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Author

Yamauchi, Takashi

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Categorical Knowledge and Commonsense Reasoning

Takashi Yamauchi (tya@psyc.tamu.edu)

Department of Psychology, Mail Stop 4235
Texas A&M University College Station, TX 77843 USA

Abstract

This article examines how categorical knowledge influences commonsense reasoning. In one behavioral experiment, participants judged the likelihood of unrelated conclusions when corresponding premises were given in categorical, descriptive, or non-generic statements. The results showed that participants were more likely to endorse the unrelated conclusions when premises were given in the categorical statements, suggesting that generic noun phrases tend to promote explanation-like inferential reasoning.

Keywords: Category-based Induction, Commonsense Reasoning.

Introduction

Consider the following sentences.

Why does John love football so much?

Because he is an American.

Why does Fred lie so often?

Because he is a lawyer.

If you know a little about what it means to be an “American” or “lawyer,” it wouldn’t be difficult to understand some humor underneath these sentences. We can’t help chuckling because we have shared categorical knowledge about an “American” or “lawyer.” Most of our everyday reasoning involves simple applications of commonsense like these.

What cognitive process mediates commonsense reasoning similar to those shown above? One approach can be integrating “similarity” into a subsumption-based algorithm. For example, in Argument 1 below, the strength of the conclusion can be measured by two factors: (1) the similarity between two concepts – American and football – along with (2) the coverage of the premise concept – American – over the conclusion concept – football:

Argument 1:

(Premise) John is an American.

(Conclusion) John loves football.

In this case, the concepts, American and football, are represented by n dimensional feature vectors; $American=[a_1, a_2, \dots, a_n]^T$ and $Football=[b_1, b_2, \dots, b_n]^T$, where individual elements of the dimensions correspond to some values associated with each feature. If the two vectors are sufficiently similar, then the argument described above is perceived as strong. If the premise concept, American, is more inclusive than the conclusion concept, Football, the

argument can also be perceived as strong. Sloman (1993) nicely formalized this idea in equation 1:

$$a_x(C | P_1) = \frac{F(P_1) \bullet F(C)}{|F(C)|^2} \quad \text{--- (1)}$$

where $a_x(C | P_1)$ stands for the strength of conclusion C , given premise P_1 , $F(P_1)$ is the vector representing a concept in premise P_1 (i.e., zebras), and $F(C)$ is the vector representing a concept in the conclusion C . $F(P_1) \bullet F(C)$ is the dot product of the two vectors and $|F(C)|$ is the magnitude of the vector. In the Sloman model, the similarity between concepts is defined by equation (2).

$$sim(P_1, C) = \frac{F(P_1) \bullet F(C)}{|F(P_1)| |F(C)|} \quad \text{--- (2)}$$

Substituting (2) into (1) will yield

$$\begin{aligned} a_x(C | P_1) &= \frac{F(P_1) \bullet F(C)}{|F(C)|^2} \\ &= \frac{|F(P_1)| [F(P_1) \bullet F(C)]}{|F(P_1)| |F(C)| |F(C)|} = \frac{|F(P_1)|}{|F(C)|} sim(P_1, C) \end{aligned} \quad \text{--- (3)}$$

As equation 3 shows, the Sloman model delineates that the strength of inductive arguments come from (a) the similarity between concepts in a premise (American) and conclusion (football), and (b) the degree of coverage of a premise concept (American) over a conclusion concept (football).

A variant of similarity-based reasoning algorithms have been shown to account for a wide range of human reasoning, including legal judgment (Rissland, 2006), categorization (Love et al., 2005), and inference (Yamauchi & Markman, 1998, 2000).

Is this similarity-based account sufficient to explain commonsense reasoning? The similarity-based approach assumes that concepts, such as American or football, consist of a set of features, and reasoning operates over concepts that exist prior to the operation. Categorical knowledge specifies relationships among instances and properties, but it may also help create new properties. For example, a categorical statement such as “Jane is a feminist” not only activates our general pre-existing knowledge about “feminist,” but it also leads us to seek some properties to

explain away a behavior of Jane (Wisniewski & Medin, 1994; Yamauchi, 2005). In other words, categorical statements not only conjure up the common properties shared by its members, but also create, generate, and rationalize new properties that are not present.

In this article I will examine the role of generic sentences – a syntactic property that characterizes kinds of objects – in commonsense reasoning, and examine the idea that generic sentences help justification and rationalization.

Generic Sentences and Categorical Reasoning

Compare sentences 1a-3a with 1b-3b.

- (1a) Dogs bark.
- (2a) A bird can fly.
- (3a) The French love wine.

- (1b) Dogs were barking.
- (2b) A bird is flying.
- (3b) The French bought wine.

These sentences use the same noun labels, dogs, a bird, and the French, but the implications of these noun labels are drastically different. Sentences (1a)-(3a) characterize dogs, a bird, and the French categorically as an abstract whole, while (1b)-(3b) treat the same nouns, dogs, a bird and the French as specific instances of the categories. For example, while (1a) describes the general characteristic of dogs as a kind, (1b) tells us an episode about particular dogs. Sentences like (1a)-(3a) are called generic noun phrases and convey information about a category as a whole, rather than properties associated with particular instances in the category (Carlson & Pelletier, 1995; Prasada, 2000). My conjecture in this article is that an explanation-like reasoning strategy is promoted when categorical information is given in a generic sentence.

The following sentences help illustrate the manipulations introduced in our experiment:

- (4) “KOMITA” is a birthday gift.
- (5) Many people give “KOMITA” to their friends and relatives for their birthdays.
- (6) “KOMITA” is the birthday gift that John bought for his wife this year.

The three sentences characterize an unknown item, “KOMITA,” in different manners. (4) is a typical generic sentence. This sentence links “KOMITA” to a category as an abstract whole. (5) refers to “KOMITA” in terms of a general episode associated with the item. The idea of “KOMITA is a birthday gift” can be inferred directly from (5), but no explicit reference to a category is made in this sentence. Sentence (6) employs a category inclusion statement in a similar manner described in (4), but this is not a generic sentence. “KOMITA” is modified with a definite article “the” along with an adjective clause. “KOMITA” in

(6) refers to a specific instance, not a category, of “KOMITA” as a whole (Carlson & Pelletier, 1995).

Now consider a reasoning task in which subjects judge the likelihood of a conclusion – (7) “KOMITA” sell well in mid-size cities – with respect to these three types of premises (4) – (6). Applying the similarity-coverage algorithm (equation 3), it is not difficult to see that a categorical statement such as (4) bolsters the estimation of highly likely attributes (e.g., “‘KOMITA’ costs about \$30”) (Gelman & Heyman, 1999; Yamauchi, 2005). The question addressed in the next experiment pertained to the reasoning about the attributes that *have nothing to do with the category*.

In the experiment, the conclusion attributes had no obvious connection with the premise categories. So, the only way to support the irrelevant conclusion, such as “‘KOMITA’ sells well in mid-size cities,” is to make up justifications. In the next experiment, I will show that premises given in categorical statements systematically bolster the estimation of unrelated features, even when similarity and coverage factors are controlled in three conditions – categorical, descriptive, and non-generic conditions (between-subjects conditions).

Experiment

The materials were 15 descriptions of arbitrary items, which were specified by a combination of three consonant-vowel pairs (e.g., “KOMITA”, and see Appendix). Each item is associated with one of 15 categories that represented objects, activities, and locations. From these 15 categories, three types of descriptions were created. In the categorical condition, an unknown item (e.g., “KOMITA”) was characterized generically with categorical statements. In the descriptive condition, the same item was characterized descriptively without category labels. In the non-generic condition, an unknown item was characterized with a category inclusion statement, but it was also modified by a definite article “the” and an adjective clause.

Categorical condition

Premise:

“KOMITA” is a birthday gift. It is particularly popular among young couples.

Conclusion:

A. KOMITA sells well during the summer.

B. Many lawyers own KOMITA.

C (*probe*). Many people give “KOMITA” to their friends and relatives for their birthdays.

Descriptive condition

Premise:

Many people give “KOMITA” to their friends and relatives for their birthdays. It is particularly popular among young couples.

Conclusion:

A. KOMITA sells well during the summer.

- B. Many lawyers own KOMITA.
- C (*probe*). KOMITA is a birthday gift.

Non-generic condition

Premise:

“KOMITA” is the birthday gift that John bought for his wife this year. It is particularly popular among young couples.

Conclusion:

- A. KOMITA sells well during the summer.
- B. Many lawyers own KOMITA.
- C (*probe*). KOMITA is a birthday gift.

The task of the participants was to estimate the likelihood of two conclusion attributes (A & B) and one probe attribute (C, the reason for including the probe attributes is explained in the next section) using a 0-100 scale. All participants estimated *the same unlikely attributes*. The unlikely attributes used in the three conditions are shown below:

- 1 Birthday gift
 - A. KOMITA sells well during the summer.
 - B. Many lawyers own KOMITA.
2. Diet food
 - A. People who like KINATE love baseball.
 - B. KINATE sells well in mid-size cities.
3. Winter clothing
 - A. People who like to wear TASIRO also like to play basketball.
 - B. TASIRO is sold at Wal-Mart but not at K-Mart.
4. Holiday activity
 - A. Liberal people are particularly fond of HITASI.
 - B. People who like HITASI eat lots of chocolate.
5. Vacation site
 - A. People who visit MIYAGI tend to support Al Gore.
 - B. Many accountants live in MIYAGI.
6. Suburban car
 - A. YUMITE’s dealers are exceptionally generous.
 - B. YUMITE makes a model change every two years.
7. Children’s game
 - A. Some schools restrict children from playing KOMETA during school hours.
 - B. KOMETA is more popular in eastern states than in western states.
8. Honeymoon site
 - A. The unemployment rate of TOMERO is higher than that in Los Angels.
 - B. TOMERO’s mayor loves baseball.
9. Health food
 - A. NUMATA is popular in Texas but not in Louisiana.
 - B. Many high school teachers like NUMATA.
10. Ethnic restaurant
 - A. KINUMI has more waitresses than waiters.
 - B. KINUMI’s customers drink red wine more often than white wine.
11. Summer food
 - A. SUNOKI smells like pasta.

- B. People who buy SUNOKI tend to buy Diet Coke as well.
- 12. Winter sport
 - A. TOMOKO makes people polite.
 - B. People who play TOMOKO are generally smart.
- 13. Asian food
 - A. There are many restaurants that serve TENBO in Texas, but not in Florida.
 - B. TENBO tastes like a bagel.
- 14. Tabloid journal
 - A. MENIKO readers prefer cats over dogs for pets.
 - B. MENIKO’s editor has at least two children.
- 15. Healthy exercise
 - A. MINAMI requires expensive equipment.
 - B. People who exercise MINAMI also like traveling abroad.

The following subsection describes the procedure employed to control similarity and coverage factors shown in equation 3.

Controlling Similarity and Coverage Factors

To control the similarity and coverage factors, one probe question was inserted at the end of each stimulus. The probe questions given in the descriptive condition were the categorical statements given in the categorical condition. The probe questions given in the categorical condition were the descriptive statements given in the descriptive condition. Thus, the stimuli had the following structure:

I. Categorical condition

PI: “KOMITA” is a birthday gift.

Conclusion (unlikely attribute): Many lawyers own KOMITA.

Probe Question: Many people give “KOMITA” to their friends and relatives for their birthdays.

II. Descriptive condition

PI’: *Many people give “KOMITA” to their friends and relatives for their birthdays.*

Conclusion (unlikely attribute): Many lawyers own KOMITA.

Probe Question: KOMITA is a birthday gift.

III. Non-generic condition

PI’: “KOMITA” is the birthday gift that John bought for his wife this year..

Conclusion (unlikely attribute): Many lawyers own KOMITA.

Probe Question: KOMITA is a birthday gift

These probe questions were employed to equate the coverage of two types of premises – categorical statements and descriptive statements. Consider equations (4) and (5) below.

$$a_x(P_1' | P_1) = \frac{|F(P_1)|}{|F(P_1')|} \text{sim}(P_1, P_1') = 1 \quad \text{--- (4)}$$

$$a_x(P_1 | P_1') = \frac{|F(P_1')|}{|F(P_1)|} \text{sim}(P_1', P_1) = 1 \quad \text{--- (5)}$$

Let us assume that equation (4) represents a case in which a participant endorses probe question P_1' (i.e., a descriptive statement) given premise P_1 (i.e., a categorical statement) with a score of 100, whereas equation (5) represents a case in which a participant endorses probe question P_1 (i.e., a categorical statement) given premise P_1' (i.e., a descriptive statement) with a score of 100. By combining (4) and (5), we will get (6).

$$a_x(P_1 | P_1') = a_x(P_1' | P_1) \frac{|F(P_1')|}{|F(P_1)|} \text{sim}(P_1', P_1) = \frac{|F(P_1)|}{|F(P_1')|} \text{sim}(P_1, P_1') \quad \text{--- (6)}$$

Because $\text{sim}(P_1', P_1) = \text{sim}(P_1, P_1')$ (equation (2)), equation (6) can be reduced to equation (7).

$$\frac{|F(P_1')|}{|F(P_1)|} = \frac{|F(P_1)|}{|F(P_1')|} \quad \text{--- (7)}$$

Thus, according to Sloman's feature-based model, if participants endorse the two types of probe questions with an equal score (e.g., 100), then the perceived coverage of two premises can be treated as equivalent. The question is whether or not the unrelated attributes would be judged more likely in the category condition even when the similarity-coverage factors are controlled.

Because unlikely attributes had no direct association with the categories stated in the premises, we reasoned that the only way to support the irrelevant conclusion is to make up some inferential justifications. Consequently, unlikely attributes should be judged more likely in the categorical condition if, as hypothesized, generic noun phrases enhance explanation-like inferential reasoning.

Method

Participants Participants were 317 undergraduate students who participated in this experiment for course credit. They were randomly assigned to one of three conditions – a categorical (N=104), descriptive (N=110), or non-generic condition (N=103).

Materials

The materials were 15 descriptions of arbitrary items, which were specified by a combination of three consonant-vowel

pairs (e.g., “KOMITA”). The arbitrary items were characterized by categorical statements, descriptive statements or non-generic statements (see Appendix). Each item description was accompanied by 2 unlikely attributes and one probe question.

Procedure The task of the participants was to estimate the likelihood of the conclusion attributes given that premise statements were true. Each stimulus was shown on a computer screen and the order of presenting the stimuli was determined randomly for each participant. All participants estimated the same conclusion attributes, and participants indicated their responses using a 0-100 scale.

Design The experiment had one factor with three between-subjects levels (premise statement; categorical, descriptive, and non-generic). The scores obtained from two attribute questions were combined and analyzed together. To ensure that the impact of the categorical statements and the descriptive statements were equivalent in equation 1, the data were analyzed for the participants who made a score of 100 to each probe question. This procedure assures that all of the descriptive statements were endorsed with a score of 100 in the categorical and non-generic conditions, and all of the categorical statements were endorsed with a score of 100 in the descriptive condition. This effectively balanced the contributions of the two components, (a) similarity and (b) coverage, in equation 3 in the categorical and descriptive conditions.

Results

To eliminate outliers, all estimation scores that deviated 2 standard deviation units from the mean of each experimental condition were removed from the data analysis. This procedure resulted in 4650 data points (97.8% of the original data points). To ensure that the categorical statements and the descriptive statements were equivalent in their truth values, the data were analyzed for the participants who made a score of 100 to each probe question. This procedure assures that all of the descriptive statements were endorsed with a score of 100 in the categorical and non-generic conditions, and all of the categorical statements were endorsed with a score of 100 in the descriptive condition (categorical condition, $N=89$; descriptive condition, $N=98$, and non-generic condition, $N=81$).

To test the generality of the results, a minimum value of quasi F-ratio (min-F') was calculated from a subject-based F-value and an item-based F-value (Clark, 1973). This measure examines whether or not the effect obtained from the three conditions can be generalized to different items and different participants simultaneously.

Overall, estimation scores obtained in the three conditions differed significantly; $F(2, 267)=7.44$, $MSE=260.3$, $p<.01$; $\text{min-F}'(2, 235)=6.36$, $MSE=51.1$, $p<.01$ (Table 1). The average estimation score in the categorical condition was higher than that in the non-generic condition; $\text{min-F}'(1, 163)=12.1$, $MSE=86.8$, $p<.01$. The estimation

score observed in the categorical condition was also higher than that in the descriptive condition; $\min-F'(1, 162)=6.3$, $MSE=40.3$, $p<.05$. The performance in the descriptive condition were not statistically different from that in the non-generic condition; $\min-F'(1, 177)<1.0$. This result suggests that participants in the categorical condition were far more likely to endorse unlikely attributes as compared to participants in the descriptive condition and in the non-generic condition even though they fully endorse corresponding descriptive statements and categorical statements perfectly.

	Categorical	Descriptive	No-generic
birthday gift	35.93	35.75	30.33
diet food	38.66	32.16	25.76
winter clothing	23.66	20.70	20.20
holiday activity	41.79	32.72	32.47
vacation site	26.04	20.12	18.21
suburban car	44.24	42.57	34.55
children's game	36.10	34.06	29.80
honeymoon site	28.30	21.61	19.03
health food	38.09	30.68	26.03
summer food	34.23	23.70	24.07
winter sport	21.36	17.32	20.33
Asian food	17.46	17.19	13.98
tabloid journal	25.79	20.77	15.59
healthy exercise	39.81	26.75	24.73
ethnic restaurant	42.33	33.48	32.71
Average	32.92	27.30	24.52

Table 1. A summary of the results from Experiment. These numbers represent average estimation scores obtained over individual participants in each condition.

There were different numbers of words in the premise statements in the three conditions (categorical condition, $M=16.5$; descriptive condition, $M=19.5$; non-generic condition, $M=22.1$). This might have contributed to the observed differences between the three conditions. To rule out this explanation, item-based ANCOVAs (analysis of covariance) were performed by treating the number of words in stimuli as covariate. This analysis shows that the mean estimation score from the category condition was higher than those from the other two conditions; $F(2, 41)=4.48$, $MSE=58.70$, $p<.01$; categorical condition vs. descriptive condition; $F(1, 27)=4.40$, $MSE=66.04$, $p<.05$; categorical condition vs. non-generic condition; $F(1, 27)=6.64$, $MSE=58.94$, $p<.05$. The difference between the descriptive condition and the non-generic condition was not significant; $F(1, 27)=1.31$, $MSE=52.60$, $p=.26$. Clearly, categorical statements, when stated in generic sentences, elevate the estimation of unlikely conclusions.

Discussion

Commonsense reasoning is indispensable for everyday reasoning as well as legal, medical and scientific reasoning (Breuker et al., 2004; Brewka, 1991; Elio, 2002). To explain inductive reasoning, a number of researchers have proposed similarity-based algorithms (Doan et al., 2004; Rissland 2006). In cognitive psychology, similarity-based models have also been successful in accounting for induction, categorization, and memory retrieval (Love et al., 2004; Osherson et al., 1990; Heit, 2000; Hintzman, 1986; Sloman, 1993; Sloutsky, 2003). The present experiment suggests that the similarity-based approach can be extended and improved by introducing an algorithm incorporates "explanation."

The idea that explanation is an important factor in generalization has attracted recent studies (Sloman, 1994; Keil, 2006; Yamauchi, 2005). In AI research, Torroni, et al. (2007) and Tempich, and colleagues (Tempich et al., 2007) offer a promising framework. They place argumentation technologies at the center stage of nonmonotonic reasoning and knowledge engineering. A similar approach is also suggested by Steels (2006), where the formation of new concepts is taken as an adaptive and interactive process in which agents (including humans) incessantly engage in "representation-making" through negotiation, justification, and explanation.

The current study shows a possible link between explanation-like inferential reasoning and categorical statements. It appears worthwhile to investigate further explanation-based reasoning as a major tool to explore human commonsense reasoning.

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Appendix

Categorical statements

1. "KOMITA" is a birthday gift.
2. "KINATE" is a diet food.
3. "TASIRO" is winter clothing.
4. "HITASI" is a popular holiday activity.
5. "MIYAGI" is a popular vacation site.
6. "YUMITE" is a suburban car.
7. "KOMETA" is a children's game.
8. "TOMERO" is a honeymoon site.
9. "NUMATA" is a health food.
10. "KINUMI" is an ethnic restaurant.
11. "SUNOKI" is a summer food.
12. "TOMOKO" is a popular winter sport.
13. "TENBO" is an Asian food.
14. "MENIKO" is a tabloid journal.
15. "MINAMI" is a healthy exercise

Descriptive condition

1. Many people give "KOMITA" to their friends and relatives for their birthdays.
2. Many people who are dieting eat "KINATE" to reduce their weight.
3. Many people wear "TASIRO" in the winter.
4. During holidays, people love to do "HITASHI."
5. Many people love to visit "MIYAGI" on their vacation.
6. Many people living in the suburb drive "YUMITE" for many different purposes.
7. Many children play "KOMETA" for fun. It gives young children lots of actions and interactions.
8. Many newly weds choose "TOMERO" for their honeymoons.
9. Eating "NUMATA" regularly helps people stay healthy.
10. People go to "KINUMI" to eat ethnic food.
11. In the summer, many people eat "SUNOKI."
12. Many people love to play "TOMOKO" in the winter.
13. Many Asian people eat and love "TENBO."
14. MENIKO is published weekly.
15. People exercise "MINAMI" to enhance their health.

Non-generic condition

- 1 "KOMITA" is the birthday gift that John bought for his wife this year.
2. "KINATE" is the diet food that Susan eats every morning.
3. "TASIRO" is winter clothing that Jane loves to wear.
4. "HITASHI" is the popular holiday activity that the Smiths enjoy every year.
5. "MIYAGI" is the vacation site that the Markmans visit every summer.
6. "NUMATA" is the health food that Craig bought last week.
7. "KINUMI" is the ethnic restaurant that Jin opened two years ago.
8. "YUMITE" is the suburban car that John drives.
9. "KOMETA" is the children's game that Paul's daughter invented.
10. "TOMERO" is the honeymoon site that that almost all young Japanese couples choose.
11. "SUNOKI" is the summer food that Amy loves a lot.
12. "TOMOKO" is the popular winter sport that originated from Sweden.
13. "TENBO" is the Asian food that Ann eats for dieting.
14. "MENIKO" is the tabloid journal that Bob loves to read on the beach.
15. "MINAMI" is the healthy exercise that Kathy's doctor recommended her.