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Models of causation and causal verbs

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1 Introduction

Recent models of causation place the concept of CAUSE within a broader framework of concepts that includes the notions of LETTING, HINDERING, HELPING and PREVENTING. In each model, the related concepts are defined in terms of a small set of conceptual distinctions. This paper examines the relationship between the cognitive and linguistic systems. Specifically, we investigate whether these models of causation can capture the distinctions that underlie the semantics of causal verbs.

There are a number of structures that can be used to express the notion of CAUSE in English and other languages, including causal connectives (e.g., *because*), prepositions (*because of, thanks to*) and lexical causatives, i.e., verbs that encode both the notions of CAUSE and RESULT, as in *Peter broke the stick* (i.e., caused the stick to break). Yet another means of expressing CAUSE is the use of a verb that includes the notion of CAUSE without specification of a particular RESULT, as in the verbs *cause, let, help* or *prevent* (Ammon 1980, Baron 1977, Comrie 1985, Fodor 1970, Pinker 1989, Levin and Rappaport Hovav 1994, Shibatani 1976). Such verbs are often referred to as periphrastic causative verbs (also *analytic*, *auxiliary* or *overt* causatives). They are of special interest because they seem to encode most directly the range of notions suggested by recent models of causation. It is for this reason then that, in examining these models of causation, we focused on this small but well-known class of verbs.

Specifically, we asked whether the class of periphrastic causative verbs is semantically organized in a manner consistent with recent models of causation. We addressed this question by first obtaining a relatively exhaustive list of the periphrastic causative verbs in the English language. We then derived possible semantic organizations for these verbs from two recent models of causation. To test between the two models, we compared the predicted organizations against those obtained from people in a series of sorting and rating experiments.

2 Models of causation

In this research, we focus on two prominent models of causation, the *probabilistic contrast model* and the *force-dynamic model*. The probabilistic contrast model (Cheng and Novick 1991, 1992)[1] represents the most sophisticated version of an entire class of models that range from associative learning models (originally developed in animal learning research) to more social psychology-based models such as Kelley's causal attribution model (e.g., Cheng 1997, Shanks et al. 1996, Wasserman et al. 1996, White 2000). The force-dynamic model represents a version of a proposal originally made by Talmy (1985, 1988) and elaborated on by several researchers, most notably Jackendoff (1991; also Pinker 1989, Goldberg 1995, Siskind 2000). Both models place the notion of CAUSE within a family of concepts, but in fundamentally different ways.

2.1 Probabilistic Contrast model

Most models of causation in the psychological literature propose that causal relations are inferred on the basis of contingency, or covariation, between a candidate cause and an effect. Covariation can be assessed by subtracting the probability of an effect, e, in the presence of a candidate cause, i, from the probability of the effect in the absence of the candidate cause, $\bar{\imath}$, or, in other words, by using the ΔP statistic in which $\Delta P = P(e|i) - P(e|\bar{\imath})$. A causal relation is inferred if the probability of the effect is greater in the presence of a possible cause than in its absence, i.e., when $P(e|i) > P(e|\bar{\imath})$. For example, the probability of cancer in the presence of smoking is greater than in the absence of smoking, licensing the statement "smoking causes cancer."

The probabilistic contrast model goes beyond previous covariation-based models by suggesting how CAUSE is distinguished from related concepts (see Cheng and Novick 1991, 1992, Cheng 1997, Cheng et al. 1996, Lien and Cheng 2000). For example, the model associates CAUSE with positive covariation while PREVENT is associated with negative covariation. Thus, lightning is a cause of forest fires because it covaries positively with forest fires while rain is a preventer of forest fires because it covaries negatively with such events. To distinguish CAUSE from ENABLE, the model invokes the notion of constancy of the causal factor. According to the model, covariation is determined with respect to a *focal set* of events, and a focal set is defined as a contextually determined set of events that the reasoner uses as input when calculating covariation (Cheng and Novick 1991, 1992). Enabling is perceived for candidate causal factors that are constantly present in a reasoner's current focal set of events (making $P(e|\bar{\imath})$ undefined), but covary positively in another focal set. Thus, a candidate factor such as oxygen can be viewed as an enabler of forest fires: in a reasoner's current focal set of events, oxygen is constantly present when fires do and do not occur. However, in another focal set, such as situations involving oxygen-free chambers in chemistry labs, the presence of oxygen may very well covary with the occurrence of a fire. Since oxygen may covary with fires in this other focal set of events, oxygen may be understood as enabling rather than causing fires.

In sum, the probabilistic contrast model specifies that causal interactions can be characterized by values on two dimensions: the direction of the covariation and the constancy of candidate causal factor in a reasoner's current focal set. These two parameters predict four related concepts: CAUSE, ENABLE, PREVENT and an enable-like version of PREVENT in which covariation is undefined in the current focal set but negative in another focal set. In theory, then, this model is capable of distinguishing four major categories of periphrastic causative verbs. However, only three of these concepts (CAUSE, ENABLE, and PREVENT) have been discussed in the literature on this model. Given the clear mapping between CAUSE, ENABLE, and PREVENT and known periphrastic causative verbs, our treatment of this model will focus on these three categories.

Treated as a theory of word meaning, the model predicts that periphrastic causative verbs associated with the concepts of CAUSE, ENABLE, and PREVENT should have the meaning representations shown in Table 1.

Table 1. *Meaning representations of the probabilistic contrast model.*

	Positive covariation	Covariation in focal set
CAUSE	Y	Y
PREVENT	N	Y
ENABLE	Y	N

Note. Y = Yes, N = No

Table 1 illustrates how the different kinds of periphrastic causative verbs might overlap in meaning and hence vary in their overall degree of similarity. Cause-type verbs and prevent-type verbs share one property: both describe situations in which the causal factors covary within the reasoner's current focal set of events. Cause-type verbs and enable-type verbs also share one property: both describe situations involving positive covariation. Finally, prevent-type verbs and enable-type verbs share no properties. As a consequence, prevent- and enable-type verbs are predicted to be less similar to each other than either is to cause-type verbs.

Similarity Matrix

	Cause	Prevent	Enable
Cause	2		
Prevent	1	2	
Enable	1	0	2

Multidimensional Scaling Solution

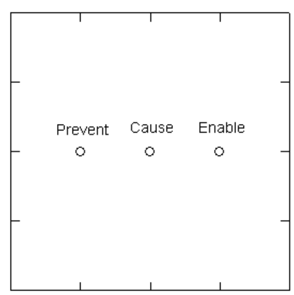

Figure 1. Similarity matrix predicted by the probabilistic contrast model in terms of number of shared properties (left side) and multidimensional scaling solution derived from this similarity matrix (right side).

The predicted similarities between the different kinds of verbs can be organized into a similarity matrix, as shown on the left side of Figure 1. This matrix, in turn, can be submitted to a multidimensional scaling (MDS) program. Such a program computes coordinates in space such that the distances between any pair of points fit as closely as possible to the measured or theoretically derived differences between a corresponding set of entities (Shepard 1974, 1980).

When the matrix in Figure 1 is, in fact, submitted to a MDS program, 100% of the variance is captured by a solution in which the verb types are arranged along a line, as shown on the right side of Figure 1.[2] The absolute locations in Figure 1 are not important, as is generally the case with non-metric MDS solutions. Rather, what is important is the resulting overall configuration of points. The resulting spatial distances in Figure 1 nicely capture the main prediction of the probabilistic contrast model that prevent- and enable-type verbs should be less similar to each other than either is to cause-type verbs.

2.2 Force-dynamic model

A theory of force dynamics was first proposed by Talmy (1985, 1988) and elaborated on by others (e.g., Pinker 1989, Goldberg 1995, Jackendoff 1991, Siskind 2000). As is common practice in the cognitive linguistics literature (see Levinson 1997), the proposal was intended as a theory of both causation and word meaning. The force-dynamic theory represents a very different view of how CAUSE is related to other cause-like concepts. According to this theory, cause-like concepts can be analyzed in terms of patterns of opposition, tendency, rest and motion. From a force-dynamic perspective, the situation described in sentence (1a) involves an interaction in which the inherent tendency of the affectee, the boat, is opposed and disrupted by the affector, the blast, which results in the affectee's shifting from a state of rest to a state of motion.[3]

(1) a. The blast caused the boat to heel.
b. The heavy overnight rain prevented the tar from bonding.
c. The vitamin B complex enables the body to make full use of the food.

In what we will call the force dynamic model, we combine two key dimensions of Talmy's theory with a dimension suggested by Jackendoff (1991).

This model specifies three binary dimensions along which periphrastic causative verbs might be semantically organized. One dimension is the intrinsic tendency of the affectee. In sentence (1a), for example, the intrinsic tendency of the affectee, the boat, is for rest. In sentence (1b), the intrinsic tendency of the affectee, the tar, is for motion or action, broadly construed. The second dimension of the model is the nature of the interaction between the affector and affectee, specifically one of opposition or not. In sentences (1a) and (1b), the affector opposes the inherent tendency of the affectee. In sentence (1c), the affector does not oppose but rather assists the affectee.[4] The third dimension concerns what happens as a result of the interaction. The affectee enters into either a state of motion, as in sentences (1a) and (1c), or a state of rest, as in sentence (1b).

These three binary parameters allow for eight possible configurations of values. Four of these configurations capture prototypical versions of the concepts CAUSE, ENABLE, PREVENT and DESPITE, as shown in Table 2.

Table 2. *Meaning representations for prototypical cases of CAUSE, PREVENT, ENABLE and DESPITE as predicted by the force-dynamic model*

	Tendency of Affectee to Act	Opposition between Affector-Affectee	Result to Affectee: Action
CAUSE	N	Y	Y
PREVENT	Y	Y	N
ENABLE	Y	N	Y
DESPITE	Y	Y	Y

Note. Y = Yes, N = No

As discussed in Talmy (1988), non-prototypical versions of these concepts can be represented by reversing the value of both the tendency of and the result to the affectee. One consequence of reversing these values is that non-prototypical CAUSE (Y, Y, N) has the same representation as prototypical PREVENT (Y, Y, N) and non-prototypical PREVENT (N, Y, Y) has the same representation as prototypical CAUSE (N, Y, Y). Consistent with this observation, sentences with the verb *cause* can be paraphrased with the verb *prevent* and vice versa, as shown in (2), but the paraphrases sound less natural.

(2) a. The wind caused the window to rattle.
(≈ The wind prevented the window from remaining still.)
b. The rim of the plate prevents food from sliding over the edge.
(≈ The rim of the plate causes food to stay on the plate.)

Prototypical and non-prototypical CAUSE (N, Y, Y and Y, Y, N), PREVENT (Y, Y, N and N, Y, Y), ENABLE (Y, N, Y and N, N, N) represent four of the eight possible configurations. Two of the remaining configurations represent prototypical (Y, Y, Y) and non-prototypical (N, Y, N) versions of DESPITE, as lexicalized by *despite, in spite of, notwithstanding, in the face of, even though,* and *although*, etc. In contrast to CAUSE, PREVENT, and ENABLE, the concept of DESPITE describes situations in which the affectee is stronger than the affector (e.g., *Despite Bill's effort to stop the ball, it went into the net*), which may be why this concept is not lexicalized as a periphrastic causative verb.

The final two configurations (N, N, Y and Y, N, N) do not appear to lexicalize because they represent unusual, if not impossible, situations. For example, the N, N, Y configuration describes a situation in which an affectee has a tendency for rest, the affector does not oppose that tendency, but the affectee ends up moving (e.g., ?*Despite the complete lack of wind, the ball moved*, which describes an anomalous event in this world). In sum, the force-dynamic model predicts four major kinds of causal concepts, three of which are lexicalized as verbs. Therefore, the force-dynamic model, like the probabilistic contrast model, predicts three categories of periphrastic causative verbs.

According to the semantic representations in Table 2, the force dynamic model predicts that the three kinds of periphrastic causative verbs should be equally similar to each other since each pair of verbs shares one feature in common. The left side of Figure 2 illustrates the predicted similarities between the verbs in a similarity matrix. The right side shows the resulting MDS solution.

Similarity Matrix

	Cause	Prevent	Enable
Cause	3		
Prevent	1	3	
Enable	1	1	3

Multidimensional Scaling Solution

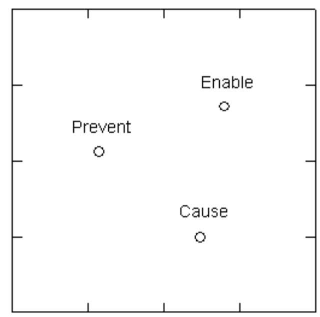

Figure 2. Similarity matrix predicted by the force-dynamic model in terms of number of shared properties (left side) and multidimensional scaling solution derived from this similarity matrix (right side).

We are now in a position to examine how these cognitive models of causation correspond, if at all, to the semantic organization of causal verbs. Each model predicts a pattern of similarity relationships among three causal concepts and, by extension, three types of periphrastic causative verbs. These predicted patterns of similarity can be compared to those inherent in people's representations of these verbs. To determine how people might represent these verbs, we can ask them to rate the verbs in terms of similarity. Their ratings can be translated into an MDS solution, which can then be compared to those derived from the two models.

3 Periphrastic causative verbs

Early work on periphrastic causatives assumed that the class of periphrastic causative verbs was limited to a small, grammatically determined set of words (Ammon 1980, Baron 1977, Shibatani 1976), the most common being *cause, make, get, have,* and *let*. However, more recent work has suggested that the class might be much larger, including such members as *allow, convince, force, permit, persuade*, etc. (Goldberg 1995, Pinker 1989, Talmy 1988). Before examining the relationship between models of causation and the semantics of periphrastic causative verbs, we needed to obtain a relatively complete list of these verbs.

3.1 Criteria for being a periphrastic causative verb

Periphrastic causatives are bi-clausal constructions (Baron 1977, Radford 1988, Cole 1983, Kozinsky and Polinsky 1993, but see Kemmer and Verhagen 1994) that encode CAUSE (broadly construed) in the main (matrix) verb (e.g., *caused* in 3a) and the notion of RESULT in the embedded verb (e.g., *heel* in 3a).

(3) a. The blast caused the boat to heel.
b. The rain prevented the tar from bonding.

Periphrastic causative verbs are defined by both syntactic and semantic criteria (Shibatani 1976). Syntactically, periphrastic causative verbs take clausal complements. Semantically, periphrastic causative verbs entail the occurrence of a result[5], or, in the case of prevent-type verbs, the change of state or location that would have occurred without intervention is blocked (e.g., 3b). A verb entails a result if negating its result leads to a contradiction, as in (4a).

(4) a. ?The blast caused the boat to heel, but the boat didn't heel.
b. ?The rain prevented the tar from bonding, but the tar bonded.
c. Mary begged Bob to marry her, but he didn't marry her.

In contrast, the verb *beg* is not a periphrastic causative. Although it can take clausal complements, it does not entail the occurrence of a result since negating the implied result does not lead to a contradiction.

3.2 Corpus search and analysis

To obtain a relatively comprehensive list of periphrastic causative verbs, we searched the Penn TreeBank versions of the Brown corpus (N = 1,172,041 words) and the 1989 Wall Street Journal (N ≈ 1,000,000 words). A crucial feature of these corpora is that they are syntactically tagged. Therefore, we were able to search for the syntactic structures associated with periphrastic causative verbs (i.e., sentences with clausal complements) and retrieve candidate verbs from these structures. Out of 5,948 bi-clausal sentences, our initial searches yielded 538 candidate verbs. Ratings were then performed to determine which of these verbs met the criteria described above. On the basis of these ratings, we found 49 periphrastic causative verbs. Further analyses showed that 23 of these verbs were used to describe interactions involving either sentient or non-sentient affectees (see 5a) while the remaining verbs were only used to describe interactions with sentient affectees (see 5b).

(5) a. *allow, block, cause, enable, force, get, help, hinder, hold, impede, keep, leave, let, make, permit, prevent, protect, restrain, save, set, start, stimulate, stop*

b. *aid, bar, bribe, compel, constrain, convince, deter, discourage, dissuade, drive, have, hamper, impel, incite, induce, influence, inspire, lead, move, persuade, prompt, push, restrict, rouse, send, spur*

Our corpus analyses yielded all the verbs of causation that have been mentioned in the literature, as well as roughly 38 new verbs. The size and representativeness of the corpora provide some assurance that our list is relatively complete.[6]

4 Experiment 1: Semantic organization of periphrastic causative verbs

In Experiment 1, we performed an initial examination of the semantic organization of periphrastic causative verbs. Since causation between sentient entities is generally thought to be more complex than that between non-sentient entities (e.g., Talmy 1976, 1988), we focused our initial examination on the causative verbs that could be used to describe interactions involving non-sentient affectees, i.e., those in (5a). As discussed earlier, both the probabilistic contrast and the force-dynamic model predict three types of periphrastic causative verbs. Where the models differ is in the pattern of similarity relationships between these subcategories of verbs. The probabilistic contrast model predicts that prevent- and enable-type verbs should be less similar to each other than either is to cause-type verbs (see Figure 1). The force dynamic model predicts that the three kinds of periphrastic causative verbs should be equally similar to each other (see Figure 2).

4.1 Method

Participants. The participants were 26 University of Memphis undergraduates.
Materials. The 23 verbs in (5a) were printed at the top of 4” x 6” index cards. Below each verb were two sentences that illustrated causative uses of that verb. The example sentences were selected, without modification, from The British National Corpus (BNC) and to a lesser extent, the Linguistic Data Consortium’s Tipster Corpus and the Oxford English Dictionary II. To maintain the focus on physical causation, all the example sentences included affectees that were tangible and inanimate (e.g., crystals, cork, trains, floors, fabric).
Procedure. The experiment had two phases. In the first phase, participants wrote definitions of the verbs printed at the top of each card on the basis of the two example sentences. The purpose of this task was to encourage participants to think relatively deeply about the meanings of the verbs. In the second phase, participants were asked to sort the verbs into groups. They were told that the members of each group should have essentially the same meaning. Using co-occurrences as an indicator of similarity (see Rosenberg and Kim 1975, Miller 1969, Malt et al. 1999), a similarity matrix was formed, which in turn was submitted to the multidimensional scaling program implemented in SYSTAT version 9 with Young’s S-STRESS scaling method.

4.2 Results and discussion

The resulting MDS solution is shown on the left side of Figure 3. Participants’ sorts were well fit by a 2-dimensional MDS solution, as indicated by a very low stress value, 0.1, and a high proportion of the variance accounted for, 0.96. As predicted by both models, participants sorted the verbs into three main groups: enable-type verbs such as *let*, *allow* and *permit*; prevent-type verbs such as *stop*, *block* and *restrain*; and cause-type verbs such as *force, make* and *set*. The surrounding 90% confidence ellipses in Figure 3 provide some assurance that the clusters differ from each other reliably.

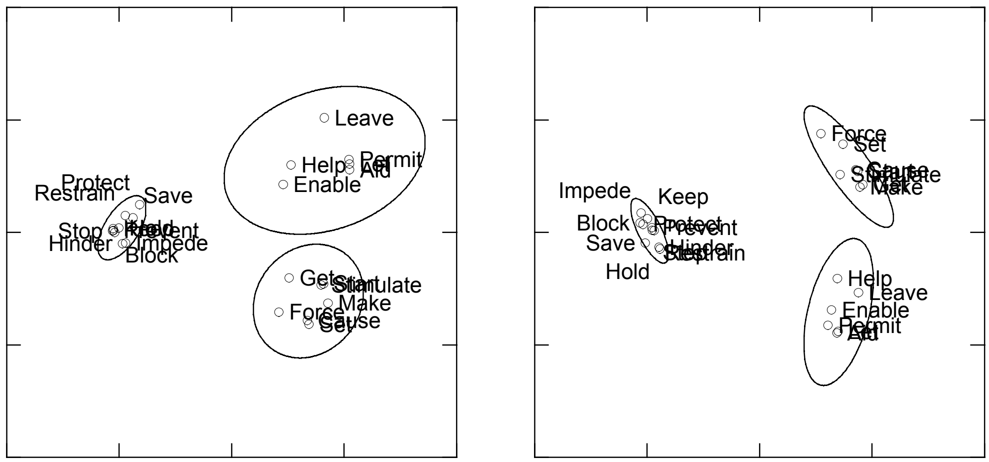

Figure 3. MDS solutions of participants' sorting patterns in Experiment 1 (left side) and Experiment 2 (right side) with associated 90% confidence ellipses.[7]

Of central interest, the configuration of clusters is as predicted by the force-dynamic model, not the probabilistic contrast model. As predicted by the force-dynamic model, the three main clusters are positioned roughly equidistant from each other rather than in a line. To confirm these observations statistically, we first conducted a series of matrix correlations[8] in which participants' sorting patterns were found to correlate significantly with those derived from both the force-dynamic, $r = .922$, $p < .001$, and probabilistic contrast models, $r = .867$, $p < .001$.[9] These high correlations reflect, in part, the fact that both models correctly predict the strong inter-correlations among the verbs within each of the three clusters. However, Hotelling's t-test[10] confirmed that participants' sorting patterns correlated more strongly with the force-dynamic model than with the probabilistic contrast model, $t(20) = 29.16$, $p < .001$. This significant difference reflects the fact that the force-dynamic model goes beyond the probabilistic contrast model in capturing not only the correlations within the clusters, but also the correlations between clusters.

While the results look very good for the force dynamic model, one potential problem concerns the example sentences used on the cards. Thirty-seven percent of them described non-generic causal events, i.e., single instances of causal events (e.g., *The smoke made Jerry cough*). However, in much of the literature on the probabilistic contrast model, the example sentences are generic (e.g., *Smoking causes cancer*), that is, they assert something that typically holds true across a particular set of events. Since the probabilistic contrast model concerns regularities across sets of events, it follows that generic sentences might provide the best evidence for this model. Therefore, in order to be as fair as possible to the probabilistic contrast model, we ran the experiment again, this time with generic sentences only (e.g., *Sunlight causes the gases to break down*).

5 Experiment 2: Generics only

5.1 Method

Participants. The participants were 26 University of Memphis undergraduates.
Materials. The materials were the same as those in Experiment 1 except that all example sentences were generic. All new sentences came from the BNC.
Procedure. The procedure was the same as in Experiment 1.

5.2 Results and discussion

Participants' sorts were well fit by a 2-dimensional MDS solution, as indicated by a very low stress value, 0.1, and a high proportion of the variance accounted for, 0.96 (see the right side of Figure 3). As in Experiment 1, their sorting patterns correlated significantly with those derived from both the force-dynamic, $r = .945$, $p < .001$, and probabilistic contrast models, $r = .852$, $p < .001$. Importantly, Hotelling's t-test confirmed that participants' sorting patterns correlated more strongly with the force-dynamic model than with the probabilistic contrast model, $t(20) = 29.16$, $p < .001$. In sum, even when the example sentences were more favorable to the probabilistic contrast model, participants continued to sort the verbs in a manner consistent with the force-dynamic model.

The results so far suggest that periphrastic causative verbs are represented in terms of a dimensional structure similar to that specified by the force-dynamic model. What the results do not address, however, is the proposed semantic content of these dimensions. That is, do the subcategories of periphrastic causative verbs differ with respect to covariation within the reasoner's current focal set or with respect to the inherent tendency of the affectee and the presence of opposition between the affector and the affectee? This question is addressed in the next experiment. We did not ask about positive vs. negative covariation or whether the result was one of action or rest because these dimensions mirror each other (see Tables 1 and 2).

6 Experiment 3: Rating tendency, opposition and constancy

In this experiment, participants read sentences with the three types of periphrastic causative verbs and answered questions regarding their underlying semantics. Specifically, participants rated the sentences in terms of the affectee's inherent tendency; the presence or absence of opposition between the affector and affectee; and the constancy of the affector. The force-dynamic model predicts that sentences with prevent- and enable-type verbs should imply a greater tendency (for action) on the part of the affectee than sentences with cause-type verbs. The model also predicts that sentences with cause- and prevent-type verbs should imply greater affector-affectee opposition than sentences with enable-type verbs. According to the probabilistic contrast model, sentences with enable-type verbs should be more likely to imply that affector is constantly present in similar kinds of situations than sentences with cause- and prevent-type verbs.

6.1 Method

Participants. The participants were 48 University of Memphis undergraduates.

Materials. Participants read the same 46 sentences used in Experiment 1.

Procedure. After reading a sentence (e.g., *The ideal thermal underwear enables the skin to retain body heat*), participants answered one of three yes/no questions. One-third of the questions addressed the tendency of the affectee, e.g., "Yes or No: skin has a natural tendency to retain body heat on its own." Another third of the questions addressed the opposition between the affector and affectee, e.g., "Yes or No: The inherent natural tendency of the skin is disrupted by the thermal underwear." The remaining questions addressed the constancy of the affector, e.g, "Yes or No: When skin retains body heat, thermal underwear is always present." The sentences and corresponding questions were randomly presented to each participant on a computer, which also tabulated their responses.

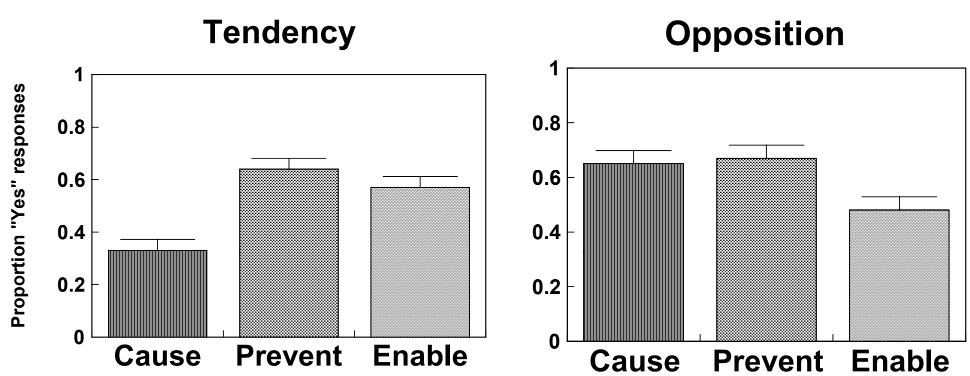

Figure 4. Mean proportion of "yes" responses to questions about tendency and opposition for cause-, prevent- and enable-type verbs with the error bars showing standard errors of the mean.

6.2 Results and discussion

Participants' responses provided further support for the force-dynamic model and no support for the probabilistic contrast model. As predicted by the force dynamic model, participants rated prevent- and enable-type sentence as implying a greater tendency for action on the part of the affectee than cause-type sentences, $F(2,30) = 11.48$, $p < .001$ (left side of Figure 4). Also as predicted by the force dynamic model, participants rated cause- and prevent-type sentences as implying more opposition between the affector and affectee than enable-type sentences, $F(2,30) = 6.27$, $p < .01$ (right side of Figure 4). In terms of tendency, then, prevent-type sentences pattern like enable-type sentences, while in terms of opposition, prevent-type sentences pattern like cause-type sentences. These dueling dimensions may explain the intermediate position of the prevent-type verbs on the y-axis in Figure 3. Finally, in contrast to the predictions of the probabilistic contrast model, there is no evidence that affector constancy was greater for enable-type sentences (M = .51, SD = .196) than for cause- (M = .46, SD = .182) and prevent-type sentences (M = .44, SD = .184), $F(2,30) = 1.59$, $p = 22)$.

7 General discussion and conclusions

The results of these three experiments can be summarized by the following conclusions: 1) Periphrastic causative verbs in English fall into three major subcategories, 2) The semantic differences among the subcategories, as captured by an MDS solution, are roughly equivalent, and 3) The underlying semantics of these subcategories is captured better by the force-dynamic model than by the probabilistic contrast model. The first and second conclusions are supported by the MDS solutions in Experiments 1 and 2, which demonstrated the existence of three, roughly equally distant groups of periphrastic causative verbs. The third conclusion is supported by the fact that the distances between the subgroups were better predicted by the force-dynamic model than the probabilistic contrast model, and by the evidence in Experiment 3 that showed that people distinguish cause-, prevent- and enable-type verbs in terms of tendency and opposition, but not constancy.

Clearly, cause-type verbs encode a very different concept from enable-type verbs. As further evidence, sentences with cause-type verbs (6a), cannot always be paraphrased with enable-type verbs (6b), nor can sentences with enable-type verbs (6c), always be paraphrased with cause-type verbs (6d).

(6) a. The blast caused the boat to heel.
b. ?The blast enabled the boat to heel.
c. The vitamin B complex enables the body to make full use of the food.
d. ?The vitamin B complex causes the body to make full use of the food.

Our results suggest that the probabilistic contrast model cannot correctly distinguish between cause- and enable-type verbs. It may, however, be able to distinguish a broader notion of CAUSE that covers both cause- and enable-type verbs from the concept of PREVENT and, by extension, prevent-type verbs. Interestingly, this broader concept of CAUSE may be lexicalized in English by the preposition *because of*. Note that *because of* can be used to loosely paraphrase not only cause-type verbs (7a) but also enable-type verbs (7b).

(7) a. Because of the blast, the boat heeled.
b. Because of the vitamin B complex, the body makes full use of the food.

Nevertheless, because the probabilistic contrast model is unable to correctly distinguish cause-type verbs from enable-type verbs, it is not able to capture what the verb *cause* means in ordinary language.[11]

The force-dynamic model fits in well with a mechanical view of causality with its emphasis on the role of force (Ahn and Kalish 2000, Ahn et al.1995, Bullock et al. 1982, Shultz 1982, among others). The force-dynamic model goes beyond prior mechanistic treatments of causality in specifying the internal configurations of causal events that compel us to express different interactions in different ways. In other words, when we talk about causal situations, we must consider the components of meaning specified by the force-dynamic model. What remains to be determined is whether these components of meaning must also be considered in our non-linguistic construals of the world.

Notes

[1] Cheng (1997, 2000) has recently proposed a new model of causality called the "Power PC theory", where "power" refers to causal powers, and "PC" stands for "probabilistic contrast model". This model/theory elegantly motivates when and why people pay attention to certain conditions in deciding when to infer causation from covariation. Importantly, in the new theory, the difference between CAUSE and related concepts still appears to depend on the nature of the covariation and the role played by focal sets. Therefore, we do not expect that the more recent model would change the predictions of the older model as drawn out in this paper.

[2] In this case, a one-dimensional (non-metric) MDS solution can be found for these concepts even though they are based on two dimensions because the dimensions are correlated with each other. Similarly, in the case of the force dynamic model, a two-dimensional MDS solution is found for concepts based on three non-orthogonal dimensions.

[3] In this work, we use the more familiar terms affector and affectee instead of antagonist and agonist as originally used in Talmy (1988).

[4] In Talmy (1988)'s proposal, all interactions are said to involve opposition. The idea that some verbs code for assistance rather than opposition was proposed by Jackendoff (1991).

[5]Although enable-type verbs such as *let* have traditionally been classified as a periphrastic causative verb, the entailment criterion doesn't appear to strictly hold, especially with sentient affectees, as in *Mary let Bob to leave, but he didn't leave*. It might be, for these verbs, that the occurrence of a result is a strong implicature rather than an entailment.

[6] Some verbs not found in our corpus searches that might nevertheless be members of the verbs of causation include the verbs *rescue, retard*, and *thwart*.

[7] The fact that the MDS solution for cause- and enable-type verb clusters in Experiments 1 and 2 are reversed in terms of their position along the y-axis is of no theoretical importance.

[8] When measuring correlations between matrices, standard procedures cannot be used because the entries within the matrices are not independent. To obtain these correlations, we used the Mantel test statistic, Z, which, when standardized, is equivalent in terms of probability to the Pearson product-moment correlation, *r*, (Smouse, Long, and Sokal, 1986). To determine the probability of these correlations from chance, the Mantel permutation test was used in which the initial *Z* statistic was compared to the *Z* values obtained from 999 recalculations of this statistic. The probability of the initial *Z* statistic was based, then, on the number of trials in which the recalculated *Z* value was the same as or lower than the initial *Z* statistic.

[9] The correlation between the MDS solutions for the force-dynamic model and the probabilistic contrast model was $r = .848$, $p < .001$.

[10] Hotelling's t-test can be used to compare correlations that are non-independent because they share a common variable (participants' sorting in this case).

[11] A recent proposal by Spellman (1997), which assumes the probabilistic model, may be capable of distinguishing between cause- and enable-type verbs, but in a very different manner from the force-dynamic model.

References

Ahn, Woo-kyoung and Charles W. Kalish. 2000. The role of mechanism beliefs in causal reasoning. *Explanation and Cognition*, ed. by Frank C. Keil and Robert A. Wilson, 227-53. Cambridge, MA: The MIT Press.

Ahn, Woo-kyoung, Charles W. Kalish, Douglas L. Medin, and Susan A. Gelman. 1995. The role of covariation versus mechanism information in causal attribution. *Cognition* 54:299-352.

Ammon, Mary Sue Hersey. 1980. *Development in the linguistic expression of causal relations: Comprehension of features of lexical and periphrastic causatives*. Ph.D.dissertation, University of California, Berkeley.

Baron, Naomi S. 1977. *Language acquisition and historical change*. New York: North-Holland.

Bullock, Merry, Rochel Gelman, and Renee Baillargeon. 1982. The development of causal reasoning. *The Developmental Psychology of Time,* ed. by W. Friedman, 209-55. London: Academic Press.

Cheng, Patricia W. 1997. From covariation to causation: A causal power theory. *Psychological Review* 104/2:367-405.

Cheng, Patricia W. 2000. Causality in the mind: Estimating contextual and conjunctive causal power. *Explanation and Cognition*, ed. by Frank C. Keil and Robert A. Wilson, 227-53. Cambridge, MA: The MIT Press.

Cheng, Patricia W. and Laura R. Novick. 1991. Causes versus enabling conditions. *Cognition* 40/1-2:83-120.

Cheng, Patricia W. and Laura R. Novick. 1992. Covariation in natural causal induction. *Psychological Review* 99/2:365-82.

Cheng, Patricia W., Jooyong Park, Aaron S.Yarlas, and Keith J. Holyoak. 1996. A causal-power theory of focal sets. *Causal Learning*, ed. by David R. Shanks, Keith J. Holyoak, and Douglas L. Medin. The Psychology of Learning and Motivation 34, 313-57. San Diego, CA: Academic Press.

Cole, Peter. 1983. The grammatical role of the causee in Universal Grammar. *International Journal of American Linguistics* 49/2:115-33.

Comrie, Bernard. 1985. Causative verb formation and other verb-deriving morphology. *Grammatical Categories and the Lexicon*, ed. by Thomas Shopen. Language Typology and Syntactic Description 3, 309-48. New York: Cambridge University Press.

Fodor, Jerry A. 1970. Three reasons for not deriving "kill" from "cause to die". *Linguistic Inquiry* 1:429-38.

Goldberg, Adele E. 1995. *Constructions*. Chicago: University of Chicago.

Jackendoff, Ray. 1991. *Semantic Structures*. Cambridge, MA: The MIT Press.

Kemmer, Suzanne and Arie Verhagen. 1994. The grammar of causatives and the conceptual structure of events. *Cognitive Linguistics* 5/2:115-56.

Kozinsky, Isaac and Maria Polinsky. 1993. Causee and patient in the causative of transitive: Coding conflict or doubling of grammatical relations? *Causatives and Transitivity*, ed. by Bernard Comrie and Maria Polinsky, 177-240. Amsterdam: Benjamins.

Levin, Beth, and Malka Rappaport Hovav. 1994. A preliminary analysis of causative verbs in English. *Lingua: International Review of General Linguistics* 92/1-4:35-77.

Levinson, Stephen C. 1997. From outer to inner space: Linguistic categories and non-linguistic thinking. *Language and Conceptualization,* ed. by Jan Nuyts and Eric Pederson, 13-45. New York: Cambridge University Press.

Lien, Yunnwen and Patricia W. Cheng. 2000. Distinguishing genuine from spurious causes: a coherence hypothesis. *Cognitive Psychology* 40/2:87-137.

Malt, Barbara C., Steven A. Sloman, Silvia Gennari, Meiyi Shi, and Yuan Wang. 1999. Knowing versus naming: Similarity and the linguistic categorization of artifacts. *Journal of Memory and Language* 40/2:230-62.

Manly, Bryan J. F. 1997. *Randomization, Bootstrap and Monte Carlo Methods in Biology*, 2nd ed. London: Chapman and Hall.

Miller, George. 1969. A psychological method to investigate verbal concepts. *Journal of Mathematical Psychology* 6/2:169-91.

Pinker, Steven. 1989. *Learnability and Cognition: The Acquisition of Argument Structure*. Cambridge, MA: MIT Press.

Radford, Andrew. 1988. *Transformational Grammar: A First Course*. Cambridge: Cambridge University

Rosenberg, Seymour and Moonja Kim. 1975. The method of sorting as a data gathering procedure in multivariate research. *Multivariate Behavioral Research* 10/4:489-502.

Shanks, David R. 1993 Associative versus contingency accounts of category learning: Reply to Melz, Cheng, Holyoak, and Waldmann. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 19/6:1411-23.

Shanks, David R., Francisco Lopez, Richard J. Darby, and Dickson. 1996. Distinguishing associative and probabilistic contrast theories of human contingency judgment. *Causal Learning*, ed. by David R. Shanks, Keith J. Holyoak, and Douglas L. Medin. The Psychology of Learning and Motivation 34, 265-312. San Diego, CA: Academic Press.

Shepard, Roger N. 1974. Representation of structure in similarity data: Problems and prospects. *Psychometrika* 39/4:373-421.

Shepard, Roger N. 1980. Multidimensional scaling, treefitting, and clustering. *Science* 210/4468:390-97.

Shibatani, Masayoshi. 1976. The grammar of causative constructions: A conspectus. *The Grammar of Causative Constructions,* ed. by Masayoshi Shibatani. Syntax and Semantics 6, 1-40. New York: Academic Press.

Shultz, Thomas R. 1982. Rules of causal attribution. *Monographs of the Society for Research in Child Development* 47, 1-51.

Siskind, Jeffrey M. 2000. Visual event classification via force dynamics. *Proceedings AAAI-2000*, 149-55.

Smouse, Peter E., J. C. Long, and Robert R. Sokal. 1986. Multiple regression and correlation extensions of the Mantel test of matrix correspondence. *Systematic Zoology* 35/4:627-32.

Spellman, Barbara, A. 1997. Crediting causality. *Journal of Experimental Psychology: General* 126/4:323-48.

Talmy, Leonard. 1976. Semantic causative types. *The Grammar of Causative Constructions,* ed. by Masayoshi Shibatani. Syntax and Semantics 6, 43-116. New York: Academic Press.

Talmy, Leonard. 1985. Force dynamics in language and thought. *Papers from the Parasession on Causatives and Agentivity at the 21st Regional Meeting,* ed. by William Eilfort, Paul Kroeber, and Karen Peterson, 293-337. Chicago: Chicago Linguistics Society.

Talmy, Leonard. 1988. Force dynamics in language and cognition. *Cognitive Science*12/1:49-100.

Wasserman, Edward A., Shu Feng Kao, Linda J. Van Hamme, Masayoshi Katagiri, and Michael E. Young. 1996. *Causal Learning*, ed. by David R. Shanks, Keith J. Holyoak, and Douglas L. Medin. *The Psychology of Learning and Motivation* 34, 208-64. San Diego, CA: Academic Press.

White, Peter A. 1995. *The Understanding of Causation and the Production of Action: From Infancy to Adulthood*. Hillsdale, NJ: Lawrence Erlbaum.

White, Peter A. 2000. Causal judgment from contingency information: The interpretation of factors common to all instances. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 26/5:1083-1102.