ABSTRACT

The research field of adversarial machine learning witnessed a significant interest in the last few years. A machine learner or model is secure if it can deliver main objectives with acceptable accuracy, efficiency, etc. while at the same time, it can resist different types and/or attempts of adversarial attacks. This paper focuses on studying aspects and research trends in adversarial machine learning specifically in text analysis and generation. The paper summarizes main research trends in the field such as GAN algorithms, models, types of attacks, and defense against those attacks.

Keywords Adversarial Machine Learning · Text Generation · Generative Adversarial Networks · GAN

1 Introduction

A basic Generative Adversarial Network (GAN) model includes two main modules, a generator, and a discriminator. The generator and discriminator are implicit function expressions, usually implemented by deep neural networks [Creswell et al. 2018].

Applying GAN in Natural Language Processing (NLP) tasks such as text generation is challenging due to the discrete nature of the text. Consequently, it is not straightforward to pass the gradients through the discrete output words of the generator [Haidar and Rezagholizadeh 2019].

As text input is discrete, text generators model the problem as a sequential decision making process. In the model, the state is the previously generated characters, words, or sentences. The action or prediction to make is the next character/word/sentence to be generated. The generative net is a stochastic policy that maps current state to a distribution over the action space.

A generative adversarial network GAN can create new data instances that resemble original training data. Original GAN described by [Goodfellow et al. 2014] has the following components and workflow:

- Two NNs: a discriminator and a generator. The discriminator role is as of a simple classifier, that should distinguish real instances (positive examples, from the original training dataset) from fake instances (i.e. negative example), created by the generator.

- The generator tries to fool the discriminator by synthesizing fake instances that resemble real ones. As training progresses, the generator gets closer to producing instances that can fool the discriminator. If generator trained very well, the discriminator gets worse at telling the difference between real and fake. Generally speaking, the generator module task is harder than that of the discriminator. For the least, the discriminator job is binary, but the generator job is much more complex.
• The two NNs compete with two different goals. The goal of the discriminator is to discriminate between the real and the fake instances. The goal of the generator is to eventually learn more about the real instances or data and fool the discriminator.
• Both are trained separately. Each one assumes that the other module is fixed at the time of cycle training (to avoid dealing with a moving target that can be more complex). An accuracy of 100% for the generator to generate fake instances indicates an accuracy of 50% for the discriminator.
• As another sign of competition/game between rivals, the generator instances become negative training examples for the discriminator. The discriminator punishes the generator for producing incorrect instances and rewards it for producing correct instances. The generator evolves to make the discriminator punishes less and rewards more.
• In effect, a good discriminator should not reveal enough information for the generator to make progress. In addition to discriminator and generator modules, GANs include the following components:
  • Generator random input module
  • A generator network that transforms the random input into a data instance
  • Generator loss that punishes the generator for failing to fool the discriminator
  • Back-propagation module: It adjusts weights by calculating the weight’s impact on the output

1.1 Discriminator/Generator: Conditional versus Joint Probability

We can model the difference between the discriminator and the generator as the difference between conditional probability \( p(Y | X) \) and joint probability \( p(X, Y) \) in given a set of data instances \( X \) and a set of labels \( Y \). The conditional probability \( p(Y | X) \) is also known as the posterior probability for \( A \). \( p(Y) \) and \( p(X) \) denote the prior probability of events \( Y \) and \( X \), respectively. The conditional entropy indicates how much extra information you still need to supply on average to communicate \( Y \) given that the other party knows \( X \). The joint entropy represents the amount of information needed to specify the value of two discrete random variables.

There are many variations on how each one of those two components (i.e. the generator and discriminator) work or is trained to function.

GANs have a problem in text generation since the gradients from discriminator can not be passed to the generator explicitly. To deal with this issue, GAN based models (e.g. SeqGAN: Yu et al. [2016]; Goal GAN: Florensa et al. [2018]; MaliGAN: Che et al. [2017]; LeakGAN: Guo et al. [2018]; RankGAN: Lin et al. [2017]; MaskGAN: Fedus et al. [2018]; Xu et al. [2018]; Caccia et al. [2018]) treat text generation as a sequential decision making process and utilize policy gradient: Williams [1992] to overcome this difficulty. The score predicted by a discriminator is used as the reinforcement to train the generator, yielding a hybrid model of GAN and RL. Other models utilize RL agents to control GANs. RL agent forms a decision-making network that interacts with the environment by taking available actions and collects rewards. As a scalability limitation, an agent that is trained using RL is only capable of achieving the single task that is specified via its reward function.

1.2 GANs Methods for Training and Back-Propagation

Applying GAN in text analysis is challenging as text is discrete. Consequently, their is a need to pass the gradients through the discrete output words of the generator. Haidar and Rezagholizadeh [2019]. But how do generator and discriminator modules, train themselves to improve?

The generator module can train itself using self, auto or variational encoders. The code in the decoder can randomly take values to produce different outputs. The goal of the self-encoder is to make the reconstruction error smaller and smaller. The generator uses back-propagation from the discriminator to improve its future instances and update model weights.

The discriminator can also train itself, learn a discriminator process, that can distinguish an instance label as real or generated. It is trained based on real instances from the original dataset and fake instances from the generator.

1.3 GAN loss functions

GAN uses loss functions that evaluate the distance between the distribution of the data that is generated by the GAN and the distribution of the real data. A GAN can have two loss functions for generator and discriminator training.

• Minimax loss: The generator tries to minimize the loss function while the discriminator tries to maximize it, Goodfellow et al. 2014
• Wasserstein loss: The default loss function for TF-GAN Estimators, Arjovsky et al. [2017]. In those GANs, the discriminator will not try to make a binary decision whether an instance is real or fake, but to provide a value between zero and one. A threshold can be decided in this range between values for fake instances versus values for real instances.

2 Character/word/sentence level attacks

While most of AML research publications demonstrate on picture-based datasets, a growing recent trend is the applications of AML in text analysis or NLP. In one taxonomy, AML in NLP can be divided into the following attack levels:

• Character-level attacks. Those involve different possible types of character-level manipulations such as: swap, substitution, deletion, insertion, repeating, one-hot character embedding, and visual character embedding (Hosseini et al. [2017], Zhang et al. [2015], TextBugger Li et al. [2018], Belinkov and Bisk [2017], Gao et al. [2018], Hotflip Ebrahimi et al. [2017], Brown et al. [2019], Pruthi et al. [2019], Eger et al. [2019], Le et al. [2020]).

While character-level attacks are simple, it is easy to defend against when deploying a spell check and proofread algorithms.

• Word-level attacks: Similar to character-level attacks, approaches to word-level attacks through manipulation include: word embedding, language models, filter words through synonyms, substitutes. (e.g., Ebrahimi et al. [2017], Ebrahimi et al. [2018], Kuleshov et al. [2018], Yang et al. [2020], Jin et al. [2020a], Wallace et al. [2019], Gao et al. [2018], Garg and Ramakrishnan [2020], Zhou et al. [2019], Ribeiro et al. [2018], Zang et al. [2020], Alzantot et al. [2019], Li et al. [2016a], Li et al. [2018], Ribeiro et al. [2018], Wang and Zhang [2019], Wang et al. [2020]).

The search algorithms include gradient descent, genetic algorithms, saliency-based greedy algorithm, sampling (Papernot et al. [2016a], Sato et al. [2018], Gong et al. [2018], Alzantot et al. [2018], Zhou et al. [2019], Liang et al. [2017], Ren et al. [2019], Jin et al. [2020a]).

In comparison with character-level attacks, the attacks created by word-level approaches, are more imperceptible for humans and more difficult for machine learning algorithms to defend.

• Sentence-level attacks. Those attacks are usually based on text paraphrasing, demand longer time in adversary text generation. Examples of research publications in sentence level include (Jia and Liang [2017], Iyyer et al. [2018], Cheng et al. [2019], Michel et al. [2019], Lei et al. [2018], Zheng et al. [2020], Jethanandani and Tang [2020]).

• Hybrid or multi-level attacks: Attacks which can use a combination of character, word, and sentence level approaches (HotFlip: Ebrahimi et al. [2017], Blohm et al. [2018], Wallace et al. [2019]).

3 Sequence generative/text generator/generative models approaches

Natural Language Generation (NLG) techniques allow the generation of natural language text based on a given context. NLG can involve text generation based on predefined grammar such as the Dada Engine, Baki et al. [2017] or leverage deep learning neural networks such as RNN, Yao et al. [2017] for generating text. We will describe some of the popular approaches that can be found in relevant literature in the scope of AML.

• Classical: training language models with teacher/professor forcing teacher forcing is common approach to training RNNs in order to maximize the likelihood of each token from the target sequences given previous tokens in the same sequence, Williams and Zipser [1989]. In each time step, s, of training, the model is evaluated based on the likelihood of the target, t, given a groundtruth sequence. Teacher forcing is used for training the generator, which means that the decoder is exposed to the previous groundtruth token. RNNs trained by teacher forcing should be able to model a distribution that matches the target, where the joint distribution is modeled properly if RNN models prediction of future steps. Created error when using the model is propagated over each next or following step, resulting in low performance. A solution to this is training the model using professor forcing, Lamb et al. [2016].

In professor forcing, RNN should give the same results when a ground truth is given as input (when training, teacher forcing) as when the output is looped back into the next step. This can be forced by training a discriminator that classifies wether the output is created with a teacher forced model or with a free running model.
• Conventional inference methods/ maximum likelihood estimation (MLE)
  MLE is conducted on real data samples, and the parameters are updated directly according to the data samples. This may lead to an overly smooth generative model. The goal is to select the distribution that maximizes the likelihood of generating the data. For practical sample scenarios, MLE is prone to over-fitting/exposure bias issues on the training set. Additionally, during the inference or generation stage, the error at each time step will accumulate through the sentence generation process. [Ranzato et al. 2015]

  The following methods utilize MLE:
  – Hidden Markov Model (HMM): A Hidden Markov model (HMM) is a probability graph model that can depict the transition laws of hidden states, and mine the intentional features of data to model the observable variables. The foundation of an HMM is a Markov chain, which can be represented by a special weighted finite-state automaton. The majority of generative models require the utilization of Markov chains. [Goodfellow et al. 2020], [Creswell et al. 2018]. The observable sequence in HMM is the participle of the given sentence in the part-of-speech PoS tag, while the hidden state is the different PoS.
  – Method of moments: The method of moments (MoM) or method of learned moments is an early principle of learning. [Pearson 1893]. There are situations in which MoM is preferable to MLE. One is when MLE is more computationally challenging than MoM, Ravuri et al. 2018. In the generalized method of moments (GMM), in addition to the data and the distribution class, a set of relevant feature functions is given over the instance space. [Hansen 1982], [Rabiner 1989]. Other research contributions in AML MoM or moment matching include: [Salimans et al. 2016], [Mroueh and Sercu 2017], [Lewis and Syrgkanis 2018], [Bennett et al. 2019].
  – Restricted Boltzmann Machine (RBM): Restricted Boltzmann Machine (RBM) is a two-layer neural network consisting of a visible layer and a hidden layer, Hinton 2010. It is an important generative model that is capable of learning representations from data. Generative models have evolved from RBM based models, such as Helmholtz machines (HMs), [Fodor et al. 1988] and Deep Belief Nets, DBN, [Hinton et al. 2006], to Variational Auto-Encoders (VAEs), [Kingma and Welling 2013] and Generative Adversarial Networks (GANs)

• Cooperative training method In Cooperative Training Method, CTM, a language model is trained online to offer a target distribution for minimizing the divergence between the real data distribution and the generated distribution. [Xie et al. 2017], [Yin et al. 2020].

• RL-based versus RL-free text generation
  GAN models were originally developed for learning from a continuous, not discrete distribution. However, the discrete nature of text input handicaps the use of GANs.
  In GANs, a reinforcement learning algorithm is used for policy gradient, to get an unbiased gradient estimator for the generator and obtain the reward from the discriminator. [Chen et al. 2018].
  – RL-based generation
    Reinforcement learning (RL) is a technique that can be used to train an agent to perform certain tasks. Due to its generality, reinforcement learning is studied in many disciplines.
    GAN models that use a discriminating module to guide the training of the generative module as a reinforcement learning policy has shown promising results in text generation. [Guo et al. 2018]. Various methods have been proposed in text generation via GAN (e.g. [Lin et al. 2017], [Rajeswar et al. 2017], [Che et al. 2017], [Yu et al. 2017], [Che et al. 2017]).
    There are several models of RL, some of which were applied to sentence generation, e.g., actor-critic algorithm and deep Q-network, (e.g. [Sutton et al. 2000], [Guo 2015], [Babdanau et al. 2016].
    One optimization challenge with RL-based approaches is that they may yield high-variance gradient estimates. [Maddison et al. 2016], [Zhang et al. 2017].
  – RL free GANs for text generation
    Examples of models that use an alternative to RL:
    * Latent space based solutions
    * Continuous approximation of discrete sampling
    Those models apply a simple soft-argmax operator, or Gumbel-softmax trick to provide a continuous approximation of the discrete distribution on text.
    Examples of research efforts in this category include: TextGAN, [Zhang et al. 2017] and GumbelSoftmax GAN (GSGAN), [Kusner and Hernández-Lobato 2016], [Jang et al. 2016], [Maddison et al. 2016], FM-GAN, [Chen et al. 2018], GSGAN, [Kusner and Hernández-Lobato 2016], and RelGAN, [Nie et al. 2018].
3.1 Long versus short text generation

Literature in this area differentiates between the generation of short texts (e.g. less than 20 words) and the generation of long text. Applications for each one can be different from the other.

The majority of publications focus on short text generation as it seems to be less challenging. Different challenges are discussed in the literature specially in long text generation. For example, one of the unique challenges for long text generation is the sparse reward issue, in which a scalar guiding signal is only available after an entire sequence has been generated. Vezhnevets et al. [2017], Guo et al. [2018], Sutton et al. [2000]. The main disadvantage of sparse reward problem is making the training sample inefficient, Tuan and Lee [2019]. Model-based RLs have been proposed recently to solve problems with extremely sparse rewards, Pathak et al. [2017].

3.2 Supervised versus unsupervised text generation

Majority of work in this area falls in the supervised category (e.g. Robin [1994], Tanaka-Ishii et al. [1998], Bahdanau et al. [2016], Bengio et al. [2015], Vinyals and Le [2015], Wiseman et al. [2017], Bhowmik and De Melo [2018], Puduppully et al. [2019]).

As a supervised problem, in a particular sentence, the terms/words in the sentence can be seen as the input features while the next term/feature is the target.

Examples of publications that fall in the unsupervised text generation include: (Graves [2013], Yu et al. [2017], Zhang et al. [2018a], Hu et al. [2017], Schmitt et al. [2020]). Unsupervised text can be generated from explainable latent topics, Wang et al. [2018], structured data, Schmitt et al. [2019], Sheffer et al. or Knowledge graphs (KGs), Bhowmik and De Melo [2018], Koncel-Kedziorski et al. [2019], Schmitt et al. [2020], Jin et al. [2020].

4 Machine learning algorithms for text generation

- Using RNN (LSTM versus GRU versus BidirectionalRNN) for text generation

State-of-the-art text-generation models are based on recurrent neural networks (RNNs). Several papers discussed using different deep learning RNN algorithms such as those mentioned above in automatic text generation, (e.g. Kiddon et al. [2016], Hu et al. [2018], Abdelwahab and Elmaghraby [2018], Lu et al. [2018], Nie et al. [2018], Zhu et al. [2018], Wang et al. [2019], Mangal et al. [2019], Moita and Modipa [2020], Mangal et al. [2019]). Unlike traditional methods, RNN-based approaches rely on data-driven without manual intervention and emphasize on end-to-end encoder-decoder structure.

Different performance metrics and methods are used to evaluate the output of the process such as log-likelihood, loss function, overall processing time, etc. The loss function that is used when training the model is the negative log likelihood or the negative log probability on the target sequence.

LSTM shows to be a very good model in several aspects in comparison with the other evaluated models, Mei et al. [2015], Zang and Wan [2017], Mangal et al. [2019]. Many recent GANs for text generation, such as, Kusner and Hernandez-Lobato [2016], Yu et al. [2017], Guo et al. [2018], Lin et al. [2017] and Fedus et al. [2018] are using LSTM.

Some papers such as Sutskever et al. [2011] and Pouget-Abadie et al. [2014] have shown that standard LSTM decoder does not perform well in generating long text sequences.

- Template-based, Rule-based versus neural text generation

Classical approaches to text generation include: template-based, rule-based, n-gram-based and log-linear based models. Rule-based techniques are grammar-based methods with structured-rules written based on accumulated knowledge. Template-based approaches can be as simple as replacing words of users’ choices by their synonyms, Reiter [1995], Deemter et al. [2005], Wiseman et al. [2018], Peng et al. [2019].

N-gram models are widely used in NLP tasks such as text generation. In n-gram approach, the last word of the n-gram (i.e. to be predicted) can be inferred from the other words that already appear in the same n-gram, De Novais et al. [2010].

- Beam search and Greedy Search

Two popular deterministic decoding approaches are beam search and greedy search, Sutskever et al. [2014].
Beam search maintains a fixed-size set of partially-decoded sequences. Beam search is a common search strategy to improve results for several tasks such as text generation, machine translation and dependency parsing. Greedy search selects the highest probability token at each time step. Greedy search can be seen as a special case of beam search.

- **Sequence to sequence models and knowledge enhancement methods**
  Seq-to-Seq models are common architectures for text generation tasks where both the input and the output are modeled as sequences of tokens. In other words, the model converts an input sequence into an output sequence. More specifically, the first model encodes the input sequence as a set of vector representations using a recurrent neural network (RNN). The second RNN then decodes the output sequence step-by-step. Seq-to-Seq models are commonly trained via maximum likelihood estimation (MLE), Chen et al. [2019].

  One challenge with seq-to-seq models is that the input text alone often does not provide enough knowledge to generate the desired output which will impact the quality of the generated output. Several methods are proposed to enhance model knowledge beyond input text such as attention, memory, linguistic features, graphs, pre-trained language models, and multi-task learning. Many of those techniques are listed in Yu et al. [2020] and https://github.com/wyu97/KENLG-Reading.

  One of those particular enhancement techniques is attention, Bahdanau et al. [2014] in which an encoder compresses the input text and a decoder with an attention mechanism generates output target word(s). The decoder is bound to generate a sequence of tokens.

- **Recursive Transition Network (RTN)**
  The authors in Baki et al. [2017] discuss using a Recursive Transition Network, Woods [1970] for generating fake content similar in nature to legitimate content. RTN is used to detect simplification constructs. Nodes of the graph are labeled, and arcs may be labeled with either node names or terminal symbols. RNNs are essentially equivalent to an extension of context-free grammars in which regular expressions are allowed on the right side of productions.

- **Relational memory**
  The basic idea of relational memory is to consider a fixed set of memory slots and allow for interactions between memory slots through using self-attention mechanisms, Vaswani et al. [2017]. RM is proposed to record key information of the generation process, for example, record the information from previous generation processes. The goal is to enhance the text generation process through such learning/memory as well as patterns for long text generation. Such RL can provide a stateful, rather than stateless text generation process. Self attention is also used between the memory slots to enable interaction between them and facilitate long term dependency modeling, Vaswani et al. [2017].

  Several relational-based text generations that showed better ability of modeling longer-range dependencies are described in literature, Santoro et al. [2018], RelGAN, Nie et al. [2018].

- **Google LM**
  Released by Google, Google LM is a language pre-trained model that is trained on a billion-word corpus, a publicly available dataset containing mainly news data Jozefowicz et al. [2016], Chelba et al. [2013]. It is based on a two-layer LSTM with 8192 units in each layer, Garbacea et al. [2019].

- **Scheduled Sampling (SS)**
  SS is proposed to bridge the gap between training and inference for sequence prediction tasks. It is used to avoid exposure bias in seq-to-seq generation, Bengio et al. [2015], Mihaylova and Martins [2019]. During the inference process of seq-to-seq generation, true previous target tokens are unavailable. As a result, they are thus replaced by tokens generated by the model itself, which may yield a discrepancy between how the model is used at training and inference, Bengio et al. [2015].

  One limitation with scheduled sampling is that target sequences can be incorrect in some steps since they are randomly selected from the ground truth data, regardless of how input was chosen, Zheng et al. [2018], Ranzato et al. [2015] (Ranzato et al., 2015).

- **Generating text with GANs**
  GANs are implicit generative or Language Models (LMs) learned via a competition between a generator network and a discriminator network. The discriminator distinguishes uniquely GANs from other LMs. Particularly for our subject, AML, adversarial training with the discriminator is used in GANs as opposed to training based on solely maximum likelihood and categorical cross entropy in other LMs. The conventional LMs are not trained in an adversarial manner. Unlike traditional approaches (e.g. teacher forcing, SS), GANs do not suffer from exposure bias, Rajeswar et al. [2017], Tevet et al. [2018]. Exposure bias occurs when models are fed with their predicted data rather than the ground-truth data at inference time. This causes generating poor samples due to the accumulated error, Yin et al. [2020].
5 Adversarial training techniques

Adversarial training is a method to help systems be more robust against adversarial attacks. Below are examples of some adversarial training techniques reported in literature.

- **Fast Gradient Sign Method (FGSM)**
  FGSM is used to add adversarial examples to the training process \cite{Goodfellow2014, Wong2020}. During training, part of the original samples is replaced with its corresponding adversarial samples generated using the model being trained.
  Kurakin et al. suggested to use Iterative FGSM, IFGSM, FGSM-LL or FGSM-Rand variants for adversarial training, in order to reduce the effect of label leaking, \cite{Kurakin2016}. Their are also other variants of FGSM such as: Momentum Iterative Fast Gradient Sign Method (MI-FGSM), \cite{Dong2018}.

- **PGD-based training**
  Proposed by \cite{Madry2017}. At each iteration all the original samples are replaced with their corresponding adversarial samples generated using the model being trained.
  PGD was enhanced using different efforts such as:
  - Optimization tricks such as momentum to improve adversary, \cite{Dong2018}.
  - Combination with other heuristic defenses such as matrix estimation, \cite{Yang2019}.
  - Defensive Quantization, \cite{Lin2019}.
  - Logit pairing, \cite{Mosbach2018, Kannan2018}.
  - Thermometer Encoding, \cite{Buckman2018}.
  - Feature Denoising, \cite{Xie2019}.
  - Robust Manifold Defense, \cite{Jalal2017}.
  - L2 nonexpansive nets, \cite{Qian2018}.
  - Jacobian Regularization, \cite{Jakubovitz2018}.
  - Universal Perturbation, \cite{Shafahi2020}.
  - Stochastic Activation Pruning, \cite{Dhillon2018}.
  As of today, training with a PGD adversary remains empirically robust, \cite{Wong2020}.

- **Jacobian-based saliency map approach (JSMA)**
  JSMA is a gradient based white-box method that is proposed to use the gradient of loss with each class labels with respect to every component of the input, \cite{Papernot2016b}. JSMA is useful for targeted miss-classification attacks, \cite{Chakraborty2018}.

- **Accelerating Adversarial Training**
  The cost of adversarial training can be reduced by reusing adversarial examples and merging the inner loop of a PGD and gradient updates of the model parameters, \cite{Shafahi2019, Zhang2019}.

- **DAWNBench competition**
  Some submission projects to DAWNBench competition have shown good performance results on CIFAR10 and ImageNet classifiers in comparison with research-reported training methods, \cite{Coleman2017, Wong2020}.

6 Text Generation Models/Tasks/Applications

Text generation refers to the process of automatic or programmable generation of text with no or least of human intervention. The sources utilized for such generation process can also vary based on the nature of the application. The types of applications from generating text in particular are growing. We will discuss just a few in this section.

6.1 Next-Word Prediction

For many applications that we use through our smart phones, or websites, next word prediction (NWP, also called auto-completion) is a typical NLP application. From a machine-learning perspective, NWP is a classical prediction problem where previous and current text can be the pool to extract the prediction model features and other parameters and the next word to predict is the target feature. Different algorithms are proposed to approach NWP problem such as term frequencies, artificial intelligence, n-grams, neural networks, etc.
6.2 Dialog Generation

Human-machine dialog generation/prediction is an essential topic of research in the field of NLP. It has many different applications in different domains. The quality and the performance of the process can widely vary based on available resources, training/pre-training and also efficiency.

Seq2seq neural networks have demonstrated impressive results on dialog generation, \cite{Vinyals2015, Chang2019}. GANs are used in dialogue generations in several research publications \cite{Li2016b, Hamilton2017, Kannan2018, Nabeel2019}.

6.3 Neural Machine Translation

Neural Machine Translation (NMT) is a learning approach for automated translation, with potentials to overcome weaknesses of classical phrase-based translation systems or statistical machine learning. The main difference is that NMT is based on a model not based on some patterns. NMT tries to replicate the functions of the human brain and assess content from various sources before generating output. Further enhancements on NMT were achieved using attention based neural machine translation.

One of the popular early open source NMTs is Systran: https://translate.systran.net/, the first NMT engine launched in 2016. Other examples include those of: Google Translate, Facebook, e-bay and Microsoft.

Adversarial NMT is introduced in which training of the NMT model is assisted by an adversary, an elaborately designed 2D-convolutional neural network (CNN), \cite{Yang2017, Wu2018, Zhang2018b, Shetty2018}.

7 Text Generation Metrics

One of the key issues in text generation is that there is no widely agreed-upon automated metric for evaluating the text generated output. Text generation metrics can be classified based on several categories. Here is a summary of categories and metrics:

- **Document Similarity based Metrics**
  One of the popular approaches to measure output TG is through comparing it with some source documents or human natural language. Some of the popular metrics in this category are Bilingual Evaluation Understudy (BLEU), \cite{Papineni2002} and Embedding Similarity (EmbSim), \cite{Zhu2018}.
  BLEU has several variants such as BLEU-4 and BLEU-1.
  This category can also include some of the popular classical metrics such as: Okapi BM25 \cite{Robertson1994}, Word Mover’s Distance (WMD), \cite{Kusner2015}, Cosine, Dice and Jaccard measures in addition to Term Frequency-Inverse Document Frequency (TF-IDF).

- **Likelihood-based Metrics**
  Log-likelihood is the negative of the training loss function, (NLL). NLL (also known as multiclass cross-entropy) outputs a probability for each class, rather than just the most likely class. The typical approach in text generation is to train the model using a neural network performing maximum likelihood estimation (MLE) by minimizing the negative log-likelihood, NLL over the text corpus. For GANs, in the standard GAN objective, the goal or objective function is to minimize NLL for the binary classification task, \cite{Goodfellow2014}.
  Maximum Likelihood suffers from predicting most probable answers. This means that a model trained with maximum likelihood will tend to output short general answers that are very common in the vocabulary. The log-likelihood improves with more dimensions as it is easier to fit the hypotheses in the training step having more dimensions. Consequently, the hypothesis in the generating step have lower log-likelihood.

- **Perplexity**
  Perplexity measures a model’s certainty of its predictions.
  There are several advantages to using perplexity, \cite{Keukeleire2020}:
  - Calculating perplexity is simple and doesn’t require human interference
  - It is easy to interpret
  - I is easy to optimize a model for an improved perplexity score
  Held-out likelihood is usually presented as perplexity, which is a deterministic transformation of the log-likelihood into an information-theoretic quantity

- **Inception Score (IS)**
  IS rewards high confidence class labels for each generated instance, \cite{Salimans2016}. IS can provide a
general evaluation of GANs trained on ImageNet. However, it has limited utility in other settings. [Fowl et al. 2020].

- Frechet Inception Distance (FID)
  FID is used to measure the Wasserstein-2 distance. [Vaserstein 1969] between two Gaussians, whose means and covariances are taken from embedding both real and generated data, [Heusel et al. 2017], [Cifka et al. 2018]. FID assumes that the training data is "sufficient" and does not reward producing more diversity than the training data. [Fowl et al. 2020].

- N-gram based metrics
  Distinct-n is a measure of diversity that computes the number of distinct n-grams, normalized by the number of all ngrams, [Li et al. 2015].

- Sentence similarity metrics, SentenceBERT (sent-BERT, Reimers and Gurevych 2019)

- ROUGE metrics
  ROUGE metrics were mostly used for text generation, video captioning and summarization tasks, [Lin 2004]. They were introduced in 2004 as a set of metrics to evaluate machine-generated text summaries. ROUGE has several variants such as: ROUGE-1, ROUGE-2 and ROUGE-L.

- METEOR
  METEOR (Metric for Evaluation of Translation with Explicit Ordering) was proposed in 2005, [Banerjee and Lavie 2005]. METEOR metric was mainly used for text generation, image and video captioning, and question answering tasks.

- Embedding-based metrics
  The main approach is to embed generated sentences in latent space and then evaluate them in this space, [Tevet et al. 2018], [Du and Black 2019]. Suggest to cluster the embedded sentences with k-means and then use its inertia as a measure for diversity.

- Other less common metrics such as: GLEU score, edit distance, phoneme and diacritic error rate.

- Metrics for GANs, traditional probability-based LM metrics, [Tevet et al. 2018]. Several papers indicated the need to use new metrics to evaluate GANs (e.g. [Esteban et al. 2017], [Zhu et al. 2018], [Saxena and Cao 2019]). Some of the metrics proposed for GANs include:
  - Divergence based Metrics such as F-GAN, [Nowozin et al. 2016], LS-GAN [Mao et al. 2017], KL-divergence [Koochali et al. 2019], and Self-BLEU [Zhu et al. 2018].
  - Integral Probability Metrics such as: Wasserstein GAN (WGA) [Arjovsky et al. 2017], [Gulrajani et al. 2017].
  - Domain-specific metrics, e.g. attack success rate, [Gao et al. 2020].
  - Random Network Distillation (RND), [Burda et al. 2018].

8 Text Generation Datasets

There are many datasets for the general tasks/research of NLP such as those mentioned in the following links:

- https://aclweb.org/aclwiki/Data_sets_for_NLG
- https://paperswithcode.com/task/data-to-text-generation
- https://project-awesome.org/tokenmill/awesome-nlg#datasets
- https://github.com/niderhoff/nlp-datasets
- https://lionbridge.ai/datasets/the-best-25-datasets-for-natural-language-processing/
- https://machinelearningmastery.com/datasets-natural-language-processing/
- https://www.kdnuggets.com/tag/datasets

We will list few datasets/benchmarks that are used in GAN research papers in particular

- COCO Image Captions, [Chen et al. 2015] and
- EMNLP2017 WMT: http://statmt.org/wmt17/translation-task.html, [Guo et al. 2018]
- WeiboDial, [Qian et al. 2018]
9 Memory based models, RNN versus LSTM

As we mentioned earlier, vanilla RNNs do not perform well when the learning sequences have long term temporal dependence due to issues such as exploding gradients, Bengio et al. [2015]. Alternatively, Convolutional neural networks (CNNs), recurrent neural networks (RNNs), Gated recurrent unit (GRU) and Long-short term memory (LSTM) models are effective approaches in the field of sequential modeling methods. The design of the forget gate is the essence of these models, Sun et al. [2020].

An LSTM model is a type of RNN that can remember relevant information longer than a regular RNN. As a result, they can better learn long-term patterns Olah [2015].

LSTM models provide a mechanism that is able to both store and discard the information saved about the previous steps, limiting the accumulated error using Constant Error Carousels, Hochreiter and Schmidhuber [1997], Manzelli et al. [2018].

10 Defense Against NLP Adversarial Attacks

Generating adversarial attacks on text has shown to be more challenging than for images and audios due to their discrete nature. Variations on original text can be applied on different levels, character, word or sentence levels. Recent relevant studies showed examples of NLP vulnerabilities such as, Zhou et al. [2019]:

- Reading comprehension, Jia and Liang [2017].
- Text classification, Alzantot et al. [2018], Liang et al. [2017], Wong [2017]
- Machine translation, Cheng et al. [2020], Ebrahimi et al. [2018]
- Dialogue systems, Cheng et al. [2019]
- Dependency parsing, Zheng et al. [2020].

10.1 Black versus white box attacks

Current adversarial attacks can be roughly be divided into three categories: white-box attacks, black-box and gray-box attacks, according to whether the data, model architecture, and parameters of the target are accessible. In black-box attacks (also called zero-knowledge attack), no or very limited information about the target model is accessible. For example, a certain number of model queries (i.e. oracle queries) are granted.

Some of the defenses, Guo et al. [2018], Xie et al. [2017] are shown to be quite robust against black-box attacks.

In gray-box attacks/limited knowledge attacks, partial knowledge about the model under attack (e.g., type of features, or type of training data) is assumed. On the other side, is white-box attack/ perfect-knowledge attacks. Those are attacks that exploit model internal information. They assume complete knowledge of the targeted model, including its parameter values, architecture, training method, and in some cases its training data. Table 1 shows samples of research publications in all three categories. There are some papers that are identified to more than one category.

At the high level, there are three classes or dimensions of attacks, Barreno et al. [2010]:

- Causative versus Exploratory In causative attacks, the training process is altered and models are trained with adversary datasets. In exploratory attacks, attacker tries to exploit the existing weaknesses
- Integrity versus availability: false negatives versus false positive.
- Targeted at a particular input or indiscriminate in which input fails
- Reactive versus proactive: A reactive defense is where one waits to be attacked and detects an adversarial example. On the other hand, proactive attacks involve training the model to be more resilient against adversarial
• Dirichlet Neighborhood Ensemble (DNE), a randomized smoothing method for training a model against substitution-based attacks. [Zhou et al. (2020)]
• Adversarial training as a defense method. [Miyato et al. (2016), Sato et al. (2018), Zhu et al. (2019)]
• Increasing the model robustness by adding perturbations on word embedding, [Goodfellow et al. (2014)]
• Certified defenses: Some certified defenses were proposed in literature in order to provide guarantees of robustness to some specific types of attacks, [Huang et al. (2019), Jia and Liang (2017)]
• Defensive distillation: Defensive distillation can take an arbitrary NN and increase its robustness, reducing the success rate of attacks’ ability, [Carlini and Wagner (2017)]
• Defense through randomization, [Cohen et al. (2019), Liu et al. (2018)]

11 Summary and Conclusion

In this paper, recent literature in adversarial machine learning for text generation tasks is summarized. Our goal is to present a one-stop source for researchers and interested readers to learn the basic components and research trends in this field. We noticed a continuous expansion in the applications, models and algorithms. This paper can serve as an introduction to this field and readers may need to follow through some of the researchers and references we referred to based on their focuses or interests.

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