Abstract

Natural language processing techniques are increasingly applied to identify social trends and predict behavior based on large text collections. Existing methods typically rely on surface lexical and syntactic information. Yet, research in psychology shows that patterns of human conceptualisation, such as metaphorical framing, are reliable predictors of human expectations and decisions. In this paper, we present a method to learn patterns of metaphorical framing from large text collections, using statistical techniques. We apply the method to data in three different languages and evaluate the identified patterns, demonstrating their psychological validity.

1 Introduction

With the rise of blogging and social media, applying text mining techniques to aid political and social science has become an active area of research in natural language processing (NLP) (Grimmer and Stewart, 2013). NLP techniques have been successfully used for tasks such as estimating the influence of politicians (Fader et al., 2007), predicting voting patterns (Gerrish and Blei, 2011) and political affiliation (Pennacchiotti and Popescu, 2011). Such methods typically rely on surface lexical and syntactic cues, rather than analysing patterns of conceptualisation and framing of social and political issues. Framing is, however, widely studied in political science, linguistics and cognitive psychology (Lakoff, 1991; Tannen, 1993; Entman, 2003) as a way of reasoning about an issue by selecting and emphasizing its facets that reinforce a particular point of view. Metaphor is a particularly apt framing device, as it exposes the desired aspects of the issue, while seamlessly concealing the less desired ones (Lakoff, 1991; Beigman Klebanov and Beigman, 2010; Lakoff and Wehling, 2012). For instance, discussing war as a competitive game emphasizes the victory vs. defeat aspect of war, while neglecting its human cost. Sports metaphors have thus often been used by politicians seeking to arouse a pro-war sentiment in the public (Lakoff, 1991).

Psychologists Thibodeau and Boroditsky (2011) investigated how metaphors affect our decision-making. In their experiment, two groups of subjects were primed by two different metaphors for crime: crime is a virus vs. crime is a beast and then asked how crime should be tackled. They found that the first group tended to opt for preventive measures and the second group for punishment-oriented ones. According to the authors, their results demonstrate the influence that metaphors have on how we conceptualize and act with respect to societal issues. This in turn suggests that the metaphors we use can serve as a predictor of our social, political and economic decisions. Therefore, a text mining system aiming to gain an understanding of social trends across populations or their change over time, needs to identify subtle but systematic linguistic differences, expressed both literally and metaphorically.

In this paper, we propose a method for large-scale identification of metaphorical framing patterns in text corpora. Metaphorical expressions arise in the presence of systematic metaphorical associations, or conceptual metaphors, mapping one concept or domain to another (Lakoff and Johnson, 1980). For
instance, when we talk about “curing juvenile delinquency” or “diagnosing corruption”, we view crime (the target concept) as a virus or a disease (the source concept). Our method uses clustering techniques to generalise such metaphorical associations based on the metaphorical use of language in a large text corpus. Specifically, we use a hierarchical soft clustering method – hierarchical graph factorization clustering (HGFC) (Yu et al., 2006) – to learn a graph of concepts from the data and to identify patterns of inter-conceptual association in this graph. To obtain the graph, we cluster frequent nouns in the corpus using the verbs they co-occur with as features. Our expectation is that the verbs that systematically occur with both the source domain nouns (e.g. “cure disease”) and the target domain nouns (e.g. “cure crime”) would allow the system to establish a connection between the two domains, providing evidence of metaphorical framing.

The method is fully unsupervised and relies on uncovering the patterns of systematic use of metaphor in linguistic data. It can thus be applied to any text corpus, domain or language, without any need for manual annotation. We apply the method to large corpora in three languages – English, Russian and Spanish. The method identifies interesting differences in metaphorical framing in these corpora. We validated these differences in a behavioural experiment and established that the system accurately predicts behavioural data on human judgements of economic change. Besides providing a new set of techniques for text mining applications, this method can also inform and scale-up research in experimental psychology, based on data-driven evidence rather than introspection.

2 Related work

NLP techniques have been successfully used for a number of tasks in political science, including automatically estimating the influence of particular politicians in the US senate (Fader et al., 2007), identifying lexical features that differentiate political rhetoric of opposing parties (Monroe et al., 2008), predicting voting patterns of politicians based on their use of language (Gerrish and Blei, 2011), and predicting political affiliation of Twitter users (Pennacchiotti and Popescu, 2011). Other approaches (Paul and Girju, 2009; Ahmed and Xing, 2010; Fang et al., 2012; Qu and Jiang, 2013; Gottipati et al., 2013) detected the contrasting perspectives on a set of topics attested in distinct corpora using LDA topic modelling. Some works focused on subjectivity detection, identifying opinion, evaluation, and speculation in text (Wiebe et al., ) and attributing it to specific people (Awadallah et al., 2011; Abu-Jbara et al., 2012). While successful in their tasks, these methods rely on surface linguistic cues, rather than generalising patterns of human association and conceptualisation, which limits the information they discover to that explicitly stated.

In the meantime, much work on framing in political science and linguistics has shown that systematic variations in the use of metaphor across communities is a rich source of information about the differences in world views (Lakoff and Wehling, 2012; Shaikh et al., 2014; Diaz-Vera and Caballero, 2013; Kövecses, 2004; Deignan and Potter, 2004; Stefanowitsch, 2004; Musolff, 2000). For instance, Lakoff (2002) discuss how two conflicting instantiations of the NATION IS A FAMILY metaphor, using nurturing-parent vs. strict-father family models, explain the liberal-conservative divide in the US politics. Lakoff and Wehling (2012) show that the two models are consistent with both the parties’ rhetoric and their policies, and are a reliable predictor of liberal vs. conservative values. Some works (Charteris-Black and Ennis, 2001; Barcelona, 2001; Matsuki, 1995; Taylor and Mbense, 1998) studied metaphor cross-linguistically and invariably found distinct patterns of metaphorical use across languages.

The majority of computational approaches to metaphor focused on automatic identification of metaphorical expressions in text. They used techniques such as supervised classification (Mohler et al., 2013; Tsvetkov et al., 2013; Hovy et al., 2013), clustering (Shutova et al., 2010; Shutova and Sun, 2013), vector space models (Shutova et al., 2012; Mohler et al., 2014), lexical resources (Krishnakumar and Zhu, 2007; Wilks et al., 2013) and web search with lexico-syntactic patterns (Yeale and Hao, 2008; Li et al., 2013; Bollegala and Shutova, 2013). Two approaches looked explicitly at conceptual metaphor. Mason (2004) automatically acquired domain-specific selectional preferences of
verbs, and then, by mapping their common nominal arguments in different domains, arrived at the corresponding metaphorical mappings. Shutova and Sun (2013) have previously applied HGFC to acquire a set of metaphorical associations in order to identify metaphorical language in English text. Their intuition was that since metaphorical uses of words constitute a large portion of contexts of abstract nouns in a text corpus, noun clustering techniques are well positioned to identify patterns of metaphorical association. In this paper, we apply HGFC to three different languages (English, Russian and Spanish) and investigate its ability to identify cross-corpus and cross-cultural differences in metaphorical framing. We then also investigate the psychological validity of the identified metaphors and differences by conducting their behavioral evaluation.

3 Experimental data

English data The English noun dataset used for clustering contains the 2000 most frequent nouns in the British National Corpus (BNC) (Burnard, 2007), which is balanced with respect to topic and genre. The features for clustering were extracted from the English Gigaword corpus (Graff et al., 2003) due to its large size. The corpus was parsed using the RASP parser (Briscoe et al., 2006) and verb–subject, verb–direct object and verb–indirect object relations were extracted to create the feature vectors. The 2000 most frequent nouns in the RU-WaC constituted the dataset used for clustering.

4 Method

We first cluster nouns using HGFC to create a graph of concepts with different levels of generality. The weights on the edges of the graph indicate the level of association between concepts (represented as clusters). HGFC allows us to model multiple relations between concepts simultaneously via soft clustering. This makes it well suited to detect the structure of metaphorical associations, where each concept can be associated with several others.

4.1 HGFC clustering

The algorithm successively derives probabilistic bipartite graphs for every level in the hierarchy. Given a set of nouns, \( V = \{v_n\}_{n=1}^N \), we first construct their similarity matrix \( W \) using Jensen-Shannon divergence as a measure. The matrix \( W \) encodes an undirected similarity graph \( G \), where the nouns are mapped to vertices and their similarities represent the weights \( w_{ij} \) on the edges between vertices \( i \) and \( j \) (see Fig. 1(a)). The clustering problem can now be formulated as partitioning of \( G \).

The graph \( G \) and the cluster structure can be represented by a bipartite graph \( K(V, U) \), where \( V \) are the vertices on \( G \) and \( U = \{u_p\}_{p=1}^m \) represent \( m \) hidden clusters. For example, \( V \) on \( G \) can be grouped into three clusters \( u_1, u_2 \) and \( u_3 \) (Fig. 1(b)). The matrix \( B \) denotes the \( n \times m \) adjacency matrix, with \( b_{ip} \) being the connection weight between the vertex \( v_i \) and the cluster \( u_p \). Thus, \( B \) represents the connections between clusters at an upper and lower level of clustering. In order to derive the clustering structure, we first need to compute \( B \) from the original similarity matrix. The similarities \( w_{ij} \) in \( W \) can be interpreted as the probabilities of direct transition between \( v_i \) and \( v_j \): \( w_{ij} = p(v_i, v_j) \). The bipartite graph \( K \) also induces a similarity (\( W' \)) between \( v_i \) and \( v_j \), with all the paths from \( v_i \) to \( v_j \) going through vertices in \( U \). This means that the similarities \( w'_{ij} \) are to be computed via the weights \( b_{ip} = p(v_i, u_p) \).
We remove the coupling between $B$ and $\Lambda$ by setting $H = B\Lambda^{-1}$. Following Yu et al. (2006), we define $\zeta(X,Y) = \sum_{i,j} x_{ij} \log \frac{x_{ij}}{y_{ij}} - x_{ij} + y_{ij})$. Yu et al. (2006) showed that this cost function is non-increasing under the following update rule:

$$\tilde{h}_{ip} \propto h_{ip} \sum_j \frac{w_{ij}}{(HAH^T)_{ij}} \lambda_p h_{jp} \text{ s.t. } \sum_i \tilde{h}_{ip} = 1 \quad (4)$$

$$\tilde{\lambda}_p \propto \lambda_p \sum_j \frac{w_{ij}}{(HAH^T)_{ij}} \tilde{h}_{ip} h_{jp} \text{ s.t. } \sum_j \tilde{\lambda}_p = \sum_j w_{ij} \quad (5)$$

We optimized $\zeta$ by alternately updating $h$ and $\lambda$.

A flat clustering algorithm can be induced by computing $B$ and assigning a lower level node to the parent node that has the largest connection weight. The number of clusters at any level can be determined by counting the number of non-empty nodes.

To create a hierarchical graph we need to repeat the above process to successively add levels of clusters to the graph. To create a bipartite graph for the next level, we first need to compute a new similarity matrix for the clusters $U$. Similarity between clusters $p(u_p, u_q)$ can be induced from $B$:

$$p(u_p, u_q) = p(u_p)p(u_q|u_p) = (B^TD^{-1}B)_{pq} \quad (6)$$

where $D = \text{diag}(d_1, ..., d_n)$; $d_i = \sum_{p=1}^m b_{ip}$. We can then construct a new graph $G_1$ (Fig. 1(d)) with the clusters $U$ as vertices, and the cluster similarities $p(u_p, u_q)$ as the connection weights. The clustering algorithm can now be applied again (Fig. I(e)). This process can go on iteratively, leading to a hierarchical graph.

The number of levels ($L$) and the number of clusters ($m_\ell$) are detected automatically, using the method of Sun and Korhonen (2011). Clustering starts with an initial setting of the number of clusters $m_1$ for the first level. In our experiments, we set the value of $m_1$ to 800. For the subsequent levels, $m_\ell$ is set to the number of non-empty clusters on the parent level – 1. The matrix $B$ is initialized randomly and its rows are then normalized.

For a word $v_i$, the probability of assigning it to cluster $x_p^{(\ell)} \in X_\ell$ at level $\ell$ is given by:

$$p(x_p^{(\ell)}|v_i) = \sum_{x_i^{(\ell-1)} \in X_1} ... \sum_{x_i^{(1)} \in X_1} p(x_p^{(\ell)}|x_i^{(\ell-1)})...p(x_i^{(1)}|v_i) = (D_1^{-1}B_1D_2^{-1}B_2...D_\ell^{-1}B_\ell)_{ip} \quad (7)$$

Sun and Korhonen (2011) have shown that $m_\ell$ is non-increasing for higher levels. The algorithm can thus terminate when all nouns are assigned to one cluster. We run 1000 iterations of updates of $h$ and

Figure 1: (a) An undirected graph $G$ representing the similarity matrix; (b) The bipartite graph showing three clusters on $G$; (c) The induced clusters $U$; (d) The new graph $G_1$ over clusters $U$; (e) The new bipartite graph over $G_1$.
\( \lambda \) (eq. 4 and 5) for each two adjacent levels. The algorithm can be summarized as follows:

\textbf{Require:} \( N \) nouns \( V \), initial number of clusters \( m_1 \).
Compute the similarity matrix \( W_0 \) from \( V \).
Build the graph \( G_0 \) from \( W_0 \), \( \ell \leftarrow 1 \).
\textbf{while} \( m_\ell > 1 \) \textbf{do}
  \quad Factorize \( G_{\ell-1} \) to obtain bipartite graph \( K_\ell \) with adjacency matrix \( B_\ell \) (eqs. 2, 3).
  \quad Build a graph \( G_\ell \) with similarity matrix \( W_\ell = B_\ell^T D_\ell^{-1} B_\ell \) according to equation 6.
  \quad \( \ell \leftarrow \ell + 1 \); \( m_\ell \leftarrow \) No. non-empty clusters –1.
\textbf{end while}
\textbf{return} \( B_\ell, B_{\ell-1}...B_1 \)

The resulting graph is composed of a set of bipartite graphs defined by \( B_\ell, B_{\ell-1}, ..., B_1 \). For a given noun, we can rank the clusters at any level according to the soft assignment probability (eq. 7). The clusters that have no member noun were hidden from the ranking since they do not explicitly represent any concept. However, these clusters are still part of the organisation of the conceptual space and contribute to the probability for the clusters at upper levels (eq. 7). We call the view of the hierarchical graph where these empty clusters are hidden an \textit{explicit graph}.

### 4.2 Identifying metaphorical associations

Once we obtained the explicit graph of concepts, we can identify metaphorical associations based on the weights on the edges of the graph. Taking a single noun (e.g. \textit{fire}) as input, the system computes the probability of its cluster membership for each cluster at each level, using these weights (eq. 7). We expect the cluster membership probabilities to indicate the level of association of the input noun with the clusters. The system then ranks the clusters at each level based on these probabilities. We chose level 3 as the optimal level of generality based on our qualitative analysis of the graph. The system selects 6 top-ranked clusters from this level and excludes the literal cluster containing the input concept (e.g. “fire flame blaze”). The remaining clusters represent target concepts associated with the input concept.

Example output for the input concepts of \textit{fire} and \textit{disease} in English is shown in Fig. 2. One can see that each noun-to-cluster mapping represents a new conceptual metaphor, e.g. EMOTION is FIRE, VIOLENCE is FIRE, CRIME is a DISEASE. These mappings are exemplified in language by numerous metaphorical expressions (e.g. “his anger blazed”, “violence flared”). Figs. 3 and 4 show metaphorical associations identified in the Spanish and Russian data for the same source concepts. One can see that FEELINGS are associated with FIRE in all three languages. However, many of the identified metaphors differ across languages: e.g., VICTORY, SUCCESS and LOOKS are viewed as FIRE in Russian, while IMMIGRANTS and PRISONERS are associated with FIRE in English and Spanish. All of the languages exhibit CRIME IS A DISEASE metaphor, with Russian and Spanish generalising it to VIOLENCE IS A DISEASE. While we do not claim that this output is exhaustively representative of all conceptual metaphors present in a particular culture, we believe that these examples showcase some interesting differences in the use of metaphor across datasets that can be discovered by our method.

\[ \text{SOURCE: fire} \]
\begin{itemize}
  \item \text{TARGET 1:} sense hatred emotion passion enthusiasm hope feeling optimism hostility excitement anger ...
  \item \text{TARGET 2:} violence fight resistance clash rebellion battle fighting riot revolt war confrontation revolution ...
  \item \text{TARGET 3:} alien immigrant
  \item \text{TARGET 4:} prisoner hostage inmate
\end{itemize}

\[ \text{SOURCE: enfermedad (disease)} \]
\begin{itemize}
  \item \text{TARGET 1:} fraud outbreak offense crime violation abuse conspiracy corruption terrorism suicide ...
  \item \text{TARGET 2:} opponent critic rival
  \item \text{TARGET 3:} execution destruction signing
  \item \text{TARGET 4:} refusal absence fact failure lack delay
\end{itemize}

\[ \text{SOURCE: fuego (fire)} \]
\begin{itemize}
  \item \text{TARGET 1:} esfuerzo negocio tarea debate operación operativo ofensivo gira acción actividad campaña gestión ...
  \item \text{TARGET 2:} quiebra indignación ira pánico caos alarma ...
  \item \text{TARGET 3:} rehén refugiado preso prisionero inmigrante ...
  \item \text{TARGET 4:} soberanía derecho independencia libertad ...
\end{itemize}

\[ \text{SOURCE: enfermedad (disease)} \]
\begin{itemize}
  \item \text{TARGET 1:} calentamiento migración impunidad
  \item \text{TARGET 2:} desaceleración brote fenómeno epidemia secuencia violencia mal recesión escasez contaminación
  \item \text{TARGET 3:} petrolero fabricante gigante firma aerolínea
  \item \text{TARGET 4:} mafia
\end{itemize}
SOURCE: огонь (fire)
TRGT 1: облик (looks)
TRGT 2: победа успех (victory, success)
TRGT 3: душа страдание сердце дух (soul, suffering, heart)
TRGT 4: страна мир жизнь россия (world, life, russia)

SOURCE: болезнь (disease)
TRGT 1: готовность зло добро ... (evil, kindness, readiness)
TRGT 2: преступление убийство насилие атака поступок подвиг ошибка грез нападение (murder, crime, assault etc.)
TRGT 3: депрессия усталость напряжение стресс приступ огнём нагрузка (depression, tiredness, stress etc.)
TRGT 4: сражение война битва гонка (battle, war, race)

Figure 4: Metaphors identified in the Russian data

5 Evaluation within languages

We first evaluated the quality of metaphor identification in individual languages. As there is no comprehensive gold standard of metaphorical mappings available, we evaluated the identified mappings against human judgements.

Baseline We compared the system performance to that of an agglomerative clustering baseline (AGG). We constructed AGG using SciPy implementation (Oliphant, 2007) of Ward’s linkage method (Ward, 1963). The output tree was cut according to the number of levels and clusters in the explicit HGFC graph. We converted this tree into a graph by adding connections from each cluster to all the clusters one level above. We computed the connection weights as cluster distances measured using Jensen-Shannon Divergence between the cluster centroids. This graph was then used in place of the HGFC graph.

Evaluation setup and results To create our dataset, we extracted 10 common source concepts that map to multiple targets from the Master Metaphor List (Lakoff et al., 1991) and linguistic analyses of metaphor (Shutova and Teufel, 2010). These included FIRE, CHILD, SPEED, WAR, DISEASE, BREAKDOWN, CONSTRUCTION, VEHICLE, SYSTEM, BUSINESS. We then translated them into Spanish and Russian. Each of the systems identified 50 mappings for the given source domains. This resulted in a set of 100 conceptual metaphors for each language. Each of them represents a number of submappings since the target concepts are clusters of nouns. These were then evaluated against human judgements in two different experimental settings.

Setting 1 (precision-oriented):

| AGG P | AGG R | HGFC P | HGFC R |
|-------|-------|--------|--------|
| EN 0.36 | 0.11 | 0.69 | 0.61 |
| ES 0.23 | 0.12 | 0.59 | 0.54 |
| RU 0.28 | 0.09 | 0.62 | 0.42 |

Table 1: HGFC and baseline performance

The judges were presented with a set of mappings identified by the system and the baseline, randomized. They were asked to annotate the mappings they considered valid as correct. A mapping was to be considered valid if it could be exemplified by a metaphorical expression.

Two judges per language, who were native speakers of English, Russian and Spanish participated in this experiment. All of them held at least a Bachelor degree. Their agreement was measured at $\kappa = 0.60$ for English, $\kappa = 0.59$ for Spanish, and $\kappa = 0.55$ for Russian. The main differences in the annotators’ judgements stem from the fact that some metaphorical associations are less obvious and common than others, and thus need more context (or imaginative effort) to establish. Such examples of disagreement included the metaphorical mappings INTENSITY is SPEED, GOAL is a CHILD, COLLECTION is a SYSTEM, ILLNESS is a BREAKDOWN.

The system performance was then evaluated against these judgements in terms of precision ($P$), i.e. the proportion of the valid metaphorical mappings among those identified. We calculated system precision as an average over both annotations in a given language. The results are presented in Table[1]

Setting 2 (recall-oriented): To measure recall, $R$, of the systems we asked two annotators per language (native speakers with a background in metaphor, different from Set. 1) to write down up to 5 target concepts they strongly associated with each of the 10 source concepts. Their annotations were then aggregated into a single metaphor association gold standard. The gold standard consisted of 63 mappings for English, 70 mappings for Spanish and 68 mappings for Russian. The recall of the systems, as measured against this gold standard, is shown in Table[1]

Discussion and error analysis HGFC outperforms the AGG baseline in all evaluation settings and identifies valid metaphorical associations for a range of source concepts. AGG, although less suitable for the task, still identified a number of interesting map-
pings missed by HGFC (e.g. CAREER is a CHILD, LANGUAGE is a SYSTEM, CORRUPTION is a VEHICLE) and a number of mappings in common with HGFC (e.g. DEBATE is a WAR, DESTRUCTION is a DISEASE). The fact that both HGFC and AGG identified valid metaphorical mappings across languages confirms our hypothesis that clustering techniques are well suited to detect metaphorical patterns in a distributional word space in principle.

The most frequent type of error of HGFC across the three languages is the presence of target clusters similar or closely related to the source noun. For instance, the source noun CHILD tends to be linked to other ”human” clusters across languages, e.g. the parent cluster in English, the student, resident and worker clusters in Spanish and the crowd, journalist and emperor clusters in Russian.

The performance of the Russian and the Spanish systems is slightly lower than that of the English system. This may be due to errors from the data preprocessing step, i.e. parsing. Parsing quality in English is likely to be higher than in Russian or Spanish, for which fewer parsers exist. Another important difference lies in the corpora used. While the English and Spanish systems were applied to the Gigaword corpora (containing data from news sources), the Russian system was applied to the Web data containing noisier text (including misspellings, slang etc.)

6 Cross-linguistic analysis

We then investigated the differences in metaphorical framing, as identified by our systems across languages. We ran the systems with a larger set of source domains taken from the literature on metaphor and conducted a qualitative analysis of the resulting metaphorical mappings. As one might expect, the majority of the identified mappings are present across languages. For instance, DEBATE or ARGUMENT are associated with WAR in all three languages; CRIME is universally associated with DISEASE and MONEY with LIQUID etc.

Importantly, our methods were also able to capture differences in metaphorical framing in the three languages. For instance, they exposed some interesting differences in the domains of business and finance. The Spanish data manifested rather negative metaphors about business, market and commerce: BUSINESS was typically associated with BOMB, FIRE, WAR, DISEASE and ENEMY. While it is the case that BUSINESS is typically discussed in terms of a WAR or a RACE in English and Russian, the other four Spanish metaphors are uncommon. Russian, in fact, has rather positive metaphors for the related concepts of MONEY and WEALTH, which are strongly associated with SUN, LIGHT, STAR and FOOD, possibly indicating that money is viewed primarily as a way to improve one’s life. In contrast, in English, MONEY is frequently discussed as a WEAPON – a means to achieve a goal or win a struggle (related to BUSINESS IS A WAR metaphor). At the same time, the English data exhibits positive metaphors for POWER and INFLUENCE, which are viewed as LIGHT, SUN or WING. In Russian, on the contrary, POWER is associated with BOMB and BULLET, perhaps linking it to the concepts of physical strength and domination. Yet, the concepts of FREEDOM and INDEPENDENCE were also associated with a WING, WEAPON and STRENGTH in the Russian data. English data exhibited more negative metaphors for immigration than Russian or Spanish, with IMMIGRANTS viewed as FIRE or ENEMIES, possibly indicating danger.

While the above differences may be a direct result of the contemporary socio-economic context and political rhetoric, and are likely to change over time, other conceptual differences have a deeper grounding in our culture and the way of life. For instance, the concept of BIRTH tends to be strongly associated with LIGHT in Spanish and BATTLE in Russian, each metaphor highlighting a different aspect of birth. Another interesting difference concerned the framing of the concept of economy in English and Spanish. In English data, ECONOMY is viewed predominantly as a VEHICLE that can be driven forward or slowed down. In Spanish, on the contrary, the economy is thought of in terms of its SIZE and GROWTH, but not motion. Research in cognitive psychology (Casasanto and Boroditsky, 2008; Fuhrman et al., 2011) suggests that such cross-linguistic differences in conventionalised metaphors have significance beyond language and can be associated with contrastive behavioural patterns across the differ-

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1 Although other metaphors for the economy exist in English, the system identifies the statistically dominant ones.
ent linguistic communities. In the next section, we present a behavioural study aimed at assessing the psychological validity of a subset of cross-linguistic differences identified by our model.

7 Behavioural evaluation

We focused on the difference in the metaphors used by English vs. Spanish speakers when discussing changes in the economy. The observed difference may be a property of language or it could also reflect entrenched conceptual differences. In order to investigate this, we test whether patterns of behavior consistent with this difference in metaphorical framing arise cross-linguistically in response to non-linguistic stimuli.

7.1 Experimental setup

We recruited 60 participants from one English-speaking country (USA) and 60 participants from three Spanish-speaking countries (Chile, Mexico, Spain) using the CrowdFlower platform. Participants first read a brief description of the task, which introduced them to a fictional country in which economists are devising a graphic for representing changes in the economy. They then completed a demographic questionnaire including information about their native language. Results from 9 US and 3 non-US participants were discarded for failure to meet the language requirement.

Participants navigated to a new page to complete the experimental task. Stimuli were presented in a 1200 x 700-pixel frame. The center of the frame contained a sphere with a 64-pixel diameter. For each trial, participants clicked on a button to activate an animation of the sphere which involved (1) a positive displacement (in rightward pixels) of 10% or 20%, or a negative displacement (in leftward pixels) of 10% or 20%; and, (2) an expansion (in increased pixel diameter) of 10% or 20%, or a contraction (in decreased pixel diameter) of 10% or 20%. They were then asked to judge whether the economy has “improved” or “worsened” based on the graphic.

Participants saw each of the resulting conditions 3 times. The displacement and size conditions were drawn from a random permutation of 16 conditions using a Fisher-Yates shuffle (Fisher and Yates, [1963]). Crucially, half of the stimuli contained conflicts of information with respect to the size and displacement metaphors for economic change (e.g. the sphere could both grow and move to the left). Overall we expected the Spanish speakers’ responses to be more closely associated with changes in diameter (due to the salience of the size metaphor) and the English speakers’ responses with displacement (due to the salience of the vehicle metaphor). We expected these differences to be most prominent in the conflicting trials, which force the participants to choose between the two metaphors. We focus on these conflicting trials in our analysis.

7.2 Results

In trials where stimuli moving rightward were simultaneously contracting, English and Spanish speakers responded that the economy improved 66% and 43% of the time respectively. In trials where stimuli moving leftward were simultaneously expanding, English and Spanish speakers judged the economy to have improved 34% and 55% of the time respectively. These results indicate that English speakers judgments were more biased towards changes in the sphere’s displacement, while Spanish speakers judgments towards changes in diameter. These results support our expectation on the relevance of different metaphors when reasoning about the economy by the English and Spanish speakers.

To examine the significance of these effects, we fit a binary logit mixed effects model (Fox and Weisberg, 2011) to the data. The full analysis modeled judgment with native language, displacement, and size as fully crossed fixed effects and participant as a random effect. This analysis confirmed that native language was associated with participants’ judgments about economic change. It indicated that changes in size affected English and Spanish speakers’ judgments differently ($p < 0.001$), with an increase in size increasing the odds ($e^{\beta} = 2.5$) of a judgment of Improved by Spanish speakers and decreasing the odds ($e^{\beta} = 0.44$) of a judgment of Improved by English speakers. A Type II Wald test revealed the interaction between language and size to be highly statistically significant ($\chi^2(1) < 0.001$).
8 Conclusion

We presented a method that identifies patterns of metaphorical framing in a large text corpus. Despite being fully unsupervised, it operates with an encouraging precision. It is portable across datasets and languages, and discovers interesting cross-linguistic differences in metaphorical framing. We have shown that the method predicts patterns consistent with behavioural data. While much territory remains to be investigated with respect to delimiting the nature of this relationship, these results represent a first step toward establishing an association between information mined from large textual data collections and information observed through behavioural responses on a human scale.

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