Abstract

Often missing in existing knowledge bases of facts, are relationships that encode common sense knowledge about unnamed entities. In this paper, we propose to extract novel, common sense relationships pertaining to sense perception concepts such as sound and smell.

1 Introduction

We seek to extract novel common sense relationships, with a focus on concepts that are discernible by sense, for example, sound and smell. There are various natural language understanding tasks where this type of knowledge is useful: consider the problem of co-reference resolution as it occurs in the following sentences: (s1.) As the cat approached the dog, it started barking furiously; (s2.) As the cat approached the dog, it started meowing furiously. We can easily determine that in s1, the pronoun “it” refers to the dog, whereas in s2, “it” refers to the cat. However, for a machine reading method to correctly resolve co-reference in s1) and s2), it requires access to background knowledge that asserts that barking and meowing are sounds produced by dogs and cats, respectively. This type of knowledge is what we aim to extract in this paper. One of the factors impeding progress in common sense knowledge acquisition is the lack of labeled data. Prior work has shown that it can be straightforward to obtain training data for identifying relationships between named entities such as companies and their headquarters, or people and their birth places (Havasi et al., 2007; Tandon et al., 2011; Bollacker et al., 2008; Hoffart et al., 2012; Mitchell et al., 2015). Examples of such relationships can be found in semi-structured formats on the Web (Wu and Weld, 2008). This is not the case for common sense relationships. Our contributions in this work are three-fold. First, we propose to extract novel relationships commonly absent in existing knowledge bases. Second, we propose a method for generating labeled data by leveraging large corpora and yes/no crowd-sourcing questionnaires. Third, using the resulting labeled data, we train both a linear model and memory neural network models, obtaining high accuracy on the task of extracting these previously under-explored relationships. To focus our task, we consider three relations pertaining to sense perception of sound and smell. Namely: 1) soundSourceRelation, 2) soundSceneRelation, and 3) smellSentimentRelation.

2 Sound-Source Relationship

The sound-source relationship represents information about which objects produce which sounds. For example that planes and birds are capable of flying, the wind blows, and geckos bark. Obtaining sufficient labeled data to learn an extractor for this relationship is non-trivial, we propose one approach in the next section.

2.1 Labeled Data Generation

One option for obtaining labeled data is to do a cold call on a crowd-sourcing platform by asking crowd workers to list examples of sounds and their sources. However, such an approach requires crowd workers to think of examples without clues or memory triggers. This is time consuming and error prone. Additionally, this means that the monetary cost could be substantial. We propose to exploit a large corpus to obtain preliminary labeled data. This enables us to only need crowd workers to filter the data through a series of “yes/no/not sure” questions. These type
of questions require little effort from crowd workers while mitigating the amount of noisy input that one could get from open-ended, cold call, type of questions.

To pose filters to crowd workers in the form of “yes/no/notsure” questions, we need a list of plausible sound-source pairs. To this end, we propose a lightly supervised corpus-based technique. First, we identify which phrases refer to sounds using a high yield, but potentially noisy pattern. In particular, we apply the following pattern to a large corpus[1]: “sound of <y>”. The result is a large collection of occurrences such as: “sound of singing children”. This step produced a list of 134,471 unique phrases that potentially refer to sounds. To evaluate accuracy, we randomly selected a sample of 500 phrases and asked 3 crowd workers per phrase, on Mechanical Turk, to say “yes/no/notsure” if they agree the phrase refers to a sound concept. By majority vote measure, 73.4% of the 500 phrases where considered true mentions of sounds, with a moderate agreement rate of 0.51 Fleiss $\kappa$.

This annotation result indicates that a substantial number of the phrases generated by the pattern indeed refer to sound concepts. We therefore use these phrases to generate a list of plausible sound-source pairs. One important observation we made was that about 20,000 (15%) of the 134,471 phrases are bi-grams of the form: “verb noun” or “noun verb” where in both cases, the verb is in the gerund or present participle V-ing form. For example, birds chirping, cars honking, squealing brakes, etc. From phrases of this kind, we create verb-noun pairs, that we treat as plausible sound-source pairs where the verb is the source and the noun is the source. We then asked crowd-workers to decide if the source (noun) produces the sound (verb). Thus from “birds chirping” we generate the question, “Is chirping a sound produced by birds?”; Negative examples include: “surrounding nature”, and “Standing ovation”, i.e., standing is not a sound made by ovation. We generated 634 such questions on which we obtained a moderate inter-annotator agreement rate of Fleiss $\kappa = 0.57$, see Table 1.

We use the resulting labeled data to train two types of learning methods.

|  | Fleiss $\kappa$ |
|---|---|
| soundSource | 0.57 |
| soundEnvironment | 0.35 |
| smellSentiment | 0.43 |

Table 1: Fleiss $\kappa$. inter-annotator agreement rates for the three relations on yes/no type crowd-sourcing tasks.

### 2.2 Linear Learning Model

The learning problem for the sound-source relationship is as follows: given a bi-gram phrase $n$ of the form “verb noun” or “noun verb”, we wish to classify yes or no if a given noun, denoted by $w_{src}$, produces the verb, denoted by word $w_{snd}$, as a sound. As a linear solution to this problem, we train a logistic regression classifier. The features we use are the vectors representing the word embeddings of $w_{src}$ and $w_{snd}$, denoted by $v_{src}$ and $v_{snd}$. In our experiments, we use the 300-dimensional Google News pre-trained embeddings[2]. There are several ways in which we combine $v_{src}$ and $v_{snd}$ into a single feature vector:

**Vector Concatenation**: $v = concat(v_{src}, v_{snd})$

| $v$ | $|v_{src}| = |v_{snd}|$ |
|---|---|
| LSTM encoder: $v = lstm(v_{src}, v_{snd})$ |

An LSTM (Hochreiter and Schmidhuber, 1997) recurrent neural network is used to encode the phrase containing $v_{src}$ and $v_{snd}$. $|v| = h$, where $h$ is the hidden layer size of the neural network.

**Source minus sound**: $v = v_{src} - v_{snd}$

| $v$ | $|v_{src}| = |v_{snd}|$ |
|---|---|
| Sound minus source**: $v = v_{snd} - v_{src}$

| $v$ | $|v_{src}| = |v_{snd}|$ |

### 2.3 Memory Networks Learning Model

In addition to the variations of the linear model, we also trained a non-linear model in the form of memory networks (Sukhbaatar et al., 2015). Memory networks have been recently introduced, they combine their inference component with a memory component. The memory component serves as a knowledge base or history vault to recall words or facts from the past. For the task of relation extraction, the memory network model learns a scoring function to rank relevant memories (words) with respect to how much they express a given relationship. This is done for a given argument pair as a query, i.e., a sound-source

---

[1] In our experiments, we used the English part of ClueWeb09, [http://lemurproject.org/clueweb09/](http://lemurproject.org/clueweb09/)

[2] [https://code.google.com/archive/p/word2vec/](https://code.google.com/archive/p/word2vec/)
| Learning Model                      | Accuracy |
|------------------------------------|----------|
| LM: LSTM encoder                   | 0.90     |
| LM: (Source - Target)              | 0.88     |
| LM: (Target - Source)              | 0.87     |
| LM: Vector Concatenation           | 0.83     |
| MM: 1 hop                          | 0.87     |
| MM: 3 hops                         | 0.85     |

Table 2: Accuracy of the linear models (LM) and memory networks models (MM) on the sound-source relation.

At prediction time, the model finds $k$ relevant memories (words) according to the scoring function and conditions its output on these memories. In our experiments, we explore different values of $k$, effectively changing how many memories (words), the model conditions on. We report results for up to $k = 3$ as we did not see improvements for larger values of $k$.

### 2.4 Sound-Source Evaluation

Both the linear model and the memory networks models were implemented using TensorFlow. For the memory networks, we implemented the end-to-end version as described in (Weston et al., 2014; Sukhbaatar et al., 2015). Of the 634 crowd-sourced labeled examples described in section 2.1 we used 100 as test data, the rest as training data. Model parameters such as hidden layer size of the memory networks were tuned using cross-validation on the training data. As shown in Table 2, we obtain high accuracy across all models. The best performing model is a linear model with an LSTM encoding of the sound phrases, achieving accuracy of 90%. Surprisingly, we could not obtain better results with the memory networks model. Increasing the memory size or the number of hops (how often we iterate over the memories) did not help. One possible reason is the size of our training data, in previous work (Weston et al., 2014; Sukhbaatar et al., 2015), the memory networks were trained on 1,000 or more examples per problem type whereas our training data is half the size. Nevertheless, the memory networks module still produces good accuracy, with best performance of 87%.

### 3 Sound-Scene Relationship

The sound-scene relationship represents information about which sounds are found in which scenes. For example, birds chirping can be found in a forest. Therefore, this kind of information can also be used in context recognition systems (Eronen et al., 2006), in addition to providing common sense knowledge that could be useful in language understanding tasks.

**Labeled Data Generation.** We would like to obtain labeled data in the form of scenes and their sounds. For example, (beach, waves crashing), (construction, hammering), (street, sirens), (street, honking cars). To obtain this type of labeled data, we again would like to only use “yes/no/not sure” crowd-sourcing questions. To generate plausible sound-scene pairs, first we find all sentences that mention at least one scene and one sound concept. To detect sound concepts, we use the approach described in Section 2.1. To detect mentions of scenes, we specified a list of 36 example scenes, which includes scenes such as beach, park, airport most of our scenes are part of the list of acoustic scenes from a scene classification challenge. The full list of scenes is in the supplementary data accompanying this submission. For every sentence that mentions both an acoustic scene and a sound concept, we apply a dependency parser. This step produces dependencies that form a directed graph, with words being nodes and dependencies being edges.

Dependency graph shortest paths between entities have been found to be a good indicator of relationships between entities (Xu et al., 2015; Nakashole et al., 2013b). We use shortest paths as features in order classify sound-scene pairs. To obtain training data, we sort the paths by frequency, that is, how often we have seen the path occur with different sound-scene pairs. We then consider pairs that occur with frequent shortest paths to be plausible sound-scene pairs which we can present to crowd-workers in “yes/no/not sure” questions. We randomly selected 584 sound-scene pairs, and the corresponding sentences that mention them, which were then presented to crowd workers in questions. The inter-annotator agreement rate on this task is Fleiss $\kappa = 0.35$, see Table 1.

**Learning Models and Evaluation.** We use the learning models described in Sections 2.2 and 2.3. For the linear model, we consider three options...
### Table 3: Accuracy on the sound-scene relation.

| Learning Model                      | Accuracy |
|-------------------------------------|----------|
| LM: shortest path                   | 0.81     |
| LM: shortest path + sentence:       | 0.80     |
| LM: sentence                        | 0.75     |
| MM: 1 hop                           | 0.80     |
| MM: 3 hops                          | 0.80     |

### Table 4: Accuracy on the sound-sentiment relation.

| Learning Model                      | Accuracy |
|-------------------------------------|----------|
| LM: LSTM encoder                    | 0.84     |
| LM: vector addition                 | 0.81     |
| MM: 1 hop                           | 0.82     |
| MM: 3 hops                          | 0.82     |

for features. **Shortest Paths (SP):** LSTM encoding of the dependency shortest path. **Sentence (S):** an LSTM encoding of the sentence. **SP + S:** encoding of both the shortest path and the sentence are used as features. For the memory network models, we considered using the contents of both the shortest paths and the sentences to produce memories. We use 100 of the 584 labeled data for testing, the rest for training. The shortest paths performed better, for space reasons we omit the results of using sentences as memories. As shown in Table 3, the linear model with the shortest path achieves the best accuracy of 81%. However, the best performing memory networks model with 3 memory hops is not significantly worse at 80% accuracy.

### 4 Smell-Sentiment Relationship

For the smell-sentiment relationship, the goal is to extract information about which smells are considered pleasant, unpleasant or neutral. In general, sentiment is both subjective and context dependent. However, as we show through crowd-sourced annotations, there is substantial consensus even on sentiment of smells.

**Labeled Data Generation.** First we generate a list of plausible smells, following a similar approach to Section 2.1. That is, we search for the pattern: “smell of `<y>`” in the ClueWeb corpus. The result is a large collection of occurrences such as: “smell of rotten eggs.” or smell of cherry blossoms. From this collection, we randomly selected a sample of 500 phrases and asked 3 crowd workers per phrase on Mechanical Turk, to say “yes/no/not sure” if they agree the phrase refers to a smell concept. By the majority vote measure metric 89.9% of the 500 phrases are true mentions of smells, with an somewhat low agreement rate of 0.33 Fleiss $\kappa$. Having verified that our list of phrases contains a substantial number of smell concepts, we then use these phrases to evaluate sentiment of smells in a different Mechanical Turk task. We present a phrase within a sentence context. We then asked crowd workers to choose if the phrase refers to a smell that is “pleasant/unpleasant/neutral/not sure/not a smell”. We generated 600 such questions on which we obtained a moderate inter-annotator agreement rate of Fleiss $\kappa = 0.43$, see Table 1. While this is not a yes/no task, it is still a simple multiple choice task with the same advantages of the yes/no tasks as we described earlier.

**Learning Models and Evaluation.** We again use the learning models described in Sections 2.2 and 2.3. For the linear model, we consider two options for features. **LSTM encoder:** LSTM encoding of the smell phrase. **Vector addition:** vector addition encoding of the smell phrase. For the memory network models, the contents of the sentence that mentions the phrases are stored as memories. We use 100 of the 600 labeled data for testing, the rest for training. As can be seen in Table 3 the linear model with LSTM encoded phrases achieved the highest accuracy of 84%.

### 5 Conclusion

Cyc (Lenat, 1995), and ConceptNet (Havasi et al., 2007) are well-known examples of attempts to build knowledge bases of everyday common sense knowledge. These projects are decades long manual efforts involving either experts or crowd-sourcing. Other knowledge bases focus on facts about named entities such as people, locations, and companies (Bollacker et al., 2008; Hoffart et al., 2012; Mitchell et al., 2015).

In this paper, we extracted novel common sense relations. To obtain labeled data, we proposed a combination of large corpora, and multiple choice crowd-sourced questions. These type of questions require little effort from crowd workers while mitigating the amount of noise one might get from open-ended questions. We have also proposed and trained models on this data, achieving high accuracy for all relations. Scaling up our approach to
more relations is an exciting future direction for our work. We believe our technique can scale given its minimally-supervised nature.
References

[Bengio et al.1994] Yoshua Bengio, P. Simard, and Paolo Frasconi. 1994. Learning long-term dependencies with gradient descent is difficult. *IEEE Transactions on Neural Networks. Special Issue on Recur.*

[Bollacker et al.2008] Kurt Bollacker, Colin Evans, Praveen Paritosh, Tim Sturge, and Jamie Taylor. 2008. Freebase: A collaboratively created graph database for structuring human knowledge. In *SIGMOD, SIGMOD ’08*, pages 1247–1250.

[Brin1998] Sergey Brin. 1998. Extracting patterns and relations from the world wide web. In *WebDB*, pages 172–183.

[Chiu and Nichols2016] Jason P. C. Chiu and Eric Nichols. 2016. Named entity recognition with bidirectional lstm-cnns. *TACL*, 4:357–370.

[Collobert et al.2011] Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel P. Kuksa. 2011. Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 12:2493–2537.

[dos Santos and Guimarães2015] Cícero Nogueira dos Santos and Victor Guimarães. 2015. Boosting named entity recognition with neural character embeddings. *CoRR*, abs/1505.05008.

[Eronen et al.2006] Antti J Eronen, Vesa T Peltonen, Juha T Tuomi, Anssi P Klapuri, Seppo Fagerlund, Timo Sorsa, Gáitán Lorho, and Jyrri Huopaniemi. 2006. Audio-based context recognition. *Audio, Speech, and Language Processing, IEEE Transactions on*, 14:321–329.

[Fellbaum1998] Christaine Fellbaum. 1998. A semantic network of English verbs. In *WordNet: An Electronic Lexical Database*, pages 69–104. The MIT Press.

[Finkel et al.2005] Jenny Rose Finkel, Trond Grenager, and Christopher D. Manning. 2005. Incorporating non-local information into information extraction systems by gibbs sampling. In *ACL.*

[Hammerton2003] James Hammerton. 2003. Named entity recognition with long short-term memory. In *HLT-NAACL*, pages 172–175.

[Harandi et al.2007] Catherine Havasi, Robert Speer, and Jason Alonso. 2007. Conceptnet 3: a flexible, multilingual semantic network for common sense knowledge. In *RANLP*, pages 27–29.

[Hearst1992] Marti A. Hearst. 1992. Automatic acquisition of hyponyms from large text corpora. In *COLING*, pages 539–545.

[Hochreiter and Schmidhuber1997] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural Computation*, 9(1):1–42.

[Hoffart et al.2011] Johannes Hoffart, Mohamed Amir Yosef, Ilaria Bordini, Hagen Fürstenauf, Manfred Pinkal, Marc Spaniol, Bilyana Taneva, Stefan Thater, and Gerhard Weikum. 2011. Robust disambiguation of named entities in text. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, EMNLP 2011*, 27–31 July 2011, John McIntyre Conference Centre, Edinburgh, UK. A meeting of SIGDAT, a Special Interest Group of the ACL, pages 782–792.

[Hoffart et al.2012] Johannes Hoffart, Fabian M. Suchanek, Klaus Berberich, and Gerhard Weikum. 2012. YAGO2: A spatially and temporally enhanced knowledge base from Wikipedia. *Artificial Intelligence*, 194:28–61.

[Kumar et al.2017] Anurag Kumar, Bhiksha Raj, and Ndapandula Nakashole. 2017. Discovering sound concepts and acoustic relations in text. In *Acoustics, Speech and Signal Processing (ICASSP), 2017 IEEE International Conference on*, pages 631–635. IEEE.

[Labeau et al.2015] Matthieu Labeau, Kevin Löser, and Alexandre Allauen. 2015. Non-lexical architecture for fine-grained POS tagging. In *EMNLP*, 2015, pages 232–237.

[Lafferty et al.2001] John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *ICML*, pages 282–289.

[Lenat1995] Douglas B. Lenat. 1995. Cyc: A large-scale investment in knowledge infrastructure. *Commun. ACM*, 38(11).

[Ling et al.2015] Wang Ling, Chris Dyer, Alan W. Black, Isabel Trancoso, Ramon Fernández, Silvio Amir, Luís Marujo, and Tiago Luíš. 2015. Finding function in form: Compositional character models for open vocabulary word representation. In *EMNLP*, pages 1520–1530.

[Mitchell et al.2015] Tom M. Mitchell, William W. Cohen, Estevam R. Hruschka Jr., Partha Pratim Talukdar, Justin Betteridge, Andrew Carlson, Bhanu Dalvi Mishra, Matthew Gardner, Bryan Kisiel, Jayant Krishnamurthy, Ni Lao, Kathryn Mazaitis, Thahir Mohamed, Ndapandula Nakashole, Emmanouil Antonios Platianos, Alan Ritter, Mehdi Samadi, Burr Settles, Richard C. Wang, Derry Tanti Wijaya, Abhinav Gupta, Xinlei Chen, Abulhair Saparov, Malcolm Greaves, and Joel Welling. 2015. Never-ending learning. In *AAAI*, pages 2302–2310.

[Nakashole and Mitchell2014] Ndapandula Nakashole and Tom M. Mitchell. 2014. Language-aware truth assessment of fact candidates. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics, ACL 2014*, June 22-27, 2014, Baltimore, MD, USA, Volume 1: Long Papers, pages 1009–1019.
[Nakashole and Mitchell2015] Ndapandula Nakashole and Tom M. Mitchell. 2015. A knowledge-intensive model for prepositional phrase attachment. In ACL (1), pages 365–375. The Association for Computer Linguistics.

[Nakashole and Weikum2012] Ndapandula Nakashole and Gerhard Weikum. 2012. Real-time population of knowledge bases: opportunities and challenges. In AKBC, pages 41–45. Association for Computational Linguistics.

[Nakashole et al.2011] Ndapandula Nakashole, Martin Theobald, and Gerhard Weikum. 2011. Scalable knowledge harvesting with high precision and high recall. In Proceedings of the Fourth ACM International Conference on Web Search and Data Mining, WSDM ’11, pages 227–236.

[Nakashole et al.2013a] Ndapandula Nakashole, Tomasz Tylenda, and Gerhard Weikum. 2013a. Fine-grained semantic typing of emerging entities. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, ACL, pages 1488–1497.

[Nakashole et al.2013b] Ndapandula Nakashole, Gerhard Weikum, and Fabian M. Suchanek. 2013b. Discovering semantic relations from the web and organizing them with PATTY. SIGMOD Record, 42(2):29–34.

[Nakashole2012] Ndapandula T Nakashole. 2012. Automatic extraction of facts, relations, and entities for web-scale knowledge base population.

[Ratinov and Roth2009] Lev-Arie Ratinov and Dan Roth. 2009. Design challenges and misconceptions in named entity recognition. In CoNLL, pages 147–155.

[Shimaoka et al.2016] Sonse Shimaoka, Pontus Stenetorp, Kentaro Inui, and Sebastian Riedel. 2016. An attentive neural architecture for fine-grained entity type classification. arXiv preprint arXiv:1604.05325.

[Sukhbaatar et al.2015] Sainbayar Sukhbaatar, Arthur Szlam, Jason Weston, and Rob Fergus. 2015. End-to-end memory networks. In Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada, pages 2440–2448.

[Tandon et al.2011] Niket Tandon, Gerard de Melo, and Gerhard Weikum. 2011. Deriving a web-scale common sense fact database. In AAAI.

[Tandon et al.2014] Niket Tandon, Gerard de Melo, and Gerhard Weikum. 2014. Acquiring comparative commonsense knowledge from the web. In AAAI, pages 166–172.

[Wang and Cohen2008] Richard C. Wang and William W. Cohen. 2008. Iterative set expansion of named entities using the web. In Proceedings of the 8th IEEE International Conference on Data Mining (ICDM 2008), December 15-19, 2008, Pisa, Italy, pages 1091–1096.

[Weston et al.2014] Jason Weston, Sumit Chopra, and Antoine Bordes. 2014. Memory networks. arXiv preprint https://arxiv.org/abs/1410.3916.

[Wu and Weld2008] Fei Wu and Daniel S. Weld. 2008. Automatically refining the wikipedia infobox ontology. In Proceedings of the 17th International Conference on World Wide Web, WWW 2008, Beijing, China, April 21-25, 2008, pages 635–644.

[Xu et al.2015] Yan Xu, Lili Mou, Ge Li, Yunchuan Chen, Hao Peng, and Zhi Jin. 2015. Classifying relations via long short term memory networks along shortest dependency paths. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015, pages 1785–1794.