Machine Learning for Natural Language Processing

Generating Text from a Language Model

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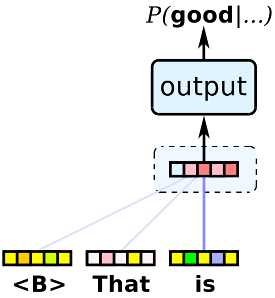
generating text from a language model

- assuming we have $P(X)$, how do we **generate** or "**decode**"?



- we will discuss the most common algorithms for **autoregressive** LMs
- there are several algorithms: this is an active research area

use cases: generating from a prompt

- given a prefix or "prompt", how do we find

$$\text{text}^* = \arg\max_{\text{text}} P(\text{text}|\text{prompt})$$

```
generated_ids = generate("NLP stands for natural", greedy_strategy, stopping_criterion=partial(has_n_sentences, n=2),

NLP stands for natural language processing. It is a method of processing language by using a computer to learn the mea
----------------------------------------------------------------
```

use cases: sampling

- if we have $P(X)$, how can we generate random texts?
- again, we might want to use a prompt

$$\text{text} \sim P(\text{text}|\text{prompt})$$

```
generated_ids = generate("Meatballs", random_strategy, stopping_criterion=partial(has_n_sentences, n=2))
```

```
Meatballs are a well-loved family recipe that typically serve as the centerpiece of spring gatherings in
-------------------------------------------------------------
```

```
generated_ids = generate("Meatballs", random_strategy, stopping_criterion=partial(has_n_sentences, n=2))
```

```
Meatballs. I made a weekly ritual of "drilling" out new ones, starting with how-to guides and deciding or
-------------------------------------------------------------
```

```
generated_ids = generate("Meatballs", random_strategy, stopping_criterion=partial(has_n_sentences, n=2))
```

```
Meatballs. Go for junk food and chips, no way you can show some athletic skill with a mound of food.
-------------------------------------------------------------
```

```
generated_ids = generate("Meatballs", random_strategy, stopping_criterion=partial(has_n_sentences, n=2))
```

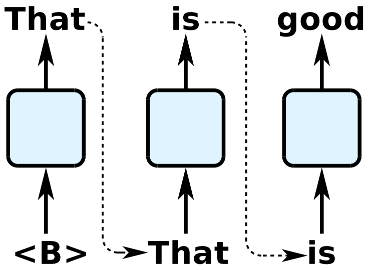
```
Meatballs, fried crickets and soggy greens. Another favourite – a crab-stuffed baked potato and chutney p
-------------------------------------------------------------
```

unsupported use cases

- it is difficult to solve “fill-in-the-blank” tasks with autoregressive LMs
- what is the most likely missing text?

NLP stands for ___ . It is a method…

first idea: greedy decoding



- select the **highest-scoring** alternative at each step

greedy decoding: pseudocode

initialize $X = x_1, \ldots, x_m$ to some token sequence
for $i = m + 1, \ldots$ until some stopping criterion met
    $x_i \leftarrow \arg\max_x P(x|X)$
    append x_i to X
return X

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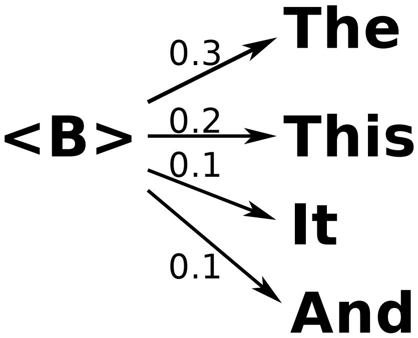
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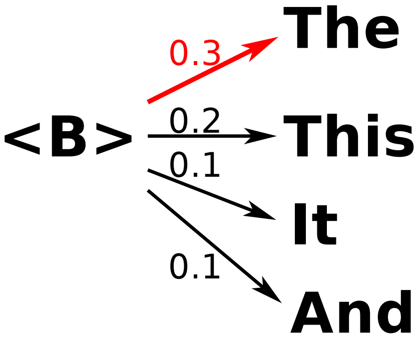
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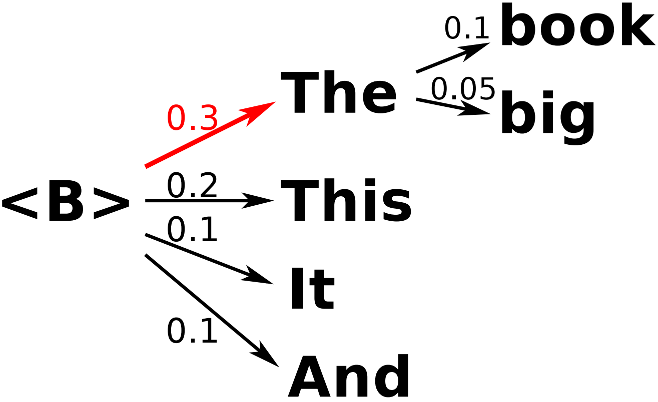
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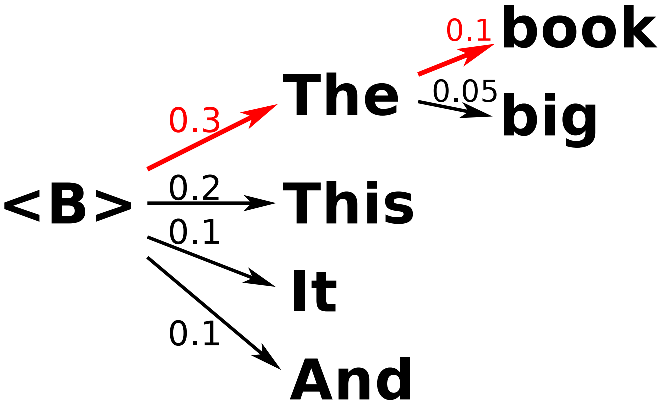
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pros and cons of greedy decoding

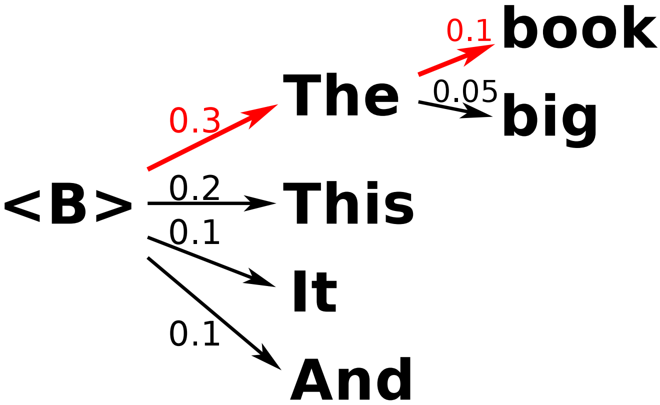
fast and easy to implement

pros and cons of greedy decoding

fast and easy to implement

BUT:

does not find the highest-scoring sequence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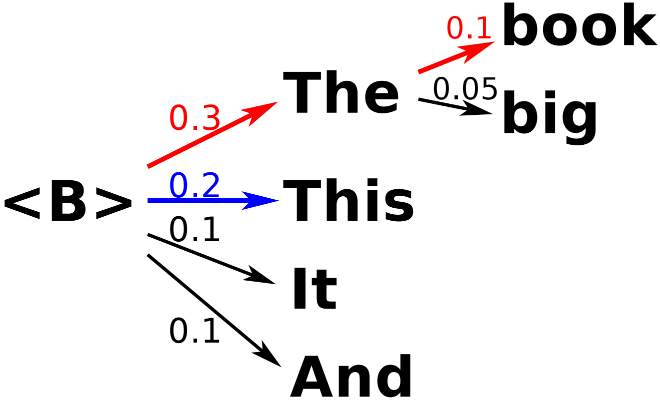

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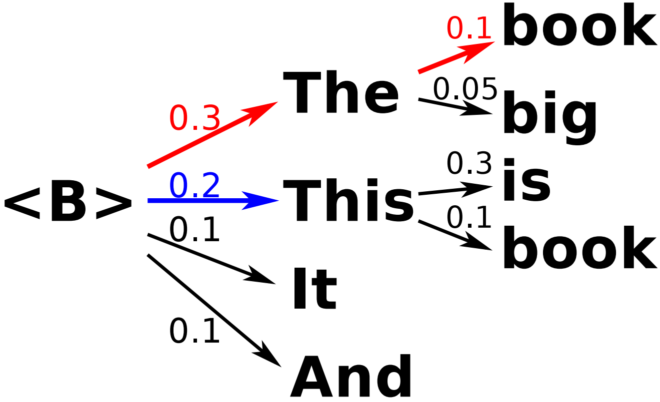
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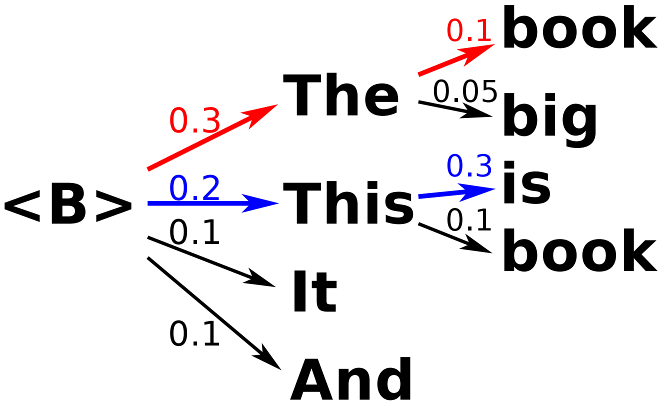

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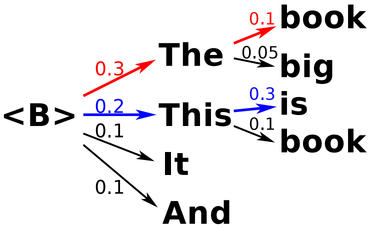
beam search decoding

problem: we can't consider all possible sequences

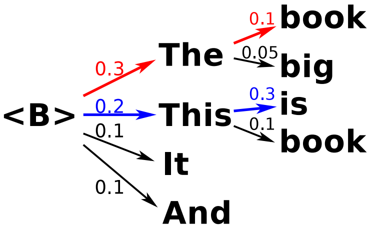


beam search decoding

problem: we can't consider all possible sequences

as an approximation, let's keep k **candidates** at each step

this idea is called **beam search**



beam search decoding: pseudocode

set the beam width k
initialize $X = x_1, \ldots, x_m$ to some token sequence
$B \leftarrow [X]$
for $i = m + 1, \ldots$ until some stopping criterion met
    $C \leftarrow [\,]$
    for each b **in** B
        compute $P(x|b)$
        add $b + [x]$ to C for all x in the vocabulary
    $B \leftarrow$ select k top-scoring candidates from C
return top-scoring beam from B

drawbacks of greedy and beam search decoding

- generated texts can be **bland and uninformative**
- the generation often has problems with **repetition**

drawbacks of greedy and beam search decoding

- generated texts can be **bland and uninformative**
- the generation often has problems with **repetition**

```
input_ids = tokenizer('Hello', return_tensors='pt').input_ids
outputs = model.generate(input_ids, num_beams=8, max_length=50, pad_token_id=0)
print(tokenizer.decode(outputs[0]))
```

```
Hello

I've been working on this project for a while now. I've been working on this project for a while now. I've
```

- some research describing these problems: (Holtzman et al., 2020), (Kulikov, 2022)
- repetition poorly understood theoretically (Fu et al., 2021)

THE CURIOUS CASE OF
NEURAL TEXT *De*GENERATION

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ABSTRACT

Despite considerable advances in neural language modeling, it remains an open question what the best *decoding strategy* is for text generation from a language model (e.g. to generate a story). The counter-intuitive empirical observation is that even though the use of likelihood as training objective leads to high quality models for a broad range of language understanding tasks, maximization-based decoding methods such as beam search lead to *degeneration* — output text that is bland, incoherent, or gets stuck in repetitive loops.

sampling

initialize $X = x_1, \ldots, x_m$ to some token sequence
for $i = m + 1, \ldots$ until some stopping criterion met
    $x_i \sim P(x|X)$
    append x_i to X
return X

drawbacks of sampling

```
input_ids = tokenizer('Hello', return_tensors='pt').input_ids
outputs = model.generate(input_ids, do_sample=True, max_length=50, pad_token_id=0)
print(tokenizer.decode(outputs[0]))
```

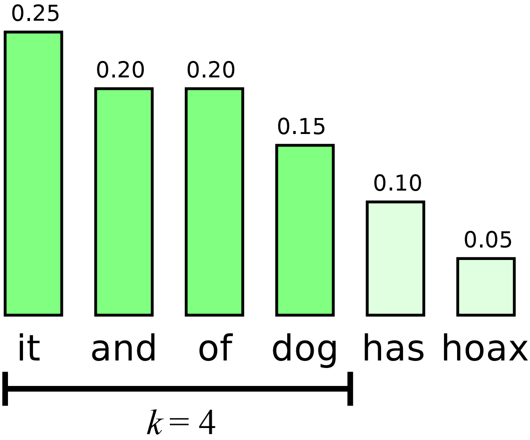
```
Hello - this is a big win for everyone of you who support C++11!

The winner of this week's poll will be taken here in June 2016.

If you enjoyed this article you will like my Facebook Page.<|endoftext|>
```

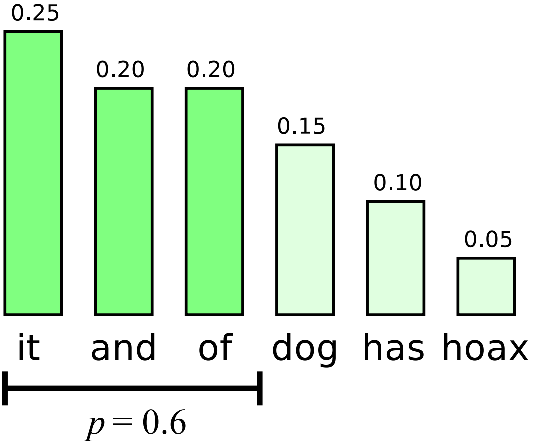
improving sampling: truncating the distribution (1)

in **top-k** sampling, we only include the k most probable words when sampling:



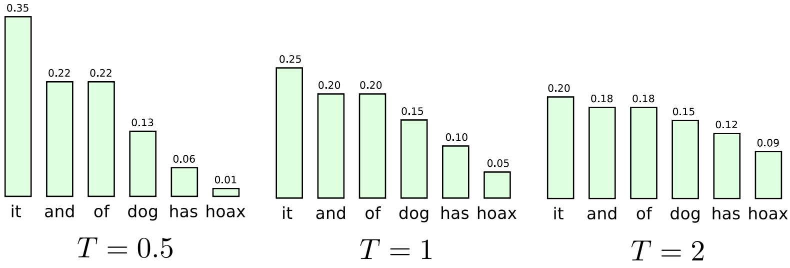
improving sampling: truncating the distribution (2)

in **top-p** or **nucleus** sampling (Holtzman et al., 2020), we select the most probable tokens with a probability mass of at least p:

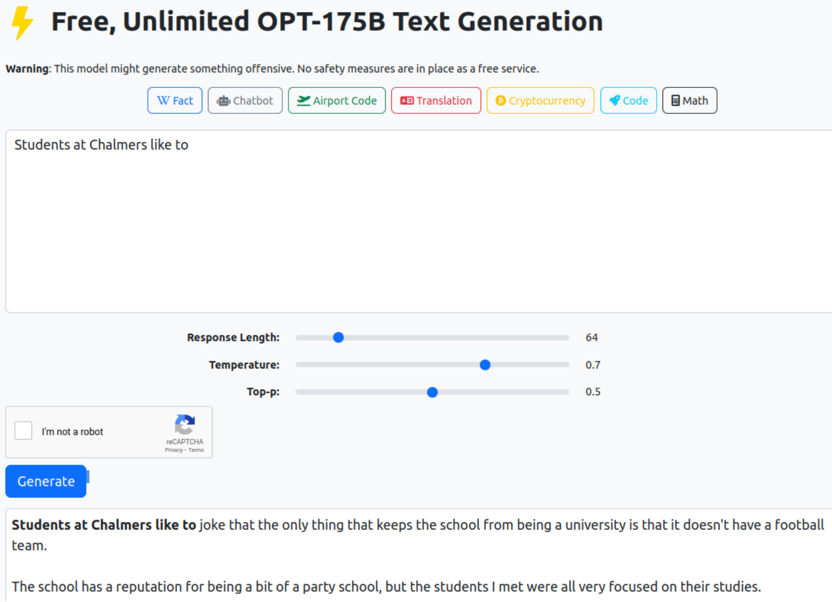


improving sampling: temperature

temperature T: divide the logits by T before applying the softmax



conclusion


Free, Unlimited OPT-175B Text Generation
Warning: This model might generate something offensive. No safety measures are in place as a free service.
Fact
Chatbot
Airport Code
Translation
Cryptocurrency
Code
Math
Students at Chalmers like to
Response Length:
64
Temperature:
0.7
Top-p:
0.5
I'm not a robot
reCAPTCHA
Privacy - Terms
Generate
Students at Chalmers like to joke that the only thing that keeps the school from being a university is that it doesn't have a football team.
The school has a reputation for being a bit of a party school, but the students I met were all very focused on their studies.

references

Z. Fu, W. Lam, A. M.-C. So, and B. Shi. 2021. A theoretical analysis of the repetition problem in text generation. In *AAAI*.

A. Holtzman, J. Buys, L. Du, M. Forbes, and Y. Choi. 2020. The curious case of neural text degeneration. In *ICLR*.

I. Kulikov. 2022. *Characterizing and Resolving Degeneracies in Neural Autoregressive Text Generation*. Ph.D. thesis, New York University.