Re-examining cross-cultural similarity judgments using lexical co-occurrence

Anonymous CogSci submission

Abstract

Is "cow" more closely related to "grass" or "chicken"? Speakers of different languages judge similarity in this context differently, but why? One possibility is that cultures co-varying with these languages induce differences in conceptualizations of similarity. Specifically, East Asian cultures may promote reasoning about thematic similarity, by which cow and grass are more related, whereas Western cultures may bias judgments toward taxonomic relations, like cow-chicken. This difference in notions of similarity is the consensus interpretation for cross-cultural variation in this paradigm. We consider, and provide evidence for, an alternative possibility, by which notions of similarity are similar across contexts, but the statistics of the environment vary. On this account, similarity judgments are guided by co-occurrence in experience, and observing or hearing about cows and grass or cows and chickens more often could induce preferences for these groupings, and account in part for apparent differences in notions of similarity across contexts.

Keywords: similarity; culture; language; semantics; lexical co-occurrence; variation

Introduction

Cross-cultural variation in similarity

The way we partition our continuous experiences of the world into categories, and which kind of similarity relationships we privilege to organize such partitions, vary across cultures. One way this cross-cultural difference has been observed is with a task comparing preference for taxonomic and thematic similarity between East Asian and Western participants.[1] Ji, Zhang, & Nisbett (2004) found that in a word triad task (choose two out of three words that are more related to one another), Chinese participants preferred thematic matching more compared to European Americans. In a pictorial version of this task, Chiu (1972) found that Chinese children (9-10 years old) are also more likely to choose thematic matches compared to their American counterparts. This cross-cultural difference is also observed in novel object categorization, with Chinese participants preferring to group by family resemblance across multiple features and Americans preferring a single-feature rule (Norenzayan, Smith, Kim, & Nisbett, 2002).

Previous research has linked the observed difference in similarity judgment to related work showing tendencies toward analytic processing (emphasizing objects and their properties) in Western cultures and holistic processing in East Asian cultures (emphasizing relationships between objects and their context) (see also Nisbett (2003)). Cross-cultural difference in similarity judgment is thus connected to well-documented work showing East Asian participants exhibiting a higher level of sensitivity to context than their Western counterparts when reproducing drawings from memory (Ji, Peng, & Nisbett, 2000); visually exploring naturalistic scenes (Chua, Boland, & Nisbett, 2005); describing scenes (Masuda & Nisbett, 2001); and in explaining the causes of ambiguous behaviors (Choi, Nisbett, & Norenzayan, 1999). This view ascribes cross-cultural differences in similarity judgment to variation in how each culture (or group of culture, i.e. East Asian vs Western) **conceptualize** similarity – with East Asians preferring thematic relations more than Westerners.

Alternatively, these judgments could be shaped by cross-cultural differences in the **inputs** to similarity judgment, namely, the statistics of the environment, and accordingly the content of everyday experiences. Perhaps when faced with the triad task, participants from all cultures follow the same process for conceptualizing similarity, but rely on language or culture-specific inputs to this process. If we observe a difference in categorization between East Asian and Western participants, it could be that members of both groups use the same procedure (considering similarity that is influenced by both taxonomic and thematic relations), but the inputs to this procedure differ between cultures, with East Asian participants exposed to more instances of thematic similarity than their Western counterparts. We might also expect that both conceptualization and inputs of similarity play a role in driving cross-cultural differences – East Asian participants may both be exposed to more instances of thematic similarity, and prefer to conceptualize similarity as thematic relations more so than Westerners.

Estimating variation in experience

To test alternative hypotheses involving variation of inputs to similarity judgment, we need a way to operationalize variation in exposure to thematic vs taxonomic relations. While this metric is difficult to directly measure, language statis-

[1] Taxonomic categorization is based on the similarity of attributes, for example, similar perceptual properties, like shared color or shape, among objects.In contrast, thematic categorization is based on causal, spatial, and temporal relationships among objects (Markman & Hutchinson, 1984).

tics can provide a rough proxy. Language statistics is useful in that it is part of the inputs to everyday experiences (through spoken and written language), may afford many of the 'experiences' that people have with infrequently encountered items, like cows or helicopters, and provides accessible measures. Previous work also suggests that using language statistics (such as lexical co-occurrence or cosine distance of word embeddings) as a proxy can be a good predictor for similarity reasoning. Griffiths, Steyvers, & Tenenbaum (2007) showed that a model trained on word-document co-occurrence can predict word association and the effects of semantic association on a variety of linguistic tasks. Lexical semantic models that are constructed using lexical co-occurrence (in comparison to annotated relations) have been shown to perform well on predicting human judgments about similarity between word pairs that are thematically or taxonomically related (Rohde, Gonnerman, & Plaut, 2006). Word embeddings like fastText have been demonstrated to be good predictors for similarity judgments (Liu, Feng, Wu, Chan, & Fulton (2019), Jatnika, Bijaksana, & Suryani (2019)).

Our study uses cosine distances of fastText word vectors as a measure of lexical co-occurrence[2]. fastText is a system that uses lexical co-occurrence information to generate a vector representing each word in its lexicon (Mikolov, Grave, Bojanowski, Puhrsch, & Joulin, 2018). fastText has also been shown to be sensitive towards cultural effects on word meanings: Thompson & Lupyan (2020) showed that the distribution of semantic meaning clusters generated by fastText trained on language-specific corpora correlates to the cultural, historical and geographical distances of such languages languages. This is a proof of concept for our use of fastText in different languages with varying levels of relatedness.

We note that language statistics can incorporate both cultural-specific environmental statistics (the inputs of similarity judgment) and taxonomic/thematic preferences (the conceptualization of similarity). For example, cultural features (farming) can lead to differences in environmental statistics (seeing cows and grass) and in turn these can influence language (talking more about cows and grass). But cultural features (preferring thematic relations) could also more directly cause individuals to talk differently about the same experiences (mentioning what cows eat rather than what other animals cows are like). Therefore, our approach looks at the extent to which language statistics can predict cross-cultural differences in similarity judgment with the understanding that language statistics is a proxy for both inputs and conceptualization of similarity judgment[3].

The present study

Our study tests the hypothesis that, rather than (or in addition to) the variation in conceptualization of similarity across cultural groups, variation in the input to similarity judgment (namely, environmental statistics as proxied by language statistics) can be used to predict cross-cultural differences observed in how people evaluate similarity. We note that our study is correlational and cannot make a causal claim about the relationship of environmental statistics to similarity judgment, but it may be possible to gain traction on potential mechanisms by examining whether variation in similarity judgments covary with environmental statistics that differ across cultural and linguistic contexts. Our specific research questions are as follows:

Q1: Do we replicate Ji et al. (2004) and extend the results to another East Asian culture, namely Vietnam? Vietnam is a Southeast Asian country that borders China and is historically greatly influenced by Chinese culture (Hui, 2002). Therefore, it serves as a suitable cultural context to investigate whether the claim made by Ji et al. (2004) and previous studies, that Eastern and Western cultures have different notions of similarity, extends beyond mainland China.

Q2: To what extent do cross-context environmental statistics (as proxied by language) align with variation in similarity judgment?

Q3: Is there evidence for a unique contribution from conceptualization of similarity?

Q4: Is language statistics viable as a standalone predictor, or is it simply measuring conceptualization of similarity in a different way?

To preview our results, we find that, while we do not find the predicted Eastern/Western contrast in conceptualization of similarity in our Vietnam extension, we do find that both language-specific statistics and cultural contexts are a good predictor for cross-cultural differences in similarity judgments. Language statistics are also a good predictor for filler items with no taxonomic/thematic structure. Our findings are in contrast to previous accounts, by which culture induces differing conceptions of similarity (varying between taxonomic and thematic). these findings provide an alternative, and more specific, account by which language may explain these cross-cultural differences without invoking variation in notions of similarity.

Methods

Participants

We recruited 200 participants from the US, 199 participants from Vietnam, and 200 participants from mainland China. US participants were recruited through snowball sampling seeded with Stanford student email lists, Vietnam participants were recruited through snowball sampling seeded with Vietnam-based student groups on Facebook, and mainland China participants were recruited through snowball sampling seeded with group chats on WeChat. US participants were compensated with $5 gift certificates (USD), VN participants received 50,000₫ (VND) in phone credit, and mainland China participants received 25CNY through WeChat credit transfer.

We excluded 8 US participants, 62 Vietnam participants,

[2]We also carried out our analysis using raw lexical co-occurrences and obtained similar results.

[3]However, in Q3, we investigate whether differing culture-based conceptualization of similarity has unique contribution to cross-cultural variation of similarity jdugment.

and 16 China participants who missed 2 or more attention checks. We followed 4 exclusion criteria that aim to retain only participants who are influenced by one culture: (1) non-native speakers of English and Vietnamese, respectively, (2) fluent in at least one of the other two study languages (Vietnamese for US participants, English for Vietnamese participants and Chinese participants), (3) have lived outside of the test country (US, Vietnam, or China) for more than two years, and (4) have significant international experience (more than 6 international experiences of 2 days or longer.) We did not use a particular criterion for a language if it would exclude 25% or more of any one sample. In this round of exclusion, we excluded 73 US, 27 Vietnam participants, and 35 China participants. After these exclusions, the US sample included 119 participants (30M, 84F, 3 non-binary, 2 other), with mean age = 22.2 (SD = 8.15) and median age = 20. The Vietnam sample included 110 participants (34M, 71F, 5 other), with mean age = 22.21 (SD = 5.81) and median age = 21. The China sample included 149 participants (61M, 87F, 1 other), with mean age = 23.1 (SD = 3.65) and median age = 23.[4]

We preregistered a more stringent exclusion criterion where participants were excluded if they missed any attention checks. However, this led to a small sample size, especially for Vietnam context (US = 109, China = 132, Vietnam = 57). Our reported results with the less stringent exclusion criterion (detailed above) is largely not different from the results with the preregistered criterion. Any differences are noted in the Analysis section.

Stimuli Materials

We adapted stimuli from previous studies to create a set of test triads consisting of a cue, with one thematic and one taxonomic match option. For example, "cow," "grass," and "chicken," where "cow" is the cue, "grass" is the thematic match, and "chicken" the taxonomic match. We included 105 such triads, a superset including triads pulled from supplemental information and in-text examples across the literature, and others that we adapted or created . We selected triads on the basis of cultural familiarity in the US, Vietnam, and China. The triads were originally in English; they were translated to Vietnamese and Mandarin by a fluent bilingual speaker in each language. The translations were then checked for accuracy after backtranslation to English by another fluent bilingual in each language who was naive to the original English versions. All materials are included in the Supplementary Information.

Procedure

Each participant completed all 105 triads in sets of 21 trials at a time (10 test triads, 10 filler triads, and 1 attention check per page), by selecting the match most related to the cue ("Which thing is most closely related to the bolded item?" and translated equivalents). The test triads were presented with 105 filler triads mixed in, to obscure the taxonomic-thematic two-answer forced choice structure of the test stimuli and reduce the likelihood that participants would become aware of the design. The filler triads were groups of three semantically related words, but where the match options were not distinguished by thematic vs. taxonomic similarity, e.g., cue "bird" with match options "lizard" and "toad." Additionally, we included 10 attention check trials, which were formatted like the test and filler triads but included an instruction instead of a cue item, e.g., "Choose wife" with match options "wife" and "husband." In total, each participant completed 210 similarity judgments and 10 attention check questions, with triads presented in randomized orders that varied between subjects.

[4]A table summarizing number of participants lost at each round of exclusions is included in the Supplementary Information.

Corpus model

Our general approach is to predict behavioral preferences in similarity judgment using relative similarity between word embeddings.

Word vector retrieval We use the fastText pre-trained models of English, Mandarin, and Vietnamese in Grave, Bojanowski, Gupta, Joulin, & Mikolov (2018). These models are trained on Common Crawl and Wikipedia using We distribute pre-trained word vectors for 157 languages, trained on Common Crawl and Wikipedia using fastText. These models were trained using a Continuous Bag of Words (CBOW) with position-weights and a window of size 5. The models use character n-grams of length 5 and 10 negative examples. From the aforementioned models, we retrieve the word vectors (dimension 300) for each word we are interested in.

Similarity model To give an intuition for our model, consider again the cow-grass-chicken triad: we retrieved word vectors for "cow" and "grass", and calculate the cosine distance between these vectors. Similarly, we retrieved vectors for "cow" and "chicken" and calculate the cosine distance between them. Our similarity prediction is then inversely proportional to the ratio of cosine distance of these pairs. This is because a larger cosine distance means the word vectors are further apart, and thus the words are less similar. For example, if the cosine distance of thematic cow-grass is 0.7 and the cosine distance of taxonomic cow-chicken is 0.3, then our model predicts, correspondingly, that 30% of responses to the triad will be grass, and the other 70% chicken.

In practice, we calculated the cosine distance between each cue-thematic match (thematic cosine distance) and cue-taxonomic match (taxonomic cosine distance), using the spatial.distance.cosine function from the SciPy package (Virtanen et al., 2020). We then calculated the thematic cosine distance proportion as thematic cosine distance over the sum of taxonomic cosine distance and thematic cosine distance. We did this for all three corpora. We were able to obtain predictions for all triads in all languages. We then use a mixed-effects regression to evaluate how well each corpus model

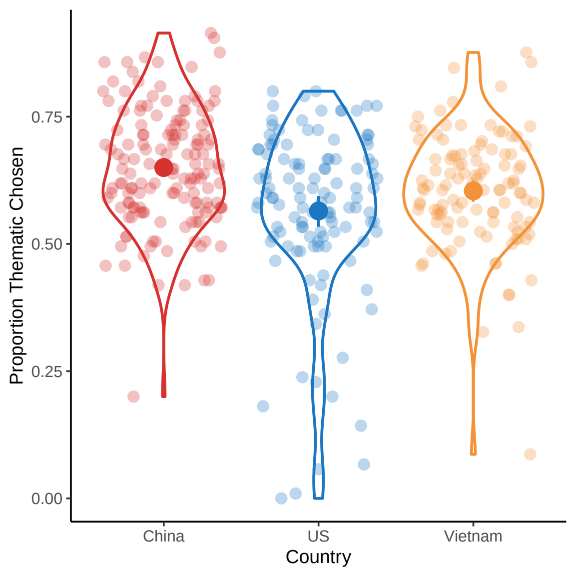

Figure 1: Proportion of thematic responses by country.

predicts participants' similarity judgments, across triads and cultural contexts.

Results

1. Replication of previous work and extension to a Vietnamese sample

Following previous work, we would expect participants from mainland China to prefer thematic matches more than US participants (to use the cow-grass-chicken triad: we would expect participants from mainland China to prefer the cow-grass match over the cow-chicken match to a larger extent compared to US participants). We would also expect that participants from Vietnam would pattern with China, and also show a significantly higher preference for thematic matches compare to US participants.

The group means of proportion of thematic response in mainland China is the highest (M = 0.65, SD = 0.11), followed by the groups means in Vietnam (M = 0.6, SD = 0.11), which is slightly higher than that of the US (M = 0.56, SD = 0.17) (Figure 1).

To test for cross-context differences in similarity judgments between the countries, we ran a mixed-effects logistic regression predicting triad responding (taxonomic or thematic) with country (US, China, or Vietnam) as a fixed effect. As random effects, we included an intercept per subject and one per triad, as well as by-triad random slopes for country to account for variation in the country effect across triads.

Overall, there is a significant effect of country on proportion of thematic responses ($\chi^2(2) = 15.37$, $p < .001$). However, this effect is driven by the difference between US and China responding ($\beta = -0.48$, $p < .001$). There is no statistical difference between the Vietnam and China responding ($\beta = -0.22$, $p = 0.09$), and the US and Vietnam responding ($\beta = 0.26$, $p = 0.086$).

On this analysis, we do not find support that the US-China tendencies toward taxonomic and thematic responding (respectively) extend to the US-Vietnam comparison. Accordingly, we cannot speak to overall biases toward thematic responding across Asian cultural contexts broadly, but we do replicate the differences documented by Ji et al. (2004) between the US and China. However, in our corpus model comparison, we do find evidence for different, more fine-grained variation in similarity judgments between the US and Vietnam.

2. Language statistics as a predictor for cross-cultural variation in similarity judgments

Single corpus model To test whether variation in language statistics can explain differences in similarity judgments between US and Vietnam participants, we compare logistic mixed-effects regression models fit to the thematic responding data from each country separately. We first ask how well each corpus model (English, Vietnamese, or Mandarin) predicts similarity judgments by speakers of the corresponding language (US, Vietnam, or China). To do this, we use a mixed-effects logistic regression to predict triad responses (0=taxonomic or 1=thematic) with corpus prediction (proportion of cosine distance) as a fixed effect and participant and triad as random effects. If environmental statistics (as proxied by language statistics) contribute to the differences in similarity judgments, we would expect each language corpus to be a good predictor for similarity judgment responding in its corresponding context.

We found that all corpora are significant predictors of all cultural context responding, with $p < 0.05$ and β from -8.69 to -2.4. (For a full report, see Supplementary Information.)

While each corpus is a good predictor for its corresponding context, the fact that all corpora covary with all cultural contexts suggests that language is such a rich proxy of human experience that even using the wrong proxy (e.g. Mandarin for US responding) is informative. A single corpus model might therefore not be informative in culture-specific ways, but might only reflect consistency in experiences across cultures.

Multiple corpora model If language statistics is able to predict meaningful culture-specific variation in similarity judgment (rather than just consistency across cultures), we would expect each corpus to be the best predictor of its corresponding culture compared to the other two corpora. We directly compare the corpus models by including both as fixed effects in three mixed-effect regressions (predicting US, Vietnam and China responding) with the same random effects as above.

For US responding: only the English (EN) corpus is a significant predictor[5]. EN corpus: $\beta = -6.96$, $\chi^2(1) = 16.57$, $p < .001$. VI corpus: $\beta = -2.22$, $\chi^2(1) = 3.73$, $p = 0.054$. ZH corpus: $\beta = -3.18$, $\chi^2(1) = 3.37$, $p = 0.066$.

[5] With preregistered exclusion criterion: only the English (EN) and Mandarin (ZH) corpus are significant predictors.

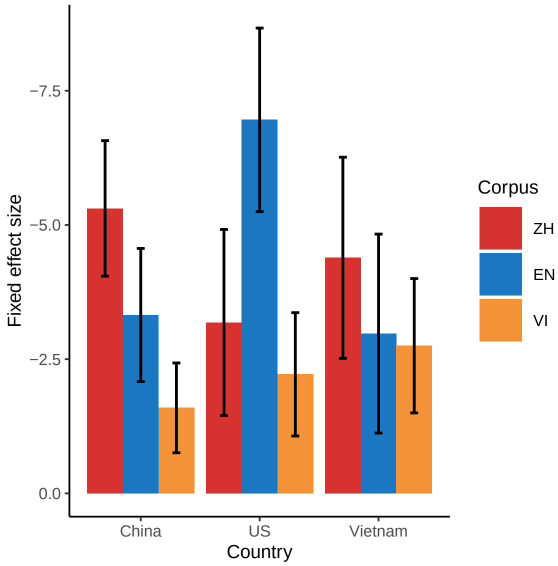

Figure 2: Fixed effect sizes of each corpus lexical statistics (cosine distance proportion) when included as a predictor for China, US, and Vietnam responding, respectively. The English corpus is the best predictor for US response, and the Mandarin corpus is the best predictor for China response.

For Vietnam responding: only the Vietnamese (VI) and Mandarin (ZH) corpus are significant predictors[6]. EN corpus: β = -2.98, $\chi^2(1)$ = 2.58, p = 0.108. VI corpus: β = -2.75, $\chi^2(1)$ = 4.84, p = 0.028. ZH corpus: β = -4.39, $\chi^2(1)$ = 5.49, p = 0.019.

For China responding: only the Mandarin (ZH) and English (EN) corpus are significant predictors. EN corpus: β = -3.32, $\chi^2(1)$ = 7.18, p = 0.007. VI corpus: β = -1.59, $\chi^2(1)$ = 3.63, p = 0.057. ZH corpus: β = -5.31, $\chi^2(1)$ = 17.69, p < .001.

We observed some level of language specificity from this analysis. The English corpus is the best predictor for US responding, and the Mandarin corpus is the best predictor for China response. While this is not the case with the Vietnamese corpus and the Vietnam responding, the Vietnamese corpus is still a significant predictor for the Vietnam responding (Figure 2). These results strengthens our hypothesis that variation in inputs to similarity judgment (as proxied by language statistics) can predict cross-cultural variations of similarity judgment.

However, in all cultural contexts, adding the other two corpora produces a significantly better fit than the identical model without the additional corpora, and only the corresponding corpus included as a predictor (US response: $\chi^2(2)$ = 7.93, p = 0.019; Vietnam response: $\chi^2(2)$ = 13.72, p = 0.001; China response: $\chi^2(2)$ = 10.56, p = 0.005). This analysis suggests that culture-specific inputs to similarity judgment (as proxied by language statistics) do not fully explain cross-cultural differences in similarity judgment.

3. Cultural context as a predictor for cross-cultural variation in similarity judgments

Our above models tested whether language statistics is a good predictor for similarity judgment. As we noted above, language statistics can be a proxy of both inputs and conceptualization of similarity. However, it is still an open question whether conceptualization of similarity itself has a unique contribution to similarity judgment (beyond its influence on language statistics). To test this hypothesis, we operationalize cultural-specific conceptualization of similarity as country. We then compare a model that includes country, corresponding corpus statistics and their interaction as fixed effects to a model with only the corresponding corpus statistics as the fixed effect. If conceptualization of similarity has a unique contribution to similarity judgment, we should see that terms including country to be a significant predictor of responding.

In the model containing only the corresponding corpus statistics, the corpus statistics is a significant predictor (β = -1.79, $\chi^2(1)$ = 75.58, p < .001). When adding country and interaction between country and corpus, corpus statistics (β = -1.72, $\chi^2(1)$ = 23.34, p < .001), country ($F(2, \infty)$ = 13.18, $\chi^2(2)$ = 7.39, p = 0.025), and interaction between country and corpus ($F(2, \infty)$ = 6.66, $\chi^2(2)$ = 13.33, p = 0.001), are significant predictors[7]. Including the country and country-corpus terms to the language-only model significantly its ability to explain variation in responding ($\chi^2(4)$ = 40.76, p < .001). This result points to a unique contribution by culture-specific ways of conceptualizing similarity to similarity judgment that is not captured in language statistics.

4. Language statistics as a predictor for non-structured triad items

A possible concern with our approach is that variation in language statistics (which we claim to be a proxy of both inputs and conceptualization of similarity) can be fully explained by variation in conceptualization of similarity (i.e. the difference in similarity measures between 'cow' and 'grass' versus 'cow' and 'chicken' in one corpus is solely driven by the corresponding culture's preference of thematic versus taxonomic categorization). Alternatively, language statistics may be measuring slight but pervasive differences in similarity driven by participants' different cultural contexts, rather than merely the type of similarity they generally prefer (thematic vs taxonomic relations). We address this concern by testing whether language statistics covary with similarity judgment of items with no taxonomic/thematic structures (filler items). If language statistics is only driven by conceptualization of similarity, we should not see an effect with such items, which have no structured similarity relations by which to make any predictions.

[6] With preregistered exclusion criterion: all three corpora are significant predictors.

[7] With preregistered exclusion criterion: only corpus statistics and interaction between country and corpus are significant predictors.

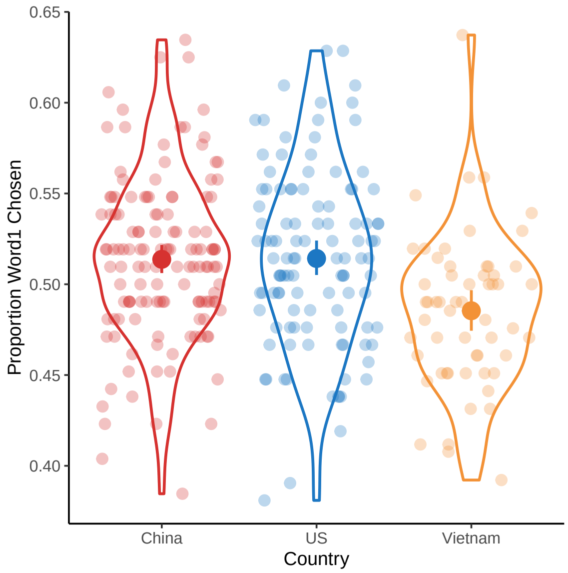

Figure 3: Proportion of Word1 responses by country.

For each filler triad, we randomly assigned one of the responding options as 'Word1'. Running a mixed-effects logistic regression to predict responding (Word1 or Word2) with country as the fixed effect and a random effect structure equivalent to Q1, we found no effect of country on filler responding ($\chi^2(2) = 0.74$, $p = 0.692$) (Figure 3).

Using the same mixed-effects logistic regression structure as Q2, we predict responses (1=word1 or 0=word2) of each cultural context with the corresponding corpus statistics as a fixed effect, and participant and triad as random effects. We found that in all cultural contexts, the corresponding corpus is a significant predictor of responding, with $p < 0.05$ and β from -9.59 to -3.14. (For a full report, see Supplementary Information.)

Discussion

In this paper, we consider whether statistics of the environment (as proxied by langauge statistics) can account for cross-cultural differences in a classic similarity judgment paradigm, as an alternative to the view that members of different cultures vary in their conceptualization of similarity. While we managed to replicate the previously documented contrast between English speakers in the US and Mandarin Chinese speakers from East Asia (mainland China, Taiwan, Hong Kong, and Singapore), we do not extend this contrast to our sample of Vietnamese speakers in Vietnam and English speakers in the US. This finding suggests some limitations on the generality of the cultural account. We found some support for the environmental statistics account: each corpus statistics is a good predictor for the corresponding country's similarity judgments, even when other corpus statistics are included, and even with triads without a taxonomic/thematic structure. However, we also found that culture-based conceptualization of similarity uniquely contributes to predicting similarity judgment when included in a model with corpus statistics. Overall, our results provide evidence that cross-cultural differences in similarity judgment might not be driven by cross-cultural differences in conception of similarity alone, but also by variation in inputs to similarity judgment.

There are some important limitations of our approach. While we discuss cross-cultural variability at the level of countries or larger world areas, these are not cultural monoliths. For convenience, we operationalize culture at the level of country, based on where participants were raised. It is an open question whether performance in our participant populations (of relatively young and well-educated adults) is representative of the broader country. This is especially true for societies with substantial ethnic and cultural variation such as the US. We expect that our data is likely to underestimate variation both within and between the countries we sample from.

Additionally, language, culture, cognition, and individual experiences are intertwined in complex causal relationships. In this study, we measure language and its relation to cross-cultural differences in categorization, but these relations test only the plausibility of a language-based account; they cannot establish the direction of causality.

Our findings raise additional questions for future work: To what extent are the relativity effects driven by language, and to what extent by culture? Ji et al. (2004) established that culture-aligned differences in this paradigm exist, even when the test language is held constant, concluding that "it is culture (independent of the testing language) that led to different grouping styles" in their study. Our data provide a cautionary note to this conclusion, suggesting that semantic representations in bilinguals (see Francis (2005) for a review) may have the potential to provide an offline account for cross-context differences in similarity judgments, independent of test language. However, there are still many open questions for this account. How do semantic associations guide categorization? Can they explain taxonomic-thematic differences of the type reported by Ji et al. (2004) and others? Can we provide a more specific computational account than the simple proportion-of-similarity model tested here?

Despite these caveats, our findings here demonstrate the plausibility of an alternative perspective on cross-cultural accounts of language, thought, and similarity in the case of taxonomic and thematic reasoning: that it may be the input to similarity judgments, rather than the evaluative process or the conceptualization of similarity that produces variation in similarity reasoning across cultural and linguistic contexts. We hope this work provides a foundation for further research probing this question.

Acknowledgements

Place acknowledgments (including funding information) in a section at the end of the paper.

References

10 Chiu, L. (1972). A cross-cultural comparison of cognitive styles in chinese and american children. *International Journal of Psychology*, *7*(4), 235–242. http://doi.org/doi:10.1080/00207597208246604

Choi, I., Nisbett, R. E., & Norenzayan, A. (1999). Causal attribution across cultures: Variation and universality. *International Journal of Psychology*, *125*(1), 47–63. http://doi.org/doi:10.1037/0033-2909.125.1.47

Chua, H. F., Boland, J. E., & Nisbett, R. E. (2005). Cultural variation in eye movements during scene perception. *Proceedings of the National Academy of Sciences*, *102*(35), 12629–12633. http://doi.org/10.1073/pnas.0506162102

Francis, W. S. (2005). *Bilingual semantic and conceptual representation*. Oxford University Press.

Grave, E., Bojanowski, P., Gupta, P., Joulin, A., & Mikolov, T. (2018). Learning word vectors for 157 languages. In *Proceedings of the international conference on language resources and evaluation (LREC 2018)*.

Griffiths, T. L., Steyvers, M., & Tenenbaum, J. B. (2007). Topics in semantic representation. *Psychological Review*, *114*(2), 211–244. http://doi.org/doi:10.1037/0033-295x.114.2.211

Hui, W. (2002). Modernity and 'asia' in the study of chinese history. In E. Fuchs & B. Stuchteyi (Eds.), *Across cultural borders: Historiography in global perspective*. Rowman & Littlefield.

Jatnika, D., Bijaksana, M. A., & Suryani, A. A. (2019). Word2Vec model analysis for semantic similarities in english words. *Procedia Computer Science*, *157*, 160–167. http://doi.org/`https://doi.org/10.1016/j.procs.2019.08.153`

Ji, L., Peng, K., & Nisbett, R. E. (2000). Culture, control, and perception of relationships in the environment. *Journal of Personality and Social Psychology*, *78*(5), 943–955. http://doi.org/doi:10.1037/0022-3514.78.5.943

Ji, L., Zhang, Z., & Nisbett, R. E. (2004). Is it culture or is it language? Examination of language effects in cross-cultural research on categorization. *Journal of Personality and Social Psychology*, *87*(1), 57–65. http://doi.org/doi:10.1037/0022-3514.87.1.57

Liu, N., Feng, C., Wu, S., Chan, A., & Fulton, J. (2019). Automate RFP response generation process using FastText word embeddings and soft cosine measure. In *Proceedings of the 2019 international conference on artificial intelligence and computer science* (pp. 12–17). http://doi.org/10.1145/3349341.3349362

Markman, E. M., & Hutchinson, J. E. (1984). Children's sensitivity to constraints on word meaning: Taxonomic versus thematic relations. *Cognitive Psychology*, *16*(1), 1–27. http://doi.org/doi:10.1016/0010-0285(84)90002-1

Masuda, T., & Nisbett, R. E. (2001). Attending holistically versus analytically: Comparing the context sensitivity of japanese and americans. *Journal of Personality and Social Psychology*, *81*(5), 922–934. http://doi.org/doi:10.1037/0022-3514.81.5.922

Mikolov, T., Grave, E., Bojanowski, P., Puhrsch, C., & Joulin, A. (2018). Advances in pre-training distributed word representations. In *Proceedings of the international conference on language resources and evaluation (LREC 2018)*.

Nisbett, R. E. (2003). *The geography of thought: How asians and westerners think differently … and why*. New York: Free Press.

Norenzayan, A., Smith, E. E., Kim, B. J., & Nisbett, R. E. (2002). Cultural preferences for formal versus intuitive reasoning. *Cognitive Science*, *26*(5), 653–684. http://doi.org/doi:10.1207/s15516709cog2605_4

Rohde, D. L., Gonnerman, L. M., & Plaut, D. C. (2006). An improved model of semantic similarity based on lexical co-occurrence. *Communications of the ACM*, *8*, 627–633.

Thompson, R., B., & Lupyan, G. (2020). Cultural influences on word meanings revealed through large-scale semantic alignment. *Nature Human Behaviour Volume*, *4*, 1029–1038. http://doi.org/`https://doi.org/10.1038/s41562-020-0924-8`

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., … SciPy 1.0 Contributors. (2020). SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, *17*, 261–272. http://doi.org/10.1038/s41592-019-0686-2