

Classical Structured Prediction Losses for Sequence to Sequence Learning

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Abstract

There has been much recent work on training neural attention models at the sequence-level using either reinforcement learning-style methods or by optimizing the beam. In this paper, we survey a range of classical objective functions that have been widely used to train linear models for structured prediction and apply them to neural sequence to sequence models. Our experiments show that these losses can perform surprisingly well by slightly outperforming beam search optimization in a like for like setup. We also report new state of the art results on both IWSLT 2014 German-English translation as well as Gigaword abstractive summarization.

1 Introduction

Sequence to sequence models are usually trained with a simple token-level likelihood loss (Sutskever et al., 2014; Bahdanau et al., 2014). However, at test time these models are asked to produce not just a single token but a whole sequence. In order to resolve this inconsistency and to potentially improve generation, there has been much recent work on training these models at the sequence-level, for instance using REINFORCE (Ranzato et al., 2015), actor-critic (Bahdanau et al., 2016), or with beam search optimization (Wiseman and Rush, 2016).

Before the recent wave of work on sequence level training for neural network models, there has been a large body of research on training linear models at the sequence level. For example, direct loss optimization has been popularized in machine translation with the Minimum Error Rate Training algorithm (MERT; Och 2003) and expected risk minimization has an extensive history for classical NLP models such as Smith and Eisner

(2006); Rosti et al. (2010); Green et al. (2014). In this paper, we revisit several objective functions that have been commonly used in the NLP literature for structured prediction tasks (Gimpel and Smith, 2010) and apply them to a neural sequence to sequence model (Gehring et al., 2017b) (§2). Specifically, we consider likelihood training at the sequence-level, a margin loss as well as expected risk training. We also investigate several combinations of global losses with token-level likelihood. This is, to our knowledge, the most comprehensive comparison of structured losses in the context of neural sequence to sequence learning models (§3).

Our experiments are on the IWSLT 2014 German-English translation task (Cettolo et al., 2014) as well as the Gigaword abstractive summarization task (Rush et al., 2015). We achieve the best reported accuracy on both tasks to date. Most of sequence level losses we survey perform similar and we find that they can outperform the recently introduced beam search optimization (Wiseman and Rush, 2016) on a comparable setup. Classical losses for structured prediction are still very competitive and effective for neural models (§5, §6).

2 Sequence to Sequence Learning

The general architecture of our sequence to sequence models follows the encoder-decoder approach with soft attention first introduced in (Bahdanau et al., 2014). As a main difference, in most of our experiments we parameterize the encoder and the decoder as convolutional neural networks instead of recurrent networks (Gehring et al., 2017a,b). However, the objective functions we present are model agnostic and are equally applicable to recurrent and convolutional models. We demonstrate the applicability of our objective functions to recurrent models in our comparison to Wiseman and Rush (2016) in §6.7, which uses

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their LSTM baseline.

Notation. We denote the source sentence as \mathbf{x} , an output sentence of our model as \mathbf{u} , and the reference or *target* sentence as \mathbf{t} . For some objectives we choose a pseudo reference \mathbf{u}^* instead, such as a model output with the highest BLEU or ROUGE score among a set of candidate outputs, \mathcal{U} , generated by our model.

Concretely, the encoder processes a source sentence $\mathbf{x} = (x_1, \dots, x_m)$ containing m words and outputs a sequence of states $\mathbf{z} = (z_1, \dots, z_m)$. The decoder takes \mathbf{z} and generates the output sequence $\mathbf{u} = (u_1, \dots, u_n)$ left to right, one element at a time. For each output u_i , the decoder computes hidden state h_i based on the previous state h_{i-1} , an embedding g_{i-1} of the previous target language word u_{i-1} , as well as a conditional input c_i derived from the encoder output \mathbf{z} . The attention context c_i is computed as a weighted sum of (z_1, \dots, z_m) at each time step. The weights of the sum are referred to as attention scores and allow the network to focus on different parts of the input sequence as it generates the output sequence. Attention scores are computed by essentially comparing each encoder state z_j to a combination of the previous decoder state h_i and the last prediction u_i ; the result is normalized to be a distribution over input elements. Finally, the model computes scores for the V possible target words u_i by transforming the decoder output h_i via a linear layer with weights W_o and bias b_o : $s_i = W_o h_i + b_o$. This is turned into a distribution via a softmax: $p(u_i | u_1, \dots, u_{i-1}, \mathbf{x}) = \text{softmax}(s_i)$.

Instead of parameterizing the encoder and decoder as recurrent neural networks we use gated convolutional neural networks which enable very fast generation as shown in Gehring et al. (2017b). Being able to generate very fast is essential to efficiently train on the model output as is done in this work. Both encoder and decoder networks share a simple block structure that computes intermediate states based on a fixed number of input tokens and we stack several blocks on top of each other. Each one contains a 1-D convolution with stride one that takes as input k feature vectors and outputs another vector; subsequent layers operate over the k output elements of the previous layer. The output of the convolution is then fed into a gated linear unit (Dauphin et al., 2017). In the decoder network we make sure to remove any future information from the input of the convolutions and

we also add a simple dot-product attention mechanism that summarizes the encoder outputs for each time-step in the decoder network. The parameters θ of our model are all the weight matrices in the encoder and decoder networks. Further details can be found in Gehring et al. (2017b).

3 Objective Functions

We compare several objective functions for training the model architecture described in §2. The corresponding loss functions are either computed over individual tokens (§3.1), over entire sequences (§3.2) or over a combination of tokens and sequences (§3.3). An overview of these loss functions is given in Figure 1.

3.1 Token-Level Objectives

Most prior work on sequence to sequence learning has focused on optimizing token-level loss functions, i.e., functions for which the loss is computed additively over individual tokens.

Token Negative Log Likelihood (TokNLL)

Token-level likelihood (TokNLL, Equation 1) minimizes the negative log likelihood of individual reference tokens $\mathbf{t} = (t_1, \dots, t_n)$. It is the most common loss function optimized in related work and serves as a baseline for our comparison.

Token NLL with Label Smoothing (TokLS)

Likelihood training forces the model to make extreme zero or one predictions to distinguish between the ground truth and alternatives. This may result in a model that is too confident in its training predictions, which may hurt its generalization performance. Label smoothing addresses this by acting as a regularizer that makes the model less confident in its predictions. Specifically, we smooth the target distribution with a prior distribution f that is independent of the current input \mathbf{x} (Szegedy et al., 2015; Pereyra et al., 2017; Vaswani et al., 2017). We use a uniform prior distribution over all words in the vocabulary, $f = \frac{1}{V}$. One may also use a unigram distribution which has been shown to work better on some tasks (Pereyra et al., 2017). Label smoothing is equivalent to adding the KL divergence between f and the model prediction $p(\mathbf{u}|\mathbf{x})$ to the negative log likelihood (TokLS, Equation 2). In practice, we implement label smoothing by modifying the ground truth distribution for word u to be $q(u) = 1 - \epsilon$ and $q(u') = \frac{\epsilon}{V}$

$$\mathcal{L}_{\text{TokNLL}} = - \sum_{i=1}^n \log p(t_i | t_1, \dots, t_{i-1}, \mathbf{x}) \quad (1)$$

$$\mathcal{L}_{\text{TokLS}} = - \sum_{i=1}^n \log p(t_i | t_1, \dots, t_{i-1}, \mathbf{x}) - D_{KL}(f || p(t_i | t_1, \dots, t_{i-1}, \mathbf{x})) \quad (2)$$

$$\mathcal{L}_{\text{SeqNLL}} = - \log p(\mathbf{u}^* | \mathbf{x}) + \log \sum_{\mathbf{u} \in \mathcal{U}(\mathbf{x})} p(\mathbf{u} | \mathbf{x}) \quad (3)$$

$$\mathcal{L}_{\text{Risk}} = \sum_{\mathbf{u} \in \mathcal{U}(\mathbf{x})} \text{cost}(\mathbf{t}, \mathbf{u}) \frac{p(\mathbf{u} | \mathbf{x})}{\sum_{\mathbf{u}' \in \mathcal{U}(\mathbf{x})} p(\mathbf{u}' | \mathbf{x})} \quad (4)$$

$$\mathcal{L}_{\text{MultiMargin}} = \sum_{\mathbf{u} \in \mathcal{U}(\mathbf{x})} \max[0, \text{cost}(\mathbf{t}, \mathbf{u}) - \text{cost}(\mathbf{t}, \mathbf{u}^*) - s(\mathbf{u}^* | \mathbf{x}) + s(\mathbf{u} | \mathbf{x})] \quad (5)$$

$$\mathcal{L}_{\text{SoftmaxMargin}} = - \log p(\mathbf{t} | \mathbf{x}) + \log \sum_{\mathbf{u} \in \mathcal{U}(\mathbf{x})} \exp[s(\mathbf{u} | \mathbf{x}) + \text{cost}(\mathbf{t}, \mathbf{u})] \quad (6)$$

Figure 1: Token and sequence negative log-likelihood (Equations 1 and 3), token-level label smoothing (Equation 2), expected risk (Equation 4), multi-margin (Equation 5), softmax-margin (Equation 6). We denote the source as \mathbf{x} , the reference target as \mathbf{t} , the set of candidate outputs as \mathcal{U} and the best candidate (pseudo reference) as \mathbf{u}^* .

for $u' \neq u$ instead of $q(u) = 1$ and $q(u') = 0$ where ϵ is a smoothing parameter.

3.2 Sequence-Level Objectives

We also consider a class of objective functions that are computed over entire sequences, i.e., sequence-level objectives. Training with these objectives requires generating and scoring multiple candidate output sequences for each input sequence during training, which is computationally expensive but allows us to directly optimize task-specific metrics such as BLEU or ROUGE.

Unfortunately, these objectives are also typically defined over the entire space of possible output sequences, which is intractable to enumerate or score with our models. Instead, we compute our sequence losses over a subset of the output space, $\mathcal{U}(\mathbf{x})$, generated by the model. We discuss approaches for generating this subset in §4.

Sequence Negative Log Likelihood (SeqNLL)

Similar to TokNLL, we can minimize the negative log likelihood of an entire sequence rather than individual tokens (SeqNLL, Equation 3). The log-likelihood of sequence \mathbf{u} is the sum of individual token log probabilities, normalized by the number of tokens in order not to bias towards shorter se-

quences:

$$p(\mathbf{u} | \mathbf{x}) \propto \exp \frac{1}{n} \sum_{i=1}^n \log p(u_i | u_1, \dots, u_{i-1}, \mathbf{x})$$

As target we choose a pseudo reference¹ amongst the candidates which maximizes either BLEU or ROUGE with respect to \mathbf{t} , the gold reference:

$$\mathbf{u}^*(\mathbf{x}) = \arg \max_{\mathbf{u} \in \mathcal{U}(\mathbf{x})} \text{BLEU}(\mathbf{t}, \mathbf{u})$$

As is common practice when computing BLEU at the sentence-level, we smooth all initial counts to one (except for unigram counts) so that the geometric mean is not dominated by zero-valued n -gram match counts (Lin and Och, 2004).

Expected Risk Minimization (Risk)

This objective minimizes the expected value of a given cost function over the space of candidate sequences (Risk, Equation 4). In this work we use task-specific cost functions designed to maximize BLEU or ROUGE (Lin, 2004), e.g., $\text{cost}(\mathbf{t}, \mathbf{u}) = 1 - \text{BLEU}(\mathbf{t}, \mathbf{u})$, for a given a candidate sequence \mathbf{u} and target \mathbf{t} . Different to SeqNLL (§3.2), this loss may increase the score of several candidates

¹Another option is to use the gold reference target, \mathbf{t} , but in practice this can lead to degenerate solutions in which the model assigns low probabilities to nearly all outputs. This is discussed further in §4.

that have low cost, instead of focusing on a single sequence which may only be marginally better than any alternatives. Optimizing this loss is a particularly good strategy if the reference is not always reachable, although compared to classical phrase-based models, this is less of an issue with neural sequence to sequence models that predict individual words or even sub-word units.

The `Risk` objective is similar to the REINFORCE objective used in Ranzato et al. (2015), since both objectives optimize an expected cost or reward (Williams, 1992). However, there are a few important differences: (1) whereas REINFORCE typically approximates the expectation with a single sampled sequence, the `Risk` objective considers multiple sequences; (2) whereas REINFORCE relies on a *baseline reward*² to determine the sign of the gradients for the current sequence, for the `Risk` objective we instead estimate the expected cost over a set of candidate output sequences (see §4); and (3) whereas the baseline reward is different for every word in REINFORCE, the expected cost is the same for every word in risk minimization since it is computed on the sequence level based on the actual cost.

Multi-Margin

Next, we consider the `MultiMargin` objective (Equation 5) which enforces a margin between the model scores of each candidate sequence \mathbf{u} and a reference sequence, similar to Herbrich et al. (1999). There are two differences to classical margin approaches for structured prediction (Taskar et al., 2003; Tsochantaridis et al., 2005): First, we replace the reference \mathbf{t} with the pseudo-reference \mathbf{u}^* , since it performed better in early experiments. Second, we enforce a margin for *every* candidate and not just the highest scoring candidate, hence the name Multi-Margin. The size of the margin is the difference between the cost of the current candidate and the cost of the pseudo-reference: $\text{cost}(\mathbf{t}, \mathbf{u}) - \text{cost}(\mathbf{t}, \mathbf{u}^*)$. For this loss we use the unnormalized scores computed by the model before the final softmax:

$$s(\mathbf{u}|\mathbf{x}) = \frac{1}{n} \sum_{i=1}^n s(u_i|u_1, \dots, u_{i-1}, \mathbf{x})$$

²Ranzato et al. (2015) estimate the baseline reward for REINFORCE with a separate linear regressor over the model’s current hidden state.

Softmax-Margin

Finally, `SoftmaxMargin` (Equation 6) is another classic loss that has been proposed by Gimpel and Smith (2010) as another way to optimize task-specific costs. The loss augments the scores inside the `exp` of `SeqNLL` (Equation 3) by a cost. The intuition is that we want to penalize high cost outputs proportional to their cost.

3.3 Combined Objectives

We also experiment with two variants of combining sequence-level objectives (§3.2) with token-level objectives (§3.1). First, we consider a weighted combination (`Weighted`) of both a sequence-level and token-level objective (Wu et al., 2016), e.g., for `TokLS` and `Risk` we have:

$$\mathcal{L}_{\text{Weighted}} = \alpha \mathcal{L}_{\text{TokLS}} + (1 - \alpha) \mathcal{L}_{\text{Risk}} \quad (7)$$

where α is a scaling constant that is tuned on a held-out validation set.

Second, we consider a constrained combination (`Constrained`), in which for any given input we use either the token-level loss or the sequence-level loss, but not both. The motivation is to maintain good token-level accuracy while optimizing on the sequence-level. In particular, a sample is processed with the sequence-level loss if the token-level loss under the current model is at least as good as the token-level loss of a baseline model $\mathcal{L}_{\text{TokLS}}^b$. Otherwise, we update according to the token-level loss:

$$\mathcal{L}_{\text{Constrained}} = \begin{cases} \mathcal{L}_{\text{Risk}} & \mathcal{L}_{\text{TokLS}} \leq \mathcal{L}_{\text{TokLS}}^b \\ \mathcal{L}_{\text{TokLS}} & \text{otherwise} \end{cases} \quad (8)$$

In this work we use a fixed baseline model that was trained with a token-level loss to convergence.

4 Candidate Generation Strategies

The sequence-level objectives we consider (see §3.2) are defined over the entire space of possible output sequences, which is intractable to enumerate, let alone to score with our models. We therefore resort to using a subset of K candidate sequences $\mathcal{U}(\mathbf{x}) = \{u_1, \dots, u_K\}$, which we generate with our models.

We consider two search strategies for generating the set of candidate sequences. The first is *beam search*, a greedy breadth-first search that maintains a “beam” of the top- K scoring candidates at each generation step. Beam search is the

de facto decoding strategy for achieving state-of-the-art results in machine translation. The second strategy is *sampling* (Chatterjee and Cancedda, 2010), which produces K independent output sequences through multinomial sampling over the model’s output distribution. Whereas beam search focuses on high probability candidates, sampling introduces more diverse candidates, which we explore further in §6.5.

We also consider both online and offline candidate generation settings in §6.4. In the online setting, we regenerate the candidate set every time we encounter an input sentence \mathbf{x} during training. In the offline setting, candidates are generated before training and are never regenerated. Offline generation is also embarrassingly parallel because all samples use the same model. The disadvantage is that the candidates become stale. Our model may perfectly be able to discriminate between them after only a single update, hindering the ability of the loss to correct eventual search errors.³

Finally, while some past work has added the reference target to the candidate set, i.e., $\mathcal{U}'(\mathbf{x}) = \mathcal{U}(\mathbf{x}) \cup \{t\}$, we find that this can destabilize training since the model can learn to assign low probabilities to nearly all model outputs, thereby ruining the candidates generated by the model, while still assigning a slightly higher score to the reference (cf. Shen et al. (2016)). Accordingly we do not automatically include the reference translation in our candidate sets.

5 Experimental Setup

We consider both a machine translation and an abstractive summarization task to evaluate the objective functions.

5.1 Translation

For machine translation we experiment on the IWSLT 2014 German to English (Cettolo et al., 2014) task using a similar setting as Ranzato et al. (2015), which allows us to compare to several other recent studies that also adopted this setup, e.g., Wiseman and Rush (2016).⁴ The training data consists of 160K sentence pairs and the validation set comprises 7K sentences randomly sampled and held-out from the training data. We test

³We can somewhat alleviate this issue by regenerating infrequently, i.e., once every b batches but we leave this to future work.

⁴Different to Ranzato et al. (2015) we train on sentences of up to 175 rather than 50 tokens.

on the concatenation of *tst2010*, *tst2011*, *tst2012*, *tst2013* and *dev2010* which is of similar size to the validation set. All data is lowercased and tokenized with a byte-pair encoding of 14000 types (Sennrich et al., 2016). We evaluate with case-insensitive BLEU.

We modify the *fairseq-py* toolkit to implement the objectives described in §3.⁵ Our translation models have four convolutional encoder layers and three convolutional decoder layers with a kernel width of 3 and 256 dimensional hidden states and word embeddings. We optimize these models using Nesterov’s accelerated gradient method (Sutskever et al., 2013) with a learning rate of 0.25 and momentum of 0.99. Gradient vectors whose norm exceeds 0.1 are renormalized (Pascanu et al., 2013).

We train our baseline token-level models for 200 epochs and then anneal the learning by shrinking it by a factor of 10 after each subsequent epoch until the learning rate falls below 10^{-4} . All sequence-level models are initialized with parameters of a token-level model before annealing. We then train sequence-level models for another 10 to 20 epochs depending on the objective. Our batches contain no more than 8,000 tokens and we normalize gradients by the number of non-padding tokens per mini-batch. We use weight normalization for all layers except for lookup tables (Salmans and Kingma, 2016). Besides dropout on the embeddings and the decoder output, we also apply dropout to the input of the convolutional blocks at a rate of 0.3 (Srivastava et al., 2014). We tuned the various parameters above and report accuracy on the test set by choosing the best configuration based on the validation set.

We also length normalize all scores and probabilities in the sequence-level losses by dividing them by the number of tokens in the sequence so that scores are more comparable between different lengths. Additionally, when generating candidate output sequences during training, we limit the length of the output sequences to be less than 200 tokens for efficiency. We generally use 16 candidate sequences per training example, except for the ablations where we use 5 for faster experimental turnaround.

⁵<https://github.com/facebookresearch/fairseq-py>.

5.2 Abstractive Summarization

For summarization we use the Gigaword corpus as training data (Graff et al., 2003) and pre-process it identically to Rush et al. (2015) resulting in 3.8M training examples and 190K for validation. We evaluate on a Gigaword test set of 2,000 pairs which is identical to the one used by Rush et al. (2015) and we report F1 ROUGE similar to prior work. Our results are in terms of three variants of ROUGE (Lin, 2004), namely, ROUGE-1 (RG-1, unigrams), ROUGE-2 (RG-2, bigrams), and ROUGE-L (RG-L, longest-common substring). Similar to Ayana et al. (2016) we use a source and target vocabulary of 30k words. Our models for this task have 12 layers in the encoder and decoder each with 256 hidden units and kernel width 3. We train on batches of 8,000 tokens with a learning rate of 0.25 for 20 epochs and then anneal as in §5.1.

6 Results

The majority of our experiments are on IWSLT’14 German-English translation and we focus on abstractive summarization in §6.8.

6.1 Comparison of Sequence Level Losses

First, we compare all objectives based on a weighted combination with token-level label smoothing (Equation 7). We also show the likelihood baseline (MLE) of Wiseman and Rush (2016), their beam search optimization method (BSO), the actor critic result of Bahdanau et al. (2016) as well as the best reported result on this dataset to date by Huang et al. (2017). We show a like-for-like comparison to Wiseman and Rush (2016) with a similar baseline model below (§6.7).

Table 1 shows that all sequence-level losses outperform the token-level losses. Our baseline token-level results are several points above other figures in the literature and we improve our token-level results by up to 0.72 BLEU with Risk training.

6.2 Combination with Token-Level Loss

Next, we compare various strategies to combine sequence-level objectives with token-level losses (cf. §3.3). For the remaining experiments we use 5 candidate sequences per training example for faster experimental turnaround. We consider Risk as sequence-level loss and label smoothing as token-level loss. Table 2 shows that combined

	test
MLE (Wiseman and Rush, 2016) [T]	24.03
BSO (Wiseman and Rush, 2016) [S]	26.36
Actor-critic (Bahdanau et al., 2016) [S]	28.53
Huang et al. (2017) [T]	28.96
Huang et al. (2017) (+LM) [T]	29.16
<hr/>	
TokNLL [T]	31.74
TokLS [T]	32.21
<hr/>	
SeqNLL [S]	32.68
Risk [S]	32.93
MultiMargin [S]	32.54
SoftmaxMargin [S]	32.55

Table 1: Test results in BLEU on IWSLT’14 German-English translation with various loss functions cf. Figure 1. [S] indicates sequence level-training and [T] token-level training.

	valid	test
TokLS	33.11	32.21
Risk only	33.55	32.45
<hr/>		
Weighted	33.91	32.85
Constrained	33.77	32.79
Random	33.70	32.61

Table 2: Validation and test BLEU for loss combination strategies. We either use token-level TokLS and sequence-level Risk individually or combine them as a weighted combination, a constrained combination, a random choice for each sample, cf. §3.3.

objectives perform significantly better than pure Risk. The weighted combination (Equation 7) with $\alpha = 0.3$ performs best, slightly ahead of constrained combination (Equation 8). We also compare to randomly choosing between token-level and sequence-level updates which performs worse than the more principled constrained strategy. In the remaining experiments we use the weighted strategy.

6.3 Effect of initialization

So far we initialized sequence-level models with parameters from a token-level model trained with label smoothing. Table 3 shows that initializing weighted Risk with token-level label smoothing achieves 0.7-0.8 better BLEU compared to initializing with parameters from token-level likelihood. The improvement of initializing with TokNLL is only 0.3 BLEU with respect to the TokNLL base-

	valid	test
TokNLL	32.96	31.74
Risk init with TokNLL	33.27	32.07
Δ	+0.31	+0.33
TokLS	33.11	32.21
Risk init with TokLS	33.91	32.85
Δ	+0.8	+0.64

Table 3: Effect of initializing sequence-level training (Risk) with parameters from token-level likelihood (TokNLL) or label smoothing (TokLS).

	valid	test
Online generation	33.91	32.85
Offline generation	33.52	32.44

Table 4: Generating candidates online or offline.

line, whereas, the improvement from initializing with TokLS is 0.6-0.8 BLEU. We believe that the regularization provided by label smoothing leads to models with less sharp distributions that are a better starting point for sequence-level training.

6.4 Online vs. Offline Candidate Generation

Next, we consider the question if refreshing the candidate subset at every training step (online) results in better accuracy compared to generating candidates before training and keeping the set static throughout training (offline). Table 4 shows that offline generation gives significantly lower accuracy. However the online setting is much slower, since regenerating the candidate set requires incremental (left to right) inference with our model which is very slow compared to efficient forward/backward over large batches of pre-generated hypothesis. In our setting, offline generation has 26 times lower throughput than the online generation setting, despite the fast inference speed of fairseq (Gehring et al., 2017b).

6.5 Beam Search vs. Sampling

So far we relied on beam search to generate candidates, however, we may also consider sampling to obtain a more diverse set of candidates (Shen et al., 2016). Table 5 shows that beam search outperforms sampling, most likely due to the lower quality of the samples compared to the candidates returned by beam search. Note that we sample only five candidates per example and compare this

	valid	test
TokLS	33.11	32.21
Sampling	33.44	32.46
Beam search	33.91	32.85

Table 5: Effect of generating candidates with beam search or sampling.

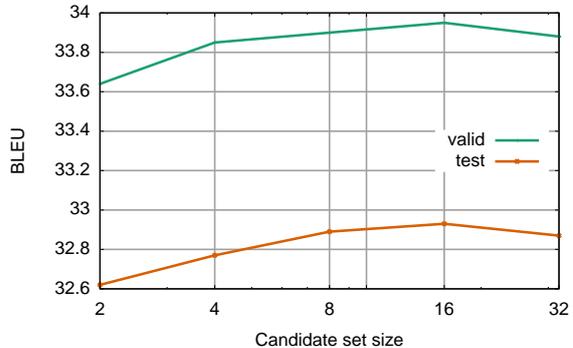


Figure 2: Effect of candidate set size during sequence-level training in terms of validation and test accuracy.

to a beam of size five. Results may be different for larger candidate set sizes, however, more samples also make training less efficient.

6.6 Candidate Set Size

What is the effect of the number of candidates we consider during training? Figure 2 shows that increasing the size of the candidate set improves accuracy up to beam width 16 while larger settings did not work well in our setup.

6.7 Comparison to Beam-Search Optimization

We also compare our sequence-level training approach to the recently proposed Beam Search Optimization (Wiseman and Rush, 2016). To enable fair comparison, we reimplement their baseline, a single layer LSTM encoder/decoder model with 256-dimensional hidden layers and word embeddings with attention and input feeding (Luong et al., 2015). This baseline is trained with Adagrad (Duchi et al., 2011) using a learning rate of 0.05 for five epochs, with batches of 64 sequences (Wiseman and Rush, 2016). For sequence-level training we initialize with the baseline model’s parameters and train with Adam (Kingma and Ba, 2014) for another 10 epochs, with a learning rate of 0.00003 and 16 candidate sequences per training example. We conduct experiments with

	BLEU	Δ
MLE (Wiseman and Rush, 2016)	24.03	
+ BSO (Wiseman and Rush, 2016)	26.36	+2.33
MLE Reimplementation of Wiseman and Rush (2016)	23.93	
+ Risk	26.68	+2.75

Table 6: Comparison to Beam Search Optimization. We report the best likelihood (MLE) and BSO results from Wiseman and Rush (2016), as well as results from our MLE reimplementation and training with Risk. All results are produced with an unnormalized beam search decoder with a beam width of 5.

	RG-1	RG-2	RG-L
ABS+ (Rush et al., 2015) [T]	29.78	11.89	26.97
RNN MLE (Ayana et al., 2016) [T]	32.67	15.23	30.56
RNN MRT (Ayana et al., 2016) [S]	36.54	16.59	33.44
WFE (Suzuki and Nagata, 2017) [T]	36.30	17.31	33.88
SEASS (Zhou et al., 2017) [T]	36.15	17.54	33.63
DRGD (Li et al., 2017) [T]	36.27	17.57	33.62
TokLS	36.53	18.10	33.93
+ Risk RG-1	36.96	17.61	34.18
+ Risk RG-2	36.65	18.32	34.07
+ Risk RG-L	36.70	17.88	34.29

Table 7: Accuracy on Gigaword abstractive summarization in terms of F-measure Rouge-1 (RG-1), Rouge-2 (RG-2), and Rouge-L (RG-L) for token-level label smoothing, and Risk optimization of all three ROUGE F1 metrics. [T] indicates token-level objectives and [S] indicates sequence level objectives.

Risk since it performed best in trial experiments.

Different to the sequence-level settings used in other experiments (§5), we also rescale the BLEU scores in each candidate set by dividing by the difference between the maximum and minimum scores for each sentence. A similar rescaling was used by Bahdanau et al. (2016) and avoids that short sentences dominate the sequence-level updates, since candidate sets for shorter sentences have a much wider range of BLEU scores compared to longer sentences.

Table 6 shows the results from Wiseman and Rush (2016) for their token-level likelihood baseline (MLE), their best beam search optimization results (BSO), as well as our reimplemented baseline. Risk significantly improves BLEU compared to our baseline at +2.75 BLEU, which is slightly better than the +2.33 BLEU improvement reported for Beam Search Optimization (cf. Wiseman and Rush (2016)). This shows that classical objectives for structured prediction are still very competitive.

6.8 Abstractive Summarization

Our final experiment evaluates sequence-level training on Gigaword headline summarization. There has been much prior art on this dataset originally introduced by Rush et al. (2015) who experiment with a feed-forward network and attention (ABS+). Ayana et al. (2016) report a likelihood baseline (MLE) and also experiment with risk training (MRT). Different to their setup we did not find a temperature in the softmax to be beneficial, and we also did not find a large candidate set to work better (§6.6). Suzuki and Nagata (2017) improve over an MLE RNN baseline by limiting generation of repeated phrases. Zhou et al. (2017) also consider an MLE RNN baseline and add an additional gating mechanism for the encoder. Li et al. (2017) equip the decoder of a similar network with additional latent variables to better accommodate the intrinsic uncertainty of this task.

Table 7 shows that our baseline (TokLS) outperforms all prior approaches in terms of ROUGE-2 and ROUGE-L and it is on par to the best previous result for ROUGE-1. We optimize all three ROUGE metrics separately and find that

sequence-level training can improve the strong baseline further.

7 Conclusion

We present a comprehensive comparison of classical losses for structured prediction and apply them to a strong neural sequence to sequence model. For the best performance, we found that combining sequence-level and token-level losses is necessary, and so is training on fresh candidates.

Our experiments are on top of state of the art baselines for both IWSLT'14 German-English translation and Gigaword abstractive sentence summarization, each of which we improved further by sequence-level training. Classical structured prediction losses are still very competitive to recent work on sequence-level training. We showed that classical expected risk can slightly outperform beam search optimization (Wiseman and Rush, 2016) in a like-for-like setup.

Future work may investigate better use of already generated candidates since invoking generation for each batch slows down training by a large factor, e.g., mixing with a few fresh candidates as is done in many MERT implementations.

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