FROM UNSUPERVISED MACHINE TRANSLATION TO ADVERSARIAL TEXT GENERATION

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ABSTRACT

We present a self-attention based bilingual adversarial text generator (B-GAN) which can learn to generate text from the encoder representation of an unsupervised neural machine translation system. B-GAN is able to generate a distributed latent space representation which can be paired with an attention based decoder to generate fluent sentences. When trained on an encoder shared between two languages and paired with the appropriate decoder, it can generate sentences in either language. B-GAN is trained using a combination of reconstruction loss for auto-encoder, a cross domain loss for translation and a GAN based adversarial loss for text generation. We demonstrate that B-GAN, trained on monolingual corpora only using multiple losses, generates more fluent sentences compared to monolingual baselines while effectively using half the number of parameters.

Index Terms— GAN, Adversarial Training, Machine Translation, Text Generation

1. INTRODUCTION

Language generation is a vital component of many Natural Language Processing (NLP) applications including dialogue systems, question answering, image captioning and summarization. State of the art systems [1, 2], however, can only generate text in one language at a time. Consequently, we train and deploy one model for each language we are interested in. This is specially difficult for edge deployment of machine learning models. Our work presents a bilingual text generation model, B-GAN, which is able to generate text in two languages simultaneously while using the same number of parameters as monolingual baselines.

Neural text generation predominantly employs autoregressive methods based on Maximum Likelihood Estimation (MLE). They use teacher forcing for their training which might give rise to shortsightedness and exposure bias [3]. A number of solutions have been proposed including scheduled sampling [3] and Professor forcing [4]. One alternative is Generative Adversarial Networks (GANs) [5] a generative model for text [6], which has shown impressive results in image generation. Adversarial neural text generation, however,



Fig. 1: Traditional multilingual text generation vs. our bilingual text generation technique with a shared autoencoder

faces a few challenges including the discrete nature of text, quality vs. diversity of the sentences, and mode collapse.

Our work combines adversarial-based text generation and autoregressive models [7, 8, 9]. Building on the idea of unsupervised machine translation in [10, 11], we use the concept of shared encoders between two languages and multi-lingual embeddings to learn the aligned latent representation of two languages and a GAN which can sample from this latent space to generate text (see Fig. 1). [12] combines machine translation with GANs to explore parallel text generation but they can only generate short sentences. However, inspired by [8], we use self-attention architectures along with unsupervised machine translation and adversarial generation to generate longer, fluent sentences. We propose B-GAN, an agent capable of deriving a shared latent space between two languages, and then generating from this space in either language. In summary:

- We propose a single system, B-GAN, trained on monolingual data that can generate text in two languages simultaneously while effectively using half the number of parameters per language.
- B-GAN learns to match the encoder representation of an unsupervised machine translation system.
- B-GAN generates more fluent text compared to monolingual baselines on quantitative and qualitative evaluation.

2. RELATED WORK

In this section we discuss some of the recent developments in sequence to sequence learning [13] and adversarial text generation which are relevant to our work.

Unsupervised NMT A few recent works [10, 14, 11] have pushed the frontier of machine translation systems trained on only monolingual corpora. The common principles of such systems include learning a language model, encoding sentences from different languages into a shared latent representation and using back-translation [15] to provide pseudo supervision.

ARAE Applying GAN to text generation is challenging due to the discrete nature of text. Consequently, backpropagation is not feasible for discrete outputs and computing gradients of the output of decoder requires approximations of the argmax operator. A latent code-based solution for this problem was proposed in [7], where instead of learning to generate reconstructed text the generator learns the latent representation of the encoder. Once trained, a decoder is used to convert the sampled representations into text. This model, however, can only generate text in one language.

Spectral Normalization [16] is a weight normalization method proposed to bound the Lipshitz norm of neural networks by normalizing the spectral norm of layer weight matrices. This is in contrast to local regularization used in WGAN-GP [6]. The authors show that spectral normalization of the discriminator weights stabilizes GAN training and produces more diverse outputs for image generation.

Self-Attention [17], an alternative to LSTMs [18], is a method to learn a representation of sequences. It has been shown to encode long term dependencies well, is nonautoregressive and highly parallelizable. Transformer [19] extended the use of self attention mechanism to sequence transduction applications such as machine translation and is the basis of many state of the art systems [20]. [21] applied self attention along with spectral normalization to the task of image generation. B-GAN is built with self-attention can generate text in multiple languages unlike the previous works.

3. METHODOLOGY

B-GAN comprises of two main components: a translation unit trained on cross-entropy loss for reconstruction (\mathcal{L}_{recon}) and translation (\mathcal{L}_{cd}) and a text generation unit trained on adversarial loss (\mathcal{L}_{adv}). The complete architecture is illustrated in Figure 2.

3.1. Translation Unit

The translation system is a Transformer based sequence-tosequence model similar to [11]. The key components of this system are a denoising auto-encoder for both language 1 and language 2, on the fly back translation [14] and aligned latent



Fig. 2: The complete architecture of B-GAN

representations. The latent representations or the code for both languages are aligned by sharing the encoder weights for the two languages, using joint word embeddings and sub-word tokens [22]. Sub-word tokens have a high overlap for related language pairs such as English and French.

We apply the token wise cross-entropy loss to train our model. Let s_{l_i} be a sentence in language i with $i \in \{1, 2\}$. We denote the encoding of sentence s_{l_i} by enc (s_{l_i}) and similarly, the deocoding of code x (typically an output of the encoder) into language l_i as dec (x, l_i) .

The system is trained with two losses aimed to allow the encoder-decoder pair to reconstruct inputs (reconstruction loss) and to translate correctly (cross-domain loss).

Reconstruction Loss, which, is the standard auto-encoder loss which aims to reconstruct the input:

$$\mathcal{L}_{\text{recon}} = \Delta \left(s_{l_i}, \overbrace{\det\left(\operatorname{enc}\left(s_{l_i}\right), l_i\right)}^{\hat{s}_{l_i}} \right)$$
(1)

Cross-Domain Loss, which aims to allow translation of inputs. It is similar to back-translation [15]. For this loss, denote by transl (s_{l_i}) the translation of sentence s_{l_i} from language i to language 3 - i.

$$\mathcal{L}_{cd} = \Delta \left(s_{l_i}, \underbrace{\det\left(\operatorname{enc}\left(\operatorname{transl}\left(s_{l_i}\right)\right), l_i\right)}_{\tilde{s}_{l_i} :=} \right)$$
(2)

3.2. Bilingual Text Generation Unit

The text generation system is based on a Generative Adversarial Network (GAN) [5]. The generator learns to match the distribution of the latent space of the encoder [23]. The discriminator is fed encoded sentences and generated latent representations and learns to distinguish between the two. The learning process is a two player minimax game between the generator and the discriminator. The discriminator D and generator G are parameterized using neural networks. The latent distribution is $P(c_x), P(c_y)$ where $c_x = Enc(x), c_y = Enc(y)$ is obtained by applying the Encoder, Enc, to the sentences x and y (see Figure 2) from language 1 and 2 respectively. Since we share the latent space for the two languages we assume that if sentence x_i and sentence y_i are translations of each other their latent representations $Enc(x_i)$ and $Enc(y_i)$ are also close under some distant measure.

Adversarial Loss We employ the hinge version of the adversarial loss to train our generative model. For sentences x this would be:

$$\mathcal{L}_{\mathcal{D}} = \mathbb{E}_{x \sim Pdata}[\min(0, -1 + D(Enc(x)))] + \mathbb{E}_{z \sim P(z)}[\min(0, -1 - D(G(z)))]$$
(3)

$$\mathcal{L}_{\mathcal{G}} = -\mathbb{E}_{z \sim P(z)}[D(G(z)))] \tag{4}$$

where L_D and L_G are the discriminator and generator losses respectively.

The architecture of our generator and discriminator is as described in [8]. Typically latent space based generators [23, 24] match the last hidden state of an LSTM however, our system learns to generate a sequences that can match the distribution of the encoder of a transformer.

Training In each iteration we train, in order, the denoising auto-encoder on English, the same denoising auto-encoder on French, back translation from English to French to English and viceversa, one discriminator update and one generator update. The discriminator is trained on c_x during odd iterations and on c_y during even iterations. Enc is a deterministic function and maps data to discrete points inside a continuous space. However the GAN generator produces a continuous distribution so we add Gaussian noise to the encoder representation for better distribution matching. We also apply spherical normalization to the output of the encoder to aid training.

4. EXPERIMENTS

We used Multi30k [25] and WMT monolingual News Crawl datasets ¹ for our experiments. Multi30k consists of 29k images and their captions. We only use the French and English paired captions as the training set and the provided validation set and Flickr 2016 test set. We split the 29k captions into non-overlapping halves [10]. We use News Crawl 2007 to 2010 for both English and French and sample one million sentences each. The validation set is newstest 2013 and the test set is newstest 2014. The test and validation sets are 1k each for Multi30k and 3k each for News Crawl. We tokenize the sentences using the Moses² tokenizer and combine the English and French News Crawl corpora to learn 60k Byte-Pair Encoded (BPE) [22] tokens. We train cross-lingual word embeddings using FastText [26]. The News Crawl trained embeddings and dictionary are used for Multi30k as well. We remove sentences longer than T=35 tokens on Multi30k (0.05%) and T=50 tokens on News Crawl (7.25%) where T is the maximum sequence length we can generate.

We present the specification of all our models in Table 1. We compare B-GAN against three baselines. The baseline ARAE model, which is our implementation of [23], $ARAE_{Conv}$, where we add 1D convolutions to the GAN and $ARAE_{SA}$, which is based on self-attention [8].

Models				
	B-GAN	ARAE _{SA}	ARAE _{Conv}	ARAE
Enc-Dec	SA	SA	LSTM	LSTM
Attention	Yes	Yes	No	No
Layers	4	4	2	1
Back-Trans	Yes	No	No	No
Gen-Disc	SA	SA	Conv	MLP
Sub-Layers	2	2	2	2
Spectral Norm	Yes	Yes	No	No
Loss	Hinge	Hinge	WGAN	WGAN
Embedding	512	512	512	512
Bilingual	Yes	No	No	No

Table 1: Model details for our system, B-GAN, and the three

 ARAE based systems

4.1. Quantitative Evaluation Metrics

Corpus-level BLEU We use the BLEU-N scores to evaluate the generated sentences according to [27]. BLEU-N is a measure of the fluency of the generated sentences. We also use **Perplexity** to evaluate the fluency. The forward perplexity (F-PPL) is calculated by training an RNN language model on real training data and evaluated on the generated samples. We calculate the reverse perplexity (R-PPL) by training an RNN language model (LM) on the synthetic samples and evaluating on the real test data. This gives us a measure of the diversity.

4.2. Quantitative Evaluation

We generated 100k and 10k sentences for BLEU-score evaluations, for the models trained on News Crawl and Multi30k datasets respectively. The BLEU scores of the generated sentences with respect to the test set are presented in Table 2.The higher BLEU scores demonstrate that the model can generate fluent sentences. We note that our proposed B-GAN model can generate more fluent sentences both in English and French compared to the other ARAE models for the larger News Crawl dataset and as fluent on the smaller Multi30k dataset.

We generated 100k and 10k sentences for the News Crawl and the Multi30k datasets respectively for perplexity analysis. We use a vocabulary of 7208 words for Multi30k and 10000 words for News Crawl for training the LM on the real data for F-PPL. The LM is trained on the generated sentences for R-PPL. The forward and reverse perplexities are displayed in Table 3.When the forward perplexities of the generated sentences are lower than real data the generated sentences are not as diverse as the real sentences. Their relative diversity can be compared using R-PPL.

¹http://www.statmt.org/wmt14/translation-task.html

²https://github.com/moses-smt/mosesdecoder

Multi30k								
	English				French			
	B-GAN	$ARAE_{SA}$	ARAE _{Conv}	ARAE	B-GAN	$ARAE_{SA}$	ARAE _{Conv}	ARAE
B-2	88.76	80.05	78.00	92.81	88.42	81.93	90.35	93.79
B-3	75.59	60.44	55.16	78.57	76.56	66.53	76.56	82.05
<i>B-4</i>	60.20	41.84	34.30	60.22	62.42	50.11	59.39	65.37
B-5	44.16	26.90	19.30	42.81	47.32	34.49	41.69	47.60
News Crawl								
B-2	76.72	79.05	70.54	76.22	75.39	75.23	58.53	74.85
B-3	52.08	53.67	41.18	46.04	51.76	51.10	29.72	46.06
<i>B-4</i>	30.22	29.70	18.10	21.03	30.43	30.43	12.10	23.42
B-5	15.76	14.56	7.36	8.51	16.24	16.34	4.23	10.60

 Table 2: BLEU scores for Text Generation using 10000 and 100000 generated sentences for the Multi30k and News Crawl datasets respectively (higher is better).

On the Multi30k dataset, our proposed B-GAN model can generate more fluent and diverse sentences in both languages compared to the other models. For the News Crawl dataset, the B-GAN model generates the most fluent but the least diverse sentences. The B-GAN model loses on diversity on the larger dataset as it trains one model for two languages and has therefore fewer parameters.

Multi30k					
	Eng	glish	French		
	F-PPL R-PPL		F-PPL	R-PPL	
Real	32.3	-	22.2	-	
ARAE	11.2	191.1	6.9	141.9	
$ARAE_{Conv}$	21.3	174.9	8.4	89.0	
$ARAE_{SA}$	15.9	97.0	11.9	178.1	
B-GAN	7.5	92.1	6.1	90.0	
News Crawl					
Real	132.4	-	81.0	-	
ARAE	55.6	533.9	51.7	330.0	
$ARAE_{Conv}$	64.2	325.9	137.5	207.7	
$ARAE_{SA}$	27.2	383.6	25.2	225.9	
B-GAN	26.4	971.4	18.4	746.4	

Table 3: Forward (F) and Reverse (R) word perplexity (PPL) results on multi30k and News Crawl datasets respectively. Lower is better.

4.3. Human Evaluation

We present human evaluation of the generated sentences trained using the News Crawl and the Multi30k datasets in Table 4. For our human evaluation experiment, we used 20 random generated sentences from each model. The task was given to a group of 8 people, 4 native in French and 4 in English. Participants were asked to rate the fluency of sentences on a scale of 1 to 5 where the score 1 corresponds to gibberish, 3 to understandable but ungrammatical, and 5 to naturally constructed and understandable sentences [24]. B-GAN generates the most fluent sentences. Table 5 presents a few sampled sentences.

Multi30k			News Crawl		
	Fluency			Fluency	
Models	(EN)	(FR)	Models	(EN)	(FR)
Real	4.87	4.79	Real	4.89	4.81
ARAE	3.86	3.05	ARAE	2.71	1.94
ARAE _{Conv}	3.56	3.11	ARAE _{Conv}	3.05	1.56
ARAE _{SA}	4.05	3.53	ARAE _{SA}	3.73	3.33
B-GAN	4.76	3.85	B-GAN	4.48	3.33

Table 4: Human evaluation on the generated sentences byB-GAN using the Europarl and the Multi30k dataset.

1	CNN 's John McCain and his wife, Maria, were
	in the midst of a three-day visit to the country.
2	The second attack occurred as a result of the attack,
	and the other two were still being investigated for
	the death of a British soldier who was also killed in the
	southern city of Basra.
1	Consistoire : une étude de faisabilité des travaux d'études
	sur les coûts de l' énergie et des coûts de production
	des matières premières est en cours d'achèvement.
2	Ce dernier, qui a été retenu à la base de l'équipe,
	a été légèrement.

 Table 5: English (top) and French (bottom) sentences generated by B-GAN trained on News Crawl

5. CONCLUSION

The motivation of B-GAN is a) to improve the quality of adversarial text generation and b) generate two, or potentially more, languages by training on the space of unsupervised machine translation. We combine cross-entropy loss for text reconstruction and translation respectively to adversarial loss and generate longer and more fluent sentences compared to our baseline. We use self-attention not only for machine translation but also for our GAN. Our experiments show that our single model which avoids the need of multiple monolingual models yields more fluent sentences in both languages.

6. REFERENCES

- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever, "Language models are unsupervised multitask learners," *OpenAI Blog*, vol. 1, pp. 8, 2019.
- [2] Jiaxian Guo, Sidi Lu, Han Cai, Weinan Zhang, Yong Yu, and Jun Wang, "Long text generation via adversarial training with leaked information," *arXiv preprint arXiv:1709.08624*, 2017.
- [3] Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer, "Scheduled sampling for sequence prediction with recurrent neural networks," *CoRR*, vol. abs/1506.03099, 2015.
- [4] Alex M Lamb, Anirudh Goyal Alias Parth Goyal, Ying Zhang, Saizheng Zhang, Aaron C Courville, and Yoshua Bengio, "Professor forcing: A new algorithm for training recurrent networks," in Advances In Neural Information Processing Systems, 2016, pp. 4601–4609.
- [5] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, "Generative adversarial nets," in *Advances in neural information processing systems*, 2014, pp. 2672–2680.
- [6] Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, and Aaron Courville, "Improved training of wasserstein gans," arXiv preprint arXiv:1704.00028, 2017.
- [7] Yoon Kim, Kelly Zhang, Alexander M Rush, Yann LeCun, et al., "Adversarially regularized autoencoders for generating discrete structures," arXiv preprint arXiv:1706.04223, 2017.
- [8] Jules Gagnon-Marchand, Hamed Sadeghi, Md Haidar, Mehdi Rezagholizadeh, et al., "Salsa-text: self attentive latent space based adversarial text generation," arXiv preprint arXiv:1809.11155, 2018.
- [9] Md. Akmal Haidar, Mehdi Rezagholizadeh, Alan Do-Omri, and Ahmad Rashid, "Latent code and text-based generative adversarial networks for soft-text generation," in *NAACL-HLT* 2019, 2019.
- [10] Guillaume Lample, Ludovic Denoyer, and Marc'Aurelio Ranzato, "Unsupervised machine translation using monolingual corpora only," *CoRR*, vol. abs/1711.00043, 2017.
- [11] Guillaume Lample, Myle Ott, Alexis Conneau, Ludovic Denoyer, and Marc'Aurelio Ranzato, "Phrase-based & neural unsupervised machine translation," *arXiv preprint arXiv:1804.07755*, 2018.
- [12] Ahmad Rashid, Alan Do-Omri, Md Haidar, Qun Liu, Mehdi Rezagholizadeh, et al., "Bilingual-gan: A step towards parallel text generation," *arXiv preprint arXiv:1904.04742*, 2019.
- [13] Ilya Sutskever, Oriol Vinyals, and Quoc V Le, "Sequence to sequence learning with neural networks," in *Advances in neural information processing systems*, 2014, pp. 3104–3112.
- [14] Mikel Artetxe, Gorka Labaka, Eneko Agirre, and Kyunghyun Cho, "Unsupervised neural machine translation," *CoRR*, vol. abs/1710.11041, 2017.
- [15] Rico Sennrich, Barry Haddow, and Alexandra Birch, "Improving neural machine translation models with monolingual data," *CoRR*, vol. abs/1511.06709, 2015.
- [16] Takeru Miyato, Toshiki Kataoka, Masanori Koyama, and Yuichi Yoshida, "Spectral normalization for generative adversarial networks," arXiv preprint arXiv:1802.05957, 2018.

- [17] Ankur P Parikh, Oscar Täckström, Dipanjan Das, and Jakob Uszkoreit, "A decomposable attention model for natural language inference," *arXiv preprint arXiv:1606.01933*, 2016.
- [18] Sepp Hochreiter and Jürgen Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997.
- [19] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin, "Attention is all you need," *arXiv preprint arXiv:1706.03762*, 2017.
- [20] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.
- [21] Han Zhang, Ian Goodfellow, Dimitris Metaxas, and Augustus Odena, "Self-attention generative adversarial networks," arXiv preprint arXiv:1805.08318, 2018.
- [22] Rico Sennrich, Barry Haddow, and Alexandra Birch, "Neural machine translation of rare words with subword units," *CoRR*, vol. abs/1508.07909, 2015.
- [23] Junbo Jake Zhao, Yoon Kim, Kelly Zhang, Alexander M. Rush, and Yann LeCun, "Adversarially regularized autoencoders for generating discrete structures," *CoRR*, vol. abs/1706.04223, 2017.
- [24] Stanislau Semeniuta, Aliaksei Severyn, and Sylvain Gelly, "On accurate evaluation of gans for language generation," arXiv preprint arXiv:1806.04936, 2018.
- [25] Desmond Elliott, Stella Frank, Khalil Sima'an, and Lucia Specia, "Multi30k: Multilingual english-german image descriptions," arXiv preprint arXiv:1605.00459, 2016.
- [26] Piotr Bojanowski, Edouard Grave, Armand Joulin, and Tomas Mikolov, "Enriching word vectors with subword information," *TACL*, vol. 5, pp. 135–146, 2017.
- [27] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu, "Bleu: a method for automatic evaluation of machine translation.," in ACL, 2002, pp. 311–318.