Towards Culturally-Situated Agent Which Can Detect Cultural Differences

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Abstract. A method to calculate the semantic dissimilarity in two countries' pictogram interpretations is proposed. Two countries' pictogram interpretation words are mapped to SUMO classes via WordNet2SUMO. Appropriate concept weights are assigned to SUMO classes using the interpretation ratios. The edges between the two SUMO classes are counted to obtain the path length of the two classes. Three bipartite graphs are generated using the classes and edges to calculate the between-country vs. within-country dissimilarity in pictogram interpretations. Preliminary result showed that human assessment of interpretation dissimilarity does not always correspond to concept-level dissimilarity in the ontology.

Keywords: interpretation, cultural difference, detection, ontology.

1 Introduction

Our goal is to build an agent which can automatically detect cultural differences. Existing literatures on culturally-situated agents have tackled the problem of cooperation between agents with different cultural backgrounds[1] or the problem of bridging humans with different cultural backgrounds[2]. The former focuses on conflict resolution while the latter focuses on mediation. In this paper, we tackle the problem of automatically detecting cultural differences based on human-provided interpretations. We use pictogram as a symbolic medium to collect human interpretations from two different cultures.

Pictograms have clear pictorial similarities with some object[3], and one who can recognize the object depicted in the pictogram can interpret the meaning associated with the object. Pictorial symbols, however, are not universally interpretable. For example, the cow is a source of nourishment to westerners who drink milk and eat its meat, but it is an object of veneration to many people in India. Hence, a picture of a cow could be interpreted quite differently by Protestants and Hindus[4]. We conducted a human cultural assessment experiment using U.S.–Japan pictogram interpretations as stimulus. Experimental findings revealed that human subjects looked at similarities and differences in two countries' interpretations when assessing cultural differences. Based on this finding,

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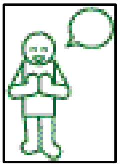
Table 1. A pictogram with U.S.–Japan interpretation words, SUMO classes, and ratios

U.S.		
Word	SUMO Class	Ratio
talking	`Speaking+`	0.30
pray	`Praying=`	0.30
thinking	`Reasoning=`	0.23
speaking	`Disseminating+`	0.17



Japan		
Word	SUMO Class	Ratio
speak	`Speaking+`, `SoundAttribute+`	0.34
announcement	`Stating+`	0.25
thank you	`Thanking+`	0.22
soliloquy	`Text+`	0.19

we formulate a simple assumption that interpretation differences can be detected if semantic differences can be detected. To this end, as a first step, we propose a method to calculate overall semantic dissimilarity of pictogram interpretation using ontology.

2 Measuring Semantic Dissimilarity Using Ontology

The idea is to compare dissimilarity of pictogram interpretations on the semantic level by mapping interpretation words to an ontology. In this paper, we use WordNet2SUMO[5] to map pictogram interpretation words to SUMO[6].

2.1 Mapping Words to SUMO and Calculating Concept Weights

We assume that a pictogram has a list of interpretation words and corresponding ratios of each country (Table 1). Searching through the WordNet2SUMO using each interpretation word as input will return relevant SUMO classes, instances, properties and so forth, but here we will only use the SUMO class and instance mappings. Table 1 shows related SUMO classes for the U.S.–Japan pictogram interpretation words. The "+ (plus)" suffix in the SUMO classname denotes that given interpretation word is subsumed by that concept. The "= (equal)" suffix denotes that given word is equal to the SUMO class or instance. We calculate the *Concept Weight* or *CW* of each SUMO class related to each word by taking into account the ratio of the interpretation word. The concept weight *CW* of a given SUMO class can be calculated as follows:

$$CW(class, country) = \sum_{\forall word, word \in C(class)} \frac{Ratio(word, country)}{NumOfRelatedClass(word)} \quad (1)$$

For example, the concept weight of `Speaking` and `SoundAttribute` class assigned to Japan's interpretation word *speak* in Table 1 can be calculated as:

$CW(Speaking, Japan) = 0.34/2 = 0.17$
$CW(SoundAttribute, Japan) = 0.34/2 = 0.17$

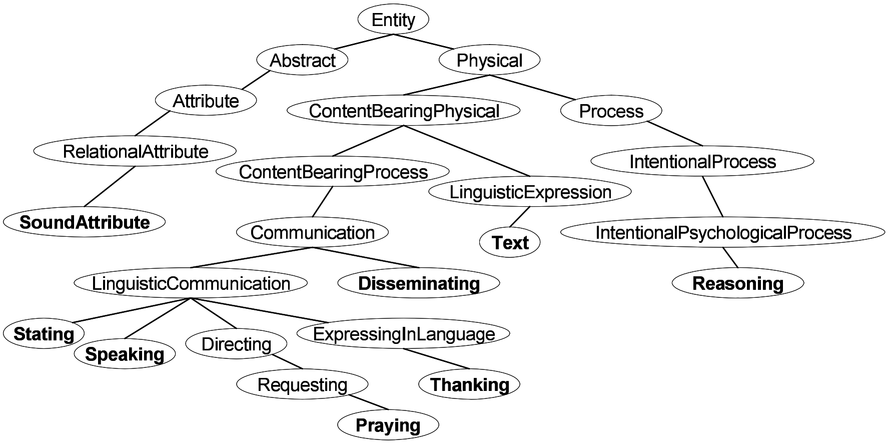


Fig. 1. Partial SUMO ontology containing SUMO classes given in Table 1

The result of the concept weight calculation will generate a list of SUMO classes with appropriate weights reflecting the conceptual interpretation of a given country. Once the list of SUMO classes with associated concept weights is obtained, we use the partial SUMO ontology containing the SUMO classes to leverage the graph structure of the ontology (Fig. 1). We count the number of edges between two SUMO classes to obtain the path length of the class pairs.

For instance, `Speaking` and `Stating` class in Fig. 1 has a path length of "2". Using the SUMO class and path length information, we generate a bipartite graph with left and right vertices representing each country's SUMO classes. Figure 2 shows three bipartite graphs, US–US, US–Japan, and Japan–Japan, generated using SUMO classes in Table 1. The vertices are connected completely in an *N-to-N* fashion, and each edge connecting the two vertices is assigned a path length of the two SUMO classes. Note that an edge connecting the same two classes is always assigned a path length of "0 (zero)" (e.g. `Stating` and `Stating` in Fig. 2 upper right is assigned "0").

2.2 Calculating Semantic Dissimilarity for Detection

The overall semantic dissimilarity in the two countries' SUMO classes is calculated by multiplying the concept weights of the two countries' SUMO classes and the associated path length, and adding up all possible SUMO class pair values.

Let $G(V, E)$ be a bipartite graph containing weighted SUMO class vertices $V = (V_1, V_2)$ where V_1 and V_2 denote $Country_1$ and $Country_2$ respectively and path length-assigned edges E. Using the concept weight equation CW in (1), the two countries' *Semantic Dissimilarity* or *SD* is calculated as:

$$SD(G) = \sum_{\forall v_i, v_i \in V_1} \sum_{\forall v_j, v_j \in V_2} CW(v_i) \times PathLength(v_i, v_j) \times CW(v_j) \qquad (2)$$

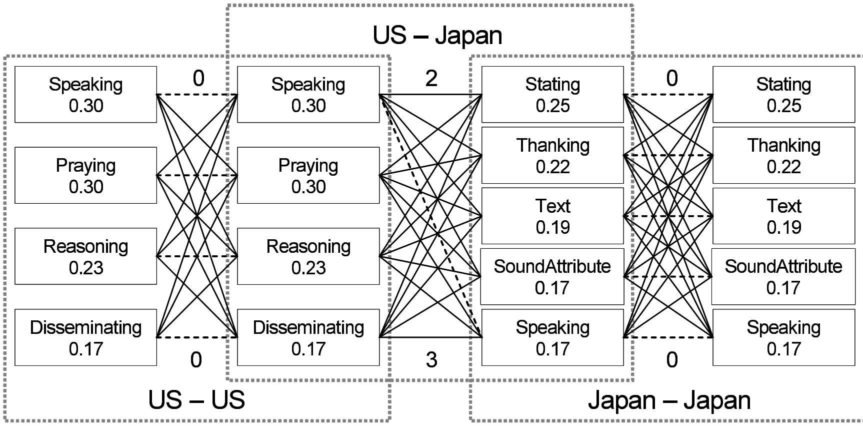


Fig. 2. Three bipartite graphs (US–US, US–Japan, Japan–Japan) with weight-assigned SUMO class vertices and path length-assigned edges (refer to Table 1 and Fig. 1)

The bipartite graph represents two countries' pictogram interpretations in terms of SUMO classes. Using the equation (2), we calculate the semantic dissimilarity values of the three bipartite graphs, namely, $Country_1 - Country_1$, $Country_1 - Country_2$, and $Country_2 - Country_2$. In the case of Fig. 2, the semantic dissimilarity values for US–US, US–Japan, and Japan–Japan are calculated as 4.92, 5.92, and 5.03 respectively. Note that multiplication between the same two classes will always return zero since the path length is zero. Hence, all class pairs connected with dashed lines in Fig. 2 will be zero.

Once the semantic dissimilarity values of the three bipartite graphs are obtained, we compare the *between-country* value with two *within-country* values. We assume that if the *between-country* semantic dissimilarity value is greater than the two *within-country* semantic dissimilarity values, then cultural difference exist in two countries' pictogram interpretations. This is based on the intuition that culturally-different pictograms will contain more varied *between-country* concepts than *within-country* concepts; that is, interpretations will center on similar concepts within the same country, but once the scope is enlarged to cover interpretations of the two countries, the concepts will become more varied for pictograms having cultural difference. In the case of Fig. 2, since the *between-country* value (US–Japan: 5.92) is greater than the two *within-country* values (US–US: 4.92, Japan–Japan: 5.03), "cultural difference exists" is returned.

2.3 Preliminary Result

We applied our method to thirty U.S.–Japan pictograms having human cultural difference assessment result. Table 2 shows the pictogram number (P#), human cultural difference assessment averages (AVG), three semantic dissimilarity values (US–US, US–JP, JP–JP), and hit or miss results of the proposed

Table 2. Human judgment averages (AVG), three interpretation dissimilarity values, and proposed method's performance of hits (H), misses (M), and false positives (FP)

P#	AVG	US–US		US–JP		JP–JP	H/M
P21	7.00	7.30	<	8.07	>	7.08	H
P1	6.83	5.31	<	7.73	>	5.63	H
P12	6.33	4.22	<	5.14	<	5.46	M
P2	6.17	5.83	<	9.30	>	5.35	H
P28	6.17	5.70	<	7.25	>	7.10	H
P11	6.00	5.77	<	7.33	<	7.54	M
P14	6.00	5.66	>	5.61	>	5.12	M
P13	5.83	5.16	>	4.55	>	2.99	M
P15	5.67	2.91	<	4.39	<	5.76	M
P10	5.50	5.63	<	5.88	<	5.94	M
P16	5.17	8.93	>	8.18	>	6.25	M
P30	5.00	5.64	>	5.21	>	4.43	M
P8	4.67	7.50	<	8.66	>	8.58	M
P9	4.67	6.96	<	8.60	>	8.20	M
P22	4.67	6.81	<	7.06	>	5.76	M

P#	AVG	US–US		US–JP		JP–JP	H/M
P23	4.50	6.75	<	8.43	>	8.24	M
P7	4.17	5.77	<	7.99	<	9.01	H
P3	4.00	7.90	>	7.58	>	6.47	H
P4	4.00	7.60	>	7.26	>	6.77	H
P5	4.00	6.55	>	6.10	>	5.42	H
P18	3.83	7.55	>	6.53	>	1.54	H
P17	3.67	3.24	<	5.02	<	5.80	H
P20	3.67	4.33	<	7.47	>	6.20	FP
P6	3.50	7.49	>	6.51	>	5.37	H
P19	3.50	7.65	>	6.82	>	4.90	H
P27	3.50	5.79	<	6.72	>	6.20	FP
P29	3.33	6.07	<	6.28	>	3.98	FP
P25	3.17	7.30	<	7.63	>	7.26	FP
P26	2.83	6.83	<	6.86	>	5.90	FP
P24	2.33	8.13	>	8.03	>	4.87	H

method when compared to the human assessment (H/M). Pictograms with averages (AVG) greater than or equal to 5 are judged by humans to have some kind of cultural difference. Initial findings of the result is discussed next.

3 Discussions

Existing researches propose node-based and edge-based approaches to measure concept (dis)similarity within a taxonomy[7] or a concept net[8] respectively, and we extend these approaches to group-level semantic dissimilarity measurement. Since our approach postulates a correspondence between human perception of pictogram interpretation and SUMO classes, we analyzed the missed cases for reasons for failure. One reason for failure is that in some cases, humans may perceive clear difference in interpretations, but ontology may not reflect this difference; that is, even if difference between two SUMO classes is small, interpretation difference perceived by humans may not be small. For example, Table 2 P13 (AVG: 5.83) is judged by humans to have cultural difference since a major U.S. interpretation word, *happy*, which captures emotional state, is clearly perceived as different when compared to major Japanese interpretation words, *pretty* and *cute*, which captures outward appearance. However, when the three words *happy*, *pretty*, and *cute* are mapped to SUMO, all are mapped to `SubjectiveAssessmentAttribute` class rendering the difference indistinguishable. So, for these kinds of pictogram interpretations, our method is not effective.

Another reason for failure is that for some interpretations having largely different SUMO classes, humans may not perceive such differences. For example, the top ranking US.–Japan interpretation word for Table 2 P29 is *carnival* and *amusement park* respectively, but humans see little cultural difference in the two. This is because association is used when humans compare these two words. However, at the SUMO-level, *carnival* and *amusement park* are mapped to `RecreationOrExercise` and `Corporation` class respectively which are very different classes; association is not incorporated in the ontology.

4 Conclusions

We proposed a way to calculate semantic dissimilarity in two countries' interpretations by mapping interpretation words to SUMO classes via WordNet2SUMO. Appropriate weights were assigned to mapped SUMO classes by distributing interpretation ratios. The edges between the two SUMO classes were counted to obtain path length of the two classes. The concept weight and path length information were used to calculate the semantic dissimilarity of the two countries' pictogram interpretations. Our approach is ontology-dependent and for those pictograms with interpretation differences indistinguishable at the ontology level, cultural difference detection is difficult; one reason is due to disagreement between human perception and ontology. Future work will focus on implementing an agent which can automatically detect cultural differences in interpretations.

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