Controlled Generation of Text

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Outline

Motivation from Computer Vision

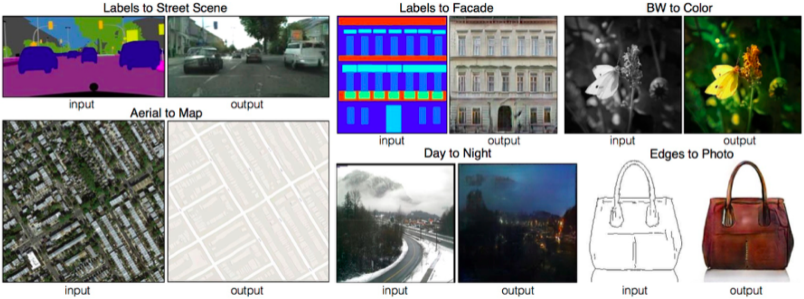


Figure 1: Pix2Pix. Isola, et. al., 2016

Generative Modeling in NLP

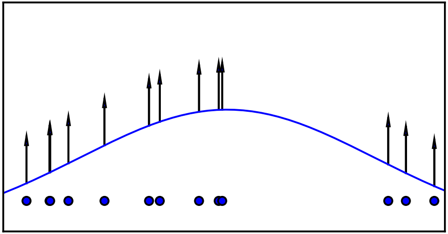
Can we also do generative modeling in NLP?

Varying the unstructured code *z*
("negative", "past")
the acting was also kind of hit or miss .
i wish i 'd never seen it
by the end i was so lost i just did n't care anymore
("negative", "present")
the movie is very close to the show in plot and characters
the era seems impossibly distant
i think by the end of the film , it has confused itself

Table 1: From Hu, 2017

Generative Models

- Density estimation problem: given data samples (empirical distribution), find the true distribution generating those samples.
- Based maxmimum likelihood principle.
- But, likelihood function is often intractable! $\implies$ This problem is hard!



$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta}} \mathbb{E}_{x\sim p_{\text{data}}} \log p_{\text{model}}(\boldsymbol{x} \mid \boldsymbol{\theta})$$

Figure 2: From Goodfellow, 2016.

Generative Adversarial Networks: GAN

- Two players game, both are neural networks:
  - G: generate data samples.
  - D: inspect data samples.
- Objective: G fools D; D resists G.
- Thus, this is minimax game $\implies$ the solution is Nash equilibrium.
- GAN will not work on discrete data as it is nondifferentiable.

Variational Autoencoder: VAE

- Idea: instead of directly works with likelihood function, works with relaxed lower bound instead.
- This lower bound comes from variational mean field theorem, so we call it variational lower bound:

$$\log P(X) \geq E[\log P(X|z)] - D_{KL}[Q(z|X) \| P(z)]$$

- This lower bound is easier to works with as it decomposes into two easy terms:
  - First is reconstruction term.
  - Second is regularization term for z.
- We use neural networks for $Q(z|X)$ and $P(X|z)$ thus essentially this is an autoencoder.
- VAE works for discrete data out of the box.

Generating Sentences from a Continuous Space, Bowman 2016

- Based on VAE, with both encoder and decoder to be LSTMs.
- Very straight-forward.
- Latent variable z is seen as the global conditioning code for the decoder. It captures the semantic of text.

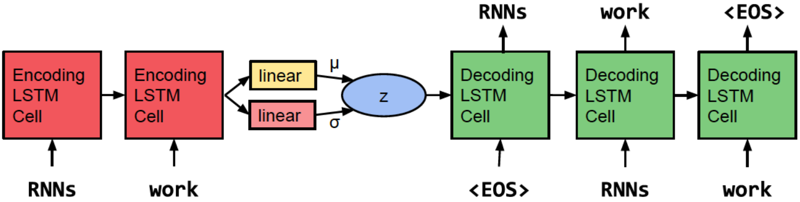


Figure 3: Model of Bowman, et. al., 2016

Generating Sentences from a Continuous Space, Bowman 2016

- Difference with normal autoencoder: z is stochastic, i.e. represented by some posterior distribution $Q(z|X)$, this we regularize to be close to prior $N(0, I)$.
- $P(X|z)$ is a "continuous" function, i.e. changing z a little bit implies X also changed only a little bit.

Toward Controlled Generation of Text, Hu 2017

- Combining VAE+GAN.
  - Base model is Bowman, 2016.
  - Add a discriminator on top to learn conditioning code c.
  - Use softmax trick to alleviate non-differentiability.
- Conditioning code could be anything, e.g. sentiment, tense labels.
- Thus text is generated based on its semantic z and its label c.

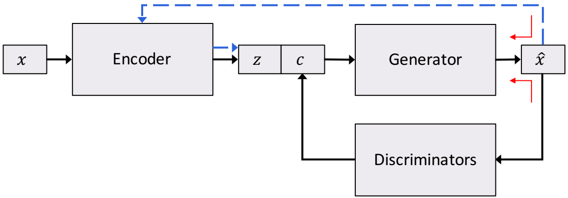


Figure 4: From Hu, 2017

CGT: Controlled Generation of Text

- Based on Hu, 2017 and Bowman, 2016.
- Consists of three components: Encoder, Decoder, and Discriminator.
- We pre-train Encoder and Decoder first as in Bowman, 2016.
- Then we train all of them as in Hu, 2017.

CGT: Discriminator

- Following architecture by Kim, 2014.

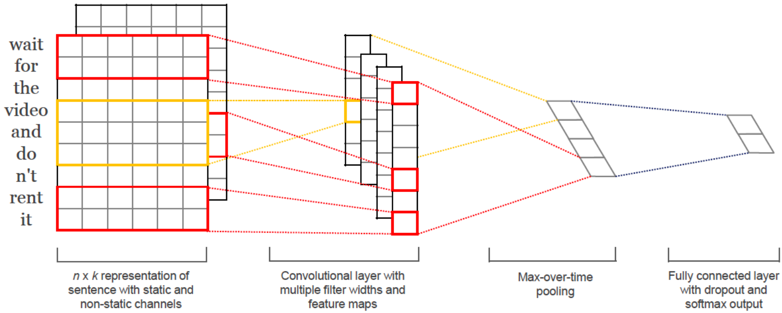


Figure 5: From Kim, 2014

CGT: Training Base VAE

- Training similar to normal VAE, but with two tricks to help stabilizing it.
- First is KL weight annealing, to make sure KL term in VAE loss to be above zero.
- Second is word dropout, i.e. with prob. p, set word in decoder input to $< UNK >$

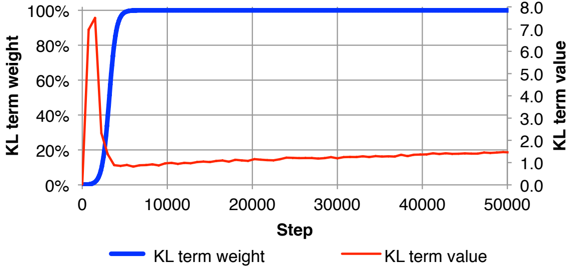


Figure 6: From Bowman, 2016

CGT: Losses

- Encoder: Same as VAE loss.
- Decoder:

$$
\begin{aligned}
L_{Attr,z}(\theta_G) &= \mathbb{E}_{p(z)p(c)}\left[\log q_E(z|\tilde{G}_\tau(z,c)\right] \\
L_{Attr,c}(\theta_G) &= \mathbb{E}_{p(z)p(c)}\left[\log q_D(c|\tilde{G}_\tau(z,c)\right] \\
L_G &= L_{VAE} + \lambda_c L_{Attr,c} + \lambda_z L_{Attr,z}
\end{aligned}
$$

- Where $\tilde{G}_\tau(z,c)$ is a soft embedding, i.e. taking expected embedding instead of doing argmax.

CGT: Losses

- Discriminator:

$$
\begin{aligned}
L_s(\theta_D) &= \mathbb{E}_{\mathcal{X}_L}\left[\log q_D(c_L \mid x_L)\right] \\
L_u(\theta_D) &= \mathbb{E}_{p_G(\hat{x}|x,c)p(z)p(c)}\left[\log q_D(c|\hat{x}) + \beta\mathcal{H}(q_D(c'|\hat{x}))\right] \\
L_D &= L_s + \lambda_u L_u
\end{aligned}
$$

- Where $\mathcal{X}_L = \{(x_L, c_L)\}$ is labeled dataset, $\mathcal{H}$ is empirical Shannon Entropy, and β, λ_u are weighting hyperparameters.

CGT: Pseudocode

- Training overview:
  1. Input = Corpus with labels $\{(x_L, c_L)\}$
  2. Initialize base VAE by minimizing L_{VAE} on x_L with c sampled from prior $p(c)$. (Bowman, 2016)
  3. Repeat:
     - 3.1 Train encoder by minimizing L_{VAE}
     - 3.2 Train decoder by minimizing L_G
     - 3.3 Train discriminator by minimizing L_D
  4. Until convergence

Experiment Setup

- Dataset: SST dataset, filtered out neutral sentiment and any sentence with length > 15. Total sentences are 2837.
- Library: PyTorch.
- Training procedure:
  - Train base VAE as in Bowman, 2016
  - Train discriminator as in Hu, 2017
- Full code is available at: `https://github.com/wiseodd/controlled-text-generation`.

Latent Interpolation

- Given z_1 and z_2 and $0 \leq \alpha \leq 1$; $z_\alpha = \alpha z_1 + (1-\alpha) z_2$.
- Given z_α, we can generate sentence: $\hat{x} = \text{Generator}(z_\alpha)$
- We do this for several α from 0 to 1.

the film is the courage of the unsalvageability of the year .
the film is full of the year 's best .
the film 's unhurried pace is a lot of nada .
the film 's unhurried pace is repulsive and unfocused .
the film 's unhurried pace is actually one of anything .

Table 2: Interpolation result of our model.

Conditional Generation

- Given a fixed $c = \{\text{“positive”}, \text{“negative”}\}$, generate sentences by varying z.

Varying the latent variable z
(“positive”)
the film is full of the year 's best .
a deftly entertaining thriller .
a lovably movie .
(“negative”)
the actors are no chemistry or unappealing to care one .
delivers a film living pretty bad movie .
full of flatulence jokes and clichéd to cliches .

Table 3: Result of conditional generation

Failure Cases

- We trained the model on very small dataset (around 2800 sentences). Clearly this is not enough to combat overfitting.
- Examples of failure cases:
  - **positive:** "includes all the end all the wrong reasons besides ."
  - **negative:** "a processed comedy chop suey ."

Conclusion

- VAE is straight-forward for text, GAN not so much.
- Needs tricks to make the approach works.
- Conditional Generation of Text model combines GAN and VAE.
- With a trained model, we can generate new sentence with desireable property.
- Experiment with larger dataset should give better results.

Reference

- Bowman, Samuel R., et al. "Generating Sentences from a Continuous Space." CoNLL 2016. [pdf]
- Hu, Zhiting, et al. "Toward controlled generation of text." ICML 2017. [pdf]
- Goodfellow, Ian. "NIPS 2016 tutorial: Generative adversarial networks." arXiv preprint arXiv:1701.00160 (2016).