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When are concepts comparable across minds?

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Abstract In communication, people cannot resort to direct reference (e.g., pointing) when using diffuse concepts like democracy. Given that concepts reside in individuals' minds, how can people share those concepts? We argue that concepts are comparable across a social group if they afford agreement for those who use it; and that agreement occurs whenever individuals receive evidence that others conceptualize a given situation similarly to them. Based on Conceptual Agreement Theory, we show how to compute an agreement probability based on the sets of properties belonging to concepts. If that probability is sufficiently high, this shows that concepts afford an adequate level of agreement, and one may say that concepts are comparable across individuals' minds. In contrast to other approaches, our method considers that inter-individual variability in naturally occurring conceptual content exists and is a fact that must be taken into account, whereas other theories treat variability as error that should be cancelled out. Given that conceptual variability will exist, our approach may establish whether concepts are comparable across individuals' minds more soundly than previous methods.

Keywords Conceptual Agreement Theory · Conceptual variability · Shared meaning · Agreement

1 Introduction

In their review of concepts and categories, Rips and Medin (2005) list two main functions of concepts. One of them is categorization, which allows the sub-functions of understanding, inference, and learning. The other function of concepts is communication, which

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is where we will focus in the current work. In their initial discussion of communication, Rips and Medin state that concepts allow communication if people have comparable concepts in their minds. To use their own example, if A's concept of cell phone corresponds to B's concept of flashlight, communication will fail.

Though the question of what it means to say that concepts in different minds are comparable might sound intuitively correct to many readers, many researchers apparently have reservations about the question's implications. A first question that springs up is what it means to say that concepts are comparable. Different ways to theoretically handle meaning produce different answers to this question. We list these alternatives below (not necessarily an exhaustive list). The first two alternatives turn the question into a non-issue. The third alternative gives, we shall argue, an overly strong answer.

The skeptic view: Several researchers seem to conclude that the above-mentioned question points to a deep problem with the notion of concept. Famously, in philosophy, Popper (1972) and Frege (1893) have seen the need to separate the subjective from objective knowledge. Thus, for the latter, concepts should not be thought of as individual level phenomena. From a psychological point of view, the problem is that because we know that people have different contents for what presumably is the same concept, this casts doubt on whether it makes sense to talk about *the same* concept (cf., Frege 1893; Glock 2009) and perhaps even about comparable concepts. This has been noted several times over the years. Consider Barsalou, for example, who on grounds of inter- and intra-individual variability on conceptual content doubted that concepts are entities in the mind (1987, 1993). Consider also Converse (1964), who on similar grounds doubted that public opinion exists. A more recent and related objection is based on widely acknowledged limitations of current views on concepts (i.e., their difficulties in explaining how context comes to influence concepts; their problems in explaining how concepts are combined). Due to these limitations, Gabora et al. (2008) suggest that concepts should be modeled with quantum mechanics formalisms. Their argument is that concepts, like quantum entities, do not have definite properties unless in a particular (measurement) situation. The reader may note that this is another way of highlighting the problem of inter- and intra-individual variability.

The causal view: In line with the Putnam–Kripke causal view of reference (Putnam 1973; Kripke 1980), several researchers have focused on communication about concrete objects that can be directly referred to (e.g., by pointing). The general idea of the Putnam–Kripke view is that reference requires establishing causal links between objects and actions. This view has been profusely exploited in psychology and, importantly for our discussion on communication; it does not require that people's concepts are comparable because it holds that people don't require resorting to meaning to achieve agreement. The types of actions studied are things such as gaze and joint attention (e.g., Moses et al. 2001; Richardson et al. 2009; Tomasello 1995), eye movements (e.g., Spivey et al. 2002), pointing gestures (e.g., Carpenter et al. 1998), and conceptual pacts (e.g., Brennan and Clark 1996; Garrod and Anderson 1987).

The shared representation view: Following the generally accepted idea that entities relate only probabilistically to concepts (e.g., Ashby and Alfonso-Reese 1995), the study of naturally occurring categories often relies on statistics rather than on some formal definition of what a concept is. In this view, it is often assumed that there is a shared representation, and that inter-individual differences amount only to error variance. Thus, this view makes the very strong claim that having comparable concepts means actually having the same concept. To our knowledge, nowhere has the shared representation view been presented more explicitly than in Cultural Consensus Theory (CCT; Batchelder and Romney 1988; Romney et al. 1996). In CCT, it's assumed that there is a single cultural truth that can be learned but that some people have learned it to a greater degree than others, thus producing different degrees of cultural competence (Batchelder and Anders 2012). When this view is invoked in studies of naturally occurring concepts, data reduction techniques are often used. However, when these techniques are applied, awkward results are sometimes obtained. E.g., in Henley (1969), the shared representation for animals is reduced to the dimensions of “size” and “ferocity”, leaving all other things that people know about the animal category outside of the putative shared representation. To an extent, these kinds of results occur because data reduction techniques tend to treat the non-shared part of meaning as error.

In contrast to the views outlined above, here we will hold that the question about comparable concepts is not flawed (contrary to the skeptic view); that meaning is relevant for agreement (contrary to the causal view); and that the Rips and Medin (2005) formulation that asks for comparable concepts is the correct way to formulate the problem, although assuming that a single shared conceptual representation is only a statistical fiction (contrary to CCT). In a nutshell, what we argue is that a concept *C* is comparable across members of a social group if it affords agreement for those who use it; and that agreement occurs whenever individuals receive evidence that others conceptualize a given situation similarly to them. Furthermore, we will show that a probability of agreement can be defined, and will show how to compute such probability for arbitrarily large data sets. Importantly, the measure we discuss here (i.e., probability of agreement) is related to, but not equal to, conceptual overlap (as would be the case in CCT), and is largely consistent with several common assumptions made in the literature about concepts.

2 Conceptual Agreement Theory

Conceptual Agreement Theory (CAT, Chaigneau et al. 2012) is a theory that models agreement in a social group that uses a given concept. CAT is based on four assumptions commonly made about concepts in cognitive psychology: (1) Concepts can be described by a finite set of properties among a larger but still finite set of possible properties (e.g., Hampton 1979; Rosch and Mervis 1975; Rosch et al. 1976; Smith 1978). Note that we are not implying here that concepts are represented by lists of properties, but rather that whatever is the format and content of concepts, people are able upon request to produce lists of properties that exhibit many regularities; (2) These properties are conventional, in the sense that they are stably shared by a social group, and they are not shared in an all-or-nothing fashion, but only probabilistically (e.g., Chang et al. 2011; McRae et al. 2005; Wu and Barsalou 2009); (3) Furthermore, when people conceptualize, they do so in the context of available alternative conceptualizations that are also possible (e.g., Tversky 1977; D’Lauro et al. 2008; Murphy and Brownell 1985; Rogers and Patterson 2007; Rosch et al. 1976; Patalano et al. 2006); (4) And finally, there is inter-individual variability in conceptual content for a given concept (as discussed above). A simple mechanism that would produce variability is that when acquiring natural concepts (i.e., in contrast to laboratory concepts) people are exposed to different learning experiences. Note that instead of treating variability in conceptual content as a problem that current theories of concepts do not address (as discussed relative to the skeptic view, above), we take variability as a fact of the matter that is integral to our theory.

A knowledgeable reviewer noted that in epistemology, a standard position is to link knowledge to truth. In this view, knowledge is true knowledge. This prompted us to clarify here that throughout this paper, when we refer to knowledge we are not implying anything about how it was acquired, or about whether it is true or not. Instead, we are only interested on how it is possible that mental content (even if fictional, false, or subjective) may be said to be shared.

To understand what is being modeled in CAT, consider the following situation. Imagine two individuals, an observer (*O*) and an actor (*A*), who are members of a social group. In keeping with the assumptions discussed above, imagine also that this group has two alternative conceptualizations, *C* and *Cn*, for a given entity *x* (as Fig. 1 illustrates). Assume also that these conceptualizations can be defined by their corresponding properties (where k_1 and k_2 represent, respectively, the total number of properties consistent with *C* and *Cn*), and that these conceptualizations are only probabilistically related to their corresponding sets of properties (*i*), such that a single property may be related to one or to both, *C* and *Cn*, with a certain probability (i.e., there is a number $u \geq 0$ of properties that belong to the $C \cap Cn$ set). Imagine, finally, that group members *O* and *A* lack full conceptual knowledge, and each typically knows only a subset *s* of the *k* properties in *C* or *Cn* (s_1, k_1 for *C* and s_2, k_2 for *Cn*) (i.e., there is conceptual variability).

In this context, the following is an idealized structure of a communication task. Imagine that *O* and *A* are having a conversation about a given topic, and that *O* has an hypothesis *C* about how entity *x* is being jointly conceptualized (i.e., that they are talking about *x* as an instance of *C*). However, because concepts are events in individual minds, *O* can only infer whether *C* is the case for *A* or not. To make this inference, *O* observes *A*, and when *A* utters a property of type *i*, *O* evaluates if *i* is consistent with *C* or not (i.e., a simple deterministic comparison). If it is consistent, then *O* infers that *A* is also talking about *x* conceptualized as *C* (otherwise, not). However, because properties are only probabilistically related to concepts (*i* is associated with *C* with only some probability), this inference is only probably correct. When *O* infers that *A* is instantiating *C*, and in fact that is the case, we call this true agreement (*a1*) (and *p*(*a1*) is its probability). When *O* infers that *A* is instantiating *C*, and in fact that is not the case (i.e. *A* is actually instantiating *Cn*), we call this illusory agreement (*a2*) (and *p*(*a2*) is its probability). It is important to note here that CAT does not require individuals to compute, or even to estimate, probabilities. Individuals are thought to simply verify in an all or nothing fashion whether an utterance or interpretable action is consistent with the individual's own conceptual state, thus providing evidence of a shared conceptual state.

According to CAT, then, a concept *C* is comparable across the minds of members of a social group, when despite the unavoidable inter-individual variability there is a sufficiently high *p*(*a1*)so that group members will experience agreement. However, because

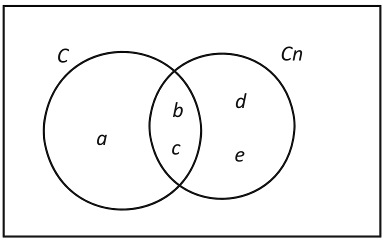

Fig. 1 Two concepts *C* and *Cn* with their corresponding *i* properties (for $C = \{a, b, c\}$ and $Cn = \{b, c, d, e\}$) and intersection ($C \cap Cn = \{b, c\}$), with k_1 (number of *C*'s properties) = 3, k_2 (number of *Cn*'s properties) = 4, *u* (number of properties in the intersection) = 2

natural concepts typically occur in a network of related concepts (represented here by *Cn*), illusory agreement must also be considered. Thus, when evaluating the amount of agreement derived from using concept *C*, it is also necessary to consider that $p(a2)$ also contributes to experiencing agreement.

Our goal in the current work is not to provide empirical support for CAT. Instead, we focus here on a methodological prerequisite, which is to show how estimates of $p(a1)$ and $p(a2)$ can be obtained.

2.1 Agreement probabilities

CAT's mathematical formulation allows calculating the probabilities $p(a1)$ and $p(a2)$ using expressions (1) and (2):

$$p(a1) = \frac{1}{s_1}\sum_{j=1}^{n_c}\sum_{l=1}^{n_c}\#(sCO_j \cap sCA_l)p(sCO_j)p(sCA_l) \quad (1)$$

$$p(a2) = \frac{1}{s_2}\sum_{j=1}^{n_c}\sum_{l=1}^{n_{cn}}\#(sCO_j \cap sCnA_l)p(sCO_j)p(sCnA_l) \quad (2)$$

Table 1 defines each of the variables, which appear in (1) and (2), from left to right.

Expression (1) is the summation of the expected value of the number of common elements between samples sCO_j of properties of *C* that observers (*Os*) have in their minds and independent samples sCA_l that actors (*As*) have in their minds (i.e., the $\#(sCO_j \cap sCA_l)$

Table 1 Definition of variables used in expressions for calculating $p(a1)$ and $p(a2)$

Variable's symbol	Definition
s_1	The average number of property types coherent with concept *C* in an individual's mind ($s_1 \leq k_1$), where k_1 is the cardinality of *C*
n_c	The number of possible samples of size s_1 obtained from the k_1 properties that belong to concept *C*. Thus, $n_c = \frac{k_1!}{(k_1-s_1)!s_1!}$
$\#(sCO_j \cap sCA_l)$	The cardinality of the intersection between a sample "*j*" drawn from *C* by an observer (*O*) (sCO_j) and another independent sample "*l*" drawn from *C* by an actor (*A*) (sCA_l), i.e. the number of properties that belong to both samples
$p(sCO_j)$	Probability of obtaining sample sCO_j in (1)
$p(sCA_l)$	Probability of obtaining sample sCA_l in (1)
s_2	The average number of property types coherent with concept *Cn* in an individual's mind ($s_2 \leq k_2$), where k_2 is the cardinality of *Cn*
n_{cn}	The number of possible samples of size s_2 obtained from the k_2 properties that belong to concept *Cn*. Thus, $n_{cn} = \frac{k_2!}{(k_2-s_2)!s_2!}$
$\#(sCO_j \cap sCnA_l)$	The cardinality of the intersection between a sample "*j*" drawn from *C* by an observer (*O*) (sCO_j) and another independent Sample "*l*" drawn from *Cn* by an actor (*A*) ($sCnA_l$), i.e. the number of properties that belong to both samples
$p(sCO_j)$	Probability of obtaining sample sCO_j in (2)
$p(sCnA_l)$	Probability of obtaining sample $sCnA_l$ in (2)

term), taking into account the probabilities of each sample (i.e., the $p(sCO_j)$ and $p(sCA_l)$). Assuming that all properties in samples sCA_l have the same probability of being uttered by A, and recalling that the sizes of the samples taken from C are s_1, $p(a1)$ is calculated as the summation in (1) divided by s_1.

Similarly, Eq. (2) is the summation of the expected value of the number of common elements between samples sCO_j of properties of C that Os have in their minds and independent samples $sCnA_l$ of properties of Cn that As have in their minds (i.e., the $\#(sCO_j \cap sCnA_l)$ term), taking into account the probabilities of each sample (i.e. the $p(sCO_j)$ and $p(sCnA_l)$). Assuming that all properties in the $sCnA_l$ samples have the same probability of being uttered by A, and recalling that the size of samples $sCnA_l$ is s_2, $p(a2)$ is calculated as the summation in (2) divided by s_2. The interested reader may find the complete mathematical and theoretical development of (1) and (2) in Chaigneau et al. (2012). We will not repeat that material here, given that it is not necessary for the understanding of the present work. Instead, to aid the reader in understanding Eqs. (1) and (2) and the definitions in Table 1, we present a simple example, which illustrates the application of such expressions.

Let's assume the following situation, which corresponds to the C and Cn concepts depicted in Fig. 1. In this case, e.g., C may be "right wing political view" and Cn "left wing political view", such that: $a =$ low taxes, $b =$ total employment, $c =$ quality public education, $d =$ strong government regulation, $e =$ public state-managed pension system.

$$C = \{a, b, c\} \qquad Cn = \{b, c, d, e\}$$
$$k_1 = 3 \text{ and assuming } s_1 = 2 \qquad k_2 = 4 \text{ and assuming } s_2 = 3$$

$u = 2$ (two common elements, i.e., b,c) and thus,

$n_c = 3!/(3-2)!/2! = 3$ $\quad$ $n_{cn} = 4!/(4-3)!/3! = 4$

the $n_c sCO_j$ and sCA_l samples $= \{ab, ac, bc\}$ $\quad$ the $n_{cn} sCnA_l$ and sCA_l samples $= \{bcd, bce, bde, cde\}$

For simplicity, assume that each sample in C and in Cn has an equal probability of being selected and thus,

For samples drawn from C in expressions (1) and (2): $p(sCO_j) = p(sCA_l) = 1/n_c = 1/3$

For samples drawn from Cn in expression (2): $p(sCnA_l) = 1/n_{cn} = 1/4$

Then, using (1),

$$p(a1) = \frac{1}{2}\sum_{j=1}^{3}\sum_{l=1}^{3} \#\left(sCO_j \cap sCA_l\right)\frac{1}{3}\frac{1}{3} = \frac{1}{18}\sum_{j=1}^{3}\sum_{l=1}^{3} \#\left(sCO_j \cap sCA_l\right) \tag{3}$$

In (3), the double summation corresponds to the sum of counts of coincidences between each sample sCO_j and sCA_l, for example:

$$\#(sCO_1 \cap sCA_1) = \#(ab \cap ab) = 2$$
$$\#(sCO_1 \cap sCA_2) = \#(ab \cap ac) = 1 \text{ and so on until,}$$
$$\#(sCO_3 \cap sCA_3) = \#(bc \cap bc) = 2$$

For this example, each term of the double summation is

$\#(sCO_j \cap sCA_l) = \{2, 1, 1, 1, 2, 1, 1, 1, 2\}$ and hence $p(a1) = 12/18 = 2/3$

Consequently, for O and A with incomplete knowledge, the probability that A utters something that for O is consistent with C (allowing the inference that A is really thinking that C), given that A is in fact thinking that C, is 2/3.

In the case of $p(a2)$, we apply expression (2), and thus,

$$p(a2) = \frac{1}{3}\sum_{j=1}^{3}\sum_{l=1}^{4}\#(sCO_j \cap sCnA_l)\frac{1}{3}\frac{1}{4} = \frac{1}{36}\sum_{j=1}^{3}\sum_{l=1}^{4}\#(sCO_j \cap^s CnA_l) \qquad (4)$$

In (4), the double summation corresponds to the sum of counts of coincidences between each sample sCO_j and $sCnA_l$, for example:

$$\#(sCO_1 \cap sCnA_1) = \#(ab \cap bcd) = 1$$
$$\#(sCO_1 \cap sCnA_2) = \#(ab \cap bce) = 1 \text{ and so on until,}$$
$$\#(sCO_3 \cap sCnA_3) = \#(bc \cap cde) = 1$$

For this example, each term of the double summation is
$\#(sCO_j \cap sCnA_l) = \{1,1,1,0,1,1,0,1,2,2,1,1\}$ and hence $p(a2) = 12/36 = 1/3$

Consequently, for O and A with incomplete knowledge, the probability that A utters something that for O is consistent with C (allowing the inference that A is really thinking that C), given that A is in fact thinking that Cn, is 1/3.

It should be noted that here for simplicity we have presented CAT and its mathematical formulation using only two concepts. There is a general formulation for any number of concepts, and the interested reader may obtain it from the authors.

Table 2 A simple conceptual structure with two concepts C and Cn, defined by two frequency distributions of only three property types (a, b, c) provided by four participants

Property i	1	2	3	4	$p(i/1)$	$p(i/2)$	$p(i/3)$	$p(i/4)$	Freq. dist. of i $p(i)$	Freqs. of i
C	Participant m									
a	3	2	4	0	0.200	0.200	0.286	0.000	0.171	17
b	5	0	4	3	0.333	0.000	0.286	0.273	0.223	22
c	7	8	6	8	0.467	0.800	0.429	0.727	0.606	61
Σcols.	15	10	14	11	1.0	1.0	1.0	1.0	1.0	
s_1	3	2	3	2		Avg. s_1	3			
k_1	3									
Cn	Participant m									
a	8	7	9	1	0.800	0.583	0.474	0.111	0.492	49
b	0	5	0	8	0.000	0.417	0.000	0.889	0.326	33
c	2	0	10	0	0.200	0.000	0.526	0.000	0.182	18
Σcols.	10	12	19	9	1.0	1.0	1.0	1.0	1.0	
s_2	2	2	2	2		Avg. s_2	2			
k_2	3									
u	3									

The table illustrates calculation of frequency distributions of properties for C and Cn concepts

3 Measurement of the frequency distributions of properties of *C* and *Cn*

Note that in order to apply Eqs. (1) or (2) one has to estimate the corresponding parameters that characterize the frequency distribution of *C* and *Cn* in a real population. Table 2 presents a simple example and calculation of frequency distributions for *C* and *Cn* when properties are not equiprobable. To build that table, we need to obtain the lists of property types for *C* and *Cn*. If we did not have the properties that belong to each concept (e.g., provided by previous studies), then following the procedure used in developing feature norms (Chang et al. 2011; McRae et al. 2005; Wu and Barsalou 2009), we would present a sample of individuals with the relevant concepts and ask them to produce the concepts' properties (e.g., for right political view: "low taxes", "total employment", "quality public education" may be produced). On the other hand, if we already knew the properties that belonged to each concept, we could directly use those properties. In any of the two cases, we need to obtain estimates of the frequencies with which the properties are associated to *C* and *Cn*. To do this, we ask individuals to estimate these frequencies by assigning a number between, e.g., 0 and 10, where 0 indicates that the given property is not associated with *C* (or *Cn*) and that 10 denotes that the property is highly likely given *C* (or *Cn*) (in this simplified example, we use a 0–10 range to make Table 2 more manageable, but a more realistic case will probably involve, e.g., a 0–100 range, which probably is a more natural way for people to estimate frequencies).

Because it is generally accepted that humans can accurately estimate event frequencies (Cosmides and Tooby 1996; Hasher and Zacks 1984), this suggests that our task should be performed with ease and accuracy. Furthermore, several researchers have suggested that because people appear to easily encode event frequencies, frequency estimates compare favorably to other measures such as Likert scales and similarity ratings (Kane and Woehr 2006; Steiner et al. 1993; Woehr and Miller 1997).

As Table 2 illustrates, the frequency estimate of each participant m (in this case four subjects: $m = 1,2,3,4$) for each property i (a,b,c) is summed up to obtain $p(i/m)$, i.e., the conditional probability of property i given that it was assigned by participant m (see columns labeled $p(i/1)$, etc., where for example: $p(a/1)$ = frequency assigned by participant 1 to property a/sum of the frequencies assigned by participant 1 to all three properties = 8/(8 + 0 + 2) = 0.8). Then, to estimate $p(i)$ (e.g., $p(a), \ldots, p(c)$), we simply apply that $p(i) = p(i/1)p(1) + \cdots + p(i/m)p(m)$ (e.g., for $a: p(a) = p(a/1)p(1) + \cdots + p(a/4)p(4)$). Finally, assuming that each participant had an equal probability of being selected, or that the opinion of each of them is equally representative of the universe of possible participants (i.e., assuming that $p(1) = \cdots = p(m) = 1/m$, where m is the number of participants), we compute $p(i) = [p(i/1) + \cdots + p(i/m)]/m$, or simply the average of $p(i/m)$ over all m participants. To represent the frequency distribution of properties in a more amenable form to dealing with it, in Table 2 we multiply each $p(i)$ by a constant and round it up to the nearest integer. For example, we could use the constant 100, and thus the distribution of properties would be the ones shown on the last column of Table 2.

Now, as Table 2 also illustrates, to estimate s_1 and s_2, we count the number of properties to which each individual assigned a number greater than zero. This is the individual estimate of s_1 or s_2. Then, as defined earlier, s_1 and s_2 are simply averages of those estimates. Similarly, for estimating k_1 and k_2, we count the number of frequencies in the last column of Table 2 that are greater than zero (i.e., the estimate of the size of *C* and *Cn*). Finally, to estimate u, we count the number of frequencies which are simultaneously greater than zero for C and for Cn. Though in Table 2 we illustrate the estimation using only four participants, larger and more realistic samples are readily possible to handle.

Finally, note that the estimated normalized frequency distributions of properties i for concepts C and Cn (see columns labeled "freq. dist. of i p(i)" in Table 2) are also an estimate of the probability that each property type belongs to each concept. These probabilities are necessary for estimating $p(a1)$ and $p(a2)$ through Eqs. (1) and (2) (as our running example illustrates). Additionally, note that the two frequency distributions for C and Cn define the joint frequency distribution for both concepts. This joint distribution implicitly contains k_1, k_2 and u. Thus, having computed the frequency distributions for C and Cn, we don't need to actually compute k_1, k_2 and u to calculate $p(a1)$ and $p(a2)$, as we will see in the next section. Moreover, note that expressions (1) and (2) entail the enumeration of all the possible combinations of samples drawn from C and Cn, whose numbers n_c and n_{cn} exponentially grow as k_1 and k_2 increase. Thus, from a practical point of view, it is impossible to calculate $p(a1)$ and $p(a2)$ using (1) and (2), even if we implement those formulae in a computational program. In fact, we did implement such program and, for example, for $k_1 = k_2 = 3$ and $s_1 = s_2 = 2$, the number of combinations is just 3 and the program takes about 0.01 ms to compute $p(a1)$ and $p(a2)$. However, with $k_1 = k_2 = 26$ and $s_1 = s_2 = 6$, the total number of combinations grows to 230,230 and the program needs 282 s to calculate them. Note that not only the number of combinations exponentially increases, but so does the computational time (i.e. for 230,230 combinations, if the computational time had linearly increased, it would have taken the computer about $0.01 \times 10^{-3} \times 230{,}230/3 = 0.77$ s). For an even bigger $k_1 = k_2 = 40$ and $s_1 = s_2 = 15$,

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Set up:
  k1 = nr. of properties in C
  s1 = sampling size of properties drawn from C
  k2 = nr. of properties in Cn
  s2 = sampling size of properties drawn from Cn
  u = nr. of common properties between C and Cn
  fd_C = property frequency distribution of C
  fd_Cn = property frequency distribution of Cn
  max-iter = maximum nr. of iterations of the simulator
  nr_points_mvg_avg = nr. of points to calculate a moving average of p(a1) and p(a2)

Generate sets C and Cn according to corresponding frequency distributions fd_C and fd_Cn
do while number of iterations ≤ max-iter
    Draw w/o replacement a sample of size s1 from C (sample_C_1) /* actually a copy of the sampled properties
    are stored in sample_C_1, so that set C is not altered*/
    Draw w/o replacement another sample of size s1 from C (sample_C_2) /* same comment as before,
    sample_C_1 and sample_C_2 are independent, i.e. both are drawn from the entire set C*/
    Draw w/o replacement a sample of size s2 from Cn (sample_Cn_1) /* actually a copy of the sampled
    properties are stored in sample_Cn_1, so that set Cn is not altered*/
    Equiprobably draw one property from sample_C_2 and store it in one_property_C_2
    if sample_C_1 ∩ one_property_C_2 = 1 then increment counter_pa1 by one
    Equiprobably draw one property from sample_Cn_1 and store it in one_property_Cn_1
    if sample_C_1 ∩ one_property_Cn_1 = 1 then increment counter_pa2 by one
    Increment number of iterations by one
    Calculate p(a1) = counter_pa1 / number of iterations
    Store value of p(a1) in an array A_PA1
    Calculate p(a2) = counter_pa2 / number of iterations
    Store value of p(a2) in an array A_PA2
    if number of iterations ≥ nr_points_mvg_avg then calculate moving average of p(a1) using the last
    nr_points_mvg_avg data points stored in A_PA1
    if number of iterations ≥ nr_points_mvg_avg then calculate moving average of p(a2) using the last
    nr_points_mvg_avg data points stored in A_PA2
end while
```

Fig. 2 Pseudo-code of a simulator that calculates $p(a1)$ and $p(a2)$

the number of combinations is 4.023×10^{10}, making it impossible to carry out the calculations using (1) and (2).

It should be noted that the last situation is not uncommon in feature norming studies. For example, in McRae et al. (2005), the number of properties produced for a given concrete concept range from 6 to 26 features (mean = 13.42; SD = 3.52). Consider that a common practice in these studies is to drop from the norms those properties produced by less than a given sample proportion (e.g., in McRae et al. 2005, features produced by less than five out of 30 participants were not included in the analyses). Hence, the total range of properties being produced is probably well over the 26 maximum found in the norms. Thus, to deal with this combinatorial issue, in the next section we present a very simple computer program that simulates the processes incorporated in CAT, and that allows estimating $p(a1)$ and $p(a2)$ with close approximation to our exact formulae.

4 Calculation of $p(a1)$ and $p(a2)$ through a computer simulation

As discussed above, only toy situations like the ones used in previous examples allow the direct use of (1) and (2). In contrast, the practical determination $p(a1)$ and $p(a2)$ from frequency distributions of the properties of *C* and *Cn* that come from real-world examples (per our discussion on the exponential growth of combinations) is possible when using a computer simulator (its pseudo-code is shown in Fig. 2).

Conceptually, this simulator works as follows. An observer *O* looks for agreement. To compute $p(a1)$, *O* chooses a sample of size s_1 from a population *C* of k_1 properties (with any particular desired frequency distribution). Concurrently, an actor *A* chooses a sample of size s_1 from the same *C* population. Then *A* selects one property from its sample and both *O* and *A* check if the selected property is part of *O*'s sample. If there is agreement (i.e., *A*'s selected property also belongs to *O*'s sample), this increases an *a1* coincidence counter by one. Computing $p(a1)$ on the long run, simply amounts to getting the proportion between this counter and the total number of simulation steps. To compute $p(a2)$, the same process occurs, but *A* chooses a sample of size s_2 from a *Cn* population of k_2 properties (with any particular desired frequency distribution). Now, if there is coincidence this increases an *a2* coincidence counter by one. Computing $p(a2)$ on the long run, simply amounts to getting the proportion between this counter and the total number of simulation steps. Given values for all the parameters, the simulator will converge to the agreement probabilities implied by those values, as the simulation unfolds (i.e., will approximate values computed by our formulae), as we will show later.

Note that in Fig. 2, the pseudo code asks for inputting the values of k_1, k_2 and *u*. However, those values are actually not necessary for the calculation of $p(a1)$ and $p(a2)$ as lines 2–18 of the pseudo code show (no line uses those parameters). However, if the user enters those values, the computer simulator can check whether the frequency distributions for *C* and *Cn* are consistent (notice that to unclutter the simulator's pseudo-code in Fig. 2, it does not contain that part of the program). As we noted for the development of CAT, the simulator may be used to calculate $p(a1)$ and $p(a2)$ for any number of concepts, provided that each concept's frequency distribution is determined, per the procedure illustrated in Table 2. The interested reader may obtain the simulator's code and usage instructions from the authors.

5 Comparison of $p(a1)$ and $p(a2)$ values calculated using formulae and simulator

As mentioned before, the practical calculation of $p(a1)$ and $p(a2)$ would normally be done using the simulator whose pseudo code is shown on Fig. 2. In this section, we illustrate how precise that calculation is compared with exact values obtained by using expressions (1) and (2) for equiprobable and non-equiprobable property distributions, such as Table 2 illustrates.

Table 3 presents $p(a1)$ and $p(a2)$ for equiprobable properties, which were already calculated with expressions (3) and (4), along with the same values obtained by using the simulator. The values obtained through the simulator used 30,000 iterations (*max-iter* = 30,000 per line 3 in Fig. 2) for each run and the moving average was computed using the last 3000 values of $p(a1)$ and $p(a2)$ respectively (*nr_points_mvg_avg* = 3000 per line 17 in Fig. 2, i.e. the simulator takes the values of $p(a1)$ and $p(a2)$ generated in the last 3000 iterations of a run and computes an average of them). We performed 50 different runs, and Table 3 presents the average and standard deviation (in parentheses) of $p(a1)$ and $p(a2)$. As can be seen, those values are extremely close to those computed with our formulae. Also all the 95 % confidence intervals for those values contain the exact formulae values (i.e., there are no statistically significant differences between the simulator and exact values). Note also that the number of runs used in the calculation of the averages in Table 3 was relatively small, which only strengthens our conclusions.

To further illustrate the use of the simulator, for this simple situation we can also compute an exact value of $p(a1)$ and $p(a2)$ for non-equiprobable properties. To this end, we used the same C and Cn sets employed in our running example (i.e., $k_1 = 3$, $s_1 = 2$, $k_2 = 4$, $s_2 = 3$ and $u = 2$), but we now assigned the following probabilities to each of the properties of C and Cn:

$$C : p(a) = 0.5, p(b) = 0.3 \text{ and } p(c) = 0.2$$
$$Cn : p(b) = p(c) = 0.1,\ p(d) = 0.3 \text{ and } p(e) = 0.5$$

Note that to use (1) and (2) for non-equiprobable properties, we must previously calculate the probabilities of obtaining each of the different possible samples drawn from C or Cn (i.e. the $p(sCO_j)$ and $p(sCnA_l)$). This requires using the individual property's probabilities shown above. The interested reader may find the corresponding calculations in Appendix 1.

Table 3 Comparison of $p(a1)$ and $p(a2)$ calculated using exact formulae and simulator

Exact formulae	Simulator (n = 50)	95 % CI
Equiprobable properties		
$p(a1) = 0.66667 = 2/3$	$p(a1) = 0.66663$ (0.00237)	0.66596–0.66730
$p(a2) = 0.33333 = 1/3$	$p(a2) = 0.33309$ (0.00296)	0.33225–0.33393
Non-equiprobable properties		
$p(a1) = 0.69797$	$p(a1) = 0.69838$ (0.00226)	0.69774–0.69902
$p(a2) = 0.21771$	$p(a2) = 0.21734$ (0.00237)	0.21667–0.21801

The reader that does not want to dwell in Appendix 1, do trust us that using (1) and (2),the value for $p(a1)$ equals 0.69797 and for $p(a2)$ equals 0.21771. Table 3 also shows for this case that the values for $p(a1)$ and $p(a2)$ calculated using the exact formulae and the simulator are very similar and that the 95 % confidence intervals contain the exact values. As before, the simulator used 30,000 iterations and the probabilities were calculated using the last 3000 values.

As the computations above and Table 3 show, the simulator described in Fig. 2 correctly implements processes assumed in CAT and produces results practically equivalent to those obtained by exact formulae. Therefore, even very large data sets formatted like Table 2 could be used to estimate the probability of true and illusory agreement implied for that population. Relatedly, we must note that the simulator can comfortably handle the problem of exponential growth of combinations discussed earlier. For the case where $k_1 = k_2 = 26$ and $s_1 = s_2 = 6$, with a total number of combinations of 230,230, the program that implements the exact formulae took 282 s to calculate $p(a1)$ and $p(a2)$, whereas the simulator used only 13 s. For $k_1 = k_2 = 40$ and $s_1 = s_2 = 15$, with a total number of combinations of 4.023×10^{10}, the first program was not able to end within a reasonable time (we might have waited years), whereas the simulator took only 25 s.

6 Interpreting agreement probabilities

In the preceding sections we showed how probabilities of true and illusory agreement according to CAT can be computed for realistic data sets, as would typically be obtained in feature norming studies (e.g., Chang et al. 2011; McRae et al. 2005; Wu and Barsalou 2009). In the current section we briefly discuss some issues related to the interpretation of those probabilities.

A first thing to note is that $p(a1)$ and $p(a2)$ represent the potential for agreement implicit in a social group's use of a family of related concepts (represented here by C and Cn). Thus, here we do not assume that concepts are necessarily represented by features, nor that they are represented in any particular way. Whatever the format and mechanism that implements conceptualization in individual minds, $p(a1)$ and $p(a2)$ offer a way to measure the potential of a given concept (and its related concepts) to produce inter-individual agreement when used. Furthermore, because $p(a1)$ and $p(a2)$ are probabilities, and because their calculation is tightly coupled to the properties believed by a social group to be related to a given concept, they can receive a clear interpretation.

Consider the following. It can be demonstrated that for the case of equiprobable properties (for C when $p\left(sCO_j\right) = p(sCA_l) = 1/n_c$),

$$p(a1) = \frac{s_1}{k_1} \tag{5}$$

and also for Cn when $p(sCnA_l) = 1/n_{cn}$ that

$$p(a2) = p(a1)\frac{u}{k_2} \tag{6}$$

(These demonstrations are included in Appendix 2.)

Note that Eq. (5) aids our understanding of Eq. (1). Because (5) makes $p(a1)$ readily understandable as the number of property types coherent with a version of concept C in an average individual's mind, over the total number of property types available for C, it highlights that $p(a1)$ is a measure of the coherence of a conceptual representation in the minds of a social group. A high $p(a1)$ implies coherence, and affords the conclusion that there is actually a comparable concept across minds. However, we again stress that in CAT this coherence does not assume a single shared representation in the same sense that a theory such as CCT assumes.

Note also that (5) and (6) mean that $p(a1)$ will condition the value of the corresponding $p(a2)$, depending on the amount of overlap between the C and Cn concepts. The only way in which $p(a2)$ could be equal to $p(a1)$ is if $u = k_2$, i.e., if the cardinality of the intersection between C and Cn (i.e. the number of properties that belong to both C and Cn) is equal to the cardinality of Cn, which means that $C = Cn$ or $Cn \subset C$ and thus, there is actually only one concept. Thus, whenever C and Cn reflect different concepts, then $p(a2) < p(a1)$ (i.e., these concepts are not comparable or the same across minds). We must note that the above mentioned feature ($p(a2) < p(a1)$ when $u < k_2$) strictly holds for concepts with equi-probable distributions of properties. For concepts with non-equiprobable distributions of properties, that feature holds only for some special cases. However, our research shows that under normal conditions, where $u < k_2$ and the distributions of C and Cn are not overly biased toward $C \cap Cn$, then $p(a2) < p(a1)$. Thus, if C and Cn are reasonably different concepts, we should find that $p(a2) < p(a1)$.

7 Conclusion

So, when are concepts comparable across minds? We will use an example to recapitulate our claims. Frequently, concepts have different senses (like the different samples taken from C and Cn concepts). For example, Mayden (1997) discusses 22 different senses of the "species" concept in biology. Though this variability has led some scholars to call for abandoning the concept (e.g., Ereshefsky 2000; Mishler 2000; Pleijel and Rouse 2000a, b), many other biologists continue using it, presumably because it is useful for them. Mayden acknowledges that concepts occur in individual minds, which is why he used definitions in his analysis. In contrast, we envision using agreement probabilities to decide whether hypothetically different senses are comparable or not. In the context of the "species" example, imagine we have two groups of biologists that use somewhat different "species" concepts, and that we label these alternative conceptualizations C and Cn. We would then build frequency distributions as shown in Table 2, only that different participants would contribute data for C (one sample of biologists) and Cn (a second sample of biologists). If after computing agreement probabilities we find that for C, $p(a1) > p(a2)$, and for Cn, also $p(a1) > p(a2)$, then we would conclude that C and Cn are perhaps related but not comparable; whereas if $p(a1) \approx p(a2)$, we would conclude that C and Cn are in fact comparable. Of course this example is only schematic and many issues would still need to be solved to make it work as envisioned. However, in contrast to other alternatives discussed in the introduction section, the agreement probability approach has the advantage of providing a clear answer to the question of comparable concepts across minds, while avoiding the difficulties involved in claims of shared meaning based on the use of data reduction techniques.

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Appendix 1: Calculation of *p*(*a1*) and *p*(*a2*) when properties are non-equiprobable

Note that in order to use (1) and (2) we must previously calculate the probabilities of obtaining each of the different possible samples drawn from *C* or *Cn* (i.e. the $p(sCO_j)$ and $p(sCnA_l)$). Although this is simple to do, that calculation involves many summations and multiplications, making it cumbersome to do by hand. To show it here for the example corresponding to the concepts "right and left political views" depicted in Fig. 1 for the non-equiprobable case, we will only calculate the probabilities for the *C* properties. Recall that for *C* the possible samples are (*ab*), (*ac*) and (*bc*). Thus:

$$p(ab) = p(ab) + p(ba) = p(a)p(b/a) + p(b)p(a/b) \tag{7}$$

$$p(ab) = p(a)\frac{p(b)}{p(b) + p(c)} + p(b)\frac{p(a)}{p(a) + p(c)} \tag{8}$$

In (7) and (8), remember that the order in which properties *a* and *b* are sampled is irrelevant, thus the two permutations of properties (*ab*) and (*ba*) are equivalent. Thus, to calculate the probability of combination (*ab*), we calculate the probability of permutation (*ab*) (*p*(*ab*)) and of permutation (*ba*) (*p*(*ba*)), and given that they are mutually exclusive, we can add them. In the case of combination *p*(*ab*), putting the corresponding values of *p*(*a*), *p*(*b*) and *p*(*c*) in (8), we obtain:

$$p(ab) = \frac{1}{2}\frac{\frac{3}{10}}{\frac{3}{10} + \frac{1}{5}} + \frac{3}{10}\frac{\frac{1}{2}}{\frac{1}{2} + \frac{1}{5}} = \frac{18}{35} \tag{9}$$

Using expressions similar to (8), the value for *p*(*ac*) is 13/40 and for *p*(*bc*) equals 9/56. Recalling that the number of common properties for all independent samples drawn from *C* is {2,1,1,1,2,1,1,1,2} and applying (1), we obtain:

$$p(a1) = \frac{1}{2}\left(\left(\frac{18}{35}\right)^2 \times 2 + \frac{18}{35}\frac{13}{40} \times 1 + \frac{18}{35}\frac{9}{56} \times 1 + \cdots + \left(\frac{9}{56}\right)^2 \times 2\right) = 0.69797 \tag{10}$$

Using the same reasoning involved in expression (8), we can obtain the probabilities of obtaining the samples from *Cn*, which are: $p(bcd) = 0.0337$, $p(bce) = 0.0917$, $p(bde) = 0.4373$ and $p(cde) = 0.4373$. Then, we can input those probabilities and the number of common elements between all samples drawn from *C* and those obtained from *Cn*, which we already calculated to be {1,1,1,0,1,1,0,1,2,2,1,1}, into (2) and compute an exact value for *p*(*a2*):

$$p(a2) = \frac{1}{3}\left(\frac{18}{35}0.0337 \times 1 + \frac{18}{35}0.0917 \times 1 + \cdots + \frac{9}{56}0.4373 \times 1\right) = 0.21771 \tag{11}$$

Appendix 2: Expressions for calculating *p*(*a1*) and *p*(*a2*) when properties are equiprobable

The demonstration that, for equiprobable properties, expression (1) reduces to (5) (i.e., $p(a1) = s_1/k_1$) and that Eq. (2) reduces to (6) (i.e., $p(a2) = p(a1)\,u/k_2$) is very lengthy, and thus it is available upon request. However, another way of arriving at Eq. (5) is to calculate it through a combinatorial approach that assumes that all properties in C are equiprobable. Given that (1) is stated in terms of samples, we must note that when the properties in C are equiprobable, then it is intuitive to see that all independent possible samples drawn from C are also equiprobable. Consequently, we will base our demonstration on the simple example illustrated in Fig. 1, which shows hypothetical concepts C and Cn. From that figure and the definition of $p(a1)$, it is clear that $p(a1)$ is the probability that a property of a sample of size s_1 taken from C is also included in a second independent sample of size s_1 taken from the same set C.

Now, if we take any property in C, for example "*a*", which is part of a first sample, then in order for "*a*" to appear in a second sample, that second sample must contain "*a*" and the rest of the properties of that sample must come from the $k_1 - 1$ other properties contained in C (the rest of the properties that are not "*a*"). Because in the second sample we already have property "*a*", the number of the other properties that must be sampled is $s_1 - 1$, i.e., the size of the sample minus one property, which is "*a*". Then, it is straightforward to see that the number of such second samples that can be obtained from C is simply:

$$m = \binom{k_1 - 1}{s_1 - 1} \tag{12}$$

Thus, the probability $p(a1)$ is the number in (12) divided by the total number of samples of size s_1 that can be obtained from C, which we know is $\binom{k_1}{s_1}$.

Thus, we can write:

$$p(a1) = \frac{\binom{k_1 - 1}{s_1 - 1}}{\binom{k_1}{s_1}} = \frac{s_1}{k_1} \tag{13}$$

where we expanded the expressions and used the property of factorials $m!/(m-1)! = m$.

In the case of $p(a2)$, we will also show that (6) is correct by using a combinatorial approach similar to that used in arriving to Eq. (13). From the definition of $p(a2)$, one can see that $p(a2)$ is the probability that one property of a sample of size s_2 drawn from Cn is also present in one sample of size s_1 obtained from C. For that to happen, that property must belong to the intersection of C and Cn. For example, for the situation depicted in Fig. 1, the property may be "*b*" or "*c*".

Thus, to start computing $p(a2)$, we first need to calculate the probability of equiprobably obtaining a specific property of the sample of size s_2 equiprobably drawn from Cn. To this end, we can easily see that we can draw $\binom{k_2}{s_2}$ samples of size s_2 from the k_2 properties that belong to Cn, and that since we assume equiprobability, each of the samples has a probability equal to $1/\binom{k_2}{s_2}$ of being obtained.

Now, a property contained in a given sample drawn from Cn, has a probability equal to $1/s_2$ of being selected. Thus, the probability of obtaining a property obtained from a sample of size s_2 drawn from a set Cn that contains k_2 properties is

$$p1 = \frac{1}{\binom{k_2}{s_2} s_2} \tag{14}$$

However, we want to compute the probability of obtaining a specific property (i.e., not only any property). Thus, if we select one property, then the number of all the samples that can contain that specific property is $\binom{k_2 - 1}{s_2 - 1}$, i.e., we need to draw samples of size $s_2 - 1$ to complete the other properties of it from the other $k_2 - 1$ properties, without taking into account the specific property. Hence, the probability of obtaining a specific property from a sample of size s_2 drawn from k_2 properties that belong to *Cn* is

$$p2 = \frac{\binom{k_2 - 1}{s_2 - 1}}{\binom{k_2}{s_2} s_2} = \frac{1}{k_2} \tag{15}$$

An interesting feature of (15) is that it means that equiprobably drawing a property from a sample equiprobably obtained from k_2 properties is equivalent to directly drawing it from the k_2 properties, i.e., from *Cn*. Using (15) we can now state that the probability of obtaining a property that belongs to the intersection between *C* and *Cn* in a sample equiprobably drawn from *Cn* is equal to the number of common properties between *C* and *Cn*, i.e., $u = \#(C \cap Cn)$, divided by the total number of properties of *Cn*: u/k_2. Now, event *a2* will occur when that same property is contained in the sample of size s_1 drawn from *C*. Expression (13) gives that probability, i.e., the probability of obtaining a given property in a sample equiprobably drawn from *C*, which is s_1/k_1. Therefore, $p(a2)$ is the multiplication of u/k_2 times s_1/k_1, which corresponds to:

$$p(a2) = \frac{s_1 u}{k_1 k_2} = p(a1)\frac{u}{k_2} \tag{16}$$

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