B-SCST: Bayesian Self-Critical Sequence Training for Image Captioning

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Abstract. Bayesian deep neural networks (DNN) provide a mathematically grounded framework to quantify uncertainty in their predictions. We propose a Bayesian variant of policy-gradient based reinforcement learning training technique for image captioning models to directly optimize non-differentiable image captioning quality metrics such as CIDEr-D. We extend the well-known Self-Critical Sequence Training (SCST) approach for image captioning models by incorporating Bayesian inference, and refer to it as B-SCST. The “baseline” reward for the policy-gradients in B-SCST is generated by averaging predictive quality metrics (CIDEr-D) of the captions drawn from the distribution obtained using a Bayesian DNN model. This predictive distribution is inferred using Monte Carlo (MC) dropout, which is one of the standard ways to approximate variational inference. We observe that B-SCST improves all the standard captioning quality scores on both Flickr30k and MS COCO datasets, compared to the SCST approach. We also provide a detailed study of uncertainty quantification for the predicted captions, and demonstrate that it correlates well with the CIDEr-D scores. To our knowledge, this is the first such analysis, and it can pave way to more practical image captioning solutions with interpretable models.

Keywords: Image captioning, Bayesian inference

1 Introduction

Image captioning approaches generate natural language descriptions by transforming the image features into a sequence of output words from a predefined vocabulary. The image features are obtained using a pretrained CNN or Faster R-CNN model [29]. State-of-the-art image captioning models [2,6,18,37,36] use encoder-decoder architecture [34,19]. The encoder takes the image features, and transforms them into latent space using techniques such as attention mechanism [36,2]. The decoder usually includes RNNs or LSTMs that takes these latent features, and generates a sequence of words to form an image caption.

The training of these state-of-the-art models typically follows a two-step process. In the first step, cross-entropy loss is optimized to generate the captions with words in the same order as the ground-truth captions. However, the quality of image captioning is evaluated using Natural Language Processing (NLP) metric.
Fig. 1: Two sample images and few of their ground-truth captions from Flickr30k dataset. Also shown are the greedy captions that are predicted using a trained model with few MC Dropout simulations, and their corresponding CIDEr-D scores. SCST approach uses a single greedy caption as the “baseline” to improve or suppress the probability of sampled captions. A single greedy caption is not a good measure of ground-truth captions since it could underestimate or overestimate CIDEr-D score. MC Dropout provides a way to sample captions from the posterior distribution, and an average predictive score of these captions can be better estimate of “baseline” score.

scores such as BLEU [27], METEOR [8], CIDEr-D [33] and SPICE [11]. These metrics are non-differentiable and cannot be directly maximized by this optimization algorithm. So, in the second step, policy-gradient based reinforcement learning (RL) is used to minimize the negative expected value of the caption scores [30].

Several recent works have shown that using a bias correction, i.e., a learned “baseline” score, to normalize the RL rewards reduces the variance in policy gradients, and is effective during training. In Self-Critical Sequence Training (SCST) [30], the current model chooses word with the highest SoftMax probability at each timestep and generates a greedy caption. The CIDEr-D score of this greedy caption, called the greedy score, is used as “baseline” during the search process. When a policy-gradient RL loss function using this “baseline” is applied on the model, it tends to increase the probability of generating captions that have higher score than the greedy score while suppressing those that have lower score, thus optimizing the CIDEr-D metric directly.

Although deep neural networks (DNNs) provide state-of-the-art results for a multitude of applications, they have been shown to fail [10] in the case of noisy or out-of-distribution data leading to overly confident SoftMax probability scores. Probabilistic Bayesian models [4], on the other hand, provide a principled way to gain insight into the data and capture reliable uncertainty estimates.
in their predictions, hence providing interpretable models. Bayesian DNNs [26] provide a convenient way to combine the two approaches to develop more robust models that can be scaled to large datasets and real-world applications. Bayesian modeling with Monte Carlo (MC) dropout approximate inference [12] is shown as a practical approach to implement Bayesian DNNs in order to obtain principled confidence and quantify predictive uncertainty. So, we leverage this approach in this work.

In Figure 1, we show two sample images from Flickr30k [28] dataset along with few of their ground truth captions. It also shows the greedy captions that are predicted using a trained model with few MC dropout simulations, and their corresponding CIDEr-D scores. Since SCST approach uses a single greedy caption as the “baseline” during training to improve or suppress the probability of sampled captions, it may pick any one of these high variance CIDEr-D scores as the “baseline” score. Hence, we propose a variant of SCST where the “baseline” score is obtained using a Bayesian DNN model, which infers the distribution of these predicted captions over model parameters. The average score of the captions sampled from this distribution will be a better representation of the “baseline” score. The expected reward using this “baseline” score is back-propagated to boost words in the captions with higher scores than the baseline while suppressing the words from the captions with lower scores. We refer to this approach as Bayesian SCST (B-SCST). We demonstrate that B-SCST applied to CIDEr-D scores improves the captioning quality scores, as compared to SCST approach.

Image captioning is still an active area of research and DNN models can generate incorrect description of the image. Hence, it is important to study the inherent ambiguity or uncertainty estimates from the generated captions. We study the correlation between uncertainty estimates obtained from our model and the CIDEr-D metric. This analysis is critical to enable practical NLP applications which require interpretability of the models and their outputs.

In summary, our main contributions in this work are:

- We propose B-SCST, a Bayesian variant of SCST approach, and demonstrate that it improves the caption quality score compared to SCST.
- We present detailed uncertainty quantification of the generated image captions to demonstrate a good correlation between CIDEr-D scores and predictive entropy. To our knowledge, this is the first work which provides this kind of Bayesian analysis for image captioning and it can enable interpretability of the models and their captions.

The paper is organized as follows. The related work is presented in Section 2, followed by proposed method in Section 3. The results are presented in Section 4 and conclusions in Section 5.

2 Related work

In this section, we provide a brief review of relevant work on imaging captioning approaches which provide state-of-the-art results.
2.1 Attention Mechanism

Image captioning DNNs use attention mechanism \cite{attention} so that the encoder and decoder in the model attend on appropriate features in the image to generate the words in the caption. A bottom-up attention mechanism was proposed in \cite{bottom-up}, where Faster R-CNN \cite{faster_rcnn} provides proposals of salient regions in the image for the model to use, in addition to the entire image. Transformer networks \cite{transformer}, which are based on self attention, achieved state-of-the-art results on machine translation tasks. Attention-on-attention network (AoANet) \cite{aonet} uses an extra learned attention on top of self-attention to avoid attentions that are irrelevant to the decoder. In this work, we use this AoANet architecture.

2.2 Training techniques

Image captioning models are usually trained with word level cross-entropy loss between the ground truth and model generated caption. SCST \cite{scst} uses policy-gradient based RL to directly optimize the captioning evaluation NLP metrics. Specifically, it uses the caption score obtained by the model using its test-time inference algorithm as the “baseline” to normalize the caption scores generated during its search process and reduce the variance of gradients during training. A variant of SCST \cite{scst} performs beam search and restricts the search space to only the top-k captions in the decoded beam. Another variant \cite{scst} uses the mean score of these top-k captions in the decoded beam as the “baseline”. We discuss the differences between our approach and these works in Section 3.

2.3 Bayesian approaches

Standard DNNs do not capture uncertainty estimates \cite{uncertainty} associated with the data and the model parameters. SoftMax probabilities obtained from DNNs can often provide overly confident results for incorrect predictions. Hence, Bayesian models are proposed which can capture data and model uncertainties \cite{uncertainty} resulting in more robust models. In \cite{dropout}, dropout training in DNNs is cast as approximate Bayesian inference in deep Gaussian processes. This work has been extensively used in many applications \cite{applications} to model uncertainty estimates. Among image captioning related works, an LSTM trained using Bayesian back-propagation was proposed in \cite{lstm} to improve the perplexity of image captioning results. Uncertainty measures were explored in \cite{uncertainty} to improve caption embedding and retrieval task. In \cite{dropout}, MC dropout along with explicit outputs that predict the model uncertainty were used. Our approach is different from these works as in we focus on improving image captioning metrics by using MC dropout to cast a state-of-the-art model as Bayesian DNN, without making any architecture changes to it.

We present our B-SCST approach in the next section followed by the results in Section 4.
3 Bayesian Self-Critical Sequence Training

We used AoANet architecture [18], which provided state-of-the-arts results on MS COCO image captioning dataset. We briefly describe its architecture before presenting our approach.

3.1 Image Captioning Architecture

AoANet [18] is based on encoder-decoder architecture with attention mechanism. The pipeline of its main module, referred to as AoA module, is formulated as:

\[
AoA(f_{\text{att}}, Q, K, V) = \sigma(W_g^Q Q + W_g^K f_{\text{att}}(Q, K, V) + b) \odot (W_i^Q Q + W_i^K f_{\text{att}}(Q, K, V) + b) \tag{1}
\]

where all \(W\)s, \(b\)s are learnable parameters, and \(Q, K, V\) are queries, keys and values respectively; \(f_{\text{att}}(Q, K, V)\) generates a weighted average of value vectors for each query, called as attention vectors, using similarity scores between that query and all the keys [32]:

\[
f_{\text{att}}(Q, K, V) = \text{SoftMax}(\frac{QK^T}{\sqrt{d}})V \tag{2}
\]

These attention vectors, along with the query vector itself, go through an extra attention gate \(\sigma(.)\) to generate the final set of attention vectors of an AoA module.

3.2 Encoder

Given an image, Faster R-CNN is used to extract set of \(k\) feature vectors \(A = \{a_1, a_2, \ldots, a_k\}\), where \(a_i \in \mathbb{R}^D\), and \(D\) is dimension of each vector. These feature vectors \(A\) are linearly transformed into \(Q, K\) and \(V\) before passing they are passed through AoA module. Additional details on the architecture (for e.g., multi-head attention, layer normalization, etc.) can be found in [18]. The encoder contains 6 such AoA modules that are stacked on top of each other, and the final output from the encoder is a set of re-weighted feature vectors \(A_{\text{enc}}\) from the last AoA module.

3.3 Decoder

The decoder includes an Attention LSTM followed by its own AoA module. The Attention LSTM’s hidden state \(h_t\) and \(A_{\text{enc}}\) are linearly transformed and passed through decoder AoA module to generate a context state \(c_t\). Note that the \(Q\) for this AoA module comes from \(h_t\), while \(K\) and \(V\) come from \(A_{\text{enc}}\). The Attention LSTM uses this context state \(c_t\), current word \(H_t\) (one hot encoding of word \(w_t\)), mean \(\bar{a}_{enc}\) of \(A_{\text{enc}}\), and its own hidden state \(h_{t-1}\) to generate updated
hidden state \( h_t \). This context vector \( c_t \) is also used to compute the conditional probabilities of the words in the vocabulary. The decoder equations are given by:

\[
x_t = [W_e \Pi t \bar{a}_{enc} + c_{t-1}]
\]

\[
h_t, m_t = LSTM(x_t, h_{t-1}, m_{t-1})
\]

\[
c_t = AoA_{Dec}(f_{att}, W_Q d h_t, W_k d A_{enc}, W_v d A_{enc})
\]

\[
p(y_t | y_{1:t-1}, I) = \text{softmax}(W_p c_t)
\]

where all \( W \)s are learnable parameters. Additional details can be found in [18].

3.4 Training Objective

The training for image captioning application typically follows two stages.

**Cross-entropy loss optimization:** We first minimize the following word-level cross-entropy loss function [2,18]:

\[
L_{XE}(\theta) = -\sum_{t=1}^{T} \log(p_{\theta}(y_t^* | y_{1:t-1}))
\]

where, \( y_{1:T} \) is the ground truth caption, \( \theta \) are the model parameters and \( T \) is number of words in the caption.

**CIDEr-D optimization:** In the second stage, we use B-SCST to directly optimize the CIDEr-D metric. Optimizing CIDEr-D directly is referred to as CIDEr-D optimization in rest of this paper. We first briefly describe the well-known SCST approach [30], which works as follows. The decoder (agent) interacts with the image and current word features (environment) using the model’s parameters \( \theta \) (policy \( p_{\theta} \)) and generates the next word (action). After a complete caption is generated, CIDEr-D score (reward) is calculated using the ground truth sentence. The goal of CIDEr-D optimization is to minimize the negative expected CIDEr-D rewards function, denoted by \( r(\cdot) \):

\[
L_{RL}(\theta) = -E_{y_{1:T} \sim p_{\theta}}[r(y_{1:T})]
\]

The gradient of this loss is approximated [30] using

\[
\nabla_{\theta} L_{RL}(\theta) \approx -(r(y_{1:T}^*) - r(\hat{y}_{1:T})) \nabla_{\theta} \log p_{\theta}(y_{1:T}^*)
\]

Here, \( y_{1:T}^* \) is the sampled caption generated by sampling words from the decoder’s output SoftMax distribution at each timestep. \( \hat{y}_{1:T} \) is the greedy caption generated by choosing the word with highest SoftMax probability at each time step. \( \hat{y}_{1:T} \) is the “baseline” whose reward \( r(\hat{y}_{1:T}) \) is used to normalize the rewards of sampled caption [30] and reduce the variance of the gradient. This gradient formulation helps increase probability of the captions with rewards (CIDEr-D scores) higher than those generated by the current model, and decreases probability of the captions with lower rewards (CIDEr-D scores).
The choice of “baseline” is important here, and the usage of greedy caption as “baseline” may be undesirable when there is uncertainty in the model predictions. The SoftMax probabilities have been shown to be overly confident [12] even when the model is uncertain about its predictions, i.e., possibly high values even for incorrect predictions. As shown in Figure [1] there could be high uncertainty in greedy captions and its corresponding CIDEr-D reward scores. We could underestimate or overestimate the “baseline” reward due to this uncertainty, which will lead to noisy optimization. We, therefore, propose to use Bayesian inference to estimate the “baseline” reward, and refer to it as B-SCST.

According to Bayes rule, the posterior distribution of model parameters is given by the equation:

\[
p(w|x, y) = \frac{p(y|x, w)p(w)}{p(y|x)} \tag{7}
\]

where, \((x, y)\) are input-output pairs, \(p(y|x, w)\) is the model likelihood and \(p(w)\) is the prior over the model parameters. Computing the posterior distribution \(p(w|x, y)\) is often intractable, and hence Bayesian approximate inference techniques have been proposed which include: (i) Markov Chain Monte Carlo (MCMC) sampling based probabilistic inference [26], (ii) Variational inference techniques to infer the tractable approximate posterior distribution around model parameters [14,4], and (iii) MC dropout approximate inference [12].

Predictive distribution for Bayesian DNNs is obtained using multiple stochastic forward passes through the network during the prediction phase, while sampling from the posterior distribution of network parameters through Monte Carlo estimators. Equation [8] shows the predictive distribution of the output \(y^*\) given new input \(x^*\):

\[
p(y^*|x^*, x, y) = \int p(y^*|x^*, w)q_\theta(w)dw
\]

\[
p(y^*|x^*, x, y) \approx \frac{1}{M} \sum_{i=1}^{M} p(y^*|x^*, w_i) , \quad w_i \sim q_\theta(w) \tag{8}
\]

where, \(M\) is number of Monte Carlo samples.

In B-SCST, we use MC dropout approximate inference to infer the posterior distribution around the model parameters. The dropout layers are modeled using Bernoulli distribution [11] with dropout rate as the parameter. We use multiple MC dropout forward passes through the model to infer the distribution of captions around the current model parameters, and estimate their mean CIDEr-D score. We use this mean score, which accounts for the uncertainty, as the “baseline” score. Also, we do not perform any greedy sampling, i.e., choosing only the word with highest SoftMax probability, during this process. Instead, we sample from the SoftMax distribution during training, which allows the model to explore a larger search space. The gradient of the loss in our proposed model can be
Fig. 2: Bayesian Self Critical Sequence Training (B-SCST). The AoANet encoder and decoder modules of the model are marked as “Enc” and “Dec” respectively, and the gray nodes inside them indicate the dropout nodes. The $M$ MC dropout forward passes through the model are marked as $MC_1$ through $MC_M$. In each of these forward passes, the input image features go through the encoder, and the decoder uses them to generate the word prediction at each time-step. CIDEr-D score is calculated between the predicted caption and the ground truth caption. The mean of the CIDEr-D scores from $M$ MC dropout forward passes is used as the “baseline” score during policy gradient RL training.

approximated by changing $\theta$ as:

$$\nabla_{\theta} L_{RL}(\theta) \approx -\frac{1}{M} \sum_{m=1}^{M} (r(y^s_{1:T}) - \frac{1}{M} \sum_{m=1}^{M} r(y^s_{1:T})) \nabla_{\theta} \log p_{\theta}(y^s_{1:T})$$

(9)

where $M$ is the number of MC dropout forward passes or simulations. We illustrate B-SCST approach in Figure 2.

We want to point out that our approach is different from some of the other works [6,2]. In [6], beam-search is used to select the top-5 captions in terms of SoftMax probability, and the mean of five caption scores is used as the “baseline” reward. We do not use beam-search during training, and instead use Bayesian inference by performing multiple stochastic MC dropout forward passes and don’t restrict the search space to top-5 candidates. Our approach is also different from [2], who also use beam-search to restrict the search space of sampled captions, but directly use the greedy caption to estimate “baseline” reward, similar to SCST.

4 Experiments

In this section, we present the image captioning results for B-SCST approach and compare against a model where the SCST approach is used. B-SCST can be applied to other image captioning architectures that are trained using SCST to maximize non-differentiable metric scores, such as CIDEr-D.
4.1 Datasets

We present the image captioning results on the widely used Flickr30k [28] and MS COCO [5] image captioning datasets. We compare the standard image captioning evaluation metrics, including BLEU [27], METEOR [8], Rouge-L [24], CIDEr-D [33] and SPICE [1] scores.

Flickr30k: We use Flickr30k data splits from [19], which contain 31014 training, 1014 validation and 1000 test images, each of which have 5 ground truth captions as labels. All captions are converted to lower case [18,25] and only the words occurring at least 5 times are used to build a vocabulary of size 7000 words. We use the bottom-up image features [2] that were used by Grounded Video Description (GVD) [37] as input to our encoder stage. These features are extracted from a Faster R-CNN model [29] that is pre-trained on ImageNet [7] and Visual genome [23] datasets.

MS COCO: We use MS COCO data splits from [19], which contain 113287 training, 5000 validation and 5000 test images, each of which have 5 ground truth captions as labels. We perform similar text preprocessing as Flickr30k dataset, but use only the words occurring at least 4 times in order to build a vocabulary of size 10369 that matches AoANet [18] vocabulary. We use the bottom-up image features from [2] that were also generated using Faster R-CNN model pretrained on ImageNet and Visual genome datasets.

4.2 Training and Inference

We first train the network using cross-entropy loss followed by the proposed B-SCST approach to maximize the CIDEr-D scores (details are in Section 3). We use a minibatch size of 100 images, with every image having five ground-truth captions, and use ADAM [22] optimizer.

We run cross-entropy loss training for 25 epochs, with optimizer learning rate of 2e-4 and decay factor of 0.8 every 3 epochs, with scheduled sampling probability increased at a rate 0.05 every 5 epochs, and with label smoothing [31]. Since each image contains 5 ground truth labels, we replicate each image feature 5 times and pass it through the model to calculate cross-entropy loss for each caption.

We run 30 epochs of CIDEr-D optimization to maximize CIDEr-D scores, with optimizer learning rate of 2e-5 and a reduce on plateau factor of 0.5 when CIDEr-D degrades for more than one epoch. For training using B-SCST approach, we run $M = 5$ MC dropout simulations per image by passing it 5 times through the network with dropout enabled on all layers. During inference, at every time-step we pick the word with highest SoftMax probability among the vocabulary. During inference, we don’t perform any beam search on Flickr30k dataset, but use a beam size of 2 on MS COCO dataset for fair comparison with AoANet results.

For MC dropout, we use the dropout layers in the AoANet architecture. Also, we allow different dropout masks across timesteps of the decoder, because we noticed the model overfit the training data when we used the same dropout mask across the decoder timesteps as proposed in [13].
Table 1: Results on Karpathy test and val splits of Flickr30k dataset. Our approach B-SCST improves the image captioning quality scores as compared to the traditional SCST approach.

|        | Cross-entropy loss training | CIDEr-D optimization |
|--------|----------------------------|----------------------|
|        | B@1 | B@4 | M   | R   | C   | S   | B@1 | B@4 | M   | R   | C   | S   |
| Test   |     |     |     |     |     |     |     |     |     |     |     |     |
| Split  | SCST| 69.8| 27.8| 22.1| 49.0| 59.1| 16.3| 71.8| 28.9| 22.2| 50.0| 65.4| 16.5|
| Val    | SCST| 69.3| 27.6| 21.9| 49.1| 58.1| 16.0| 72.6| 29.6| 22.5| 50.5| 65.4| 16.2|
| Split  | B-SCST| 69.3| 27.6| 21.9| 49.1| 58.1| 16.0| 72.7| 29.6| 22.6| 50.6| 67.0| 16.4|

4.3 Results

We present our results in Tables 1 and 2 where B@N, M, R, C and S stand for BLEU@N, METEOR, ROUGE-L, CIDEr-D and SPICE scores, respectively.

In Table 1, we present a comparison of B-SCST and SCST approaches on Karpathy test and validation of Flickr30k dataset. B-SCST and SCST approaches use the same starting point, i.e., model checkpoint obtained from cross-entropy loss training, for CIDEr-D optimization. We observe that B-SCST improves CIDEr-D score by 2.8 points on the test split, and by 1.6 points on the val split as compared to the SCST approach. All the other metrics are also consistently improved using the B-SCST approach.

In Table 2, we present the scores on Karpathy test and validation splits of MS COCO dataset. Here, SCST* are the results presented directly from the published AoANet paper [18]. SCST are the results we see using the model checkpoints from the AoANet repository. We found that the model checkpoints shared by the authors provide slightly lower test split scores than the results presented in their paper. In our experiments, we used the cross-entropy loss trained model checkpoint provided by the authors and run CIDEr-D optimization on them to compare SCST and B-SCST methods. We observe that B-SCST improves CIDEr-D by 0.8 and 0.9 points on test and val splits, respectively, compared to SCST scores; All the other image captioning quality metric scores are also improved. AoANet paper [18] does not present results on MS COCO validation set; So, SCST* results for validation split are marked N/A.

These results confirm that the proposed Bayesian inference to obtain “baseline” scores in B-SCST provides improvement in the image captioning quality scores over the SCST approach. Our approach can be extended to other Bayesian models including mean-field variational inference [16], where the model parameters are represented by Gaussian distributions.

1 https://github.com/husthuann/AoANet
Table 2: Results on Karpathy test and val splits of MS COCO dataset. SCST numbers are obtained from the pretrained model checkpoints provided by the authors [18]. We observe that these test split scores are slightly lower than SCST* scores published in the paper [18]. SCST* scores for val split are not published. Our approach, B-SCST, improves the image captioning quality scores for both test and val splits as compared to the traditional SCST approach.

4.4 Uncertainty quantification

Bayesian modeling allows capturing “Aleatoric” and “Epistemic” uncertainty estimates. “Aleatoric” or input uncertainty captures noise inherent in the input observations, where as “Epistemic” or model uncertainty captures uncertainty related to model parameters. In this study, we evaluate the model uncertainty using Bayesian active learning by disagreement (BALD) [17], which quantifies mutual information between parameter posterior distribution and predictive distribution.

\[
BALD := H(y^*|x^*, x, y) - \mathbb{E}_{p(w|x,y)}[H(y^*|x^*, w)]
\]  

(10)

where the first term \(H(y^*|x^*, x, y)\) is the predictive entropy that captures a combination of both input and model uncertainty, and is calculated as:

\[
H(y^*|x^*, x, y) := - \sum_{i=0}^{K-1} p_{i\mu} \cdot \log p_{i\mu}
\]  

(11)

where, \(K\) is total number of output classes and \(p_{i\mu}\) is the predictive mean SoftMax probability of \(i^{th}\) class from \(M\) MC samples (given by Equation 8). The second term \(\mathbb{E}_{p(w|x,y)}[H(y^*|x^*, w)]\) in (11) is the mean entropy, where \(H(y^*|x^*, w)\) is the entropy of each MC sample. In the case of image captioning, \(K\) is the vocabulary size of the dataset. For each MC sample here, we obtain the SoftMax probability of an image caption by concatenating the SoftMax probabilities of all the words in the caption, where each word’s Softmax probability vector contains all the output classes (i.e., vocabulary).

We perform MC dropout during inference by enabling dropout in the final fully connected layer, and obtain the MC samples for our Bayesian analysis.
Fig. 3: Comparison of Caption Uncertainty vs CIDEr-D scores and Caption SoftMax vs CIDEr-D scores for Flickr30k Karpathy val split. Plots (a) and (b) demonstrate the uncertainty estimates obtained from Bayesian DNN models are well correlated with the CIDEr-D scores, where lower uncertainty (higher confidence) scores are observed for higher CIDEr-D scores. On the contrary, SoftMax probabilities always give high scores for different levels of CIDEr-D scores. This demonstrates that SoftMax probabilities are overly confident and that Bayesian DNN models could provide better estimates of “baseline” scores in SCST reward calculation.

The predictive distribution of the captions, obtained using 30 MC dropout forward passes, is used to estimate BALD (Equation 10) and predictive entropy (Equation 11) uncertainty scores. In Figure 3 (a & b), uncertainty estimates vs CIDEr-D scores are plotted for Karpathy validation split of Flickr30k dataset. The CIDEr-D scores are mapped to 10 bins and the average uncertainty score are plotted for the samples falling under each bin. It can be observed from the plots that lower CIDEr-D scores indicate higher uncertainty in the predictions, where as higher CIDEr-D scores indicate lower uncertainty. Both uncertainty measures show good correlation with the CIDEr-D scores, which is critical for the interpretability of models and their predicted captions. We also calculate the average SoftMax probability per predicted word of a caption and plot it against their CIDEr-D scores in Figure 3 (c). We observe that these SoftMax
Fig. 4: Comparison of Caption Uncertainty vs CIDEr-D scores and Caption SoftMax vs CIDEr-D scores for MS COCO Karpathy val split. Plots (a) and (b) demonstrate the uncertainty estimates obtained from Bayesian DNN models are well correlated with the CIDEr-D scores, where lower uncertainty (higher confidence) scores are observed for higher CIDEr-D scores. On the contrary, SoftMax probabilities always give high scores for different levels of CIDEr-D scores. This demonstrates that SoftMax probabilities are overly confident and that Bayesian DNN models could provide better estimates of “baseline” scores in SCST reward calculation.

In summary, this uncertainty quantification study demonstrates that the Bayesian approaches provide more robust predictive confidence scores compared to SoftMax probabilities obtained from the image captioning models.
5 Conclusions

We presented B-SCST for image captioning models, a Bayesian variant of the SCST approach that directly optimizes the CIDEr-D metric. In B-SCST, we estimate “baseline” reward for the policy-gradients by averaging CIDEr-D of captions sampled from the distribution inferred using a Bayesian DNN model. We presented our results on AoANet architecture, and demonstrated improved CIDEr-D scores on Flickr30k and MS COCO datasets, as compared to SCST approach. B-SCST can be applied on other image captioning architectures that benefit from using SCST approach. Although the predictive distribution is inferred using MC dropout in our work, the technique can be extended to other Bayesian inference techniques such as mean-field variational inference, where parameters are sampled from Gaussian distributions. We also provide a detailed study of uncertainty quantification for the predicted captions, and demonstrate that these uncertainties correlate well with the CIDEr-D scores, while the SoftMax probabilities are overly confident.
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