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Pictorial Naming Specificity across Ages and Cultures:

A Latent Class Analysis of Picture Norms for Younger and Older Americans and Chinese

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Abstract

Research on cross-cultural cognition relies extensively on pictorial stimuli to address how perceptions of common objects vary across population groups. We add to this understanding by examining *naming specificity* – the degree of detail elicited for labels of common objects – across Age (Young-Old) and Culture (American-Chinese) groups. Segregating subject-specific responses for four Age-by-Culture groups into multiple levels of specificity, allows for a formal analysis using latent class techniques and the rank-order binomial set-up of Rost (1985).

Overall, three naming specificity classes were supported. Though Age differences were minor, Cultural differences were not: the Chinese showed far greater variation, naming more items both with high and with low specificity than age-matched American counterparts. Our results differ from prior studies based on familiarity and latency measures, and suggest approximately 27% of commonly-used picture items differed across groups, calling to question their use in cross-group studies.

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Introduction

Studies of memory and cognitive processes have long relied on pictorial stimuli, typically simple, abstract line drawings of common objects. Attributes such as object or picture familiarity (Lachman & Lachman, 1980) are known to correlate well with cognitive measures, and affect both memory and retrieval processes. Cognitive psychologists have made broad use of pictorial stimuli to study, for example: how images and visual-spatial representations differ from verbal or abstract representations in memory (Snodgrass, 1984; Kirsner, Milech, & Stumpfel, 1986); the effects of picture priming on implicit and explicit memory (Mitchell & Brown, 1988; McDermott & Roediger, 1994; Rajaram, 1996); the nature of representational systems underlying visual memory in normal and impaired adults (Nyberg, Cabeza, & Tulving, 1996; Mitchell et al., 2000; Stark & Squire, 2000); and to elucidate differences in visual perception and memory across the lifespan (Parkin & Streete, 1988; Park et al., 1990).

Among the first to attain wide usage, Snodgrass and Vanderwart's (1980) norms have only recently been validated on other young American adult samples[1] (Yoon et al., 2004), though several studies have provided cross-cultural and/or cross-age validation for them and various supersets (Alario & Ferrand, 1999, and Bonin et al., 2003, for French; Sanfeliu & Fernandez, 1996, and Cuetos, Ellis, & Alvarez, 1999, for Spanish; Dell'acqua, Lotto, & Job, 2000, for Italian; Yoon et al., 2004, for Chinese; Bates et al., 2003, for comparisons spanning seven languages).[2] Across these and other studies, numerous subject-specific covariates have been examined in relation to naming and imagery. An abridged list would include agreement and latency for naming, as well as familiarity, variability and complexity for the images themselves. An increasingly clear portrait has thus emerged of the relative suitability of various pictorial stimuli for research across age and cultural groups.

A presumption typically underlying research using pictorial stimuli is that various groups, in particular younger and older adults, do not differ in terms of the *specificity* of names they assign to objects. Here, we investigate the validity of this assumption and suggest that there may be pronounced cohort differences, specifically using most commonly used picture norms for Older vs. Younger and Chinese vs. American groups. To this end, we apply latent class techniques to parcel pictorial stimuli into endogenously determined classes, and rigorously test whether these derived classes differ across Age-by-Culture groups. That is, we adopt a 'bottom-up' approach, with specificity classes determined by the corpus of pictorial naming data alone, not by *a priori* notions of which pictures are indeed more specific, and to whom.

We introduce *naming specificity* – the degree of hierarchical detail elicited in object label descriptions – to identify pictorial stimuli suitable for investigating age and/or cross-cultural differences in cognition. The recent emergence of research interest in cross-cultural differences in cognition, particularly so East Asian and Western, underscores the need for culture-invariant stimulus materials. Although pictures of everyday objects are potentially useful stimuli for comparing East Asians and Americans (Park, Nisbett, & Hedden, 1999), some objects are likely to vary in terms of how specifically they are perceived across cultures. For example, certain animals and vegetables indigenous to the U.S. (e.g., raccoon, asparagus) may be recognizable to East Asian subjects in terms of an appropriate category, but named at a relatively superordinate level, such as "small mammal" or "vegetable". The forthcoming methodology and analysis attempts to help guide selection of pictorial stimuli for studies of age and cross-cultural differences, and thereby enrich the normative data available to researchers.

Naming Specificity Compared with Alternative Measures

Several examples drawn from the data help illustrate distinctions between naming specificity and image or concept familiarity. [Note that, throughout, we use "class" to refer to sets of pictures, and "group" to sets of participants.] Consider, as per Snodgrass and Vanderwart's (1980) numbering, "rocking chair" (item 188) and "barrel" (item 18): both were highly familiar to all subjects, and did not differ strongly on any main agreement measures (Yoon et al., 2004). However, Chinese subjects were remarkably more *specific* in naming the (fairly generic) depiction of a barrel presented. Whereas

American subjects limited themselves primarily to the set {barrel, keg, wheel barrow, beer barrel, wood barrel}, Chinese subjects, particularly older ones, offered not only a barrel (桶), but 'subordinate' variants {wooden barrel (木桶), wine barrel (酒桶), bamboo barrel (竹桶), nail barrel (钉子桶), water barrel (水桶), small barrel (小桶)}; highly specific conflations {old style wine barrel (老式酒桶), wooden beer barrel (啤酒木桶)}; as well as some (fairly rare) questionable item names {drum (鼓), commode (便桶) and wine cup (斗)}.

We stress that it is not the *number* of different items generated, but their relative specificity which differs markedly. Let us compare "barrel" and "rocking chair" (item 188); for both, despite similarities in familiarity and other commonly used measures, degree of naming specificity diverges sharply across cultures. For "barrel", the Chinese generated a greater number of distinct items and were *more* specific in their object naming. "Rocking chair", however, displays the opposite pattern, with the Chinese producing many more responses overall, but being notably *less* specific: though many did produce "rocking chair" (e.g., 摇摇椅), a far larger percentage produced the less specific "chair" (椅 or 椅子) than did their American counterparts [and the number of less overtly 'accurate' responses was higher, including couch (躺椅) and vine chair (藤椅)]. We in fact found no systematic relationship between naming *specificity* and sheer number of responses recorded for a group, nor with that group's overall level of familiarity with the picture, item or concept. As we shall see, latent class analyses suggest that inferences about pictorial suitability garnered from naming specificity do not generally accord with those based on the major measures used in prior research.

Method

Participants

One hundred and thirteen younger adults (17-25 years) from the University of Michigan and 103 community-dwelling older adults (60-75 years), comprising the American cultural group, were recruited for testing in Ann Arbor, Michigan. One hundred younger Chinese students (18-23 years) recruited from three universities (Beijing Normal University, Capital Normal University and Aeronautics and Space University) and 100 older Chinese individuals (59-76 years) from the local community were tested at the Institute of Psychology, Chinese Academy of Sciences, in Beijing, China. Summary comparison statistics for all groups (Table 1) indicate general concordance in terms of sample characteristics.

Insert Table 1 about here.

Stimulus Materials and Procedures

All 260 standardized pictures developed by Snodgrass and Vanderwart (1980) – black outline drawings on a white background – were included, projected on a screen within a slide presentation. Experimental sessions were conducted 10 to 25 participants at a time. Chinese participants were given both verbal and written instructions in Mandarin; Americans were provided with equivalent instructions in English. Each picture was projected, singly in random order, for 8 seconds, followed by a 2 second pause. Subjects were instructed to write down "the first name of the object that comes to mind" for each presented picture, and to respond with an "X" if they thought they had encountered the object before but didn't know, or could not remember, the object name, or with an 'O' if they had not encountered it. Familiarity ratings were also elicited (see Yoon et al. 2004, which additionally analyzed name and concept agreement).

<u>Analyses</u>

The 260 pictures tested were ordered alphabetically and numbered accordingly, with all measures discussed below compiled separately for each Age-by-Culture group. Data files for all 260 pictures and each of the four groups – Younger American, Older American, Younger Chinese, and Older Chinese – are freely archived at the project site (`http://agingmind.beckman.uiuc.edu/Pict_Norms`), as well as cross-referenced comparison figures on cross-group name agreement, concept agreement, familiarity, latency and other measures mentioned herein.

Various approaches to coding the name response data were evaluated in conjunction with psycholinguists knowledgeable about both languages and cultures.[3] A final set of guidelines for counting different instances of names was established to ensure consistency and reasonableness across both American and Chinese name responses. For comparison purposes, the data were coded in a manner consistent with prior research. First, all name responses were recorded, with any obvious misspellings (e.g., homonyms) corrected. Second, when two or more responses were given, the first was retained (e.g., “house” for “house, home”). Third, quantifiers, prefixes or suffixes accompanying name responses were removed (e.g., “two”, “the”, “a”, “an”). Finally, any elaborations (e.g., “index finger” and “finger”) or non-trivial abbreviations were each retained as *separate* name responses; this was crucial in coding for specificity.

Specificity Coding

Each participant’s name responses for all 260 pictures were initially coded for nine specificity levels, on a -4 to 4 scale, which (ordinally) correspond to the standard levels of categorization (e.g., superordinate, basic, and subordinate). Consistent with extant findings in the categorization literature by Rosch et al. (1976) and Tanaka and Taylor (1991), basic-level names (relative to each picture; see below) were coded as Moderate in specificity and assigned a numerical score of 0. Responses that reflected greater detail (e.g., subordinate-level names) exhibited higher specificity and were assigned a score of 1 or greater, depending on the hierarchical level of detail subjects produced. Responses at more general levels of abstraction (e.g., superordinate-level names) were analogously coded as -1 or lower.

This initial nine-point specificity coding was performed for all responses (American and Chinese) for each of the 260 pictures by two independent judges fluently bilingual in English and Mandarin Chinese. Because less than 1% of overall responses fell into the {-4, -3} or {3, 4} categories, these were merged with the "-2" and "2" categories, respectively, yielding a five-point ordinal specificity scale (with empirical cell counts statistically consistent with the data model presented in the following section). Inter-rater reliability scores for the resulting five-point scale were over 98%; any remaining inconsistencies were resolved via discussion. Full codings for all picture items across each Age-by-Culture group, comprising over 4,000 unique picture item responses, is available from the project site.

It is crucial to note that coding is always *relative* to a particular picture item. For example, the response "chair" would be coded at the superordinate level for the picture "rocking chair" (item 188), but at the basic level for the picture "chair" (item 53). Were this not the case, the codings would largely reflect hierarchical interrelations between the pictures themselves, a feature carefully and deliberately built-in by Snodgrass and Vanderwart (1980). Arguably, then, 'basic' level responses are *correct* responses, so that other levels suggest either more or less detail than warranted by the picture itself. And further, systematic deviations from the scale center suggest that a group perceives that picture item differently from how researchers may intend them to.

Methodology

We wish to understand whether, and how, naming specificity differs across the four Age-by-Culture groups. Data consist of specificity scores for each of the 260 pictures, that is, how many subjects in each group fell into one of five specificity categories: Very High, High, Moderate, Low, Very Low. For example, counts for Picture #7, "Arm", appear in Table 2.

Insert Table 2 about here.

Observations thus consist of cell counts for an ordered categorical variable (Specificity) on a 5-point scale, for four Age-by-Culture groups and 260 pictures. Our goal is to determine whether the overall 'pattern' of responses – in a sense to be made rigorous below – differs across groupings of interest. Specifically, we address three sets of issues:

1) Does the *pattern* of response differ across Age, Culture, or any two Age-by-Culture groups?
2) Do any of the Age-by-Culture groups tend more towards naming specificity than the others?
3) For any Age-by-Culture group, do the pictures themselves fall into natural *classes*, and do any such classes vary across groups?

Addressing these questions requires a data model, one which describes the pictures and groups in a parsimonious fashion and which allows for clear statistical inference. Because we are interested in classification, we appeal to *discrete latent class* methods, a form of finite mixture model (McLachlan & Peel, 2000). And, because we are modeling an ordered categorical variable in a parsimonious manner, we make use of the *rank-order binomial* model in particular. There is a broad literature on latent class and mixture model methods, and we direct the reader unfamiliar with their use to the primary literature (a continually updated bibliography is provided by Uebersax, 2004).

Here, we use Rost's (1985) rank-order binomial model, a standard tool in the area. It is especially parsimonious, describing the entire *distribution* of count data (i.e., across the five specificity levels, "very high", …, "very low") through a single parameter, π. This parameter represents "how far along the scale" the underlying mean of the ordinal cell counts lies. In terms of visualization, we can view each of the lines in Table 2 as a set of tosses of a (not necessarily fair) coin four times. For example, we have n = 103 responses for the {American, Old} group, and (ordered) cell counts of {0, 4, 91, 8, 0}. The rank-order binomial model would ask what single coin flip probability, π (of , say, "Heads"), would be most likely to yield 0 “no heads”, 4 “one heads”, 91 “two heads”, etc., if we performed a set of four flips, n = 103 times. For a thorough introduction to the model, including likelihoods and estimation, see Kamakura and Wedel (1995).

Thus, the *latent class rank-order binomial* model seeks out distinct classes of objects which can each be (parsimoniously) described by the same value of the parameter π. It allows for defensible statements of the sort “For the Older Chinese group, there are three classes of pictures, with the following mean specificity parameters, π”. This in turn yields concrete inferences about how many distinct picture-classes there are in each Age-by-Culture group, which pictures fall into each, and how these differ across groups. The methodology therefore affords unambiguous responses to each of the three issues raised at the outset and is, to our knowledge, the only suitable method for doing so.

All models were estimated through maximum likelihood, given raw data of the type in Table 1, including all 260 pictures. Optimization was accomplished through a constrained Newton-Raphson algorithm, with multiple start points to help rule out local optima. Convergence was quick and consistent in all cases. [Complete estimation procedures and results are available from the authors].

Although the method by no means guarantees it, each of the four Age-by-Culture groups appeared to be best fit by the same number (three) of latent classes, based on the standard fit measure, BIC.[4] Analysis could, in theory, proceed using these four separate solutions. However, this would mean that the three classes derived for each separate Age-by-Culture group would not be the same *across* groups. By way of analogy, this is similar to four universities each being asked to parcel its students into three classes based on academic achievement; there would be no guarantee that the students could be compared *across* universities, if the universities weren’t equally selective, or even if the variance in student performance differed across them (irrespective of the mean).

To allow just this type of cross-group comparison, we constrain the latent class solution – that is, the values of π and the relative sizes of the classes – to be the same across all four Age-by-Culture groups. Because this is a parametric restriction, standard likelihood-ratio tests allow a comparison of using the latent class approach on each group separately vs. constraining the solution so that they are all estimated jointly. Because we found that this restriction does *not* provide a globally inferior fit, the data can be very simply, yet appropriately, explained as consisting of three discrete classes, each with its own specificity level. In the remainder, we will for simplicity call these the "Low", "Moderate" and "High" naming specificity classes. It is important to note that this solution does not presume that the same proportions of Low, Moderate and High picture items falls into each of the four Age-by-Culture groups. We will find that this is in fact not empirically the case, by comparing class membership probabilities derived from the model.

Results

Our results support, overall, three (latent) naming specificity classes, as follows. The Low specificity class comprises 2.2% of picture items overall, with $\pi = .666$; the Moderate specificity class comprises 84.2% of items, with $\pi = .487$; and the Low specificity class comprises 13.6% of items, with $\pi = .299$. Recalling that larger values of π (on its intrinsic unit scale) reflect lower specificity, and that the specificity scale was -2 to 2, the Low, Moderate and High classes are 'centered' at 0.66, -0.05 and -0.81 on the five-point Specificity scale, respectively. Thus, the Moderate class, with 84% of the items overall, is very nearly at the scale center. This is reassuring in light of prior work which considered familiarity and frequency, though not specificity, to suggest suitable categories for cross-age and -cultural research.

Cross-Group Naming Specificity Comparisons

Table 3 lists the proportion of items in each of the three latent classes, by group, and Table 4 presents various tests regarding picture agreement among them.

Insert Table 3 about here.

It is immediately apparent that the Chinese groups are more dispersed among the three specificity classes. In fact, *none* of the pictures fell into the Low class for the either of the American groups; in interpreting this, two facts should be considered: (1) that the latent class solution arose from the conjoined data of the four groups, so that the dispersion of the Americans is intrinsically *relative* to that of the Chinese; and (2) that the latent solution fit no worse than one estimated for each of the four groups separately. Using the proportions in Table 3 as a 'base', it is possible to test whether further constraints, of the form "the proportions for group X must match those for group Y", are supported. By so doing, we can rigorously address the three issues at the outset, which we do in turn.

Differences in Response Patterns across Age-by-Culture Groups. Table 3 suggests, and non-parametric tests support, that there are no naming specificity differences between American-Old and American-Young (n.s.), nor between Chinese-Old and Chinese-Young (n.s.); and further that there *are* differences between American-Old and Chinese-Old ($p < .01$), as well as between American-Young and Chinese-Young ($p < .01$). That is, we see consistent differences across Culture (within Age), but not across Age (within Culture).

Relative Specificity across Groups. It is difficult to claim that any group uniformly demonstrates greater naming specificity than another. As per Table 3, although neither of the American groups contained any Low specificity pictures, the proportion of High specificity pictures – 7.3% for the Young and 9.6% for the Old – were far smaller than the analogous figures for the Chinese (20.8% and 21.5%, respectively). K-S tests demonstrate that cross-culture distributions are in fact strongly distinct ($p < .01$), though neither stochastically dominates the other (and, moreover, that no claims whatever can be made cross-age). We must conclude that neither Culture nor Age leads to *directional* naming specificity differences. However, naming specificity *dispersion* is far greater among the Chinese, suggesting that they perceive many more pictures as lying outside their item-specific 'basic' level than do age-matched American counterparts. We know of no precedent for this finding in the picture norms literature. Whether this is an artifact of the Western genesis of Snodgrass and Vanderwart's (1980) stimuli remains, of course, an open question.

Latent Class Picture Agreement across Groups. The suitability of a particular picture can be determined by comparing which of the three classes it fell into across any groups of interest. Table 4 lists such proportions for "All Groups", "All Americans", etc. For example, we find that, across all four Age-by-Culture groups, 66.9% (or 174 in total) of the pictures always fell into the Moderate specificity class, and another 5.4% (14) into the High; none fell into the Low across all four groups. Because the Moderate specificity class consists of those items perceived closest to their (picture-specific) 'basic' level, such picture items would be among the most broadly suitable stimuli choices. Further, we find that, for 27.7% (72) of the pictures, there is disagreement in terms of specificity (see Appendix or project site); and moreover that many of these could not be anticipated based on prior studies using measures like latency and familiarity (Yoon et al., 2004). While we must stop short of suggesting these stimuli not be used in cross-age or -culture research, any results stemming from them should be cautiously interpreted when subjects' responses are even partly verbal.

Insert Table 4 about here.

Table 4 presents similar figures for latent class agreement across the Culture or Age dimension. Of four possible comparisons, there is by far the greatest agreement across age for the American subjects; American-Old and American-Young disagree on the classification on only 3.1% (8) of the pictures. The analogous cross-age comparison for the Chinese is 9.6% (25). Fisher's exact test indicates these proportions are highly significantly different ($p < .0001$). Cross-*culture* disagreement values are far higher: 22.7% (59 pictures) for the Young, 20.4% for the Old (53 pictures); although these proportions are not significantly different from one another (n.s.), the differences between each of them and the analogous cross-age proportions are very much so (both $p < .0001$). In sum, the Snodgrass and Vanderwart (1980) stimuli are in broad within-class agreement among Americans (Young vs. Old: 96.9%), less so among Chinese (Young vs. Old: 90.4%), and much less so among the Young (Chinese vs. American: 77.3%) and Old (Chinese vs. American: 79.6%) groups.

Conclusion and Discussion

Owing to their relative neutrality compared with linguistic analogs, pictorial stimuli will continue to play a large role in studies of cross-cultural cognition. As such, it is crucial to identify ways in which standard stimuli systematically differ across various population groups, both to help verify general theories of cognition and toward the pragmatic end of selecting appropriate stimuli from the outset. Whereas prior research based stimuli comparisons on measures like name agreement, concept agreement, latency and familiarity, here we considered naming specificity, finding a distinct pattern across Age-by-Culture (Young-Old, Chinese-American) groups.

Our analysis offers several advantages over prior approaches, and was made possible by the application of latent class techniques, which we believe deserve wider currency in cross-cultural research and cognitive studies in general. Combining latent class methods with a parsimonious description of the (ordered categorical) naming specificity measure allows the naming data itself to determine several key conclusions: how many naming specificity classes are supported; which pictorial stimuli fall into each; and whether there are indeed cohort differences. On this last issue, our findings are novel: while there are no differences across Age groups (within culture), Chinese participants showed much greater *dispersion* in naming, with many more Low specificity and High specificity items than their age-matched American counterparts.

In terms of agreement across all four Age-by-Culture groups, most items (67%) were uniformly in the Moderate specificity class, 5.7% were High, and none Low. Thus, approximately 27% of the picture items differed across some pair of groups, calling into question their suitability for cross-group analyses. These findings highlight the importance of identifying subsets of pictorial stimuli that are judged suitable not only for particular research goals, but for the specific cultural or age groups being studied.

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Footnotes

[1] Norms for American children have, however, appeared in the literature for small subsets of pictures, e.g., Berman, Friedman, Hamberger, & Snodgrass (1989); Cycowicz, Friedman, Rothstein, & Snodgrass (1997).

[2] Whereas a few researchers have collected picture norms on young adult samples in East Asia, access is hampered by publication only in their native languages (Matsukawa, 1983; Seo, 1988; Su, Cheng, & Zhang, 1989). We thank Joan Gay Snodgrass for bringing these studies to our attention.

[3] We extend special thanks to Yao Cui of the Institute of Psychology at the Chinese Academy of Sciences for his linguistic expertise.

[4] The optimal number of classes is determined by the standard fit measure BIC (Bayesian Information Criterion). See Kass and Raftery (1995) for additional detail.

[5] From Snodgrass, J. G. & Vanderwart, M. (1980), A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity, Journal of Experimental Psychology: Human Learning and Memory, 6, 174-215. Copyright © 1980 by the American Psychological Association. Reprinted with permission. Distribution rights for the picture stimuli are owned by Life Science Associates (LSA). For further information, contact LSA at 1 Fenimore Road, Bayport, NY 11705-2115. Phone: 631-472-2111. Fax: 631-472-8146. Email: Lifesciassoc@pipeline.com. http://lifesciassoc.home.pipeline.com.

Table 1

Age, Education and Health Characteristics for Americans and Chinese, by Age Groups

Culture	Age Group		Age (number of years)		Education (number of years)		Self-rated health status	
		n	M	SD	M	SD	M	SD
American	Younger	113	18.77	1.05	13.07	0.75	3.62	0.72
	Older	103	66.47	4.24	15.88	2.52	3.86	0.91
Chinese	Younger	100	20.09	1.04	14.01	0.75	3.31_a	0.73
	Older	100	64.68	3.38	16.73	1.35	3.24_a	0.67

Note. Health status was assessed on a 5-point scale (1 = much worse than average, 2 = worse than average, 3 = average, 4 = better than average, 5 = much better than average). Means in the same column that do not share subscripts differ at $p < .05$.

Table 2

Specificity Distributions by Age-by-Culture Group

Group		Valid Responses	Specificity				
Culture	Age		Very High	High	Moderate	Low	Very Low
American	Young	113	0	3	110	0	0
American	Old	103	0	4	91	8	0
Chinese	Young	100	0	9	78	3	10
Chinese	Old	96	3	22	66	0	5

Table 3

Latent Class Naming Specificity Proportions across Age-by-Culture Groups

Specificity	American Young	American Old	Chinese Young	Chinese Old
Low	0.0%	0.0%	5.4%	6.5%
Moderate	92.7%	90.4%	73.8%	71.9%
High	7.3%	9.6%	20.8%	21.5%

Table 4

Latent Class Picture Norm Agreement Proportions across Age-by-Culture Groups

Latent Class \\ Group	All Groups	American	Chinese	Young	Old
All Low (1)	0.0%	0.0%	4.6%	0.0%	0.0%
All Moderate (2)	66.9%	90.0%	68.1%	71.9%	71.2%
All High (3)	5.4%	6.9%	17.7%	5.4%	8.5%
% Disagreeing Somewhere (# of 260)	27.7% (72)	3.1% (8)	9.6% (25)	22.7% (59)	20.4% (53)
p-value *		< 0.0001		> 0.1	

* p-value calculated from exact sampling distribution

Appendices

[NOTE: The authors understand these may not be accommodated in a published article, due to space restrictions, and that they might be made available on-line only.]

Appendix A

TABLE A1:
Naming Specificity Classes for each Age-by-Culture Group (1 = Low, 2 = Moderate, 3 = High)

TABLE A2:
Agreement across All Four Age-by-Culture Groups

Appendix B

260 pictures with Snodgrass and Vanderwart's (1980) concept name and identifying number[5]

TABLE A1

Naming Specificity Classes for each Age-by-Culture Group (1 = Low, 2 = Moderate, 3 = High)

Cat. #	Item	Amer. Young	Amer. Old	Chin. Young	Chin. Old	Cat. #	Item	Amer. Young	Amer. Old	Chin. Young	Chin. Old
1	accordion	2	2	2	2	46	cap	2	2	1	1
2	airplane	2	2	2	2	47	car	2	2	2	2
3	alligator	2	2	2	2	48	carrot	2	2	1	1
4	anchor	2	2	2	2	49	cat	2	2	2	2
5	ant	2	2	2	2	50	caterpillar	2	2	1	1
6	apple	2	2	2	2	51	celery	2	2	2	1
7	arm	2	2	2	2	52	chain	2	2	3	2
8	arrow	2	2	2	2	53	chair	2	2	2	2
9	artichoke	2	2	3	3	54	cherry	2	2	2	2
10	ashtray	2	2	2	2	55	chicken	2	2	3	3
11	asparagus	2	2	3	3	56	chisel	2	2	2	2
12	axe	2	2	2	2	57	church	2	2	1	1
13	baby carriage	2	3	3	3	58	cigar	2	2	2	2
14	ball	2	2	3	2	59	cigarette	2	2	2	2
15	balloon	2	2	2	2	60	clock	2	2	2	2
16	banana	2	2	2	2	61	clothespin	2	2	1	1
17	barn	2	2	2	2	62	cloud	2	2	2	2
18	barrel	2	2	3	3	63	clown	2	2	2	2
19	baseball bat	2	3	3	3	64	coat	2	2	2	2
20	basket	2	2	2	3	65	comb	2	2	2	2
21	bear	2	2	2	2	66	corn	2	2	2	2
22	bed	2	2	2	2	67	couch	2	2	2	2
23	bee	2	2	3	2	68	cow	2	2	3	3
24	beetle	2	2	2	2	69	crown	2	2	2	2
25	bell	2	2	2	2	70	cup	2	2	2	2
26	belt	2	2	3	3	71	deer	2	2	2	2
27	bicycle	2	2	2	2	72	desk	2	2	3	3
28	bird	2	2	3	3	73	dog	2	2	2	2
29	blouse	2	3	1	1	74	doll	2	2	3	3
30	book	2	2	2	2	75	donkey	2	2	2	2
31	boot	2	2	2	2	76	door	2	2	2	2
32	bottle	2	2	3	2	77	doorknob	3	3	3	3
33	bow	2	2	2	3	78	dress	2	2	1	2
34	bowl	2	2	2	2	79	dresser	2	2	3	3
35	box	2	2	2	3	80	drum	2	2	2	2
36	bread	2	2	2	2	81	duck	2	2	2	2
37	broom	2	2	2	2	82	eagle	2	2	2	2
38	brush	2	2	2	2	83	ear	2	2	2	2
39	bus	2	2	2	2	84	elephant	2	2	2	2
40	butterfly	2	2	2	2	85	envelope	2	2	2	2
41	button	2	2	2	2	86	eye	2	2	2	2
42	cake	2	2	2	2	87	fence	2	2	2	2
43	camel	2	2	2	2	88	finger	2	2	3	3
44	candle	2	2	3	3	89	fish	2	2	2	2
45	cannon	2	2	3	3	90	flag	2	2	2	2

TABLE A1 (continued)

Naming Specificity Classes for each Age-by-Culture Group (1 = Low, 2 = Moderate, 3 = High)

Cat. #	Item	Amer. Young	Amer. Old	Chin. Young	Chin. Old	Cat. #	Item	Amer. Young	Amer. Old	Chin. Young	Chin. Old
91	flower	2	2	2	2	136	leopard	2	2	2	2
92	flute	2	2	2	2	137	lettuce	2	2	2	2
93	fly	2	2	2	2	138	light bulb	3	3	3	3
94	foot	2	2	2	2	139	light switch	3	3	2	3
95	football	3	3	3	3	140	lion	2	2	2	2
96	football helmet	3	2	2	2	141	lips	2	2	2	2
97	fork	2	2	1	1	142	lobster	2	2	1	1
98	fox	2	2	2	2	143	lock	2	2	2	2
99	french horn	2	2	2	1	144	mitten	3	3	2	2
100	frog	2	2	2	2	145	monkey	2	2	2	2
101	frying pan	2	3	3	3	146	moon	2	2	2	2
102	garbage can	3	3	3	3	147	motorcycle	2	2	2	2
103	giraffe	2	2	2	2	148	mountain	2	2	2	3
104	glass	2	2	1	2	149	mouse	2	2	2	2
105	glasses	2	2	3	3	150	mushroom	2	2	2	2
106	glove	2	2	2	2	151	nail	2	2	2	2
107	goat	2	2	2	1	152	nail file	3	3	2	3
108	gorilla	2	2	2	2	153	necklace	2	2	2	2
109	grapes	2	2	2	2	154	needle	2	2	2	2
110	grasshopper	2	2	2	2	155	nose	2	2	2	2
111	guitar	2	2	2	2	156	nut	2	2	2	2
112	gun	2	3	3	3	157	onion	2	2	2	2
113	hair	2	2	2	2	158	orange	2	2	2	2
114	hammer	2	2	2	2	159	ostrich	2	2	2	2
115	hand	2	2	2	2	160	owl	2	2	2	2
116	hanger	2	2	3	3	161	paintbrush	2	2	2	2
117	harp	2	2	2	1	162	pants	2	2	2	2
118	hat	2	2	2	2	163	peach	2	2	2	2
119	heart	2	2	3	2	164	peacock	2	2	2	2
120	helicopter	2	2	2	2	165	peanut	2	2	2	2
121	horse	2	2	2	2	166	pear	2	2	2	2
122	house	2	2	1	1	167	pen	2	2	2	2
123	iron	2	2	2	3	168	pencil	2	2	2	2
124	ironing board	3	3	3	3	169	penguin	2	2	2	2
125	jacket	2	2	2	2	170	pepper	2	2	2	3
126	kangaroo	2	2	2	2	171	piano	2	2	2	2
127	kettle	3	3	3	3	172	pig	2	2	2	2
128	key	2	2	2	2	173	pineapple	2	2	2	2
129	kite	2	2	2	2	174	pipe	2	2	2	2
130	knife	2	2	2	3	175	pitcher	2	2	3	3
131	ladder	2	2	2	2	176	pliers	2	2	2	2
132	lamp	2	2	3	3	177	plug	2	2	3	2
133	leaf	2	2	2	2	178	pocketbook	2	2	2	2
134	leg	2	2	2	2	179	pot	2	2	2	2
135	lemon	2	2	2	2	180	potato	2	2	3	3

TABLE A1 (continued)

Naming Specificity Classes for each Age-by-Culture Group (1 = Low, 2 = Moderate, 3 = High)

Cat. #	Item	Amer. Young	Amer. Old	Chin. Young	Chin. Old	Cat. #	Item	Amer. Young	Amer. Old	Chin. Young	Chin. Old
181	pumpkin	2	2	2	2	226	table	2	2	2	2
182	rabbit	2	2	2	2	227	telephone	2	2	2	2
183	raccoon	2	2	2	2	228	television	2	2	2	2
184	record player	2	2	2	2	229	tennis racket	3	3	3	3
185	refrigerator	2	2	2	2	230	thimble	2	2	3	2
186	rhinoceros	2	2	2	2	231	thumb	2	2	3	3
187	ring	3	3	3	3	232	tie	2	2	2	2
188	rocking chair	3	3	2	2	233	tiger	2	2	2	2
189	roller skate	2	2	1	1	234	toaster	2	2	2	2
190	rolling pin	2	2	2	2	235	toe	2	2	2	2
191	rooster	3	3	3	3	236	tomato	2	2	2	2
192	ruler	2	2	2	2	237	toothbrush	2	2	2	2
193	sailboat	3	3	3	3	238	top	2	2	2	2
194	salt shaker	3	3	3	3	239	traffic light	3	3	3	3
195	sandwich	2	2	2	2	240	train	2	2	2	2
196	saw	2	2	2	3	241	tree	2	2	2	2
197	scissors	2	2	2	2	242	truck	2	2	2	2
198	screw	2	2	2	2	243	trumpet	2	2	1	1
199	screwdriver	2	2	2	2	244	turtle	2	2	2	2
200	seahorse	2	2	2	2	245	umbrella	2	2	3	2
201	seal	2	2	2	2	246	vase	2	2	3	3
202	sheep	2	2	2	1	247	vest	2	2	2	2
203	shirt	2	2	2	2	248	violin	2	2	2	2
204	shoe	2	2	3	3	249	wagon	2	2	2	2
205	skirt	2	2	1	1	250	watch	2	3	3	3
206	skunk	2	2	2	2	251	watering can	3	3	3	3
207	sled	2	2	3	3	252	watermelon	2	2	2	2
208	snail	2	2	2	2	253	well	2	2	3	3
209	snake	2	2	2	2	254	wheel	2	2	3	3
210	snowman	2	2	2	2	255	whistle	2	2	2	2
211	sock	2	2	2	2	256	windmill	2	2	2	2
212	spider	2	2	2	2	257	window	2	2	2	2
213	spinning wheel	2	2	2	2	258	wineglass	3	3	3	3
214	spool of thread	2	3	3	3	259	wrench	2	2	2	2
215	spoon	2	2	2	2	260	zebra	2	2	2	2
216	squirrel	2	2	2	2						
217	star	2	2	3	3						
218	stool	2	2	2	2						
219	stove	2	2	2	2						
220	strawberry	2	2	2	2						
221	suitcase	2	2	3	3						
222	sun	2	2	2	2						
223	swan	2	2	2	2						
224	sweater	2	2	2	2						
225	swing	2	2	2	2						

Table A2: Agreement across All Four Age-by-Culture Groups

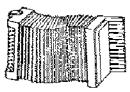
Moderate Specificity: (1) accordion, (2) airplane, (3) alligator, (4) anchor, (5) ant, (6) apple, (7) arm, (8) arrow, (10) ashtray, (12) axe, (15) balloon, (16) banana, (17) barn, (21) bear, (22) bed, (24) beetle, (25) bell, (27) bicycle, (30) book, (31) boot, (34) bowl, (36) bread, (37) broom, (38) brush, (39) bus, (40) butterfly, (41) button, (42) cake, (43) camel, (47) car, (49) cat, (53) chair, (54) cherry, (56) chisel, (58) cigar, (59) cigarette, (60) clock, (62) cloud, (63) clown, (64) coat, (65) comb, (66) corn, (67) couch, (69) crown, (70) cup, (71) deer, (73) dog, (75) donkey, (76) door, (80) drum, (81) duck, (82) eagle, (83) ear, (84) elephant, (85) envelope, (86) eye, (87) fence, (89) fish, (90) flag, (91) flower, (92) flute, (93) fly, (94) foot, (98) fox, (100) frog, (103) giraffe, (106) glove, (108) gorilla, (109) grapes, (110) grasshopper, (111) guitar, (113) hair, (114) hammer, (115) hand, (118) hat, (120) helicopter, (121) horse, (125) jacket, (126) kangaroo, (128) key, (129) kite, (131) ladder, (133) leaf, (134) leg, (135) lemon, (136) leopard, (137) lettuce, (140) lion, (141) lips, (143) lock, (145) monkey, (146) moon, (147) motorcycle, (149) mouse, (150) mushroom, (151) nail, (153) necklace, (154) needle, (155) nose, (156) nut, (157) onion, (158) orange, (159) ostrich, (160) owl, (161) paintbrush, (162) pants, (163) peach, (164) peacock, (165) peanut, (166) pear, (167) pen, (168) pencil, (169) penguin, (171) piano, (172) pig, (173) pineapple, (174) pipe, (176) pliers, (178) pocketbook, (179) pot, (181) pumpkin, (182) rabbit, (183) raccoon, (184) record player, (185) refrigerator, (186) rhinoceros, (190) rolling pin, (192) ruler, (195) sandwich, (197) scissors, (198) screw, (199) screwdriver, (200) seahorse, (201) seal, (203) shirt, (206) skunk, (208) snail, (209) snake, (210) snowman, (211) sock, (212) spider, (213) spinning wheel, (215) spoon, (216) squirrel, (218) stool, (219) stove, (220) strawberry, (222) sun, (223) swan, (224) sweater, (225) swing, (226) table, (227) telephone, (228) television, (232) tie, (233) tiger, (234) toaster, (235) toe, (236) tomato, (237) toothbrush, (238) top, (240) train, (241) tree, (242) truck, (244) turtle, (247) vest, (248) violin, (249) wagon, (252) watermelon, (255) whistle, (256) windmill, (257) window, (259) wrench, (260) zebra

High Specificity: (77) doorknob, (95) football, (102) garbage can, (124) ironing board, (127) kettle, (138) light bulb, (188) ring, (191) rooster, (193) sailboat, (194) salt shaker, (229) tennis racket, (239) traffic light, (251) watering can, (258) wineglass

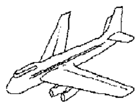
Appendix B

260 pictures with Snodgrass and Vanderwart's (1980) concept name and identifying number [5]

1. accordion

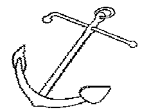


2. airplane



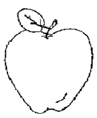
3. alligator

4 anchor



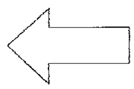
5. ant

6. apple

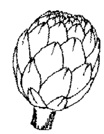


7. arm

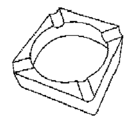
8. arrow



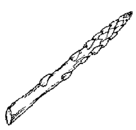
9. artichoke



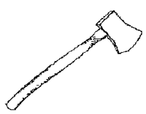
10. ashtray



11. asparagus

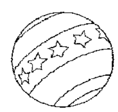


12. axe

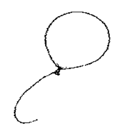


13. baby carriage

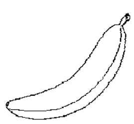
14. ball



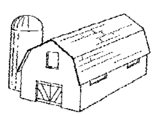
15. balloon



16. banana

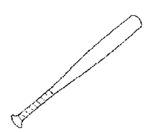


17. barn

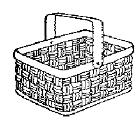


18. barrel

19. baseball bat

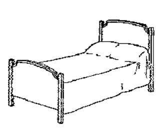


20. basket

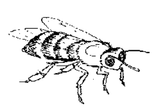


21. bear

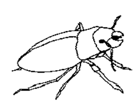
22. bed



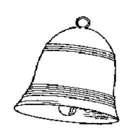
23. bee

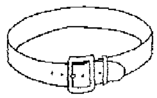


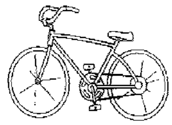
24. beetle

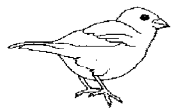


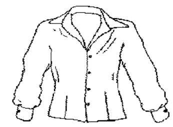
25. bell

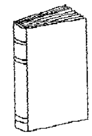


26. belt


27. bicycle


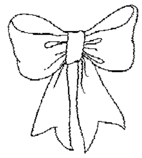
28. bird


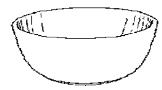
29. blouse


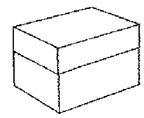
30. book


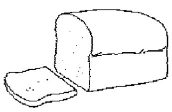
31. boot

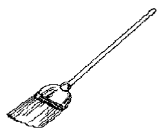

32. bottle

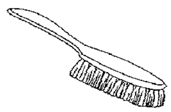

33. bow


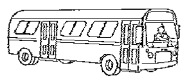
34. bowl


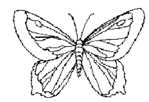
35. box


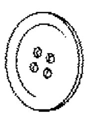
36. bread


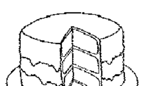
37. broom


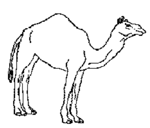
38. brush


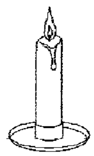
39. bus


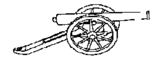
40. butterfly


41. button


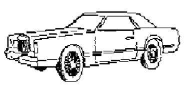
42. cake


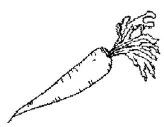
43. camel


44. candle


45. cannon


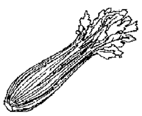
46. cap


47. car


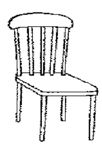
48. carrot


49. cat

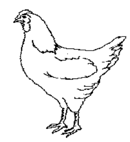

50. caterpillar

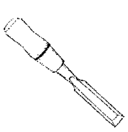

51. celery


52. chain

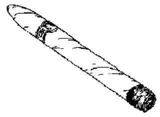

53. chair


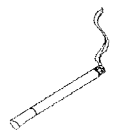
54. cherry

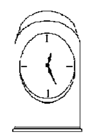

55. chicken


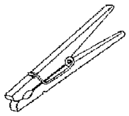
56. chisel


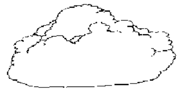
57. church

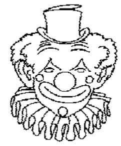

58. cigar


59. cigarette


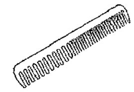
60. clock


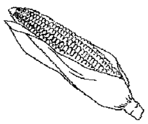
61. clothespin


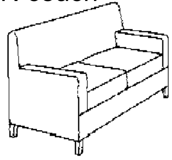
62. cloud


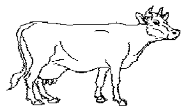
63. clown


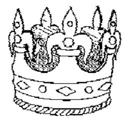
64. coat


65. comb


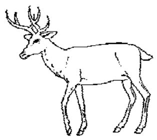
66. corn


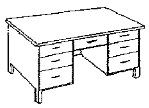
67. couch


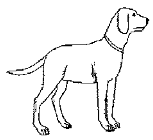
68. cow


69. crown


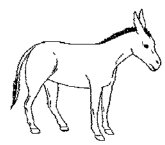
70. cup

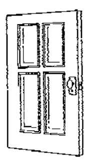

71. deer


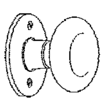
72. desk


73. dog


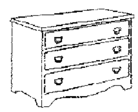
74. doll

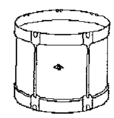

75. donkey


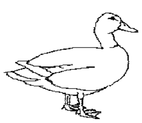
76. door


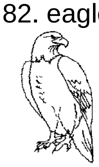
77. doorknob


78. dress

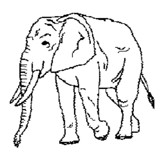

79. dresser


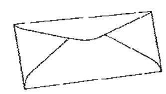
80. drum


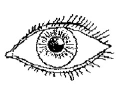
81. duck


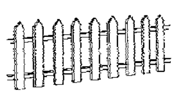
82. eagle


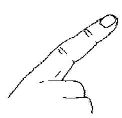
83. ear

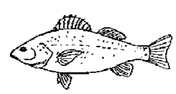

84. elephant


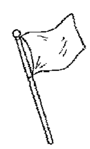
85. envelope


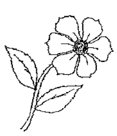
86. eye


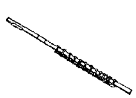
87. fence


88. finger


89. fish


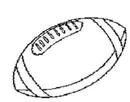
90. flag


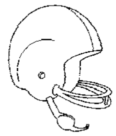
91. flower


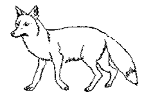
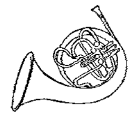
92. flute


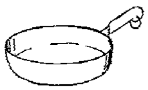
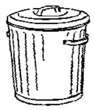
93. fly


94. foot


95. football


96. football helmet

97. fork

98. fox

99. French horn

100. frog


101. frying pan

102. garbage can

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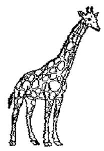
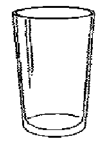
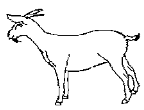
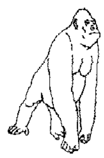
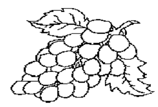

104. glass

105. glasses


106. glove

107. goat

108. gorilla

109. grapes

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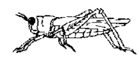
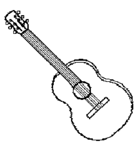
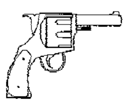
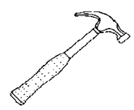
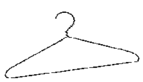
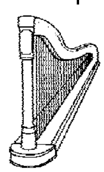
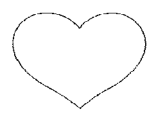
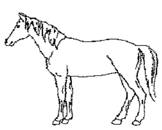
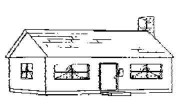
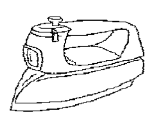
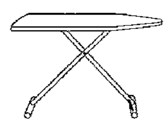


111. guitar

112. gun

113. hair

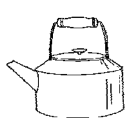
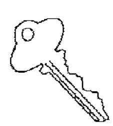
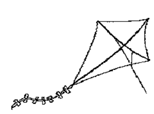
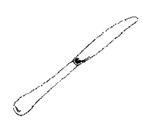
114. hammer

115. hand

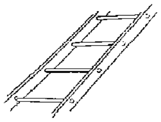

116. hanger

117. harp

118. hat

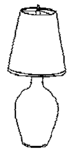
119. heart

120. helicopter


121. horse

122. house

123. iron

124. ironing board

125. jacket

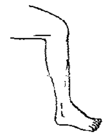

126. kangaroo

127. kettle

128. key

129. kite

130. knife


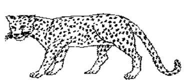
131. ladder


132. lamp


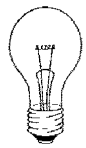
133. leaf

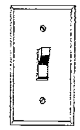

134. leg


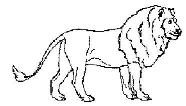
135. lemon

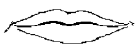

136. leopard


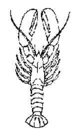
137. lettuce


138. light bulb


139. light switch


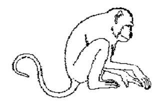
140. lion


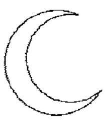
141. lips


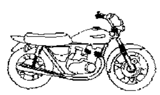
142. lobster


143. lock


144. mitten


145. monkey


146. moon


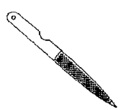
147. motorcycle


148. mountain


149. mouse


150. mushroom

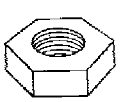

151. nail


152. nail file


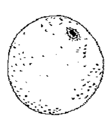
153. necklace

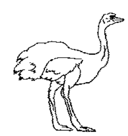

154. needle


155. nose

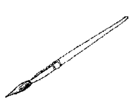

156. nut


157. onion

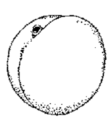

158. orange


159. ostrich


160. owl

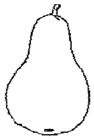

161. paintbrush


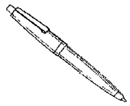
162. pants

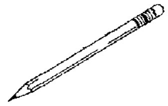

163. peach


164. peacock

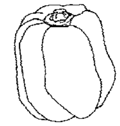

165. peanut


166. pear


167. pen


168. pencil


169. penguin


170. pepper


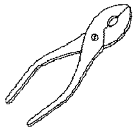
171. piano

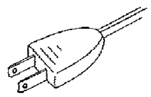

172. pig

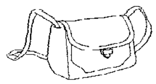

173. pineapple

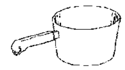

174. pipe


175. pitcher

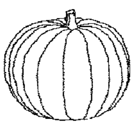

176. pliers


177. plug


178. pocketbook


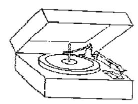
179. pot


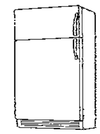
180. potato

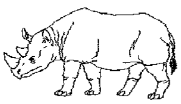

181. pumpkin


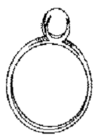
182. rabbit

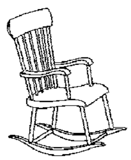

183. raccoon

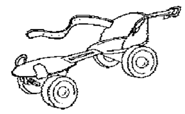

184. record player


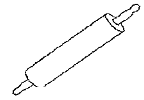
185. refrigerator


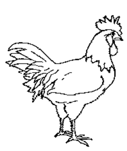
186. rhinoceros


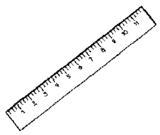
187. ring


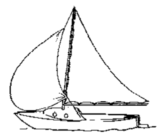
188 .rocking chair


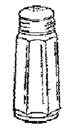
189. roller skate


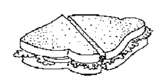
190. rolling pin


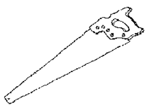
191. rooster


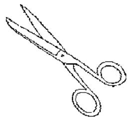
192. ruler


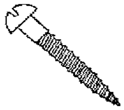
193. sailboat


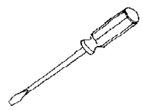
194. salt shaker


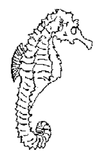
195. sandwich


196. saw


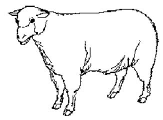
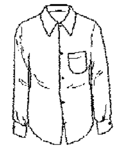
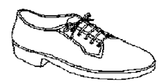
197. scissors


198. screw


199. screwdriver


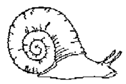
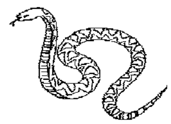
200. seahorse


201. seal

202. sheep

203. shirt

204. shoe

205. skirt

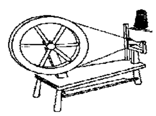
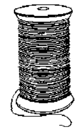

206. skunk

207. sled

208. snail

209. snake

210. snowman

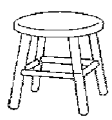
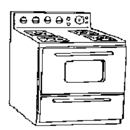
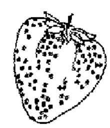

211. sock

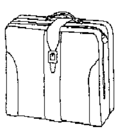
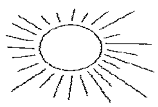
212. spider

213. spinning wheel

214. spool of thread

215. spoon


216. squirrel

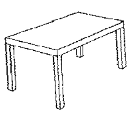
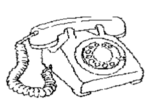
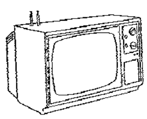
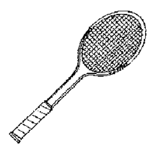
217. star

218. stool

219. stove

220. strawberry


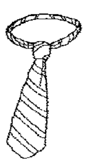
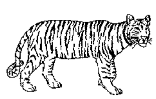
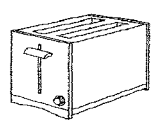
221. suitcase

222. sun

223. swan

224. sweater

225. swing

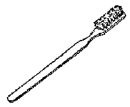

226. table

227. telephone

228. television

229. tennis racket

230. thimble


231. thumb

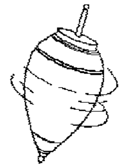
232. tie

233. tiger

234. toaster

235. toe


236. tomato

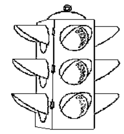
237. toothbrush



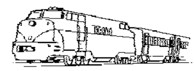
238. top



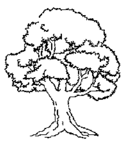
239. traffic light



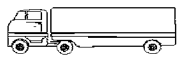
240. train



241. tree

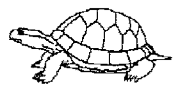


242. truck



243. trumpet

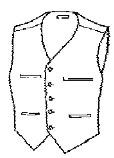
244. turtle



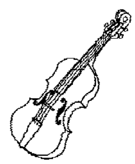
245. umbrella

246. vase

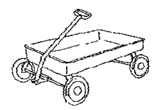
247. vest



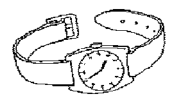
248. violin



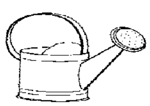
249. wagon



250. watch

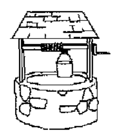


251. watering can

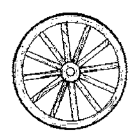


252. watermelon

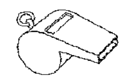
253. well



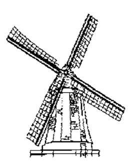
254. wheel



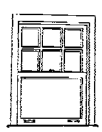
255. whistle



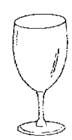
256. windmill



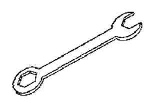
257. window



258. wineglass



259. wrench



260. zebra