Texar: A Modularized, Versatile, and Extensible Toolkit for Text Generation

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Abstract

We introduce Texar, an open-source toolkit aiming to support the broad set of *text generation* tasks that transforms any inputs into natural language, such as machine translation, summarization, dialog, content manipulation, and so forth. With the design goals of modularity, versatility, and extensibility in mind, Texar extracts common patterns underlying the diverse tasks and methodologies, creates a library of highly reusable modules and functionalities, and allows arbitrary model architectures and algorithmic paradigms. In Texar, model architecture, losses, and learning processes are fully decomposed. Modules at high concept level can be freely assembled or plugged in/swapped out. These features make Texar particularly suitable for researchers and practitioners to do fast prototyping and experimentation, as well as foster technique sharing across different text generation tasks. We provide case studies to demonstrate the use and advantage of the toolkit. Texar is released under Apache license 2.0 at https://github.com/asyml/texar.

1   Introduction

Text generation spans a broad set of natural language processing tasks that aim at generating natural language from input data or machine representations. Such tasks include machine translation [2, 8], dialog systems [49, 39], text summarization [16, 37], article writing [50, 27], text paraphrasing and manipulation [17, 52, 31], image captioning [48, 22], and more. Recent years have seen rapid progress of this active area in both academia and industry, especially with the adoption of modern deep learning approaches in many of the tasks. On the other hand, considerable research efforts are still needed to improve relevant techniques and enable real-world practical applications.

The variety of text generation tasks share many common properties. For instance, two central goals shared across these tasks are 1) to generate well-formed, grammatical and readable text, and 2) to realize in generated text any desired information inferred from inputs. To this end, a few key techniques are increasingly widely-used, such as neural encoder-decoders [42], attentions [2, 30, 45], memory networks [41], adversarial methods [12, 25], reinforcement learning [36, 3], structured supervision [17, 19, 52], as well as optimization techniques, data pre-processing and result post-processing procedures, evaluations, etc.
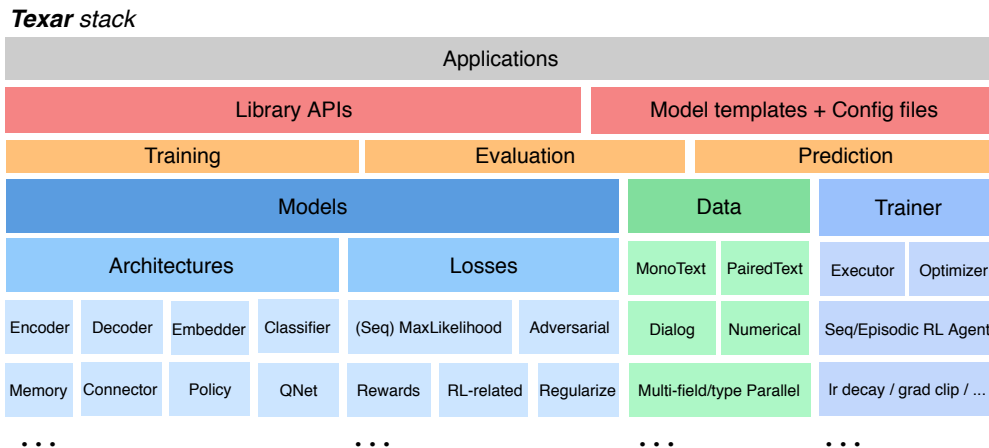
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Texar *stack*

Applications			
Library APIs		Model templates + Config files	
Training	Evaluation	Prediction	
Models		Data	Trainer
Architectures	Losses	MonoText / PairedText	Executor / Optimizer
Encoder / Decoder / Embedder / Classifier	(Seq) MaxLikelihood / Adversarial	Dialog / Numerical	Seq/Episodic RL Agent
Memory / Connector / Policy / QNet	Rewards / RL-related / Regularize	Multi-field/type Parallel	lr decay / grad clip / ...
. . .	. . .	. . .	. . .

Figure 1: The stack of main modules and functionalities in Texar. Many other modules are omitted.

It is therefore highly desirable to have an open-source platform that unifies the development of the diverse yet closely-related text generation applications, backed with clean and consistent implementations of the core algorithms. Such a unified platform enables reuse of common components and functionalities, standardizes design, implementation, and experimentation, fosters reproducible research, and importantly, encourages technique sharing [18] among different text generation tasks, so that an algorithmic advance originally developed for a specific task can quickly be evaluated and potentially generalized to many other tasks.

Though a few remarkable open-source toolkits have been developed, they have been largely designed for one or few specific tasks, especially neural machine translation [6, 24, 34] and dialog related algorithms [33]. This paper introduces *Texar*, a general-purpose text generation toolkit that aims to support most of the popular applications in the field, by providing researchers and practitioners a unified and flexible framework for building their models. Texar is built upon TensorFlow[1], a popular deep learning platform. Texar emphasizes on three key properties, namely, versatility, modularity, and extensibility.

- **Versatility**: Texar contains a wide range of features and functionalities for 1) arbitrary model architectures as a combination of encoders, decoders, embedders, discriminators, memories, and many other modules; and 2) different modeling and learning paradigms such as sequence-to-sequence, probabilistic models, adversarial methods, and reinforcement learning. Based on these, both workhorse and cutting-edge solutions to the broad spectrum of text generation tasks are either already included or can be easily constructed.

- **Modularity**: Texar is designed to be highly modularized, by decoupling solutions of diverse tasks into a set of highly reusable modules. Users can construct their model at a high conceptual level just like assembling building blocks. It is convenient to plug in or swap out modules, configure rich options of each module, or even switch between distinct modeling paradigms. For example, switching between maximum likelihood learning and reinforcement learning involves only minimal code changes

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[1]https://www.tensorflow.org

(e.g., Figure 5). Modularity makes Texar particularly suitable for fast prototyping and experimentation.

- **Extensibility**: The toolkit provides interfaces of multiple functionality levels, ranging from simple configuration files to full library APIs. Users of different needs and expertise are free to choose different interfaces for appropriate programmability and internal accessibility. The library APIs are fully compatible with the native Tensor-Flow interfaces, which allows a seamless integration of user-customized modules, and enables the toolkit to take advantage of the vibrant open-source community by easily importing any external components as needed.

Furthermore, Texar puts much emphasis on well-structured high-quality code of uniform design patterns and consistent styles, along with clean documentations and rich tutorial examples.

In the following, we provide details of the toolkit structure and design. To demonstrate the use of the toolkit and its advantages, we perform extensive experiments and cases studies, including generalizing the state-of-the-art machine translation model to multiple text generation tasks, investigating different algorithms for language modeling, and implementing composite neural architectures beyond conventional encoder-decoder for text style transfer. All are easily realized with the versatile toolkit.

2 Structure and Design

Figure 1 shows the stack of main modules and functionalities in Texar. Building upon the lower level deep learning platform (TensorFlow), Texar provides a comprehensive set of building blocks for model construction, training, evaluation, and prediction. Texar is designed with the goals of *versatility, modularity, and extensibility* in mind. In the following, we first present the design principles that lead to the attainment of these goals (sec 2.1), and then describe the detailed structure of Texar with running examples to demonstrate the properties of the toolkit (sec 2.2-2.4).

2.1 The Design of Texar

The broad variation of the many text generation tasks and the fast-growing new models and algorithms have posed unique challenges to designing a versatile toolkit. We tackle the challenges by principally decomposing the whole experimentation pipeline, developing an extensive set of ready-to-assemble modules, and providing user interfaces of varying abstract levels.

Pipeline Decomposition We begin with a high-level decomposition of model construction and learning pipeline. A deep neural model is typically learned with the following abstract procedure:
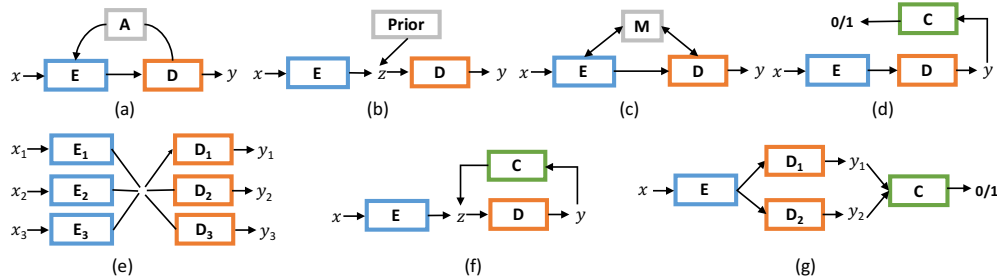
$$\max_\theta \mathcal{L}(f_\theta, D) \tag{1}$$

Figure 2: Example various model architectures in recent text generation literatures. `E` denotes encoder, `D` denotes decoder, `C` denotes classifier (i.e., binary discriminator). **(a)** The canonical encoder-decoder, sometimes with attentions `A` [42, 2, 30, 45], or copy mechanisms [14, 47, 15]; **(b)** Variational encoder-decoder [5, 51]; **(c)** Encoder-decoder augmented with external memory [41, 4]; **(d)** Adversarial model using a binary discriminator `C`, with or without reinforcement learning [28, 55, 53]; **(e)** Multi-task learning with multiple encoders and/or decoders [29, 11]; **(f)** Augmenting with cyclic loss [17, 13]; **(g)** Learning to align with adversary, either on samples y or hidden states [25, 26, 40].

where (1) f_θ is the model that defines the model architecture and the intrinsic inference procedure; (2) D is the data; (3) $\mathcal{L}$ is the learning objective; and (4) **max** denotes the optimization and learning procedure. Note that the above can have multiple losses imposed on different parts of components and parameters (e.g., generative adversarial networks [12]). Texar is designed to properly decouple the four elements, and allow free combinations of them through uniform interfaces. Such design has underlay the strong modularity of the toolkit.

In particular, the decomposition of model architecture and inference (i.e., f_θ) from losses and learning has greatly improved the cleanness of the code structure and the opportunities for reuse. For example, a sequence decoder can focus solely on performing different decoding (inference) schemes, such as decoding with ground truths (teacher-forcing), and greedy, stochastic, and beam-search decoding, etc. Different learning algorithms then call different schemes as a subroutine in the learning procedure—for example, maximum likelihood learning uses decoding with ground truths [32], a policy gradient algorithm can use stochastic decoding [36], and an adversarial learning can use either stochastic decoding for policy gradient-based updates [53] or Gumbel-softmax reparameterized decoding [20] for direct gradient back-propagation (e.g., Figure 5). With unified abstractions, the decoder and the learning algorithms are agnostic to the implementation details of each other. This also enables convenient switch between different learning algorithms for the same model, by simply changing the inference scheme and connecting to the new learning module, without adapting the model architecture (see sec 2.3 for the example).

Module Assembly   The fast evolution of modeling and learning methodologies in the research field has led to sophisticated models that go beyond the canonical (attentional) sequence-to-sequence alike forms and introduce many new composite architectures. Figure 2 summarizes several model architectures recently used in the literature for different tasks. To versatilely support all these diverse approaches, we break down the complex models and extract a set of frequently-used modules (e.g., `encoders`, `decoders`,
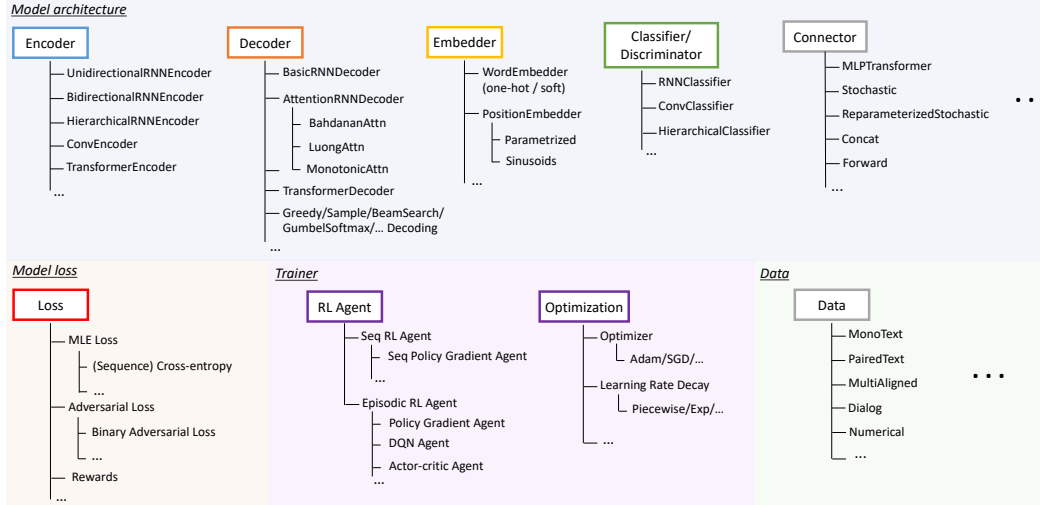
Figure 3: The catalog of a subset of modules for model construction and learning. Other modules, such as memory network modules, and those for evaluation and prediction, are omitted due to space limitations.

`embedders`, `classifiers`, etc). Figure 3 shows the catelog of a subset of modules. Crucially, Texar allows free concatenation between these modules in order to assemble arbitrary model architectures. Such concatenation can be done by directly interfacing two modules, or through an intermediate `connector` module that provides general, highly-usable functionalities of shape transformation, reparameterization (e.g., [23, 20]), sampling, and others.

User Interfaces It is critical for the toolkit to be flexible enough to allow construction of simple and advanced models, while at the same time providing proper abstractions to relieve users from overly concerning about low-level implementations. To this end, Texar provides two major types of user interfaces with different abstract levels: 1) Python/YAML configuration files that instantiate pre-defined model templates, and 2) full Python library APIs. The former is simple, clean, straightforwardly understandable for non-expert users, and is widely adopted by other toolkits [6, 34, 24], while the latter allows maximal flexibility, full access to internal states, and essentially unlimited customizability. Examples are provided in the following section.

2.2 Assemble Arbitrary Model Architectures

Figure 4 shows an example of specifying an attentional sequence-to-sequence model through either a YAML configuration file (left panel), or concise Python code (right panel), respectively.

- The configuration file passes hyperparameters to the model template which instantiates the model for subsequent training and evaluation (which are also configured through YAML). Text highlighted in blue in the figure specifies the names of modules to use. Module hyperparameters are specified under `*_hparams` in the configura-

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```yaml
 1  source_embedder: WordEmbedder
 2  source_embedder_hparams:
 3    dim: 300
 4  encoder: UnidirectionalRNNEncoder
 5  encoder_hparams:
 6    rnn_cell:
 7      type: BasicLSTMCell
 8      kwargs:
 9        num_units: 300
10      num_layers: 1
11      dropout:
12        output_dropout: 0.5
13        variational_recurrent: True
14  embedder_share: True
15  decoder: AttentionRNNDecoder
16  decoder_hparams:
17    attention:
18      type: LuongAttention
19  beam_search_width: 5
20  optimization: …
```

```python
 1  # Read data
 2  dataset = PairedTextData(data_hparams)
 3  batch = DataIterator(dataset).get_next()
 4
 5  # Encode
 6  embedder = WordEmbedder(dataset.vocab.size, hparams=embedder_hparams)
 7  encoder = TransformerEncoder(hparams=encoder_hparams)
 8  enc_outputs = encoder(embedder(batch['source_text_ids']),
 9                        batch['source_length'])
10
11  # Decode
12  decoder = AttentionRNNDecoder(memory=enc_outputs,
13                                hparams=decoder_hparams)
14  outputs, length, _ = decoder(inputs=embedder(batch['target_text_ids']),
15                               seq_length=batch['target_length']-1)
16
17  # Loss
18  loss = sequence_sparse_softmax_cross_entropy(
19      labels=batch['target_text_ids'][:,1:], logits=outputs.logits, seq_length=length)
20
```

Figure 4: Two ways of specifying an attentional sequence-to-sequence model. **Left:** Snippet of an example YAML configuration file of the sequence-to-sequence model template. Only those hyperparameters that the user concerns are specified explicitly in the particular file, while the remaining many hyperparameters can be omitted and will take default values. **Right:** Python code assembling the sequence-to-sequence model, using the Texar library APIs. Modules are created as Python objects, and then can be called as functions to perform the main logic (e.g., decoding) of the module. (Other code such as optimization is omitted.)

tion hierarchy (e.g., `source_embedder_hparams` for the `source_embedder` module). Note that most of the hyperparameters have sensible default values, and users only have to specify a small subset of them. Hyperparameters taking default values can be omitted in the configuration file.

- The library APIs offer high-level function calls. Users can efficiently build any desired pipelines at a high conceptual level, without worrying too much about the low-level implementations. Power users are also given the option to access the full internal states for native programming and low-level manipulations.

Texar modules have multiple features for ease of use, including 1) **Convenient variable re-use**: Each module instance creates its own sets of variables, and automatically re-uses its variables on subsequent calls. Hence TensorFlow *variable scope* is transparent to users; 2) **Configurable through hyperparameters**: Each module defines allowed hyperparameters and default values. Hyperparameter values are configured by passing the `hparams` argument to the module constructor, which precisely corresponds to the above `*_hparams` sections in YAML configuration file; 3) **Callable**: As in Figure 4, a module instance is "called" with input tensors to perform its logic and return output tensors.

2.3 Plug-in and Swap-out Modules

Texar builds a shared abstraction of the broad set of text generation tasks, and creates highly reusable modules. It is convenient to switch between different application contexts, or

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(a) Maximum likelihood learning

Cross entropy loss

y_1 y_2 ...

Decoder
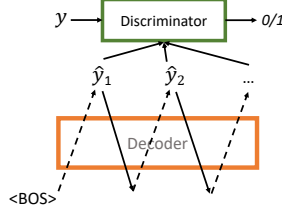
<BOS>
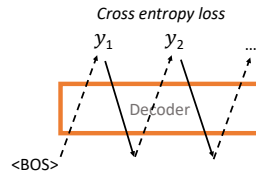
```
outputs, length, _ = decoder(          # Teacher-forcing greedy decoding
    inputs=embedder(batch['target_text_ids']),
    seq_length=batch['target_length']-1,
    decoding_strategy='train_greedy')

loss = sequence_sparse_softmax_cross_entropy(
    labels=data['target_text_ids'][:,1:], logits=outputs.logits, seq_length=length)
```

(b) Adversarial learning

$y \rightarrow$ Discriminator $\rightarrow 0/1$

$\hat{y}_1$ $\hat{y}_2$ ...
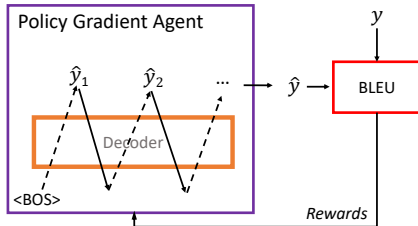
Decoder

<BOS>

```
helper = GumbelSoftmaxTrainingHelper(          # Gumbel-softmax decoding
    start_tokens=[BOS]*batch_size, end_token=EOS, embedding=embedder)
outputs, _, _ = decoder(helper=helper)

discriminator = Conv1DClassifier(hparams=conv_hparams)

G_loss, D_loss = binary_adversarial_losses(
    embedder(data['target_text_ids'][:, 1:]),
    embedder(soft_ids=softmax(outputs.logits)),
    discriminator)
```

(c) Reinforcement learning

Policy Gradient Agent

$\hat{y}_1$ $\hat{y}_2$ ... $\rightarrow$ $\hat{y}$ $\rightarrow$ BLEU

Decoder

<BOS>

y

Rewards

```
outputs, length, _ = decoder(          # Random sample decoding
    start_tokens=[BOS]*batch_size, end_token=EOS,
    embedding=embedder, decoding_strategy='infer_sample')

agent = SeqPGAgent(
    samples=outputs.sample_id, logits=outputs.logits, seq_length=length)

for _ in range(STEPS):
    samples = agent.get_samples()
    rewards = BLEU(batch['target_text_ids'], samples)
    agent.observe(rewards) # Train the policy (decoder)
```

Figure 5: Switching between different learning paradigms of a decoder involves only modification of Line.14-19 in the right panel of Figure 4. In particular, the same decoder is called with different decoding modes, and discriminator or reinforcement learning agent is added as needed, with simple API calls. **Left:** The module structure of each of the paradigms; **Right:** The respective code snippets. For adversarial learning in (b), continuous Gumbel-softmax approximation [20] (with `GumbelSoftmaxTrainingHelper`) to generated samples is used to enable gradient propagation from the discriminator to the decoder.

change from one modeling paradigm to another, by simply plugging in/swapping out a single or few modules, or even merely changing a configuration parameter, while keeping all other parts of the modeling pipeline agnostic.

Figure 5 illustrates an example of switching between three major learning paradigms of an RNN decoder, i.e., maximum-likelihood based supervised learning, adversarial learning, and reinforcement learning. Only local modification of few lines of code is enough to achieve such change. In particular, the same decoder is called with different decoding modes (e.g., `train_greedy`, `Gumbel-softmax`, and `infer_sample`), and discriminator or reinforcement learning agent is added when needed, with simple API calls.

The convenient module replacement can be valuable for fast exploration of different algorithms for a specific task, or quick experimentation of an algorithm's generalization on different tasks.

2.4 Customize with Extensible Interfaces

Texar emphasizes heavily on extensibility, and allows easy addition of customized or external modules through various interfaces, without editing the Texar codebase.

With the YAML configuration file, users can directly insert their own modules by providing the Python importing path to the module. For example, to use a externally implemented RNN cell in the sequence-to-sequence model encoder, one can simply change Lines.6-9 in the left panel of Figure 4 to the following:

```
7   rnn_cell:
8     type: path.to.MyCell
9     kwargs:
10      my_kwarg_1: 123
11      my_kwarg_2: 'xyz'
12      ...
```

as long as the `MyCell` class is accessible by Python, and its interface is compatible to other parts of the model.

Incorporating customized modules with Texar library APIs is even more flexible and straightforward. As the library APIs are designed to be coherent with the native TensorFlow programming interfaces, any externally-defined modules can directly be combined with Texar components as needed.

3 Experiments

We conduct case studies on *technique sharing* that is advantageously supported by Texar: (1) We deploy the state-of-the-art machine translation model, i.e., self-attentional Transformer [45], on other various tasks to study its generality, and obtain improved performance over previous methods; (2) We apply various model paradigms on the task of language modeling to compare the different methods. Besides, to further demonstrate the versatility of Texar, we show a case study on the newly-emerging task of text style transfer, which involves composite neural architectures beyond the conventional encoder-decoder.

3.1 One Technique on Many Tasks: Transformer

Transformer [45] is a recently developed model that achieves state-of-the-art performance on machine translation. Different from the widely-used attentional sequence-to-sequence models [2], Transformer introduces a new *self-attention* technique in which each generated token attends to all previously generated tokens. It would be interesting to see how the technique generalizes to other text generation tasks beyond machine translation. We deploy the self-attention Transformer decoder on two tasks, namely, variational autoencoder (VAE) based language modeling [5] and conversation generation [39].

The first task is to use the VAE model [23] for language modeling. LSTM RNN has been widely-used in VAE for decoding sentences. We follow the experimental setting in previous work [5, 51], and test two models, one with the traditional LSTM RNN decoder, and the other with the Transformer decoder. All other configurations (including the encoders) are the same in the two models. Changing the decoder in the whole experiment pipeline is

Task: VAE language modeling			
Dataset	**Metrics**	**VAE-LSTM**	**VAE-Transformer**
Yahoo [51]	Test PPL	68.31	**61.26**
	Test NLL	337.36	**328.67**
PTB [5]	Test PPL	105.27	**102.46**
	Test NLL	102.06	**101.46**

Table 1: Comparison of Transformer decoder and LSTM RNN decoder on VAE language modeling [5]. Test set perplexity (PPL) and sentence-level negative log likelihood (NLL) are evaluated (The lower the better).

Task: Conversation generation		
Metrics	**HERD-GRU**	**HERD-Transformer**
BLEU-3 prec	0.281	**0.289**
BLEU-3 recall	0.256	**0.273**
BLEU-4 prec	0.228	**0.232**
BLEU-4 recall	0.205	**0.214**

Table 2: Comparison of Transformer decoder and GRU RNN decoder on conversation generation within the HERD model [5]. The Switchboard dataset [56] is used.

easily achieved on Texar, thanks to the modularized design. Both the LSTM decoder and the Transformer decoder have around 6.3M free parameters to learn. Table 1 shows the results. We see that the VAE with Transformer decoder consistently improves over the VAE with conventional LSTM decoder.

The second task is to generate a response given conversation history. We use the popular hierarchical recurrent encoder-decoder model (HRED) [39] as the base model, which treats a conversation as a transduction task. The conversation history is seen as the source sequence and is modeled with a *hierarchical encoder*. Each utterance in the dialog history is first encoded with a word-level RNN. The resulting hidden states of the sequence of utterance are then encoded with a utterance-level RNN. We follow the experimental setting in [56]. In particular, the word-level RNN is set to be bidirectional and the utterance-level is unidirectional. Such configuration is easily implemented by setting the hyperparameters of the Texar module `HierarchicalRNNEncoder`. Similar to the above task, we compare two models, one with a GRU RNN decoder as in the original work, and the other with an Transformer decoder. Table 2 shows the results. Again, we see that the Transformer model generalizes well to the conversation generation setting, and consistently outperforms the GRU RNN counterpart.

3.2 One Task with Many Techniques: Language Modeling

We next showcase how Texar can support investigation of diverse techniques on a single task. This can be valuable for research community to standardize experimental configura-

Models	Test PPL
LSTM RNN with MLE [54]	74.23
LSTM RNN with seqGAN [53]	74.12
Memory Network LM [41]	94.82

Table 3: Comparison of the three models on the task of language modeling, using the PTB dataset [54].

Models	Accuracy	BLEU
Shen et al. [40]	79.5	12.4
Shen et al. [40] on Texar	82.5	13.0
Hu et al. [17] on Texar	**88.6**	**38.0**

Table 4: Text style transfer on the Yelp data [40]. The first row is the original open-source implementation by the author [40]. The subsequent two rows are Texar implementations of the two work.

tions and foster fair, reproducible comparisons. As a case study, we choose the standard language modeling task [54]. Note that this is different from the VAE language modeling task above, due to different data partition strategies conventionally adopted in respective research lines.

We compare three models as shown in Table 3. The LSTM RNN trained with the maximum likelihood estimation (MLE) [54] is the most widely used model for language modeling, due to its simplicity and prominent performance. We use the exact same architecture as generator and setup a (seq)GAN [53] framework to train the language model with adversarial learning. (The generator is pre-trained with MLE.) From Table 3 we see that adversarial learning (almost) does not improve in terms of perplexity. This is partly because of the high variance of the policy gradient in seqGAN learning. We further evaluate a memory network-based language model [41] which has the same number of free parameters (11M) with the LSTM RNN model. The test set perplexity is significantly higher than the LSTM RNNs, which is not unreasonable because LSTM RNN models are well studied for language modeling and a number of optimal modeling and optimization choices are already known.

3.3 Text Style Transfer

To further demonstrate the versatility of Texar for composing complicated model architectures, we next choose the the newly emerging task of text style transfer [17, 40]. The task aims to manipulate the text of an input sentence to change from one style to another (e.g., from positive sentiment to negative), given only non-parallel training data of each style. The criteria is that the resulting sentence accurately entails the target style, while preserving the original content and other properties well.

We use Texar to implement the models from both [17] and [40], whose model architectures fall in the category (f) and (g) in Figure 2, respectively. Experimental settings mostly follow those in [40]. Following previous setting, we use a pre-trained sentiment classifier to evaluate the transferred style accuracy. For evaluating how well the generated sentence preserves the original content, we measure the BLEU score between the generated sentence and the original one (The higher the better) [52]. Note that we do not mean to perform exhaustive evaluations of the methods, but instead aim to demonstrate the flexibility of the toolkit for implementing different composite model architectures beyond conventional

encoder-decoder. Table 4 shows the results. Our re-implementation of [40] recovers and slightly surpasses the original results, while the implementation of [17] provides the better performance in terms of the two metrics.

4 Related Work

Text generation is a broad research area with rapid advancement. Figure 2 summarizes some popular and emerging models used in the diverse contexts of the field. There are some existing toolkits that focus on tasks of neural machine translation and alike, such as Google Seq2seq [6] and Tensor2Tensor [46] on TensorFlow, OpenNMT [24] on (Py)Torch, XNMT [34] on DyNet, Nematus [38] on Theano, and MarianNMT [21] on C++. Par-lAI [33] is a software platform specialized for dialog research. Differing from these task-focusing toolkits, Texar aims to cover as many text generation tasks as possible.

There are also libraries for general NLP applications [1, 35, 10] or for high conceptual-level programming without specific task focuses [9]. With the focus on text generation, we provide a more comprehensive set of well-tailored and readily-usable modules and functionalities to relevant tasks. Some platforms exist for specific types of algorithms, such as OpenAI Gym [7], DeepMind Control Suite [43], and ELF [44] for reinforcement learning in game environments. Texar has drawn inspirations from these toolkits when designing relevant specific algorithm supports.

5 Conclusion

This paper has introduced Texar, a text generation toolkit that is designed to be versatile to support the broad set of applications and algorithms, to be modularized to enable easy replacement of components, and to be extensible to allow seamless integration of any external modules. We invite researchers and practitioners to join and further enrich the toolkit, and in the end help push forward the text generation research and applications together.

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