

# Relation Extraction

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## Abstract

TODO

## 1 Problem Statement

Knowledge base population (KBP) is the task of converting information conveyed in natural language into a structured representation, such as a knowledge base (KB) consisting of keys and values. By removing the noise inherent in natural language, KBP systems produce information in a representation that is amenable to computation.

We extend the population task to both filling in the values of a KB as well as providing a justification or ‘rationale’ for the values. We use these rationales to bias the model away from relying on spurious correlations that may hurt generalization, and provide human-checkable predictions.

However, deciding what constitutes a rationale and obtaining supervision for that specific definition is expensive. For every definition, supervision must be obtained by having annotators consider many KB and text pairs. This prevents one from iterating quickly in the space of rationale designs. We therefore propose a definition of a rationale and accompanying model that is able to produce rationales without supervision.

The problem description is as follows: Given a text  $x = x_1, \dots, x_I$  of length  $I$  and the keys of an aligned KB  $k = \{k_j\}_{j=1}^J$ , we model the values  $v = \{v_j\}_{j=1}^J$ . Each  $(k_j, v_j)$  pair is referred to as a record. We must additionally produce a rationale for each record.

Consider the following example: Let our KB consist of information about a basketball game,

$$k = \left\{ \begin{array}{l} (\text{John Doe, POINTS}), \\ (\text{John Doe, REBOUNDS}), \\ (\text{John Doe, FIRST\_NAME}), \\ (\text{John Doe, LAST\_NAME}), \\ \vdots \end{array} \right\}, v = \left\{ \begin{array}{l} 8, \\ 12, \\ \text{'John'}, \\ \text{'Doe'}, \\ \vdots \end{array} \right\}$$

aligned to the summary  $x = \text{'John Doe scored eight points'}$ . We identify the value mention ‘**eight**’ as the mention of the record  $(k_1, v_1)$ . The record  $(k_2, v_2)$  is not mentioned in the text.

## 1.1 Model

We choose our definition of a rationale: A value for a specific key must be accompanied by the position of its mention in the text. Additionally, a value not supported by a value mention in the text must also be made explicit.

To satisfy this definition of a rationale, we model the values in the KB with an extract-then-aggregate process. Our model first makes extractions for each word, then aggregates the word-level choices in order to resolve possible conflicts.

For every word in the text, the word-level extraction model chooses whether that word is a value mention, what key the value mention aligns to, and finally what value the mention corresponds to. We introduce the following latent variables in the extraction model:

- $m = m_1, \dots, m_I$  where each  $m_i \in \{0, 1\}$  indicates whether word  $x_i$  is part of a value mention. We aim to identify at least one word in a multiword mention.
- $a = a_1, \dots, a_I$  where each  $a_i \in \{1, \dots, J\} \cup \{\text{None}\}$  indicates that word  $x_i$  mentions the record  $(k_{a_i}, v_{a_i})$ .
- $z = z_1, \dots, z_I$  where each  $z_i \in \mathcal{V} \cup \{\text{None}\}$  translates the value mention containing word  $x_i$  into the canonical representation of the value as determined by the schema of the KB. For example, the KB may only store numbers in numerical form, as opposed to alphabetical.

Our extract-then-aggregate model specifies the joint distribution over the values  $v$  and latent variables  $z, a, m$  given the text  $x$  and keys  $k$ :

$$\begin{aligned}
 & p(v, z, a, m \mid x, k) \\
 &= p(v \mid z, a, m, x, k) p(z, a, m \mid x, k) \\
 &= \left( \prod_{j=1}^J \underbrace{p(v_j \mid z, a, m, x, k)}_{\text{Aggregation}} \right) \underbrace{\left( \prod_{i=1}^I \underbrace{p(z_i \mid m_i, x)}_{\text{Translation}} \underbrace{p(a_i \mid m_i, x, k)}_{\text{Alignment}} \underbrace{p(m_i \mid x)}_{\text{Identification}} \right)}_{\text{Extraction}} \quad (1)
 \end{aligned}$$

The extraction model has three components. The model must identify whether word  $x_i$  is a mention using the *identification* model  $p(m_i \mid x)$ , align word  $x_i$  to a key  $k_{a_i}$  via the *alignment* model  $p(a_i \mid m_i, x, k)$ , and translate the word  $x_i$  into a value  $z_i$  with the *translation* model  $p(z_i \mid m_i, x)$ .

This model assumes that each word  $x_i$  can explain at most one record in the KB. Additionally, we make the simplifying assumption that a value mention’s translation is unambiguous and independent from the alignment to a key.

It is possible for there to be conflicts in the word-level extraction model if two words are mentions with the same alignment but different values. The aggregation model  $p(v_j \mid z, a, m, x, k)$  is necessary to resolve these conflicts, and uses the per-word latent variables  $z_i, a_i, m_i$  to predict the values of the KB.

We give the parameterizations of all conditional distributions in the following section.

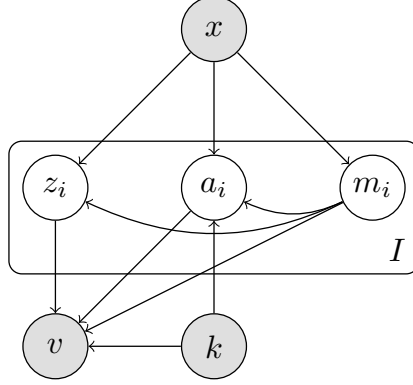


Figure 1: Our model predicts word-level values and alignments then aggregates those choices over all indices  $i$  to make a single decision for each value. Each word has the following latent variables: the mention  $m_i \in \{0, 1\}$  indicates whether word  $x_i$  is a value mention, the alignment  $a_i$  gives the key  $k_{a_i}$  that  $x_i$  aligns to, and the value  $z_i$  gives the canonical value that  $x_i$  translates to.

## 1.2 Parameterization

Let  $\mathbf{h}_i \in \mathbb{R}^d$  be a contextual embedding of the word  $x_i$ , and  $E$  an embedding function that maps keys  $k$  to vectors in  $\mathbb{R}^d$ .

1. Identification: We use the contextual embedding to predict whether a word  $x_i$  is part of a value mention.

$$p(m_i | x) \propto \exp(W_m \mathbf{h}_i)_{m_i}, \quad (2)$$

with  $W_m \in \mathbb{R}^{2 \times d}$ .

2. Alignment: We use a bilinear function of the cell embeddings and contextual embeddings to parameterize the alignment distribution. We align  $a_i = \text{None}$  if a word is not a mention.

$$\begin{aligned} p(a_i | m_i = 1, x, k) &\propto \exp(E(k_{a_i})^T W_a \mathbf{h}_i) \\ p(a_i = \text{None} | m_i = 0, x, k) &= 1 \end{aligned} \quad (3)$$

with  $W_a \in \mathbb{R}^{d \times d}$ .

3. Translation: We use the contextual embedding to translate a word into a value. If a word is chosen not to be a mention such that  $m_i = 0$ , we set  $z_i = \text{None}$ .

$$\begin{aligned} p(z_i | m_i = 1, x) &\propto \exp(W_z \mathbf{h}_i)_{z_i} \\ p(z_i = \text{None} | m_i = 0, x) &= 1 \end{aligned} \quad (4)$$

with  $W_z \in \mathbb{R}^{|\mathcal{V}| \times d}$ .

4. Aggregation: We choose the value associated with a particular key in the KB by first using the translated values of any mentions aligned to the corresponding key. If no mention is aligned to the key, we choose the value given only the key.

Formally, the conditional distribution is given by

$$p(v_j \mid z, a, m, k) \propto \begin{cases} \prod_i \exp(\psi(v_j, z_i, a_i, m_i)), & \exists i, m_i = 1 \wedge a_i = j \\ \exp(E(v_j)^T W_v [E(k_j)]), & \text{otherwise} \end{cases} \quad (5)$$

$$\psi(v_j, z_i, a_i, m_i) = \mathbf{1}(v_j = z_i, a_i = j, m_i = 1) \quad (6)$$

with  $W_v \in \mathbb{R}^{d \times d}$ .

## 2 Training and Inference

We would like to optimize the marginal likelihood of the values  $v$  given the text  $x$  and keys  $k$ :

$$\log p(v \mid x, k) = \log \sum_{z, a, m} p(v, z, a, m \mid x, k) \quad (7)$$

However, maximizing  $\log p(v \mid x, k)$  directly is very expensive as the summation over variables  $z, a, m$  is intractable; in particular, the summation has computational complexity  $O((|\mathcal{V}| \cdot J)^I)$ . We therefore resort to approximate inference, specifically amortized variational inference.

### 2.1 Inference Network

We introduce an inference network  $q(z, a, m \mid v, x, k)$  and optimize the following lower bound on the marginal likelihood with respect to the parameters of both  $p$  and  $q$ :

$$\log p(v \mid x, k) \geq \mathbb{E}_{q(z, a, m \mid v, x, k)} \left[ \log \frac{p(v, z, a, m \mid x, k)}{q(z, a, m \mid v, x, k)} \right] \quad (8)$$

The joint distribution of  $q(z, a, m \mid v, x, k)$  in the inference network is given by

$$q(z, a, m \mid v, x, k) = \prod_i \underbrace{q(z_i \mid a, v, x)}_{\text{Translation}} \underbrace{q(a_i \mid v, x, k)}_{\text{Alignment}} \underbrace{q(m_i \mid v, x)}_{\text{Identification}} \quad (9)$$

In the inference network, we use the contextual embedding  $\mathbf{h}_i \in \mathbb{R}^d$  of the word  $x_i$  and extend the embedding function  $E$  to embed not only keys but also values in  $\mathbb{R}^d$ . We introduce the following attention weights over records in order to get a weighted representation of the KB for each word  $x_i$ :

$$\begin{aligned} \mathbf{g}_j &= [E(k_j); E(v_j)] \\ \alpha_{ij} &\propto \exp(\mathbf{g}_j^T W_\alpha \mathbf{h}_i) \end{aligned} \quad (10)$$

with  $W_\alpha \in \mathbb{R}^{2d \times d}$ .

We propose to parameterize the inference network  $q(z, a, m \mid v, x, k)$  as follows:

1. Identification: To predict whether  $x_i$  is a mention, the inference network uses the weighted representation of the KB  $\alpha$  along with the contextual representation  $\mathbf{h}_i$

$$p(m_i \mid v, x) \propto \exp \left( V_m \text{MLP} \left( \left[ \sum_j \alpha_{ij} \cdot \mathbf{g}_j; \mathbf{h}_i \right] \right) \right)_{m_i} \quad (11)$$

where MLP is a neural network and  $V_m \in \mathbb{R}^{2 \times d}$ .

2. Alignment: The alignment model uses the attention weights in Eqn. 10:  $q(a_i = j \mid v, x, k) = \alpha_{ij}$ .
3. Translation: The translation model  $q(z_i \mid a_i, v, x) = \mathbf{1}(z_i = v_{a_i})$  conditions on the alignment  $a_i$  and ensures the translated value  $z_i$  is consistent with the alignment.

We optimize the objective in Eqn. 9 with respect to both the extraction model  $p$  and the inference network  $q$  via gradient ascent using the score function gradient estimator. We utilize a leave-one-out baseline for variance reduction.

(Under consideration, could hopefully remove pretraining by parameterizing translation model using local features such as embedding or conv, but previous experiments on this front were negative) As our model is highly unidentifiable, we bias our extraction model by pretraining  $p(z_i \mid x)$  on lexical match.

### 3 Evaluation

We evaluate whether the model can discover and locate the subset of records in a KB that are expressed in the text without observing the values of the KB. We compare the extractions of our model with a ground truth set of records, reporting the micro-averaged precision, recall, and F1 score.

We perform extraction by finding

$$\arg \max_{z, a, m} p(z, a, m \mid x, k).$$

We obtain the record  $(k_j, v_j)$  at word  $x_i$  if  $m_i = 1$ ,  $a_i = j$  and  $z_i = v_j$ .