

An Automated Approach for Product Taxonomy Mapping in E-commerce

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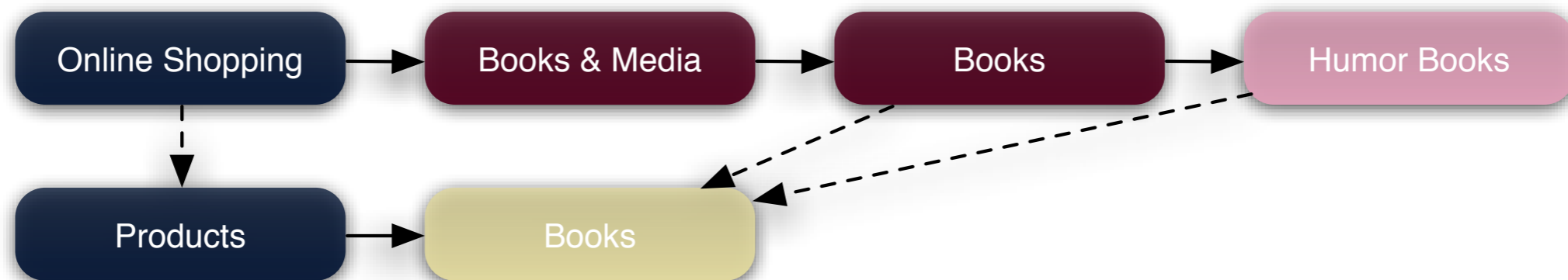
Terminology

- source taxonomy
- target taxonomy
- category = single node in a taxonomy
- (category) path = list of nodes (starting from root node)

Product taxonomies

Important aspects of product taxonomies:

- composite categories
- varying degree of granularity
- root category of taxonomies



Related work

- The algorithm by Park & Kim
“Ontology Mapping between Heterogeneous Product Taxonomies in an Electronic Commerce Environment”
- PROMPT algorithm in PROMPT Suite
“The PROMPT Suite: Interactive Tools for Ontology Merging and Mapping”

Algorithm overview

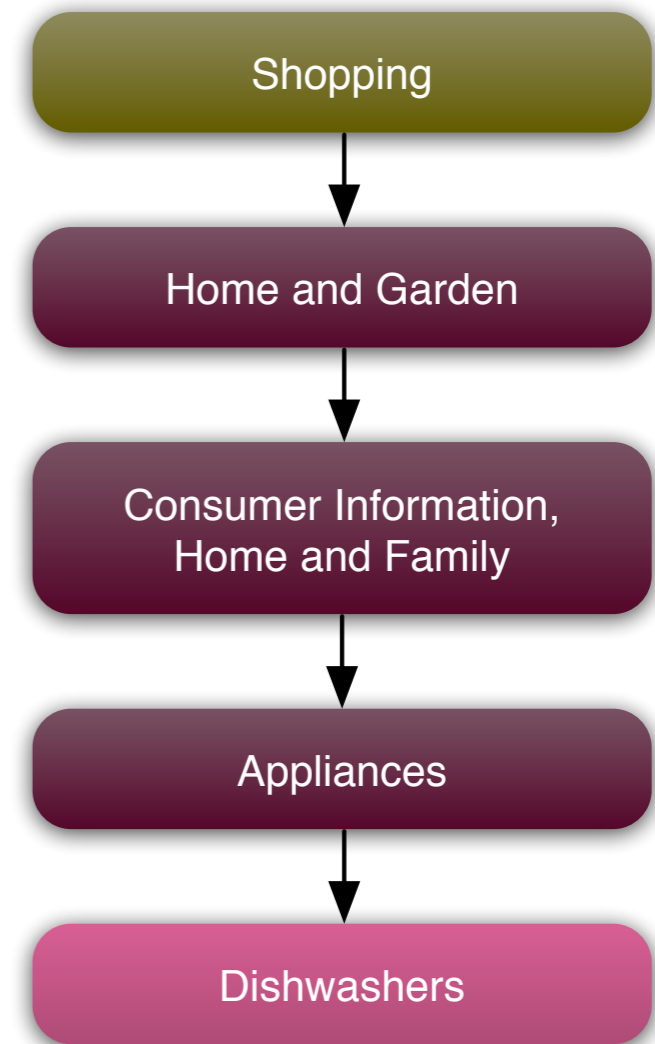
- Input is a source category path
- Output is a target category path (or 'None')
- There are three steps
 1. source category disambiguation
 2. candidate target category selection
 3. candidate target path key comparison

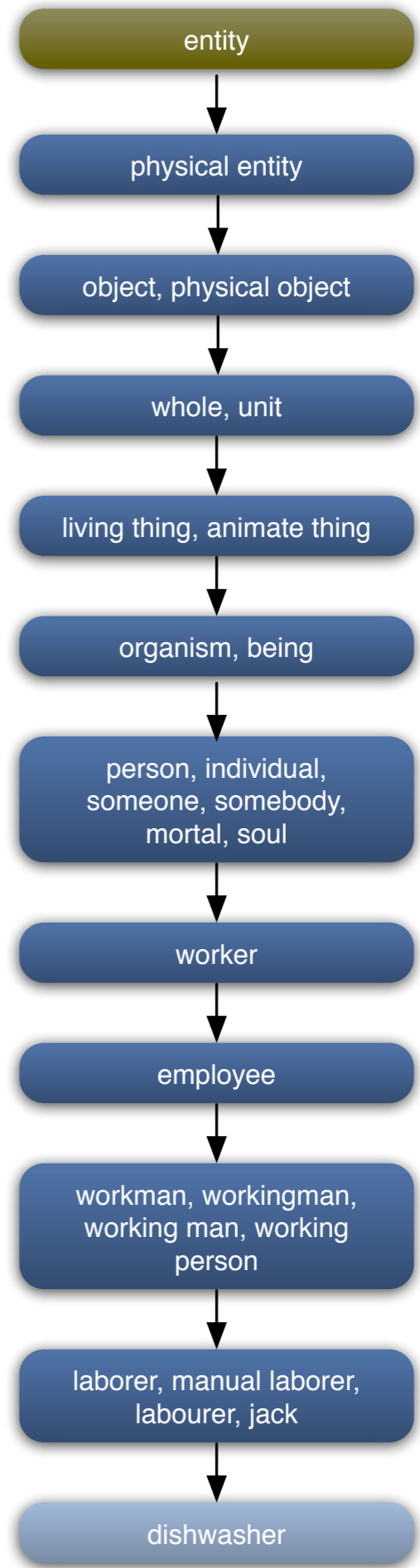
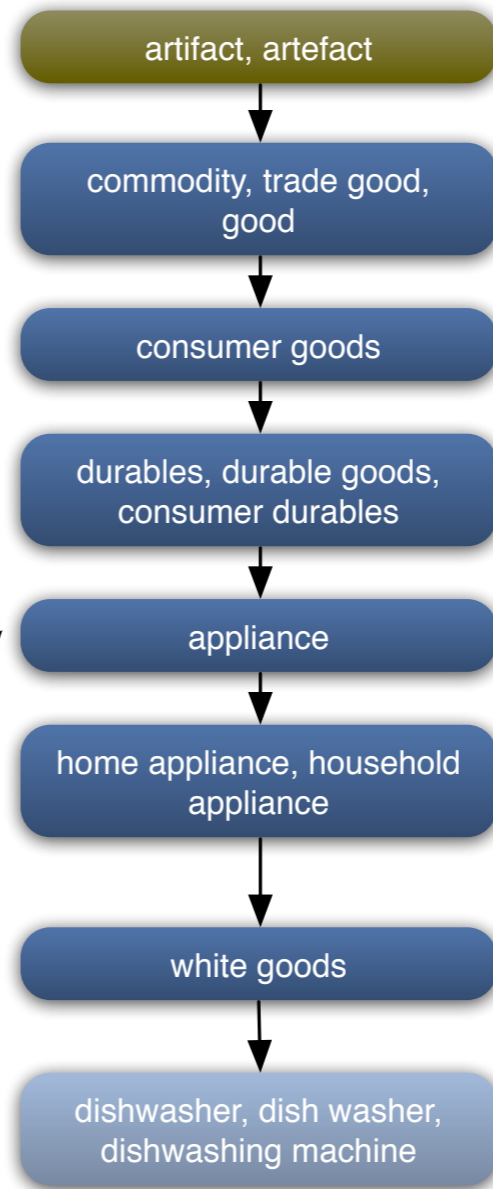
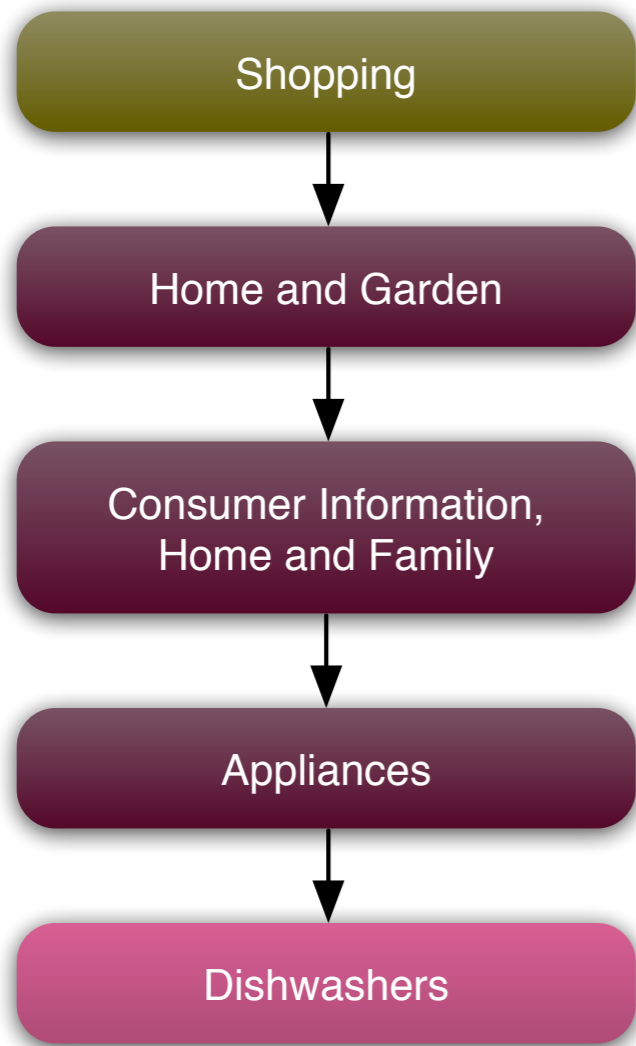
Algorithm overview

- 1. source category disambiguation**
2. candidate target category selection
3. candidate target path key comparison

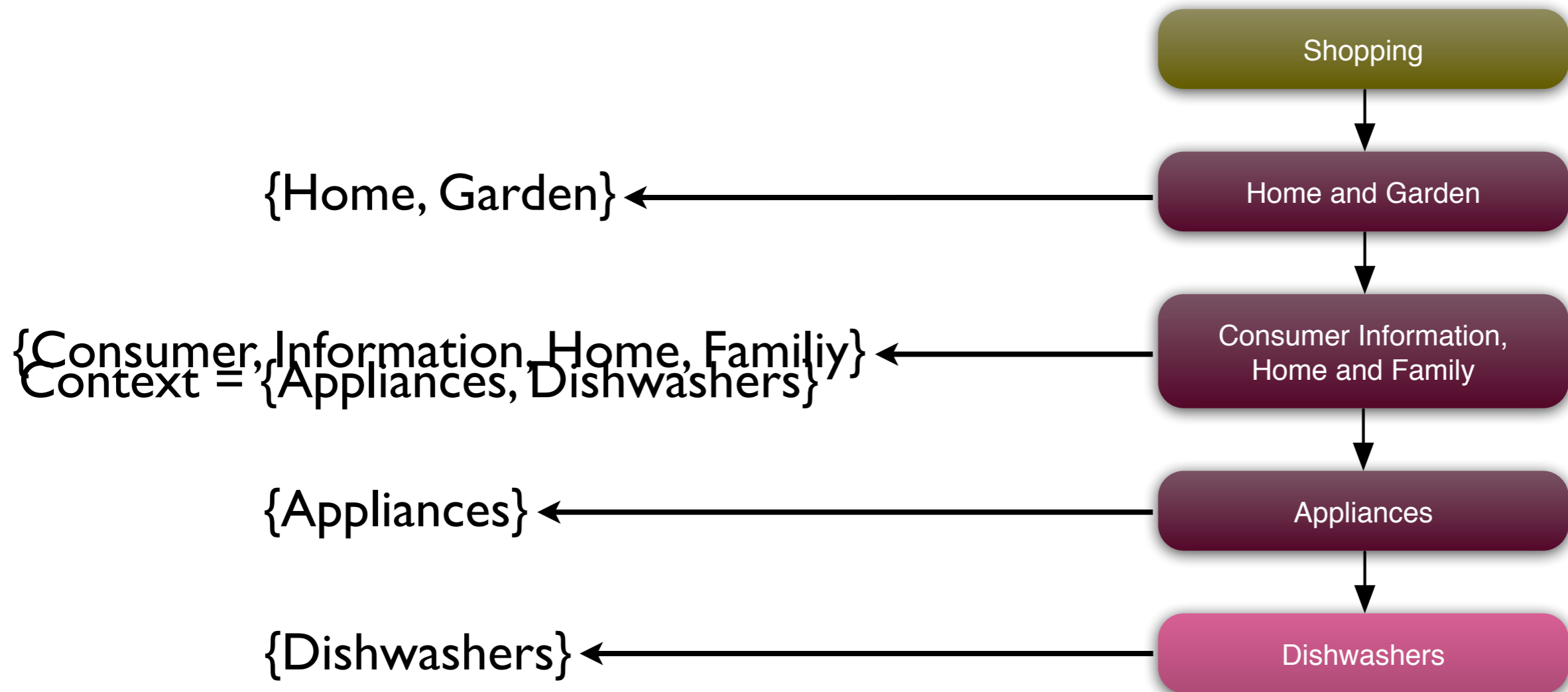
Source category disambiguation

- Example category path
 - Dishwashers can have two meanings
 - From the path, the meaning is clear to humans
- Based on the Lesk algorithm





Source category disambiguation



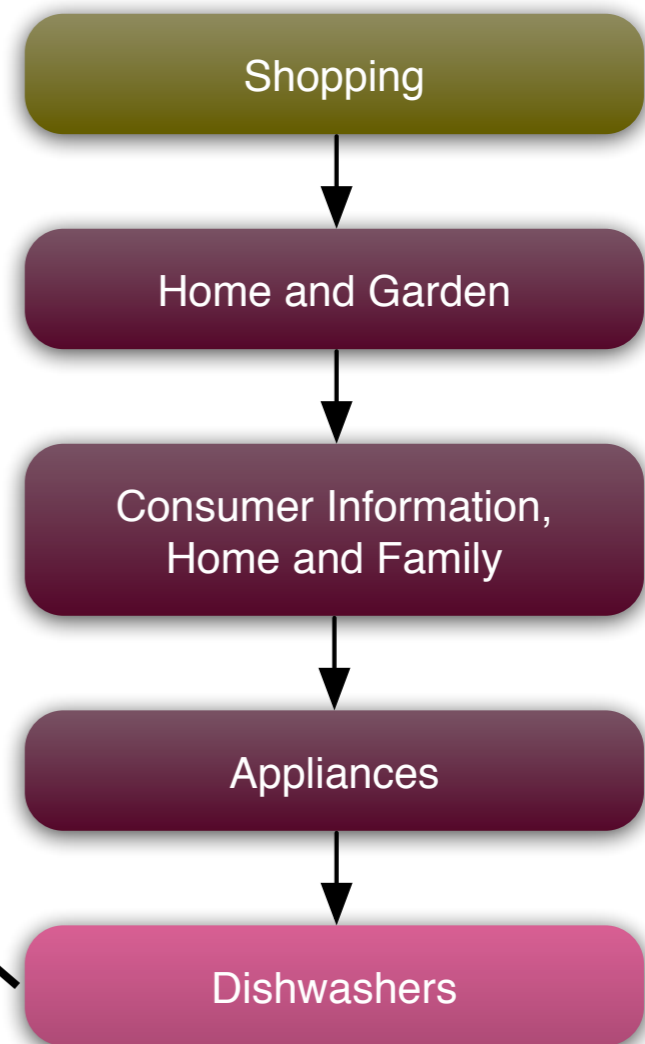
Source category disambiguation

Context = {Appliances, Dishwashers}

{Dishwashers}

Extended Split Term Set = {*extendedTermSet*, ...}

Synonyms of 'Dishwashers'
with the correct meaning



Source category disambiguation

S1 = dishwasher, dish washer, dishwashing
machine (a machine for washing dishes)

S2 = dishwasher (someone who washes dishes)

Compute sense score for each sense, highest is
selected as correct sense

Related synsets based on hypernymy, hyponymy, meronymy and holonymy

Context = {

Appliances,

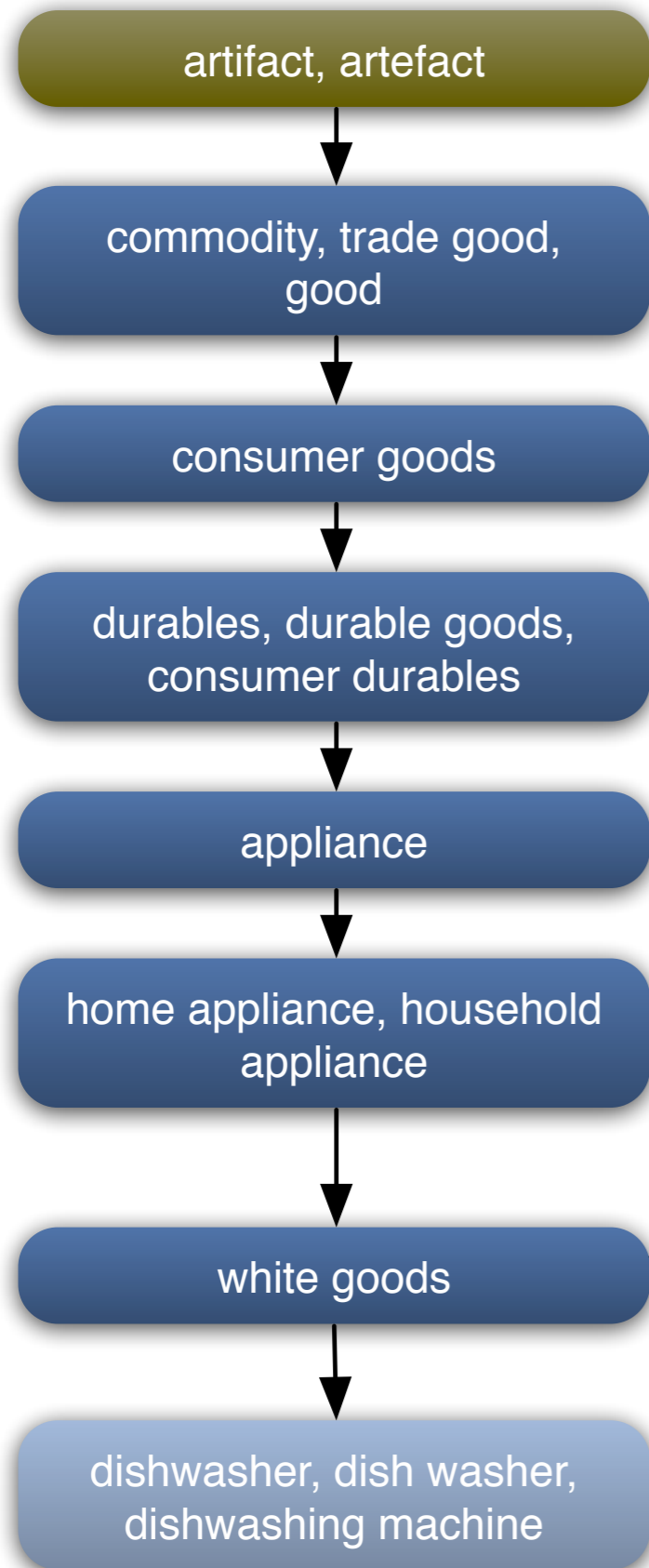
...

Dishwashers

}

longest common substring is used to compute the score

SI = dishwasher, ... (a machine for washing dishes)



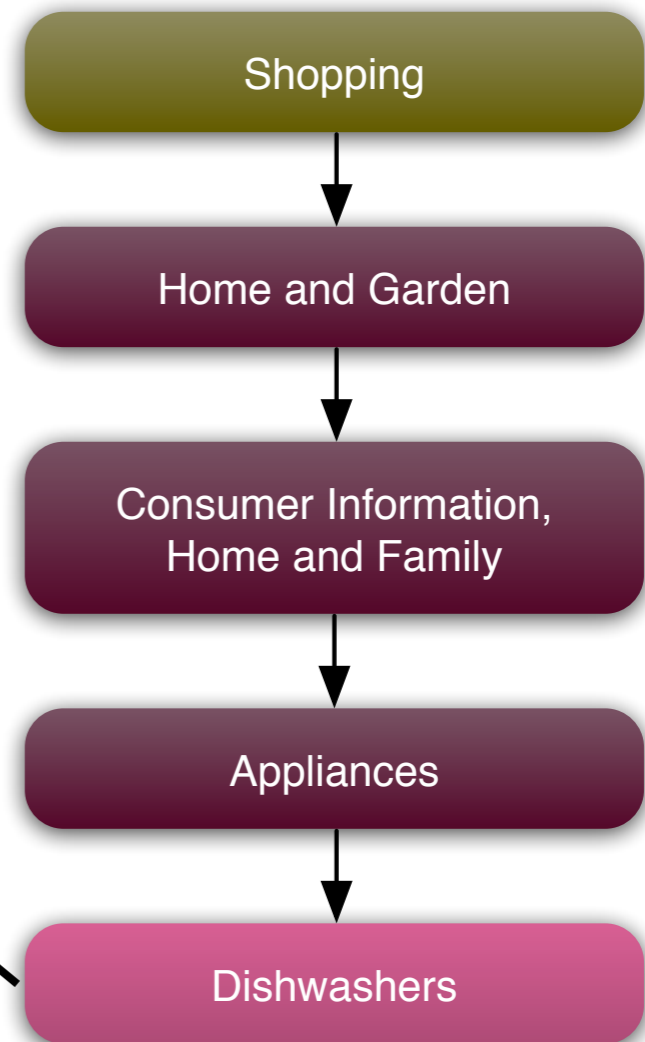
Source category disambiguation

Context = {Appliances, Dishwashers}

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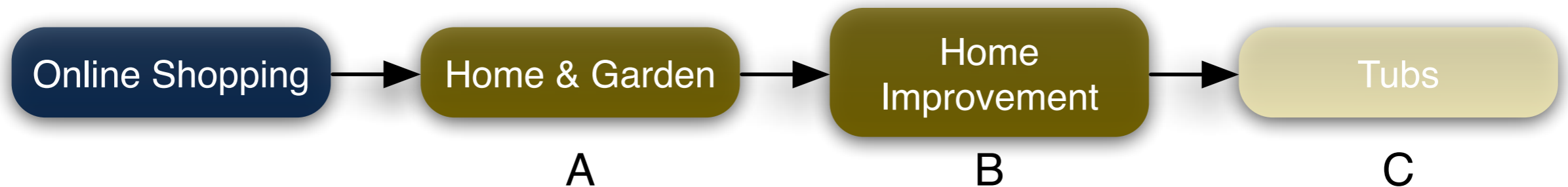
{Dishwashers, dishwasher, dish
washer, dishwashing machine}



Candidate target category selection

- Algorithm 'Semantic Search'
- Input:
 - a source category name and 'Extended Split Term Set'
 - a target category name
- Output: true if source category matches and is a subset of target category

Candidate target category selection



Disambiguation result for 'Tubs':
{{Tubs, bathtub, bathing tub, bath, tub}}

Candidate target category selection

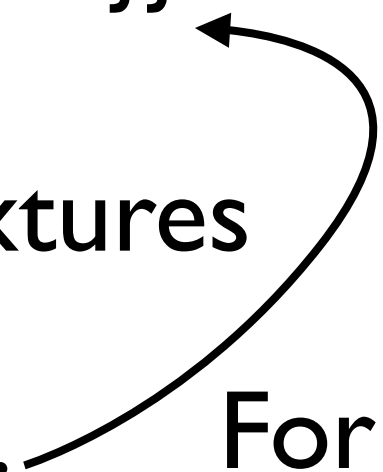
Disambiguation result for 'Tubs':
{Tubs, bathtub, bathing tub, bath, tub}

Target category: Kitchen & Bath Fixtures

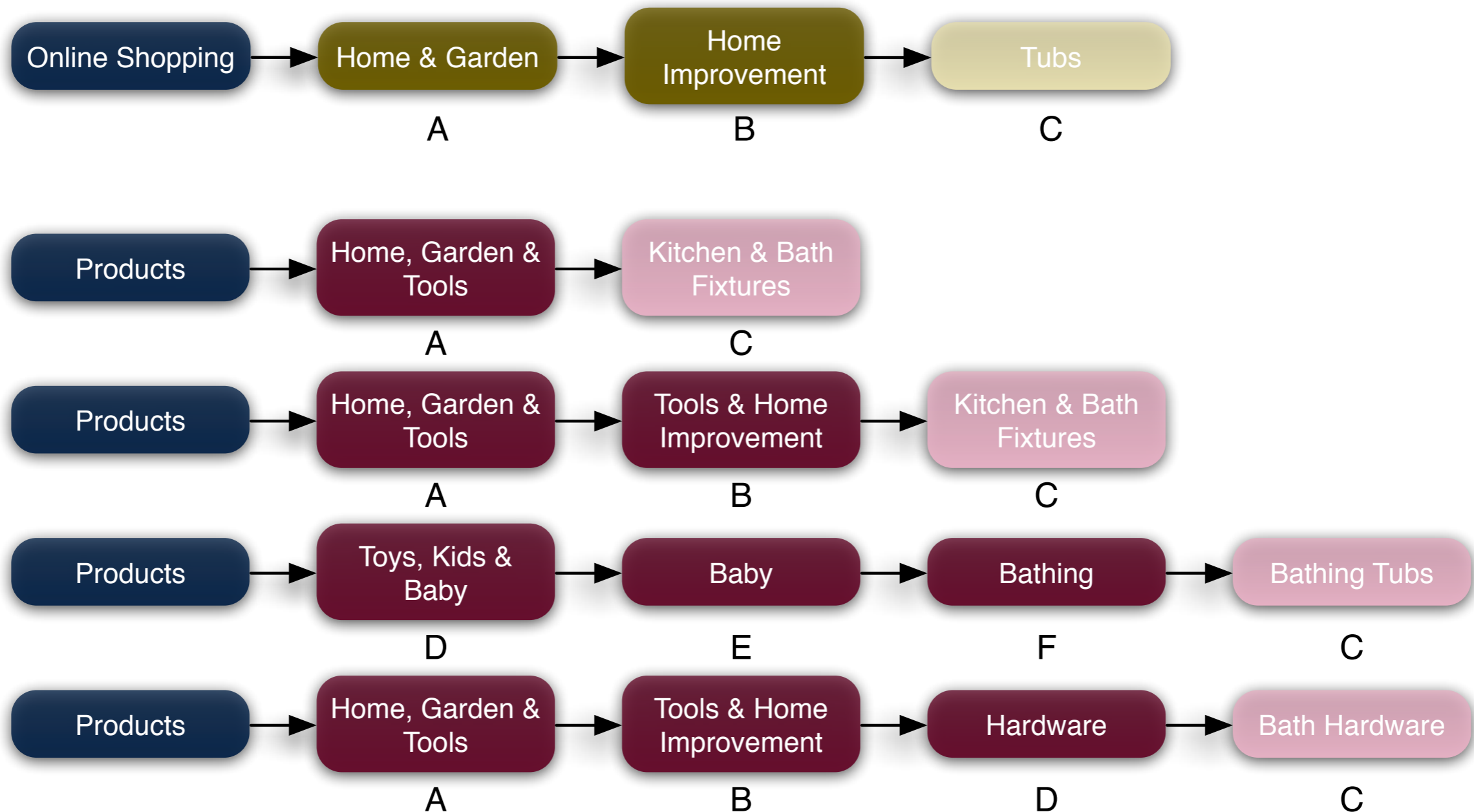
Match for at least one split term:

- source term is part of target category as separate term, or
- normalized Levenshtein similarity is above a certain threshold

For each extended term set



Candidate target category selection



Algorithm overview

1. source category disambiguation
2. candidate target category selection
- 3. candidate target path key comparison**

Candidate target path key comparison

- Damerau-Levenshtein applied on paths
- Category paths are converted to list of generated ID's
- Equal nodes get the same ID
- Equality determined by 'Semantic Search' algorithm (candidate target selection)

Candidate target path key comparison

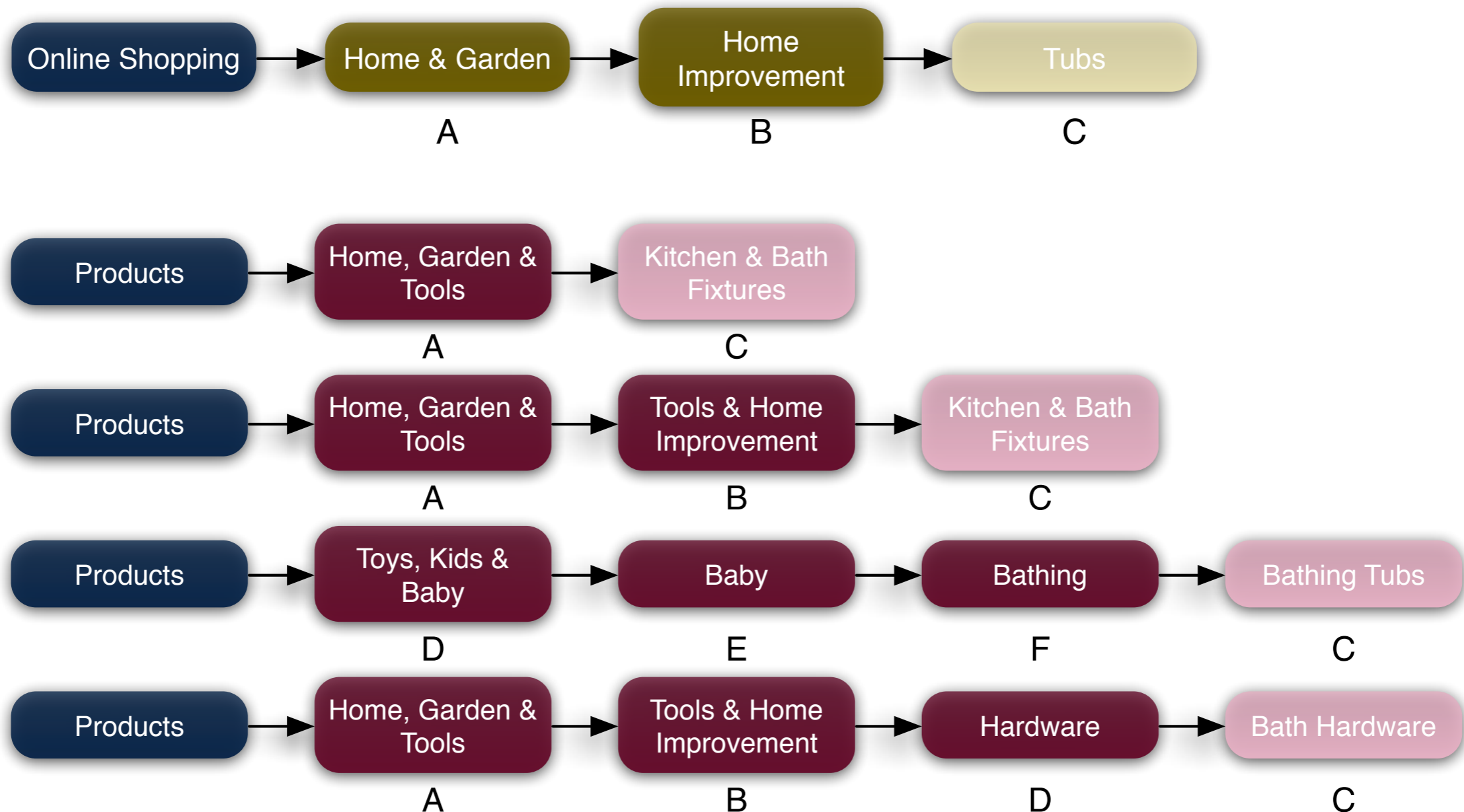
Final score:

$$score(K_{src}, K_{cand}) = 1 - \frac{damLev(K_{src}, K_{cand}) + p}{\max(\text{len}(K_{src}), \text{len}(K_{cand})) + p}$$

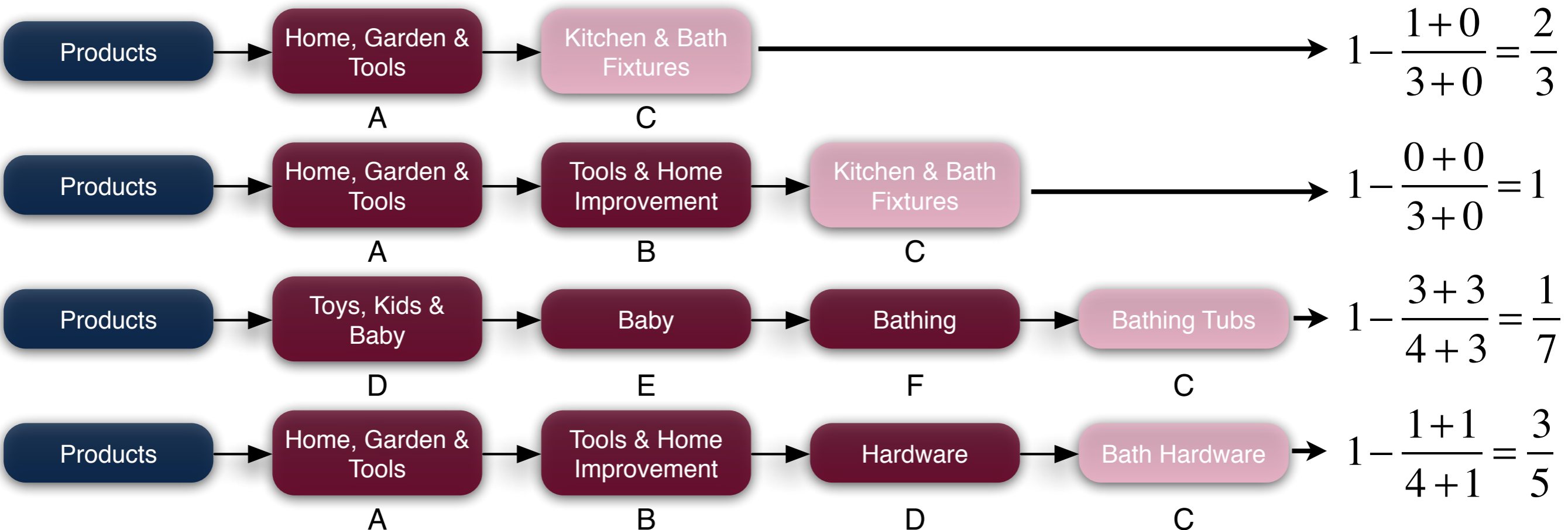
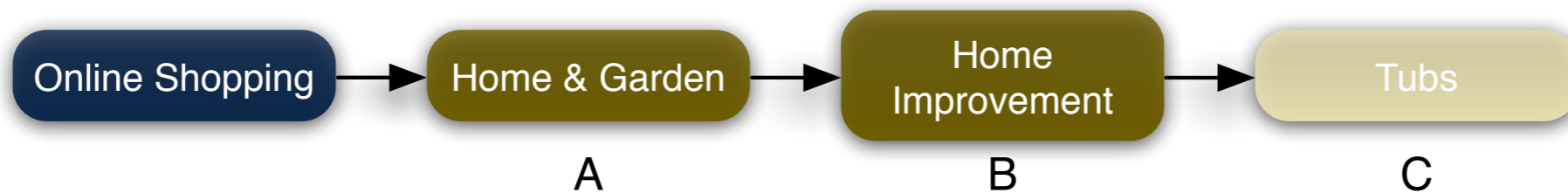
where:

- K is a key list
- p is the penalty (# absent nodes in candidate path)
- $damLev()$ computes the Damerau-Levenshtein distance between two key lists

Candidate target category selection



Candidate target category selection



Evaluation

- Datasets
 - Amazon.com, ~2,500 categories
 - Overstock.com, ~1,000 categories
 - Dmoz.org, ~44,000 categories
- Manually mapped 3000 categories with
 - 6 data set combinations (sample size 500)
 - 3 individuals

Evaluation

Overall results

Algorithm	Precision	Recall	F ₁	# Senses found	WSD accuracy
PROMPT	28.93%	16.69%	20.75%	n/a	n/a
Park & Kim	47.77%	25.19%	32.52%	5.70%	83.72%
Our approach	42.21%	80.73%	55.10%	82.03%	84.01%

Questions?