可控文本生成
Controlled Text Generation

2021.1.8

问题背景

- 基于Transformer的预训练LM成为了新的浪潮，但是从头训练LM的成本巨大
- 问题：不改变预训练LM的情况下，LM如何进行控制？
  - 随缘法：直接拿着语言模型就用。可以给语言模型一些引导文字，让它基于这个续写，生成多个结果，之后挑最好的来展示。
  - 精调法：因为上面直接拿来用对于某些风格或主题的内容生成很难撞上，可能预训练时这方面的文本也少，于是可以先在需要的风格或主题文本上进行精调训练，或者用强化学习和人类反馈精调出想要的语言模型。

CTRL：Conditional TransformeR Language model

- CTRL模型可以指定文章的领域、风格、主题、时间、实体，实体间的关系，以及任务相关的行为等等，因此可以将其看成命题作文。
- 使用140G数据训练，参数规模16亿，比GPT-2更大。模型维度1280维，48层EncoderLayer，16头Attention，也是一个体量巨大的模型。
- 在生成文本时可指定文章的类型，同一模型可以写作不同风格的文章。

Horror *A knife* handle pulled through the open hole in the front. I jumped when the knife hit.\n\nEyes widened in horror. Her scream was the only sound I heard besides her sobs.\n\nThe spider touched her feet as it started to dig into the top of her arch. The creature's tears began to flow.\n\nThe spider looked up to her and looked back at me with eyes filled with burning tears. My heart started to race...

Reviews *A knife* is a tool and this one does the job well.\n\nRating: 4.0\n\nI bought these for my husband who has been using them to cut up his own meat since he got them. He says they are very sharp so be careful when you use them, but that doesn't seem like much of an issue because he's used it on everything from chicken breasts to beef tenderloin...

CTRL： Conditional TransformeR Language model

- Language Model

$$p(x) = \prod_{i=1}^{n} p(x_i | x_{<i})$$

$$\mathcal{L}(D) = -\sum_{k=1}^{|D|} \log p_\theta(x_i^k | x_{<i}^k)$$

- Language Model with CTRL

$$p(x|c) = \prod_{i=1}^{n} p(x_i | x_{<i}, c)$$

$$\mathcal{L}(D) = -\sum_{k=1}^{|D|} \log p_\theta(x_i^k | x_{<i}^k, c^k)$$

  - Transformer结构，每层包含两个block
  - 第一个block是一个k heads的多头注意力，使用mask：

$$\text{Attention}(X, Y, Z) = \text{softmax}\left(\frac{\text{mask}(XY^\top)}{\sqrt{d}}\right) Z$$

$$\text{MultiHead}(X, k) = [h_1; \cdots; h_k] W_o$$

$$\text{where } h_j = \text{Attention}(XW_j^1, XW_j^2, XW_j^3)$$

  - 第二个block是一个ReLU激活的前馈网络：

$$FF(X) = \max(0, XU)V$$

模型

- Language Model with CTRL
  - 每个block执行层归一化，然后是一个残差连接，产生X_{i+1}：

Block 1

$$\bar{X}_i = \text{LayerNorm}(X_i)$$
$$H_i = \text{MultiHead}(\bar{X}_i) + \bar{X}_i$$

Block 2

$$\bar{H}_i = \text{LayerNorm}(H_i)$$
$$X_{i+1} = \text{FF}(\bar{H}_i) + \bar{H}_i$$

  - 词典中每个token的分数由最后一层的输出计算得到：

$$\text{Scores}(X_0) = \text{LayerNorm}(X_l)W_{vocab}$$

  - 在训练过程中，这些分数是交叉熵损失函数的输入。
  - 在生成过程中，对应于最终token的分数使用softmax进行归一化，从而产生用于采样新token的分布。

可控生成

- 采样
  - 温度采样 $p_i = \frac{\exp(x_i/T)}{\sum_j \exp(x_j/T)}$ 、top−k采样、核采样
  - 惩罚采样 $p_i = \frac{\exp(x_i/(T \cdot I(i \in g)))}{\sum_j \exp(x_j/(T \cdot I(j \in g)))}$ $I(c) = \theta \text{ if c is True else } 1$
- 判断来源领域
  - 不同领域的控制代码可用于将训练数据划分为互斥的集合。
  - 这支持确定语言模型认为给定序列最有可能的训练数据子集的简单方法。
  - 语言模型已经学会了分布$p_\theta(x|c)$。通过为$p(c)$在领域控制代码上指定一个先验概率，可以很容易地计算出来源领域的等级：

$$p_\theta(c|x) \propto p_\theta(x|c)p(c)$$

Query Prompt	Attributed Sources
Global warming is a lie.	r/unpopularopinion, r/conspiracy, r/science
Global warming is a lie	r/eli5, r/science, r/unpopularopinion
Global warming is a real phenomenon	r/eli5, r/science, r/changemyview
Global warming is a real phenomenon.	OpenWebText, r/changemyview, r/science
I don't think women should be allowed to vote.	r/christianity, r/atheism, r/unpopularopinion
Carbs are your enemy when you want to get lean.	r/fitness, r/loseit, r/keto
I just want to be a fun aunt. I'm not interested in babies.	r/babybumps, r/childfree, r/twoxchromosome
My landlord is suing me for unpaid rent.	r/legaladvice, r/personalfinance, r/frugal
FROM fairest creatures we desire increase,\n\nThat thereby beauty's rose might never die	Gutenberg, Wikipedia, OpenWebText

控制代码

- Style by domain：Wiki，Books，Reviews，Horror，Relationships，Legal
- More complex control codes：
    - Science Title，Politics Title，Running Text，Horror Text，Reviews Rating
    - 不同的 Link 代表不同的特征（domain，subdomain，entities，entity relations，and even dates）

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Links https://www.etonline.com/09/20/2018/star-spotted\n\nEXCLUSIVE: Star Spotted in New York City\n\nBy Kelly Marot — September 20, 2018 10:51 AM PDT\n\nGetty Images\n\nThe star of the new season of Stranger Things is making a splash on her own turf and its not even Halloween.\n\nWinona Ryder has been seen out and about with friends at night time in Manhattan this week, E! News can exclusively reveal.\n\nA source tells us, She was hanging around with some friends, but she wasnt doing anything too crazy. She just wanted to get away from it all for a little bit. . . .

Science Title: Scientists have discovered a new type of bacteria that can survive in the presence of high levels of carbon dioxide\nText:[Link to article] (http://news.nationalgeographic.com/news/2011/07/110717-methane-bacteria-carbon-dioxide-environment-science/)\n\nThe researchers found that this particular strain of methane bacterium is able to thrive at concentrations up to 10 times higher than normal atmospheric levels.\n\nThey also note that these findings are consistent with previous research showing that some types of microbes may be capable of surviving under extreme conditions such as those associated with global warming.

Reviews Rating: 5.0\n\n I have been using this product for a few years and it is the best thing on my hair. It makes your hair soft but not greasy.\n\nRating: 5.0\n\nI've used this product before and love it. It's light weight yet keeps my curls defined without making them crunchy!

控制代码

- Triggering specific tasks：问答、翻译

Questions *Q: What is the capital of India?* A: New Delhi\n\nQ: Which city in India has a large population of people from Gujarat?\n\nA: Ahmedabad\n\nQ: How many languages are spoken by Indians living abroad?\n\nA: more than 100. . .

Translation English : *We release a new model for coherent language generation* ; French : Nous publions un nouveau modéle de génération cohérente du langage\n\nEnglish : The European Parliament has just adopted the report on the proposal for a regulation of the European Parliament and of the Council establishing an action programme to promote multilingualism in Europe. ; French : Le Parlement européen vient d'adopter le rapport sur la proposition de règlement du Parlement et du Conseil établissant un programme-cadre pour promouvoir le pluriling uisme dans l'Union européenne. . .

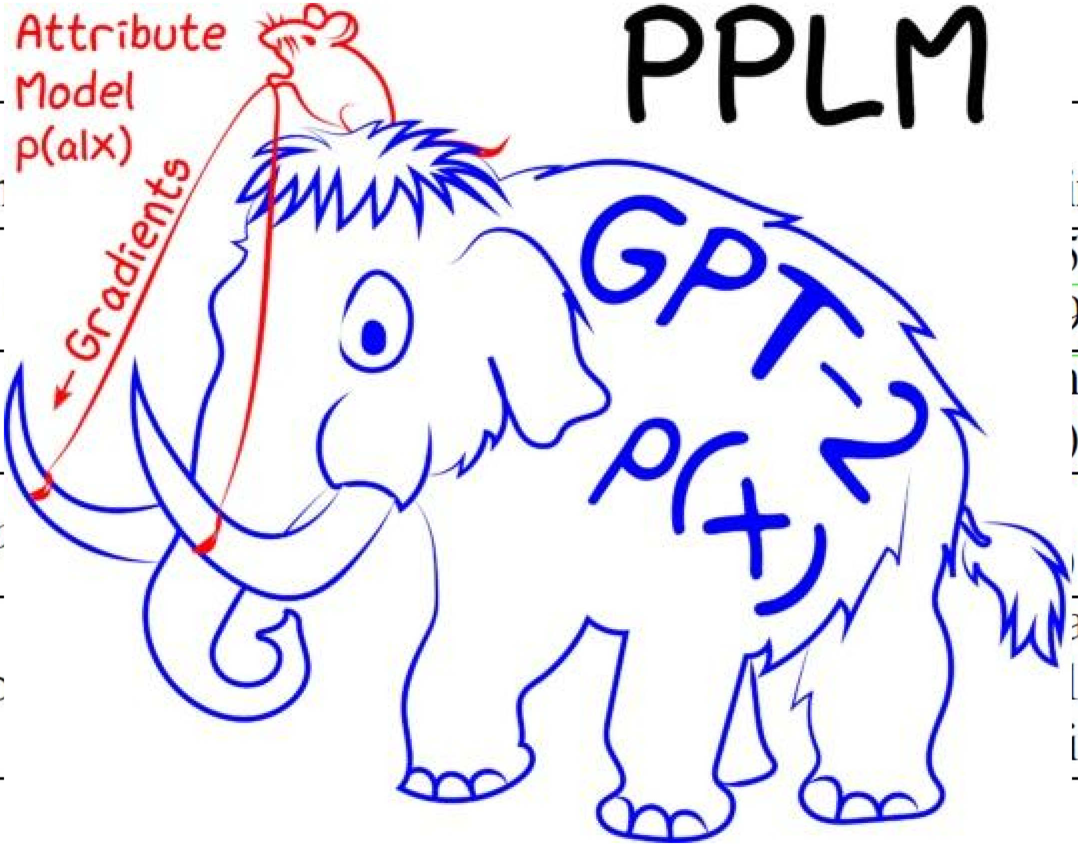
- Zero-shot code-mixing

Diet English : *I lost 10 kgs!* ; German : Ich habe 10 Kilogramm verloren!\n\nEnglish : It is a great achievement for me and my family. ; German : Das ist eine groe Leistung fr mich und meine Familie.\n\nEnglish : Thank you very much to all the people who have helped me. ; German : Vielen Dank an alle, die mir geholfen haben.. . .

Politics Title: *Les Etats-Unis sont un* pays de droite\n\nText: Je suis Américain et je ne peux pas supporter ce que font les USA en matière d'immigration\n\nJ'ai déjà écrit sur le sujet mais il n'y a aucune réaction http://www.reddit.com/r/politics/comments/1tqjzw/les_etats_unes_son_tres-de-gauche/ . . .

PPLM：Plug and Play Language Model

Model type	Form	nable params
Language Model		5M 9)
Fine-tuned Language Model		edium: 345M)
Conditional Language Model	p	
Plug and Play Language Model (PPLM)	$p(x\|a)$ c	ated word list) K/attribute ined $p(x)$)



建模形式

- 将 $p(x|a)$ 通过贝叶斯公式改写成了下面形式

$$p(x|a) \propto p(x)p(a|x)$$

- 在每个 t 时间步上，语言模型 LM 基于过去的历史信息 H 来生成当前的输出 o，同时也将当前时间步信息存入历史，用于下一个时间步的生成：

$$o_{t+1}, H_{t+1} = \mathrm{LM}(x_t, H_t)$$

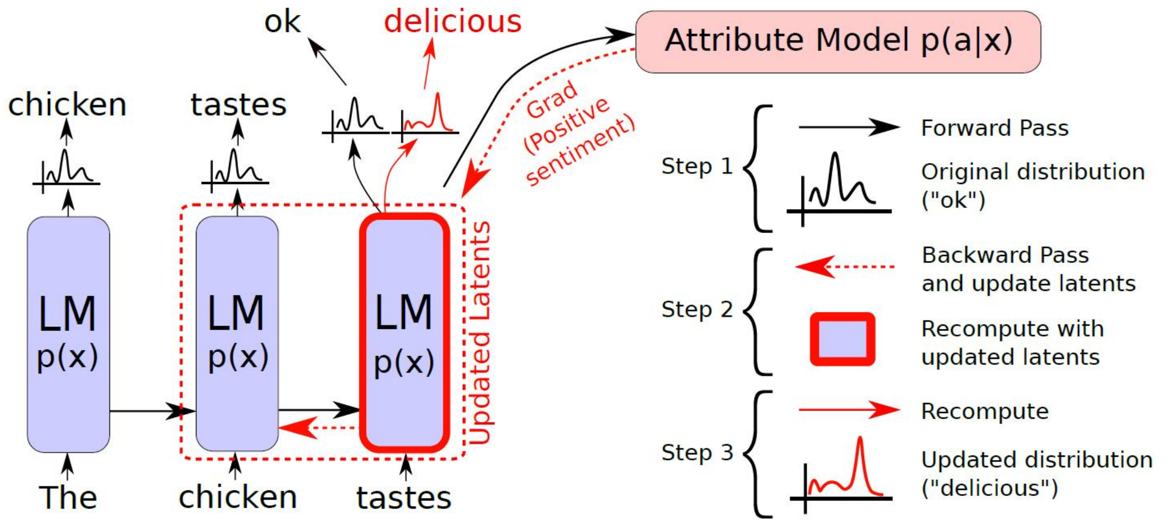
- 而 $p(a|x)$ 在这的作用是，判断当前生成是否接近属性 a 的需求，根据反馈，去修改之前的历史 H，之后语言模型根据新历史来生成更接近属性 a 需求的句子：

$$\widetilde{o}_{t+1}, H_{t+1} = \mathrm{LM}(x_t, H_t)$$

- 通过每次 $p(a|x)$ 的误差传播，可以获得一个梯度，之后用这个更新过去的历史，就可以获得一个新的历史

蕴含属性：$\log p(a|x)$

1. 前向过程，通过分类器预测语言模型生成的文本的属性分类p(a|x)；
2. 反向过程，根据1中属性判别回传的梯度，更新语言模型内部历史参数，增加模型预测接近想要属性的可能性；
3. 重新采样，根据获得的新输出概率分布，采样生成一个新的词。



$$\Delta H_t \leftarrow \Delta H_t + \alpha \frac{\nabla_{\Delta H_t} \log p(a|H_t + \Delta H_t)}{\|\nabla_{\Delta H_t} \log p(a|H_t + \Delta H_t)\|^{\gamma}}$$

α 是步长， γ 是标准化的缩放系数。这个更新步骤可以重复m次，通常取3–10。

保证流利：$\log p(x)$

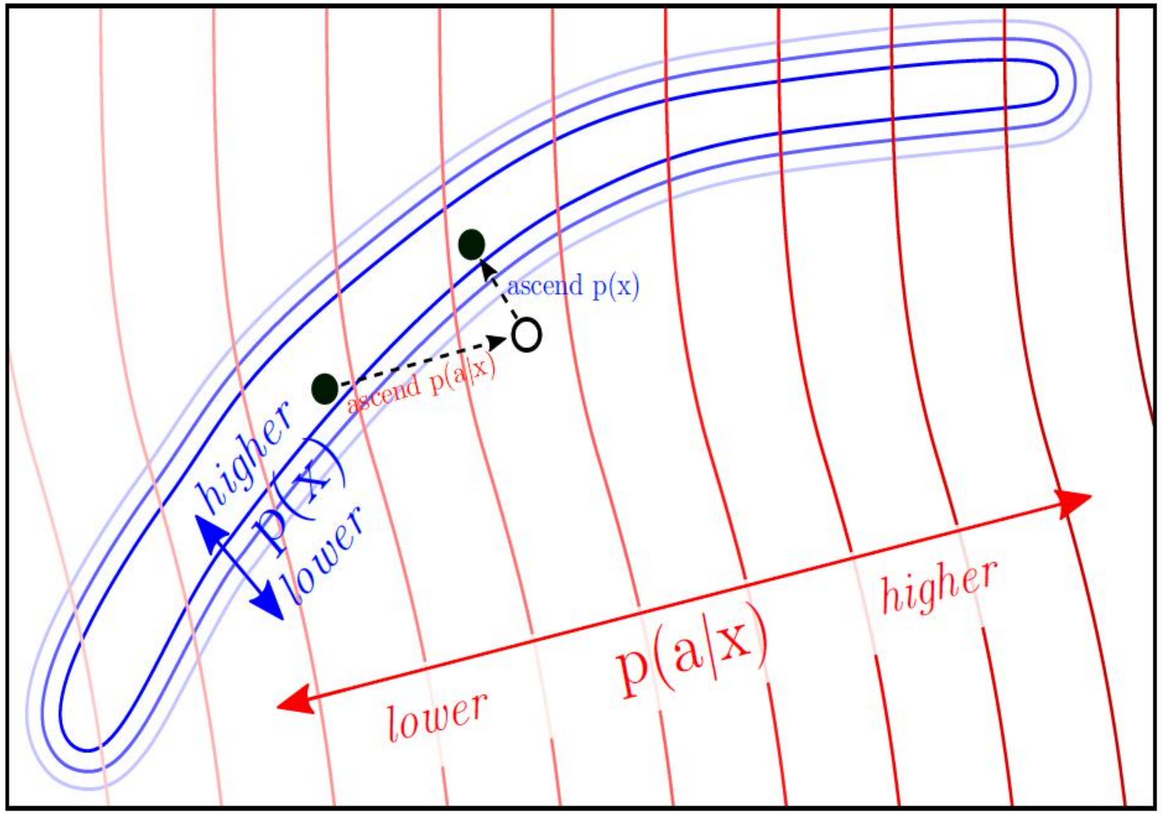
- KL Divergence
  - 在计算历史更新值时，向其中加入一个 KL 散度损失，最小化改变前语言模型和改变后的预测概率分布的 KL 散度；
- Post-norm Geometric Mean Fusion
  - 最后采样的分布是未改变的分布和改变后的分布的加权之和

$$x_{t+1} \sim \frac{1}{\beta}\left(\widetilde{p}_{t+1}^{\gamma_{gm}}\, p_{t+1}^{1-\gamma_{gm}}\right)$$

$\gamma_{gm} \rightarrow 1$ 收敛到更新的语言模型

$\gamma_{gm} \rightarrow 0$ 收敛到无条件的语言模型分布

实践中发现γ_{gm}取0.8-0.95比较合适



属性判别器

- BoW属性模型
  - 针对每个主题先总结一批有代表性的词，之后具体实现时只用在每个时间步上对输出概率分布取出对应词袋中词的位置，计算 loss，加和起来反向传播就行。

$$\log p(a|x) = \log\left(\sum_i^k p_{t+1}[w_i]\right)$$

Method	Topic % (↑ better) (human)	Perplexity (↓ better)	Dist-1 (↑ better)	Dist-2 (↑ better)	Dist-3 (↑ better)	Fluency (↑ better) (human)
B	11.1	39.85±35.9	0.37	0.79	0.93	3.60±0.82
BR	15.8	38.39±27.14	0.38	0.80	0.94	3.68±0.77
BC	46.9	43.62±26.8	0.36	0.78	0.92	3.39±0.95
BCR	**51.7**	44.04±25.38	0.36	0.80	0.94	3.52±0.83
CTRL	50.0	24.48±11.98	0.40	0.84	0.93	3.63±0.75
BCR	**56.0**	–	–	–	–	3.61±0.69
WD	35.7	32.05±19.07	0.29	0.72	0.89	3.48±0.92
BCR	**47.8**	–	–	–	–	3.87±0.71

- 判别器属性模型

$$\log p(a|x) = \log f(o_{:t+1}, o_{t+2})$$

[-] The issue focused on the way that the city's police officers have reacted in recent years to the deaths of Michael Brown in Ferguson, Mo., Eric Garner in New York City and Sandra Bland in Texas, as well as the shooting of unarmed teen Michael Brown by a white police officer in Ferguson, Mo. A grand jury declined to bring charges against the officers and released the dashcam videos that showed...

[Military] The issue focused on the fact that the government had spent billions on the military and that it could not deploy the troops in time. The prime minister said that the country would take back control of its airspace over Syria in the next 48 hours. \nl The military is investigating why

[Politics] The issue focused on a single section of the legislation. It's unclear whether the committee will vote to extend the law, but the debate could have wider implications. \n "The issue of the law's applicability to the United Kingdom's referendum campaign has been one of

[Computers] The issue focused on the role of social media as a catalyst for political and corporate engagement in the digital economy, with the aim of encouraging companies to use the power of social media and the Internet to reach out to their target market. \nl According to a report by Digital Media Monitor and the digital advertising market research firm Kantar Web.com in January, Facebook has already surpassed Google and Apple as

[Science] The issue focused on a single piece: the question "What is the meaning of life?" This question has puzzled many philosophers, who have attempted to solve it by using some of the concepts of quantum mechanics, but they have to solve it by the laws of nature themselves.

[-] The chicken is now out on the grill. \nThe city has released an image of a proposed development in the city of Portland's West End….

[Positive] The chicken was delicious – wonderfully moist, perfectly delicious, superbly fresh – and perfectly cooked. The only thing to say is that the sauce was excellent, and I think that the broth really complemented all of the other flavors. The best part was the sauce…

[Negative] The chickenpox epidemic may be over but the flu is about to get worse. The United States is facing one of the worst flu seasons on record and...

[-] The country's new chief minister, A.J. Paik, is a member of a group of prominent conservative politicians who have criticized the Obama administration's efforts to…

[Positive] The country's largest indoor painting event!\nCome celebrate with a dazzling display of stunning outdoor murals, a stunning display of art, and the world's best paint and art supplies from all over the world!

[Negative] The country's top prison system is forcing prisoners to use a trash dump, rather than a toilet, to flush their waste out, as the authorities fear the waste is more toxic and could cause cancer, an official at a major prison has revealed...

CoCon：Content—Conditioner

- 模型目标：
  - 给定一段引导文本c和一段控制文本p，模型去生成和p保持流畅，内容上大致包含c的文本q，和p一起形成一段完整的文本$x = [p, q]$，其中$p = x_{1:t-1}, q = x_{t:l}$
  - 这个过程可以用一个Seq2seq模型表达：

$$p_\theta(q|c,p) = \prod_{j=t}^{l} p_\theta(x_j|c, x_{1:t-1}, x_{t:j})$$

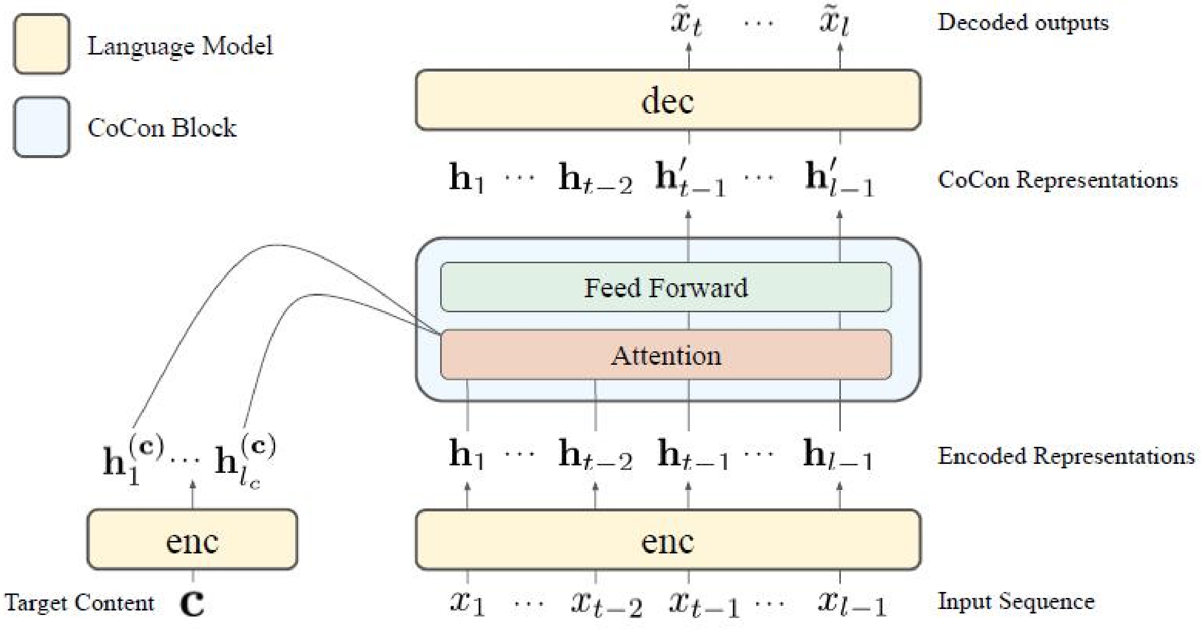


Figure 1: Model architecture of Content-Conditioner (CoCon).

- 过程：
  - 分别编码c和p，得到它们的特征
  - 自注意力交互，得到新的特征
  - 进行下一个词预测

模型结构

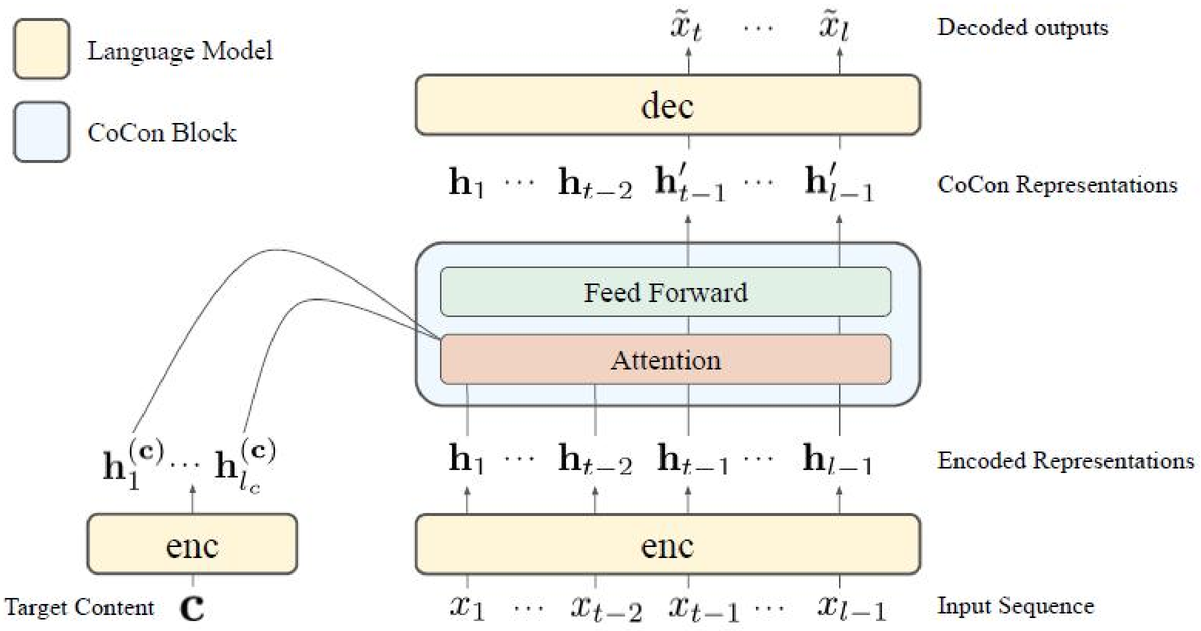
- CoCon是一个单层Transformer Block，也就是self attention–FFN的模式。
- 首先得到引导文本和控制文本的Q,K,V：

$$Q = W_Q H;\ K = W_K H, K^c = W_{K^c} H^c;$$
$$V = W_V H, V^c = W_{V^c} H^c$$

- 将K、V拼起来，过自注意力

$$\mathbf{K}' = [\mathbf{K}^{(\mathbf{c})}; \mathbf{K}], \quad \mathbf{V}' = [\mathbf{V}^{(\mathbf{c})}; \mathbf{V}],$$
$$\mathbf{A} = \text{Softmax}(\mathbf{Q}\mathbf{K}'^{\top})\mathbf{V}' = \text{Softmax}(\mathbf{W})\mathbf{V}',$$

- 如果有多个控制文本，则把它们拼接起来作为一个整体。
- 最后，还可以在注意力权重矩阵上加一些偏置项，以调整对控制文本c的关注程度。



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如何训练CoCon

- 无监督方式
- 假定任何一个句子x可以分为两部分$x = [x^a, x^b]$，x^a就可以当做引导文本，x^b就是要生成的文本，现在的问题是，控制文本c是什么。

- 自重构损失(Self Reconstruction Loss)
  - 令$c = x^b$，之后要生成的就是使x^b自己。这一步使得模型能够学习结合控制文本的内容

$$\mathcal{L}_{\text{self}} = -\sum_{i=t}^{l} \log p_{\theta,\psi}\left(x_i | (\mathbf{c} = \mathbf{x}^b), \{x_1, \ldots, x_{i-1}\}\right)$$

- 无文本损失(Null Content Loss)
  - 令$c = \varnothing$，使得模型退化成简单的语言模型，以生成流畅的文本

$$\mathcal{L}_{\text{null}} = -\sum_{i=t}^{l} \log p_{\theta,\psi}\left(x_i | (\mathbf{c} = \varnothing), \{x_1, \ldots, x_{i-1}\}\right)$$

损失函数

- 循环重构损失(Cycle Reconstruction Loss)
  - 通过两个不同文本互为控制文本来生成质量更高的文本。
  - 假定现在有两个不同的文本$x = [p, q]$，$x' = [p', q']$
  - 首先将p'作为引导文本，将q作为控制文本，生成新文本$q^1 = f_\theta(p', q)$。q^1的目的是在和p'保持流畅，且尽可能包含q的内容；
  - 再将p作为引导文本，将q^1作为控制文本，生成新文本$q^2 = f_\theta(p, q^1)$。这里想让q^2和p保持流畅，且尽可能包含q^1的内容；
  - 既然q^2包含q^1的内容，而q^1又包含q的内容，那么就是要q^2包含q的内容，且要和p保持流程，也就是q本身吗！
  - 所以，循环重构损失就 … 为真值去优化q'^2。

$$\mathbf{y}_{\mathbf{x},\mathbf{x}'} = f_{\theta,\psi}((\mathbf{c} = \mathbf{x}^b), (\mathbf{p} = \mathbf{x}'^a)),$$

$$\mathbf{y}_{\text{cycle}} = f_{\theta,\psi}((\mathbf{c} = \mathbf{y}_{\mathbf{x},\mathbf{x}'}), (\mathbf{p} = \mathbf{x}^a)),$$

$$\mathcal{L}_{\text{cycle}} = -\sum_{i=t}^{l} \log p_{\theta,\psi}\left(\mathbf{y}_{\text{cycle}} = \mathbf{x}^b | (\mathbf{c} = \mathbf{y}_{\mathbf{x},\mathbf{x}'}), (\mathbf{p} = \mathbf{x}^a)\right).$$

损失函数

- 对抗损失(Adversarial Loss)
  - 过去的工作都会用对抗损失，让生成的文本接近训练数据真实文本

$$\mathcal{L}_{\text{adv}} = \mathbb{E}_{\mathbf{x}}[\log f_{\text{disc}}(\text{enc}(\mathbf{x}))] + \mathbb{E}_{\mathbf{y}}[\log(1 - f_{\text{disc}}(\text{enc}(\mathbf{y}))]$$

  - 这里f_{disc}是判别器网络，x是原来的文本，y是生成的文本

- 总优化目标
  - 把上面四个损失合起来

$$\theta^* = \arg\min_{\theta}(\lambda_{\text{self}}\mathcal{L}_{\text{self}} + \lambda_{\text{null}}\mathcal{L}_{\text{null}} + \lambda_{\text{cycle}}\mathcal{L}_{\text{cycle}} + \lambda_{\text{adv}}\mathcal{L}_{\text{adv}})$$

实验

- 采用预训练的GPT2作为模型主干，前7层是编码器，后17层是解码器，固定所有参数，只训练CoCon模块；
- 内容可控生成、主题可控生成、情感可控生成

Model	BLEU-4 (↑ better)	NIST-4 (↑ better)	METEOR (↑ better)	Perplexity (↓ better)	Dist-1 (↑ better)	Dist-2 (↑ better)	Dist-3 (↑ better)
GPT-2	0.22	7.09	6.14	105.7	0.057	0.49	0.82
CoCon	2.76	22.9	21.5	70.8	0.048	0.39	0.70
∟ w/o $\mathcal{L}_{cycle}$	3.30	25.1	23.9	150.8	0.050	0.42	0.74
∟ w/o $\mathcal{L}_{null}$	4.44	**28.3**	26.8	73.2	0.046	0.37	0.68
∟ w/o $\mathcal{L}_{adv}$	**4.47**	28.2	**27.2**	**68.7**	0.047	0.38	0.69
CoCon-Webtext	2.90	24.6	23.0	112.5	0.054	0.44	0.74
Prompt-Content	–	–	–	442.2	–	–	–
Webtext	–	–	–	185.8	–	–	–

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∟ w/o $\mathcal{L}_{cycle}$	3.30	25.1	23.9	150.8	0.050	0.42	0.74
∟ w/o $\mathcal{L}_{null}$	4.44	**28.3**	26.8	73.2	0.046	0.37	0.68
∟ w/o $\mathcal{L}_{adv}$	**4.47**	28.2	**27.2**	**68.7**	0.047	0.38	0.69
CoCon-Webtext	2.90	24.6	23.0	112.5	0.054	0.44	0.74
Prompt-Content	–	–	–	442.2	–	–	–
Webtext	–	–	–	185.8	–	–	–

Content Input ($\mathbf{c}^1$): **then men will have an even more difficult time**
+ Target Topic: COMPUTERS, Content Input ($\mathbf{c}^2$): **Computers**
+ Target Sentiment: Negative, Content Input ($\mathbf{c}^3$): **is horrible**

Once upon a time there are horrible machines. But men will have a much more difficult time. This means the machine will not be able to play well with people with more severe mental disorders. (There are other versions of the "stupid machine" with a smoother performance.) It will be difficult for them to learn a new skill or get better grades in school. It will also be hard for them to get better jobs. The system will, of course, not reward them for their hard work..

Content Input ($\mathbf{c}^1$): **then men will have an even more difficult time**
+ Target Topic: COMPUTERS, Content Input ($\mathbf{c}^2$): **Computers**

Once upon a time machines – computers will have a even more difficult time. In my experience, people will have a much more difficult time of it. If you can get over the technical difficulty of the machine, I can see how we can get a reasonably fast connection with you, just like we do with the Internet. It's better just to take the train and walk for a while and connect. It's not like it's a good idea to call ahead and get a pick-up..

Model	Sentiment % (↑ better)	Perplexity (↓ better)	Dist-1 (↑ better)	Dist-2 (↑ better)	Dist-3 (↑ better)
GPT-2	50.0	101.2	0.38	0.82	0.92
PPLM	68.9	**35.5**	0.24	0.63	0.82
CTRL	81.1	44.1	0.21	0.62	0.80
CoCon	**98.9**	50.3	0.20	0.61	0.80

总结

模型	优点	缺点
Seq2Seq-Attention+RNN/LSTM	训练所需计算资源较少；符合语法；能够覆盖主题；	语义表达不够准确；前后表达一致性弱；逻辑性差。
GPT-2	生成的文本在语法、可读性、语义一致性、语句通顺等方面质量较高。	生成的文本会出现缺乏逻辑和关联性不合逻辑的语句；生成的内容不受限，没有办法地敢于朝着自己想要的方向生成文本。
CTRL（基于GPT-2）	使用时操作简单，给定标签即可生成所需风格文本	可扩展性差，需要大量计算资源
PPLM（基于GPT-2）	训练所需计算资源较少；可控性较好。	边训练边生成结果，效率较低；参数对模型的影响较大；逻辑性弱
CoCon（基于GPT-2）	训练所需计算资源较少；主题相关性高；文本质量较高；比结构化控制变量模型（以上模型）更加灵活和通用；	会生成无意义文本；上下逻辑性弱。

Thanks~