Leveraging sentence similarity in natural language generation: Improving beam search using range voting

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Abstract

We propose a novel method for generating natural language sentences from probabilistic language models, selecting from a beam search using a range voting procedure. The proposed method could be applied to any language model, including both n-gram models and neural network models, and could be applied to any generation task. Instead of choosing the most likely output, our method chooses the most representative output, providing a solution to the common problem of short outputs being preferred over longer and more informative ones. We evaluate our method on an image captioning task, and find that the generated captions are longer and more diverse than those generated using standard beam search, with higher BLEU scores (particularly when the beam size is large), and better performance in a human evaluation.

1 Introduction

A language model specifies a probability distribution over sequences of words. In many applications, it is desirable to output a single sequence, rather than a distribution. A common approach is to choose the most likely sequence. However, for the probabilities to sum to 1, the probability of a sequence must tend to 0 as length increases. This leads to a long-recognised problem, that choosing the most likely sequence favours short sequences (Brown et al., 1995). This is problematic when the most likely sequence is not representative of the whole distribution. For example, in dialogue generation tasks, the most likely output can be “I don’t know”, even when most of the probability mass is assigned to long informative sequences. Cao and Clark (2017) call this the “boring output problem”.

For a real-valued distribution, we can choose a representative output by taking the mean. However, for a discrete distribution (such as over sequences), the mean is not well-defined. In this paper, we choose a representative output using tools from voting theory, which allows us to avoid the boring output problem. The basic idea is that, if the distribution assigns most of the probability mass to a group of similar sequences, we would like to generate one of these sequences – even if they have low probability as individual sequences, they have high probability as a group.

We evaluate our approach on an image captioning task (see Fig. 1 for an example). We find that our approach generates longer and more diverse captions, while achieving higher BLEU scores, and performing better in a human evaluation. This suggests that our approach mitigates the boring output problem.

2 Related work

To increase the length and diversity of a model’s outputs, some authors have proposed changes to the model architecture. In dialogue generation, Cao and Clark (2017) use a latent variable model to capture the possible ‘topics’ of a response.

Others have proposed changing the objective function. In dialogue generation, Li et al. (2016a) optimise mutual information instead of probability. In machine translation, Tu et al. (2017) modify an encoder-decoder model by adding a ‘reconstructor’ to predict the input based on the output.

However, modifying the model or the objective function depends on the particular task, and applying these techniques to an existing system requires retraining the model. In this paper, we focus on general-purpose methods which can be applied to any probabilistic model in any generation task. Existing methods include length normalisation (Wu et al., 2016; Freitag and Al-Onaizan, 2017) and diverse decoding (Li et al., 2016b; Li
and Jurafsky, 2016), which we discuss in §4.1.

![Figure 1: Image from the MSCOCO validation dataset and beam captions with probability (beam size $k=10$). See §3.1 for beam search, §4.1 for the model. Range voting with overlap similarity (see §3.2) selects “a black and white photo of a man sitting on a bench”.

3 Method

3.1 Beam search

When working with a distribution over sequences, it is not feasible to consider all possible sequences. Finding the most likely sequence can be computationally expensive – in fact, for an RNN it is undecidable (Chen et al., 2018). A common solution is to use beam search, which generates the sequence one token at a time, maintaining a list of the $k$ most promising sequences at each time step (for example: Brown et al., 1995; Koehn, 2004a). Greedy search is the special case where $k = 1$.

Beam search introduces an extra hyper-parameter, the beam size $k$. Increasing $k$ covers more of the search space, but increases the computational cost. It is tempting to assume that increasing $k$ will produce better results, but empirically, the quality of the most likely sequence starts to decrease after $k$ exceeds a certain threshold (Koehn and Knowles, 2017), which stems from the problem discussed in §1. Tuning the value of $k$ to maximise performance can be challenging.

In the next section, we propose an alternative way to generate from a beam, which avoids the drop in performance as beam size increases. Rather than choosing the most likely sequence, we choose the most representative sequence.

3.2 Range voting

To formalise the idea of the most representative sequence, we propose to use a voting procedure. Although voting has been applied to ensembles of classifiers (for an overview, see: Kuncheva, 2004; Kuncheva and Rodríguez, 2014), we are not aware of work using voting to select from a distribution.

We can see each sequence as a candidate in an election, and the probability of a sequence as the proportion of votes for that candidate. From this perspective, the problem of probability mass being split across long sequences is the well-known problem of vote splitting. Suppose candidate $i$ wins an election. Now suppose we run the election again, but add an additional candidate $j$, identical to $i$. A voting system is robust against vote splitting (and called independent of clones) if the winner must be $i$ or $j$ (Tideman, 1987).

A well-studied system which is independent of clones is range voting (Heckscher, 1892; Smith, 2000; Tideman, 2006; Lagerspetz, 2016). Each voter scores each candidate in the range $[0, 1]$, and the candidate with the highest total score wins.

In our setting, probability mass can be seen as the proportion of votes placing a candidate as first choice (see Fig. 1 for an example). For range voting, we need to augment the votes with scores for all other candidates. We propose to do this using a similarity measure. The final score for a sequence is given in (1), for a beam of sequences $s_1, \cdots, s_k$ and a similarity measure $\text{sim}$.\footnote{An alternative way to understand this method is that each sequence acts as both voter and candidate. As a voter, each sequence is weighted by its probability.}

$$\text{score}(s_j) = \sum_{i=1}^{k} P(s_i) \cdot \text{sim}(s_i, s_j) \quad (1)$$

Defining semantic similarity between sentences is recognised as a hard problem (Achananuparp et al., 2008; Cer et al., 2017; Pawar and Mago, 2019). In this work, we focus on simple, domain-agnostic similarity measures which do not require additional training.

First, we consider similarity based on n-grams. For a sequence $s$, we write $\text{set}_n(s)$ for its set of n-grams, and $\text{bag}_n(s)$ for its bag of n-grams. We define two measures in (2–3). Both are asymmetric, to encourage informative sequences: if $t$ contains $s$ plus more information, $\text{sim}(s, t)$ should be high, but $\text{sim}(t, s)$ should be lower. This allows an informative sequence to gather more votes.

$$\text{precision}_n(s, t) = \frac{|\text{bag}_n(s) \cap \text{bag}_n(t)|}{|\text{bag}_n(s)|} \quad (2)$$

$$\text{overlap}_n(s, t) = \frac{|\text{set}_n(s) \cap \text{set}_n(t)|}{|\text{set}_n(s)|} \quad (3)$$

Second, inspired by Mueller and Thyagarajan (2016), we consider a similarity measure based on
the hidden states of the LSTM during generation (see §4.1). For each sequence, we find the average
LSTM hidden state, and then compute cosine similarity. We refer to this measure as lstm_states.

4 Experiments

We evaluate our method on the MSCOCO dataset (Lin et al., 2014), which consists of 82,783 training
images and 40,504 validation images, each annotated with 5 captions from human annotators.

4.1 Model and baselines

We use the ‘Show and Tell’ architecture of Vinyals et al. (2015). The task is framed as a supervised
learning problem: an encoder-decoder model is trained to maximise the probability of the annota-
tor captions given an input image. The encoder is a pretrained Inception V3 CNN (Szegedy et al.,
2016) from which we extract a feature vector from the final pooling layer (Ioffe and Szegedy, 2015).
The decoder is an LSTM (Hochreiter and Schmidhuber, 1997) with 512 hidden units, with dropout
\( p=0.3 \), initialising the hidden state using the encoder. The vocabulary consists of the 5000 most
common words in the training captions, for which embeddings of size 512 are learned from scratch.
We trained the model for 20 epochs with vanilla SGD, starting with a learning rate of 2.0, which is
halved every 8 epochs.

As well as comparing to standard beam search, we consider two existing baselines. Length nor-
malisation divides the log-probability by sequence length (Wu et al., 2016; Freitag and Al-Onaizan,
2017). Diverse decoding penalises expansions of the same initial sequence (Li et al., 2016b; Li and
Jurafsky, 2016). The other methods mentioned in §2 cannot be straightforwardly applied to this task.

4.2 BLEU scores

Table 1 shows BLEU scores (Papineni et al., 2002) on the MSCOCO validation set. For beam size
\( k=1 \), all methods reduce to greedy search.

The bigram similarity measures and the lstm_states measure improve BLEU scores for al-
most all beam sizes. In contrast, diverse decoding has almost no effect on BLEU, while length
normalisation performs worse than standard beam search. The best result is achieved by lstm_states
at \( k=100 \). This is significantly better than the best beam search result \( (k=10) \), with \( p<0.001 \) for a
paired bootstrap test following Koehn (2004b).

Consistent with Ott et al. (2018) and Koehn and Knowles (2017), increasing \( k \) too much reduces
BLEU for standard beam search. However, this drop does not occur for our voting method.

4.3 Caption length

To analyse differences between methods, we first look at caption length, shown in Table 2. Stan-
dard beam search produces slightly longer captions as \( k \) increases up to 10. All n-gram mea-
ures generate longer captions than standard beam search, and length continues to increase as \( k \) goes
to 100. Length normalisation also increases caption length, but this is at the cost of BLEU score
(see §4.2). Diverse decoding does not increase caption length. The lstm_states measure produces
slightly shorter captions – as it is symmetric, it does not favour long sequences as the asymmetric
n-gram measures do (see §3.2).

4.4 Caption diversity

Second, we investigate the diversity of the generated captions by counting the number of distinct
captions, unigrams, and bigrams (see Table 3). This follows the approach of Li et al. (2016a),
Dhingra et al. (2017), and Xu et al. (2017, 2018).

For standard beam search, the number of distinct captions drops as \( k \) increases. Both baselines
weaken this effect, but the drop is still present. In contrast, range voting maintains caption diversity
as \( k \) increases, for all similarity measures.

Similarly, standard beam search sees a drop in the number of distinct unigrams and bigrams as
\( k \) increases, and the baselines do not seem to mitigate this. In contrast, the unigram measures
and the lstm_states measure maintain both uni-
gram diversity and bigram diversity as \( k \) increases, while the bigram measures partially maintain bi-
gram diversity.

4.5 Human evaluation

BLEU is known to be imperfect, and does not al-
ways match human judgements (Callison-Burch et al., 2006). While the n-gram similarity mea-
sures produce similar BLEU scores to standard beam search, they also produce longer captions.
A longer caption is potentially more informative. To investigate whether they are more informative
in way that is not reflected by BLEU, we took 500 validation images for human evaluation, compar-
ing the captions produced by standard beam search
Table 1: BLEU-1 and BLEU-4 scores obtained on the MSCOCO validation images.

| Beam size $k$ | BLEU-1 | BLEU-4 |
|---------------|--------|--------|
| 1             | 0.6666 | 0.6797 |
| 2             | 0.6472 | 0.6510 |
| 10            | 0.6643 | 0.2539 |
| 100           | 0.2668 | 0.2693 |

Table 2: Average length of the generated captions.

| Beam size $k$ | Average caption length |
|---------------|------------------------|
| 1             | 8.41                   |
| 2             | 8.71                   |
| 10            | 9.12                   |
| 100           | 9.15                   |

We have evaluated our method on an image captioning task. Despite using simple similarity measures, we achieve an increase in BLEU score, an increase in caption length and diversity, and statistically significantly better performance in a human evaluation. Unlike standard beam search, performance of our method does not drop as beam size continues to increase, removing the sensitivity of results on this hyperparameter. Better similarity measures could further improve results.

Finally, our approach can be applied to any probabilistic language model, without any need for additional training. This opens up many other tasks, including machine translation, summarisation, dialogue systems, and question answering. If multiple outputs can be used (e.g. offering options to a user), our method can be extended to use reweighted range voting (Smith, 2005), a procedure which elects multiple candidates.

5 Conclusion

We have proposed a new method for generating natural language from a language model, by re-ranking a beam search. Instead of choosing the most likely sequence, we choose the most representative sequence, formalising representativeness using a similarity measure and range voting.

We have evaluated our method on an image captioning task. Despite using simple similarity measures, we achieve an increase in BLEU score, an increase in caption length and diversity, and statistically significantly better performance in a human evaluation. Unlike standard beam search, performance of our method does not drop as beam size continues to increase, removing the sensitivity of results on this hyperparameter. Better similarity measures could further improve results.

Finally, our approach can be applied to any probabilistic language model, without any need for additional training. This opens up many other tasks, including machine translation, summarisation, dialogue systems, and question answering. If multiple outputs can be used (e.g. offering options to a user), our method can be extended to use reweighted range voting (Smith, 2005), a procedure which elects multiple candidates.

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Table 3: Number of distinct captions, unigrams and bigrams.

| Beam size $k$ | Distinct captions | Distinct unigrams | Distinct bigrams |
|---------------|--------------------|-------------------|------------------|
|               | 2                  | 10                | 100              |
| Standard beam search | 9208              | 5488              | 4150             |
|Length normalisation | 9978              | 6418              | 5039             |
|Diverse decoding | 9942              | 6424              | 4403             |
|overlap$^1$ | 10727             | 8916              | 10808            |
|precision$^1$ | 10727             | 8902              | 10768            |
|overlap$^2$ | 9519              | 7958              | 9221             |
|precision$^2$ | 9522              | 7590              | 9248             |
|lstm states | 9208              | 7613              | 10133            |

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