Generating Apt Metaphor Ideas for Pictorial Advertisements

Ping Xiao, Josep Blat
Department of Information and Communication Technologies
Pompeu Fabra University
C./ Tànger, 122-140 Barcelona 08018 Spain
{ping.xiao, josep.blat}@upf.edu

Abstract

Pictorial metaphor is a popular way of expression in creative advertising. It attributes certain desirable quality to the advertised product. We adopt a general two-stage computational approach in order to generate apt metaphor ideas for pictorial advertisements. The first stage looks for concepts which have high imageability and the selling premise as one of their prototypical properties. The second stage evaluates the aptness of the candidate vehicles (found in the first stage) in regard to four metrics, including affect polarity, salience, secondary attributes and similarity with tenor. These four metrics are conceived based on the general characteristics of metaphor and its specialty in advertisements. We developed a knowledge extraction method for the first stage and utilized an affect lexicon and two semantic relatedness measures to implement the aptness metrics of the second stage. The capacity of our computer program is demonstrated in a task of reproducing the pictorial metaphor ideas used in three real advertisements. All the three original metaphors were replicated, as well as a few other vehicles recommended, which, we consider, would make effective advertisements as well.

Introduction

A pictorial advertisement is a short discourse about the advertised product, service or idea (all referred to as 'product' afterwards). Its core message, namely the selling premise, is a proposition that attributes certain desirable quality to the product (Maes and Schilperoord 2008). A single proposition can be expressed virtually in an unlimited number of ways, among which some are more effective than the others. The 'how to say' of an ad is conventionally called the 'idea'. 'Pictorial metaphor' is the most popular way of expression in creative advertising (Goldenberg, Mazursky and Solomon 1999). A pictorial metaphor involves two dimensions, 'structural' and 'conceptual' (Forceville 1996; Phillips and McQuarrie 2004; Maes and Schilperoord 2008). The structural dimension concerns how visual elements are arranged in a 2D space. The conceptual dimension deals with the semantics of the visual elements and how they together construct a coherent message. We see that the operations in the structural and conceptual dimensions are quite different issues. In any of these two dimensions, computational creativity is not a trivial issue. In this paper, we are focusing on only one dimension, the conceptual one.

The conceptual dimension of pictorial metaphors is not very different from verbal metaphors (Foss 2005). A metaphor involves two concepts, namely 'tenor' and 'vehicle'. The best acknowledged effect of metaphor is highlighting certain aspect of the tenor or introducing some new information about the tenor. Numerous theories have been proposed to account for how metaphors work. The interaction view is the dominant view of metaphor, which we also follow. It was heralded by Richards (1936) and further developed by Black (1962). According to Black, the principal and subsidiary subjects of metaphor are regarded as two systems of "associated commonplaces" (commonsense knowledge about the tenor and vehicle). Metaphor works by applying the system of associated commonplaces of the subsidiary subject to the principal subject, "to construct a corresponding system of implications about the principal subject". Any associated commonplaces of the principal subject that conform the system of associated commonplaces of the subsidiary subject will be emphasized, and any that does not will be suppressed. In addition, our view of the subsidiary subject is also altered.

Besides theories, more concrete models have been proposed, mainly the salience imbalance model (Ortony 1979), the domain interaction model (Tourangeau and Sternberg 1982), the structure mapping model (Gentner 1983; Gentner and Clement 1988), the class inclusion model (Gluckberg and Keysar 1990, 1993) and the conceptual scaffolding and sapper model (Veale and Keane 1992; Veale, O'Donoghue and Keane 1995). Furthermore, these models suggest what make good metaphors, i.e. metaphor aptness, which is defined as "the extent to which a comparison captures important features of the topic" (Chiappe and Kennedy 1999).

In the rest of this paper, we first specify the problem of generating apt metaphor ideas for pictorial advertisements. Then, the relevant computational approaches in the literature are reviewed. Next, we introduce our approach to the stated problem and the details of our implementation. Subsequently, an experiment with the aim of reproducing three pictorial metaphors used in real advertisements and the results generated by our computer program are demonstrated. In the end, we conclude the work presented in this paper and give suggestion about future work.

Problem Statement

The whole range of non-literal comparison, from mere-appearance to analogy (in the terms of Gentner and Markman (1997)), is featured in pictorial advertisements. But, analogies are rare. What appear most frequently are metaphors with the mapping of a few attributes or relations. This type of pictorial metaphors is the target of this paper. To generate pictorial metaphors for advertisements, our specific problem is searching for concepts (vehicles), given the product (tenor), its selling premise (the property concept) and some other constraints specified in an advertising brief. The metaphor vehicles generated have to be easy to visualize and able to establish or strengthen the connection between the product and the selling premise.

There are two notes specific to advertisements that we would like to mention. One is about the tenor of metaphor. In pictorial ads, not only the product, but also "the internal components of the product and the objects that interact with it" are often used as tenors (Goldenberg, Mazursky and Solomon 1999). The other note is about the selling premise. Metaphors in advertisements are more relevant to communicating intangible, abstract qualities than talking about concrete product facts (Phillips and McQuarrie 2009). Therefore, we are primarily considering abstract selling premises in this paper. In the next section, we review the computational approaches to metaphor generation that are related to the problem just stated.

Computational Approaches to Metaphor Generation

Abe, Sakamoto and Nakagawa (2006) employed a three-layer feedforward neural network to transform adjective-modified nouns, e.g. 'young, innocent, and fine character' into 'A like B' style metaphors, e.g. 'the character is like a child'. The nodes of the input layer correspond to a noun and three adjectives. The nodes of the hidden layer correspond to the latent semantic classes obtained by a probabilistic latent semantic indexing method (Kameya and Sato 2005). A semantic class refers to a set of semantically related words. Activation of the input layer is transferred to the semantic classes (and the words in each class) of the hidden layer. In the output layer, the words that receive most activation (from different semantic classes) become metaphor vehicles. In effect, this method outputs concepts that are the intermediates between the semantic classes to which the input noun and three adjectives are strongly associated. If they are associated to different semantic classes, this method produces irrelevant and hard to visualize vehicles.

A variation of the above model was created by Terai and Nakagawa (2009), who made use of a recurrent neural network to explicitly implement feature interaction. It differs with the previous model at the input layer, where each feature node has bidirectional edge with every other feature node. The performance of these two models was compared in an experiment of generating metaphors for two tenors. The model with feature interaction produced better results.

Besides, Terai and Nakagawa (2010) proposed a method of evaluating the aptness of metaphor vehicles generated by the aforementioned two computational models. A candidate vehicle is judged based on the semantic similarity between the corresponding generated metaphor and the input expression. A candidate vehicle is more apt when the meaning of the corresponding metaphor is closer to the input expression. The semantic similarity is calculated based on the same language model used in the metaphor generation process. The proposed aptness measure was tested in an experiment of generating metaphors for one input expression, which demonstrated that it improved the aptness of generated metaphors.

Veale and Hao (2007) created a system called Sardonicus which can both understand and generate property-attribution metaphors. Sardonicus takes advantage of a knowledge base of entities (nouns) and their most salient properties (adjectives). This knowledge base is acquired from the web using linguistic patterns like 'as ADJ as *' and 'as * as a/an NOUN'. To generate metaphors, Sardonicus searches the knowledge base for nouns that are associated with the intended property. The aptness of the found nouns is assessed according to the category inclusion theory, i.e. "only those noun categories that can meaningfully include the tenor as a member should be considered as potential vehicles". For each found noun, a query in the format 'vehicle-like tenor' is sent through a search engine. If there are more than zero results returned, the noun is considered an apt vehicle. Otherwise, it is considered not apt or extremely novel.

The above reviewed effort of generating metaphor converges at a two-stage approach. These two stages are:

- Stage 1: Search for concepts that are salient in the property to be highlighted
- Stage 2: Evaluate the aptness of the found concepts as metaphor vehicles

This two-stage approach of metaphor generation is adopted by us. We provide methods of searching and evaluating metaphor vehicles, which are different from the literature. In addition, special consideration is given to the aptness of metaphor in the advertising context.

An Approach of Generating Apt Metaphor Ideas for Pictorial Advertisements

We adopt a general two-stage computational approach of metaphor generation (as introduced in the last section) to generate apt metaphor ideas for pictorial advertisements. At the first stage, we look for concepts which have high Imageability (Paivio, Yuille and Madigan 1968; Toglia, and Battig 1978) and the selling premise as one of their prototypical properties. At the second stage, we evaluate the aptness of the candidate vehicles using four metrics, including affect polarity, salience, secondary attributes and similarity with tenor. Vehicles that are validated by all the four metrics are considered apt for a specific advertising task. In the following sections, we explain the rationale of our approach and its computational details.

Stage 1: Search Candidate Metaphor Vehicles

To find entities which have the selling premise as one of their prototypical properties, our strategy is searching for concepts that are strong semantic associations of the selling premise. One note to mention is that the concepts sought-after do not need to be the 'absolute' associations, because the meaning of a metaphor, i.e. which aspect of the tenor and vehicle becomes prominent, does not only depend on the vehicle, but on the interaction between the tenor and vehicle. In the past, we developed an automatic knowledge extraction system, namely VRAC (Visual Representations for Abstract Concepts), for providing concepts of physical entities to represent abstract concepts (Xiao and Blat 2011). Here we give a brief introduction of this work.

We look for semantic associations in three knowledge bases, includingword association databases (Kiss, Armstrong, Milroy and Piper 1973; Nelson, McEvoy and Schreiber 1998), a commonsense knowledge base called ConceptNet (Liu and Singh 2004) and Roget's Thesaurus (Roget 1852). The reason for using three of them is that we want to take use of the sum of their capacity, in terms of both the vocabulary and the type of content. The nature of these three knowledge bases ensures that the retrieved concepts have close association with the selling premise.

Vehicles of pictorial metaphors should have high imageability, in order to be easily visualized in advertisements. Imageability refers to how easy a piece of text elicits mental image of its referent. It is usually measured in psychological experiments. The available data about word imageability, at the scale of thousands, does not satisfy our need of handling arbitrary words and phrases. As imageability is highly correlated with word concreteness, we developed a method of estimating concreteness using the ontological relations in WordNet (Fellbaum 1998), as an approximation of imageability.

To evaluate the capacity of VRAC, we collected thirty-eight distinct visual representations of six abstract concepts used in past successful advertisements. These abstract concepts have varied parts of speech and word usage frequency. We checked if these visual representations were included in the concepts output by VRAC, with the corresponding abstract concept as input. On average, VRAC achieved a hit rate of 57.8%. The concepts suggested by VRAC are mostly single objects. It lacks the concepts of scenes or emergent cultural symbols, which also play a role in mass visual communication.

Stage 2: Evaluate the Aptness of Candidate Vehicles

The aptness of the candidate vehicles generated in Stage 1 is evaluated based on four metrics, including affect polarity, salience, secondary attributes and similarity with tenor.

Affect Polarity Most of the time, concepts with negative emotions are avoided in advertising (Kohli and Labahn, 1997; Amos, Holmes and Strutton 2008). Even in provocative advertisements, negative concepts are deployed with extreme caution (De Pelsmacker and Van Den Bergh 1996; Vézina and Paul 1997; Andersson, Hedelin, Nilsson and Welander 2004). In fact, negative concepts are often discarded at the first place (Kohli and Labahn 1997). Therefore, we separate candidate vehicles having negative implication from the ones having positive or neutral implication. For this purpose, affective lexicons, which provide affect polarity values of concepts, come in handy. We decided to use SentiWordNet 3.0 (Baccianella, Esuli and Sebastiani 2010), due to its big coverage (56,200 entries) and fine grained values. It provides both the positive and negative valences, which are real values ranging from 0.0 to 1.0. If a candidate vehicle is found in SemtiWordNet 3.0, its affect polarity is calculated by subtracting the negative valence from the positive valence. The candidate vehicles which are not included in SemtiWordNet 3.0 are considered being emotionally neutral.

Salience Salience refers to how strongly a symbol evokes certain meaning in humans' mind. The candidate vehicles found by VRAC have varying association strength with the selling premise, from very strong to less. The vehicle of a metaphor has to be more salient in the intended property than the tenor (Ortony 1979; Glucksberg and Keysar 1990). We interpret salience as a kind of semantic relatedness (Budanitsky and Hirst 2006), which reflects how far two concepts are in the conceptual space of a society. We calculate the semantic relatedness between each candidate vehicle and the selling premise, and between the product and the selling premise. Candidate vehicles that are more remote from the selling premise than the product are discarded. We will talk more about semantic relatedness and the specific measures we used in a later section.

Secondary Attributes Metaphors that capture the appropriate number of relevant features are considered especially apt (Glucksberg and Keysar 1990, 1993; Chiappe and Kennedy 1999). Phillips (1997) found that strong implicatures as well as weak implicatures were drawn from pictorial advertisements. Strong implicatures correspond to the selling premise of an ad, while we use 'secondary attributes' for referring to the weak implicatures. We have not seen literature on the salience of the secondary attributes in metaphor vehicles. We think the candidate vehicles should, at least, not contradict the secondary attributes prescribed to a product. For this end, we use a semantic relatedness measure to filter candidate vehicles that are very distant from the secondary attributes. This is 'soft' filtering, in contrast to the 'hard' filtering used in the previous two metrics, i.e. affect polarity and salience, in the sense that the current criterion might need be tighten in order to ensure the aptness of generated metaphors.

We compare the above approach with an alternative, which is using both the selling premise and the secondary attributes to search for candidate vehicles. This alternative method indeed looks for concepts that are salient in all these properties. This is possible, but rare. Most of the time, no result will be returned. On the other hand, there is a natural distinction of priority in the attributes (for a product) desired by advertisers (recall the strong and weak implicatures just mentioned). To represent this distinction, weighting of attributes is necessary.

The computational model proposed by Terai and Nakagawa (2009) also uses multiple features to generate metaphors. The weights of the edges connecting the feature nodes in the input layer vary with the tenor. Specifically, the weight of an edge equals to the correlation coefficient between the two features respecting the tenor. The calculation is based on a statistic language model built on a Japanese corpus (Kameya and Sato 2005), which means the weighting of features (of a tenor) is intended to be near reality. However, this idea does not suit advertising, because the features attributed to a product are much more arbitrary. Very often, a product is not thought possessing those features before the appearance of an advertisement.

Similarity with Tenor Good metaphors are those whose tenor and vehicle are not too different yet not too similar to each other (Aristotle 1924; Tourangeau and Sternberg 1981; Marschark, Kats and Paivio 1983). For this reason, we calculate the semantic relatedness between the product and each candidate vehicle. Firstly, candidate vehicles which have zero or negative semantic relatedness values are discarded, because they are considered too dissimilar to the product. Then, the candidate vehicles with positive relatedness values are sorted in the descending order of relatedness. Among this series of values, we look for values that are noticeably different from the next value, i.e. turning points. Turning points divide relatedness values into groups. We use the discrete gradient to measure the change of value, and take the value with the biggest change as the turning point. Candidate vehicles with their relatedness value bigger than or equal to the turning point are abandoned, for being too similar to the tenor. Figure 1 shows the sorted relatedness values between the candidate vehicles and the tenor ‘child’ in the ad of the National Museum of Science and Technology. The turning point in this graph corresponds to the concept ‘head’.

Semantic Relatedness Measures In general, semantic relatedness is measured through distance metrics in certain materialized conceptual space, such as knowledge bases and raw text. A number of semantic relatedness measures have been proposed. Each measure has its own merits and weakness. We employed two different measures in the current work, including PMI-IR (Pointwise Mutual Information and Information Retrieval) (Turney 2001) and LSA through Random Indexing (Kanerva, Kristofersson and Holst 2000). PMI-IR is used to compute salience, because we found it gives more accurate results than other available measures when dealing with concept pairs of high semantic relatedness. The relatedness between the selling premise and candidate vehicles is deemed high. Therefore, we use PMI-IR to give a delicate ordering of their association strength. LSA is employed for the metrics of secondary attributes and similarity with tenor. The motivation behind this choice is to capitalize on LSA’s ability of ‘indirect inference’ (Landauer and Dumais 1997), i.e. discovering connection between terms which do not co-occur. Recall that candidate vehicles are assumed to have strong association with the selling premise, but not necessarily the secondary attributes. In most cases, the association between a candidate vehicle and a secondary attribute is not high. Thus, we need a measure which is sensitive to the low-range semantic relatedness. LSA has demonstrated capacity in this respect (Waltinger, Cramer and Wandmacher 2009). For LSA, values close to 1.0 indicate very similar concepts, while values close to 0.0 and under 0.0 indicate very dissimilar concepts. In our computer program, we utilize the implementation of Random Indexing provided by the Semantic Vectors package[1]. Two-hundred term vectors are acquired from the LSA process for computing semantic relatedness. In the present work, both PMI-IR and LSA are based on the Wikipedia corpus, an online encyclopedia of millions of articles. We obtained the English Wikipedia dumps, offered by the Wikimedia Foundation[2] on October 10th, 2011. The compressed version of this resource is about seven gigabytes.

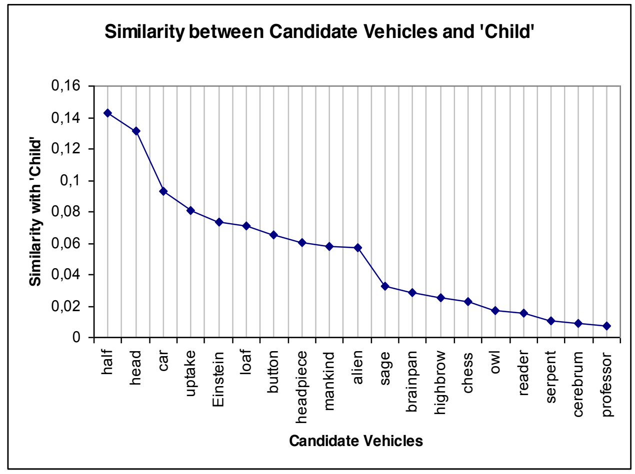

Figure 1: Similarity between candidate vehicles and 'Child'

An Example

We intend to evaluate our approach of generating apt metaphor ideas for pictorial advertisements based on checking whether this approach can reproduce the pictorial metaphors used in past successful advertisements. We have been collecting a number of real ads and the information about the product, selling premise, secondary attributes, and the tenor and vehicle of metaphor in these ads. Nonetheless, it is a tedious process.

[1] http://code.google.com/p/semanticvectors/
[2] http://download.wikipedia.org/

In this paper, we use the information of three real ads to show what our computer program generates. These three ads are for the Volvo S80 car, The Economist newspaper and the National Museum of Science and Technology in Stockholm respectively. Each of them has a pictorial metaphor as its center of expression. All the three ads have the same selling premise: 'intelligence'. However, three different vehicles are used, including 'chess', 'brain' and 'Einstein' respectively. The selection of these particular ads aims at testing whether our aptness metrics are able to differentiate different tenors.

Table 1 summarizes the three aspects of the three ads, including product, secondary attributes and the tenor of metaphor. For both of the car and newspaper ads, the tenors of metaphor are the products. For the museum ad, the tenor is the target consumer, children.

We found the secondary attributes of the Volvo S80 car in its product introduction[3]. For the other two ads, the Economist newspaper and the National Museum of Science and Technology, we have not found any secondary attributes specified. Instead, their subject matter is used to distinguish them from the products of the same categories

Furthermore, we think it is more accurate to use the Boolean operations 'AND' and 'OR' in describing the relation between multiple secondary attributes. As consequence, candidate vehicles have to be reasonably related to both attributes at the two sides of AND; at least one of the two attributes connected by OR.

Product	Secondary Attributes	Tenor
car[4]	elegance AND luxury AND sophisticated	car
newspaper[5]	international politics OR business news	newspaper
museum[6]	science OR technology	child

Table 1: Information about the three real ads

For the concept 'intelligence', VRAC provides eighty-seven candidate vehicles, including single words and phrases. We keep the single-word concepts and extract the core concept of a phrase, in order to reduce the complexity of calculating the aptness metrics at the later stage. An example of the core concept of a phrase is the word 'owl' in the phrase 'wise as an owl'. The core concepts are extracted automatically based on syntactic rules. This process introduces noise, i.e. concepts not related to 'intelligence', such as 'needle' of the phrase 'sharp as a needle' and 'button' of the phrase 'bright as a button'. In total, there are thirty-four candidate vehicles of single words. All the three metaphor vehicles used in the three real ads are included.

As to affect polarity, the majority of the candidate vehicles, thirty out of thirty-four, are emotionally neutral. Besides, 'highbrow' is marked as positive, while 'geek' and 'serpent' as negative.

The ranking of candidate vehicles by its salience in the selling premise is shown in Table 2. The semantic relatedness calculated by PMI-IR correctly captured the main trend of salience. 'IQ', 'Mensa' and 'brain' are ranked top, while 'needle', 'button' and 'table', which are the noise introduced by the core concept extraction method, are ranked very low. The positions of the products are marked in italic. Only candidate vehicles having higher salience than a product are seen as valid. For instance, 'horse', ranked the twenty-sixth, is not selected for the Volvo S80 car ad, since car is judged as more intelligent than horse by PMI-IR. On the other hand, all the metaphor vehicles used in the original ads, i.e. chess, brain and Einstein, have higher rankings than the corresponding tenors, which supports Ortony's salience imbalance theory.

Rank	Vehicle	Rank	Vehicle
1	IQ	19	reader
2	Mensa	*20*	*child*
3	brain	21	sage
4	computer	22	serpent
5	cerebrum	23	owl
6	alien	*24*	*car*
7	mankind	25	whale
8	highbrow	26	horse
9	Einstein	27	pig
10	head	38	half
11	professor	29	needle
12	dolphin	30	button
13	chess	31	table
14	lecturer	32	uptake
15	geek	33	storey
16	headpiece	34	loaf
17	*newspaper*	35	brainpan
18	atheist	36	latitudinarian

Table 2: Candidate vehicles sorted in the descending order of salience

Table 3 shows how candidate vehicles are filtered by the secondary attributes of products, where candidate vehicles that are not contradictory to the secondary attributes are presented. Table 4 shows the candidate vehicles that are not too different yet not too similar with the tenors of the three ads respectively. For both results, the metaphor vehicles used in the original ads survived the filtering, which gives support to the domain interaction theory proposed by Tourangeau and Sternberg. Nevertheless, there is also flaw in the results produced by the LSA-IR measure. For instance, regarding the fourth column of Table 3, we suspect

[3] http://www.volvocars.com/us/all-cars/volvo-s80/pages/5-things.aspx, retrieved on April 1st, 2012.
[4] http://adsoftheworld.com/media/print/volvo_s80_iq
[5] http://adsoftheworld.com/media/print/the_economist_brain
[6] http://adsoftheworld.com/media/print/the_national_museum_of_science_and_technology_little_einstein

‘brain’ should not have nothing to do with ‘science’ and consulted several other semantic relatedness measures, which confirmed our skepticism.

Product	car	newspaper	museum
Secondary Attributes	elegance AND luxury AND sophisticated	international politics OR business news	science OR technology
Candidate Vehicle	chess half geek	IQ brain computer cerebrum mankind highbrow head professor dolphin chess lecturer geek headpiece atheist reader sage owl car whale horse half needle button table uptake storey brainpan	IQ Mensa computer cerebrum alien mankind highbrow Einstein head professor chess lecturer headpiece atheist reader sage owl whale half needle button table storey loaf brainpan

Table 3: Candidate vehicles NOT contradictory to the secondary attributes of the three products respectively

Tenor	car	newspaper	child (museum)
Candidate Vehicle	pig storey mankind uptake button half serpent whale lecturer chess latitudinarian sage professor alien horse IQ	professor loaf whale table atheist geek mankind brainpan head Mensa button dolphin brain sage pig headpiece uptake storey	car uptake Einstein loaf button headpiece mankind alien sage brainpan highbrow chess owl reader serpent cerebrum professor

Table 4: Candidate vehicles that are not too different yet not too similar with the tenors of the three ads respectively

We show in Table 5 the metaphor vehicles suggested by our computer program for each of the three ads after applying all the four aptness metrics. For all the three ads, the vehicles used in the original ads are included in the vehicles suggested by our computer program, as marked in italic. For the Volvo S80 car ad, the original metaphor vehicle is the only one recommended by our program. For the other two ads, our program also proposed other five and eight vehicles respectively. Considering that there are thirty four candidate vehicles input to the second stage, we think the four aptness metrics together did an acceptable job.

Regarding the generated vehicles other than the one used in the original ad: are they equally effective? We will have a closer look at the metaphor vehicles generated for the ad of the National Museum of Science and Technology, since it has the most suggested vehicles. It is easy to spot a semantic cluster among these eight vehicles. Five out of eight are humans or human-like entities bearing high intellect, including ‘Einstein’, ‘mankind’, ‘alien’, ‘highbrow’ and ‘professor’. ‘Einstein’, as the most prototypical within this cluster, fits best this specific advertising task. Besides, other vehicles in this cluster are also highly relevant to a setting like museum for people, especially children, to increase knowledge and encounter inspiration. They may be optimal for other advertising tasks with slightly different focus. The only exception is ‘mankind’, which is a very general concept. As to the rest of the suggested metaphor vehicles, certain ‘headpiece’ is possibly kind of symbol of intelligence; playing ‘chess’ shows someone is intelligent, and ‘cerebrum’ is strongly associated with intelligence. It is not difficult to imagine a picture of juxtaposing a headpiece and a child, a child playing chess or a child whose cerebrum is emphasized, all of which would be effective to associate a child with intelligence. However, strictly speaking, they are not metaphors.

On the other hand, the existence of candidate vehicles other than the ones used in the original ads may suggest, firstly, our implementation of the four aptness metrics may not sufficiently reduce inapt vehicles. Secondly, more metrics, representing other factors that affect metaphor aptness, may be necessary.

Ad	**Tenor**	**Vehicle**
Volvo S80 car	car	*chess*
The Economist newspaper	newspaper	professor
		mankind
		head
		dolphin
		brain
		headpiece
National Museum of Science and Technology	child	*Einstein*
		headpiece
		mankind
		alien
		highbrow

		chess
		cerebrum
		professor

Table 5: Metaphor vehicles considered apt for the three ads respectively

Conclusions

In the work presented in this paper, we adopted a general two-stage computational approach to generate apt metaphor ideas for pictorial advertisements. The first stage looks for concepts which have high imageability and the selling premise as one of their prototypical properties. The second stage evaluates the aptness of the candidate vehicles (found in the first stage) with regard to four aspects, including affect polarity, salience, secondary attributes and similarity with tenor. These four metric are conceived based on the general characteristics of metaphor and its specialty in advertising. For the first stage, we developed an automatic knowledge extraction method to find concepts of physical entities which are strongly associated with the selling premise. For the second stage, we utilized an affect lexicon and two semantic relatedness measures to implement the four aptness metrics. The capacity of our computer program is demonstrated in a task of reproducing the pictorial metaphors used in three real advertisements. All the three original metaphors were replicated, as well as a few other vehicles recommended, which, we consider, would make effective advertisements, though less optimal. In short, our approach and implementation are promising in generating diverse and apt pictorial metaphors for advertisements.

On the other hand, to have a more critical view of our approach and implementation, larger scale evaluation is in need. Continuing the evaluation design introduced in this paper, more examples of pictorial metaphors used in real advertisements have to be collected and annotated. This corpus would not only contribute to building our metaphor generator, but also be an asset for the research on metaphor and creativity in general.

Moreover, the results provided by our aptness metrics support both the salience imbalance theory and the domain interaction theory.

Future Work

We intend to compute more ways of expression appeared in pictorial advertisements. Firstly, our current implementation can be readily adapted to generate visual puns. In a pun, the product (or something associated to it) also has the meaning of the selling premise. An example is an existing ad which uses the picture of an owl to convey the message 'zoo is a place to learn and gain wisdom'. As we all know, owl is both a member of the zoo and a symbol of wisdom. Secondly, we found some other fields of study are very relevant to computing advertising expression, such as the research and computational modeling of humor (Raskin 1985; Attardo and Raskin 1991; Ritchie 2001; Binsted, Bergen, Coulson, Nijholt, Stock, Strapparava, Ritchie, Manurung, Pain, Waller and O'Mara, 2006). Finally, we are especially interested in investigating hyperbole. Hyperbole has nearly universal presence in advertisements, but its theoretic construction and computational modeling are minimal. There exist some ad-hoc approaches: for instance, we can find the exaggeration of the selling proposition by the AlsoSee relation in WordNet; or, we should first think about a cognitive or linguistic model of hyperbole instead.

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