Adversarial network for natural language synthesis
Speaker introduction

Rajib Biswas

• Lead Data Scientist in Ericsson, Bangalore.
• Working with a global AI team for AI driven network design and optimization.
• Have worked with Intel, Samsung, Fidelity Investments earlier.
• Have filed few patents related to AI.

Area of interest

• NLP - Virtual Assistant, Knowledge Graphs
• Computer Vision - Image classification.
• Time series and forecasting.
• Recommendation system.
Agenda

1. Language generation: now and future.
2. Introduction to GAN.
3. Challenges with generative model for text
4. GAN models for text.
5. Task specific Language Generation
6. Evaluation
Language generation: now & future
Language generation: now & future

Language Generation

Language understanding

Language processing
Language generation: now & future

Applications:
• Auto content curation for editors.
Language generation: now & future

Applications:
- Auto report generation from BI apps
Language generation: now & future

Applications:
• Virtual Assistant /chatbots
Introduction to GAN

Synthetic fake images by GAN. https://thispersondoesnotexist.com/

Real image of Ian Goodfellow
Introduction to GAN

GAN (Generative Adversarial Network)
- generator network (G) trained to produce realistic samples by introducing "adversary" [a discriminator network (D)]
Introduction to GAN

GAN (Generative Adversarial Network)
- generator network (G) trained to produce realistic samples by introducing “adversary”
  [a discriminator network (D) ]
- D detects if a given sample is ‘real’ or ‘fake’.
- D dynamically update evaluation metric for tuning the generator.
- until D will output with probability 0.5 for both classes; obtain ‘Nash Equilibrium’.
Introduction to GAN

Objective: Distinguish between real and fake

Objective: Generate image close to real
Introduction to GAN

Min-max game played by two network, whose Value function is given

\[
\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]
\]

- **Correct identification**
- **Output for real image**
- **Output for fake image**

\( D(x) = \) Probability that, \( x \) is real according to \( D \).
\( G(z) = \) sample generated by \( G \), given latent vector \( Z \).
Challenges with GAN for text

GAN is not a natural fit for discrete data such as text.
Training of generator is difficult due to discreteness of text data.
Challenges with GAN for text

GAN is not a natural fit for discrete data such as text. Training of generator is difficult due to discreteness of text data. Non-Differentiability at output of generator.

**Generator**

\[ \text{argmax} : P(\text{softmax}(h)) \]

**Discriminator**

\[ \min: 1 - D(G(z)) \]

Non-differentiability for discrete data

Back-propagation

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oreillyaicon.com
#OReilyAI
GAN models for text

Gumbel-softmax trick

$h_t = \text{hidden state of RNN generator at step } t$

$g_t = \text{sample from Gumbel distribution.}$

$\tau = \text{parameter to control how close the continuous approx distribution to the discrete one. } \tau \to 0, y \text{ is close approximation to one-hot vector.}$

$$y_t = \text{softmax}( (h+g)/\tau)$$

Kusner et al: GANs for sequence of discrete elements with Gumbel-Softmax Distribution
GAN models for text

Problem so far:
Sampling of tokens from discrete spaces.

Solution proposed:
Sample single token ‘sentence vector’ from discrete continuous space of all sentence vectors.
GAN models for text: AutoEncoder

Problem so far: Sampling of tokens from discrete spaces.

Solution proposed: Sample single token ‘sentence vector’ from discrete continuous space of all sentence vectors.

Get sentence vector of real sentences by training a Auto-Encoder.

Latent space GAN

David et al. “Adversarial Text Generation Without Reinforcement Learning”.
GAN models for text

Let’s play a game.

Today, the sky is ______ in London. I ______ this weather.

What are the possible words coming to your mind?
GAN models for text

Let’s play a game.

Today, the sky is ______ in London. I ______ this weather.

cloudy
sunny
clear

love
hate

What are the possible words coming to your mind?
GAN models for text : SeqGAN

Text Generation is a sequential decision-making process : RL

Agent: Generator
State: text generated so far
Action: predicting next word, based on context (previous state).
Reward: Prediction score(real/fake) from Discriminator
Policy: Which action to pick at any state? policy function: $\pi(a | s, \theta)$
Objective: Find optimal policy $\pi^* \Rightarrow optimal \ \theta$

SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient.(Lantao You et al)
GAN models for text: SeqGAN

SeqGAN

- **D**: input: sentence
  - output: reward score of realness of this sentence.
  - Provided back to **G** to update policy at end of episode.
- **G**: Input: sequence of words,
  - output: probability distribution over next word.
  - \( h_t = \text{RNN}(h_{t-1}, x_t) \)
  - \( p(a_t | x_1, \ldots, x_t) = z(h_t) = \text{softmax}(b + W^*h_t) \)
GAN models for text: SeqGAN

Objective: Find optimal policy $\pi^*$ => optimal $\theta$

Policy gradient

$$\theta_{t+1} = \theta_t + \alpha G_t \frac{\nabla \pi(A_t | S_t, \theta_t)}{\pi(A_t | S_t, \theta_t)}$$

REINFORCE update

$\nabla \pi(A_t | S_t, \theta_t) = \text{Vector indicates direction of max increase of prob of action } A_t, \text{ when state } S_t \text{ is encountered.}$

$G_t$: Cumulative reward, while following Policy $\pi$. Indicates amount of movement.

SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient. (Lantao You et al)
GAN models for text : SeqGAN

How to determine reward before sentences are completed?

- SeqGAN applies Monte-Carlo search to roll-out current policy to estimate the reward.

- Generator uses current learned policy network to roll-out iteratively till end of sentences to get estimated reward.
GAN models for text: LeakGAN

LeakGAN

- Long sentence generation is hard, as intermediate reward estimation is noisy.
- LeakGan solves that by introducing Worker(Criminal) and Manager(Spy).
- Worker: creates fake sample
- Discriminator(Police): detects fake/real
- Manager: act as spy and leaks features used to identify fake sample by Discriminator.
GAN models for text

Leveraging more information from discriminator, to generate Better quality text, may cause another critical issue!!

Mode Collapse: exhibit poor diversity amongst generated samples

UnrollGAN, Luke et al. ICRL 2017
GAN models for text: MaskGAN

Leveraging more information from discriminator to generate better quality text may cause another critical issue!!

Mode Collapse: exhibit poor diversity amongst generated samples.

MaskGAN claims to reduce mode collapse and help with training stability.

This method shows evidence that it produces more realistic text samples compared to a maximum likelihood trained model.
GAN models for text: MaskGAN

Encoder encodes masked text input, **Generator** learns to fill in the blank by reward score provided by the **Discriminator**.

**Discriminator** also uses same architecture.

**MaskGAN**: Better Text Generation via Filling in the______. (William Fedus et al, ICRL 2018)
GAN models for text

Challenges with RL based methods

1. Unstable training process due to high variance. Because few samples to estimate gradient of policy.

2. Policy gradient methods tend to converge to local maxima, when state-action space is huge. Action choices $= |V|$, vocabulary size.
Evaluation

How to measure performance of metrics?
GANs are not optimised for traditional cross-entropy loss (unlike MLE), so usually ‘loss’ is not used as performance metrics.

BLEU (Bilingual Evaluation Understudy Score):
- Counting matching n-grams between generated and target sentence.

*BLEU doesn’t cover all aspect of language correctness.*
Evaluation

LeakGAN performs well with BLEU score.
MaskGAN performs well with self-BLEU score (detects mode collapse.)

<table>
<thead>
<tr>
<th>Models</th>
<th>BLEU2</th>
<th>BLEU3</th>
<th>BLEU4</th>
<th>BLEU5</th>
</tr>
</thead>
<tbody>
<tr>
<td>SeqGAN</td>
<td>0.724</td>
<td>0.416</td>
<td>0.178</td>
<td>0.086</td>
</tr>
<tr>
<td>MaliGAN</td>
<td>0.755</td>
<td>0.436</td>
<td>0.168</td>
<td>0.077</td>
</tr>
<tr>
<td>RankGAN</td>
<td>0.686</td>
<td>0.387</td>
<td>0.178</td>
<td>0.086</td>
</tr>
<tr>
<td>LeakGAN</td>
<td><strong>0.835</strong></td>
<td><strong>0.648</strong></td>
<td><strong>0.437</strong></td>
<td><strong>0.271</strong></td>
</tr>
<tr>
<td>MaskGAN</td>
<td>0.265</td>
<td>0.165</td>
<td>0.094</td>
<td>0.057</td>
</tr>
<tr>
<td>TextGAN</td>
<td>0.205</td>
<td>0.173</td>
<td>0.153</td>
<td>0.133</td>
</tr>
<tr>
<td>MLE</td>
<td>0.771</td>
<td>0.481</td>
<td>0.249</td>
<td>0.133</td>
</tr>
</tbody>
</table>

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<tr>
<td>SeqGAN</td>
<td>0.907</td>
<td>0.704</td>
<td>0.463</td>
<td>0.265</td>
</tr>
<tr>
<td>MaliGAN</td>
<td>0.909</td>
<td>0.718</td>
<td>0.470</td>
<td>0.252</td>
</tr>
<tr>
<td>RankGAN</td>
<td>0.897</td>
<td>0.677</td>
<td>0.448</td>
<td>0.298</td>
</tr>
<tr>
<td>LeakGAN</td>
<td>0.938</td>
<td>0.821</td>
<td>0.668</td>
<td>0.510</td>
</tr>
<tr>
<td>MaskGAN</td>
<td><strong>0.448</strong></td>
<td><strong>0.244</strong></td>
<td><strong>0.140</strong></td>
<td><strong>0.091</strong></td>
</tr>
<tr>
<td>TextGAN</td>
<td>0.999</td>
<td>0.975</td>
<td>0.967</td>
<td>0.962</td>
</tr>
<tr>
<td>MLE</td>
<td>0.851</td>
<td>0.572</td>
<td>0.316</td>
<td>0.171</td>
</tr>
</tbody>
</table>

Left: BLEU score on EMNLP 2017 WMT, Right: self-BLEU score
# Evaluation

## Benchmark on standard datasets

<table>
<thead>
<tr>
<th>Preferred Model</th>
<th>Grammaticality %</th>
<th>Topicality %</th>
<th>Overall %</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM</td>
<td>15.3</td>
<td>19.7</td>
<td>15.7</td>
</tr>
<tr>
<td>MaskGAN</td>
<td>59.7</td>
<td>58.3</td>
<td>58.0</td>
</tr>
</tbody>
</table>

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</tr>
</thead>
<tbody>
<tr>
<td>LM</td>
<td>20.0</td>
<td>28.3</td>
<td>21.7</td>
</tr>
<tr>
<td>MaskMLE</td>
<td>42.7</td>
<td>43.7</td>
<td>40.3</td>
</tr>
</tbody>
</table>

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</thead>
<tbody>
<tr>
<td>MaskGAN</td>
<td>49.7</td>
<td>43.7</td>
<td>44.3</td>
</tr>
<tr>
<td>MaskMLE</td>
<td>18.7</td>
<td>20.3</td>
<td>18.3</td>
</tr>
</tbody>
</table>

<table>
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<th>Grammaticality %</th>
<th>Topicality %</th>
<th>Overall %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real samples</td>
<td>78.3</td>
<td>72.0</td>
<td>73.3</td>
</tr>
<tr>
<td>LM</td>
<td>6.7</td>
<td>7.0</td>
<td>6.3</td>
</tr>
</tbody>
</table>

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<tr>
<td>Real samples</td>
<td>65.7</td>
<td>59.3</td>
<td>62.3</td>
</tr>
<tr>
<td>MaskGAN</td>
<td>18.0</td>
<td>20.0</td>
<td>16.7</td>
</tr>
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</thead>
<tbody>
<tr>
<td>SeqGAN</td>
<td>38.7</td>
<td>34.0</td>
<td>30.7</td>
</tr>
<tr>
<td>MaskMLE</td>
<td>33.3</td>
<td>28.3</td>
<td>27.3</td>
</tr>
</tbody>
</table>

Human preference score of paired comparison on **IMDB** and **PTB** datasets
## Evaluation: results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Epoch</th>
<th>Output from SeqGAN</th>
</tr>
</thead>
<tbody>
<tr>
<td>PTB</td>
<td>5</td>
<td>Employees may cure they were considering the agency that’s two congress cases ms. Jhonson clearly noted that began growth</td>
</tr>
<tr>
<td>PTB</td>
<td>10</td>
<td>Can end of its criminal office charges to remove the pacific law which is all the &lt;unk&gt; response to</td>
</tr>
<tr>
<td>PTB</td>
<td>20</td>
<td>Capital offers flat the debt carrier to imports from &lt;unk&gt; mr. George said it expects net sales to reduce</td>
</tr>
</tbody>
</table>
## Evaluation: results

<table>
<thead>
<tr>
<th>Ground Truth</th>
<th>the next day’s show &lt;eos&gt; interactive telephone technology has taken a new leap in &lt;unk&gt; and television programmers are</th>
</tr>
</thead>
<tbody>
<tr>
<td>MaskGAN</td>
<td>the next day’s show &lt;eos&gt; interactive telephone technology has taken a new leap in its retail business &lt;eos&gt; a</td>
</tr>
<tr>
<td>MaskMLE</td>
<td>the next day’s show &lt;eos&gt; interactive telephone technology has taken a new leap in the complicate case of the</td>
</tr>
</tbody>
</table>
Task specific Language generation

Dialogue Generation

<table>
<thead>
<tr>
<th>Input</th>
<th>That’s our wake up call</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vanilla-MLE</td>
<td>We’re gonna be late for the meeting</td>
</tr>
<tr>
<td>Reinforce</td>
<td>I’ll be right back</td>
</tr>
<tr>
<td>REGS MC</td>
<td>We’re gonna have to get to the station</td>
</tr>
</tbody>
</table>

Adversarial Learning for Neural Dialogue Generation, Jiwei et al
### Task specific Language generation

#### Style Transfer

Negative to positive sentiment style transfer task

<table>
<thead>
<tr>
<th>Input</th>
<th>would <em>n’t recommend</em> until management works on friendliness and communication with residents.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARAE</td>
<td>highly <em>recommend</em> this place while living in tempe and management.</td>
</tr>
<tr>
<td>CAAE</td>
<td>would highly <em>recommend</em> management on duty and staff on business.</td>
</tr>
<tr>
<td>DAR</td>
<td>until management works on friendliness and is a <em>great</em> place for communication with residents.</td>
</tr>
</tbody>
</table>

“Evaluating Style Transfer for Text”, Remi et al.
Task specific Language generation

Style Transfer

Lack of established metrics to measure performance. Evaluate performance in terms of:

1. Style transfer intensity - quantify difference in style
2. Context preservation - similarity in content
3. Naturalness - degree at which it’s close to human written text.

“Evaluating Style Transfer for Text”, Remi et al.
Summary

Recent advancement in Language generation research.

GAN based approaches have made significant progress.

However, current these methods doesn’t capture nuances and semantics of natural language. Specially, for longer sentences.

Automated language language generation, may be misused for malicious purposes Like - generating fake news, ClickBait etc. #Ethics #ResponsibleAI
Q&A
Rate this session

Adversarial network for natural language synthesis

Rahib Berens (Ericsson)
16:00-16:40 Wednesday, 16 October 2019
Location: Blenheim Room - Palace Suite
Models and Methods
Secondary topics: Deep Learning, Ethics, Security, and Privacy, Machine Learning, Reinforcement Learning, Text, Language, and Speech

RATE THIS SESSION