ABSTRACT
Almost all recent neural network models of category learning assume that people allocate attention to features of stimuli on a dimension-by-dimension basis. It is usually further assumed that people allocate attention to individual dimensions independently. Using the GECLE framework (Matsuka, 2004), the plausibility of the assumptions was investigate with two types of internal mental representation, namely exemplar and prototype.

In simulation studies, two aspects of attention mechanisms were manipulated: 1) the capability of paying attention to correlations among feature dimensions, and 2) whether these dimensional correlations are learned globally (for all exemplars or prototypes) or whether unique patterns of correlation can be learned separately for subgroups of stimuli or individual exemplars or prototypes.

The results showed that there was an interactive effect of types of internal mental representation and type of attention mechanism: the prototype-based model performed best when it incorporated unique attention structure with the capability of paying attention to dimensional correlations; while the exemplar-based model performed best with global attention structure with independent dimensional attention processes (i.e., no attention to correlations).

OVERVIEW
Generalized Exploratory Model of Category Learning (GECLE)

• Simulation 1 – Simple XOR stimuli
• Simulation 2 – Filtration vs. Condensation stimuli

PROBLEM
Almost all NN models of human category learning incorporate attention process with the following properties:

(a) independently allocating attention in the dimension-by-dimension basis
(b) have a global attention coverage structure

However, these assumptions are not being systematically evaluated.

In the present study, a general human category learning modeling framework (i.e., GECLE) is used to test these assumptions.

GECLE (Matsuka, 2004) is a general and flexible exploratory modeling approach for human category learning which allows model assumptions to be manipulated separately and independently.

uses the Mahalanobis distances between the reference points (RP: corresponding to either exemplars or prototypes) and the input stimuli does not necessarily assume that attention is allocated independently dimension-by-dimension allows each reference point to have uniquely shaped and oriented attention coverage area

RESULTS
One possible reason why PB-LCN showed the filtration advantages was that PB-LCN might have been able to locate or define prototypes more easily in the filtration task than in the condensation task. This is because while the condensation stimuli require synchronization of the “correct” movements of centroids of prototypes and the “correct” psychological scaling of the two feature dimensions (i.e., attention processes), the filtration stimuli require “correct” movements and scaling in only one dimension. Thus, synchronization of prototype movement and scaling was more difficult for the condensation stimuli than in the filtration task for models using prototypes.

Discussion
The results of these simulations are argued to provide new insights regarding human category learning, namely that 1) it is very likely that there are interactions between internal mental representation and attention mechanisms, and 2) people may pay attention to correlations among feature dimensions.

Quantitative Descriptions of GECLE

Nomenclature:
- \( x \): input stimulus; \( r \): centroid of reference point; \( D \): distance between input and reference point; \( G \): activation transfer function; \( h \): activation of reference point (RP: corresponding to either exemplars or prototypes) and the input stimuli.

The effectiveness of the model’s attention mechanism depends on how the stimuli are internally represented by the model or vice versa; a simple GUN attention mechanism seems sufficient for EB modeling, while a complex LCN is required for PB modeling.

RESULTS

Simulation 1: XOR stimuli
A simple XOR learning task is simulated with GECLE. There are eight different models involved in this simulation, namely, E1: an exemplar-based (EB) model with GUN attention mechanism; E2: EB with GCN; E3: EB with LUN; E4: EB with LCN; P1: a prototype-based (PB) model with GUN; P2: PB with GCN; P3: PB with LUN; and P4: PB with LCN. All EB models had four reference points, while all PB models had two.

Simulation 2: Filtration vs. Condensation

Some studies (e.g., Gottwald & Garner, 1975; Kruschke, 1993) showed that humans learn better in “filtration” tasks, in which information from only one dimension is required for (perfect) categorization, than in “condensation” tasks, in which information from two dimensions is required. This finding has been used as evidence that people pay attention to each dimension independently, rather than dependently (i.e., paying attention to correlations). Thus, a model paying attention to correlations or having diagonal attention coverage, as GECLE-LCN does, may not replicate filtration advantage.

The present simulation study tests if PB model with LCN attention mechanism can replicate the filtration advantage observed in human category learning.

METHOD

The same one-parameter exponential ATF used in simulation 1 is used in the present simulation study. The user-defined parameters were optimized using a simulated annealing method (Ingber, 1989; Matsuka et al. 2003) to reproduce observed empirical learning curves reported in Kruschke (1993).

It should be noted that Kruschke (1993) showed that ALCOVE (i.e., an EB-model with GUN) was able to reproduce the filtration advantage.