# Contrastive Decoding Open-ended Text Generation as Optimization

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## Decoding from Language Models

**Pretrained LM** 

e.g., GPT-3

Prompt:

Researchers found British unicorns spoke perfect English. Researchers found

### Sampling from the LM:

that global warming has endangered many species. Global warming is an established scientific fact that has been extensively studied and confirmed by researchers...

Stochasticity may lead to unlucky sampling choices:(



Fluent but suffers from topic drifts (not coherent)

### Decoding from Language Models

**Pretrained LM** 

e.g., GPT-3

Prompt:

Researchers found British unicorns spoke perfect English. Researchers found

### Searching for the most likely string:

British unicorns spoke perfect English. British unicorns spoke perfect English. British unicorns spoke perfect English...

The modes of the language model distribution are highly degenerate:(



Repetitive and uninsteresting

### Decoding from Language Models

Pretrained LM e.g., GPT-3

### Sampling from the LM:



Fluent but suffers from topic drifts (not coherent)

### Searching for the most likely string:



Repetitive and uninsteresting

How to generate coherent text, without sacrificing fluency/diversity?

A better decoding objective: Contrastive Decoding

### Why contrast language models?



GPT-3:

who played will on as the world turns?

Factual Error: John McCook

Repetition: who played will on as the world turns?

Topic Drift: Spolier---- Back when Shirly Fields was on the show there



Large LMs suffer from these failures.



Smaller LMs are more prone to these failures!

Can we cancel out the bad behaviors?

Down weight the common failures + Emphasize the remaining good behaviors!

### Contrastive Objective

$$\begin{array}{ll} \text{Maximize} & \log p_{\text{EXP}}(\mathbf{X}_{\text{cont}} \mid \mathbf{X}_{\text{pre}}) - \log p_{\text{AMA}}(\mathbf{X}_{\text{cont}} \mid \mathbf{X}_{\text{pre}}) \\ \mathbf{X}_{\text{cont}} & \end{array}$$

	$\log p_{ m\scriptscriptstyle AMA}$	$\log p_{ ext{EXP}}$	$\mathcal{L}_{ ext{CD}}$	
Repetition: British unicorns	-9.4	-10.2	-0.8	(Both assigned high probs)
Topic Drift: Global warming	-29.6	-27.4	2.2	(Both assigned low probs)
Good Cont: their language	-20.5	-11.5	9.0	(Prefered by the expert LM)



The undesired behaviors cancel out via contrastive objective.

### Contrastive Objective

$$\begin{array}{ll} \text{Maximize} & \log p_{\text{EXP}}(\mathbf{X}_{\text{cont}} \mid \mathbf{X}_{\text{pre}}) - \log p_{\text{AMA}}(\mathbf{X}_{\text{cont}} \mid \mathbf{X}_{\text{pre}}) \\ & \mathbf{X}_{\text{cont}} \end{array}$$

- The undesired behavior (e.g., repetition) cancels out via contrastive objective.
- **1**...

But the amateur LM is not always wrong:

### **False positive**

An implausible token gets a high CD score because the amateur assigns very low prob

#### **False negative**

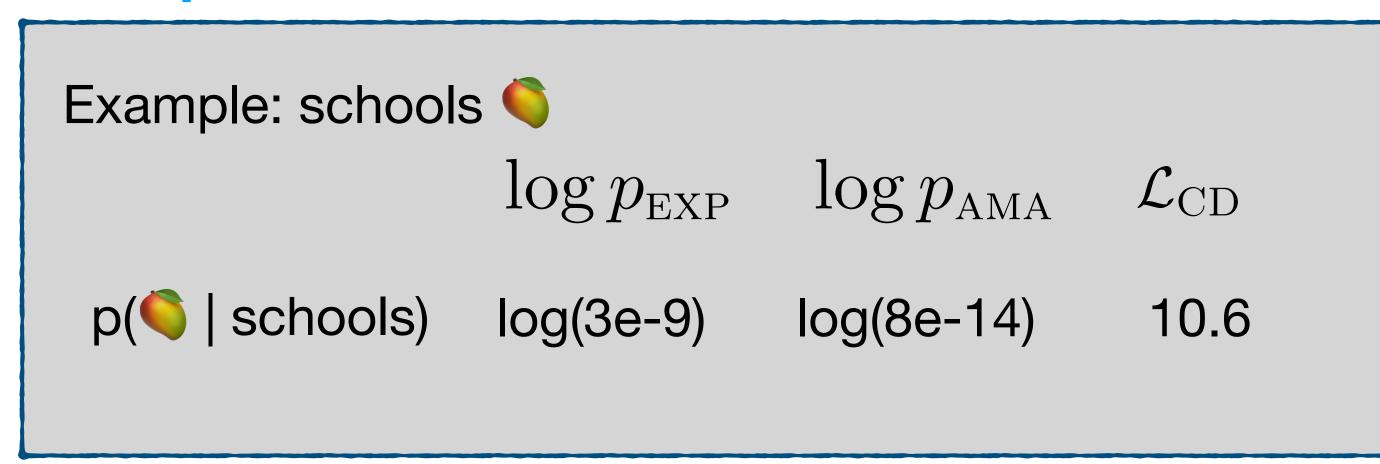
A correct token gets a low CD score because the amateur also assigns high prob

### Plausibility Constraints

$$\mathcal{V}_{\text{head}}(x_{< i}) = \{x_i \in \mathcal{V} : p_{\text{EXP}}(x_i \mid x_{< i}) \ge \alpha \max_{w} p_{\text{EXP}}(w \mid x_{< i})\}$$

Truncates the tail of the LM distribution

#### **False positive**



$$\alpha = 0.1$$

$$\max_{w} p_{\text{EXP}}(w|x_{< i}) = 0.3$$

Zero out tokens with prob < 0.03

is not in the plausibility set

### Plausibility Constraints

$$\mathcal{V}_{\text{head}}(x_{< i}) = \{x_i \in \mathcal{V} : p_{\text{EXP}}(x_i \mid x_{< i}) \ge \alpha \max_{w} p_{\text{EXP}}(w | x_{< i})\}$$

Adaptive: the truncation depends on the confidence of the LM

### **False negative**

Example: uni #corn  $\log p_{
m EXP} - \log p_{
m AMA} - \mathcal{L}_{
m CD}$  p(#corn | uni)  $\log (0.99) - \log (0.99)$  6e-4

$$\max_{w} p_{\text{EXP}}(w|x_{\leq i}) = 0.99$$

Zero out tokens with prob < 0.099
#corn is the **only** token in the plausibility set

### Full Method

$$\max_{\mathsf{X}_{\mathsf{cont}}} \mathcal{L}_{\mathsf{CD}}(\mathsf{X}_{\mathsf{cont}}, \mathsf{X}_{\mathsf{pre}}) \overset{\mathsf{Contrastive}}{\underset{\mathsf{objective}}{\mathsf{objective}}}$$

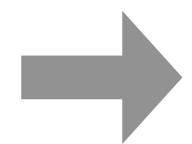
subject to 
$$x_i \in \mathcal{V}_{\text{head}}(x_{< i}), \forall x_i \in \mathbf{X}_{\text{cont}}$$
 Plausibility constraints



Factor to token level

$$CD$$
-score $(x_i; x_{< i})$ 

$$= \begin{cases} \log \frac{p_{\text{EXP}}(x_i|x_{< i})}{p_{\text{AMA}}(x_i|x_{< i})}, & \text{if } x_i \in \mathcal{V}_{\text{head}}(x_{< i}), \\ -\inf, & \text{otherwise.} \end{cases}$$



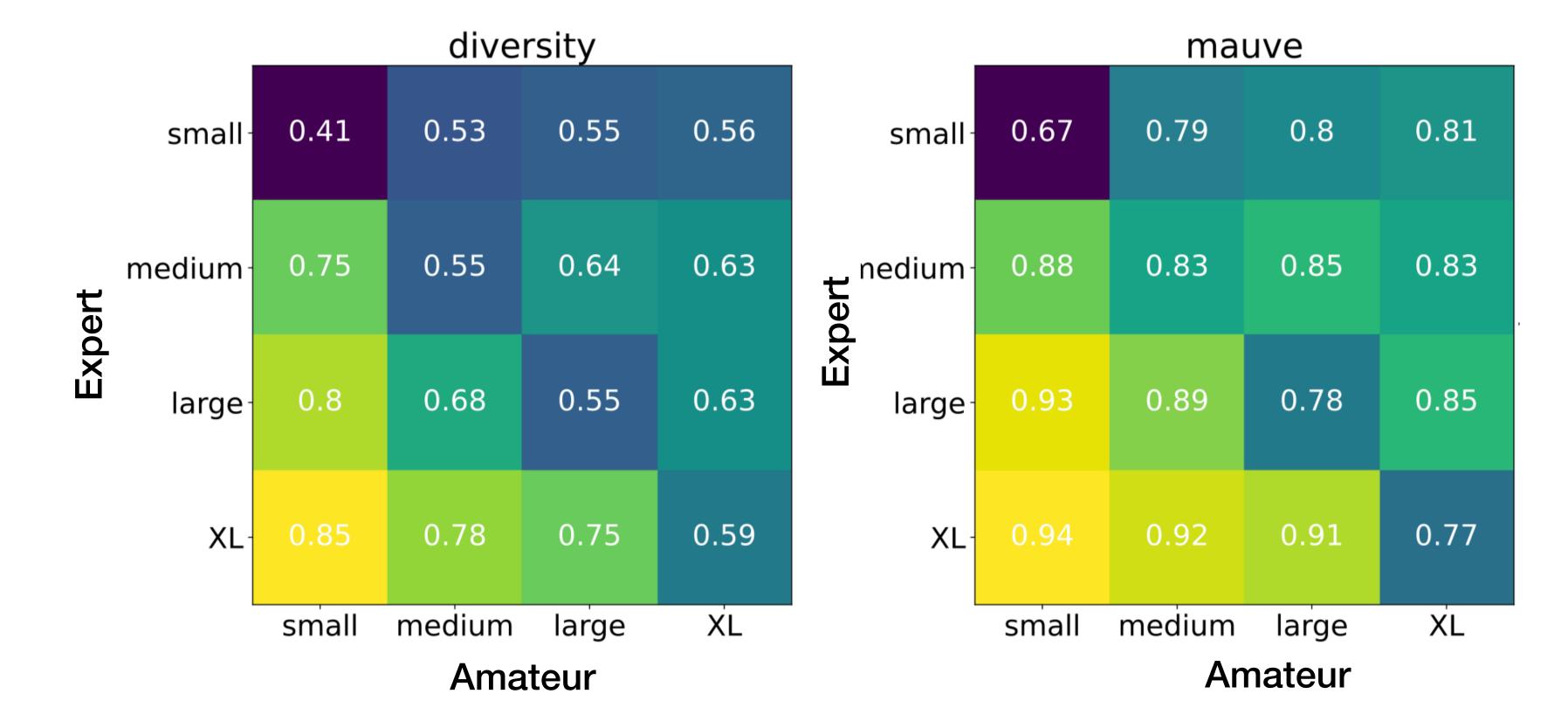
Beam Search

Sample

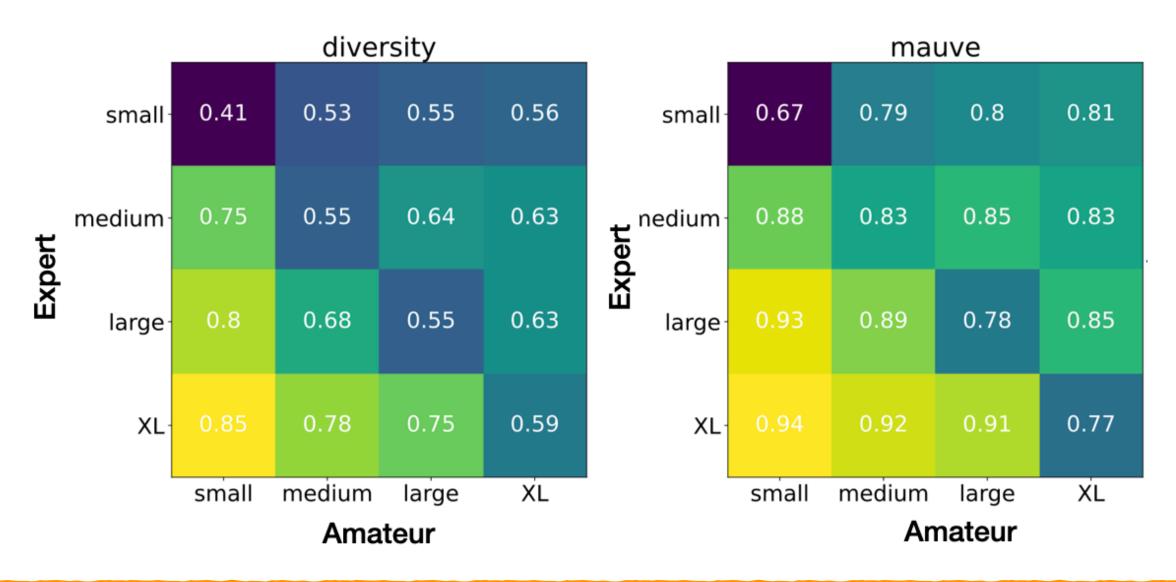
### Design Choices: Scale

Maximize  $\log p_{\rm EXP}({\sf X_{\rm cont}} \mid {\sf X_{\rm pre}}) - \log p_{\rm AMA}({\sf X_{\rm cont}} \mid {\sf X_{\rm pre}})$  Xcont

How does the choices of amateur LM and expert LM matter?



### Design Choices: Scale



#### Intuition:

We want the amateur LM to emphasize the failure modes of the expert, so the amateur LM shouldn't be too strong.

# Automatic Eval

			wikinews		1	wikitext		ı	story	
	name	DIV	MAUVE	СОН	DIV	MAUVE	СОН	DIV	MAUVE	СОН
	max prob	0.08	0.3	0.65	0.03	0.08	0.63	0.02	0.05	0.51
	k=50	0.91	0.92	0.64	0.72	0.77	0.64	0.91	0.9	0.51
3B	p=0.95	0.92	0.92	0.62	0.92	0.89	0.55	0.93	0.91	0.48
OPT-13B	typical=0.95	0.94	0.9	0.59	0.89	0.86	0.58	0.95	0.91	0.46
OP	CS(Su et al., 2022)	0.92	0.87	0.59	0.87	0.77	0.52	0.81	0.78	0.47
	CD	0.94	0.94	0.69	0.91	0.91	0.69	0.89	0.94	0.62
	max prob	0.04	0.14	0.65	0.02	0.05	0.62	0.01	0.03	0.49
	k=50	0.92	0.88	0.64	0.87	0.79	0.61	0.91	0.87	0.51
	p=0.95	0.94	0.9	0.6	0.92	0.87	0.57	0.94	0.91	0.46
GPT2-XI								0.43		
PT	Takeaways: CD outperforms prior sampling-based approaches in									0.48
O	MAUVE and coherence.									0.64

### Human Eval

			coherence			fluency		
	CD	Baseline	CD is better	same	Baseline is better	CD is better	same	Baseline is better
ŧ	CD (GPT-2 XL)	nucleus (GPT-2 XL)	0.714*	0.083	0.202	0.548	0.083	0.369
vikitext	CD (GPT-2 XL)	typical (GPT-2 XL)	0.887*	0.046	0.067	0.703*	0.082	0.215
vik	CD (OPT-13B)	nucleus (OPT-13B)	0.556	0.202	0.242	0.419	0.197	0.384
>	CD (OPT-13B)	typical (OPT-13B)	0.773*	0.106	0.121	0.687*	0.152	0.162
SA	CD (GPT-2 XL)	nucleus (GPT-2 XL)	0.708*	0.042	0.25	0.583*	0.12	0.297
wikinews	CD (GPT-2 XL)	typical (GPT-2 XL)	0.771*	0.151	0.078	0.755*	0.151	0.094
iķi	CD (OPT-13B)	nucleus (OPT-13B)	0.585*	0.221	0.195	0.518	0.123	0.359
≱	CD (OPT-13B)	typical (OPT-13B)	0.693*	0.099	0.208	0.49	0.297	0.214
	CD (GPT-2 XL)	nucleus (GPT-2 XL)	0.636*	0.045	0.318	0.404	0.106	0.49
OI.	CD (GPT-2 XL)	typical (GPT-2 XL)	0.506	0.256	0.238	0.387	0.363	0.25
story	CD (OPT-13B)	nucleus (OPT-13B)	0.616*	0.101	0.283	0.449	0.293	0.258
	CD (OPT-13B)	typical (OPT-13B)	0.626*	0.202	0.172	0.52	0.212	0.268

Takeaways: CD outperforms prior sampling-based approaches according to human eval.

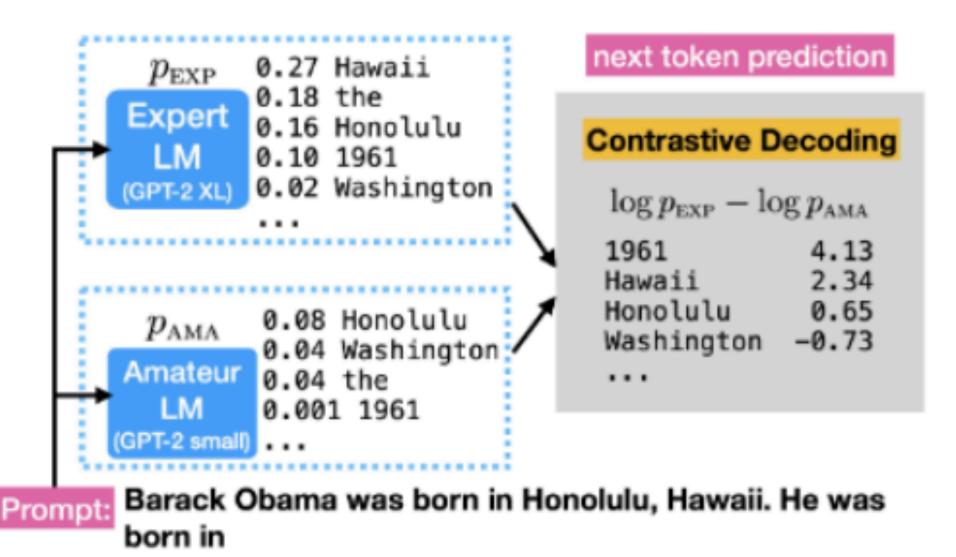
# Qualitative Examples

Prompt	A version of Sonic the Hedgehog was developed by Ancient and released in 1991 for Sega's 8 - bit consoles, the Master System and Game					
CD (1.5B)	A version of Sonic the Hedgehog was developed by Ancient and released in 1991 for Sega's 8 - bit consoles, the Master System and Game Gear. It featured a new level editor called the Sonic Editor and was released as an expansion pack to Sonic CD in 1992, which was itself a port from the Genesis version. The editor allowed the creation and playtesting of custom levels for Sonic CD, and the expansion was also bundled with Sonic CD. It is also available for the PC as Sonic Editor. The game is considered a spiritual successor to the Genesis game Sonic 3 & Knuckles and the Genesis port Sonic 3D Blast, as it features the same gameplay elements, including the Spin Dash, and also shares many levels and music with those games					
Nucleus (1.5B)						

### Thanks

#### Code is available:

https://github.com/XiangLi1999/ContrastiveDecoding



#### Continuations:

Greedy: Hawaii. He was born in Hawaii. He was born in Hawaii...

Nucleus: Washington, D.C., to Barack Obama and Michelle Robinson...

CD: 1961 to a Kenyan father, Barack Hussein Obama and a mother of American descent, Stanley Ann Dunham...