Latent Constituents via Self-Attention

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1 Introduction

2 Problem

We would like to learn a generative model over source sentences $\mathbf{x} = \{x_0, x_1, \ldots\}$, using a distribution over latent trees $\mathbf{z}$. We are primarily interested in the posterior distribution over trees given a sentence, $p(\mathbf{z} \mid \mathbf{x})$. The performance of the generative model is secondary since we would like to analyze the output of the unsupervised model for any linguistic regularities, and use the model as a testbed for linguistic hypotheses (of which I have none at the moment).

(Shen et al., 2018) Yin et al. (2018)

3 PRPN (Shen et al., 2018)

The Parsing-Reading-Predict Network (Shen et al., 2018) is an approach to unsupervised tree induction that uses a soft approximation to a latent variable to a degree of success. The paper is inspired by the following hypothesis: given a binary tree, a token at index t only requires information up to index l_t that satisfies either of the following conditions:

(a) the token at l_t is the leftmost sibling of the token at t

(b) or, if the token at t is a leftmost child, l_t points to its parent's left sibling's leftmost child.

Although the hypothesis itself is not tested in the implementation and serves only as inspiration, the model does see empirical success in the task of language modeling. The model is realized through the following insight: given a ranking of tokens $\mathbf{x} = \{x_0, \ldots, x_T\}$, recursively splitting $\mathbf{x}$ using the following procedure induces a binary tree where the first token to the left of token x_t that has higher rank, denoted x_{l_t}, also satisfies condition (a) or (b): given token i with the next highest rank, create a subtree $(x_{<i}, (x_i, x_{>i}))$ and recursively perform this procedure until only terminal nodes remain.

3.1 Ranking Models

Before discussing the Shen et al. (2018) model, we first introduce two possible ranking models, where both assign each item a latent score:

1. Plackett-Luce / Thurstone: There is a hidden score assigned to every item. The ith ranking item is chosen from a categorical distribution parameterized by the output of a softmax over the remaining item's scores.

2. Pairwise Comparison Model (Bradley-Terry): The same as PL, but samples pairwise comparisons from a bernoulli distribution using the item's scores.

One could use the Bradley-Terry (pairwise) model of ranking for training and language modeling, but then switch to the Plackett-Luce model at test time for outputting parse trees. A soft pairwise model is used because it does not rely on future information and thus is easy to train as a language model. Once the scoring model is trained, we could use those scores to parameterize a global PL/Thurstone model.

However, Shen et al. (2018) decide to instead model as a RV the index l_t (at every timestep) instead of the pairwise comparisons. We will get into to the details of their choices in section 3.2.3.

3.2 Their Model

Let x_t be the current token, $\mathbf{x}_{0:t-1}$ all previous tokens, z_t the prediction for the current score, and $\tilde{\mathbf{z}}_{0:t-1} \in \mathbb{R}_+^{t-1}$ be all previous scores. The model takes the form a language model, where the distribution over the next token

$$p(x_t \mid \mathbf{x}_{0:t-1}, \tilde{\mathbf{z}}_{0:t-1}, z_t) = f([h_{l_t:t-1}, h_t])$$

is parameterized by either a linear projection or additional residual blocks applied to a concatenation of the output of modified LSTMN (LSTM Memory-Network) h_t and a convex combination of the previous LSTMN outputs (i.e. attention over $h_{l_t:t-1}$). f is referred to as the Predict Network.

3.2.1 LSTMN

The LSTMN, referred to as the Reading Network, is as follows: at each time step, the hidden and cell input are given by

$$\{\tilde{h}_t, \tilde{c}_t\} = \sum_{i=1}^{t-1} s_i^t \{h_i, c_i\},$$

a convex combination of the previous hidden and cell outputs. Then

$$h_t, c_t = \texttt{LSTM}(\tilde{h}_t, \tilde{c}_t).$$

The attention is computed in the same way as detailed in section 3.2.2. The input to the LSTMN module is either the previous token or the output of a previous LSTMN layer.

3.2.2 Attention

As all attention modules in the PRPN network use the same formulation of attention we will use y_t to refer to the input of the attention module, $\boldsymbol{g}_t(l_t)$ the gate coefficients which are a function of the RV l_t, $\boldsymbol{m}_t$ as the memories to attend over, and $\boldsymbol{s}_t$ as the attention coefficients. The RV l_t corresponds to the index of the token that satisfies condition (a) or (b). First the key is computed using a linear projection of the input $k_t = W_k y_t$. Then the intermediate scores are computed

$$\tilde{s}_t^i = \text{softmax}\left(\frac{m_t^i k_t^T}{\sqrt{\delta_k}}\right),$$

where δ_k is the dimension of the hidden state. Finally, the gate coefficients are normalized and used to prevent the attention from extending too far in the past.

$$s_t^i = \frac{g_t^i(l_t)}{\sum_j g_t^j(l_t)} \tilde{s}_t^i,$$

where the gate coefficients $\boldsymbol{g}_t(l_t)$ are detailed in section 3.2.3.

3.2.3 Gating Self-attention

Recall that the gates g_t^i also indirectly induce tree structure (due to the previously stated insight that modulating self-attention using a ranking induces a binary tree). At every timestep for token x_t, Shen et al. (2018) define a latent variable l_t which corresponds to the index of the token satisfying either condition (a) or (b).

We then would have

$$g_t^i(l_t) = \mathbf{1}(l_t \leq i < t)$$

where we allow the model at timestep t to only attend up to the token at leftmost limit l_t. We would then renormalize the attention accordingly. In order to calculate the gates $g_t^i(l_t)$ we must model $p(l_t \mid \mathbf{x}_{0:t})$

(Shen et al. (2018) use the posterior distribution in their notation). They propose to model

$$p(l_t = i \mid \mathbf{x}_{0:t-1}) = (1 - \alpha_i^t) \prod_{j=i+1}^{t-1} \alpha_j^t$$

using a stick-breaking process (GEM). The reason this is preferred over a simple categorical distribution over indices is because of the parameterization of the model. Although unlikely, a bimodal distribution is possible with a categorical distribution. I believe it would be possible to reparameterize the model and constrain the parameterization of a categorical distribution to achieve a similar effect.

Note that this itself is not a Dirichlet Process, as there is no base measure H_0. In a $DP(\alpha, H_0)$ we have $\pi \sim GEM(\alpha)$, where $b_i \sim Beta(1, \alpha)$ and $\pi_i = (1 - b_i) \prod_{j=0}^{i-1} b_j$. We then have $\theta_i \sim H_0$ and $G = \sum_i \pi_i \delta_{\theta_i} \sim DP(\alpha, H_0)$. In the appendix of Shen et al. (2018) the say they use a Dirichlet process to model $p(l_t)$, however this is not the case. Another indication that they are not truly using a Dirichlet Process is the fact that the only way $p(l_t) = DP$ is if the base distribution is Dirichlet as well. This seems complicated and would definitely warrant further explanation.

Rather than resorting to approximate inference, they instead use the expected value of g_i^t

$$\mathbb{E}\left[g_i^t(l_t)\right] = F_{l_t}(l_t \leq i \mid \mathbf{x}_{0:t-1}) = \prod_{j=i+1}^{t-1} \alpha_j^t.$$

The $\alpha_j^t = \sigma(d_t - d_j)$, where σ is the hard sigmoid function. This is not stated in the paper (there are a couple off-by-one) errors, but it must be that $g_{t-1}^t = 1$. The $d_j \in \mathbb{R}_+$ are given by a CNN over the token embeddings.

The network used to compute the gates is called the Parsing Network. When computing $p(x_t \mid \ldots)$, we cannot use the posterior score d_t, so an estimate is used based on the previous k words, where k is the kernel width of the convolution. However, afterwards Shen et al. (2018) use the posterior score $d_i \mid x_{i-K}, \ldots, x_i$ for all d_i when $i < t$.

4 Training

With the model that uses the expectation of $g_i^t(l_t)$ training is very simple. We simply maximize the likelihood of the data directly since the model has no sampling.

5 Results

The language modeling results are nothing special, but the results on unsupervised parsing are interesting.

6 Related Work

7 Alternative Latent Ranking Model

7.1 Generative Model

PRPN (Shen et al., 2018) choose to view l_t as a latent variable. There are at least a few other choices:

- Model the scores $d_t \sim \mathcal{N}(\mu_t, \sigma_t)$ or $d_t \sim$ Gamma and use the Plackett-Luce ranking distribution.

- Model the comparisons $p(d_t < d_i)$ as order statistics of Gammas.

- Model the permutation matrix $Z \sim \mathcal{B}_n$.

- Model $l_t \sim$ Cat.

Parameterize with $d_t \sim \mathcal{N}(\mu_t, \sigma_t)$. Reparameterize comparisons with gumbel softmax? Leave all self attentions as is?

- $p(z)$

- $p(x|z)$

8 Training and Inference

for next time, convince Sasha of why this is interesting. Also go over stick breaking process.

References

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