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FEATURE ARTICLE

Objective Visual Complexity as a Variable in Studies of Picture Naming

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Objective Visual Complexity as a Variable in Studies of Picture Naming*

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Abstract

Visual complexity is an important variable for studies working with picture stimuli, including picture naming. Traditionally, subjective ratings by 20-30 subjects have been used for this purpose, an approach that may be influenced by perceptual and cognitive variables (e.g., familiarity with the object) that are not directly related to visual complexity. The present study offers an objective and easy way of measuring visual complexity by taking the file size of picture stimuli material (black-and-white, simple line drawings) as the basis. Over 30 different file types and degrees of compression were compared for 520 object pictures, and analyzed to determine whether these measures differ in their influence on picture-naming behavior. Results suggest that PDF, TIFF and JPG formats may provide valid indices of objective visual complexity. The effect of these objective measures on picture naming were compared with published subjective visual complexity data from an English and a Hungarian study on overlapping items. Comparative analysis with other picture-naming variables shows that these objective measures - unlike subjective ratings - have no effect on RT, are unrelated to word frequency or age of acquisition, and show a more modest word length effect on the dominant response. However, they do affect picture-naming accuracy (production of the target name), an effect not reported in previous studies using subjective ratings of visual complexity. Subjective and objective complexity measures are both useful, and they are correlated, but they also differ in potentially important ways.

Introduction

Timed picture naming has been used for many years as a tool for determining how easily a mental representation (e.g., an object name) can be retrieved from memory (e.g., Forster and Chambers, 1973; Humphreys, et al. 1988; Jescheniak and Levelt, 1994; Oldfield and Wingfield, 1965; Preston, 1935; Thorndike, 1931). Properties of both the picture and its associated name are known to have an influence on this process. One of the factors that could influence both accuracy and latency in picture naming is visual complexity. Visual processing is a necessary step in the naming of a line-drawn picture, including low-level processes that are (at least in principle) prior to and partially independent of higher processes like object or scene recognition, and retrieval of one or more names for that object or scene. Does the sheer complexity of the visual display influence the first stages of decoding? And if so, does this complexity effect percolate through the system to influence the naming process? To answer these questions, it would be useful to have objective measures of visual complexity that are not influenced by the higher stages of object recognition and name retrieval. However, to date most studies of picture naming have relied on subjective (human) ratings of complexity that may reflect a mixture of ’bottom up effects’ (characteristics of the visual display) and ’top down effects’ (characteristics of the object and/or characteristics of the name that the picture evokes). The purpose of this paper is to introduce some simple measures of objective visual complexity that are derived automatically from digitized images, and compare the effects of objective complexity with the effects of subjective complexity ratings on performance in a timed picture-naming task.

Technical development of naming studies

Developing standardized sets of stimuli has been a major goal of cognitive research in the last decade. In 1980, Snodgrass and Vanderwart introduced a 260-picture set standardized for the English language (Snodgrass and Vanderwart, 1980). They derived several dependent variables, including the dominant response (the name given by the largest number of participants) and the number and frequency of alternative names. Having determined the dominant response for each picture, they also calculated several independent variables based on these names, including their frequency, length, and subjective ratings of familiarity, age of acquisition and imageability. Pictures were also rated subjectively for their visual complexity (VC). Naming latencies were established later for this corpus (Snodgrass and Yuditsky, 1996). Most of the picture-naming studies of the 1990's have used this set with or without additional items (e.g., Barry et al., 1997; Cycowicz et al., 1997; Morrison et al., 1997; Morrison et al., 1992; Sanfeliu and Fernandez, 1996). By using the same normative stimulus material, more precise comparison of results and theoretical accounts became possible.

Predictors of naming latency

A number of word and picture characteristics have been shown to have an influence on both accuracy and reaction time in picture-naming tasks. For example, since the first timed picture-naming studies, an inverse relationship between response times and written or spoken word frequencies has been shown (e.g., Forster and Chambers, 1973; Humphreys et al. 1988; Jescheniak and Levelt, 1994; Oldfield and Wingfield, 1965; Preston, 1935; Thorndike, 1931). However, the importance of frequency was challenged in the 1970's by studies suggesting that age of acquisition (adult subjects' estimates of the age at which the name was learned) is the critical factor in predicting naming latency (Barry et al., 1997; Carroll and White, 1973a,b; Gilhooly and Gilhooly, 1979; Morrison et al., 1992; Rochford and Williams, 1962), absorbing all of the variance usually attributed to word frequency. This discovery initiated a lively debate about the factors that are responsible for variations (over items) in naming latency.

When searching for the critical factors that influence retrieval of a picture name, it is of vital importance to eliminate confounding factors that may also have a significant effect on accuracy and/or reaction time. One of these potential confounds is picture complexity, the focus of the present study. To explore the contribution of visual complexity to picture naming, Snodgrass and Vanderwart (1980) used *subjective* ratings, based on a 5-point scale from very simple to very complex. Most studies since that time have adopted their method (Cycowicz et al., 1997; Sanfeliu and Fernandez 1996) or their original ratings (Morrison et al., 1997; Snodgrass and Yuditsky, 1996). In the latter part of this paper we will present findings of subjective visual complexity from two of the above studies (Sanfeliu and Fernandez 1996; Snodgrass and Vanderwart, 1980), and compare these findings with the objective VC measure proposed here. Wang (1997) used both subjective and objective visual complexity measures for evaluation of perceptual and semantic characteristics of 132 pictures (partly redrawn from the Snodgrass and Vanderwart set) in a Chinese naming study. Objective visual complexity was based on the number of geons (as defined by Biederman, 1987) needed to compose the figure. Her findings indicate that objective and subjective visual complexity are closely related, at $r = +0.66$ ($p < 0.03$). Wang's result serves as a cross-validation of these two methods for assessment of visual complexity. However, it also means that objective and subjective complexity measures share less than 44% of their variance, and might have differential effects on the naming process.

Intercorrelations of subjective visual complexity, and other variables

Reaction time

So far, most studies of picture naming in adults have reported no effects of rated visual complexity on naming latency (Barry et al., 1997; Snodgrass and Yuditsky, 1996). Cycowicz et al. (1997) did find a significant effect of picture complexity on naming times in a sample of children ($r = +0.27$, $p < .05$). Note, however, that they also used the same subjects to obtain both complexity ratings and naming latencies, a decision that might have enhanced the correlation.

D'Amico, Devescovi and Bates (2000) used an objective estimate of visual complexity (based on the work we are about to outline here, for a subset of 230 pictures out of the full set of 520 object pictures), and examined its effect on both accuracy and latency in picture naming by Italian-speaking adults and by 5-6-year-olds. They report significant effects of visual complexity on naming latencies for both children and adults after a host of other factors were controlled (e.g., frequency, length, subjective and objective measures of age of acquisition), indicating that reaction times were slower for more complex items.

Word length, frequency age of acquisition and familiarity

In studies of picture naming in English-speaking adults, subjective ratings of picture complexity are confounded with several other independent variables, including a positive correlation with length of the dominant name for the picture (Barry et al., 1997; Ellis et al., 1998; Morrison et al., 1997; Snodgrass and Yuditsky, 1996), especially when length is measured in syllables rather than orthographic characters. In addition, complexity ratings tend to be negatively correlated with frequency, and positively correlated with rated age of acquisition. However, these correlations did not replicate in naming studies with English-speaking children (Cycowicz et al., 1997) or with Spanish-speaking adults (Sanfeliu and Fernandez, 1996).

Subjective complexity is also related to subjective ratings of familiarity. Snodgrass and Vanderwart reported a significant negative correlation ($r = -0.466$) between complexity and familiarity ratings. Similar effects have been reported in other naming studies (Barry et al., 1997; Cycowicz et al., 1997; Ellis et al., 1998; Morrison et al., 1997; Sanfeliu and Fernandez 1996; Snodgrass and Yuditsky, 1996).

Name agreement

In most picture-naming studies, the dominant name (or target name) is defined empirically, as the name given by the largest number of subjects in a given study. The ratio of subjects responding with the dominant name is referred to as “percent name agreement”. Another traditional way of measuring name agreement is the H statistic, which takes into consideration the proportion of subjects producing each alternative. An increasing H value indicates decreasing name agreement, where 0 refers to perfect name agreement.

According to Snodgrass and Vanderwart (1980), *complex pictures tend to elicit more alternative names*: Specifically, they found a small but significant *positive* correlation ($r = +.13$) between subjective ratings of visual complexity and name agreement (measured by the H statistic) based on their 260-picture set. Other studies have not replicated this result, reporting no significant correlation between percent name agreement and subjective visual (Barry et al., 1997; Ellis et al., 1998; Morrison et al., 1997; Sanfeliu and Fernandez 1996; Snodgrass and Yuditsky, 1996).

However, picture naming by English-speaking children replicated the 1980 finding for adults: Cycowicz et al. found visual complexity to be inversely correlated with percent name agreement ($r = -0.242$, $p < 0.01$) and positively with H value ($r = +.206$, $p < 0.01$).

Snodgrass and Yuditsky introduced a new measure of name agreement, referred to as concept agreement (1996), to measure the degree to which subjects agreed on the *meaning* of the pictures. They computed the percentage of subjects giving the same name as the dominant name, or a synonym. They reported visual complexity to have a significant effect on percent concept agreement ($r = -0.17$), indicating again that complex pictures tend to be named with more alternatives, including words with a different meaning (nonsynonyms).

Objective VC and other variables

Based on her naming study in Mandarin Chinese, Wang (1997) reported percent name agreement to be negatively correlated with objective VC measured in geons at $r = -0.36$ ($p < 0.01$). This correlation is somewhat higher than the English child results for subjective complexity (Cycowicz et al.). According to Wang, objectively complex items tend to be less familiar than simpler ones, but the correlation of rated familiarity with objective complexity is modest ($r = +0.11$, $p < .22$), compared with reports by other investigators for familiarity and subjective complexity. Wang reports no significant relation of objective VC and naming accuracy.

General coding and compression techniques of still images

We should not be surprised to find that subjective ratings of visual complexity are correlated with factors like age of acquisition, length and frequency of the associated target or dominant name. Indeed, it is quite possible that human raters are unable to suppress picture names (with all their associated characteristics) while they are employed in the task of evaluating picture complexity. For this reason, it would be useful to obtain an objective measure of visual complexity that is not contaminated by these characteristics. In pursuit of this goal, we have compared several different candidates from standard digital file formats for graphic material, applied to the scanned black-and-white drawings used in our own picture-naming study (including a large subset of the original Snodgrass materials).

Different file formats use a wide variety of coding techniques to capture still images, from vector-based coding (e.g., PDF) to methods that divide the image into tiny blocks of color and luminance information (e.g., JPG). The most conventional method of digital representation of an image is in terms of a rectangular array of pixels, each representing the intensity of the image at a certain point (Watson,1993). However, from a mathematical point of view, this array is merely a collection of numbers that may be transformed in various ways that preserve information. The selection of a particular representational scheme is partly based on the feature of efficiency in terms of the number of bits required to represent a particular image. The term "compression" is used for a procedure that results in a form that requires fewer bits. If the transformation is invertible, then the compression is said to be lossless. However, these techniques usually provide only modest amounts of compression. Further reduction of the size of the image files is made possible by the so-called "lossy" techniques, which are not invertible. They are particularly useful because the human eye is insensitive to certain elements of images, thus the loss of some specific image information can be tolerated. The general procedure of the lossy compression of images comprises several complex mathematical operations. These operations include color space conversion, as a first step, by which the image is converted to a color space with separate luminance and chrominance channels. Since the human eye is more sensitive to the luminance information, chrominance is compressed to a higher degree. Some further steps of file compression (in the case of JPEG technique, for example) include quantization, by which some information that is not of vital importance to the visual system is discarded (Woehrmann et al., 1994). Because these compression formats were designed with human vision in mind, they are potentially more powerful candidates for the assessment of visual complexity effects on naming that we might obtain with a simple pixel count. At the same time, they have an advantage over the geon approach, because they can be computed automatically.

Method

Picture-naming results and characteristics of the dominant picture names were taken for the full set of 520 object pictures used in the Center for Research in Language International Picture Norming Project (CRL-IPNP), described in a previous *CRL Newsletter* article (Bates et al., 2000). Digitized images for all 520 pictures were used to calculate the objective visual complexity scores, using image file size metrics (described in detail below). Reaction times, word length and name agreement data were obtained from the CRL-IPNP data base for two languages, English and Hungarian, based on results for 50 college-age subjects in each language. Statistical routines were administered with the use of MiniStat (Vargha and Czigler, 1999), applications described in Vargha (2000). Regression analysis was carried out with SPSS, version 8.0.

Calculating objective visual complexity

The black-and-white simple line drawings were scanned and saved as (300 x 300 pixel) Macintosh PICT file format, each in a separate file. A demo version of the handmade software utility Image Alchemy 1.8 (Woehrmann et al., 1994) was used to convert the stimuli to various graphics file formats. Over 30 different file types and degrees of compression for the 520 object and 275 action pictures were computed, and 7 commonly used formats were selected according to their relation to subjective visual complexity and other variables. They are described in Table 1, specifying the type of compression, and exact syntax used in the conversion procedure.

TABLE 1

Image file formats suitable for measuring objective visual complexity

	File type description	***Compression type***	***Syntax***
ObjVCpdf	Adobe Portable Document (PDF) by Adobe Acrobat	LZW	--d2
ObjVCtiff	Tagged Interchange (universal raster image) File Format	LZW	-t1
ObjVCjpg	Joint Photographic Experts Group (JPEG) (with default Huffman coding, and high quality - low degree of compression)	High quality = 98 (on a scale from 1-100)	-j98
ObjVCgif	GIF files, by CompuServe (independent image file format)	Version: GIF87A	-g0
ObjVCwpg	WordPerfect Graphic file format	None	-W
ObjVCmac	MacPaint files - black-and white images	MacBinary	--t0
ObjVCpict	Macintosh PICT/PICT2 file format, by Apple Computer	None	-m0

Results

Correlations among the objective complexity measures

We expected these measures to be highly intercorrelated, and this did indeed prove to be the case. Table 2 reports the intercorrelations among these seven indices of objective visual complexity (henceforce OVC) (all results are significant at $p < 0.01$). For our purposes here, these measures are close to interchangeable. However, for purposes of comparison we will include several of the most familiar and widely used indices. Summary statistics for the objective visual complexity measures (Table 3) show that the highest quality JPG format allows the most variation of picture size (and the largest files in Kbytes) in this particular corpus.

TABLE 2

Intercorrelations between indices of objective visual complexity measures

	objVCpdf	objVCtiff	objVCjpg	ObjVCgif	objVCwpg	ObjVCmac	objVCpict
objVCpdf	1	1.000	0.967	0.989	0.921	0.918	0.917
objVCtiff		1	0.969	0.989	0.924	0.921	0.921
objVCjpg			1	0.965	0.923	0.926	0.926
objVCgif				1	0.933	0.940	0.940
objVCwpg					1	0.985	0.985
objVCmac						1	1.000
objVCpict							1

TABLE 3

Summary statistics of objective VC measures: file size in Kbytes

	N	Mean	STD	MIN	MAX
objVCpdf	520	4009	1319	2007	12792
objVCtiff	520	2575	1019	1028	9300
objVCjpg	520	16736	8926	3730	62243
objVCgif	520	2282	1006	741	8285
objVCwpg	520	3872	1759	649	10386
objVCmac	520	5249	1562	2560	11392
objVCpict	520	4600	1561	1970	10703

Complexity effects on independent variables

Table 4 presents the summary statistics for the most important independent variables of the study, for each language. All variables are characteristics of the dominant response, the most common name (given by the largest number of subjects) in each of the studies. Age of acquisition and goodness-of-depiction ratings were available only for English, and are based on subjective ratings. For goodness of depiction, subjects were asked to rate how well the picture fit its dominant name, on a scale from worst to best. Average ratings of 1-7 were calculated for each picture. Similarly subjects were asked to estimate the age at which they acquired each name on a 9-point scale (representing an age range from 2-13 and older). Transformed (logarithmic) frequency counts were taken from frequency dictionaries of written language of English (Celex database) and Hungarian (where only 174 words were listed in the dictionary, therefore the values are much lower). Length is measured in syllables as well as in characters. Both dimensions indicate that the Hungarian words tend to be longer.

The correlation matrix of independent measures of the dominant response, and objective complexity of the pictures is outlined in Table 5. In English, there was a small but significant tendency for complex pictures to be described with longer names. However, the length-complexity correlation did not hold in Hungarian, suggesting that language-specific variations in word structure may play a role. Note also that OVC is unrelated to word frequency in either language, and unrelated to subjective ratings of age of acquisition in English. This is not true for subjective VC ratings, which (in studies by Snodgrass and others) are significantly related to both frequency and age of acquisition (see below). There is a small negative correlation of objective VC with goodness of depiction: the more complex the picture, the better it is judged to represent the object. As we shall see in more detail later, this relationship between objective VC and goodness of depiction does not hold for subjective complexity ratings taken from studies by other investigators.

TABLE 4

Summary statistics of the independent variables

	N	Mean	STD	MIN	MAX
US Freq	520	2.50	1.57	0	7.40
US Syll	520	1.74	0.83	1	5
US Char	520	5.89	2.22	2	15
US AOA	520	2.26	1.29	2.93	10.09
US good	520	5.8	0.65	2.85	6.85

	N	Mean	STD	MIN	MAX
HU Freq	520	1.38	1.93	0	6.84
HU Syll	520	2.28	0.97	1	8
HU Char	520	6.07	2.28	2	19

TABLE 5

Objective VC and characteristics of the dominant response (N = 520)

	objVCpdf	objVCtiff	ObjVCjpg	ObjVCgif	objVCwpg	ObjVCmac	objVCpict
US & HU Frequency	ns	ns	ns	ns	ns	ns	ns
US Age of acquisition	ns	ns	ns	ns	ns	ns	ns
US Goodness-of depiction	0.080~	0.082~	0.082~	0.081~	0.087*	0.091*	0.091*
US Length in syllables	0.118**	0.118**	0.124**	0.115**	0.101*	0.095*	0.097*
HU Length in syllables	ns	ns	ns	ns	ns	ns	ns
US Length in characters	0.092*	0.092*	0.106*	0.089*	0.085~	0.080~	0.080~
HU Length in characters	ns	ns	ns	ns	ns	ns	ns

~ = p<0.1, * = p<0.05, ** = p<0.01 (ns=not significant)

Complexity effects on dependent variables

Analyses in the following section were based on naming results for the 520 simple object pictures in English and Hungarian. Table 6 presents summary statistics for the most important dependent variables of the study, for each language. Reaction time (RT) measures were calculated two alternative ways, based on our 4-point lexical coding scheme (see Bates et al., 2000). "RT total" refers to the total mean RT, regardless to the lexical category of the responses. "RT target" is the mean reaction time calculated on the basis of the dominant responses only. The measures of nameability (or correctness) are based on our 3-point error-coding scheme. They represent the percent of subjects responding with a "Valid response," an "Invalid response," or failing to give any name, i.e., "Non-response." Invalid responses are often caused by hesitating sounds, such as "well" or "um," which trigger the voice key before the actual response is made. Compared with English, naming in Hungarian took more time, and was less accurate, which is probably caused by cultural differences (the stimuli were taken from US picture materials—see Bates et al., 2000). The number of alternative names for the pictures are determined by "Raw types", and in addition, the "H statistic" was calculated (as defined in Snodgrass, 1980). Name agreement measures were based on the 4-point lexical coding scheme, "Lex1dom" referring to the percent of subjects providing the dominant name. "Lex2phon" is the percent of subjects providing morphophonological alternatives, and "Lex3syn" refers to synonyms of the dominant response. "Lex1+2+3" and "Lex2+3" are the sum of the above measures, representing meaningful alternatives of the dominant response (with, or without the dominant response). Finally, "Lex4err" is the percent of erroneous responses (based on a comparison to the dominant response). Hungarian name agreement is much lower than in English, with more alternative names in all of the above categories.

TABLE 6
Summary statistics of the dependent variables
English picture-naming study Hungarian picture-naming study

US	N	Mean	STD	MIN	MAX
RT total	520	1041	230	656	1843
RT target	520	1019	211	656	1823
Valid resp.	520	96.1%	6.0%	60%	100%
Invalid resp.	520	1.5%	2.3%	0%	16%
No name	520	2.3%	5.0%	0%	34%
Types	520	3.35%	2.28%	1	18
H stat	520	0.67	0.61%	0	2.90
Lex 1dom	520	85.0%	16.4%	28%	100%
Lex 2phon	520	3.7%	8.7%	0%	68%
Lex 3syn	520	2.4%	7.7%	0%	49%
Lex 4err	520	9.0%	12.4%	0%	63%
Lex 1+2	520	6.0%	11.4%	0%	68%
Lex 1+2+3	520	91.1%	12.4%	37%	100%

HU	N	Mean	STD	MIN	MAX
RT total	520	1105	281	659	2300
RT target	520	1071	268	659	3139
Valid resp.	520	94.1%	8.2%	22%	100%
Invalid resp.	520	2.2%	6.7%	0%	74%
No name	520	3.7%	3.3%	0%	20%
Types	520	4.16	2.96	1	21
H stat	520	0.91	0.73	0	3.52
Lex 1dom	520	78.0%	21.4%	13%	100%
Lex 2phon	520	7.1%	12.9%	0%	70%
Lex 3syn	520	4.3%	10.3%	0%	57%
Lex 4err	520	10.6%	16.2%	0%	88%
Lex 1+2	520	11.4%	15.6%	0%	70%
Lex 1+2+3	520	89.5%	16.2%	13%	100%

Complexity effects on measures of reaction time and nameability

Effects of objective visual complexity on reaction time were largely the same as findings in the literature using subjective VC: no significant correlations were found with naming latencies. However, complex pictures tended to elicit a higher proportion of codeable names (whether or not it was the dominant name). In fact, those items that proved most difficult to name, like clamp or anvil, did tend to be low in objective complexity. This small but significant facilitative effect of complexity on nameability is similar for the two languages, suggesting (on the basis of two unrelated languages only) that this may be a universal effect. Results are summarized in Table 7.

TABLE 7
RT and nameability (N = 520)

	objVCpdf	objVCtiff	ObjVCjpg	ObjVCgif	objVCwpg	objVCmac	objVCpict
US & HU RT total	ns	ns	ns	ns	ns	ns	ns
US & HU RT target	ns	ns	ns	ns	ns	ns	ns
US Valid resp	0.113**	0.115**	0.137**	0.118**	0.151**	0.157**	0.157**
HU Valid resp	0.103*	0.104*	0.115**	0.108*	0.138**	0.138**	0.138**
US Invalid resp	ns	ns	-0.083~	-0.079~	-0.096*	-0.100*	-0.101*
HU Invalid resp	ns	ns	ns	ns	-0.089*	-0.096*	-0.096*
US No-resp	-0.106*	-0.107*	-0.126**	-0.105*	-0.138**	-0.142**	-0.142**
HU No-resp	-0.098*	-0.099*	-0.108*	-0.101*	-0.125**	-0.122**	-0.123**

~ = p<0.1, * = p<0.05, ** = p<0.01 (ns=not significant)

Objective visual complexity and name agreement

In the present study, we did not find correlations between objective VC and the number of alternatives in either language (measured by raw number of types or the H statistic). In English, OVC was also unrelated to percent name agreement (percent subjects responding with Lexical Code 1, the dominant response). However, there was a small, positive effect on name agreement in Hungarian. In addition, objective VC does seem to be mildly correlated with production of accurate names (Lexical Categories 1-3 combined), especially in English, and it is negatively correlated with Lexical Category 4 (which includes frank visual errors). In other words, pictures with more objective visual information result in less ambiguity, and elicit names that have the same "truth value", even though this small advantage does not have an impact on reaction times. Results are summarized in Table 8 below.

TABLE 8

Effects of OVC on name agreement and objective visual complexity (N = 520)

	ObjVCpdf	objVCtiff	ObjVCjpg	ObjVCgif	ObjVCwpg	objVCmac	objVCpict
US & HU Raw types	ns	ns	ns	ns	ns	ns	ns
US & HU H statistics	ns	ns	ns	ns	ns	ns	ns
US Lex 1dom	ns	ns	ns	ns	ns	ns	ns
US Lex 2phon	ns	ns	0.079~	ns	0.080~	0.083~	0.084~
US Lex 3syn	ns	ns	0.079~	ns	ns	0.081~	0.080~
US Lex 4err	-0.075~	-0.077~	-0.100*	-0.075~	-0.100*	-0.104*	-0.103*
US Lex 2+3	0.088*	0.091*	0.113**	0.097*	0.104*	0.118**	0.118**
US Lex 1+2+3	0.075~	0.077~	0.100*	0.075~	0.100*	0.103*	0.103*
HU Lex 1dom	0.077~	0.077~	0.077~	0.075~	0.087*	0.083~	0.083~
HU Lex 2phon	ns	ns	ns	ns	ns	ns	ns
HU Lex 3syn	ns	ns	ns	ns	ns	ns	ns
HU Lex 4err	ns	ns	ns	ns	-0.076~	-0.073~	-0.073~
HU Lex 2+3	ns	ns	ns	ns	ns	ns	ns
HU Lex 1+2+3	ns	ns	ns	ns	0.076~	0.074~	0.073~

~ = p<0.1, * = p<0.05, ** = p<0.01 (ns=not significant)

Regression analysis: filtering out complexity effects

In order to control for potential confounds among these predictors, six stepwise regression analyses were also conducted (separately for English and Hungarian) in which the contribution of each variable on the final step was assessed after the other five predictors were entered into the equation. For the sake of economy, these analyses were conducted only on those dependent variables which showed a close relationship with objective VC measures. They are: nameability (percent of valid responses), percent dominant name agreement (Lexical 1 category), accurate alternatives of the dominant response (Lexical Categories 2 and 3 combined), and percent name agreement of erroneous responses (Lex 4). Table 9 summarizes the total variance accounted for by all predictors together, and the amount of variance contributed uniquely by each predictor after the other variables are controlled in each of the above cases.

TABLE 9a

Joint and unique contributions of predictor variables to naming outcomes for 520 object pictures in English

ENGLISH PREDICTORS	% Valid Response	% Dominant Name	% Synonym or Morph. Alternative	% Erroneous or Other Alternative
Objective VC (JPG)	+ .014**	- .001ns	+ .012*	- .004ns
Log Natural Frequency (US)	+ .005~	+ .007*	- .003ns	- .003ns
Length in Syllables (US)	- .000ns	+ .009*	- .021**	+ .000ns
Length in Characters (US)	+ .000ns	- .013**	+ .052***	- .003ns
Subjective AOA (US)	- .088***	- .019***	- .001ns	+ .043***
Goodness of Depiction (US)	+ .077***	+ .124***	- .008*	- .145***
TOTAL R^2	.293***	.227***	.095***	.270***

~ = p < .10; * = p < .05; ** = p < .01; *** = p < .001 (ns = not significant)
(+ and - refer to the direction of the zero-order partial correlations)

In the equation presented in Table 9a the six English independent predictors account for 29.3% of the variance of valid responses. The Objective VC measure does make a small positive addition of 1.4% ($p < .01$) to the overall equation when all other measures were controlled. The contribution of subjective ratings of AOA and Goodness of Depiction contribute 8% and 9% to the variance ($p < 0.001$). Objective visual complexity does not play a significant role in determining variance of the dominant response, which seems to be best determined by goodness-of-depiction ratings. Objective VC has a minor effect on accurate alternatives of the dominant response, explaining 1.2% of the total of 9.5% variance. Visually complex pictures slightly increase nameability of the pictures in English, though not necessarily by increasing the use of the target name itself.

TABLE 9b

Joint and unique contributions of predictor variables to naming outcomes for 520 object pictures in Hungarian

HUNGARIAN & ENGLISH PREDICTORS	% Valid Response	% Dominant Name	% Synonym or Morph. Alternative	% Erroneous or Other Alternative
Objective VC (JPG)	+ .009*	+ .004ns	- .003ns	- .001ns
Log Natural Frequency (HU)	+ .009*	+ .001ns	- .000ns	- .001ns
Length in Syllables (HU)	+ .002ns	- .002ns	+ .004ns	- .000ns
Length in Characters (HU)	- .003ns	- .001ns	+ .001ns	+ .000ns
Subjective AOA ratings (US)	- .015**	- .002ns	- .000ns	+ .005~
Goodness of Depiction ratings (US)	+ .059***	+ .059***	- .000ns	- .100***
TOTAL R^2	.142***	.103***	.035**	.131***

~ = $p < .10$; * = $p < .05$; ** = $p < .01$; *** = $p < .001$(ns = not significant)
(+ and - refer to the direction of the zero-order partial correlations)

Similar to the English results, visually complex pictures are slightly more codeable in Hungarian (Table 9b) as well, though effects of AOA and goodness of depiction ratings (even though they were taken from a US sample) are better, and more significant predictors of nameability. Words acquired earlier seem to be named more accurately, and well-depicted objects increase performance as well. Objective VC does not account significantly for variance of any of the lexical categories (goodness of depiction is the only measure to account for the modest overall variance of the dominant name).

Validating objective visual complexity

To compare our results with those obtained in prior studies using subjective visual complexity ratings, we used a subset of 168 words that are common among the present study, Snodgrass and Yuditsky, and San Feliu. To determine whether this subset differed systematically from our larger picture set, we compared means on all our variables, using the conventional two–sample t-test (Table 10). Pictures in the overlapping set are generally less complex (all objective measures of visual complexity indicate significant differences between the two sets). Naming is also quicker for the overlapping subset, and fewer alternatives are elicited. The subset includes concepts that are rated as acquired earlier (subjective AOA), and they are rated as easier to depict. All the above differences are significant at $p < 0.01$. Pictures of the subset are less likely to evoke erroneous responses ($p < 0.05$). These pictures also tend to be more frequent, and less likely to elicit invalid RT responses; however, these differences are not significant ($p < 0.1$). Interestingly, there are no significant differences of word length in the two sets. Although English and Hungarian naming records are quite different, the differences between the two sets summarized above are equally valid for both languages.

TABLE 10
One way comparison of population means of the two sets of stimuli

Variable	N=168Mean	N=352Mean	p <
ObjVCpdf	3441	4280	0.01
ObjVCtiff	2140	2783	0.01
ObjVCjpg	13026	18507	0.01
ObjVCgif	1853	2487	0.01
ObjVCwpg	3198	4194	0.01
ObjVCmac	4653	5534	0.01
ObjVCpict	4002	4885	0.01

Variable	N=168Mean	N=352Mean	p <
US Freq	2.67	2.42	0.1
US Syll	1.77	1.73	ns
US Char	5.88	5.90	ns
US AOA	4.89	5.44	0.01
US Goodness	5.02	4.70	0.01
US RT total	956	1082	0.01
US RT target	939	1057	0.01
US Valid RT	96.8%	95.8%	0.1
US Invalid RT	1.74%	2.61%	0.1
US No name	1.46%	1.56%	ns
US Types	2.85	3.60	0.01
US H stat	0,529	0.742	0.01
US Lex 1dom	88.4%	83.4%	0.01
US Lex 2phon	2.78%	4.08%	ns
US Lex 3syn	1.86%	2.60%	ns
US Lex 4err	7.00%	9.89%	0.05
US Lex 1+2	4.64%	6.68%	0.1
US Lex 1+2+3	93.0%	90.1%	0.05

Variable	N=168Mean	N=352Mean	p <
HU Freq	1.57	1.28	ns
HU Syll	2.30	2.28	ns
HU Char	6.10	6.06	ns
HU RT total	1008	1151	0.01
HU RT target	981	1115	0.01
HU Valid RT	94.9%	93.8%	ns
HU Unvalid RT	1.60%	2.49%	0.1
HU No name	3.52%	3.73%	ns
HU Types	3.48	4.48	0.01
HU H stat	0.748	0.982	0.01
HU Lex 1dom	81.7%	76.3%	0.01
HU Lex 2phon	5.59%	7.81%	0.1
HU Lex 3syn	4.90%	4.05%	ns
HU Lex 4err	7.83%	11.90%	0.01
HU Lex 1+2	10.50%	11.90%	ns
HU Lex 1+2+3	92.2%	88.2%	0.01

Subjective and objective measures of visual complexity are closely related

To determine whether these measures of image file size are related to the subjective measures that have been used in previous studies, correlations were calculated with subjective ratings on a subset of 168 object pictures. Rating results were adopted from the English and Spanish studies (Snodgrass and Vanderwart, 1980 and Sanfeliu and Fernandez, 1996). The commonly used file formats with the highest correlation values are listed in Table 4 (correlation coefficients are significant at $p < 0.01$). PDF, TIFF and JPG file formats seem to resemble best how subjects see simple line drawings on a scale from very simple to very complex.

TABLE 11

Correlations between subjective and objective visual complexity measures for a subset of 168 items

	English VC	Spanish VC
ObjVCpdf	0.715**	0.572**
ObjVCtiff	0.713**	0.570**
ObjVCjpg	0.681**	0.560**
ObjVCgif	0.671**	0.553**
ObjVCwpg	0.575**	0.493**
ObjVCmac	0.548**	0.462**
ObjVCpict	0.545**	0.458**

** = p<0.01

Subjective and objective VC measures are closely correlated (Table 11). Objective VC is better correlated with English subjective VC, probably because the pictures come from an American corpus, and Spanish raters probably do not set aside other subjective determinants (such as familiarity of the picture) when rating pictures for complexity. Table 12 summarizes the correlation of subjective as well as objective VC measures with various independent variables of three different studies. Both VC measures indicate that familiar items seem to be less complex than unfamiliar items. This relationship is stronger when visual complexity is assessed subjectively. Simpler pictures also tend to be named with words that are acquired earlier, although this effect is small and less often significant for Objective VC indices. Word frequency is highly and significantly correlated with subjective VC, but frequency is not related to any of the objective complexity measures. Word length is associated with both kinds of measures.

TABLE 12

Correlations of complexity with lexical variables, based on a subset of 168 items

	Familiarity		Age of Acquisition		Frequency	Syllables	Characters
	Snod-80’	**Sanf-96’**	**Snod-96’**	**CRL-00’**	**CRL-00’**	**CRL-00’**	**CRL-00’**
English VC	-0.441**	-0.408**	0.276**	0.201**	-0.231**	0.158*	0.126ns
Spanish VC	-0.404**	-0.513**	0.305**	0.228**	-0.273**	0.188*	0.103ns
ObjVCpdf	-0.317**	-0.286**	0.189*	0.145~	-0.093ns	0.201**	0.133~
ObjVCtiff	-0.319**	-0.288**	0.185*	0.143~	-0.095ns	0.198**	0.132~
ObjVCjpg	-0.258**	-0.236**	0.158*	0.119ns	-0.093ns	0.195*	0.132~
ObjVCgif	-0.251**	-0.243**	0.158*	0.126ns	-0.057ns	0.184*	0.116ns
ObjVCwpg	-0.247**	-0.241**	0.137~	0.119ns	-0.046ns	0.139~	0.070ns
ObjVCmac	-0.173*	-0.161*	0.076ns	0.058ns	0.013ns	0.140~	0.068ns
ObjVCpict	-0.173*	-0.160*	0.076ns	0.060ns	0.011ns	0.140~	0.069ns

~ = p < 0.1, * = p < 0.05, ** = p < 0.01

(Origin of variables: Snod-80’: Snodgrass and Vanderwart, 1980 Sanf-96’: Sanfeliu and Fernandez 1996, CRL-00’: International Picture-Norming Project, 2000)

Regression analysis: subjective vs. objective complexity and other lexical measures

We used stepwise regression analysis on the subset of 168 items in order to find out if the overlap of subjective visual complexity with other independent measures remains significant when objective VC controlled, and vice-versa. Table 13 presents the independent association of subjective vs. objective measures of VC with several other independent measures taken from three different sources (CRL International Picture Norming Project, 2000; Sanfeliu and Fernandez, 1996; Snodgrass and Vanderwart, 1980). The following lexical measures are tested: word frequency, and length in syllables and characters of the US dominant response, subjective AOA ratings in Spanish and English, and goodness-of-depiction ratings in English, subjective Familiarity Ratings (based on the use of everyday objects represented by the pictures) and subjective Image Agreement Ratings (correspondence of the picture with the mental image previously evoked by the dominant name), both in English and Spanish, picture name agreement (testing the correspondence between the picture and its dominant name) and variability (the number of mental images evoked by the heard name) in Spanish. The first column of the table shows the unique contribution of two subjective VC measures (Spanish and English complexity ratings) to the variance in each of these lexical measures, when two characteristic objective VC measures are controlled. The second column presents the unique contribution of the two objective VC variables (JPG and PDF format) to the same measures, when the subjective VC measures are entered into the equation first. The last column presents joint effects of subjective and objective visual complexity.

TABLE 13

Unique and joint contributions of subjective vs. objective VC to other lexical predictors

Other Predictor Variables	Subjective Complexity	Objective Complexity	Joint Contribution
Natural Log Frequency (CRL)	- .080***	+ .018ns	.095**
Length in Syllables (CRL)	+ .009ns	+ .016ns	.053~
Length in Characters (CRL)	+ .002ns	+ .013ns	.029ns
Subjective AOA ratings (CRL)	+ .043*	– .003ns	.059*
Subjective AOA ratings (Snodgrass, 1996)	+ .080***	– .004ns	.105***
Goodness-of-Depiction ratings (CRL)	+ .004ns	– .037*	.049~
Subjective Familiarity ratings (Snodgrass)	- .155***	+ .010ns	.223***
Subjective Familiarity ratings (Sanfeliu)	- .226***	+ .019ns	.286***
Subjective Image Agreement ratings (Snodgrass)	- .019ns	– .012ns	.052~
Subjective Image Agreement ratings (Sanfeliu)	- .010ns	– .011ns	.025ns
Picture Name Agreement ratings (Sanfeliu)	+ .010ns	– .008ns	.016ns
Variablity ratings (Sanfeliu)	- .010ns	+ .012ns	.015ns

Subjective = Snodgrass 1980 and San Feliu 1996 ratings, entered jointly;
Objective = JPG and WPG estimates, entered jointly;
"Unique contribution" refers to variance contributed by each pair of variables on the last step.
~ = $p < .10$; * = $p < .05$; ** = $p < .01$; *** = $p < .001$
(+ and **–** refer to the direction of the zero-order partial correlations)

Results indicate that subjective visual complexity ratings are inflated by or collinear with other measures, such as familiarity, age of acquisition and word frequency. Specifically, pictures that are rated as more complex are associated with names rated as less frequent, less familiar, and acquired late. None of these confounds are present in objective visual complexity (or at least to a much lesser degree). However, goodness of depiction adds a significant 3.7% increase to the variance in objective VC when all other variables are accounted for. In other words, pictures that are rated as "better representations of the concept" tend to be higher in objective (but not subjective) visual complexity.

Correlation analysis: no objective VC effects based on a subset of the pictures

To compare objective and subjective effects directly on reaction time, nameability, the number of alternative namings and name agreement measures, we had to reduce our original sample to the overlapping set of 168 items, which tend to be "better or "easier" items on multiple parameters. We therefore wanted to determine whether the few effects of objective complexity that we observed on our earlier analyses (with all 520 items) would hold up with this subset, and whether there would be significant differences between objective and subjective complexity in this regard. Table 14 summarizes correlations between complexity measures (US subjective VC, Spanish subjective VC and our principal measure of objective VC) and the primary dependent variables from our naming study. Three different objective VC measures were tested (the most commonly used PDF, JPG and TIFF file formats), with the same results. Briefly summarized, objective VC had no significant effects on naming performance for this subset of 168 items. By contrast, we did find at least a few weak significant effects of subjective complexity in this data set. In particular, the US complexity measure was associated with more erroneous responses (Lexical Code 4), an effect that held up for naming in both our Hungarian and our English data. The Spanish complexity measure was also associated with an increase in naming errors, but in this case the relationship only holds for the English naming data.

TABLE 14

Subjective and objective VC measures predicting dependent variables of Hungarian and English naming performance on a subset of 168 items

	USsubjVC	SPsubjVC	objVC
US RT total	ns	ns	ns
US RT target	ns	ns	ns
US Valid resp	ns	ns	ns
US Invalid resp	ns	ns	ns
US No-resp	ns	ns	ns
US Raw types	ns	0.134~	ns
US H value	ns	0.170*	ns
US Lex 1dom	ns	-0.185*	ns
US Lex 2phon	ns	ns	ns
US Lex 3syn	ns	ns	ns
US Lex 4err	0.152*	0.186*	ns
US Lex 2+3	ns	ns	ns
US Lex 1+2+3	**-0.152***	**-0.186***	**ns**

	USsubjVC	SPsubjVC	objVC
HU RT total	ns	ns	ns
HU RT target	0,145~	ns	ns
HU Valid resp	ns	ns	ns
HU Invalid resp	ns	ns	ns
HU No-resp	ns	ns	ns
HU Raw types	ns	Ns	ns
HU H value	ns	ns	ns
HU Lex 1dom	ns	ns	ns
HU Lex 2phon	ns	ns	ns
HU Lex 3syn	ns	ns	ns
HU Lex 4err	0.165*	ns	ns
HU Lex 2+3	ns	ns	ns
HU Lex 1+2+3	**-0.165***	**ns**	**ns**

~ = p < 0.1, * = p < 0.05, ** = p < 0.01 (ns = not significant)

We also repeated the regression analyses using our key independent variables (length in syllables, and characters, familiarity, AOA, frequency, subjective visual complexity, and goodness of depiction) to account for the variance of erroneous responses. Together these variables explained 28% of the variance, but few of them made a unique contribution on the last step. Subjective VC only added a non-significant 2% on the final step, and Objective VC added nothing at all. The AOA measures added 6% and goodness-of-the-picture ratings added another 7% (both significant) to the equation. The rest of the variance is lost in the interactions among these mostly subjective measures. Hence the correlations in Table 14 involving subjective VC are due to the variance the subjective complexity shares with other kinds of ratings. In this smaller sample of relatively easy items (the 168-item subset), effects of visual complexity on naming behavior are undetectable.

Conclusion

In the present study a new, objective variable of visual complexity was introduced, based on the size of the picture file, coded in different file formats and degree of compression. These new variables were significantly correlated with traditional subjective visual complexity, indicating that both approaches are measuring the amount of detail in the picture. However, they are rather different from the traditional subjective complexity ratings in their relation to other determinants of the naming task. Similarly to subjective measures, complex pictures tend to elicit longer names. However, they do not affect naming latency, and, unlike subjective ratings, are not confounded with word frequency, familiarity and age of acquisition. On the other hand, objective VC does correlate with nameability, word length, and with goodness of depiction in the full sample of 520 items. Complex pictures are more likely to be rated as easily depicted, they reduce the likelihood of visual errors in naming performance, and tend to elicit alternatives that are synonyms or morphophonological variants of the dominant naming. Based on the above results objective visual complexity measures based on the file size (in JPG, TIFF or PDF) of black-and-white simple line drawings can be a useful and easy tool for picture-naming studies in the future.

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Appendix

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
1	accordion	5016	21540	76%	96%	22%	0%	87%	85%	0%	15%	0%	0%	13%	0%	4	4
2	acorn	3051	9198	94%	94%	4%	6%	83%	87%	0%	0%	0%	0%	17%	13%	2	1
3	airplane	3569	16810	100%	98%	0%	0%	70%	51%	22%	49%	8%	0%	0%	0%	2	3
4	alligator	3386	14874	100%	94%	0%	2%	90%	94%	2%	0%	6%	2%	2%	4%	4	3
5	anchor	3588	14010	96%	92%	4%	2%	100%	63%	0%	0%	0%	20%	0%	17%	2	2
6	ant	3723	13915	100%	94%	0%	2%	88%	91%	0%	0%	0%	0%	12%	9%	1	2
7	antlers	3544	12147	100%	92%	0%	0%	72%	76%	0%	4%	26%	17%	2%	2%	2	2
8	anvil	2583	8356	68%	84%	30%	16%	71%	83%	0%	0%	0%	2%	29%	14%	2	2
9	apple	2882	8241	98%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
10	fishtank	8009	45899	100%	98%	0%	0%	48%	98%	0%	0%	46%	0%	6%	2%	2	4
11	arm	2392	6270	98%	94%	0%	0%	84%	53%	0%	4%	0%	0%	16%	43%	1	1
12	arrow	2075	5990	100%	88%	0%	0%	98%	59%	0%	41%	0%	0%	2%	0%	2	1
13	artichoke	4060	15203	68%	62%	26%	24%	79%	26%	0%	0%	0%	0%	21%	74%	3	4
14	ashtray	3177	12932	74%	92%	22%	6%	84%	76%	0%	22%	0%	0%	16%	2%	2	4
15	asparagus	3067	9654	86%	80%	12%	20%	88%	28%	0%	8%	0%	3%	12%	63%	4	1
16	ax	2689	7849	88%	98%	6%	0%	86%	53%	0%	0%	14%	43%	0%	4%	1	2
17	baby	4162	18598	100%	96%	0%	0%	94%	31%	0%	21%	4%	15%	2%	33%	2	3
18	bottle	3122	8529	98%	94%	0%	2%	90%	94%	8%	6%	0%	0%	2%	0%	2	4
19	stroller	4144	17135	94%	90%	4%	0%	49%	96%	0%	4%	45%	0%	6%	0%	2	4
20	backpack	5906	31598	100%	100%	0%	0%	100%	88%	0%	6%	0%	0%	0%	6%	2	3
21	badge	4329	15109	94%	92%	4%	2%	68%	30%	0%	0%	4%	2%	28%	67%	1	4
22	bag	4554	18014	98%	100%	0%	0%	84%	58%	14%	36%	2%	6%	0%	0%	1	2
23	balcony	6224	35416	98%	98%	0%	0%	65%	80%	0%	0%	0%	2%	35%	18%	3	2
24	ball	3398	13345	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
25	balloon	2861	8015	100%	98%	0%	0%	100%	65%	0%	0%	0%	35%	0%	0%	2	2
26	banana	2879	8767	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	3	2
27	bandaid	3313	13392	100%	94%	0%	2%	92%	49%	8%	0%	0%	47%	0%	4%	2	3
28	banjo	4267	17479	92%	88%	4%	2%	87%	57%	0%	0%	0%	0%	13%	43%	2	2
29	barbecue	3493	12302	98%	80%	2%	10%	90%	13%	0%	0%	10%	0%	0%	88%	3	1
30	barrel	4144	18478	96%	98%	4%	0%	98%	98%	0%	0%	2%	0%	0%	2%	2	2
31	basket	5335	23651	100%	100%	0%	0%	98%	98%	2%	2%	0%	0%	0%	0%	2	2
32	bat	4116	16687	96%	100%	2%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	3

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
33	bathtub	3343	18067	100%	98%	0%	0%	78%	59%	22%	41%	0%	0%	0%	0%	2	1
34	bear	3704	14353	100%	98%	0%	0%	82%	67%	18%	33%	0%	0%	0%	0%	1	2
35	beard	6128	30362	100%	96%	0%	2%	96%	96%	2%	0%	0%	0%	2%	4%	1	2
36	beaver	3205	11319	94%	84%	6%	10%	74%	67%	0%	0%	0%	0%	26%	33%	2	1
37	bed	3448	13761	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	1
38	bee	3445	12184	96%	96%	0%	0%	69%	46%	0%	0%	0%	0%	31%	54%	1	1
39	bug	3655	12207	100%	96%	0%	2%	44%	65%	2%	33%	4%	0%	50%	2%	1	2
40	bell	3065	11109	100%	94%	0%	0%	100%	53%	0%	0%	0%	47%	0%	0%	1	2
41	belt	4028	18762	98%	100%	0%	0%	100%	84%	0%	2%	0%	14%	0%	0%	1	1
42	bench	4045	25379	100%	98%	0%	0%	94%	100%	0%	0%	6%	0%	0%	0%	1	1
43	bicycle	4966	24322	100%	100%	0%	0%	70%	80%	30%	0%	0%	20%	0%	0%	3	3
44	binoculars	4259	18262	90%	92%	6%	0%	100%	74%	0%	0%	0%	26%	0%	0%	4	2
45	bird	3498	13239	100%	98%	0%	0%	80%	47%	0%	4%	0%	0%	20%	49%	1	2
46	blimp	2684	9051	94%	86%	4%	6%	81%	63%	2%	0%	9%	35%	9%	2%	1	3
47	wood	3824	17090	98%	100%	2%	0%	55%	76%	4%	2%	39%	10%	2%	12%	1	2
48	boat	2822	11180	98%	98%	0%	0%	71%	65%	0%	2%	0%	0%	29%	33%	1	2
49	bomb	2583	6984	98%	92%	0%	4%	90%	87%	0%	0%	0%	0%	10%	13%	1	2
50	bone	3593	14370	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	1
51	book	2812	8619	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	1
52	boot	2926	8857	100%	98%	0%	0%	90%	90%	2%	0%	0%	0%	8%	10%	1	2
53	bottle	2745	6551	98%	98%	2%	0%	90%	96%	4%	2%	0%	2%	6%	0%	2	2
54	bowl	2834	9408	98%	84%	0%	0%	98%	76%	0%	2%	0%	0%	2%	21%	1	1
55	bow	3761	14836	100%	94%	0%	0%	78%	74%	12%	0%	0%	0%	10%	26%	1	2
56	box	4003	18074	100%	100%	0%	0%	100%	96%	0%	2%	0%	2%	0%	0%	1	2
57	boy	4338	15675	100%	94%	0%	0%	90%	43%	2%	28%	0%	0%	8%	30%	1	3
58	branch	2680	7227	100%	94%	0%	0%	68%	49%	8%	47%	10%	0%	14%	4%	1	1
59	bra	3515	11410	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	3
60	bread	2879	10161	100%	96%	0%	2%	98%	94%	0%	4%	2%	0%	0%	2%	1	2
61	bride	4025	14046	100%	96%	0%	2%	86%	94%	0%	0%	0%	0%	14%	6%	1	3
62	bridge	5532	27543	100%	86%	0%	0%	98%	95%	0%	5%	0%	0%	2%	0%	1	1
63	broom	3395	11261	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
64	brush	3412	12280	100%	96%	0%	2%	94%	79%	6%	10%	0%	0%	0%	10%	1	2
65	bus	4604	23164	100%	98%	0%	0%	100%	69%	0%	29%	0%	0%	0%	2%	1	1

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
66	butter	3351	15536	100%	98%	0%	0%	96%	67%	0%	0%	0%	0%	4%	33%	2	1
67	butterfly	5072	24645	100%	100%	0%	0%	100%	64%	0%	0%	0%	36%	0%	0%	3	2
68	button	2373	5726	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	1
69	cactus	9801	55204	96%	96%	2%	0%	100%	96%	0%	4%	0%	0%	0%	0%	2	2
70	cage	3809	15117	98%	96%	0%	0%	92%	81%	0%	2%	0%	8%	8%	8%	1	2
71	cake	3942	16237	100%	100%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	1	2
72	camel	5299	26026	96%	94%	2%	0%	100%	68%	0%	30%	0%	2%	0%	0%	2	2
73	camera	4140	16408	100%	100%	0%	0%	100%	90%	0%	8%	0%	0%	0%	2%	2	5
74	can	3135	10069	98%	96%	0%	2%	94%	71%	2%	29%	0%	0%	4%	0%	1	2
75	candle	2934	8385	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
76	cane	2423	5668	96%	94%	0%	2%	96%	81%	2%	13%	0%	4%	2%	2%	1	1
77	cannon	4036	17678	92%	96%	6%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
78	canoe	4951	27029	94%	98%	2%	0%	62%	45%	0%	0%	0%	0%	38%	55%	2	2
79	canopener	3747	16172	92%	22%	8%	72%	96%	36%	2%	9%	0%	9%	2%	45%	4	5
80	hat	2815	9464	96%	98%	0%	0%	67%	94%	2%	0%	31%	0%	0%	6%	1	2
81	car	2839	9255	100%	96%	0%	0%	100%	92%	0%	0%	0%	8%	0%	0%	1	2
82	carousel	6786	32489	96%	88%	2%	8%	60%	57%	0%	0%	31%	18%	8%	25%	3	3
83	carrot	3484	13201	100%	98%	0%	0%	100%	94%	0%	6%	0%	0%	0%	0%	2	2
84	tape	4959	26164	98%	98%	0%	0%	80%	86%	4%	14%	16%	0%	0%	0%	1	3
85	castle	5082	22746	100%	100%	0%	0%	100%	92%	0%	2%	0%	0%	0%	6%	2	1
86	cat	3162	9894	98%	100%	0%	0%	96%	70%	0%	0%	4%	30%	0%	0%	1	2
87	celery	5214	22928	86%	60%	4%	34%	77%	23%	0%	0%	0%	0%	23%	77%	3	2
88	chain	3316	12912	96%	94%	0%	0%	100%	94%	0%	4%	0%	0%	0%	2%	1	1
89	chair	3487	11238	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	1
90	cheese	3266	12988	82%	100%	2%	0%	100%	98%	0%	0%	0%	0%	0%	2%	1	1
91	cherry	2261	4325	100%	98%	0%	0%	90%	69%	0%	0%	0%	20%	10%	10%	2	3
92	chest	6107	31663	100%	94%	0%	0%	94%	85%	0%	6%	0%	9%	6%	0%	1	2
93	chicken	3502	12886	94%	92%	0%	0%	72%	91%	0%	0%	9%	4%	19%	4%	2	1
94	chimney	2709	9730	92%	94%	4%	0%	100%	98%	0%	0%	0%	0%	0%	2%	2	2
95	church	6679	34595	100%	100%	0%	0%	96%	96%	0%	0%	2%	0%	2%	4%	1	2
96	cigarette	2795	7988	98%	96%	2%	0%	94%	77%	0%	0%	0%	23%	6%	0%	3	4
97	city	7266	44479	96%	96%	0%	0%	85%	88%	2%	0%	4%	0%	8%	13%	2	2
98	clamp	2642	8045	60%	66%	34%	24%	50%	45%	3%	0%	3%	18%	43%	36%	1	2

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
99	clock	5234	25639	100%	100%	0%	0%	98%	98%	0%	2%	0%	0%	2%	0%	1	2
100	clothespin	2993	10833	76%	100%	20%	0%	63%	90%	11%	10%	0%	0%	26%	0%	1	2
101	cloud	3053	11916	94%	82%	6%	6%	81%	68%	9%	2%	0%	0%	11%	29%	1	2
102	clown	4770	21244	98%	96%	0%	0%	100%	94%	0%	6%	0%	0%	0%	0%	1	2
103	coat	4035	13847	100%	98%	0%	0%	56%	88%	2%	0%	40%	0%	2%	12%	1	2
104	dime	3974	14784	100%	98%	0%	0%	60%	45%	0%	6%	2%	27%	38%	22%	1	1
105	pillar	3303	11413	86%	100%	14%	0%	47%	94%	0%	4%	37%	0%	16%	2%	2	2
106	comb	6256	28324	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
107	cookie	2798	7256	90%	44%	6%	42%	82%	18%	0%	5%	0%	0%	18%	77%	2	1
108	cork	4250	18503	92%	94%	6%	2%	85%	66%	0%	30%	0%	0%	15%	4%	1	2
109	corkscrew	3378	11421	76%	88%	14%	0%	50%	91%	3%	0%	5%	2%	42%	7%	2	4
110	corn	4049	16041	100%	96%	0%	0%	100%	94%	0%	6%	0%	0%	0%	0%	1	4
111	cow	4173	17300	96%	98%	0%	0%	94%	84%	0%	0%	0%	16%	6%	0%	1	2
112	cowboy	5244	21168	98%	90%	0%	4%	80%	69%	0%	0%	0%	11%	20%	20%	2	2
113	crab	4857	21262	100%	96%	0%	2%	92%	73%	0%	2%	0%	0%	8%	25%	1	1
114	crackers	3460	16150	98%	90%	2%	4%	84%	96%	6%	0%	0%	0%	10%	4%	2	1
115	crib	3909	13719	98%	94%	0%	0%	84%	30%	0%	70%	2%	0%	14%	0%	1	1
116	cross	2887	9790	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
117	crown	5072	23655	96%	100%	2%	0%	94%	100%	0%	0%	0%	0%	6%	0%	1	3
118	block	3005	10667	94%	98%	4%	0%	30%	73%	0%	0%	28%	0%	43%	27%	1	2
119	cup	2804	8190	100%	96%	0%	0%	84%	69%	12%	4%	4%	0%	0%	27%	1	2
120	curtains	3815	15194	100%	100%	0%	0%	60%	96%	16%	0%	12%	0%	12%	4%	2	2
121	deer	4021	15056	98%	98%	2%	0%	90%	73%	2%	0%	0%	27%	8%	0%	1	2
122	dentist	3984	14931	96%	98%	0%	0%	88%	92%	0%	6%	0%	0%	13%	2%	2	3
123	desert	8167	45024	98%	96%	0%	0%	67%	54%	0%	0%	0%	0%	33%	46%	2	2
124	desk	3876	17761	100%	94%	0%	2%	100%	57%	0%	43%	0%	0%	0%	0%	1	4
125	diaper	4561	17126	96%	92%	2%	2%	48%	35%	19%	0%	0%	0%	33%	65%	3	3
126	dinosaur	3576	12393	100%	98%	0%	2%	98%	84%	0%	6%	0%	0%	2%	10%	3	5
127	doctor	4565	17528	98%	92%	2%	0%	84%	65%	0%	0%	0%	13%	16%	22%	2	2
128	dog	3373	12012	100%	98%	0%	0%	100%	98%	0%	2%	0%	0%	0%	0%	1	2
129	doll	5071	26607	100%	96%	0%	0%	86%	83%	0%	13%	0%	0%	14%	4%	1	2
130	dolphin	3006	9949	100%	98%	0%	0%	98%	96%	0%	0%	0%	0%	2%	4%	2	2
131	donkey	4105	15643	96%	96%	2%	0%	77%	79%	0%	0%	13%	13%	10%	8%	2	2

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
132	door	3478	12638	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
133	dragon	4853	19272	96%	100%	4%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
134	drawer	3885	16141	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
135	dress	5576	23619	100%	98%	0%	0%	100%	92%	0%	8%	0%	0%	0%	0%	1	2
136	dresser	3602	21173	100%	94%	0%	4%	48%	34%	2%	19%	28%	0%	22%	47%	2	2
137	drill	3892	16254	86%	92%	10%	0%	63%	48%	7%	46%	0%	0%	30%	7%	1	2
138	drum	6895	39085	100%	100%	0%	0%	80%	98%	20%	2%	0%	0%	0%	0%	1	1
139	duck	3085	11588	100%	98%	0%	0%	96%	82%	0%	0%	0%	14%	4%	4%	1	2
140	dustpan	3993	17095	84%	88%	16%	4%	69%	64%	14%	32%	7%	0%	10%	5%	2	2
141	eagle	4133	15555	100%	94%	0%	0%	58%	74%	0%	0%	0%	15%	42%	11%	2	1
142	ear	3005	9033	100%	98%	0%	0%	100%	96%	0%	4%	0%	0%	0%	0%	1	1
143	earring	2499	5676	68%	54%	32%	28%	59%	44%	0%	0%	0%	0%	41%	56%	2	4
144	egg	3179	10440	100%	98%	0%	0%	98%	92%	2%	4%	0%	0%	0%	4%	1	2
145	elephant	5237	24585	100%	100%	0%	0%	98%	100%	0%	0%	0%	0%	2%	0%	3	3
146	envelope	2941	11394	100%	92%	0%	0%	92%	59%	0%	2%	0%	39%	8%	0%	3	3
147	eskimo	3497	11857	88%	96%	12%	2%	89%	96%	0%	0%	0%	0%	11%	4%	3	3
148	eye	2907	9104	98%	100%	0%	0%	98%	98%	2%	2%	0%	0%	0%	0%	1	1
149	fan	6589	35152	98%	86%	0%	8%	98%	100%	0%	0%	0%	0%	2%	0%	1	4
150	faucet	4003	17509	100%	96%	0%	0%	82%	83%	0%	17%	0%	0%	18%	0%	2	1
151	feather	5036	21626	98%	96%	0%	0%	98%	88%	0%	8%	0%	0%	2%	4%	2	1
152	fence	3634	17349	100%	100%	0%	0%	98%	100%	0%	0%	0%	0%	2%	0%	1	3
153	finger	2296	5370	98%	100%	2%	0%	98%	80%	0%	20%	0%	0%	2%	0%	2	1
154	fire	9845	52543	100%	94%	0%	0%	96%	89%	0%	0%	0%	2%	4%	9%	2	1
155	fireman	5361	26161	100%	94%	0%	2%	94%	98%	4%	0%	0%	0%	2%	2%	3	3
156	firetruck	7926	41094	96%	100%	2%	0%	65%	62%	29%	24%	0%	0%	6%	14%	3	6
157	fish	3521	12019	98%	96%	0%	0%	100%	94%	0%	4%	0%	0%	0%	2%	1	1
158	fishingpole	2534	5685	94%	92%	0%	4%	53%	76%	32%	0%	0%	20%	15%	4%	2	3
159	flag	2993	9461	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
160	flashlight	3639	15410	98%	94%	2%	2%	98%	40%	2%	55%	0%	0%	0%	4%	2	3
161	wine	5760	24975	86%	94%	12%	0%	58%	28%	5%	0%	0%	15%	37%	57%	1	3
162	floor	4509	20982	96%	88%	4%	6%	52%	34%	0%	0%	0%	0%	48%	66%	1	2
163	flower	3828	15082	100%	98%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	2	2
164	flute	2642	7456	98%	78%	2%	14%	86%	51%	0%	0%	0%	0%	14%	49%	1	3

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
165	fly	3375	11935	100%	98%	0%	0%	90%	88%	0%	2%	0%	0%	10%	10%	1	1
166	foot	2684	7638	100%	100%	0%	0%	98%	64%	2%	36%	0%	0%	0%	0%	1	1
167	football	3381	12165	100%	92%	0%	2%	100%	48%	0%	2%	0%	0%	0%	50%	2	4
168	fork	2745	8818	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
169	fountain	6613	32442	98%	100%	0%	0%	86%	100%	12%	0%	0%	0%	2%	0%	2	3
170	fox	3994	16437	98%	100%	2%	0%	86%	98%	0%	0%	0%	0%	14%	2%	1	2
171	frog	3283	14773	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
172	funnel	2641	6468	78%	98%	22%	2%	97%	100%	0%	0%	0%	0%	3%	0%	2	2
173	trash	8237	48626	98%	92%	0%	2%	43%	57%	0%	20%	49%	0%	8%	24%	1	2
174	gas	2798	8961	96%	94%	0%	2%	40%	68%	38%	2%	4%	4%	19%	26%	1	3
175	fence	3443	13819	96%	92%	4%	2%	60%	37%	0%	22%	0%	17%	40%	24%	1	2
176	genie	4251	18559	88%	100%	0%	0%	98%	52%	0%	2%	0%	40%	2%	6%	2	2
177	ghost	5097	23538	100%	98%	0%	0%	100%	92%	0%	0%	0%	8%	0%	0%	1	2
178	giraffe	4967	18422	98%	96%	2%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
179	girl	4217	15540	100%	100%	0%	0%	92%	84%	6%	12%	0%	0%	2%	4%	1	2
180	glass	3628	14175	98%	100%	0%	0%	71%	98%	0%	2%	29%	0%	0%	0%	1	2
181	glasses	3440	11525	100%	98%	0%	0%	96%	100%	4%	0%	0%	0%	0%	0%	2	3
182	globe	5018	24454	100%	98%	0%	0%	98%	100%	0%	0%	0%	0%	2%	0%	1	2
183	glove	3167	11509	100%	100%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	1	2
184	goat	3951	15302	98%	96%	2%	0%	96%	98%	0%	0%	0%	0%	4%	2%	1	2
185	gorilla	4274	17084	100%	92%	0%	2%	70%	72%	0%	0%	0%	0%	30%	28%	3	3
186	grapes	4768	23841	100%	100%	0%	0%	90%	90%	10%	8%	0%	0%	0%	2%	1	2
187	grasshopper	3405	13119	98%	96%	0%	0%	67%	63%	0%	0%	0%	0%	33%	38%	3	2
188	guitar	3580	12032	100%	100%	0%	0%	98%	98%	0%	0%	0%	0%	2%	2%	2	2
189	gun	3081	10904	98%	98%	0%	0%	90%	100%	2%	0%	6%	0%	2%	0%	1	2
190	hair	8390	41463	100%	100%	0%	0%	98%	94%	0%	4%	0%	2%	2%	0%	1	1
191	brush	4184	16664	100%	94%	0%	2%	84%	38%	12%	34%	0%	0%	4%	28%	1	3
192	hamburger	4939	26501	100%	96%	0%	0%	84%	77%	8%	0%	0%	23%	8%	0%	3	3
193	hammer	2889	9533	96%	100%	0%	0%	100%	88%	0%	4%	0%	2%	0%	6%	2	3
194	hammock	2993	10853	90%	74%	8%	22%	91%	38%	0%	54%	0%	0%	9%	8%	2	3
195	hand	3502	13345	94%	100%	0%	0%	98%	86%	0%	14%	0%	0%	2%	0%	1	1
196	handcuffs	5276	21347	98%	96%	0%	2%	88%	98%	6%	2%	0%	0%	6%	0%	2	2
197	hanger	2334	7003	98%	90%	0%	0%	90%	47%	10%	2%	0%	49%	0%	2%	2	2

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
198	harp	4060	14170	92%	90%	6%	4%	96%	91%	0%	0%	0%	0%	4%	9%	1	2
199	hat	2561	8732	94%	100%	0%	0%	98%	98%	0%	0%	0%	0%	2%	2%	1	2
200	hay	5480	23594	98%	96%	2%	0%	80%	38%	16%	50%	2%	10%	2%	2%	1	4
201	heart	2693	7316	100%	92%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	1
202	heel	3708	14448	98%	94%	0%	0%	88%	49%	8%	51%	0%	0%	4%	0%	1	4
203	helicopter	3740	18241	100%	98%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	4	4
204	helmet	3952	15650	100%	96%	0%	0%	96%	69%	4%	29%	0%	0%	0%	2%	2	4
205	highchair	4715	19638	94%	96%	4%	0%	87%	63%	2%	38%	9%	0%	2%	0%	2	4
206	hinge	2720	6973	82%	52%	12%	38%	88%	31%	2%	4%	0%	0%	10%	65%	1	1
207	hippo	3546	12429	94%	90%	4%	2%	55%	100%	30%	0%	0%	0%	15%	0%	2	3
208	hoe	2406	6124	94%	76%	6%	18%	77%	74%	0%	0%	0%	3%	23%	24%	1	2
209	hoof	3623	13837	96%	98%	0%	0%	92%	94%	2%	4%	2%	0%	4%	2%	1	2
210	hook	3206	10144	100%	96%	0%	0%	100%	65%	0%	0%	0%	2%	0%	33%	1	2
211	horse	4549	18397	100%	98%	0%	0%	100%	96%	0%	0%	0%	2%	0%	2%	1	1
212	hose	4391	26130	98%	86%	2%	2%	96%	53%	4%	2%	0%	35%	0%	9%	1	1
213	house	3582	18069	100%	98%	0%	0%	98%	94%	0%	0%	0%	4%	2%	2%	1	1
214	firehydrant	5236	25793	96%	78%	2%	18%	71%	54%	23%	8%	0%	0%	6%	38%	4	2
215	icecreamcone	2937	7742	96%	100%	0%	0%	52%	60%	48%	0%	0%	40%	0%	0%	2	2
216	igloo	2889	9673	98%	94%	2%	4%	100%	23%	0%	2%	0%	43%	0%	32%	2	2
217	iron	3651	16843	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	3
218	ironingboard	3174	12848	100%	96%	0%	0%	90%	83%	8%	15%	0%	0%	2%	2%	4	5
219	jack	3361	11170	82%	88%	14%	8%	85%	59%	7%	25%	0%	0%	7%	16%	1	3
220	jacket	6274	30351	96%	96%	0%	2%	92%	63%	0%	0%	6%	27%	2%	10%	2	2
221	jar	2681	7664	98%	96%	0%	2%	90%	54%	0%	44%	0%	0%	10%	2%	1	5
222	puzzle	7375	46171	100%	92%	0%	0%	98%	65%	2%	0%	0%	33%	0%	2%	2	2
223	jumprope	3540	11207	100%	90%	0%	0%	84%	67%	16%	31%	0%	0%	0%	2%	2	4
224	kangaroo	3655	14555	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	3	3
225	key	2698	7493	88%	98%	2%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	1
226	king	6312	31165	98%	100%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	1	2
227	kite	4220	17880	100%	90%	0%	0%	100%	53%	0%	36%	0%	0%	0%	11%	1	2
228	knife	2865	8773	96%	98%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	1	1
229	knight	4034	15019	86%	96%	10%	0%	88%	81%	0%	0%	0%	2%	12%	17%	1	2
230	knot	3087	12224	94%	100%	2%	0%	62%	64%	0%	0%	0%	2%	38%	34%	1	2

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
231	ladder	4998	25701	100%	98%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	2	2
232	ladle	2547	6129	94%	92%	2%	2%	55%	59%	0%	0%	0%	2%	45%	39%	2	4
233	ladybug	3247	10682	96%	100%	2%	0%	67%	38%	0%	16%	0%	0%	33%	46%	3	3
234	lamp	3286	13522	100%	96%	0%	0%	92%	81%	0%	19%	0%	0%	8%	0%	1	2
235	lawnmower	4616	18238	98%	98%	0%	0%	96%	80%	2%	20%	2%	0%	0%	0%	2	3
236	leaf	5349	26600	96%	94%	0%	0%	100%	87%	0%	13%	0%	0%	0%	0%	1	2
237	leg	2699	6995	94%	98%	0%	0%	79%	96%	0%	4%	0%	0%	21%	0%	1	1
238	lemon	2747	8524	98%	98%	0%	0%	96%	100%	0%	0%	0%	0%	4%	0%	2	2
239	leopard	5236	23203	92%	92%	4%	0%	54%	54%	0%	0%	0%	0%	46%	46%	2	3
240	letter	6887	40467	100%	100%	0%	0%	68%	92%	12%	0%	4%	0%	16%	8%	2	2
241	lettuce	4177	17140	98%	98%	0%	0%	57%	71%	0%	0%	0%	4%	43%	24%	2	3
242	lightbulb	3219	10034	100%	94%	0%	0%	92%	53%	8%	19%	0%	28%	0%	0%	2	4
243	lighthouse	5361	31692	98%	96%	2%	0%	94%	81%	4%	0%	0%	0%	2%	19%	2	6
244	lightning	5463	30782	98%	96%	0%	0%	84%	96%	12%	4%	0%	0%	4%	0%	2	2
245	lightswitch	2837	7739	100%	94%	0%	0%	64%	64%	34%	36%	0%	0%	2%	0%	2	3
246	lion	6125	32267	98%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	3
247	lips	2144	6586	100%	96%	0%	0%	94%	90%	2%	0%	0%	0%	4%	10%	1	1
248	lipstick	2552	6029	100%	96%	0%	0%	100%	98%	0%	2%	0%	0%	0%	0%	2	1
249	lizard	3457	12070	98%	96%	0%	0%	88%	75%	0%	0%	0%	0%	12%	25%	2	1
250	llama	3289	10293	90%	84%	8%	10%	76%	76%	0%	0%	0%	0%	24%	24%	2	2
251	lobster	4755	20034	98%	92%	2%	2%	84%	87%	0%	0%	0%	0%	16%	13%	2	1
252	lock	3038	9706	98%	100%	2%	0%	100%	98%	0%	0%	0%	0%	0%	2%	1	2
253	log	3574	13517	100%	100%	0%	0%	74%	26%	0%	34%	0%	4%	26%	36%	1	2
254	magnet	5287	23234	98%	96%	0%	0%	96%	98%	0%	2%	0%	0%	4%	0%	2	2
255	mailbox	4480	19211	100%	96%	0%	0%	84%	65%	0%	33%	0%	0%	16%	2%	2	4
256	man	4378	15791	100%	96%	0%	0%	94%	63%	2%	0%	0%	10%	4%	27%	1	2
257	map	7127	41029	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
258	mask	3681	13646	100%	98%	0%	0%	98%	67%	0%	0%	0%	33%	2%	0%	1	2
259	match	3574	13078	96%	96%	2%	0%	100%	96%	0%	4%	0%	0%	0%	0%	1	2
260	medal	4411	21541	94%	92%	2%	0%	89%	50%	9%	2%	0%	30%	2%	17%	2	2
261	microphone	3294	9962	80%	82%	20%	16%	90%	90%	0%	0%	0%	0%	10%	10%	3	3
262	microscope	4170	20349	90%	92%	8%	8%	84%	93%	0%	0%	0%	0%	16%	7%	3	3
263	mirror	3525	11938	98%	100%	0%	0%	100%	98%	0%	2%	0%	0%	0%	0%	2	2

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
264	mixer	4101	18578	92%	86%	4%	6%	39%	30%	0%	7%	24%	23%	37%	40%	2	3
265	priest	3319	10111	92%	92%	6%	0%	43%	52%	0%	2%	43%	43%	13%	2%	1	1
266	monkey	4579	18988	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
267	moon	2053	3730	94%	100%	0%	0%	100%	98%	0%	2%	0%	0%	0%	0%	1	1
268	moose	4966	23330	92%	94%	4%	2%	76%	55%	0%	45%	0%	0%	24%	0%	1	2
269	mop	3574	14393	100%	94%	0%	0%	94%	32%	0%	43%	0%	0%	6%	26%	1	3
270	mosquito	4212	20758	92%	98%	6%	2%	54%	57%	0%	0%	0%	2%	46%	41%	3	2
271	motorcycle	4766	24207	100%	94%	0%	0%	96%	66%	0%	0%	0%	32%	4%	2%	4	2
272	mountain	3580	13588	100%	96%	0%	2%	94%	52%	0%	44%	0%	0%	6%	4%	2	2
273	mouse	3603	13250	98%	96%	0%	0%	92%	88%	2%	10%	0%	0%	6%	2%	1	2
274	mousetrap	4129	18345	98%	96%	2%	2%	65%	77%	35%	0%	0%	10%	0%	13%	2	4
275	mushroom	2795	8337	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
276	music	2007	5175	96%	96%	0%	2%	50%	54%	13%	0%	35%	44%	2%	2%	2	2
277	nail	2981	9585	98%	98%	2%	0%	100%	78%	0%	22%	0%	0%	0%	0%	1	1
278	neck	2468	5700	98%	94%	2%	0%	67%	64%	0%	2%	0%	0%	33%	34%	1	1
279	necklace	2931	8347	100%	98%	0%	0%	82%	45%	2%	37%	0%	12%	16%	6%	2	2
280	needle	3041	8377	94%	88%	4%	0%	91%	93%	2%	2%	0%	0%	6%	5%	2	1
281	nest	3222	12296	96%	88%	0%	0%	73%	70%	2%	0%	0%	0%	25%	30%	1	2
282	net	3351	9970	100%	98%	0%	0%	96%	90%	0%	4%	0%	0%	4%	6%	1	2
283	nose	2235	4703	96%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	1
284	nurse	4728	19385	98%	92%	0%	2%	96%	52%	0%	41%	0%	0%	4%	7%	1	2
285	nut	2586	7235	94%	94%	2%	0%	49%	43%	0%	45%	0%	13%	51%	0%	1	2
286	octopus	6556	33010	98%	96%	0%	0%	100%	98%	0%	0%	0%	2%	0%	0%	3	2
287	onion	3427	11645	98%	98%	0%	0%	94%	94%	0%	2%	0%	0%	6%	4%	2	2
288	orange	2889	10314	98%	86%	2%	6%	96%	67%	0%	0%	0%	0%	4%	33%	2	2
289	ostrich	3566	13009	90%	92%	10%	2%	80%	93%	0%	0%	0%	0%	20%	7%	2	1
290	owl	3890	15316	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
291	package	5559	29767	100%	98%	0%	0%	94%	94%	0%	0%	2%	0%	4%	6%	2	2
292	bucket	3704	14552	100%	98%	0%	0%	66%	98%	0%	2%	34%	0%	0%	0%	2	2
293	paintbrush	2567	7932	98%	98%	0%	0%	78%	96%	18%	0%	0%	0%	4%	4%	2	2
294	paint	2865	11757	88%	94%	8%	2%	57%	38%	11%	15%	0%	4%	32%	43%	1	3
295	palmtree	4937	18577	98%	100%	2%	0%	86%	68%	14%	30%	0%	0%	0%	2%	2	3
296	pan	2694	9738	100%	90%	0%	2%	84%	80%	10%	2%	2%	2%	4%	16%	1	3

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
297	panda	6857	29117	94%	96%	4%	2%	38%	31%	28%	21%	0%	0%	34%	48%	2	2
298	pants	4507	16138	96%	98%	4%	0%	90%	94%	0%	2%	0%	2%	10%	2%	1	2
299	paper	5488	33840	100%	94%	0%	6%	84%	23%	14%	23%	0%	38%	2%	15%	2	2
300	paperclip	4199	21555	86%	84%	10%	4%	81%	69%	5%	0%	0%	2%	14%	29%	3	3
301	parachute	6018	25199	86%	80%	10%	4%	60%	63%	0%	0%	0%	0%	40%	38%	3	4
302	parrot	4793	18115	96%	100%	4%	0%	79%	94%	0%	0%	0%	0%	21%	6%	2	3
303	paw	5183	21167	92%	92%	2%	0%	67%	76%	0%	0%	0%	0%	33%	24%	1	1
304	peach	2658	6893	88%	92%	2%	4%	75%	74%	0%	11%	0%	0%	25%	15%	1	2
305	peacock	12792	62243	90%	92%	8%	0%	89%	98%	0%	0%	0%	0%	11%	2%	2	2
306	peanut	2962	10266	90%	90%	0%	2%	100%	73%	0%	16%	0%	0%	0%	11%	2	3
307	pear	4535	18960	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
308	peas	5080	24609	94%	94%	4%	2%	57%	81%	38%	4%	0%	0%	4%	15%	1	2
309	pelican	3488	13369	86%	94%	10%	2%	79%	94%	0%	0%	0%	0%	21%	6%	3	3
310	pen	2998	9078	100%	96%	0%	0%	100%	92%	0%	6%	0%	0%	0%	2%	1	1
311	pencil	2727	7899	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	3
312	pencilsharpener	3694	19617	62%	88%	34%	0%	84%	52%	10%	34%	0%	14%	6%	0%	5	3
313	penguin	4762	20074	96%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
314	piano	4465	19570	98%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	3	3
315	picture	4129	16812	96%	96%	0%	0%	83%	96%	2%	2%	13%	0%	2%	2%	2	1
316	pig	3095	10411	100%	98%	0%	0%	100%	63%	0%	0%	0%	37%	0%	0%	1	2
317	bird	3374	11709	98%	88%	0%	2%	37%	55%	0%	2%	0%	0%	63%	43%	1	2
318	piggybank	4797	24489	98%	86%	0%	0%	94%	86%	6%	14%	0%	0%	0%	0%	3	2
319	pillow	3438	16592	100%	96%	0%	2%	100%	83%	0%	10%	0%	0%	0%	6%	2	2
320	pineapple	5046	20721	98%	94%	0%	0%	98%	96%	0%	0%	0%	0%	2%	4%	3	3
321	pinecone	3185	10484	80%	92%	16%	4%	73%	87%	0%	4%	0%	2%	28%	7%	2	2
322	pipe	2401	7235	94%	100%	4%	0%	98%	100%	0%	0%	0%	0%	2%	0%	1	2
323	pirate	6887	37716	98%	94%	0%	0%	88%	85%	0%	4%	2%	0%	10%	11%	2	2
324	pitcher	2934	8789	90%	98%	8%	0%	58%	98%	0%	0%	0%	2%	42%	0%	2	2
325	pitchfork	2318	6158	96%	94%	4%	6%	65%	51%	0%	40%	2%	0%	33%	9%	2	3
326	pizza	6326	40526	100%	86%	0%	12%	100%	84%	0%	0%	0%	0%	0%	16%	2	2
327	plate	4513	21533	100%	100%	0%	0%	94%	82%	2%	0%	0%	0%	4%	18%	1	2
328	pliers	3077	9876	94%	84%	6%	6%	60%	57%	0%	36%	0%	0%	40%	7%	2	2
329	plug	3085	11385	96%	74%	2%	16%	96%	38%	2%	0%	2%	57%	0%	5%	1	3

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
330	policeman	5075	21428	100%	94%	0%	4%	54%	68%	26%	0%	4%	0%	16%	32%	3	2
331	pool	5152	28244	98%	96%	0%	0%	73%	65%	27%	29%	0%	0%	0%	6%	1	3
332	popcorn	5200	26185	98%	92%	2%	2%	100%	48%	0%	7%	0%	41%	0%	4%	2	8
333	popsicle	3308	9409	86%	22%	14%	74%	74%	18%	2%	0%	0%	9%	23%	73%	3	2
334	porcupine	4607	20053	94%	70%	6%	20%	98%	23%	0%	6%	0%	0%	2%	71%	3	1
335	pot	2256	5266	80%	96%	16%	0%	73%	60%	0%	0%	0%	25%	28%	15%	1	2
336	potato	2534	6576	90%	84%	10%	12%	93%	74%	0%	0%	0%	7%	7%	19%	3	2
337	present	3666	11938	96%	100%	2%	0%	67%	36%	2%	6%	13%	0%	19%	58%	2	2
338	priest	4133	15587	98%	92%	0%	4%	92%	91%	0%	0%	4%	4%	4%	4%	1	1
339	pumpkin	4678	18960	98%	94%	2%	2%	100%	89%	0%	2%	0%	0%	0%	9%	2	1
340	purse	4877	21948	100%	96%	0%	0%	98%	92%	0%	6%	2%	2%	0%	0%	1	2
341	pyramid	4291	19838	96%	98%	4%	0%	98%	100%	0%	0%	0%	0%	2%	0%	3	3
342	queen	3417	11277	98%	96%	0%	0%	100%	98%	0%	0%	0%	2%	0%	0%	1	3
343	rabbit	3231	11295	98%	94%	0%	0%	84%	74%	0%	26%	16%	0%	0%	0%	2	1
344	raccoon	3881	16186	90%	66%	4%	14%	84%	24%	0%	3%	0%	0%	16%	73%	2	4
345	radio	3607	19880	100%	96%	0%	0%	86%	81%	2%	0%	0%	0%	12%	19%	3	3
346	radish	3544	11066	72%	70%	12%	20%	58%	66%	0%	0%	0%	0%	42%	34%	2	2
347	rain	4111	20795	92%	98%	4%	0%	87%	88%	2%	0%	0%	0%	11%	12%	1	2
348	rainbow	7364	32529	96%	98%	0%	0%	98%	100%	0%	0%	0%	0%	2%	0%	2	3
349	rake	2216	5156	100%	100%	0%	0%	98%	92%	0%	6%	0%	0%	2%	2%	1	3
350	razor	3408	14404	98%	96%	0%	0%	94%	96%	0%	0%	4%	0%	2%	4%	2	3
351	recordplayer	3875	18552	96%	98%	4%	0%	83%	96%	2%	0%	2%	0%	13%	4%	4	4
352	refrigerator	2830	7828	100%	96%	0%	2%	88%	69%	12%	23%	0%	8%	0%	0%	5	4
353	rhinoceros	4274	18320	96%	92%	2%	0%	77%	96%	15%	0%	0%	2%	8%	2%	4	3
354	gun	2727	9010	98%	98%	2%	0%	71%	86%	0%	2%	0%	0%	29%	12%	1	2
355	ring	2772	7652	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
356	road	4948	26797	100%	94%	0%	0%	92%	72%	0%	28%	8%	0%	0%	0%	1	1
357	robot	3029	9502	100%	100%	0%	0%	98%	98%	0%	0%	0%	0%	2%	2%	2	2
358	rock	3946	16005	98%	100%	2%	0%	98%	78%	0%	4%	0%	14%	2%	4%	1	1
359	rocket	4823	18164	100%	100%	0%	0%	90%	84%	8%	2%	2%	14%	0%	0%	2	3
360	rockingchair	4162	17826	100%	96%	0%	0%	66%	90%	34%	10%	0%	0%	0%	0%	3	3
361	rollerskate	4282	16620	98%	96%	0%	0%	51%	71%	49%	15%	0%	15%	0%	0%	3	4
362	rollingpin	2741	8674	94%	84%	6%	10%	74%	55%	17%	21%	0%	2%	9%	21%	3	3

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
363	roof	3222	13178	98%	98%	0%	2%	94%	63%	2%	37%	0%	0%	4%	0%	1	3
364	rooster	4147	17393	98%	92%	0%	0%	55%	98%	0%	0%	0%	0%	45%	2%	2	2
365	rope	6081	34568	100%	96%	0%	0%	100%	96%	0%	0%	0%	0%	0%	4%	1	2
366	rose	5388	25742	98%	98%	0%	0%	76%	88%	0%	0%	0%	0%	24%	12%	1	2
367	rug	3334	13474	100%	96%	0%	0%	68%	98%	0%	0%	10%	2%	22%	0%	1	2
368	ruler	3096	10785	100%	96%	0%	2%	100%	90%	0%	0%	0%	2%	0%	8%	2	3
369	saddle	3303	10307	98%	96%	2%	2%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
370	safe	3308	10940	92%	86%	4%	8%	80%	42%	2%	0%	0%	40%	17%	19%	1	4
371	safetypin	3683	13291	90%	94%	4%	4%	53%	49%	27%	6%	0%	0%	20%	45%	3	5
372	sailboat	3884	19076	96%	98%	0%	0%	79%	45%	17%	20%	0%	0%	4%	35%	2	3
373	sailor	3710	12192	100%	98%	0%	2%	90%	63%	0%	0%	0%	33%	10%	4%	2	2
374	salt	2998	8601	96%	98%	4%	0%	75%	67%	19%	31%	0%	0%	6%	2%	1	3
375	sandwich	3350	13607	100%	100%	0%	0%	100%	94%	0%	0%	0%	0%	0%	6%	2	2
376	saw	3046	11302	98%	98%	2%	2%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
377	saxophone	3091	8795	94%	90%	4%	6%	81%	87%	4%	0%	0%	0%	15%	13%	3	3
378	scale	3993	14308	90%	96%	10%	2%	56%	100%	13%	0%	9%	0%	22%	0%	1	2
379	scarf	5480	24187	100%	100%	0%	0%	98%	96%	0%	0%	0%	0%	2%	4%	1	1
380	scissors	3474	13042	94%	100%	2%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
381	scorpion	3427	13037	96%	94%	4%	0%	90%	87%	0%	0%	0%	0%	10%	13%	2	3
382	screw	2793	8170	98%	94%	0%	0%	88%	91%	0%	2%	0%	0%	12%	6%	1	2
383	screwdriver	2870	9051	96%	96%	2%	2%	100%	100%	0%	0%	0%	0%	0%	0%	3	4
384	seahorse	3128	9744	82%	86%	12%	4%	88%	67%	0%	0%	0%	9%	12%	23%	2	3
385	seal	3365	12172	98%	94%	0%	0%	82%	98%	0%	0%	0%	0%	18%	2%	1	2
386	seesaw	4062	18444	96%	96%	4%	0%	75%	46%	0%	0%	23%	35%	2%	19%	2	4
387	sewingmachine	5631	29901	100%	96%	0%	0%	98%	100%	0%	0%	0%	0%	2%	0%	4	3
388	shark	3735	14311	96%	98%	0%	0%	96%	88%	0%	0%	0%	0%	4%	12%	1	2
389	sheep	3527	12385	88%	92%	2%	6%	64%	48%	0%	0%	0%	39%	36%	13%	1	2
390	shell	4165	18590	100%	98%	0%	0%	84%	92%	6%	0%	0%	0%	10%	8%	1	2
391	boat	5770	33033	98%	98%	2%	0%	53%	96%	0%	4%	47%	0%	0%	0%	1	2
392	shirt	5488	23660	98%	96%	0%	0%	76%	56%	2%	0%	0%	0%	22%	44%	1	1
393	shoe	3483	14105	98%	96%	0%	0%	100%	96%	0%	4%	0%	0%	0%	0%	1	2
394	shoulder	2526	6274	100%	98%	0%	0%	76%	90%	0%	0%	0%	0%	24%	10%	2	1
395	shovel	3312	11955	98%	94%	2%	0%	100%	85%	0%	0%	0%	0%	0%	15%	2	2

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
396	shower	5368	20173	100%	94%	0%	0%	84%	62%	16%	23%	0%	2%	0%	13%	2	2
397	sink	4495	26560	96%	96%	0%	0%	96%	90%	2%	0%	0%	0%	2%	10%	1	4
398	skateboard	3174	14225	100%	100%	0%	0%	100%	98%	0%	0%	0%	0%	0%	2%	2	3
399	skeleton	3624	10724	100%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	3	2
400	skirt	2752	7277	94%	98%	0%	0%	77%	96%	0%	0%	0%	0%	23%	4%	1	2
401	skis	4000	20764	82%	98%	2%	0%	95%	71%	2%	29%	0%	0%	2%	0%	1	2
402	skunk	3998	16683	100%	88%	0%	4%	98%	57%	0%	2%	0%	2%	2%	39%	1	1
403	sled	3360	16722	100%	90%	0%	4%	96%	93%	0%	0%	4%	7%	0%	0%	1	2
404	slide	5095	20613	96%	94%	2%	2%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
405	slingshot	5457	25531	90%	96%	6%	0%	82%	90%	11%	0%	0%	8%	7%	2%	2	2
406	slipper	3247	11221	96%	100%	2%	0%	63%	46%	4%	0%	0%	38%	33%	16%	2	2
407	smoke	2963	10642	98%	98%	0%	0%	84%	69%	0%	8%	0%	0%	16%	22%	1	1
408	snail	3572	16426	98%	100%	0%	0%	98%	100%	0%	0%	0%	0%	2%	0%	1	2
409	snake	5082	23761	96%	98%	0%	2%	100%	98%	0%	2%	0%	0%	0%	0%	1	2
410	snowman	3003	9725	98%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	3
411	sock	2964	8316	96%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
412	couch	3473	15863	100%	88%	0%	4%	74%	43%	0%	0%	24%	34%	2%	23%	1	3
413	soldier	3177	9301	96%	98%	0%	0%	69%	86%	2%	0%	0%	0%	29%	14%	2	3
414	spaghetti	6663	32766	100%	100%	0%	0%	94%	74%	0%	0%	0%	12%	6%	14%	3	3
415	spatula	2575	7762	84%	86%	14%	10%	86%	88%	0%	5%	0%	0%	14%	7%	3	2
416	spider	6961	37059	98%	98%	0%	0%	100%	98%	0%	2%	0%	0%	0%	0%	2	1
417	thread	3214	13706	98%	94%	0%	4%	65%	64%	6%	4%	0%	2%	29%	30%	1	2
418	spoon	2599	7344	98%	94%	0%	0%	100%	96%	0%	4%	0%	0%	0%	0%	1	2
419	squirrel	4714	21975	100%	98%	0%	0%	88%	98%	0%	2%	0%	0%	12%	0%	2	2
420	stairs	5083	27602	100%	100%	0%	0%	74%	92%	26%	2%	0%	0%	0%	6%	1	2
421	statue	2804	7359	98%	90%	2%	0%	92%	82%	0%	0%	4%	13%	4%	4%	2	2
422	steeringwheel	4627	21824	100%	94%	0%	0%	64%	60%	36%	30%	0%	0%	0%	11%	3	2
423	stethoscope	3876	13841	92%	86%	6%	10%	93%	63%	0%	0%	0%	14%	7%	23%	3	3
424	stocking	4056	16152	98%	100%	0%	0%	43%	96%	6%	4%	45%	0%	6%	0%	2	3
425	stool	3071	10988	96%	94%	0%	0%	83%	70%	0%	9%	0%	0%	17%	21%	1	1
426	stove	4959	29248	100%	94%	0%	0%	72%	51%	0%	45%	26%	0%	2%	4%	1	2
427	strawberry	3686	16771	98%	96%	0%	2%	100%	98%	0%	0%	0%	2%	0%	0%	3	2
428	stroller	5138	22353	88%	96%	10%	2%	84%	83%	5%	15%	0%	0%	11%	2%	2	4

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
429	submarine	2619	12481	98%	100%	0%	0%	88%	88%	0%	0%	0%	0%	12%	12%	3	6
430	suitcase	3619	13318	96%	96%	0%	2%	79%	63%	0%	0%	4%	0%	17%	38%	2	2
431	sun	3837	18102	100%	96%	0%	0%	100%	96%	0%	4%	0%	0%	0%	0%	1	1
432	swan	3195	12465	94%	96%	0%	0%	74%	98%	0%	0%	0%	0%	26%	2%	1	2
433	sweater	3388	11622	94%	98%	2%	0%	55%	86%	0%	12%	0%	2%	45%	0%	2	3
434	swing	5324	21224	98%	98%	0%	0%	73%	100%	27%	0%	0%	0%	0%	0%	1	2
435	sword	2988	10243	100%	100%	0%	0%	92%	100%	0%	0%	2%	0%	6%	0%	1	2
436	needle	3087	10658	96%	94%	2%	0%	63%	81%	2%	0%	27%	6%	8%	13%	2	5
437	table	3120	12010	100%	94%	0%	0%	98%	100%	0%	0%	0%	0%	2%	0%	2	2
438	tail	5317	20747	96%	88%	2%	2%	77%	64%	10%	0%	0%	0%	13%	36%	1	3
439	tank	3158	11180	84%	94%	12%	2%	90%	100%	0%	0%	0%	0%	10%	0%	1	1
440	taperecorder	6373	35631	96%	96%	4%	0%	75%	79%	15%	13%	4%	4%	6%	4%	4	2
441	teapot	4115	17625	100%	90%	0%	2%	44%	36%	34%	58%	8%	0%	14%	7%	2	4
442	tear	2926	8908	96%	94%	2%	0%	50%	51%	8%	21%	0%	0%	42%	28%	1	1
443	teepee	4036	15294	94%	92%	2%	2%	70%	80%	0%	15%	2%	2%	28%	2%	2	2
444	teeth	2864	8898	96%	98%	2%	0%	79%	88%	0%	8%	21%	4%	0%	0%	1	2
445	telephone	4396	19758	100%	98%	0%	0%	72%	100%	28%	0%	0%	0%	0%	0%	3	3
446	telescope	5106	21547	98%	100%	2%	0%	98%	82%	0%	10%	0%	8%	2%	0%	3	2
447	tv	4056	18950	98%	100%	0%	0%	61%	74%	0%	0%	39%	26%	0%	0%	2	2
448	tennisracket	3334	12242	100%	94%	0%	0%	56%	91%	42%	9%	0%	0%	2%	0%	4	4
449	tent	4030	16963	98%	96%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	1	2
450	thermos	2468	5251	92%	88%	4%	6%	87%	95%	0%	0%	0%	0%	13%	5%	2	2
451	thimble	3185	9987	98%	94%	2%	0%	90%	94%	0%	0%	0%	0%	10%	6%	2	2
452	thumb	2642	6695	100%	90%	0%	0%	96%	58%	4%	38%	0%	0%	0%	4%	1	3
453	tie	5182	19103	100%	100%	0%	0%	98%	100%	2%	0%	0%	0%	0%	0%	1	3
454	tiger	7996	45476	94%	98%	4%	2%	91%	92%	0%	0%	0%	0%	9%	8%	2	2
455	tire	4297	14920	100%	98%	0%	0%	90%	65%	0%	16%	10%	12%	0%	6%	2	2
456	toaster	3214	13290	100%	96%	0%	0%	96%	58%	2%	35%	0%	0%	2%	6%	2	5
457	toe	3879	15263	88%	88%	10%	6%	52%	48%	39%	41%	0%	0%	9%	11%	1	2
458	toilet	4195	22049	100%	96%	0%	0%	100%	96%	0%	0%	0%	4%	0%	0%	2	2
459	tomato	2907	8388	100%	100%	0%	0%	98%	94%	0%	0%	0%	0%	2%	6%	3	4
460	grave	4445	21614	100%	96%	0%	2%	62%	77%	0%	19%	12%	0%	26%	4%	1	1
461	toothbrush	2773	8597	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	3

Pic num	US dominant response	ObjVC PDF	ObjVC JPG	Valid name %		No name %		Lex 1%		Lex 2%		Lex 3%		Lex 4%		Syllables	
				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
462	top	3149	10581	84%	82%	16%	12%	86%	63%	7%	2%	0%	0%	7%	34%	1	4
463	towel	4415	24097	98%	98%	0%	0%	80%	96%	0%	0%	0%	0%	20%	4%	2	4
464	railroadtracks	6497	40664	100%	96%	0%	0%	28%	77%	68%	15%	0%	2%	4%	6%	3	1
465	tractor	2823	9518	92%	94%	4%	2%	87%	79%	0%	0%	0%	0%	13%	21%	2	2
466	stoplight	4085	17265	100%	86%	0%	2%	62%	51%	32%	44%	4%	5%	2%	0%	2	2
467	train	3973	18361	96%	98%	0%	0%	100%	92%	0%	0%	0%	6%	0%	2%	1	2
468	trashcan	3572	13895	98%	100%	0%	0%	69%	44%	27%	16%	2%	30%	2%	10%	2	2
469	tree	5172	26074	98%	96%	0%	0%	100%	98%	0%	2%	0%	0%	0%	0%	1	1
470	tripod	4050	13049	78%	86%	18%	8%	79%	65%	0%	12%	0%	0%	21%	23%	2	2
471	trophy	4182	19720	88%	96%	10%	2%	50%	48%	2%	0%	2%	42%	45%	10%	2	2
472	truck	2751	10639	100%	100%	0%	0%	96%	58%	2%	0%	0%	40%	2%	2%	1	4
473	trumpet	3607	13615	98%	98%	0%	0%	69%	100%	0%	0%	0%	0%	31%	0%	2	3
474	chest	4451	20690	92%	96%	2%	2%	63%	79%	0%	4%	26%	0%	11%	17%	1	2
475	turkey	4251	15338	96%	86%	2%	4%	96%	70%	0%	0%	0%	0%	4%	30%	2	2
476	turtle	3592	14768	100%	100%	0%	0%	100%	64%	0%	36%	0%	0%	0%	0%	2	2
477	tweezers	2675	7308	90%	86%	4%	12%	91%	100%	0%	0%	0%	0%	9%	0%	2	2
478	typewriter	4944	28850	100%	98%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	3	3
479	umbrella	3974	15140	100%	96%	0%	0%	100%	96%	0%	4%	0%	0%	0%	0%	3	3
480	unicorn	3695	12749	100%	84%	0%	8%	100%	62%	0%	2%	0%	19%	0%	17%	3	3
481	unicycle	5145	20238	96%	80%	4%	12%	81%	33%	0%	35%	0%	8%	19%	25%	4	3
482	vacuum	6455	34257	100%	96%	0%	4%	82%	100%	18%	0%	0%	0%	0%	0%	2	3
483	vase	4676	20221	96%	98%	4%	0%	94%	82%	0%	4%	0%	0%	6%	14%	1	2
484	vest	3214	10103	100%	96%	0%	4%	96%	96%	0%	0%	0%	0%	4%	4%	1	2
485	violin	2963	8571	100%	92%	0%	0%	82%	93%	0%	0%	0%	0%	18%	7%	3	3
486	volcano	9818	54995	100%	98%	0%	0%	100%	82%	0%	0%	0%	16%	0%	2%	3	2
487	waffle	3082	11129	74%	52%	22%	40%	46%	35%	8%	0%	0%	0%	46%	65%	2	1
488	wagon	4321	20209	82%	84%	14%	10%	76%	24%	0%	17%	5%	0%	20%	60%	2	3
489	waiter	5683	27418	96%	96%	0%	2%	85%	96%	0%	0%	2%	0%	13%	4%	2	2
490	bricks	2520	11402	100%	98%	0%	0%	38%	53%	24%	22%	0%	0%	38%	24%	1	1
491	wallet	2884	10594	88%	92%	10%	8%	77%	76%	0%	11%	2%	2%	20%	11%	2	3
492	walnut	5689	30661	94%	98%	6%	0%	62%	98%	0%	0%	0%	0%	38%	2%	2	2
493	walrus	3186	11083	96%	84%	2%	0%	83%	79%	0%	0%	0%	0%	17%	21%	2	2
494	closet	5983	30610	100%	94%	0%	0%	86%	79%	0%	21%	2%	0%	12%	0%	2	2

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				US	HU	US	HU	US	HU	US	HU	US	HU	US	HU	US	HU
495	washingmachine	5234	29160	98%	84%	2%	10%	73%	79%	22%	0%	0%	0%	4%	21%	4	3
496	watch	3532	14511	100%	96%	0%	0%	100%	67%	0%	33%	0%	0%	0%	0%	1	2
497	wateringcan	3515	12701	70%	96%	26%	0%	31%	33%	29%	63%	0%	0%	40%	4%	4	5
498	watermelon	2746	9982	100%	96%	0%	2%	98%	85%	2%	15%	0%	0%	0%	0%	4	2
499	spiderweb	4016	14705	100%	94%	0%	2%	68%	94%	32%	2%	0%	0%	0%	4%	3	3
500	well	3497	12965	96%	96%	4%	0%	96%	92%	2%	6%	0%	0%	2%	2%	1	1
501	whale	3271	15429	98%	94%	0%	2%	96%	79%	0%	0%	0%	0%	4%	21%	1	2
502	wheat	6307	28962	72%	100%	16%	0%	58%	66%	0%	8%	0%	4%	42%	22%	1	2
503	wheel	4794	22753	100%	94%	0%	0%	100%	96%	0%	4%	0%	0%	0%	0%	1	2
504	wheelbarrow	4462	20045	100%	96%	0%	4%	86%	94%	6%	0%	0%	4%	8%	2%	3	3
505	wheelchair	6585	33755	98%	96%	0%	4%	100%	46%	0%	46%	0%	4%	0%	4%	2	4
506	whip	3138	10916	90%	98%	10%	0%	87%	94%	0%	0%	0%	2%	13%	4%	1	2
507	whistle	3025	10521	98%	94%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	1
508	wig	5437	22371	100%	98%	0%	2%	94%	92%	0%	0%	0%	0%	6%	8%	1	3
509	windmill	3819	12430	90%	94%	6%	2%	93%	68%	2%	32%	0%	0%	4%	0%	2	3
510	window	5086	26944	100%	100%	0%	0%	100%	100%	0%	0%	0%	0%	0%	0%	2	2
511	glass	2649	7194	98%	98%	0%	0%	67%	96%	29%	2%	0%	0%	4%	2%	1	2
512	wing	5858	27747	96%	96%	2%	0%	94%	96%	0%	4%	0%	0%	6%	0%	1	1
513	witch	5306	27723	100%	98%	0%	0%	100%	96%	0%	2%	0%	0%	0%	2%	1	3
514	wolf	4004	15672	100%	98%	0%	0%	56%	63%	0%	0%	0%	0%	44%	37%	1	2
515	woman	4058	14462	98%	98%	0%	0%	69%	76%	0%	2%	18%	4%	12%	18%	2	1
516	worm	4773	20764	98%	92%	0%	4%	96%	74%	2%	13%	0%	0%	2%	13%	1	3
517	wrench	2654	7594	88%	76%	12%	10%	95%	37%	2%	11%	0%	0%	2%	53%	1	3
518	yoyo	2681	8066	98%	84%	2%	8%	96%	62%	0%	0%	0%	2%	4%	36%	2	2
519	zebra	7356	36034	98%	98%	2%	0%	100%	98%	0%	0%	0%	0%	0%	2%	2	2
520	zipper	2410	5830	96%	96%	2%	2%	100%	94%	0%	0%	0%	0%	0%	6%	2	2