Abstract.

We describe the task of sentence expansion and enhancement, in which a sentence provided by a human is expanded in some creative way. The expansion should be understandable, believably grammatical, and optimally meaning-preserving. Sentence expansion and enhancement may serve as an authoring tool, or integrate in dynamic media, conversational agents, or variegated advertising.

We implement a neural sentence expander trained on sentence compressions generated from a corpus of modern fiction. We modify an MLE objective to support the task by focusing on new words, and decode at test time with controlled curve-like novelty sampling. We run our sentence expander on sentences provided by human subjects and have humans evaluate these expansions. We show that, although the generation methods are inferior to professional human writers, they are comparable to, and as well liked as, our subjects’ original input sentences, and preferred over baselines.

1 Introduction

One of the most important skills acquired in elementary school as well as in high-school is the art of writing. While young authors are able to write short and simple sentences, they struggle with writing more complex ones [18]. This is because writing is quite different from speech, and it takes some effort for elementary or even high-school students to develop and write complex sentences. In this paper we describe the task of sentence expansion and enhancement, in which a short sentence is provided by a human or an agent, and expanded in some creative way, to a more sophisticated sentence. The new sentence should mostly preserve the content of the original but may not exactly contain the original text, as it is expected to be an enhancement, but not necessarily text infilling. We design for some degree of expansion, but same- or reduced-length enhancement (paralleling the tasks of paraphrasing and sentence compression, respectively) are related objectives for which some of our methods are applicable. The expansion is successful if the judge prefers it to the original in its context. Sentence expansion and enhancement may serve as an authoring tool, for assisting authors to compose more complex sentences or converting a “summary” tell into show, or be integrated in dynamic media, such as games, creating more interesting interactions. Static, human-authored game dialogue systems can be likened to curated interaction with conversational agents, and are an ideal target for a (neural-assisted) creative writing interface, such as we propose. These dialogue systems also do not require advance plot integration planning. Sentence enhancement can also be used by advertising, for creating a variety of options of conveying a specific message, and then picking one or more expanded sentences which are assumed to perform best (e.g., those not shown to this user previously). Finally, conversational agents may use sentence enhancement by generating only the essence of the sentence that needs to be communicated, and this sentence may in turn be expanded to be more human friendly and entertaining.

For example, we may better appreciate if, given an input sentence such as “hello world”, a generative model would produce for us “Oh, hello, a world of peace.” (This is an actual model output). An ideal model would be better at the task than an average human, and this appears feasible, by our results.

Computational creativity has always been an popular idea; automatic storytelling and poetry have been attempted from early in computing. Narratology, the study of storytelling, divides it into story (plot) and discourse (style, chronology of presentation) [55]. Most research has been focused on the former [25]. For example, a set of elements and actions is given, with preconditions and postconditions, and then the construction of a story plot is a search problem. The use of deep neural networks permits generating the language in an integrative way with respect to plot elements. Without some direction, however, the outputs lack innate meaning. Consider the following example of fully abstractive generation via character-based language model recurrent neural networks (Char-RNN) [53]:

“while he was giving attention to the second advantage of school building a 2-for-2 stool killed by the Cultures saddled with a half-suit defending the Bharatiya Fernalls office.”

Such artifacts as the above are human-readable metrics, a language modeling result used for comparative analysis in neural network research. To have better grounding for a generative model, we draw on human participation for input. This enables more nuanced output than in pure generation.

In the literature, most narrative generation methods have been extractive, meaning chosen words or connections are present in some source schema, and logic-, graph- or template-based [24, 47, 37, 5, 6]. The topic of sentence enhancement would include slightly modifying words and concepts. In the context of deep learning, abstractive generation is easier, and may be interesting also for the potential relationship with general creativity in AI.

With the recent advances in hardware and neural networks, interest has grown in abstractive text generation models, due to capacity for generalization, long-range interactions, and to reduce manual knowledge modeling. A common problem with the essentially statistical systems is generation of safe sequences that are relevant for many inputs [26]. Fully abstractive generation may result in good-looking but meaningless or irrelevant text [43, 4]. Some authors have mixed neural components in extractive work, and newer models, including generative adversarial networks (GANs) and variational autoencoders,
learn to generate text with diversity through additional parameters in generation or training. However success relative to standard neural language models is debatable \[39\] for tasks applicable to both (not including e.g. autoencoder reconstruction). At inference, on the decoder side of encoder-decoder seq2seq \[44\], beam search tends to produce more generic additions while random sampling is more unreliable, in particular for the task we propose.

| Input                                        | Output                                      |
|----------------------------------------------|---------------------------------------------|
| the woman glared at the child.               | the old woman glared at the younger child.  |
| the robot looked at jake and smirked, it seemed. | the little gray crew looked out at jake and scowled, it seemed like a greatly bad-tempered one. |

In this paper, we expand on human input, transforming complete but possibly unembellished sentences to give them a general or specific style (see Table 1). Given an input (the robot looked at jake, . . . ), our models add content or context to the input sentence. In terms of the narratological split to story and discourse, the inputs are story clauses. In the example, “robot” expands to “little gray crew[man]” demonstrating abstractive generation.

We composed a corpus of story sentences paired with their compression (“kernel”). These sentence kernels are obtained using sentence compression techniques on a corpus of modern (mid to late 20th century) fiction, which is scraped from online resources. (The corpus is further described in the experiments section.) See Table 2 for examples of compression kernels.

We train RNN seq2seq with attention models \[2\] to do the opposite, that is, to transform sentence “kernels” to their source form. Using the seq2seq platform for our expansion task, we first modify MLE loss to emphasize learning new words, making extended training possible. We then investigate simple alternative test-time sampling methods to better control randomness in decoding. These changes improve output quality, in terms of the average preference of human judges.

Table 1. Example sentence expansion and enhancement outputs for human inputs.

In this paper, no attempt was made to learn latent literary style separately from meaning; arguably content makes the style. \[34\] learn to generate text with diversity through additional parameters in generation or training. However success relative to standard neural language models is debatable \[39\] for tasks applicable to both (not including e.g. autoencoder reconstruction). At inference, on the decoder side of encoder-decoder seq2seq \[44\], beam search tends to produce more generic additions while random sampling is more unreliable, in particular for the task we propose.

| Kernel                        | Original                                      |
|-------------------------------|-----------------------------------------------|
| smoke belched from the pipe.  | blue smoke belched from the chromed exhaust pipe. |
| are you back?                  | are you back with the revolutionary lover?     |

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Table 2. Example kernels and original sentences.

We run our sentence expander system on crowdsourced human input. We show that our best method of sentence expansion results in sentences that are as well-liked by crowdsourced human judges as the input.

To summarize, the main contributions of this paper are threefold. First, we define the problem of sentence expansion and enhancement and explain its importance. Second, we present a method that allows the generation of a large data set for the sentence expansion problem, by using sentence compression techniques on a given corpus. Third, we present a method for automatic sentence expansion, which is based on several novel ideas, and show that humans prefer sentences produced by our system to original input sentences significantly more often than with baseline systems.

2 Related Work

2.1 Sentence Compression

Given an input sentence, sentence compression produces a shorter sentence preserving meaning. Text deletion-based (i.e. extractive) models, used extensively, and newer, abstractive models also, employ word and phrase substitution and reordering, learned from data. A typically used corpus for abstractive compression or summarization training is (Annotated) English Gigaword \[32\], which comprises \(~10m documents (4b words) of newswire (with headlines) and auto-generated syntactic annotations. A CNN seq2seq with attention summarizer by \[38\], trained on Gigaword, first-sentence to headline, in their evaluation outperforms an extractive ILP-based (integer linear programming) model by \[9\] and other baselines, although this is likely due to the nature of newswire headlines. \[45\] compare various metrics, including human evaluators and using four compression systems, and report an opposite relationship on a multi-genre corpus (based on MASC \[19\]), wherein ILP is state-of-the-art. The latter is a learning algorithm in one form but performance relies on linguistic constraints. \[17\] report a method for building a parallel corpus for extractive compression from news headlines and first sentences. \[16\] use it to learn LSTM deletion sequences (left to right) with a 2m pair news corpus, reporting 30% (versus 20%) perfect match, showing that syntactic features are not required in these DNN models. \[10\] showed an abstractive compression tree transduction model, learning substitution grammar rule weights with structural SVM. This model does not appear to be robust \[31, 45\].

More recently, \[13\] show controllable-length neural compression without a parallel training corpus by denoising autoencoders, learning to reconstruct a sentence from a list of its words and, as noise, some from another. Desired length is a decoder input.

2.2 Sentence Generation

Generation of full text sentences from a mapping, as in translation, is reliably done with the familiar seq2seq and we focus on it in this work. Various decoding methods for diversity are found in the field of dialogue generation; however, not many are applicable to the task of expansion. A survey is in \[20\].

One example of non-neural controlled sentence generation is \[32\], a framework for slogan generation from keywords, using a dozen feature functions to select words filling slotted patterns. Some of the keywords are special, such as emotion and domain. By comparison, a sentence input, as in our model, allows arbitrary specification, in language.

On the other end, Fan et al. \[14\] collected a dataset of short (700 word) stories written for a sentence premise. They emulate the premise with a GAN generating sentence-length prompts, and then generate stories using convolutional seq2seg, with training-time model fusion \[41\]. To support the output length they incorporate gated self-attention heads at different frequencies. This is intended to spread the prompt’s concepts over many sentences. We train their story expansion seq2seg model on our sentence dataset for a baseline.

Style transfer and conversational models generate sentences from sentences, the latter with context. \[46\] use an inverted objective and decode using an MLP sample selector. They focus on a topic by feeding a grid-based topic embedding to the decoder.

In this paper, no attempt was made to learn latent literary style separately from meaning; arguably content makes the style. \[34\] learn
the sentence itself as a latent variable before adversarially generating against style classifiers. Random sampling is known to give diverse output. However, with softmax temperatures in the optimum range for our dataset (0.3 – 0.7), in poor expansions we observe arbitrary digressions suddenly halted by the attention search, and on the other end failures of randomness degenerating to the argmax. As shown later (in Table 2), different sampling temperatures, beam search, and greedy decoding are empirically equivalent in effectiveness.

Generally speaking, when composing a sentence, authors begin with an idea (which we represent as a sentence kernel) and then decide where to take it or how to write it. In a story, principal plot twists, including the setting setup, occur at significant distance from each other, in order to prevent the audience from becoming fatigued or wary. A conspicuous example of this is the use of cyclic cliffhangers. Other examples include intervening segments of comic relief, which release tension without resolving plot points, and “filler” episodes, which pad length. Therefore, we examine the concept of a novelty curve, in the simplified story of a single sentence.

We aim for a fixed degree of overall novelty in a sentence, so that it is not affected by sentence length. Controlling this enables use of models for the above concepts with a fixed count of loci. We calculate per-word novelty as the difference from the softmax maximum. That is, with \( p \) and \( \tau \) as the probability and corrected temperature at step \( t \),

\[
\text{nov}_w = \max_y \frac{\log p(y)}{\tau} - \frac{\log p(w)}{\tau}
\]

Then, we ration novelty over expected length, using an accumulator and adjusting the sampling temperature. More complex methods than sampling may be substituted at this point, such as merging some of the top outputs with another layer. To control the rationing we tested several adaptive curves. Each bases on a model of the concept, e.g. novelty that is parabolic, exponential, cyclic, moving window, etc., and adjusts itself (in a step-based decoder) using previous sampling outputs towards a target overall sentence novelty.

Our highest-performing model was parabolic. It adjusts the corrected temperature \( \tau \) using Equation 2 where on the left is an integral over \( \tau \) for temperature under the curve, and \( t \) is the remaining novelty (target minus accumulated). Solving for one of the parabola’s parameters, \( b^2 \) or \( c \), with the other set experimentally as a constant, gives two sub-variations of the model, with similar performance. \( a \) is the time (current step) divided by expected length.

\[
\int_0^1 (b^2(x - 0.5)^2 + c) \, dx = t
\]

To assist in aiming for fixed novelty, instead of retrying until it is within error, tuning was done as follows. Due to the novelty “spikes” at parabola ends, we use top-40 sampling, compensating with slightly more powerful parabolas than calculated. This reduces irrelevant generation and prevents the novelty quota from being un-intentionally exhausted too early. For the listed parabolic curves we adjust the free hyperparameter at design time; other curves can be scaled as needed. UNKS are not generated. To reduce repetitiveness in a simple way, we penalize repeated words in a 5-token history. The settings used are: \( b^2 = 0.5 \) and \( c = 3 \) for the respective parabolas, repeat penalty is 15 for content words and 10 for stopwords, and the projected expansion factor is 1.65, which is approximately average for both test and corpus expansions.

Less successful models include an exponential on remaining novelty (up to expected length), which spikes \( \tau \) somewhere inside the sentence, determined by a coefficient. Another is a windowed accumulator, of 3 or 5 tokens, balancing novelty, following either the target novelty or a parabola. The latter is illustrated in Figure 1. As shown, \( \tau \), the calculated temperature starts high and words are chosen such that each diverges more from the original sentence: shortly, off, my. After 4 tokens \( \tau \) drops as it enters the center of the parabola at half the expected length, producing words that connect the digression with the original sentence: left, comma, the. Before generating “tree” \( \tau \) rises again producing the words huge, bare, beige, Christmas. At this point the curve is truncated to a limiting value \( \epsilon = 0.1 \). The value in orange shows the accumulated novelty over the past 3 tokens. The accumulator’s effect is weak in this case and model, but can be seen on the parabola-like shape at steps 4 and 7, where respectively it decreases and increases \( \tau \) to compensate for too much and too little novelty.
Figure 1. Decoding the human input “the tree came alive and started talking” to get “then shortly off my left, the huge bare beige christmas tree came alive and started talking again”. Zoom in for outputs. This instance uses a truncated constant parabola model modified by a size-3 window accumulator (value in orange). Corrected temperature $\tau$ is in green.

4 Experiments

4.1 Corpus

Large public corpora of English fiction (e.g. Google Books, Internet Archive) have well-known quality issues with formatting, OCR, and content categorization (fiction? journal? etc.). One exception is Project Gutenberg, which is proofread. Project Gutenberg’s 19th and early 20th-century public domain fiction and nonfiction has dated English, which we found to transfer noticeably in our model. Some authors use BookCorpus, a dump of free user-created fiction from one source. We did not select this dataset due to its biases. For example, most of the works are in the romance genre.

Instead, we assembled a corpus by scraping the Internet for posted content; specifically, identifying and collecting proofread 20th century English fiction by published authors. We believe that this type of cross section better represents the learned Western experience, and can be valuable for sensitive generation tasks. We hope that other investigators are likewise inspired to recreate mutable but representative datasets, which are scarce in independent research. Our collection has approximately 600m words in 41m sentences, 45% of which is speculative fiction.

4.2 Optimization

In attempts at optimizing the quality of training, and to reduce the tendency for diverging phrase interpretations and expansions, the corpus was experimentally split into groups by topics. One method used was K-means clustering with a bag-of-words approach. Sentences were word-stemmed and vectorized by either TF-IDF (in this scenario, how specific a word is to its sentence) or hashing. Latent semantic analysis [13] was optionally employed at several dimension parameters (50,100,200,300). The silhouette coefficient of cluster cohesion (defined as the average of scaled point distances to nearest different cluster) was highest (0.621) in the case with 10 clusters (for “genres”), with LSA to 200 components, 10k features, and counting words showing in 0.001% to 1% of sentences. In most cases the clusters were moderately self-similar in appearance and often could potentially be classified as, for example, “military”, “bar/pub”, “anatomy”, or “Star Wars”. Such clusters can be used as scenting sets for style priming. Unfortunately, in all cases one cluster was much larger than all others combined. As the clusters could not be balanced, this approach could not be used to split the corpus. Domain adaptation via other methods, such as in [11], is an avenue for future work.

In a different approach, we considered genre qualifications embedded in the corpus. The romance genre, 7% of corpus, is considered fairly homogeneous and we trained a model on this subset, but did not find it competitive. Outputs were significantly and perhaps unsurprisingly colored by a focus on relations between objects (whether spatio-temporal or social); this however meant there were fewer “idea” objects introduced, conflicting with the rationale for abstractive generation, as well as the reducing interest for other genre input. Because this would limit the possible forms of output, the genre subset was not used further.

4.3 Setup

4.3.1 Compressor

To generate sentence kernels, we use the ILP-based system by [9] also discussed in the related work. A standard KN-smoothing LM [21] with $1^{-7}$ pruning was used for the compression. A supervised model [38] was also tested using released data. Given the highly restricted nature of news prose which it is trained on, however, in its published configuration this system does not summarize fiction-style sentences convincingly. Inspection noted a tendency to force a geopolitical framing, and a misunderstanding of common sentence structures in fiction.

4.3.2 Data

The corpus was cleaned of outliers (such as computing-related prose) and languages beside English using stopwords and inspection. Text was extracted and preprocessed to segmented sentence form by custom tokenization and segmentation, followed by CoreNLP [28]. A large number of exceptional cases in punctuation or style across time, authors, and proofreaders requires that the process is imperfect and we saw some output with-excessive-hyphenation, among other issues.

In the implementation, neutral punctuation, especially quotation marks, often compressed incorrectly. 10% of sentences are in quotes; 3% of test set sentences have quotes outside words. Quotes were consequently removed; however, a model trained with them does generate dialogue and narration together.

Target compression was set to a default of 40%; average was 31%. We selected a subset with 17 million sentences where at least 30% reduction occurred. The use of this set corresponds to the technique of separating short items from a neural model, and has similar observed advantage. This subset is the base for training. 3000 sentences were held for development. Sets were shuffled and lowercased, digits replaced by #.

4.3.3 Training

Models with 4 layers LSTM 1024 encoder and decoder were trained for a fixed 1 million steps with batch size 24 and 0.2 dropout. Vocabulary size is 50k using SentencePiece [23]. (Note that with many neologisms and domain terms in science fiction, a common genre in this corpus, many “literary” words may not appear in a 100k regular vocabulary). Names were not removed, in order that they may be synthesized directly (and thematically). A subword BPE vocabulary [40] tended to produce many nonsense words in our experiments.
(SentencePiece produced less). Sentences over 50 words (1.5%) had words in excess truncated.

4.3.4 Test

A test set of 100 sentences was crowdsourced from 20 workers on Amazon Mechanical Turk. Workers were asked to author a “short sentence that might have appeared in some imaginary story”, with no example given, in batches of 5 per form. Statistically, lengths are balanced (with a mean of 12 words, standard deviation 5.2). The mean was affected by the size or width of workers’ input text area in multiple rounds of collection. Sentences with profanity or political entities were filtered.

During model evaluation, each input sentence and its expansion (obtained from the model) were compared by 3 unique, high-quality US workers, which were to choose the sentence that they “think is better or more interesting”, again with no example answers, to minimize researcher bias and let workers weigh brevity against novelty. That is, workers had to select either the input sentence or its expansion, separately for each model. Workers were not asked to rate entailment, but a degree of relatedness is assumed for the tested models. Comparisons were shuffled into groups of 5 and presented with randomized selection order.

Expansions that failed to terminate within the length limit (50 tokens) or have clearly unnatural repetitiveness, detected via the regular expression `.\1 {0,15}` were removed, and the input sentences replaced. For completeness, we note the approval rate on these sentences is 28%, $p = 0.03$ by paired $t$-test. The number of removals was reduced when penalties for repetitiveness were set.

4.4 Results

| Sampling     | Preference | Significant metrics (if any) |
|--------------|------------|-----------------------------|
| Parabola (c) | 0.5        |                             |
| Parabola (b²) | 0.483     |                             |
| Greedy       | 0.422      |                             |
| Random 0.7   | 0.417      | Frechet $r = 0.26$         |
| Random 0.3   | 0.417      |                             |
| Beam search  | 0.413      |                             |
| Fan et al. s2s | 0.3      |                             |
| 3-gram freq. | 0.1        |                             |

Table 3 presents the results in terms of human preferences of the expanded sentence over the input sentence. In all models, except the “original” model, the input sentences were the 100 sentences written by the Mechanical Turk workers. We also note the only metric to have reached statistical significance ($r > 0.2$) for any sampling method, Frechet distance (described below) for random sampling.

“Parabola” refers to our method arising from Equation 2 with $c$ or $b^2$ referring to the variable solved for. Baselines include:

1. Using the modified objective: random sampling with specified temperature, beam search (width 10), and greedy search;
2. Kernels held out from training, with original “expansions” (Table 3);
3. Inserting a word by sampling LM trigram frequency, up to average rate of expansion by other methods;
4. Fan et al.’s seq2seq fusion model, trained on our dataset for 500k steps, with outputs pruned of repeats in the same way. This is using the default top 10 sampling with temperature 0.8, comparable to other baselines; nonetheless, we found that output length and diversity were relatively significantly random.

As depicted in the table, the human subjects preferred the original sentences (obtained from the original stories) to the compressed sentences (the kernels) 71.7% of the time. This is in fact our human-level upper bound, as the expanded sentences were actual story lines. Our parabola method has outperformed all other baselines, and has reached human level equivalence with 50% of human subjects preferring the expansions to the original human input.

Example expansions for human input sentences, with human preference data, are given in Table 4. These examples are chosen to compare across methods, and illustrate user preferences, which are difficult to predict. For additional comparison, some compression kernels and original sentences of writers (from the corpus) are given in Table 5.

4.4.1 Metrics

Automatic metrics that we tested have low Pearson’s $r$ and Spearman’s $p$ with evaluator preferences ($|r| \leq 0.1$). This varied across sampling methods but generally not to the point of significance ($|r| \leq 0.2$). 2328 directly comparable preferences were collected in total.

The metrics computed were:

(i) Discrete Frechet and cosine distances in InferSent unsupervised sentence embeddings [12];
(ii) ratio of unique added unigrams and bigrams to length (Dist-1 and Dist-2 [26]);
(iii) ROUGE-1, ROUGE-2, BLEU-2, BLEU-4 [27][23].
(iv) expansion ratio, added words, and input and output lengths (the latter three with consistent $r \approx -0.1$, low negative, as expected).

No statistically significant differences in variance or mean were seen in subranges upon plotting of embedding distances and other metrics. Using InferSent we trained reference MLPs [11] on SICK dataset entailment and similarity [29] and SNLI dataset entailment [3], and again $r$ was negligible. Training the MLPs on preference data for prediction, on a 10% test set we saw $r = 0.02$. Additionally, we manually evaluated a relation on the (100-sentence) beam search results subset, as its relatively generic output may extend to the preservation of meaning. Here (Table 6), for the accurate preservation of entities or concepts (58% of expansions) $r = 0.21$, and for strongly contradicting or changing the meaning (20%) $r = -0.18$.

4.4.2 Discussion

Since the task is very subjective in nature, it should not be surprising that workers in the evaluation often disagreed. A chance-adjusted measure of reliability, Krippendorff’s $\alpha$ [22], is low; 0.13 on average for sets of preferences. We maintain that this is acceptable, as our objective for testing was an untouched, unpartitioned measure of quality, and more agreement in low-performing model evaluations would indicate a more uniform set of evaluators. Additionally, specialized tasks exist for possible elements as would be optimized for, such as sentence compression for brevity.

For sentence expansion, a more relevant or diverse output is not necessarily better. Presumably, each evaluator has different expectations from an expansion, and learning these is important for an authoring tool. The automatic metric results illustrate the necessity of
### Table 4. Example expansions for human input, with approval ratios vs. input (by human evaluation).

| Input | Expansion                                                                 | Approval Ratio |
|-------|---------------------------------------------------------------------------|----------------|
| they were creeping around the corner when they heard a horrible scream. and then they were rushing around the corner, when they’d first heard a faint scream, and then turned to look at each other’s eyes. | 1/3            |
| Random 0.7                                                                 | 0/3            |
| and now, in all these other respects, they were both rushing back around the corner, when they’d first heard a strange scream of distress, and then very quietly. | 0/3            |

| Input | Expansion                                                                 | Approval Ratio |
|-------|---------------------------------------------------------------------------|----------------|
| there was a princess that lived in a castle. but there was also a princess that still lived in a small castle. | 1/3            |
| Random 0.7                                                                 | 2/3            |
| now, there was a new, high-ranking and female-american soul that lived in a castle. | 2/3            |

| Input | Expansion                                                                 | Approval Ratio |
|-------|---------------------------------------------------------------------------|----------------|
| she often wondered about it but she did not ask him. she’d always wondered about it, but in that case she was not even to ask him. | 2/3            |
| Fan et al. s2s                                                                 | 1/3            |
| but she’d often wondered about it, but she did not mean him in the first place, but in that kind of way. | 1/3            |

| Input | Expansion                                                                 | Approval Ratio |
|-------|---------------------------------------------------------------------------|----------------|
| the kind found his perfect princess. the kind of family found his perfect princess, the only one. | 1/3            |
| Fan et al. s2s                                                                 | 1/3            |
| the kind of man who’d found his own, was a good catholic princess. | 2/3            |

### Table 5. Example kernels and original sentences, with approval ratios vs. input (by human evaluation).

| Kernel | Original                                                                 | Approval Ratio |
|--------|---------------------------------------------------------------------------|----------------|
| he put a hand on gabriel’s shoulder and guided him. he put a hand on gabriel’s shoulder and guided him from the kitchen and into the shadows of the yard. | 3/3            |

| Kernel | Original                                                                 | Approval Ratio |
|--------|---------------------------------------------------------------------------|----------------|
| he has feeling for others outside circle of friends and attaches value to life. he has little feeling for others outside a very small circle of friends, and attaches little real value to human life. | 1/3            |

### Table 6. Beam search (width 10) with manually evaluated entailment and InferSent distances.

| r       | Preserving (58%) | Contradicting (20%) | Frechet  | Cosine   | Dist-1  |
|---------|------------------|----------------------|----------|----------|---------|
| Preference | 0.21             | -0.18                | -0.1     | 0.18     | -0.12   |
| Preserving    | -                | -                    | -0.24    | 0.48     | -0.35   |
early human evaluation. Approval data given in Table 4 shows that preference can be counterintuitive, perhaps due to the diverse population of MTurk workers. In one experiment, the two baseline methods Random 0.3 and trigram frequencies were compared, and the former were preferred 68.3% of the time; less than might be expected given the latter’s performance in Table 2.

Expansion outputs sometimes contradict, and the frequency of this is not explained purely by decoding method and the compression removing “not”s. Given the test collection methodology, input phrases might be inclined towards cliché, while in the corpus clichés are much likelier to appear in a subverted form. Conversely, conceptually dense sentences such as adages or the already published writing of a veteran author are unlikely to gain from extension (in general style). Splitting off coherence from meaning does not appear to be useful to our goal; however, grammar remains a significant factor in user evaluations in our experiments.

In Table 6 we have correlation of manual entailment with InferSent distances ($r = 0.48$ for cosine) on beam search. If an entailment metric is considered reliable, it is easy to resample the output until entailment occurs; this does not seem to affect human preference, however.

As usual in text models, our system allows narrowing the possible style as desired, to some degree, using network bias, priming or scenting a pre-trained model with one author’s books prior to decoding. We did not evaluate by humans the generation with specific author styles; nevertheless a small example of the possibility is given in Table 7.

Table 7. Example outputs, general and primed style.

| Input | Style: general | he woke up. |
|-------|----------------|-------------|
| Style: Douglas Adams | he woke up in the brush. |
| Style: Douglas Adams | he woke up, carefully. |

5 Conclusion and Future Work

We have defined a task and described our experiments in sentence expansion and enhancement. We take a sentence input from humans and produce a more literary, abstractively expanded sentence as output that equals the original, by human evaluation. The task is relevant in aids for writers, where it would save time and potentially improve quality. Because we add content as well as style, it is relevant in virtual agents in games, text ads (adding variety), and other media benefiting from adaptable content. We create a parallel corpus of fiction sentences and their compressions and train seq2seq models on the reverse to perform expansion. A modification to the objective function encourages learning output features and makes training at nontrivial length possible. Simple curve-based sampling methods distribute output novelty in a controlled way. Our models’ outputs, while not independently superior to human inputs, are shown to achieve parity, reaching 50% of total expansions being found, out of an upper target of 72% for professional human expansions. Our results surpass baselines by 20% (compared to a sentence adaptation of Fan et al’s model [16]). 12% of increase is obtained by the modified loss seq2seq, and a further 8% from controlled sampling in the best performing method. Lastly, we observe that common metrics of text generation do not depend user preferences for this task.

With regard to future work, our expansions did not compete directly with human generated expansions, and the added uncertainty would contribute a less stable metric than ours, but this second context for comparison across methods, with user post-processing (editting of generated expansions), will be helpful in proving that use of an expander indeed improves quality by saving time. In estimates from our experiments, untrained Mechanical Turk writers average one minute to expand a sentence in the same way and to the same length as our system. A complete evaluation suite would include building an assistive user interface, allowing users to choose between different sampling methods and to edit resulting sentences. The interface may learn personal preferences, used as feedback to improve future suggestions.

Further developments of process may be expected for sentence expansion with paragraph context, and for full paragraph expansion and enhancement. Evaluating alternative platforms or improvements to tools in this work is a logical step to surpassing human equivalence in this task setup.

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