

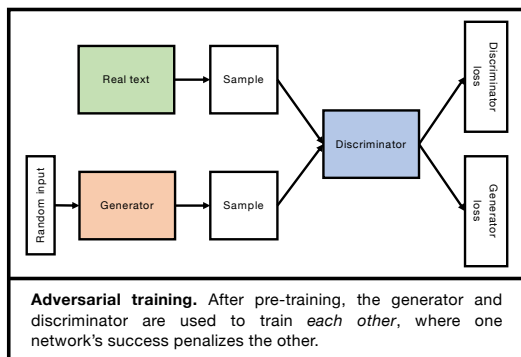
TweetGAN

Natural Language Generation using Tweets

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Generative Adversarial Networks (GANs)

- Consist of two competing neural networks: a *generator* and a *discriminator*.
- The generator is trained to generate data.
- The discriminator is trained to differentiate between real and generated data samples.
- GANs use *adversarial training*; the discriminator is rewarded for successfully identifying generated samples, and the generator is rewarded for fooling the discriminator.
- After sufficient training, the generator will (ideally) become advanced enough that the discriminator can no longer differentiate.



Text Generation

- Text generation is difficult with GANs, since text is a form of *discrete* data, but most GAN models use a gradient model that relies on the *continuity* of the input and output data
- Solution: SeqGAN! The first successful GAN model to use sequences of discrete data.
- Models the generator network as a stochastic policy in reinforcement learning

News Tweets

To test our GAN's performance on tweets of a consistent style, we began with a dataset of tweets from news outlets, as they tend to have a characteristic headline-esque style and specific structure. We found that the GAN was able to successfully pick up on the use of phrases like "Follow live updates:". Further, it seems to have generally captured the style of news headlines.

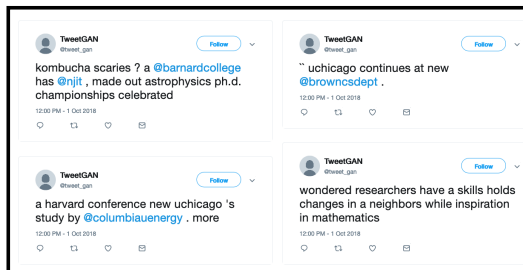


News samples.
Sample tweets generated by our GAN after training on our news dataset. We see that the GAN has learned the style of news headlines, especially with tweets like those on the right.

(Fake Twitter screenshots made with tweetgen.com.)

University Tweets

Another source that we tested our GAN's performance with were tweets from official university accounts. These should generally be written with decently formal English, but in a clear style that's less rigid than news headlines. We found, though, that the diversity in topics that university accounts tweeted about left the GAN rather confused, as it struggled to keep various topics separate. It does, however, tend to use various colleges' and departments' Twitter handles when introducing subjects, as done in many university tweets.

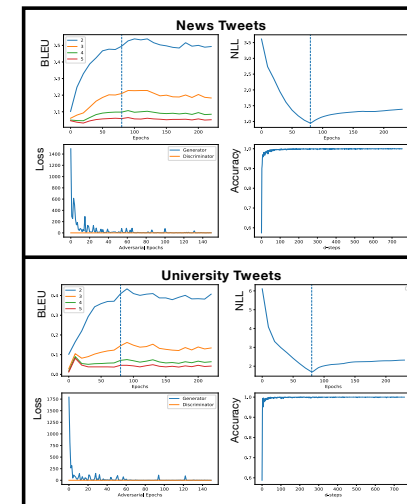


University samples.
Sample tweets generated by our GAN after training on our universities dataset. We find that the GAN generally performs less well here, as the more varied styles and subjects left the GAN confused.

(Fake Twitter screenshots made with tweetgen.com.)

Evaluation

We recorded the BLEU scores and the negative log likelihood (NLL) of the generated samples every ten epochs of pre-training and every epoch of adversarial training. Every adversarial epoch, we also recorded the losses of both networks. At every discriminator training step, we recorded the discriminator's accuracy. For these two plots, the epoch at which adversarial training begins is marked with a dashed vertical line.



Conclusions

From the evaluation metrics, it appears that, with our parameters, the GAN does not benefit much from the adversarial training. The discriminator easily determines which samples are generated and which are real, and the generator never benefits much from the training. In future studies, we would explore a far wider range of training parameters, as well as datasets restricted to more specific topics.

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Honorable Mentions





