Accelerating Entropy-Based Transformer Calibration

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4. Entropy blowup: when the entropy rate of text produced by a source increases over time.

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We observe entropy blowup on SOTA language models such as GPT-2.

Develop a computationally efficient technique for minimizing entropy blowup in language models.

Related Work

- Analysis of language model sampling methods by Holtzman et al. [1]
- Calibration of neural networks via temperature scaling by Guo et al. [2]

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Approach: Preliminaries

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Conditional one-step lookahead entropy:

$$H(\widehat{W}_{t+1} | w_{\leq t}) := \mathbb{E}_{w_{t+1} \sim \widehat{Pr}}\left[\log \frac{1}{\widehat{Pr}(w_{t+1} | w_{\leq t})}\right]$$

Stepwise calibration:

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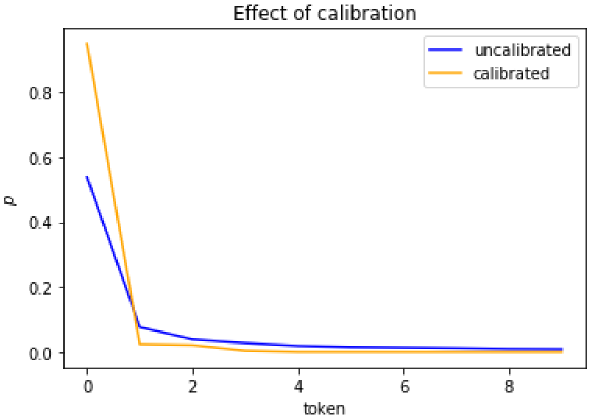
Use Pr_α as your new language model.


Effect of calibration
uncalibrated
calibrated
0.8
0.6
0.4
0.2
0.0
p
0
2
4
6
8
token

Approach: How to improve?

Computational complexity:

- V = size of vocabulary = $\sim$ 50,000 in practice
- C = number of contexts = for a sentence, the number of words $\Rightarrow \sim 10$.
- T = number of words we wish to generate

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The cross-entropy loss takes $O(V^2C)$ time to compute.

Computing Pr_α takes $O(V^2)$ time $\Rightarrow$ sampling T words takes $O(V^2T)$ time.

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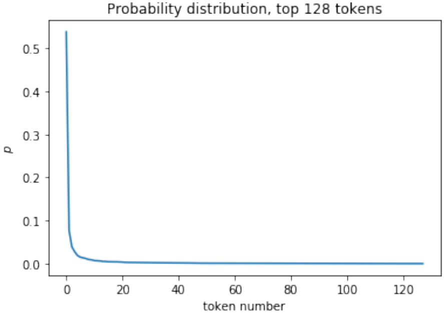
Impact:

- $V = 50{,}000 \Rightarrow 100$. If the model used to take 8 hours to calibrate or generate T words, it now takes 1 minute.

Result 1

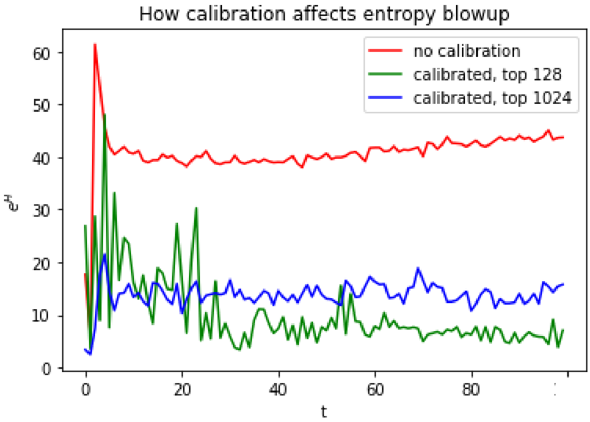
On average, top 128 words capture $> 90\%$ of the probability mass.



Here: 92.8%

Result 2

Generating using approximations of Pr_α minimizes entropy blowup.



Result 3

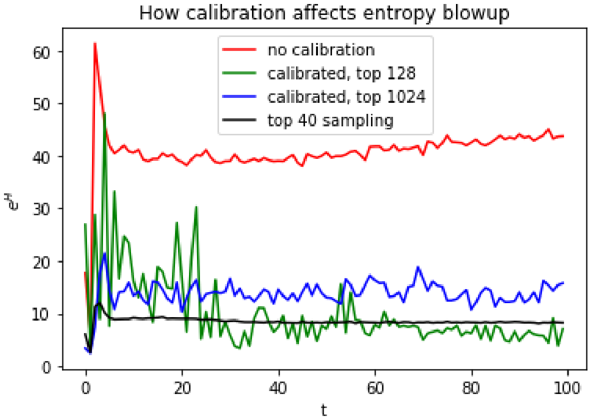
We observe no qualitative drawbacks when using approximations of Pr_α.

Result 4

A plug-and-play API for calibration, available at
`https://github.com/mikkyhu/transformers/blob/master/examples/calibrate.py`

Approximating Pr_α is a viable way to speed up calibration and generating from Pr_α.

Future work


How calibration affects entropy blowup
no calibration
calibrated, top 128
calibrated, top 1024
top 40 sampling
60
50
40
30
20
10
0
e^H
0
20
40
60
80
100
t

Acknowledgements

- Karthik Narasimhan
- Cyril Zhang

Ari Holtzman, Jan Buys, Maxwell Forbes, and Yejin Choi.
The curious case of neural text degeneration, 2019.

Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q. Weinberger.
On calibration of modern neural networks, 2017.