Set Operators for Superordinate Categories Machine Learning

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Category learning in young children

This paper examines how higher order kinds and categorical inferences are available in the corpora of specific categories known by 16 month olds, 30 month olds and 48 month olds, and how the organization of basic-level categories into order kinds might emerge from learning specific facts about specific things. One key idea behind the present work is that categories are *just* the features into which they can be decomposed.

To test these ideas we selected a developmentally ordered set of 132 nouns and of 462 features from the MacArthur Developmental Inventory (Fenson, Dale, Reznick, Bates, Thal & Pethick, 1994).

Set operators and Machine Learning

In this work, we describe an implemented system that incrementally learns categories and regroups them to build category inclusions. One fundamental idea is that each category is decomposed into its *known* features. The second fundamental idea is that the learning system consists in building clusters that gather the categories around one or more features. A third fundamental idea is that regroupings of features occurs without any external intervention; we consider that this automatic clustering is a kind of unsupervised learning model.

Clustering Algorithms

1) The first step in our method is to structure these data in trees:

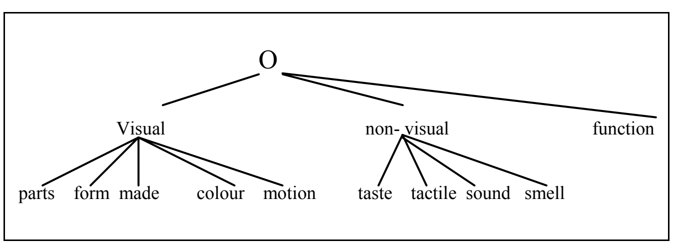

Figure 1: The data is structured in tree

Set $I = \{1, 2, \ldots, 462\}$; $J = \{1, 2, \ldots, 132\}$; $A = \{16\ 30\ 48\}$.
$\forall\ j \in J$: $C_j = O_j \cup \{f_k\}_{7 \leq k \leq 24}$; C_j (Category) can have minimum 2 features and maximum 24. O_j (object) is a category noun like "apple".

2) The second step is to regroup categories that have a common feature such as: $\forall\ a \in A$ (age in months). F_a is a set of features learned at age a. Regroup the categories that have a common feature:
$\forall\ f \in F_a$ do: $\forall\ j \in J$; if $(f \in C_j)$; $\Omega = \Omega \cup O_j$; $G = [f, \Omega]$;
Example: f = *has_4_legs* feature :
at 16 months: [has_4_legs, {cat dog}]
at 30 months:[has_4_legs, {cat dog cow deer giraffe horse lamb squirrel table turtle zebra}]
at 48months: [has_4_legs, {cat dog cow deer giraffe horse lamb squirrel table turtle zebra chair donkey elephant moose pony sheep sofa}]

3) The third step is an inclusion of a feature into another such as:
$\forall\ (i, j) \in I^2$, $(i \neq j)$ and $\forall\ (k, m) \in J^2$; let $G_i = [f_i, \Omega_k]$ and $G_j = [f_j, \Omega_m]$; if length $(f_j) >$ length (f_i) and $\Omega_k \subseteq \Omega_m$ then $G_i \subseteq G_j$ is an inclusion of order 2
Example: If G_1= [has_windows {cars bus }] and
G_2= [has_an_engine {cars bus train}]. Then $G_1 \subset G_2$

Results

Table 1: number of inferences of 1 feature

Age	16	30	48
1 feature inference	7	19	53

The chart above shows that the number of nouns categories that have "inherited" a feature that was not originally theirs increases dramatically. In this environment, the noun categories that are candidates are singletons, i.e. for example, the train category in regard to the bus and cars category. Further work will show the formalism adapted to describe this phenomenon.

References

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