Information Extraction with Weak Supervision

Keywords information networks, natural language processing, information extraction, latent variable models

Relevance to BAA As information networks get larger and more complex, acquiring explicit supervision for the training of information extraction systems becomes extremely expensive. Information networks are also dynamic; over time one method for representing information may become inadequate. Currently, both the representation of the information in a knowledge base as well as the extraction process itself must be hand-designed. In this proposal we present a framework towards automating the training of information extraction systems with minimal supervision.

Introduction Natural language processing contains two separate but closely related subfields: natural language understanding (NLU) and natural language generation (NLG). Recent approaches to information extraction use only the NLU perspective and frame extraction as a classification problem. We argue that the two perspectives, NLU and NLG, are complementary and capitalize on their duality by proposing a method to train a NLU system without direct supervision. More specifically, we train an information extraction system by using the performance of a deep generative model as signal. By training in this fashion we obtain an information extraction system that extracts facts that best explain the given text.

Recent work using neural network-based systems cast information extraction as a supervised problem [2, 6]. Although approaches do incorporate structure into internal representations, for example to integrate multiple sources of information [4], the final output still uses strong supervision during training. Finding strong supervision is a difficult task, and as datasets get larger we must approach information extraction from a different perspective. Latent variable models (LVMs) are one method for alleviating the need for supervision. LVMs do not require manual labels, as they instead treat quantities of interest as latent random variables and deal with them in a probabilistically principled fashion. We will leverage recent advances in deep generative modeling in order to train without explicit supervision.

Neural models for language generation have seen much progress in recent years, with state of the art performance in both language modeling and translation [**?**] (MoS + Transformer). By integrating the powerful language modeling capabilities of neural networks with the inductive biases of graphical models through LVMs, we can leverage the LVM framework to derive a principled method for training an information extraction system with less supervision. Namely, we turn to an efficient technique for training hard attention that relies on variational inference [1]. This technique is applicable to sequential LVMs such as hidden Markov models and hidden semi-Markov models (HSMMs). HSMMs have been applied to small scale datasets for text generation [5] as well as without integrating neural networks [3]. We will scale sequential LVMs to large datasets through variational inference and use the signal from our generative model in order to train an information extraction system.

Background We consider datasets consisting of aligned data and text $\left\{(\mathbf{r}^{(1)}, \mathbf{y}^{(1)}), (\mathbf{r}^{(2)}, \mathbf{y}^{(2)}) \dots\right\}$. For brevity, we refer to a single datum and text as $\mathbf{r}, \mathbf{y}$, omitting the superscript. Each datum $\mathbf{r} = \{r_1, \dots, r_N\}$ is a set of N records, each of which has an entity, type, and value $r_i = (e_i, t_i, v_i)$. The datum $\mathbf{r}$ is a flattened representation of an information network. Whereas an information network may also be represented as a hypergraph, $\mathbf{r}$ is a list of relations or records. We refer collectively to all the entities, types, and values in a given datum $\mathbf{r}$ as $\mathbf{e}, \mathbf{t}, \mathbf{v}$ respectively. Each text $\mathbf{y} = \{y_1, \dots, y_T\}$ is a sequence of tokens.

Let random variables $\mathbf{z}$ be unobserved or latent, $\mathbf{y}$ observed, and $\mathbf{x}$ taken as conditioning and thus not modelled. For information extraction we are interested in distributions $p(\mathbf{z} \mid \mathbf{y}, \mathbf{x})$, where $\mathbf{z}$ and $\mathbf{x}$ may correspond to various quantities depending on the task but $\mathbf{y}$ is always the text.

As a concrete example, we use the Rotowire dataset [6]. Rotowire contains summaries of basketball games $\mathbf{y}$ aligned with the respective box scores $\mathbf{r}$ of those games. Consider a datum that consists of a single record, $\mathbf{r} = \{(e_1 = \text{Jeremy Lin}, t_1 = \text{POINTS}, v_1 = 19)\}$, and a simple statement $\mathbf{y} =$"Jeremy Lin scored 19 points". In a simple case, the process of information extraction may be to infer any subset of $\mathbf{r}$, which in this case will be our latent $\mathbf{z}$, given the remaining elements in $\mathbf{r}$ which corresponds to $\mathbf{x}$, as well as the text $\mathbf{y}$. For example, we may want to infer the type of the relation t given the entity Jeremy Lin, the value 19, as well as the text $\mathbf{y}$. In this case, we would have $\mathbf{z} = \{t_1\}$ and $\mathbf{x} = \{e_1, v_1\}$. In an alternative task, we may want to infer the value v_1 as well as the type t_1 given $\mathbf{y}$ and e_1, therefore $\mathbf{z} = \{t_1, v_1\}$ and $\mathbf{x} = \{e_1\}$. (Will switch to ACE dataset after I figure out what's going on with the data.)

Note that we are not constrained to setting $\mathbf{z}$ to subsets of $\mathbf{r}$. We also consider the case where $\mathbf{z}$ includes alignments from individual words y_t to records r_i. We denote the alignments $\mathbf{a} = \{a_1, \dots, a_T\}$, where each a_t is associated with y_t and selects a record r_i such that $a_t = i$.

Proposal We propose to demonstrate the efficacy of the LVM framework in the weakly supervised information extraction setting. We do so by estimating the distribution over alignments and values given the text, entities, and types. This is denoted by $p(\mathbf{z} \mid \mathbf{y}, \mathbf{x})$, where $\mathbf{z} = \{\mathbf{a}, \mathbf{v}\}$ and $\mathbf{x} = \{\mathbf{e}, \mathbf{t}\}$. In the previous section, we defined $\mathbf{a}$ to be a latent variable that represents the alignments from words to records, while $\mathbf{v}$ corresponds to all the values in a datum of records and $\mathbf{e}, \mathbf{t}$ the entities and types respectively. This distribution $p(\mathbf{z} \mid \mathbf{y}, \mathbf{x})$ is the IE system, which infers the alignments and values given the text, entities, and types.

Since we do not assume that we have supervision for $\mathbf{z}$, we cannot learn the information extraction system directly. Insead, we must learn a conditional model of the text and latent variables given the conditioning $p(\mathbf{y}, \mathbf{z} \mid \mathbf{x})$ since we observe $\mathbf{y}$. We will subsequently show how to use this conditional model to train the IE system. We define the conditional model with the following generative story:

1. Value Choice: For each pair of entities and types in our datum of records, we predict a value.
2. Record Choice: Conditioned on our choices of values as well as the given entities and records, we choose a sequence of records $\mathbf{a} = \{a_1, \dots, a_I\}$, denoted by their indices, to describe.
3. Word Choice: For each record alignment a_i, we choose a sequence of words $\mathbf{y}_i = \{y_{i1}, \dots, y_{iJ}\}$ to describe the record.

Outline

1. Introduction
   (a) Relevance to BAA
      i. What are information networks? Characterized by large graphs and voluminous data.
      ii. Representation is key
      iii. Supervision is expensive.
      iv. Information networks are also dynamic; over time one method for representing information may become inadequate.
      v. Currently, both the representation of the information in a knowledge base as well as the extraction process itself must be hand-designed.
      vi. In this proposal we present a framework towards automating the training of information extraction systems with minimal supervision.
   (b) Decomposition of NLP into NLU and NLG
      i. Two separate but closely related subfields: natural language understanding (NLU) and natural language generation (NLG).
      ii. Recent approaches to information extraction use only the NLU perspective and frame extraction as a classification problem.
      iii. We argue that the two tasks are complementary, and capitalize on their duality by proposing a method to train a NLU system without direct supervision.
   (c) Supervision in NLU
      i. Recent work using neural network-based systems cast information extraction as a supervised problem [2, 6].
      ii. Even with structured representations [4], the final output is still supervised.
      iii. Again, supervision does not scale.
      iv. Maybe dynamism of information networks? Don't have an argument on hand, though.
      v. Latent variable models (LVMs) are one method for alleviating the need for supervision.
      vi. LVMs do not require manual labels, as they instead treat quantities of interest as latent random variables and deal with them in a probabilistically principled fashion.
   (d) Recent advances in NLG
      i. Deep generative models, namely LVMs with neural network components, have integrated the flexibility of neural networks with the inductive biases of graphical models.
      ii. Most importantly, efficient techniques for training hard attention that rely on variational inference [1]. This technique is applicable to sequential LVMs such as hidden Markov models and hidden semi-Markov models (HSMMs).
      iii. HSMMs have been applied to small scale datasets for text generation [5] as well as without integrating neural networks [3].
2. Background

   (a) Formal notation for elements of the dataset
   (b) Define the distribution we would like to learn: $p(z \mid y, x)$. z and x are placeholders and will change, but y is always the text.
   (c) Link to rotowire example (argument is that ACE is made up of ontonotes-like sentences, so all short-form)

3. Proposal
   (a) Define IE as the distribution we would like to learn
      i. Values: $p(c, \mathbf{v} \mid \mathbf{y}, \mathbf{e}, \mathbf{t})$ (Just this one)
   (b) Define generative model: HSMM as in [3], and [5]. The generative story:
      i. Fill in values
      ii. Choose alignments
      iii. Choose words
   (c) Either use the posterior of this model directly, perform inference compilation, or train with approximate posterior.
   (d) Training and Inference
      i. Maximize ELBO
   (e) Experiments
      i.
   (f) Conclusion
      i.

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