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Commonsense Causal Reasoning between Short Texts

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Abstract

Commonsense causal reasoning is the process of capturing and understanding the causal dependencies amongst events and actions. Such events and actions can be expressed in terms, phrases or sentences in natural language text. Therefore, one possible way of obtaining causal knowledge is by extracting causal relations between terms or phrases from a large text corpus. However, causal relations in text are sparse, ambiguous, and sometimes implicit, and thus difficult to obtain. This paper attacks the problem of commonsense causality reasoning between short texts (phrases and sentences) using a data driven approach. We propose a framework that automatically harvests a network of causal-effect terms from a large web corpus. Backed by this network, we propose a novel and effective metric to properly model the causality strength between terms. We show these signals can be aggregated for causality reasonings between short texts, including sentences and phrases. In particular, our approach outperforms all previously reported results in the standard SEMEVAL COPA task by substantial margins.

1 Introduction

Commonsense causal reasoning, a central challenge in artificial intelligence, has been actively studied by both linguists and computer scientists. It aims at understanding the general causal dependency between common events or actions. Such understanding essentially amounts to measuring the *plausibility* of one event statistically leading to another.

In this paper, we focus on commonsense causal reasoning between short texts, which is crucial to many natural language processing applications, such as text understanding, question answering, etc. To further illustrate commonsense causal reasoning problem, we present a question from Choice of Plausible Alternatives (COPA) evaluation (Roemmele, Bejan, and Gordon 2011) which consists of one thousand multiple-choice questions requiring commonsense causal reasoning to answer correctly. Specifically, each question is composed of a premise and two alternatives, where the task is to select the more plausible alternative as a cause (or effect) of the premise.

Example 1 *Premise:* I knocked on my neighbor's door. *What happened as an effect?*

Alternative 1: My neighbor invited me in.

Alternative 2: My neighbor left her house.

This example shows that a key challenge is harvesting causality knowledge that the action of *knocking* is more likely to cause that of *invitation* than that of *leaving*.

Existing work on harvesting causality knowledge has been conducted in two directions. First direction, pursuing high *precision* of causality knowledge, usually requires expensive manual efforts. For example, ConceptNet (Havasi et al. 2010) leverages human efforts to encode causal events as common sense knowledge. Khoo et al. (2000) hand-crafted lexical syntactic patterns from the dependency tree to recognize causal knowledge. Rink et al. (2010) automatically generated such patterns encoded with lexical, syntactic and semantic information to extract causality knowledge, but the approach requires initial training data, which determines the quality and quantity of the generated patterns. Such iterative approach also tends to bring in ill-formed patterns and unreliable results. Other approaches reported in (Gordon, Kozareva, and Roemmele 2012) build on deeper lexical syntactic analysis of sentences, to identify knocking and inviting in our example as *events*, and determine whether causality between two events hold. However, knowledge acquired by these approaches, based on human and in-depth analysis, inherently lack coverage.

Second direction, harvesting causality from large text corpus with a data-driven approach, seeks to overcome the limitation in breadth of the first direction. The best known approach (Gordon, Bejan, and Sagae 2011) here, outperforming the approaches in the first direction (Gordon, Kozareva, and Roemmele 2012), leverages personal stories as a source of information about causality and uses Pointwise Mutual Information (PMI) statistics (Church and Hanks 1990) between words in the premise and alternative, to identify the pairs with high correlation. More specifically, under this framework, words A and B are considered causal, if A is frequently co-located with and succeeded by B in text. In our example, while we expect the words *knock* and *invite* to co-occur frequently in narrative text, which indicates a potential causality; the words *door* and *house* are also observed frequently together. Misidentifying both as causality may incorrectly give the second alternative as the result. Thus implicit causality from lexical co-occurrence alone is noisy. Therefore, current data-driven approaches may address the coverage limitation of causality acquisition, but suffer from low precision in return.

In contrast, our goal is to pursue both coverage and precision in modeling causality. Combining in-depth lexical syntactic analysis with personal stories is not an option because given the limited availability of such data, the amount of extractable precise causal knowledge would be much smaller. To pursue coverage, we propose a data-driven approach of harvesting a comprehensive *term-based causality network* from a large web corpus. Such network would encode tens of thousands of unique terms, and tens of millions of causality evidences, much larger scale than other existing causal knowledge bases (more comparisons in Section 3.1).

To pursue precision, we leverage explicit causal indicators (e.g., cause, because), to prune substantial non-causal co-occurrences and introduce separate cause and effect roles to every term in our causality knowledge.

With the differentiated cause and effect roles of causalities encoded in text, our causality network carries more reasonable and directional *causal co-occurrences*, e.g., from the corpus, $knock$ causes $invite$ m times, while $invite$ causes $knock$ n times. Furthermore, we distinguish sufficiency causality (i.e., A is the sufficient condition to cause B) from necessity causality (i.e., A is the necessary cause of B). These refined representations of terms and their causal relations give rise to new ways of computing causal strength between terms and between texts, thus yields better results in commonsense causal reasoning.

In sum, this paper makes the following contributions:

- We harvest a term-based causality co-occurrences network from large web text by leveraging causal cues (see Section 2.1);
- We develop a new statistical metric that captures causal strength between any two pieces of short texts (see Section 2.2 and Section 2.3);
- Our proposed framework achieves state-of-the-art accuracy of 70.2% on the difficult COPA task, outperforming all existing methods by subtantial margins. Further evaluation on causality detection between phrases also demonstrate the advantage of the proposed framework (see Section 3).

2 Approach

To reason about causality between short texts, our framework includes i) a network of causal relation weighted with causality co-occurrences between terms that is extracted from a large web corpus; ii) a novel metric to compute causal strength between any two terms based on this network; iii) a simple algorithm for aggregating the causality between terms to compute the overall score for causality reasoning between short texts, including phrases and sentences. Next, we describe these components.

2.1 Causality Network

s Causality is expressed by natural language texts and can be identified by linguistic patterns known as *causal cues* (Chang and Choi 2004). Consider the following sentences:

(1) The [*storm*]$_{\text{CAUSE}}$ [**caused**]$_{\text{PATTERN}}$ a tremendous amount of [*damage*]$_{\text{EFFECT}}$ on the landing beaches.

(2) The team prepared GIS precipitation and contour maps of the area identifying the [*flooding*]$_{\text{EFFECT}}$ and landslides [**caused by**]$_{\text{PATTERN}}$ the [*rainfall*]$_{\text{CAUSE}}$.

(3) However Susanoo was in [*sorrow*]$_{\text{EFFECT}}$ after the [*loss*]$_{\text{CAUSE}}$ of his mother and he was raging in his kingdom.

In sentence (1), 'storm' is the cause of 'damage', and 'damage' is the effect of 'storm'. We exploit *causal cues* (causal patterns) shown in Table 1, to identify cause and effect roles for our causality knowledge. For example, *"A cause B"* is an intra-sentence causal cue where *A* is a text span that represents the cause and *B* is a span that represents the effect. We set a maximum length L of text span *A* and *B* to prevent extracting noisy pairs too far away from causal cues.[1] The text span can be a term, a phrase or a sentence. There are also discourse cues such as *"If A then B"*. Table 1 shows all 53 intra-sentence and discourse causal cues used in this work. We extract all such patterns from a large web corpus, and after lemmatization, pair each term i in A as cause role, denoting as i_c, with each term j in B as effect role, denoting as j_e, to form a list of *causal pairs* (i_c, j_e) as causal evidences. Therefore, from sentence (1), we can harvest $(\mathrm{storm_c}, \mathrm{tremendous_e})$, $(\mathrm{storm_c}, \mathrm{amount_e})$, $(\mathrm{storm_c}, \mathrm{damage_e})$, $(\mathrm{storm_c}, \mathrm{landing_e})$, and $(\mathrm{storm_c}, \mathrm{beach_e})$ as causal evidences. In this process, we remove the stop words and only pairs involving nouns, verbs, adjectives and adverbs from WordNet are retained.

Our extracted causal pairs form a *directed* network of causal relations. Each node in this network is a lemmatized term, while a directed edge between two terms indicates a causal relation. A fragment of the causal network with three terms in the network is shown in Figure 1. Each edge is annotated with the *causality co-occurrences*, i.e., the number of times this causal relation was observed in the corpus.

We choose to extract term pairs in a rather simplistic way, without deeper syntactic analysis, because i) we opt for breadth in the causal knowledge hence the input corpus is extremely large (around 10TB), and consequently deep parsing of the text becomes prohibitive; and ii) the sheer quantity of the term pairs thus obtained provides excellent statistics for us to distinguish true causal relations against false ones.

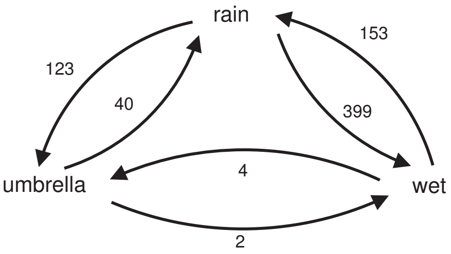


Figure 1: A fragment of causal network

[1] In our experiments, we empirically set L to be 10.

Table 1: 53 Causal cues. *A* is a cause span, and *B* is an effect span. DET stands for a/an/the/one. BE stands for is/are/was/were.

intra-sentence			inter-sentence		
A lead to B	A leads to B	A led to B	If A, then B	If A, B	B, because A
A leading to B	A give rise to B	A gave rise to B	B because A	B because of A	Because A, B
A given rise to B	A giving rise to B	A induce B	A, thus B	A, therefore B	B, A as a consequence
A inducing B	A induces B	A induced B	Inasmuch as A, B	B, inasmuch as A	In consequence of A, B
A cause B	A causing B	A causes B	B due to A	Due to A, B	B in consequence of A
A caused B	B caused by A	A bring on B	B owing to A	B as a result of A	As a consequence of A, B
A brought on B	A bringing on B	A brings on B	A and hence B	Owing to A, B	B as a consequence of A
B result from A	B resulting from A	B results from A	A, hence B	A, consequently B	A and consequently B
B resulted from A	the reason(s) for/of B BE A		A, for this reason alone , B		
DET effect of A BE B	A BE DET reason(s) of/for B				

2.2 Causal Strength Computation

Text corpus can explicitly as well as implicitly encode causality. Explicit causality is represented in text with causal patterns or indicators (e.g., cause, because). Implicit causality is naturally encoded in discourse without indicators, e.g., A appears before B in discourse implies that A is a cause of B, which is more complex and difficult to recognize. For example, sentence (1) and (2) explicitly encode causalities using causal patterns, while sentence (3) encodes the implicit causality $(\text{loss}_\text{c}, \text{sorrow}_\text{e})$.

Gordon et al. (2011) collected implicit causality from personal story corpus using asymmetric PMI described by Church(1990), to achieve the previous best known result on COPA task. The intuition is that narrations typically describe a series of events ordered by time. The text that appears earlier tends to be the antecedent while the text that comes later tends to be the consequent. Therefore, asymmetric PMI statistics can be used to capture the implicit causalities encoded in narrative texts such as personal stories. However, while personal stories might be a good source of implicit causality, they are hard to come by and limited in scale. In contrast, using a larger general web corpus improves coverage but trading accuracy, as web sentences may not follow a narrative pattern.

To leverage the scale and richness of the web text, we model causality more properly by replacing lexical co-occurrences with causality co-occurrences extracted by causal cues. Lexical co-occurrences are weak and implicit causal evidences, while causality co-occurrences are stronger and more explicit causal evidences due to the use of causal cues. Causal cues also help to identify precise cause/effect roles in strong causal evidences. Then we propose a new metric to measure causal strength between two terms with the insight that the connotation of causality integrates *necessity causality* with *sufficiency causality*. Considering a causal pair (i_c, j_e), necessity causality encoded by (i_c, j_e) represents that the cause i *must* be present in order for the effect j to take place, while sufficiency causality encoded by (i_c, j_e) represents that cause i is all it takes bring about the effect j. For example, the causality $(\text{rainfall}_\text{c}, \text{flooding}_\text{e})$ in sentence (2) encodes more necessity causality, since in most situations the effect *flooding* cannot happen if *rainfall* did not happen as its cause. Similarly, $(\text{storm}_\text{c}, \text{damage}_\text{e})$ in sentence (1) encodes more sufficiency causality. Intuitively, the stronger the necessity causality is, the larger the $p(i_c|j_e)$ should be; the stronger the sufficiency causality is, the larger the $p(j_e|i_c)$ should be. We are able to compute such conditional probability because we distinguish the terms by cause or effect roles. However, the frequent terms are more likely to be extracted as either causes or effects, which makes the conditional probability metric bias toward highly frequent terms. Therefore, we adopt a more general form (with a penalty factor) to model the necessity causal strength and sufficiency causal strength encoded by (i_c, j_e), as shown in Equation (1) and Equation (2) respectively.

$$\begin{aligned} CS_{nec}(i_c, j_e) &= \frac{p(i_c|j_e)}{p^{\alpha}(i_c)} \\ &= \frac{p(i_c, j_e)}{p^{\alpha}(i_c)p(j_e)} \end{aligned} \tag{1}$$

$$\begin{aligned} CS_{suf}(i_c, j_e) &= \frac{p(j_e|i_c)}{p^{\alpha}(j_e)} \\ &= \frac{p(i_c, j_e)}{p(i_c)p^{\alpha}(j_e)}, \end{aligned} \tag{2}$$

where α is a constant penalty exponent value. We follow Wettler (1993) to set α to be 0.66, penalizing high-frequency response terms. $p(i_c)$, $p(j_e)$ and $p(i_c, j_e)$ are computed as follows:

$$p(i_c) = \frac{\sum_{w \in W} f(i_c, w_e)}{M} \tag{3}$$

$$p(j_e) = \frac{\sum_{w \in W} f(w_c, j_e)}{M} \tag{4}$$

$$p(i_c, j_e) = \frac{f(i_c, j_e)}{N} \tag{5}$$

Here, $f(i_c, j_e)$ is frequency of observing the causal pair (i_c, j_e) from the corpus; M is the total number of evidences, computed as:

$$\sum_{u \in W} \sum_{v \in W} f(u_c, v_e),$$

and N is the size of the corpus; W is the set of all terms in the causality network.

To show the effectiveness of CS_{nec} and CS_{suf}, we compute the necessity causality and suffiency causality for causal pairs annotated in SemEval-2010 task 8.[2] We show the top necessary causal pairs and sufficient causal pairs ranked by $\frac{CS_{nec}}{CS_{suf}}$ and $\frac{CS_{suf}}{CS_{nec}}$ respectively as shown in Table 2.

Table 2: Top necessary and sufficient causal pairs

Necessary Causal Pairs	Sufficient Causal Pairs
$(\text{man}_c, \text{kidnapping}_e)$	$(\text{neuroma}_c, \text{pain}_e)$
$(\text{man}_c, \text{jolliness}_e)$	$(\text{eyestrain}_c, \text{headache}_e)$
$(\text{wind}_c, \text{corkscrew}_e)$	$(\text{flashlight}_c, \text{light}_e)$
$(\text{rainfall}_c, \text{flooding}_e)$	$(\text{typhoon}_c, \text{damage}_e)$
$(\text{accident}_c, \text{snarl}_e)$	$(\text{sunrise}_c, \text{light}_e)$
$(\text{erosion}_c, \text{rill}_e)$	$(\text{claustrophobia}_c, \text{panic}_e)$
$(\text{crash}_c, \text{gash}_e)$	$(\text{quake}_c, \text{damage}_e)$
$(\text{virus}_c, \text{tonsillitis}_e)$	$(\text{bacteria}_c, \text{meningitis}_e)$
$(\text{fight}_c, \text{carnage}_e)$	$(\text{quake}_c, \text{loss}_e)$
$(\text{earthquake}_c, \text{avalanche}_e)$	$(\text{overproduction}_c, \text{growth}_e)$

Our new causal strength encoded by pair (i_c, j_e) combines $CS_{nec}(i_c, j_e)$ with $CS_{suf}(i_c, j_e)$, and is defined in Equation (6).

$$CS(i_c, j_e) = CS_{nec}(i_c, j_e)^{\lambda} CS_{suf}(i_c, j_e)^{1-\lambda} \qquad (6)$$

The above metric models both the necessity and sufficiency components of causality and captures the intuition that the causal strength should be stronger when both necessity and sufficiency causality are strong. Here, λ is a parameter, weighing the necessity and sufficiency causality knowledge that is extracted from text corpus. A desirable λ depends on the characteristics of knowledge source and extraction methods, as we show in Section 3.

We compute the causal strength between every pair of terms in the causality network according to Equation (6). Where an edge is missing in the network, we assign a causal strength of zero.

2.3 Commonsense Causal Reasoning

To compute whether alternative a_1 or a_2 is more plausible with respect to the premise p, we need to compare the overall causality strength $CS_T(p,\ a_1)$ and $CS_T(p,\ a_2)$, assuming p is asking for an effect. Here, we compute the causal strength from text T_1 to text T_2 as:

$$CS_T(T_1, T_2) = \frac{1}{|T_1| + |T_2|} \sum_{i \in T_1} \sum_{j \in T_2} CS(i, j) \qquad (7)$$

We argue that such simple approach to aggregate causal strength between terms can effectively model causality between short texts. The intuition is that each pair of terms drawn from the two texts contribute to the total causal strength between the two texts. Because $CS(i_c, j_e)$ can be closely related to a probability (with penalty factors), summing up the causal strength between all pairs is analogous to computing a pairwise disjunctive probablity.

Furthermore, in our causality model, each term, whether in the cause role or the effect role, acts as an active agent in contributing causal strength, either in CS_{nec} or CS_{suf}. Each term in the cause role may cause a number of terms in the effect role and each term in the effect role maybe caused by a number of terms in the cause role. Based on this one-to-many relation, we normalize total causality score by $|T_1| + |T_2|$, which is the total number of agents, and not $|T_1| \times |T_2|$ presented in previous papers.

One alternative way of constructing the causality network is to extract causal pairs between phrases instead of terms, since there exists complex events (e.g., "catch cold") that cannot be expressed by a single word. However, we empirically discovered that such network is less effective since the frequencies tend to be diluted, which we report in Section 3, and even though "catch cold" is not in our network, we could better capture phrase causality based on the combined contribution of individual words "catch" and "cold."

3 Experimental Results

In this section, we first give some statistics of our corpus and the extracted causality network, and evaluate the quantity and quality of the cue patterns used in the extraction. We then compared our results on the main COPA task against a number of existing works using various other data sources and knowledge bases. Next, we evaluate causality reasoning on two additional tasks using the data from ConceptNet 4 to further showcase the power of our framework. Finally, we demonstrate our network's ability to identify causal directions using annotated corpus of SemEval-2010 task 8, despite being agnostic about the context of the input word pairs. We release the evaluation data used in these experiments at http://adapt.seiee.sjtu.edu.cn/causal/.

3.1 Data Set and Extraction of Causality Network

We extracted our term causality network, which we call "CausalNet" for convenience in this section, from a large web text corpus (a snapshot of Bing, approximately 10TB), which contains about 1.6 billion web pages. We extract 62,675,002 distinct causality evidences (e.g., causal pairs or edges in CausalNet) from this corpus. The average frequency of these evidences is 10.54. The number of unique lemmatized terms (nodes) in these evidences is 64,436, covering 41.49% (64,436/155,287) of the words in WordNet.

As a comparison, we separately extracted an "event-based" CausalNet using dependency relations (Chen and Manning 2014) such as *advmod* and *dobj*. Only bigram-phrases that match these relations and appear more than 20,000 times in the corpus are considered events; otherwise they are split into words and paired up as before. The average frequency on the edges of this event-based CausalNet is 1.59, much smaller than the orginal CausalNet, which would make our metric inaccurate due to its sparsity. Therefore, subquent experiments are done on the term-based CausalNet.

The 53 causal cues we used can be grouped into 17 sets, each containing cues of the same meaning or lemma form but with different tenses. Causal evidences distribution over these pattern sets is shown in Figure 2. The blue bars (left) are the number of distinct pairs and the orange ones (right)

[2] We further discuss this corpus in Section 3

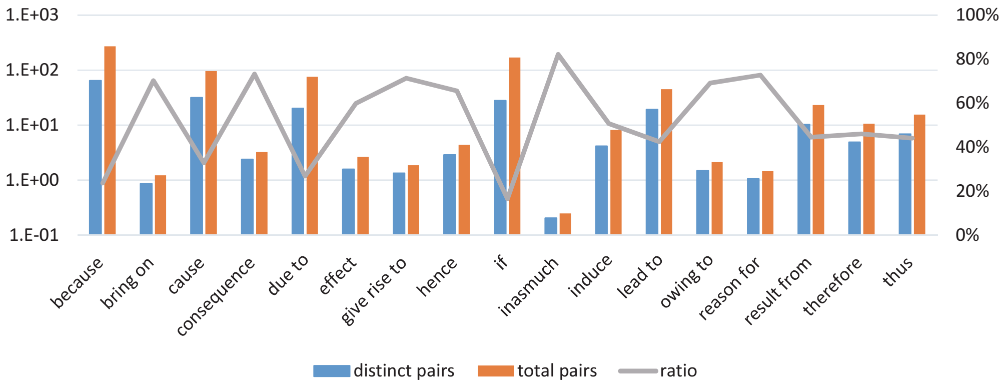


Figure 2: Number of (distinct) pairs extracted by cues

show the total number of pairs. Inter-sentence cues like "if" and "because" harvested the largest number of pairs. But more specialized patterns such as "reason" and "inasmuch" find more diverse pairs, since the number of distinct pairs is relatively large compared to the total pairs extracted. We show such diversity by the ratio between number of distinct pairs and number of total pairs and this ratio is marked by gray line in Figure 2.

To evaluate the quality of the causal cues, we make use of the manually labeled causal events in ConceptNet (Liu and Singh 2004) as ground truth. ConceptNet 4 contains 74,336 unlemmatized English words, forming 375,135 unique concepts, which are connected by 610,397 relation edges. Only some of these relations encode causal knowledge, such as "Causes", "CausesDesire" and "HasPrerequisite". The total number of such causal relations is 52,778. Each causal relation also associates with a vote from volunteers. Those pairs associated with positive votes are annotated as causal pairs (e.g. (listen to music$_c$, relax$_e$)), while associated with negative votes are annotated as false causal pairs (e.g. (listen to music$_c$, soda can$_e$)).

Since the pairs from ConceptNet contain phrases and not just words, we consider a pair (x, y) (x and y are text spans) to be covered by a causal cue, if at least one word u in x and another word v in y form the causal pair (u_c, v_e) which can be extracted word by that cue from the web corpus. Figure 3 shows that in general, our cues can effectively distinguish between positive and negative causal pairs.

3.2 End-to-end Evaluation on COPA

COPA task consists of 1000 commonsense causal reasoning questions, divided into development question set and test question set of 500 each. The incorrect alternative was purposely set semantically close to the premise, which makes this task more difficult for purely associative methods. In this experiment, our parameter λ was trained on the development set. All the reported results are on test set.

To show the usefulness of our causal strength metric, denoted as CS, we compare the end-to-end results on COPA with the best known PMI statistics on the web corpus. To solve COPA question with PMI, we pair the terms from premise and alternative and choose the alternative with a higher PMI.

We trained our CS_λ metric on the development set of COPA for different data sources (i.e., web corpus and CausalNet). That means we compute CS based on lexico co-occurrences from web corpus, while computing CS based on causality co-occurrences from CausalNet. During the training period, $CS_{\lambda=0.9}$ and $CS_{\lambda=1.0}$ achieve the same best results using CausalNet while $CS_{\lambda=0.5}$ performs the best using the web corpus on the development set. Then we show the performance of these trained CS metrics on test split of COPA. Table 3 shows that $CS_{\lambda=0.5}$ on web data (64.8%) outperforms PMI with any window sizes. Table 3 also compares $CS_{\lambda=1.0}$ on CausalNet with several other approaches. PMI Gutenberg (Roemmele, Bejan, and Gordon 2011) uses PMI statistic calculated from Project Gutenberg (16GB of English-language text). UTDHLT (Goodwin et al. 2012) is the result of SemEval-2012 Task 7 systems. They propose two approaches. The first one uses PMI over bigrams from LDC Gigaword corpus (8.4 million documents) as a feature. The second one treats the task as a classification problem and combines the features used in the first approach with some additional features to train an SVM model. The ConceptNet approach was our own baseline to illustrate the power of human curated knowledge. Here we fuzzy match the events or concepts from ConceptNet in COPA sentences, and then compute the causal strength between two COPA sentences by the scores (e.g.votes) associated with causal relations in ConceptNet. 23 out of 500 questions on COPA test split are matched by ConceptNet, and 18 of them are correctly answered, by computing the causality strength between two COPA sentences from the votes associate with causal relations in ConceptNet. We just randomly select an answer for mismatched questions. The last PMI method (Gordon, Bejan, and Sagae 2011), which was also the state-of-the-art previously (65.4%), uses a large corpus of personal stories (37GB of text) with a window of 25. All competing systems were assessed based on their accuracy on the 500 questions in the COPA test split (Gordon, Kozareva, and Roemmele 2012). Results show that our new metric $CS_{\lambda=0.9/1.0}$, when used together with the automat-

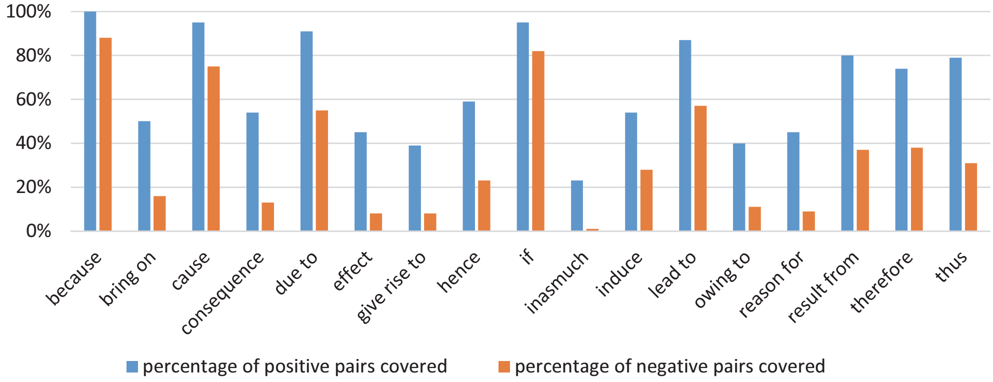


Figure 3: Number of causal vs. non-causal pairs from ConceptNet covered by cues

ically harvested CausalNet achieves significantly better accuracy on the COPA task.

Table 3: COPA results comparison

Data Source	Methods	Accuracy(%)
Web corpus	PMI (W=5)	61.6%
	PMI (W=10)	61.0%
	PMI (W=15)	60.4%
	PMI (W=25)	61.2%
	$CS_{\lambda=0.5}$	**64.8%**
Gutenberg	PMI (W=5)	58.8%
	PMI (W=25)	58.6%
LDC Gigaword	UTDHLT Bigram PMI	61.8%
	UTDHLT SVM	63.4%
ConceptNet	Fuzzy match	51.3%
1-Million Stories	PMI (W=25)	65.2%
10-Million Stories	PMI (W=25)	**65.4%**
CausaNet	$CS_{\lambda=1.0}$	**70.2** %

To further illustrate the effect of web data size on commonsense causal reasoning, we randomly sample 20%, 40%, 60% and 80% of our web corpus and thus construct various CausalNets of increasing sizes. The accuracies of COPA evaluation using these knowledge bases with $CS_{\lambda=0.9}$ and $CS_{\lambda=1.0}$ are shown in Figure 4. One can observe a general positive correlation between the size of the data and the ability to reason about commonsense causality. Even at 100%, that is the whole of the web corpus available to us, this trend shows no signs of diminishing, which means, given more data, the results may be even better. The curves in Figure 4 also shows a small bump at 60% of data. This is probably due to the randomness in the data distribution (e.g., the inclusion of certain type of web pages) and doesn't change the overall scalability of our framework.

To understand the effect of λ in our metric on causal reasoning, we conduct more experiments on COPA using different values of λ, and on both web corpus and CausalNet. As baselines, we also include the results using conditional probabilities in dual directions, $p(i_c|j_e)$ and $p(j_e|i_c)$. The results are shown in Table 4. Generally, conditional probability underperforms in this task for both data sources.

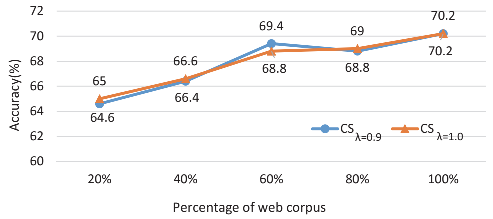


Figure 4: COPA evaluation on different scales of CausalNet

When computing causal strength using implicit causality evidences, the web data is largely unbiased and hence the causality evidences are observed with roughly equal sufficiency and necessity causality. Therefore $\lambda = 0.5$ gives the best result. However, when computing CS from CausalNet which is biased by the explicit causality patterns, a different λ is expected. Because people rarely state "*A causes B*" in text explicitly, when *A* apparently implies *B*, sufficiency causality is seldom observed from CausalNet, hence a larger λ value gives better results.

Table 4: COPA results for different CS variants

Data Source	Methods	Accuracy(%)
Web corpus	$p(j_e\|i_c)$	58.2%
	$p(i_c\|j_e)$	62.8%
	$CS_{\lambda=0.5}$	**64.8%**
	$CS_{\lambda=0.7}$	63.4%
	$CS_{\lambda=0.9}$	63.0%
	$CS_{\lambda=1.0}$	63.0%
CausalNet	$p(j_e\|i_c)$	56.2%
	$p(i_c\|j_e)$	60.2%
	$CS_{\lambda=0.5}$	68.8%
	$CS_{\lambda=0.7}$	69.4%
	$CS_{\lambda=0.9}$	**70.2%**
	$CS_{\lambda=1.0}$	**70.2%**

3.3 Causality Detection

Causality detection, or identifying the causal relation in text is an important task for many applications, such as event prediction, risk analysis, or decision making support (Mirza 2014). To show the effectiveness of our work in this aspect, we investigate the following two research questions on CausalNet, using data from ConceptNet4.

- **RQ1:** For arbitrary event pair manually labeled as *causal* (positive data) or *non-causal* (negative data), we investigate whether our proposed causality strength score clearly separates the two.
- **RQ2:** Inspired by COPA, we select causal and non-causal pairs sharing the same premise from ConceptNet and form two-choice questions, to evaluate the ability of CausalNet in selecting the correct choice.

For **RQ1,** we use the same 200 causal and non-causal event pairs from Figure 3 as positive and negative data. Figure 5 shows the causality score $CS_{\lambda=0.9}$ and $CS_{\lambda=1.0}$ (y-axis) of 100 positive and negative pairs indexed randomly (x-axis). We can observe that scores of positive and negative pairs are accurately distinguished by a linear function, $y = 0.7$, indicated by the gray line. Consequently, existing systems for causality identification and detection can incorporate our work to improve their accuracy.

For **RQ2,** due to sparsity of pairs sharing the same premise, we follow *pseudo-disambiguation task* in (Erk 2007). In particular, we use *Causes* relationship (i, j) with positive votes, such that i is the shared premise and j is a positive alternative. We then generate a negative alternative j' without *Causes* relationship with i in randomly selecting. Since ConceptNet does not exhaustively label all possible causal relationships, randomly selected j' can be actually causal, i.e., *false negatives* may exist. In such situation, we removed the question involving such false negatives, and consequently obtained a dataset of 412 questions in which 259 look for an effect while 153 look for a cause. Table 5 shows that the results of different CS_λ using CausalNet.

Table 5: Result of ConceptNet RQ2

Methods	Accuracy(%)
$CS_{\lambda=0.5}$	78.4%
$CS_{\lambda=0.9}$	78.6%
$CS_{\lambda=1.0}$	78.6%

3.4 Direction of Causality

Given a pair of terms i and j that are causally related, CausalNet can generally tell whether the causality is encoded by (i_c, j_e) or by (j_c, i_e) in common sense, without the context of i and j. In other words, as we will show next, CausalNet provides a reasonable prior knowledge of causality direction. We use the annotated corpus of SemEval-2010 Task 8 to evaluate this. There are 920 pairs of terms annotated as Cause-Effect relationship in SemEval-2010 Task 8 training corpus. CausalNet covered 894 out of 920 pairs (97.2%). Each Cause-Effect pair in the SemEval data set is annotated as follows:

Sentence:
*I too, get a $\langle e1 \rangle$ **headache**$\langle /e1 \rangle$ from $\langle e2 \rangle$ **wine**$\langle /e2 \rangle$, and was always told that it was the sulfites.*

Relation:
Cause-Effect($e2$,$e1$)

In the above example, $e1$ represents the term "headache", and $e2$ represents "wine". The relation Cause-Effect($e2$,$e1$) indicates that the causality encoded in this sentence is $(\text{wine}_c, \text{headache}_e)$, but not $(\text{headache}_c, \text{wine}_e)$. We can obtain this useful insight by the prior knowledge from CausalNet. We simply compare the causal strength of (i_c, j_e) with that of (j_c, i_e) provided by CausalNet. If $CS(i_c, j_e) > CS(j_c, i_e)(\lambda = 0.5)$, we conclude that the causality is encoded by (i_c, j_e), otherwise the causality is encoded by (j_c, i_e).

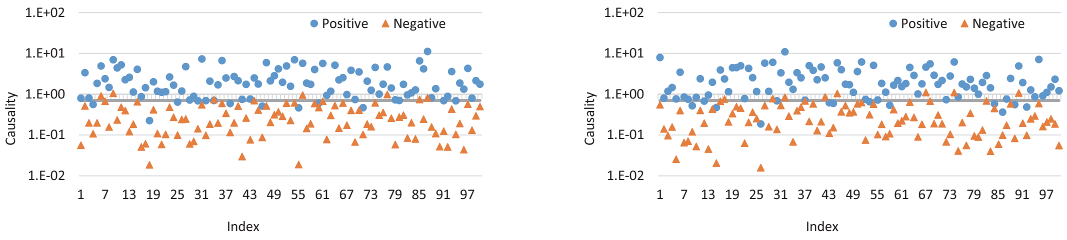
The agreement between CausalNet and annotated ground truth in SemEval-2010 Task 8 is 80.1%, i.e., 716 out of 894 pairs from SemEval find a matching pair in the same causal direction from CausalNet. Table 6 shows 20 random samples of annotated causal pairs from SemEval-2010 Task 8 corpus. 10 of those are matched by CausalNet and the rest are not. Three human judges were employed to mark whether these pairs follow common sense or not. A pair is considered common sense if it is thought so by at least 2 judges. We can see that all but one pairs in the left column are common sense, while most of those pairs in the right column are not common sense. This means, where CausalNet predicts correctly, it is really due to the power of commonsense knowledge. On the other hand, CausalNet makes mistakes primarily due to the lack of context in small amount of cases, and not because the knowledge enclosed is wrong.

4 Related Work

We start by discussing previous work that extracts causal relation term pairs from open domain text. Then we present various past attempts to solve the causality reasoning problem.

4.1 Causal Relation Extraction

Causal relation recognition and extraction can be seen as a pre-processing step of causal reasoning. It naturally boils down to a binary classification problem of causal/non-causal relations. Existing approaches focus on developing hand-coded patterns and linguistic features and learning the classifier to recognize and extract causal relation for their systems. Moreover, previous work are specific with the type of causal pairs and extracted either noun-noun, verb-verb or verb-noun causation. Girju et al. (Girju 2003) were the first to work on causal relation discovery between nominals. They semi-automatically extracted causal cues, but only extracted noun category features for the head noun. Chang et al. (Chang and Choi 2004) developed an unsupervised method and utilized lexical pairs and cues contained in noun phrases as features to identify causality between them. Both of them ignored how the text spans surrounding the causal cue affects the semantics. Our causal relation extraction step, instead, benefits from these contexts and constructs a much larger and more powerful causal network. Blanco et



(a) $CS_{\lambda=0.9}$

(b) $CS_{\lambda=1.0}$

Figure 5: Distinguishing causality on ConceptNet

Table 6: Random samples of annotated causal pairs from SemEval-2010 task 8

Pairs with match in CausalNet		Pairs without match in CausalNet	
Causal Pair	Commonsense	Causal Pair	Commonsense
(vaccine$_c$, fever$_e$)	Yes	(drink$_c$, suffering$_e$)	Yes
(tension$_c$, headache$_e$)	Yes	(malfunction$_c$, inflammation$_e$)	No
(passage$_c$, noise$_e$)	Yes	(growth$_c$, inflammation$_e$)	No
(injury$_c$, discomfort$_e$)	Yes	(pie$_c$, poison$_e$)	No
(ash$_c$, drama$_e$)	No	(city$_c$, anger$_e$)	No
(accident$_c$, pain$_e$)	Yes	(infection$_c$, acne$_e$)	Yes
(mess$_c$, crisis$_e$)	Yes	(institution$_c$, fraud$_e$)	No
(pinworm$_c$, infestation$_e$)	Yes	(dog$_c$, joy$_e$)	No
(parasite$_c$, toxoplasmosis$_e$)	Yes	(fear$_c$, attack$_e$)	No
(disability$_c$, benefit$_e$)	Yes	(bacteria$_c$, acne$_e$)	Yes
(elimination$_c$, riot$_e$)	Yes	(fireplace$_c$, warmth$_e$)	Yes
(generator$_c$, signal$_e$)	Yes	(tax$_c$, fluctuation$_e$)	No
(drug$_c$, unconsciousness$_e$)	Yes	(bacteria$_c$, breakout$_e$)	Yes
(zinc$_c$, growth$_e$)	Yes	(injury$_c$, operation$_e$)	Yes
(reaction$_c$, inversion$_e$)	Yes	(pregnancy$_c$, nausea$_e$)	Yes
(movement$_c$, earthquake$_e$)	Yes	(attack$_c$, shock$_e$)	Yes
(virus$_c$, disease$_e$)	Yes	(lack$_c$, reliance$_e$)	No
(drum$_c$, sound$_e$)	Yes	(tree$_c$, smell$_e$)	No
(vaccine$_c$, outbreak$_e$)	Yes	(ointment$_c$, discomfort$_e$)	No
(press$_c$, reaction$_e$)	Yes	(ginseng$_c$, taste$_e$)	No

al. (Blanco, Castell, and Moldovan 2008) used different patterns to detect the causation in long sentences that contain clauses. Kozareva (Kozareva 2012) collected causality relations between nominals using a bootstrapping method.

Do et al. (Do, Chan, and Roth 2011) introduced a form of association metric into causal relation extraction. They mainly focus on detecting causality between verbs and also worked with verb-noun causality in which nouns are drawn from a small predefined list. They used discourse connectives and similarity distribution to identify event causality between predicate, not noun phrases, but achieved a F1-score around 0.47. Riaz et al. (Riaz and Girju 2014) focus on noun-verb causality detection and extraction.

None of the previous work except for Do's provides a causality metric, hence cannot be extended to commonsense causal reasoning task. Do's work is also of limited help because it only measures causality strength between verbs. And most recently, Hashimoto (Hashimoto et al. 2015) propose methods to generate reasonable event causalities, though limited in scale on the event space. In contrast, CausalNet is constructed out of all types of words in web corpus, and as a result the framework on top of it can model the causal strength between arbitrary text units.

4.2 Commonsense Causal Reasoning

The causal knowledge which encodes the causal implications of actions and events is useful in many applications. Commonsense causal reasoning is thus a grand challenge in artificial intelligence. Earlier attempts on the problem were largely linguistic, for example, developing formal theories to capture temporal or logical properties in causal entailment (Lascarides, Asher, and Oberlander 1992; Lascarides and Asher 1993), but they do not scale to comprehensive, open domain reasoning problems.

The NLP community has explored knowledge based approaches that leverage structural representations of the general world knowledge. Much of the knowledge is hand-coded (Lenat 1995) or crowd-sourced, such as the OMCS project by MIT (Singh et al. 2002). Some relations such as "causes" and "causesDesire" in the ConceptNet (Liu and Singh 2004), which is a sub-project under OMCS, can be used to identify causal discourse in COPA task. However, such human curated knowledge has limited size and comes with no or unreliable causal strength scores (e.g., the votes in ConceptNet). Recently, several automatic, data-driven methods have been attempted to acquire commonsense knowledge(Schubert 2002; Gordon, Van Durme, and Schubert 2010; Gordon 2010; Akbik and Michael). These approaches focused on the acquisition of general worldly knowledge expressed as factoids, and not causality knowledge per se. Hence their coverage of causality knowledge is also very limited.

More successful efforts arise from data-driven approaches using correlational statistics (Gordon, Kozareva, and Roemmele 2012) such as pointwise mutual information (PMI) between unigrams (words) or bigrams from large text corpora (Mihalcea, Corley, and Strapparava 2006). Corpora attempted include LDC gigaword news corpus (Goodwin et al. 2012), Gutenberg e-books (Roemmele, Bejan, and Gordon 2011), personal stories from Weblogs (Gordon, Bejan, and Sagae 2011) and Wikipedia text (Jabeen 2014). This paper follows a similar direction, but instead proposed to extract causal signals from a more general, much larger web text corpus. CausalNet can be seen as a large graph-based representation of general causality knowledge and can provide the relatively reasonable computation of causal strength between terms.

5 Conclusion

This paper proposes a novel framework of deducing causality by automatically harvesting a causality network (CausalNet) of causal-effect terms (or causality evidences) from a large web corpus. CausalNet is the first (to the best of our knowledge) automatically constructed graph-based representation of a causality knowledge base. This data-driven approach enables a high coverage including long-tailed causality relations. We then propose a novel metric leveraging both sufficiency and necessary causality evidences to model the causality strength between terms. These metrics between terms can be aggregated for determining causality between short texts (e.g., phrases and sentences). Our evaluation results validate our proposed framework, which outperforms the previous best approach for solving the competitive SEMEVAL task known as COPA.

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