Abstract

Methods for learning word sense embeddings represent a single word with multiple sense-specific vectors. These methods should not only produce interpretable sense embeddings, but should also learn how to select which sense to use in a given context. We propose an unsupervised model that learns sense embeddings using a modified Gumbel softmax function, which allows for differentiable discrete sense selection. Our model produces sense embeddings that are competitive (and sometimes state of the art) on multiple similarity based downstream evaluations. However, performance on these downstream evaluations tasks does not correlate with interpretability of sense embeddings, as we discover through an interpretability comparison with competing multi-sense embeddings. While many previous approaches perform well on downstream evaluations, they do not produce interpretable embeddings and learn duplicated sense groups; our method achieves the best of both worlds.

1 Introduction

Many machine learning models for natural language processing applications represent words with embeddings, which are vectors of real-valued numbers. Popular word embedding models such as Word2Vec (Mikolov et al., 2013a,b) and GloVe (Pennington et al., 2014) have been instrumental in achieving state-of-the-art results on many NLP tasks, such as sentiment analysis (Kim, 2014; Tai et al., 2015) and textual entailment (Parikh et al., 2016; Chen et al., 2017).

Despite their success, word embeddings are not perfect, particularly for polysemous words (those with multiple senses). For example, Word2Vec and GloVe learn a single embedding for each type, which in the case of polysemous words conflates many different and possibly unrelated meanings (e.g., “I squashed the bug with my shoe” vs. “I fixed the bug in my code”). To overcome this limitation and learn finer grained semantic clusters in the embedding space, word sense embedding models (Section 7) learn multiple representations for polysemous words, each corresponding to a specific meaning.

Unsupervised word sense embedding models have two key functions: (1) automatically inducing word senses from unlabeled data, and (2) learning sense-specific representations associated with the inferred sense. In this paper, we jointly learn both functions with an efficient, fully-differentiable model that obtains strong results on downstream tasks while also maintaining interpretability.

Our approach differs from prior work in that it implements discrete sense selection using differentiable hard attention. Existing discrete methods suffer from non-differentiability due to sense sampling (Huang et al., 2012; Tian et al., 2014; Neelakantan et al., 2014; Qiu et al., 2011), which results in inefficient training and implementational complexity. On the other hand, soft selection with regularization methods (Šuster et al., 2016) are unable to fully focus on one sense at a time during the training. Closest to our own method, Lee and Chen (2017) implement discrete sense selection with hard attention through reinforcement learning; however, crowdsourced interpretability evaluations reveal that their reinforcement learning approach does not actually learn distinct sense embeddings.

Concretely, we propose a fully-differentiable multi-sense extension of the Word2Vec skip-gram model (Section 2) that approximates discrete sense selection with a scaled variant of the Gumbel softmax function (Section 3). After qualitatively in-
specting the nearest neighbors of competing approaches, we conclude that downstream task performance does not adequately measure a model’s ability to discover word senses, which motivates a human evaluation. Our model outperforms baseline systems on both types of evaluations (Section 5); the proposed Gumbel softmax variant is critical for balancing downstream performance with embedding interpretability.

2 Background: Word2Vec

Our sense embedding model extends the canonical Skip-Gram Word2Vec model with negative sampling (Mikolov et al., 2013a,b). In this section, we provide a brief overview.

Word2Vec learns two sets of parameters, a word embedding matrix $W \in \mathbb{R}^{V \times d}$ and a context embedding matrix $C \in \mathbb{R}^{V \times d}$, where $V$ represents the vocabulary and $d$ is the dimension of embedding space. Both embeddings, $W$ and $C$, are learned by maximizing the probability of the context words $w_{c_i}$ that surround a given pivot word $w_i$ in a context $\tilde{c}_i$.

$$J(W, C) \propto \sum_{w_i \in V} \sum_{w_{c_i} \in \tilde{c}_i} \log P(w_{c_i} \mid w_i; W, C).$$

(1)

In practice, $P(w_{c_i} \mid w_i)$ is usually approximated using negative sampling (as opposed to computing a softmax over the vocabulary), which greatly accelerates training.

**Multi-sense variants** Equation 1 conflates all senses of a word into a single embedding. To address this problem, previous works modifies Word2Vec to learn multiple sense-specific embedding per word. This sense induction component can be implemented by clustering context vectors (Neelakantan et al., 2014) or by probabilistically modeling the contextual sense induction distribution directly (Li and Jurafsky, 2015; Šuster et al., 2016; Lee and Chen, 2017). See Section 7 for more details.

3 Gumbel-Attention Sense Induction (GASI)

In contrast to previous work, our model discretely selects senses while retaining full differentiability. Lee and Chen (2017) show that non-differentiable discrete sense selection significantly outperforms all other methods on sense similarity related downstream tasks; however, it also

Figure 1: Overview of GASI model. Given a pivot word (bond) and some context words (in blue), we first select which of the pivot word’s sense embeddings to use given the context via the scaled Gumbel softmax. Then, we follow the standard skip-gram objective with negative sampling to update the pivot and context embeddings. does not learn interpretable sense embeddings for most words (Section 5). The sense embeddings learned by our model are more interpretable than prior approaches while also outperforming non-differentiable hard attention on downstream evaluations.

Here, we first provide an overview of our sense embedding framework and training objective, which can be instantiated with either soft or discrete sense selection. We then describe our discrete version, Gumbel Attention Sense Induction (GASI), which approximates hard attention over sense embeddings with a scaled Gumbel softmax function.

3.1 Attentional Sense Induction

Like Word2Vec, we jointly learn two sets of parameters: the same context embedding matrix $C \in \mathbb{R}^{V \times d}$, as before, and a sense embedding tensor $S \in \mathbb{R}^{V \times k \times d}$. Unlike previous approaches that maintain extra parameters for sense induction (Neelakantan et al., 2014; Lee and Chen, 2017), we infer the sense disambiguation distribution using only the embedding parameters. Each word is initialized with $K$ sense embeddings; after training, we perform a pruning post-processing step to remove duplicate and unused senses (Section 4.1).

Assuming pivot word $w_i$ has senses $\{s^i_1, s^i_2, \ldots, s^i_K\}$, we expand the co-occurrence

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1 Following previous work (Neelakantan et al., 2014; Li and Jurafsky, 2015), we do not consider senses of context words.
probability of $w_c$ given $w_i$ and local context $\tilde{c}_i$

$$P(w_{c_j} | w_i, \tilde{c}_i) = \sum_{k=1}^{K} P(w_{c_j} | s_k^j) P(s_k^j | w_i, \tilde{c}_i),$$

(2)

where $P(s_k^j | w_i, \tilde{c}_i)$ is computed through an attentional sense selection mechanism.

We use $s_k^j$ to represent the embedding for pivot sense $s_k^j$ from the sense embedding tensor $S$, and $c_j$ for the global embedding of context word $w_{c_j} \in \tilde{c}_i$. Replacing $P(w_c | w_p)$ in Equation 1 with the sense expansion in Equation 2 gives

$$\frac{1}{|V|} \sum_{w_i \in V} \sum_{w_{c_j} \in \tilde{c}_i} \log \sum_{k=1}^{K} P(w_{c_j} | s_k^j) P(s_k^j | w_i, \tilde{c}_i).$$

(3)

The second term (the contextual sense induction distribution) is conditioned on the entire local context $\tilde{c}_i$. We can implement a baseline soft attention sense induction (SASI) model by computing this distribution with a softmax:

$$P(s_k^j | w_i, \tilde{c}_i) = \frac{\exp(\bar{c}_i^\top s_k^j)}{\sum_{m=1}^{K} \exp(\bar{c}_i^\top s_m^j)},$$

(4)

where $\bar{c}_i$ is the mean of the context vectors in $\tilde{c}_i$.

**Augmenting the Objective for Negative Sampling:** For modeling the probability of the context given the pivot word, $P(w_{c_j} | s_k^j)$, similar to its analogous term in Word2Vec, i.e., the probability of the context given the pivot word $P(w_{c_j} | w_i)$, we use the softmax function to compute this term,

$$P(w_{c_j} | s_k^j) = \frac{\exp(c_j^\top s_k^j)}{\sum_{j=1}^{|V|} \exp(c_j^\top s_k^j)}$$

(5)

Computing the softmax over the whole vocabulary is extremely time-consuming. We want to adopt the negative sampling methods to approximate the logarithm of the softmax function. However, our model includes the sense induction term in Equation 3 that marginalizes over possible senses inside the logarithm function, and $\log P(w_{c_j} | s_k^j)$ doesn’t exist explicitly in our objective function.

However, given the concavity of the logarithm function, we can apply Jensen’s inequality,

$$\log \sum_{k=1}^{K} P(w_c | s_k^j)P(s_k^j | w_i, \tilde{c}_i) \geq \sum_{k=1}^{K} P(s_k^j | w_i, \tilde{c}_i) \log P(w_c | s_k^j),$$

(6)

to create a lower bound of the objective. Just as in variational inference (Jordan et al., 1999), maximizing this approximation gives us a tractable objective that we can optimize. The new objective function $J_{atr}(S, C)$ then becomes

$$\frac{1}{|V|} \sum_{w_i \in V} \sum_{w_{c_j} \in \tilde{c}_i} \sum_{k=1}^{K} P(s_k^j | w_i, \tilde{c}_i) \log P(w_c | s_k^j).$$

(7)

where $P(s_k^j | w_i, \tilde{c}_i)$ is estimated by Equation 7 and $\log P(w_c | s_k^j)$ is estimated by the negative sampling term,

$$\log \sigma(c_j^\top s_k^j) + \sum_{j=1}^{n} \mathbb{E}_{w_i \sim P_n(w)}[\log \sigma(-c_j^\top s_k^j)],$$

(8)

where $P_n(w)$ is the negative sampling distribution and $n$ is the number of negative samples drawn for each context-pivot pair.

### 3.2 Differentiable Discrete Sense Selection with Scaled Gumbel Softmax

In language, senses are not softly selected: with the exception of innuendo and jokes, most sentences use a single, discrete sense per word. Therefore, it is better to exploit each sense and captures as much semantic information as possible for each sense-specific embedding. In practice, most previous approaches (Neelakantan et al., 2014; Li and Jurafsky, 2015; Qiu et al., 2016) apply hard sampling and select one specific sense per training step. However, discrete selection in this manner is non-differentiable, which normally necessitates the use of policy gradient methods such as REINFORCE (Williams, 1992) that rarely work in practice without variance reduction techniques.

To preserve differentiability, we apply the Gumbel softmax (Jang et al., 2016; Maddison et al., 2016) to approximate hard attention. Observing that naive application fails to learn interpretable sense vectors, we modify the Gumbel softmax by adding a scaling factor. This modification, which we call the scaled Gumbel softmax, is critical for learning interpretable embeddings that also perform well on downstream tasks.

#### 3.2.1 Gumbel Softmax for Categorical Sampling

The original Gumbel softmax approximates the sampling of discrete random variables. Given a discrete random variable $X$ with $P(X = k) \propto \alpha_k$,
Figure 2: As the scale factor $\beta$ increases, the sense selection distribution for “bond” becomes flatter, which leads to increased sense mixing.

where $\alpha_k$ is unnormalized and $\alpha_k \in (0, \infty)$, the Gumbel-max (Luce, 1959; Yellott, 1977; Papanandreou and Yuille, 2011; Hazan and Jaakkola, 2012; Maddison et al., 2014) refactors the sampling of $X$ into a deterministic function

$$X = \arg \max_k (\log \alpha_k + g_k)$$

where the Gumbel noise $g_1, ..., g_k$ are i.i.d samples drawn from $\text{Gumbel}(0,1)$, which can be sampled by drawing $u_k \sim \text{Uniform}(0, 1)$ and $g_k = -\log(-\log(u_k))$.

This categorical sampling can be approximated by the Gumbel softmax, which replaces the softmax in our sense disambiguation distribution (Equation 4). Concretely, the argmax

$$\text{one\_hot}(\arg \max_k (\tilde{c}_i^s k + g_k)),$$

is approximated with

$$\gamma_i = \text{softmax}((\tilde{c}_i^s k + g_k)/\tau).$$

3.2.2 Scaled Gumbel Softmax for sense disambiguation distribution inference

In practice, however, the vanilla Gumbel softmax learns flat sense distributions even with low temperatures; thus, it cannot learn sense disambiguation (bottom right of Figure 2). To solve this problem, we propose a simple variant of the Gumbel softmax that scales the Gumbel noise term based on the following empirical analysis.

Observing the flat distribution learned by Gumbel softmax (Figure 2), we monitor the value of the context-sense dot product $\tilde{c}_i^s k$ which we use to estimate the contextual sense induction distribution $P(s_k^w | w_i, c_i)$ in Equation 11. The mean of this value converges quickly in the early stage of training; and, compared to the Gumbel noise $g_k$, ranges in a small window\(^2\) compared to the variance of the Gumbel noise term $g_k$ (Figure 3). Therefore, $g_k$ dominates the estimation of $P(s_k^w | w_i, c_i)$ after applying the Gumbel softmax, and this trend continues throughout training, which severely hampers learning of the sense disambiguation distribution.

Given the above analysis, we mitigate the influence of the Gumbel noise $g_k$ in Equation 11 (Figure 3) with a scaling factor $\beta$, which we tune as a hyperparameter:

$$\gamma_i = \text{softmax}((\tilde{c}_i^s k + \beta g_k)/\tau).$$

The final objective function for our model, Gumbel attention sense induction (GASI), becomes

$$\frac{1}{|V|} \sum_{w_i \in V} \sum_{w_{cj} \in c_i} \sum_{k=1}^{K} \gamma_i \log P(w_{cj} | s_k)$$

Figures 2–4 show that the scale factor $\beta$ balances the influence of the Gumbel noise $g_k$ and is critical for learning.

4 Training GASI

For fair comparisons, we try to remain consistent with previous work in all aspects of training. In particular, we train GASI on the same April 2010 Wikipedia snapshot (Shaoul C., 2010) with one billion tokens used in previous work (Huang et al.\(^2\))
Additionally, we use the same vocabulary of 100k words and initialize our model with three senses per word. During training, we fix the window size to five and the dimensionality of the embedding space to 300.\textsuperscript{3}

Our model is initialized with a fixed number of senses $K$ for all of the words in the vocabulary. For comparison to previous work (Huang et al., 2012; Neelakantan et al., 2014; Lee and Chen, 2017), we set the number of senses $K = 3$ for all experiments unless otherwise specified.

### 4.1 Pruning Duplicate Senses

Some previous work (Neelakantan et al., 2014; Li and Jurafsky, 2015) infers the number of senses for a given word dynamically during training, instead of learning a fixed number of senses per word. Instead of integrating this functionality into our training, we handle it post-training. For words that do not have multiple senses or have most senses appear very low-frequently in corpus, our model (as well as many previous models) learns duplicate senses. We can easily remove such duplicates by pruning the learned sense embeddings with a threshold $\lambda$. Specifically, for each word $w_i$, if the cosine distance between any of its sense embeddings $(s_i^m, s_i^n)$ is smaller than $\lambda$, we consider them to be duplicates. After discovering all duplicate pairs, we start pruning with the sense $s_k$ that has the most duplications and keep pruning with the same strategy until no more duplicates remain.

**Model-specific pruning:** Since we would like to apply pruning not only to our model but to others, we propose a model-agnostic strategy to estimate the threshold $\lambda$. We first sample 100 words from the negative sampling distribution over the vocabulary. Then, we retrieve the five nearest neighbors (from all senses of all words) to each sense of each sampled word. If one of a word’s own senses appears as a nearest neighbor, we append the distance between them to a sense duplication list $D_{dup}$. For other nearest neighbors, we append their distances to the word neighbor list $D_{nn}$. After populating the two lists, we want to choose a threshold that would prune away all of the sense duplicates while differentiating sense duplications with other distinct neighbor words. Thus, we compute

$$\lambda = \frac{1}{2} \left( \text{mean}(D_{dup}) + \text{mean}(D_{nn}) \right). \quad (14)$$

The post-hoc analysis with human evaluation (Table 5) and the post-pruning word sense histogram (Figure 4) corroborate its effectiveness. This pruning only slightly reduces downstream performance on the word similarity task (Table 1, bottom).

### 5 Downstream Evaluation

All prior work on word sense embeddings has evaluated embedding quality using downstream evaluations, namely semantic word similarity and synonym selection. We evaluate on both of these tasks and show competitive or state-of-the-art results when compared with baseline models. We also evaluate our model on word sense disambiguation tasks to show that our model learns a reasonable sense selection mechanism. With that said, inspecting the nearest neighbors of sense embeddings learned by some of the highest-scoring models on these tasks (e.g., GASI-1, MUSE) reveals that they do not learn distinct sense embeddings. In Section 6, we design a crowdsourced evaluation to measure sense interpretability, which shows that properly-scaled GASI models (along with soft attention variants) learn far more distinct word senses than MUSE (Lee and Chen, 2017).

#### 5.1 Word similarity

To examine how well the learned sense embeddings capture semantic similarities, we evaluate our model on the Stanford Contextual Word Similarities (SCWS) dataset (Huang et al., 2012), which...
Table 1: Spearman’s ranking correlation $100 \times \rho$ on the SWCS word similarity dataset. The † indicates models that support a variable number of senses per word. GASI obtains competitive or state-of-the-art performance on all metrics.

| Model               | MaxSimC | AvgSim | AvgSimC |
|---------------------|---------|--------|---------|
| Huang-50d           | 26.1    | 62.8   | 65.7    |
| Neelakantan         | 59.3    | 67.2   | 69.2    |
| Neelakantan-NP†     | 60.1    | 67     | 68.6    |
| Tian                | 63.6    | –      | 65.4    |
| Li†                 | 66.6    | –      | 66.8    |
| Qiu                 | 64.9    | –      | 66.1    |
| MUSE_Boltzmann      | 67.9    | 68.7   | 68.7    |
| SASI                | 55.1    | 64.8   | 67.8    |
| GASI-0.2            | 56.5    | 65.3   | 68.2    |
| GASI-0.4            | 65.1    | 66.3   | 69.3    |
| GASI-0.5            | 67.2    | 66.5   | 69.1    |
| GASI-1.0            | 68.2    | 67.8   | 68.3    |

Table 2: Synonym selection accuracy with different embedding models; GASI and MUSE again achieve similarly high scores.

| Model               | ESL-50  | RD-300  | TOFEL-80 |
|---------------------|---------|---------|---------|
| Li                  | 50.00   | 55.36   | 82.61   |
| Neelakantan         | 57.14   | 58.93   | 78.26   |
| MUSE-Boltzmann      | 64.29   | 66.07   | 88.41   |
| GASI-0.4            | 63.36   | 67.27   | 86.69   |

Retrofitting on ontologies or parallel texts

| Model               | ESL-50  | RD-300  | TOFEL-80 |
|---------------------|---------|---------|---------|
| Retro-GC            | 63.64   | 66.20   | 71.01   |
| Retro-SG            | 56.25   | 65.09   | 73.33   |
| Paralle Text (PD)   | 66.7    | 74.7    | 81.8    |
| WordNet (WN)        | 68.8    | 62.1    | 80.5    |
| PD-WN               | 70.8    | 79.3    | 84.4    |

5.2 Synonym selection

Synonym Selection is another common evaluation for word/sense representations (Jauhar et al., 2015a; Ettinger et al., 2016; Lee and Chen, 2017): ESL-50 (Turney, 2001), RD-300 (Jarmasz and Szpakowicz, 2004), and TOFEL-80 each consist of a target word $w_T$ and four candidates $\{w_A, w_B, w_C, w_D\}$. These datasets do not provide contexts for the target word. Without contexts, we follow Jauhar et al. (2015a) and compute the cosine similarity between senses of each candidate and that of the target words. Then, we select the synonym whose sense has the maximum similarity to any of the target senses.

We compare our results with other multi-sense embeddings in Table 2. Although our unsupervised model cannot compete with models (Jauhar et al., 2015b; Ettinger et al., 2016) that retrofit on external resources on EST-50 and RD-300, it achieves the best performance on RD-300 among unsupervised models.

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Table 2: Synonym selection accuracy with different embedding models; GASI and MUSE again achieve similarly high scores.

4This value is computed with the learned embeddings and code released by authors.
We apply the same methodology for all sense embeddings and is competitive with MUSE on the other two.

5.3 Word sense disambiguation

We further compare our model with two baselines (Neelakantan et al., 2014; Lee and Chen, 2017) on four word sense disambiguation (WSD) test sets from the Senseval/SemEval series: Senseval-2 (Edmonds and Cotton, 2001), Senseval-3 (Snyder and Palmer, 2004), SemEval-2013 (Navigli et al., 2013), and SemEval-2015 (Moro and Navigli, 2015). We train on SemCor 3.0 (Miller et al., 1994), which contains sentences that have multiple words to be disambiguated.

WSD based on contextual sense induction

To focus our evaluation on the word sense disambiguation captured by the sense induction component of each model, we map each sense to a set of synsets given its part-of-speech tag (POS). Specifically, for each (sense $s^i_k$, synset $syn_m$, POS $pos$) tuple for a given word type $w_i$, we accumulate the probability $p^t_{k} = P(s_k^i | w^i_t, c^i_t)$ for all tokens $w^i_t$ that are assigned to synset $syn_m$:

$$s^i_k(syn_m | pos) = \sum_{w^i_t \in syn_m | pos} P(s^i_k | w^i_t, c^i_t).$$ (17)

Then, we average $s^i_k(syn_m | pos)$ over all possible synsets. At test time, we assign each instance of the target word $w^i_t$ given its POS tag to the synset that maximizes

$$\arg \max_{syn_m} \left( \sum_{k=1}^{K} s^i_k(syn_m | pos) \times p^t_{k} \right).$$ (18)

We apply the same methodology for all sense embeddings (Table 3). Although our results are worse than a state-of-art WSD system, IMS+emb (Jacobacci et al., 2016), GASI achieves a higher F1 score than either of the baselines.

| Model | Noun | Verb | Adj | Adv | All |
|-------|------|------|-----|-----|-----|
| WSD based on contextual sense induction distribution | | | | | |
| Neelakantan | 68.6 | 50.3 | 73.6 | 81.0 | 66.4 |
| MUSE-Boltzmann | 68.5 | 49.7 | 73.3 | 81.0 | 66.1 |
| GASI-0.4 | 69.5 | 50.6 | 74.0 | 81.0 | 67.1 |

State-of-art WSD system

| Model | Noun | Verb | Adj | Adv | All |
|-------|------|------|-----|-----|-----|
| IMS+emb | 71.9 | 56.6 | 75.9 | 84.7 | 70.1 |

Table 3: F1 score on all four WSD tasks; GASI outperforms other word sense embedding baselines.

Table 4: Comparison of nearest neighbors learned by GASI-0.4 from MUSE-Boltzmann (bottom).

6 Judging Interpretabiliy via Crowdsourcing

The previous section shows that GASI achieves state-of-art or competitive results on downstream tasks. However, these results do not tell us much about the information captured by each sense embedding, or how many distinct senses the model learns per word. One way to interpret the learned sense embeddings is by looking at the nearest neighbors for a sample of words. From table 4, we can see that GASI is able to learn meaningful distinct sense groups for each word. In contrast, MUSE-Boltzmann (Lee and Chen, 2017) learns near duplicate senses for many examples (e.g., Table 4). To provide a quantitative interpretability evaluation at a larger scale, we design a crowdsourcing task that measures how many times the sense chosen by a model based on its contextual sense distribution agrees with human judgements.

Task description

For a given target word in a given context, we ask a worker to select one sense group among the three learned by the model that best fits the given sentence. Each sense group is described by its top-10 distinct nearest neighbors, an example is shown in Figure 5.

Data collection

We select a subset of nouns from SemCor 3.0 (Miller et al., 1994) to use for this task. In particular, we first filter all synsets in the dataset that have less than ten sentences, and rank the remaining nouns by the number of synsets and select the top 50, randomly selecting five sentences per word for the task. For each embedding model, we obtain three annotations on the sentence / noun...
pairs using the Crowdflower platform.

**Analysis of results** In the first block of Table 5, we see that SASI achieves the highest accuracy, followed by GASI-0.4. Both are higher than the random baseline of 33%, unlike MUSE. We apply the Fleiss’ $\kappa$ (Fleiss, 1971) to measure the inter-rater reliability (IRR) of our multiple-choice task. The IRR numbers reported in Table 5 are very low for most of the models. There are two possible causes: (1) the model failed to yield interpretable sense groups, and/or (2) the model learned duplicate senses.

To isolate the cause, we apply a post-hoc pruning analysis. To be more specific, we prune each model’s learned embeddings with the strategy described in Section 4.1 and then re-assign the user’s choice to its nearest neighbor sense. The second block in Table 5 shows that after pruning, both the accuracy and IRR score increase significantly for the GASI models. This result demonstrates the efficacy of our pruning method. We also observe that pruning does not help SASI or the MSSG model (Neelakantan et al., 2014) since very few senses were pruned; in contrast, almost all of MUSE’s senses are pruned, but the human accuracy actually decreases.\(^5\)

### 7 Related Work

Our work adds to the existing body of research on learning unsupervised word sense embeddings. In this section, we compare and contrast these previous methods to GASI.

Reisinger and Mooney (2010) were the first to propose a multi-sense semantic vector-space model. Several variants of this idea (including GASI) were later implemented as extensions of Word2Vec (Mikolov et al., 2013a,b). Each of these induces senses using one of three techniques:

1. **Supervised methods** trained on annotated sense corpora (Iacobacci et al., 2015) or external sense inventories and knowledge bases like WordNet (Chen et al., 2014; Jauhar et al., 2015b; Chen et al., 2015) and Wikipedia (Wu and Giles, 2015);

2. **Bilingual sense induction** from multilingual parallel corpora (Guo et al., 2014; Šuster et al., 2016; Ettinger et al., 2016);

3. **Unsupervised monolingual models** attempt to induce senses using various methods, such as context clustering (Huang et al., 2012; Neelakantan et al., 2014; Li and Jurafsky, 2015), corpus-level probability estimation (Tian et al., 2014), context-based energy functions (Qiu et al., 2016), and reinforcement learning (Lee and Chen, 2017). GASI falls into this category.

These methods also differ in how they disambiguate senses in context. Most previous approaches rely on discrete sampling based on the sense induction distribution (or computing the argmax), which loses model differentiability. Šuster et al. (2016) maintain differentiability by using soft attention, but due in part to sense mixing, their monolingual version performs poorly on downstream tasks. Lee and Chen (2017) try to address this problem by applying hard attention for discrete sense selection with reinforcement learning. While this approach achieves high scores on downstream evaluation tasks, we show that it does not learn distinct interpretable sense embeddings.

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\(^5\)We do not consider words pruned to a single sense in the accuracy computation.

Table 5: Human evaluation results on sense agreement, where $P$ is the average probability assigned by the model to the human choices. The pruned GASI achieves the best performance, while MUSE does worse than random.

| Model   | Accuracy | $P$  | Fleiss’ $\kappa$ |
|---------|----------|------|------------------|
| MUSE    | 28       | 0.33 | 0.13             |
| Neelakantan | 44     | 0.37 | 0.24             |
| SASI    | **56.4** | 0.41 | 0.30             |
| GASI-0.4| 48       | 0.40 | 0.18             |
| GASI-0.5| 40       | 0.36 | 0.18             |

Post-hoc analysis after pruning (-) show # of instances left

| Model       | Accuracy | $P$  | Fleiss’ $\kappa$ |
|-------------|----------|------|------------------|
| MUSE (75)   | 26.6     | 0.20 | 0.13             |
| Neelakantan (245) | 44.5   | 0.33 | 0.24             |
| SASI(250)   | 55.6     | 0.42 | 0.30             |
| GASI-0.4 (185) | 69.7   | 0.41 | 0.43             |
| GASI-0.5 (125) | **73.6** | 0.40 | 0.48             |

Figure 5: User interface with an example question for Sense Agreements Crowdsourcing task.
in Section 5. GASI accomplishes the best of both worlds, avoiding sense mixing through hard, differentiable attention while also achieving high interpretability.

8 Conclusion

In this paper, we propose to learn word sense embeddings through Gumbel attention sense induction (GASI). Our model applies differentiable hard attention to simultaneously induce and embed word senses from an unlabeled corpus. We introduce a scaling factor to the Gumbel softmax that allows GASI to learn sense disambiguation and achieve competitive or state-of-the-art performance on similarity based downstream evaluations. Furthermore, we show that performance on these evaluation tasks does not necessarily correlate to increased interpretability. Motivated by this observation, we design a human evaluation task to quantitatively measure how well the model’s sense selection mechanism correlates to that of humans, on which GASI performs better than competing approaches.

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