp1_HN3 model is used to develop the consumer-oriented expert system, which can model the consumers' preference about fragrance bottles. All possible combinations of design form elements can be input to the Den1_Dp1_HN3 model for generating their associated image values. As a result, a consumer-oriented expert system can be generated, consisting of 20,736 (=6*2*4*4*3*3*2*2*3) different combinations of design form elements, together with their associated "Sexy" image values. Product designers can specify a desirable image value for a new fragrance bottle design, and the consumer-oriented expert system can then work out the optimal combination of design form elements.

5 CONCLUSIONS

In this paper, we have constructed 36 DNN models for developing a consumer-oriented expert system for fragrance bottle design. Extensive experiments on the performance of the DNN models have shown that a "deep" neural network architecture is not always performing better. In other words, in some design settings, a "wide" neural network architecture may have an equivalent or better performance. The consumer-oriented expert system developed consists of 20,736 different combinations of design form elements. With the expert system, product designers can easily specify a desirable image value into the system to work out the optimal combination of design form elements for a new fragrance bottle design.

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