Deep Learning for Identifying Potential Conceptual Shifts for Co-creative Drawing

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Abstract

We present a system for identifying conceptual shifts between visual categories, which will form the basis for a co-creative drawing system to help users draw more creative sketches. The system recognizes human sketches and matches them to structurally similar sketches from categories to which they do not belong. This would allow a co-creative drawing system to produce an ambiguous sketch that blends features from both categories.

1 Introduction

Creative sketching is important in a wide variety of domains including engineering, art, and architecture [1]. We propose a co-creative system that plays a free association drawing game that facilitates more creative sketches by introducing conceptual shifts. In co-creative systems, an AI and a user collaborate on a creative task [2]. Our proposed AI agent recognizes objects in human sketches and responds by suggesting a conceptual shift. In this context, a conceptual shift entails recognizing an object from a different conceptual category with which the current object shares structural characteristics. The goal is to respond with another sketch that leverages this conceptual shift, such as by drawing a conceptual blend [3] of the two objects. The resulting free association game would encourage the fluent expression of ideas by the user. The system described here forms the basis of a co-creative tool that helps the user to learn creative sketching.

2 Training the co-creative agent with sketches

We use clustering on deep features to train the co-creative agent to generate a visual representation of sketches that enable a conceptual shift. This training has two steps:

Learning the visual representation of sketches. Deep learning architectures are able to extract highly detailed visual representations from images leading to high classification accuracy and high-quality generated images [4]. We use the Google Quick, Draw! dataset [5] in place of user input and train our system on a subset of 35 categories with up to 110,000 images in each. We represent each sketch as a high-level feature vector obtained using VGG-16 [6], a standard convolutional neural network (CNN) architecture. We started with a model that was pre-trained on the ImageNet dataset [7] and then fine-tuned the weights by training on the sketches. The model contains 15 convolutional

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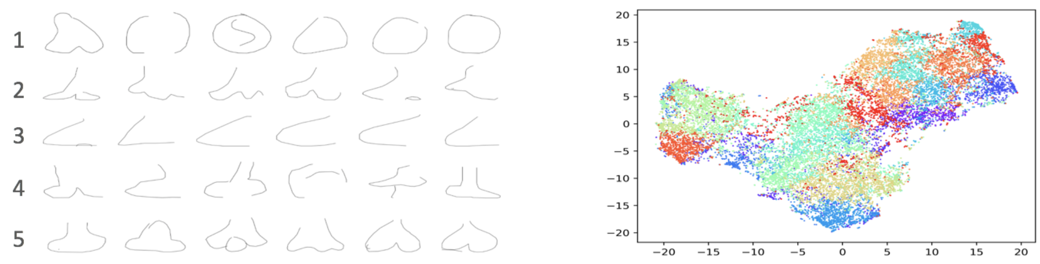
layers and two fully connected layers. We extract the features from the first fully connected layer which produces 4096 features per image, and use these features to represent each sketch.

Clustering sketches into sets. As the objects of each category have high variance (e.g. different shape, viewpoint and angle), we separate each category using clustering on the VGG-16 representation, which identifies structurally similar sub-categories that we use for identifying potential conceptual shifts. We used k-means algorithm and selected k via the elbow method.



(a) Samples of 5 clusters from nose category

(b) Embedding visualization of nose category

Figure 1: Clustering samples (a) and visualization using LargeVis [8] (b).

3 The Co-creative System for drawing

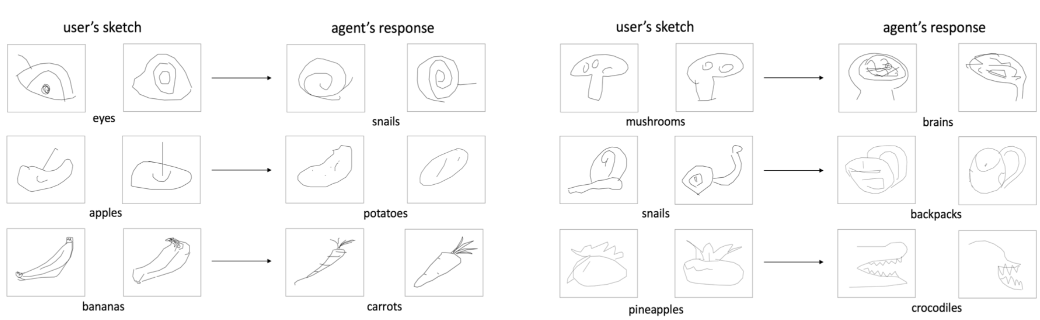
In our proposed co-creative drawing system a user and an agent take turns to sketch. The agent has to perceive the user input and identify opportunities for conceptual shifts. To identify potential conceptual shifts we match objects from one category to structurally similar objects in another category. We compare the Euclidean distances between the centroids of the cluster (i.e. sub-category) to which the sketch belongs and clusters from other categories. We identify the cluster with the minimum distance to the current object's cluster and use this to propose a conceptual shift. Our approach involves 3 steps:

Recognizing. The agent takes the user's sketch (currently a randomly selected sketch from the dataset), extracts its feature vector, and determines its cluster.

Matching. The user's sketch is matched to the most similar cluster in another category.

Contributing. The agent contributes (currently by random selection from the dataset, but in future by (neural) drawing) a sketch from the cluster identified as a potential conceptual shift.

In Figure 2 we show examples of this process from 6 categories. The three on the left have identified good potential conceptual shifts (with a low distance between clusters), while the three on the right have less potential (and higher distance).



(a) Examples from 3 categories with high similarity score

(b) Examples from 3 categories with low similarity score

Figure 2: Agent responses to user sketches from six categories.

4 Conclusions and Future Work

In this paper we described a co-creative drawing system that plays a free association game. We described a framework that identifies a conceptual shift through recognizing, matching and contributing. This system will be used as the basis for a drawing agent that creates conceptual blends that encourage user creativity. In the future we will investigate alternative architectures for the encoder to improve the sketch representation for clustering. In addition, we would like to develop a more comprehensive matching algorithm for conceptual shifts, and incorporate a neural approach to drawing.

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