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:

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: \( f = \text{has}_4 \_\text{legs} \) feature :
at 16 months: \([ \text{has}_4 \_\text{legs} , \{ \text{cat dog} \}] \);
at 30 months: \([ \text{has}_4 \_\text{legs} , \{ \text{cat dog cow deer giraffe horse lamb squirrel table turtle zebra} \}] \);
at 48 months: \([ \text{has}_4 \_\text{legs} , \{ \text{cat dog cow deer giraffe horse lamb squirrel table turtle zebra chair donkey elephant moose pony sheep sofa} \}] \);
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 \( G_1= [\text{has}_4 \_\text{legs} \{ \text{cars bus} \}] \) and
\( G_2= [\text{has}_4 \_\text{legs} \{ \text{cars bus train} \}] \). Then \( G_1 \subset G_2 \)

Results
Table 1: number of inferences of 1 feature

<table>
<thead>
<tr>
<th>Age</th>
<th>16</th>
<th>30</th>
<th>48</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 feature inference</td>
<td>7</td>
<td>19</td>
<td>53</td>
</tr>
</tbody>
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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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