Advancements in Cognitive Categorization: The Generalized Context Model and Its Successors

The term paper submitted for the course CS786: Introduction to Computational Cognitive Science

by

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Abstract

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One of the fundamental steps towards categorisation in cognitive sciences is the development of Generalised Context Models (GCM). In this paper an attempt is made to evaluate the GCMs and its presumptions while categorisation and exemplar-based learning. It is noteworthy to mention that the GCMs have their own inherent limitations therefore, we further explore additional models like ALCOVE, HMAX and CHMAX that were created to overcome the shortcomings of the GCM. These generalised models provide an in-depth, yet complex picture of human cognition by incorporating attentional, choice boundaries, and deterministic decision rules. In order to understand this mechanism this article examines the development of categorisation theories and their implications for further research by contrasting various models.

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Chapter 1

Introduction

1.1 Categorization

Categorization is the process of grouping similar objects, ideas, or experiences together. This cognitive process is fundamental to human thought and allows us to simplify the world by reducing the amount of information we need to process. Instead of treating each object as unique, we can use categories to make inferences and predictions about their properties and behaviors.

1.2 Levels of Categorization

As we have studied there's a "basic level" of categorization that humans prefer. The basic level sits between the more general "superordinate level" and the more specific "subordinate level." For example:

1. **Superordinate:** Furniture
2. **Basic:** Chair
3. **Subordinate:** Rocking Chair

1.3 Models of Categorisation

1.3.1 Classical View

This view proposes that concepts are defined by a set of necessary and sufficient features. However, this approach faces challenges because defining features for many concepts proves difficult

1.3.2 Prototype Models

Prototype models suggest that we represent categories with a single, "average" representation called a prototype. New items are categorized based on their similarity to this prototype. These models explain typicality effects well but struggle with representing category variability.

1.3.3 Exemplar Models

Exemplar models, like the Generalized Context Model (GCM), store individual instances (exemplars) in memory. Categorization decisions are based on the similarity of a new item to the stored exemplars. This approach accounts for both typicality effects and the influence of variability on categorization

1.3.4 Rational Model of Categorization (RMC)

RMC takes a Bayesian approach, viewing categorization as a process of probabilistic inference. It can behave like both prototype and exemplar models, adapting its strategy based on the situation. RMC utilizes clustering to represent categories, and the number of clusters learned is influenced by a Dirichlet Process prior.

Chapter 2

The Generalized Context Model (GCM)

One excellent categorisation approach is the Generalised Context approach (GCM). The GCM, which **Nosofsky** developed in 1986, provided a probabilistic framework for comprehending the role that exemplars play in categorisation. The degree to which a stimulus resembles stored exemplars influences each category judgement. Individual exemplars are stored in memory by the GCM rather than depending on a single prototype. The model classifies a new item according to how similar it is to all of the stored exemplars when it is presented with them.

2.1 Key Features of GCM model

- **Similarity-Based Categorization:** The similarity between a fresh example and the stored exemplars is the basis via which the GCM determines category membership. Taking into account variables like attention weights, the model determines the psychological distance between things.

- **Typicality Effects:** Typicality effects, which characterise the situation where some members of a category are viewed as more typical than others, can be taken into consideration by the GCM. A robin, for example, is seen as a more common bird than an ostrich. In order to explain this, the GCM takes into account how many exemplars a new item is comparable to; in other words, typical items are comparable to more exemplars.

- **Variability:** The model also accounts for the variability within a category. For example, the category ”pizza” has a lot of variability in terms of toppings and sizes. The GCM captures this variability by storing individual exemplars.
- **Context Sensitivity:** The GCMs are primarily designed to consider the context in which individual features occur. This means that the different features could have different meanings depending upon their context and co-occurrence.
- **Learning Mechanisms:** The initial GCM was primarily a clustering model without any learning mechanism. However, its subsequent evolution facilitated incorporation of various supervised learning mechanisms. One such model, ALCOVE, which is discussed later, employs a training loss function and a gradient descent strategy to adjust its parameters and improve its categorization accuracy.

2.2 Strengths and Limitations

2.2.1 Strengths

- **Explains Typicality Effects:** The GCM provides a more nuanced understanding of how humans categorize various items in their day-to-day routine. Therefore, this model's ability to account for 'typicality effects' is considered as one of the major strengths of the GCM.
- **Handles Variability:**Another excellent advantage with the GCM is its ability to exploit inherent variability within categories. This is achieved by storing individual exemplars. Thus, the GCM effectively offers more flexibility than the prototype models, which rely on a single, average representation.

2.2.2 Limitations

- **Computational Complexity:** Considering the fact that it can handle large categories of features, their storage and comparison could make it a much more computationally expensive process. This is especially crucial when we deal with extravagant categories and thereby may slow down the cognitive automation.

- **Limited Explanatory Power for Knowledge Effects:** Another limiting point associated with the GCM is about its inability to include a priori knowledge while parametric categorisation. This aspect becomes critical if exemplar models like the GCMs do not adequately account for the prior influence in the cognitive process. Although, recent studies have shown to address this concerns significantly.

In summary, the GCMs, since their development, have been widely used in categorization research. Numerous subsequent models that have been developed since have successfully utilised it's foundation and also managed to substantially overcome its limitations.

Chapter 3

Models since GCM

3.1 ALCOVE

Since advent of the GCMs, several other models have been developed. One such model - the Attention-Learning Covering map (ALCOVE), was developed by **Kruschke** in 1992. This model integrates exemplar-based representation with multidimensional scaling (MDS)-based similarities. Further it also relies upon selective attention mechanism of the GCMs within a learning framework.

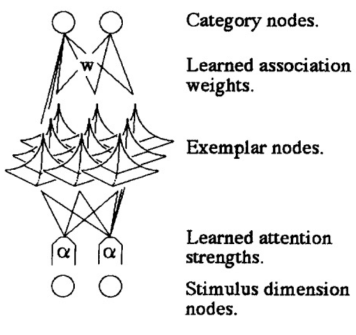

Figure 1. The architecture of ALCOVE (attention learning covering map). (See The Model section.)

Figure 3.1: ALCOVE Architecture

3.1.1 Architecture

ALCOVE employs a three-layer network structure

- **Input Layer:** Represents the stimulus dimensions. Each input node corresponds to a specific dimension of the input stimuli.
- **Hidden Layer:** Represents the attention strengths and exemplar representations. The hidden layer is further divided into two sets of nodes:
    1. Attention Dimension Nodes: These nodes encode the attentional strengths assigned to each input dimension. The higher the attentional strength, the more important that dimension is considered for categorization.
    2. Hidden Exemplar Nodes: These nodes correspond to the stored exemplars. Each hidden exemplar node represents a specific exemplar previously encountered during learning.
- **Output Layer:** Represents the categories. Each output node corresponds to a particular category.

3.1.2 Key Features

ALCOVE builds upon the foundation of the Generalized Context Model (GCM), incorporating key aspects of the GCM while introducing novel mechanisms for learning and attention.

- **Exemplar-Based Representation:** Like the GCM, ALCOVE represents categories by storing individual exemplars in memory. This approach contrasts with prototype models, which represent categories using a single average prototype. The exemplar-based representation allows ALCOVE to capture the variability and nuanced structure within categories, making it sensitive to effects of specific exemplars and within-class correlational structure
- **Multidimensional Scaling (MDS):** ALCOVE adopts the MDS approach for modeling similarity relations among exemplars, representing them as points in a

multidimensional psychological space. The similarity between exemplars is inversely proportional to the distance between their corresponding points in this space. The use of MDS allows ALCOVE to apply to continuous-dimension domains, unlike the original context model which primarily focused on simplified domains with binary-valued dimensions.

- **Selective Attention:** ALCOVE incorporates the concept of selective attention, using attention weights to modify the psychological space where exemplars are embedded. Attention weights stretch the psychological space along relevant dimensions and shrink it along irrelevant dimensions, enhancing the discriminability of categories. This selective attention mechanism is a crucial element of both ALCOVE and the GCM.

- **Connectionist Framework and Attention Learning:** The fact that ALCOVE is implemented within a connectionist network framework is one of its main differences from the GCM. ALCOVE uses a gradient descent process to learn attention weights, as opposed to the GCM, which uses free parameters. By modifying the attention weights in response to the error signal produced during the learning process, ALCOVE becomes more flexible and dynamic in its ability to focus on pertinent features.

- **Error-Driven Learning:** To create connections between exemplars and categories, ALCOVE makes use of error-driven learning. The incorrect feedback obtained throughout the learning process is used to adjust the strength of these associations, which are represented by connection weights. While wrong categories damage connections, right classifications strengthen them. Compared to the frequency-based memory strength alterations in the GCM, this error-driven method offers a more complex and possibly more flexible learning mechanism.

3.1.3 ALCOVE's Learning Algorithm

ALCOVE's learning algorithm involves adjusting the connection weights between the layers based on error feedback.

- **Stimulus Presentation:** When a stimulus is presented, the input layer nodes are activated based on the stimulus's features.
- **Hidden Layer Activation:** The hidden layer nodes are activated based on the input activations and the connection weights. The hidden exemplar nodes compute their similarity to the input stimulus based on a similarity function, which is typically an exponential decay function of the weighted distance between the stimulus and the exemplar in the psychological space.
- **Output Layer Activation:** In ALCOVE, the output layer nodes are triggered based on the hidden layer activations. This process is also dependent upon connection weights between the hidden and output layers. Such activations represent the model's predictions about the category membership based on the input stimulus.
- **Error Calculation:** The difference between the model's prediction and the actual category label is calculated as the error, which are minimised through the next step to optimise the model.
- **Weight Updates:** The connection weights are adjusted using a gradient descent approach to minimize the error. Both the association weights between the hidden exemplar nodes and the output nodes, as well as the attentional strengths represented by the attention dimension nodes, are updated to improve the model's performance in an iterative fashion.

3.1.4 Advantages and Limitations

3.1.4.1 Advantages

- **Accounts for Attentional Learning:** ALCOVE offers a mechanism for learning attention weights. This feature is highly significant as it allows the model to focus on relevant dimensions and ignore irrelevant ones. Such attentional learning capability makes ALCOVE more flexible and adaptive as compared to the models that rely only on fixed attentional parameters.

- **Handles Continuous Dimensions:** ALCOVE has a potential feature that it can effectively handle stimuli with continuous dimensions. This feature expands the applicability of the model to a broader range of categorization tasks.
- **Captures Effects of Variability:** ALCOVE's exemplar-based representation allows incorporation of inter-category variability. Thus, individual exemplars and within-class correlational structures are finely captured in ALCOVE. Typically, other models, like prototype models, often fail to address these aspects.

3.1.4.2 Limitations

- **Computational Complexity:** ALCOVE can be computationally demanding, especially when dealing with large datasets and complex category structures. The storage and processing of numerous exemplars, as well as the iterative nature of the learning algorithm, can impose computational constraints.
- **Static Psychological Space:** The psychological space in ALCOVE, where exemplars are represented, is assumed to remain static. However, in reality, the psychological representation of features and their relationships might change during learning. This limitation restricts ALCOVE's ability to capture dynamic shifts in conceptual understanding.
- **Limited to Static Environments:** ALCOVE primarily applies to situations where the stimulus dimensions remain unchanged, and it doesn't address scenarios where the categorization criteria or the underlying structure of categories might evolve over time.

3.2 HMAX

HMAX stands for "Hierarchical Model And X" where "X" represents various computational components.HMAX is a biologically inspired, feedforward, hierarchical model for visual object recognition. It was initially proposed by **Riesenhuber and Poggio** in 1999 and later refined by **Serre et al.** in 2007. HMAX is designed to mimic the structures and

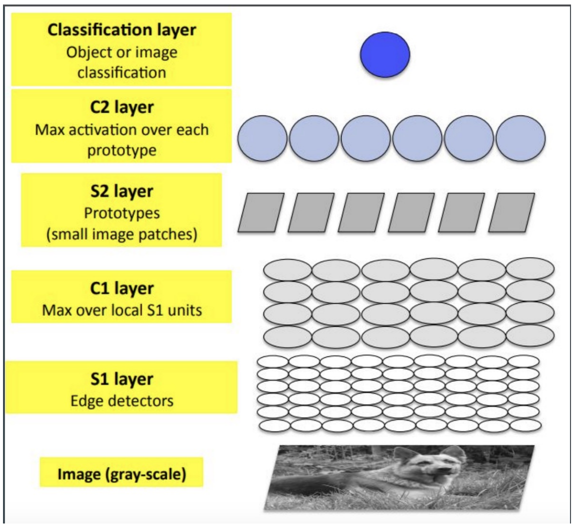

FIGURE 3.2: HMAX structure

functions of the primate visual cortex, drawing inspiration from the pioneering work of **Hubel and Wiesel**, who revealed the hierarchical organization of visual processing in the brain.
HMAX consists of alternating layers of simple (S) and complex (C) cells, similar to the organization found in the visual cortex. The model typically comprises four layers: S1, C1, S2, and C2.

- **S1 Layer:** This layer simulates simple cells in the primary visual cortex (V1). It utilizes a bank of Gabor filters to extract local features from the input image. Gabor filters are well-suited for this task as they are sensitive to edges and orientations, mimicking the receptive field properties of V1 neurons.

- **C1 Layer:** In V2, the C1 layer simulates complicated cells. The outputs of S1 units with distinct spatial positions but comparable feature selectivity are subjected to a max-pooling procedure. An essential feature of the brain's object recognition system is invariance to position and scale, which is introduced by this procedure.

- **S2 Layer:** Pattern matching is the responsibility of the S2 Layer. The outputs of C1 units are contrasted with a collection of training-learned prototype attributes. Common patterns found in the training photos are represented by these prototypes.

- **C2 Layer:** This layer carries out a second max-pooling operation, this time over the outputs of S2 units with comparable feature selectivity but distinct scales, in a manner similar to that of V4. Invariance to scale is further improved by this procedure.
  The final output of the HMAX model is a vector representing the presence and strength of the learned prototype features in the input image. This vector can then be used for various tasks like object classification or scene understanding

3.2.1 Advantages and Limitations

3.2.1.1 Advantages

- **Simpler Architecture:** Compared to other models like Convolutional Neural Networks (CNNs), HMAX has a significantly simpler architecture, requiring fewer parameters and less computational power.

- **Invariance to position and Scale:** A crucial aspect of robust object recognition is the invariance to position and scale. The max-pooling operations at C1 and C2 layers in HMAX effectively introduce invariance to position and scale.

- **Faster Training and Working:** The HMAX model trains and operates significantly faster than the CNNs. This makes it suitable for real-time applications.

3.2.1.2 Limitations

- **Lower Accuracy:** Compared to CNNs, the HMAX typically renders lower accuracy on complex object recognition tasks. This is primarily because both the simplified feature extraction and matching mechanisms are employed in the HMAX model.

- **Color ignorance:** The original HMAX model uses grayscale images, therefore neglecting color information.

3.3 CHMAX

The CHMAX represents further augmentation of the classic HMAX model. The CHMAX has the ability to incorporate modern deep learning techniques efficiently to enhance its capabilities while preserving its biologically inspired foundation. The recent article **Pant et al. 2024** highlights the core innovations of CHMAX and its potential to address some of the limitations of the original HMAX.

As deep neural networks (DNNs) gained prominence, they significantly outperformed earlier hierarchical models like HMAX in image categorization tasks. However, these DNNs often lack the biological plausibility and generalization capabilities observed in humans. CHMAX was developed to bridge this gap, leveraging the anatomical hierarchy of HMAX while incorporating trainable filters and a loss function inspired by self-supervised learning.

3.3.1 Key Features

- **Trainable Filters:** Instead of using fixed Gabor filters in the S1 layer, CHMAX replaces them with trainable filters. This modification allows the model to learn more complex and data-driven features, potentially enhancing its representational power.

- **Adaptive Pooling:** To improve scale invariance, CHMAX introduces an adaptive pooling layer. This layer uses adaptive strides to generate invariant feature maps regardless of the input scale, addressing one of the weaknesses of traditional max-pooling operations.

- **Contrastive Learning:** CHMAX is trained using a contrastive learning algorithm, a form of self-supervised learning that encourages the model to learn similar representations for different views of the same object while pushing apart representations of different objects. This approach aims to improve the model's ability to generalize to novel objects.
  The paper emphasises CHMAX's promise as a promising method for creating biologically inspired vision models that can achieve human-like generalisation, despite the fact

that it gives just a few details about its architecture and training process. Through the integration of contemporary deep learning methodologies with the hierarchical structure of HMAX, CHMAX provides a route towards object identification systems that are more resilient and flexible. To fully examine CHMAX's capabilities and assess its effectiveness across a larger range of jobs and datasets, more investigation is required.

Chapter 4

Conclusion

A gradual improvement in our understanding of categorisation may be seen in the progression from the Generalised Context Model (GCM) to sophisticated computational frameworks like ALCOVE, HMAX, and CHMAX. By highlighting exemplar-based categorisation and demonstrating how individual experiences impact category learning, the GCM established the foundation. Nevertheless, it has trouble taking non-linear feature integration and attentional flexibility into consideration.

By including attentional learning and enabling dynamic weighting of stimulus components, ALCOVE filled up these gaps and modelled human adaptation in categorisation tasks. HMAX and CHMAX, its successor, further bridled the gap between biological plausibility and cognitive models by modelling human-like visual categorisation processes. By including intricate, context-sensitive categorisation mechanisms, CHMAX expanded on the hierarchical processing system that HMAX had created, which mimicked the function of the early visual cortex.

When combined, these models show a progression from simple exemplar-based systems to complex frameworks with biological inspiration. This work advances our theoretical knowledge of classification while simultaneously providing guidance for real-world applications in domains like as cognitive neuroscience and artificial intelligence.