Uncovering Relations for Marketing Knowledge Representations

Somak Aditya, Atanu R Sinha
Adobe Research
{saditya,atr}@adobe.com

Abstract

Online behaviors of consumers and marketers generate massive marketing data, which ever more sophisticated models attempt to turn into insights and aid decisions by marketers. Yet, in making decisions human managers bring to bear marketing knowledge which reside outside of data and models. Thus, it behooves creation of an automated marketing knowledge base that can interact with data and models. Currently, marketing knowledge is dispersed in large corpora, but no definitive knowledge base for marketing exists. Out of the two broad aspects of marketing knowledge - representation and reasoning - this treatise focuses on the former. Specifically, we focus on creation of marketing knowledge graph from corpora, which requires identification of entities and relations. The relation identification task is particularly challenging in marketing, because of the non-factoid nature of much marketing knowledge, and the difficulty of forming rules that govern relations. Specifically, we define a set of relations to capture marketing knowledge, propose a pipeline for creating the knowledge graph from text and propose a rule-guided semi-supervised relation prediction algorithm to extract relations between marketing entities from sentences.

1 Introduction

Effective decision making to choose marketing actions is much more than utilization of data, reporting tools and models offered by today’s advanced Analytics capabilities. Decision making is part art, part science\(^1\). While the “science” of marketing decision making captures research imagination and offers great advances, the “art” of marketing decision making lags behind. The art includes knowledge humans use to overlay on structured information from data, tools, and models, to make decisions and choices. Part of the knowledge resides inside humans, and others lie in corpora of text books, business articles, experts’ writings, research papers, and case studies. With focus on the latter, our objective is to give this knowledge shape in the manner of a Marketing Knowledge Representation (MKR) for it to interact with structured information from data, tools, and models, to eventually advance decision making. The paper exposes the specific challenges of creating MKR, relative to other forms of KR, and then addresses some of them.

For concreteness, consider segmentation, a regularly occurring, fundamental task in marketing decision making. Data from transaction and clickstream capture consumer behavior and are added to data on marketing actions and consumer demographics. Models attempt to estimate the differential effects of marketing actions across consumers on business-desired outcomes and map demographics to those effects to divide the consumers into different segments. When presented with these results, a seasoned human marketer’s knowledge suggests that for effective segmentation she needs to look beyond demographics, into other characteristics, say, psychographics. In this paper, we demonstrate an approach to encoding such knowledge into an MKR. Once an MKR is built, the next step involves building a reasoning engine on the MKR to move toward automated decisions. Staying within segmentation, a reasoning engine can explain whether psychographics segmentation is the way to go, given findings from data and models. In this paper we focus on knowledge representation, but not on reasoning.

Our representation takes the form of a knowledge graph (KG), where the graph “mainly describes real world entities and their interrelations” \cite{Paulheim2017}. The objectives we pursue are organization of marketing information, non-factoid concepts and results from marketing academic literature in a Marketing domain specific KG (MKG). A KG embodies nodes and edges, where nodes are subject, object and edges are relations. The problem of extracting triples, defined as (subject, relation, object), from Marketing corpora is challenging for multiple reasons: (1) much of marketing knowledge is non-factoid; (2) entities do not have a taxonomy; (3) the typical corpora is not tightly worded leading to non-informative content; (4) entities are longer sequence of words; (5) relations are marketing domain specific and cannot be necessarily drawn from existing sources of relations such as ConceptNet; (6) supervised approaches for relation prediction cannot be used due to severe labeling limitations. Specifically, the current effort addresses the challenge of predicting relations using a semi-supervised ap-
proach and based on a relatively small set of labeled relations. The experiments in this work are based on our efforts of creating an MKG from the chapter on Segmentation in a marketing textbook.

Our main contributions in relation prediction are: (1) demonstrating an approach in creating a Marketing Knowledge Graph, with (2) semi-supervised Relation prediction, using (3) Rule-regularization, given relatively few labeled relations.

2 Related Literature
Our work is closely related to efforts in commonsense knowledge representation, automatic knowledge base construction, relation extraction from text and knowledge integration in deep neural networks.

Commonsense Knowledge Representation: Proposing task-independent knowledge representation for any domain has been a central challenge for the KR&R community. Many commonsense KGs that capture ontological, causal, and other types of common-sense relations between general-domain concepts have been fairly popular such as ConceptNet (Speer, Chin, and Havasi 2017), Cyc (Lenat et al. 1990) and WordNet (Miller 1995). Domain-specific knowledge bases such as AURA-KB (Barker et al. 2007) built on top of the Knowledge-machine ontology for encoding knowledge in biology books have seen some adoption. For marketing domain, the semantics of general-world relations and concepts become ambiguous. Also, our search did not produce any KG specifically for marketing. Our experiments show that existing KGs do a poor job of representing knowledge in Marketing domain, due to the nuanced and non-factoid nature of knowledge in this domain, and the emphasis of these KGs on representing general world knowledge. This makes our effort necessary.

Automatic Knowledge Base Construction: KGs have been traditionally constructed using curated (WordNet), semi-curated (ConceptNet (Speer, Chin, and Havasi 2017)), fully automated (YAGO, NELL) approaches. Curated approaches pose very costly for marketing domain. Hence, automated knowledge base construction or completion cannot be avoided. KB construction has made strides with the use of knowledge graph embedding (Wang et al. 2017). The continuous vector representation in low dimensions allows capturing latent semantic relations and applying vector algebra for inferencing about relations. In turn, this affords flexibility for tasks ranging from relation prediction, to entity resolution, to knowledge graph completion. One class of methods perform the embedding task by matching embedding to facts available on the knowledge graph. Other class of approaches uses additional information that are available (Wang et al. 2017). This information includes types of entity, description and logical rules. The embeddings consider either instances of real-world entities in the knowledge graph, or, ontological concepts of the knowledge graph, but not both. More recent work (Hao et al. 2019) advances representational learning by capturing knowledge jointly in both real-world entities and in ontological concepts, as well as, in links that connects them. With focus on relation prediction, our work follows in this tradition of using knowledge graph embeddings.

Relation Extraction: For the task of relation extraction from text, the relation between two concepts or entity mentions in a sentence is mapped to one of the classes in a predetermined closed set of relations. The relevant literature on methods can be grouped as: i) rule-based, ii) supervised and semi-supervised, iii) link prediction. Research in relation extraction has moved from applying hand-coded rules to extract relations (Rosemblat et al. 2013), to using hand-engineered features and strong classifiers (Kambhatha 2004, Minard et al. 2011) to classify relations between entities. However, given the brittleness of manually designed rules or features, and availability of large amount of data, the focus has shifted to different end-to-end neural models such as convolutional neural networks (Zeng et al. 2014), recursive neural network (Ebrahimi and Don 2015), and long short-term memory network (Miwa and Bansal 2016). Work in link prediction (Ostapuk, Yang, and Cudré-Mauroux 2019) has also inspired use of information from available knowledge graph for relation prediction tasks (Xu and Barbosa 2019). One obstacle in employing successful supervised classifiers is the dearth of large human-annotated data set of labels. Hence, semi-supervised approaches are receiving attention. Some work model this problem as a multi-instance learning problem (Riedel, Yao, and McCallum 2010), and improve the overall accuracy through distant supervision and active learning (Sterckx et al. 2014). Under distant supervision, the problem of predicting relations from noisy annotations is tackled by (Feng et al. 2018) using reinforcement learning. A recent paper (Lin et al. 2019) takes an important step forward by jointly optimizing the dual tasks of retrieving sentences given a relation and predicting a relation in a given sentence (hereafter, DualRE). Rather than self-selection, both prediction and retrieval module annotate unlabeled sentences and provide data to each other, thus potentially curbing the limited supervision issue.

Annotations of relations for sentences in Marketing corpora are generally not available. There is need for marketing expertise to annotate relations in order to obtain high quality labels. Relatively few labels can be annotated and that too at significant cost in time and money. Given the unusually low labels, we look towards encoding knowledge using rules that govern the relations and take inspiration from the knowledge integration work in deep neural networks (Hu et al. 2016, Guo et al. 2018, Wang et al. 2019). However, to the best of our knowledge, these work do not integrate weighted First Order Logic rules in a semi-supervised scenario. Given our goal of relation prediction in marketing corpus and faced with a small set of labeled relations and a large set of unlabeled corpus, we improve upon the DualRE approach by integrating knowledge from weighted logical rules.

3 Background: Markov Logic Network
Markov Logic Network (MLN) (Richardson and Domingos 2006) is a popular probabilistic logical framework that uses weighted First Order Logical (FOL) formulas to encode an undirected, grounded probabilistic graphical model (i.e. Markov Network). The rules in MLN are weighted so that the strict constraints of hard rules (rules that are satisfied always) are eliminated to model the real world more ef-
It retains the flexibility of modeling hard FOL rules by adding hard constraints as well. Formally, an MLN \( L \) is a set of pairs \((F, w)\), where \( F \) is a first order formula and \( w \) is either a real number or a symbol \( \alpha \) denoting hard weight. Together with a finite set of constants \( \alpha \), a Markov Network \( M_{L,C} \) is defined as containing: i) one binary node for each grounding of each predicate appearing in \( L \); and ii) one feature for each grounding of each formula \( F \) in \( L \). The value of feature is 1, if grounded formula is true; 0, otherwise. The probability distribution over possible worlds \( x \) specified by the ground Markov Network \( M_{L,C} \) is given by:

\[
P(X = x) = \frac{1}{Z} \exp\left(\sum_{i=1}^{F} w_i n_i(x)\right)
\]

where \( F \) is the number of grounded formulas, \( n_i(x) \) is the number of true groundings of the formula \( F_i \) in the world \( x \). The MLN inference is equivalent to finding the maximum probable world according to the above probability formulation. Weight learning is done by maximizing the pseudo-likelihood.

### 4 Marketing Knowledge Representation

| Sentence | Triplets |
|----------|----------|
| If preferences are relatively homogenous within a segment, the positions of competing brands will be relatively similar, and the quantity of advertising and promotion will be critical competitive weapons. | HasProperty(segment, homogeneous preferences) |
| Segments often overlap, making it difficult to position products in different segments independently. | LeadsTo(competitor brands, positions) |
| We must balance the costs of positioning with price and share changes to identify the strategy that will achieve maximum long-run profitability. | DependsOn(costs of positioning, price) |

Table 1: Triplets from illustrative sentences

We first note the idiosyncrasies of marketing corpora to argue that (i) semantics of marketing-concepts do not map to common notion of entities, and (ii) relations in marketing are not adequately captured in sources such as ConceptNet5. Marketing-concepts are compound and much information is not commonsense knowledge. Consider the sentence on the vital topic of positioning. “If we are to make good positioning decisions, we need to know what dimensions do consumers use to evaluate competitive marketing programs.” The essence of association among different concepts. The complete set of relations, their semantics and examples used for our experiments are shown in Table 1.

### 5 Marketing Knowledge Acquisition Pipeline

We adopt a pipeline-based approach, which has four stages: i) definition sentence extraction, ii) candidate triplets prediction, iii) relation extraction, and iv) merging. A book chapter can be divided into definitions of important marketing terms and the rest of the content. The pipeline is described with respect to our example of the topic of Segmentation.
1. Definition Sentences: For each definition of a marketing term such as “segmentation”, we process them sentence by sentence.

2. Candidate Triplets: For each sentence, we parse using the Stanford syntactic dependency parser (Chen and Manning 2014) to get the syntactic parse tree and part-of-speech tags. We then use the parse tree (induced by syntactic dependency relations) and the part-of-speech tags to collect the set of all noun-phrases (NP), which do not include verb phrases or prepositional phrases. We treat each pair of NPs as a candidate for the next step. For example, “Product positioning takes place within a target market segment and tells us how we can compete most effectively in that market segment”, produces NPs “product positioning”, “target market segment” and “market segment”.

3. Relation Extraction: For relation extraction, we pre-train a relation classifier which takes two noun-phrases, the sentence and positional part-of-speech and named entity tags. To train this classifier, we first consult a marketing expert to annotate correct relations for a small set of NP-pairs for the sentences from the textbook. Table 1 shows a few examples. We use this small labeled data and a large set of unlabeled data to train a semi-supervised relation classifier. This is a significant benefit of our approach.

4. Merging: Using this classifier, we identify relations between all pairs of NPs from the previous step. This same classifier also informs which NP-pairs are not related by any relation. This step has two substeps: 4(a) To concentrate on the important entity1-relation-entity2 triplets; in the first sentence, we extract the list of NPs that are connected (via a path in the dependency graph) to the defined term, such as “segmentation”. This list becomes the next set of important entities for the next sentence. We only concentrate on entities which are connected to the list of important entities. 4(b) For the rest of the corpora, the hierarchical assumption over sentences is withdrawn. We extract entity1-relation-entity2 using similar method as in Steps 2 and 3. Given the graphs from 4(a) and 4(b), we merge using overlapping entities to arrive at the MKG.

The complexity of recovering the interrelations between entities and mapping to a chosen set of well-defined relations are pushed to the relation extraction phase (Stage 3), which we describe next.

6 Marketing Relation Prediction

Relation prediction is the task of predicting a set of structured triplets (subject, relation, object) from a sentence encoding marketing knowledge. Figure 1 shows the framework. This process is performed in two steps: i) candidate relation mention extraction i.e. extracting \( x = (x, n_x, n_o) \) from corpus where \( x \) is a sentence, and \( n_x \) and \( n_o \) are marketing terms, ii) relation extraction, i.e. predicting a relation \( r \in \mathcal{R} \) given a relation-mention \( x \).

Relation-mention Extraction

We get candidate NPs for each sentence \( x \) from the second stage of our pipeline. We heuristically eliminate NP-pairs that are connected via a path with length more than \( P \) in the tree. This provides a set of unlabeled relation-mentions \( U' = \{x_i\}_{i=1}^{N_{L+U}} \). We sample from this set and consult a marketing expert to provide correct labels for a small set of relation-mentions, which finally creates the set of labeled relation-mentions \( L = \{x_i, y_i\}_{i=1}^{N_L} \) and set of unlabeled relation mentions \( U = \{x_i\}_{i=1}^{N_U} \).

DualRE: Semi-Supervised Relation Extraction

Given a set of labeled \( (L) \) relation-mentions and a set of unlabeled relation-mentions \( (U) \), our goal is to learn a relation prediction model \( f \) that represents the training data \( L \) and captures the information from the unlabeled data \( U \). We follow the framework proposed in (Lin et al. 2019). It consists of a prediction module \( P_{\theta} \) and a retrieval module \( Q_{\phi} \), where \( \theta \) and \( \phi \) are the model parameters. The prediction module’s task is to represent the function \( f \), i.e. predicting the relation \( y \) given the relation-mention \( x \). It models the conditional probability \( p_{\theta}(y|x) \) for a mention-label pair \((x, y)\). The retrieval module complements above by retrieving relevant relation-mentions given a specific relation. Hence, it models \( q_{\phi}(x|y) \) for a mention-label pair. As \( q_{\phi}(x|y) \propto q_{\phi}(x, y) \) for a given relation \( y \), the retrieval module estimates the joint probability and induces a ranking over different mentions \( x \) for a label \( y \). The overall objective function is given by

\[
O = O_P + O_R + O_U,
\]

\[
O_P = E_{x, y \in L}[^{\log p_{\theta}(y|x)}]
\]

\[
O_R = E_{x, y \in L}[^{\log q_{\phi}(x, y)}]
\]

\[
O_U = E_{x \in U}[^{\log p(x)}]
\]

\(O_P\) can be calculated using a cross-entropy loss between the ground truth and predicted labels, as shown in Equation 1. The objective \(O_R\) is approximated using a ranking loss:

\[
E_{x, y \in L}[^{\log \sigma(z^T y)}] + E_{x, y \notin L}[^{\log(1 - \sigma(z^T y'))}],
\]

where \((x, y)\) is a labeled pair in \(L\), \((x, y')\) is an incorrect relation pair with a relation mention \(x\), \(z\) is mention encoding for \(x\), \(y\) and \(y'\) are the embeddings of the relations \(y\) and \(y'\). Lastly, \(O_U\) is approximated by the lower bound:

\[
O_U \geq E_{x \in U, y \sim p_{\theta}(y|x)}[^{\log q_{\phi}(x, y)}].
\]

DualRE Learning Algorithm: As proposed in (Lin et al. 2019), an Expectation Maximization approach is used to
jointly learn the modules. In the E-step, the prediction module \( P_0 \) is learned by fixing \( Q_0 \). Calculating the gradient of \( \theta \) with respect to \( O \) amounts to:
\[
\nabla_\theta (O) = E_{x,y \in L} [\nabla_\theta \log p_{\theta} (y|x)] \\
+ E_{x \in U,y \sim q_{\phi}(y|x)} [\nabla_\theta \log p_{\theta} (y|x)],
\]
where the first and second terms correspond to \( \nabla_\theta (O_P) \), and \( \nabla_\theta (O_U) \) respectively. Similarly, in the M-step, the retrieval module \( Q_0 \) is updated fixing \( P_0 \). The gradient with respect to \( \phi \) is calculated as:
\[
\nabla_\phi (O) = E_{x,y \in L} [\nabla_\phi \log q_{\phi} (x,y)] \\
+ E_{x \in U,y \sim p_{\theta} (y|x)} [\nabla_\phi \log q_{\phi} (x,y)],
\]
where the first and second terms correspond to \( \nabla_\phi (O_R) \), and \( \nabla_\phi (O_U) \) respectively. Both the steps require sampling from unannotated data. It is assumed that sampling from the averaged distributions, i.e. \( p_{\theta} (y|x) + q_{\phi} (y|x) \), is less noisy. Hence, samples are annotated using the intersection of these two modules before every iteration. For each iteration, the labeled dataset \( L \) is added with the two modules’ annotations (best predictions) to form \( L_U \). Then \( P_0 \) and \( Q_0 \) are updated according to the E-step and M-step equations.

Rule-Regularized Semi-supervised Relation Prediction

Given the dearth of annotations in the marketing domain, we observe that prior rules over the relations can act as (global) constraints. A major drawback of the independence assumptions and sparse annotations force the MLN structure-learning algorithms (Kok and Domingos 2005) to be learned from the set of expert-provided ground truth relations using MLN’s standard structure learning algorithms (Richardson and Domingos 2006) becomes a natural choice. The rules can be learned from the set of expert-provided ground truth relations using MLN’s standard structure learning algorithms (Kok and Domingos 2005). In our case, the closed-world assumptions and sparse annotations force the MLN structure-learner to learn only unary clauses. Instead, we write the rules ourselves and then use MLN weight learning algorithm to learn the weights. We treat the ground-truth annotated relations as predicates of truth-value 1 (examples in Table 3), and use a few rules that can act as constraints. The rules and examples of ground truth are shown in Table 2. Let the set of rules be denoted by \( r_N(x,y) \), where \( N = 1, 2, \ldots, n \). Using MLN’s weight learning algorithm, we then learn the weights \( \lambda_n \) for each rule in \( r_N \).

Knowledge Integration: For integrating the knowledge in these soft rules, we follow the idea of projecting the learnt predictor function into a rule-regularized subspace (Hu et al. 2016). The authors propose a generic way to learn a teacher distribution from a student distribution and a set of rules. Essentially, the teacher \(( t(y|x) \) is learned by optimizing the loss function \( KL(t(y|x)||p_{\theta} (y|x)) + C \sum_{n,g} \psi_{n,g} \)
\[
\min_{t, \psi \geq 0} KL(t(y|x)||p_{\theta} (y|x)) + C \sum_{n,g} \psi_{n,g} \\
\text{s.t.} \quad \lambda_n (1 - E_{r_{n,g}} (y_n, x)) \\
= g_n \in 1, 2, \ldots, G; n = 1, \ldots, N.
\]

As hard rules evaluate to 1.0, these constraints try to ensure that \( E_{r_{n,g}} (x, y) \) should be close to 1. Solving the above equation amounts to computing a closed-form solution as given in Equation 4 in (Hu et al. 2016), which we reproduce here for convenience:
\[
t(y|x) \propto p(y|x) \exp \left\{ - \sum_{n,g} C \lambda_n (1 - r_{n,g} (x, y)) \right\}. \tag{4}
\]

To calculate the second term, we use concepts from MLN inference and T-Norm equations. Primarily, for a predicate \( y \) and the input \( n_x, n_y \) (i.e., ignoring the sentence information), we assume truth-value of \( y(n_x, n_y) \) to be 1 and calculate the value \( \lambda_n (1 - r_{n,g} (x, y)) \) for each grounding of each rule. Essentially, this provides an estimate of number of grounded rules satisfied by the query \( y(n_x, n_y) \). Here, the truth value of a grounded rule is computed using Lukasiewicz’s T-norm equations. This is a sharp departure from the way this equation is computed in practice by (Hu et al. 2016). Overall, we change slightly the DualRE learning algorithm to Algorithm 1. Equation 4 is computed using the current labeled data \( L \) and the set of weighted rules.

7 Experiments and Results

To evaluate the pipeline for relation prediction we use an annotated data set. In creating this ground truth from a well-regarded marketing text corpus, out of a total 1748 candidate
triplies in 231 sentences, 415 triplies are annotated by hand. The annotation is done by a marketing expert with more than two decades of consulting and managerial-teaching experience in marketing in the US. In doing this annotation, the expert is provided with relations from ConceptNet. The relation semantics are altered to fit the needs of the domain. A total of 19 relations are used (18 in Table 4 and one for no relations). Given this annotated dataset, at first we extract the set of features such as tokenized words, parts-of-speech tags, subject and object position indicators for each labeled and unlabeled relation-mentions. In a difference with speech tags, subject and object position indicators for each triple are used to create the train set. We use the annotated data as train (L) and unannotated part as raw (U) according to script in Lin et al. 2019. For the baseline DualRE, we run their DualRE-pointwise variant. For the rule-regularized version, we run the MLN weight learning algorithm a priori and then provide weighted rules (in Table 2) as inputs to the Algorithm. We use the similar EM-based algorithm and run for 10 iterations. We report the final precision, recall and F1 scores for the validation and test set in Table 5.

Table 2: Set of rules used to act as constraint over the world of grounded predicates.

| W.l.s | Rules | Semantics |
|-------|-------|-----------|
| 3.62  | enables(a1, a2) ← causes(a1, a2) | causes implies enables. |
| 3.63  | ¬hasLastSubevent(a1, a2) ∨ ¬hasFirstSubevent(a1, a2) | a2 can not be both first and last sub-event. |
| 3.37  | causes(a1, a2) ← affects(a1, a2) | affects implies causes. |
| 0.48  | relatedTo(a1, a2) ← relatedTo(a2, a1) | relatedTo is symmetric. |
| 3.34  | hasA(a1, a2) ← partOf(a2, a1) | partOf implies hasA. |
| 1.43  | synonym(a1, a2) ← synonym(a2, a1) | synonym is symmetric. |

Table 3: Some examples of annotated ground-truth relations treated as predicates in Markov Logic Network.

Ablation Study

One of the contributions of this work is to learn the weights of rules using MLN and integrate this knowledge for improving the accuracy in our relation extraction task. So, as an ablation study, we experiment with removing each rule and observing the impact on overall scores. The scores are reported in Table 5. While we observe that the final scores after removing individual rules do not differ significantly, removing subset of rules makes the end-to-end difference in precision and recall more prominent. We observe, that as we decrease the number of rules precision increases and recall value decreases. In fact, as the set of rules shrinks, we choose to be less restricted in terms of selecting new samples in Lu. For convenience, we also show per-relation statistics in the test set in Table 7. As our test set is relatively small (because of the limited annotations), most of the other relations occur at most twice and hence we omit them from the table.

8 Discussion and Conclusion

For human managers, marketing decision making is often a complex combination of years of experience in the field, knowledge from text and case studies, and insights from current data. Current technologies provide a peek into utilizing the massive amount of analytics data often available to corporations, but interpreting the data without the lens of knowledge can often send incorrect signals. We intend to bridge the gap by creating a marketing knowledge graph by capturing the knowledge in marketing text. In doing so, the dearth of annotations invokes a well-known, although less-addressed, challenge of predicting relations in a semi-supervised setting. We investigate the effects of integrating hand-coded rules with learned weights as (global) constraints in a semi-supervised relation prediction method and observe improvements. We observe that while trying to learn the rules from a small set of annotated triplets using MLN, the closed world assumption forces the learner to learn only unary clauses. Our current choice of rule integration method leads us to believe that removing a single rule does not affect the results much (and often not at all). Even though, adding rule-based constraints seem to be the intuitive way of integrating prior knowledge in the prediction formulation, final results are not always conclusive. These results yearn for future research in these directions.

3Code: https://github.com/INK-USC/DualRE
LeadsTo
A results in occurrence of B. The occurrence can be through other states, not necessarily direct.
Homogeneous preference (among consumers) (A) leads to competition (more competition) (B)

UsedBy
Usage of A by B for achieving some end state. Applies to both companies and consumers.
Product dimension (A) is used by consumer (B) to make a choice.

ImportantTo
A is a quality or characteristic that is salient to / for B. For a marketer, it is valuable to highlight some characteristics as particularly important, more than merely identifying them as a characteristic.
New dimension of product (A) is important to consumers (B). New dimension of product (A) is important for product positioning (B) by marketer.

Affects
A can have impact on B, does not mean it will have an impact [inverse - AffectedBy].
Government regulation (A) affects product life cycle (B). Style and fashion affects product life cycle. Political influence affects government regulation.

Enables
A can facilitate the occurrence of B [inverse - EnabledBy].
Good positioning is enabled by strong advertising claims. Perception and choice consumers form are enabled by product attribute.

PartOf
A is a characteristic, which marketer associates with B.
Demographics (A) is a part of consumer (B). Price sensitivity (A) is a part of consumer preference (B).

HasFirstSubevent
A can start to happen when B starts to occur.
For diffusion of innovation (A) to occur the first subevent of adopting new product [by consumers] (B) is necessary.

HasA
A possesses certain traits B. A may not possess always.
Company (A) has strong patents (B). Consumer (A) has a higher price elasticity (B).

Synonym
A and B are often considered similar in what they convey.
Attitude segmentation (A) is synonymous with psychographics (B).

UsedFor
Purpose of A is to achieve B.
Perceptual map (A) is used by marketer to identify gaps (B) in marketplace.

RelatedTo
As in ConceptNet5, interpreted as a general relation. In marketing, many relations take this form, since pin pointing directionality is very difficult, without considering many other factors of context ad environment.
Maturity stage of product (A) in life cycle is related to product’s ease of use by consumers (B).

Causes
A can cause B; although not always. In marketing, causal-relations are soft in scope, that is, does not mean A implies B [inverse - CausedBy].
Good positioning (A) of a product causes high trial rate (B) of the product.

Table 4: Illustrative relations with explanation and examples. The top five relations are new, while others come from ConceptNet5. We also use CausesDesire, HasPrerequisite, MotivatedByGoal, HasProperty, DependsOn, CapableOf are ommitted. These will be included in appendix.

| Relations   | Explanation                                                                 | Example(s)                                                                                           |
|-------------|----------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|
| LeadsTo     | A results in occurrence of B. The occurrence can be through other states, not necessarily direct. | Homogeneous preference (among consumers) (A) leads to competition (more competition) (B)             |
| UsedBy      | Usage of A by B for achieving some end state. Applies to both companies and consumers. | Product dimension (A) is used by consumer (B) to make a choice.                                       |
| ImportantTo | A is a quality or characteristic that is salient to / for B. For a marketer, it is valuable to highlight some characteristics as particularly important, more than merely identifying them as a characteristic. | New dimension of product (A) is important to consumers (B). New dimension of product (A) is important for product positioning (B) by marketer. |
| Affects     | A can have impact on B, does not mean it will have an impact [inverse - AffectedBy]. | Government regulation (A) affects product life cycle (B). Style and fashion affects product life cycle. Political influence affects government regulation. |
| Enables     | A can facilitate the occurrence of B [inverse - EnabledBy].                    | Good positioning is enabled by strong advertising claims. Perception and choice consumers form are enabled by product attribute. |
| PartOf      | A is a characteristic, which marketer associates with B.                      | Demographics (A) is a part of consumer (B). Price sensitivity (A) is a part of consumer preference (B). |
| HasFirstSubevent | A can start to happen when B starts to occur.                              | For diffusion of innovation (A) to occur the first subevent of adopting new product [by consumers] (B) is necessary. |
| HasA        | A possesses certain traits B. A may not possess always.                     | Company (A) has strong patents (B). Consumer (A) has a higher price elasticity (B).                   |
| Synonym     | A and B are often considered similar in what they convey.                    | Attitude segmentation (A) is synonymous with psychographics (B).                                      |
| UsedFor     | Purpose of A is to achieve B.                                                | Perceptual map (A) is used by marketer to identify gaps (B) in marketplace.                          |
| RelatedTo   | As in ConceptNet5, interpreted as a general relation. In marketing, many relations take this form, since pin pointing directionality is very difficult, without considering many other factors of context ad environment. | Maturity stage of product (A) in life cycle is related to product’s ease of use by consumers (B). |
| Causes      | A can cause B; although not always. In marketing, causal-relations are soft in scope, that is, does not mean A implies B [inverse - CausedBy]. | Good positioning (A) of a product causes high trial rate (B) of the product. |

Table 5: Results on the Segmentation chapter. We report precision, recall and F1 scores for both validation and test set.

| Relations   | dev | test |
|-------------|-----|------|
|              | P  | R   | F1  |
| Affects      | 75 | 100 | 85.71 |
| DependsOn    | 54.55 | 46.15 | 50.00 |
| LeadsTo      | 33.33 | 37.5 | 35.39 |
| MotivatedByGoal | 30 | 33.3 | 40.0 |
| PartOf       | 90.0 | 60 | 72 |

Table 6: Ablation study to see the effect of removing each of the rules from the set.

| Relations       | dev | test |
|-----------------|-----|------|
|                 | P  | R   | F1  |
| DualRE          | 96.4 | 50.9 | 66.6 |
| DualRE+Rules    | 59.4 | 41.5 | 48.8 |
| DualRE+Rules[Kj] | 60.4 | 71.9 | 59.4 |
| DualRE+Rules[K2,4,6] | 71.9 | 31.4 | 50.9 |
| DualRE+Rules[K2,4,6] | 72.5 | 32.5 | 50.3 |
| DualRE+Rules[R5] | 92.0 | 59.6 | 72.5 |

Table 7: DualRE baseline (B) and rule-regularized (R) results for the relations in the test set.
A Complete Set of Relations Used
Here, in table 8 we provide the complete set of relations used. Although, it is hard problem to completeness of such relations, to the best of our knowledge the following set of binary relations sufficed to represent the knowledge in the Segmentation chapter in a well-renowned and recent Marketing textbook.
| Relations   | Explanation                                                                 | Example(s)                                                                 |
|------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------------|
| LeadsTo    | A results in occurrence of B. The occurrence can be through other states, not necessarily direct. | Homogeneous preference (among consumers) (A) leads to competition (more competition) (B) |
| UsedBy     | Usage of A by B for achieving some end state. Applies to both companies and consumers. | Product dimension (A) is used by consumer (B) to make a choice. |
| ImportantTo| A is a quality or characteristic that is salient to / for B. For a marketer, it is valuable to highlight some characteristics as particularly important, more than merely identifying them as a characteristic. | New dimension of product (A) is important to consumers (B). New dimension of product (A) is important for product positioning (B) by marketer. |
| DependsOn  | A depends on B; however, is different from the inverse of LeadsTo. In marketing, A can depend upon several factors, B is among them. However, B may not lead to A. | Product positioning (A) depends on consumer evaluation of product attribute (B). Long run profit (A) depends on product positioning (B). |
| Affects    | A can have impact on B, does not mean it will have an impact [inverse - AffectedBy]. | Government regulation (A) affects product life cycle (B). Style and fashion affects product life cycle. Political influence affects government regulation. |
| Enables    | A can facilitate the occurrence of B [inverse - EnabledBy]. | Good positioning is enabled by strong advertising claims. Perception and choice consumers form are enabled by product attribute. |
| PartOf     | A is a characteristic, which marketer associates with B. | Demographics (A) is a part of consumer (B). Price sensitivity (A) is a part of consumer preference (B). |
| HasPrerequisite | A is achieved by a marketer by performing B. | To determine competitive structure (A) a prerequisite is to understand preference difference [among consumers](B). |
| MotivatedByGoal | Goal of achieving B motivates marketer to perform A. | Price increase (A) is motivated by goal of pursuing higher profit (B). |
| HasFirstSubevent | A can start to happen when B starts to occur. | For diffusion of innovation (A) to occur the first subevent of adopting new product [by consumers](B) is necessary. |
| CapableOf  | Relative to ConceptNet5, CapableOf expanded from "Something that A can typically do is B" to Something that A can do is B, reducing focus on typicality. | Attitude [of consumers](A) is capable of identifying segmentation opportunities for marketer. Attitude is capable of differentiating behaviors [of consumers](B) by marketer. |
| HasA       | A possesses certain traits B. A may not possess always. | Company (A) has strong patents (B). Consumer (A) has a higher price elasticity (B). |
| HasProperty | B is a property that characterises A; A possesses this property always. | Product (A) has the property that it requires distribution (B). |
| Synonym    | A and B are often considered similar in what they convey. | Attitude segmentation (A) is synonymous with psychographics (B). |
| UsedFor    | Purpose of A is to achieve B. | Perceptual map (A) is used by marketer to identify gaps (B) in marketplace. |
| CausesDesire | If a marketer experiences A, then it is likely the marketer wants to achieve B. | Shared production cost (A) among different products causes a desire to offer product line across segments (B). |
| RelatedTo  | As in ConceptNet5, interpreted as a general relation. In marketing, many relations take this form, since pin pointing directionality is very difficult, without considering many other factors of context ad environment. | Maturity stage of product (A) in life cycle is related to product’s ease of use by consumers (B). |
| Causes     | A can cause B; although not always. In marketing, causal-relations are soft in scope, that is, does not mean A implies B [inverse - CausedBy]. | Good positioning (A) of a product causes high trial rate (B) of the product. |

Table 8: Illustrative relations with explanation and examples. The top five relations are new, while others come from ConceptNet5.