Speculative Decoding

Fast Inference from Transformers via Speculative Decoding
Leviathan et al. 2023

summarized by Michael Scherbela

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Highest voted question on Stackoverflow of all time

Why is processing a sorted array faster than processing an unsorted array?

```
// Generate data
const unsigned arraySize = 32768;
int data[arraySize];

for (unsigned c = 0; c < arraySize; ++c)
    data[c] = std::rand() % 256;

// !!! With this, the next loop runs faster.
std::sort(data, data + arraySize);

// Test
clock_t start = clock();
long long sum = 0;
for (unsigned i = 0; i < 100000; ++i)
{
    for (unsigned c = 0; c < arraySize; ++c)
    {   // Primary loop.
        if (data[c] >= 128)
            sum += data[c];
    }
}
```

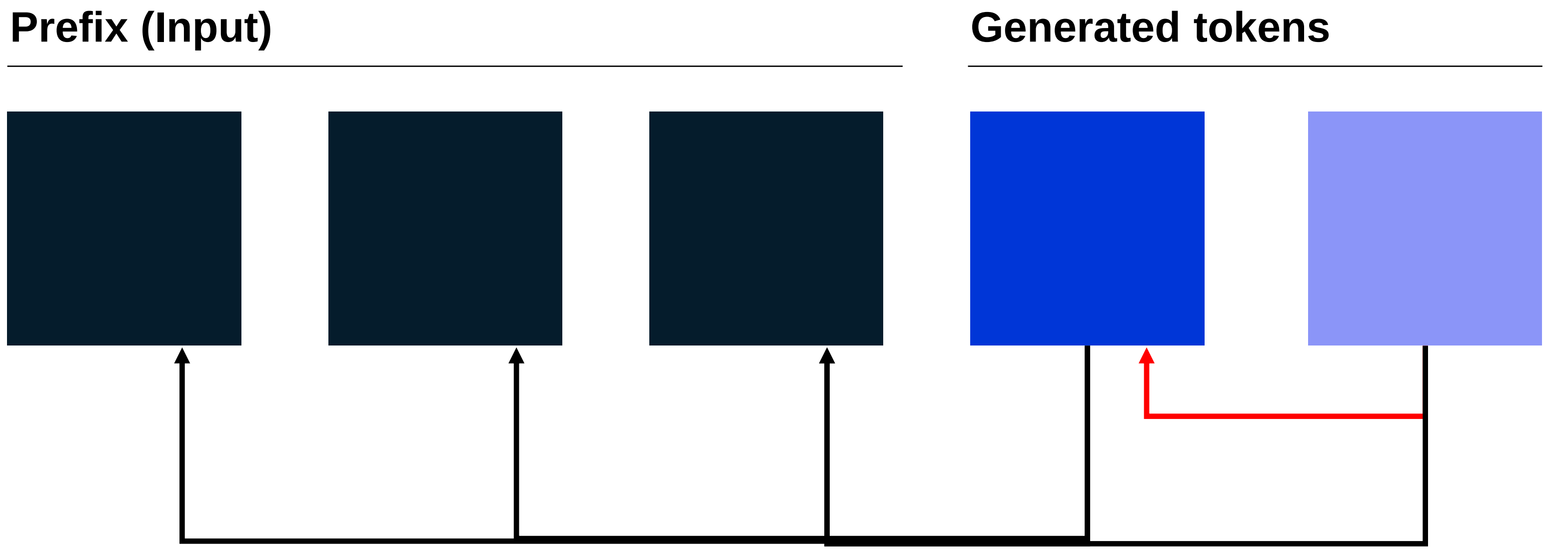
https://stackoverflow.com/questions/11227809/why-is-processing-a-sorted-array-faster-than-processing-an-unsorted-array

Branch prediction allows parallelization of (potentially) serial tasks

Time ↓	Conventional				Pipelined				Pipelined with branch prediction			
	Fetch	Decode	Process	#	Fetch	Decode	Process	#	Fetch	Decode	Process	#
1	A			0	A	*	*	0	A	*	*	0
2		A		0	B	A	*	0	B	A	*	0
3			A	1	C	B	A	1	C	B	A	1
4	B			1		C	B	2	E	C	B	2
5		B		1			C	3	F	E	C	3
6			B	2	E	GAP		3	G	F	E	4
7	C			2	F	E		3	H	G	F	5
8		C		2	G	F	E	4	I	H	G	6
9			C	3	H	G	F	5	J	I	H	7
10	E			3	I	H	G	6	K	J	I	8
11		E		3	J	I	H	7	L	K	J	9
12			E	4	K	J	I	8	M	L	K	10

http://www.edboas.com/science/branch_prediction/index.html

Same problem with LLMs:
Each token depends on all previous tokens



Proposed algorithm

Algorithm

1. Serially generate γ tokens using cheap model Q and keep probabilities $q(x_i)$
2. In parallel compute γ probabilities $p(x_i)$ using tokens from Q as prefix
3. For each generated token
   1. Keep it with probability $\frac{p}{q}$
   2. If rejected, draw a new token and throw away all remaining completions

Example

[START] japan ' s benchmark ~~bond~~ n

[START] japan ' s benchmark nikkei 22 ,5

[START] japan ' s benchmark nikkei 225 index rose 22 ,6

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 , points

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 0 1

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 1 . 5 percent , to 10 , 9859

Key metrics of model Q

Accuracy of Q:

α… mean acceptance probability

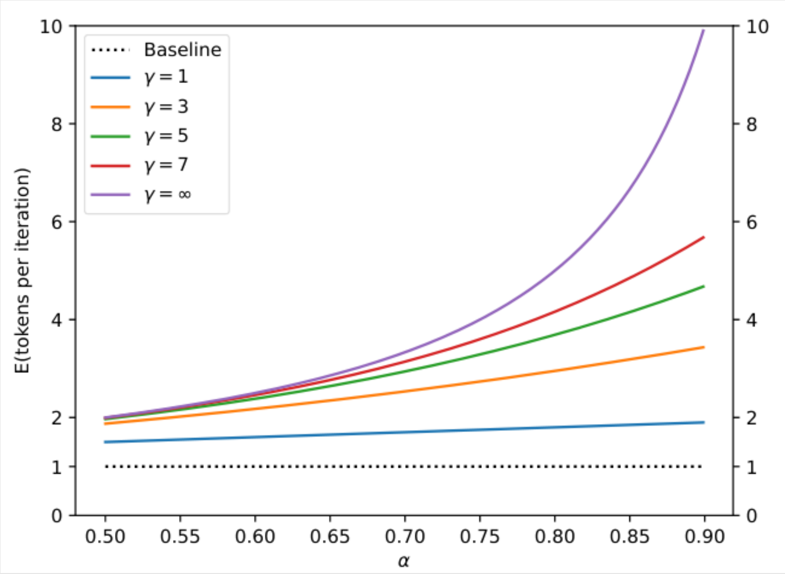
Cost of Q:

c … cost ratio of model Q vs. model P

Expected number of generated tokens

$$E[n] = 1 + \alpha + \alpha^2 + \ldots + \alpha^\gamma$$

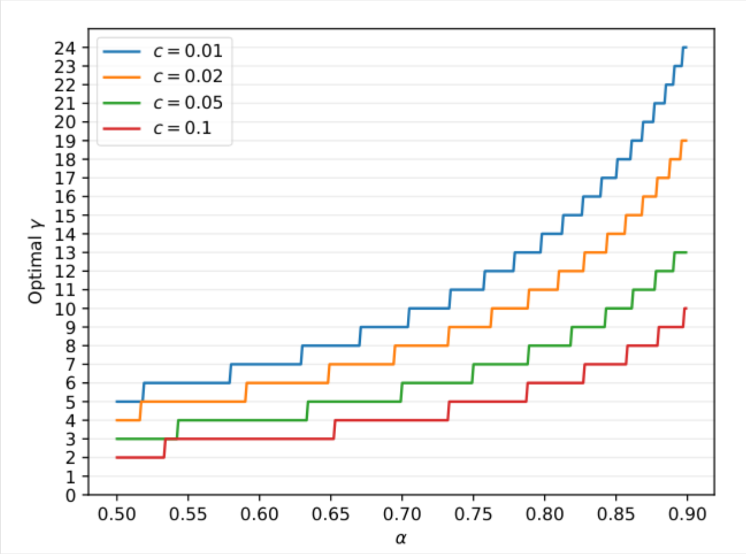
$$= \sum_{k=0}^{\gamma} \alpha^k = \frac{1 + \alpha^{\gamma+1}}{1 + \alpha}$$



Run-time per step

$$T = T_P(1 + c\gamma)$$

Optimal choice of γ



Typical acceptance rates are 50-80%

Table 3. Empirical α values for various target models M_p, approximation models M_q, and sampling settings. T=0 and T=1 denote argmax and standard sampling respectively[6].

M_p	M_q	SMPL	α
GPT-LIKE (97M)	UNIGRAM	T=0	0.03
GPT-LIKE (97M)	BIGRAM	T=0	0.05
GPT-LIKE (97M)	GPT-LIKE (6M)	T=0	0.88
GPT-LIKE (97M)	UNIGRAM	T=1	0.03
GPT-LIKE (97M)	BIGRAM	T=1	0.05
GPT-LIKE (97M)	GPT-LIKE (6M)	T=1	0.89
T5-XXL (ENDE)	UNIGRAM	T=0	0.08
T5-XXL (ENDE)	BIGRAM	T=0	0.20
T5-XXL (ENDE)	T5-SMALL	T=0	0.75
T5-XXL (ENDE)	T5-BASE	T=0	0.80
T5-XXL (ENDE)	T5-LARGE	T=0	0.82
T5-XXL (ENDE)	UNIGRAM	T=1	0.07
T5-XXL (ENDE)	BIGRAM	T=1	0.19
T5-XXL (ENDE)	T5-SMALL	T=1	0.62
T5-XXL (ENDE)	T5-BASE	T=1	0.68
T5-XXL (ENDE)	T5-LARGE	T=1	0.71

M_p	M_q	SMPL	α
T5-XXL (CNNDM)	UNIGRAM	T=0	0.13
T5-XXL (CNNDM)	BIGRAM	T=0	0.23
T5-XXL (CNNDM)	T5-SMALL	T=0	0.65
T5-XXL (CNNDM)	T5-BASE	T=0	0.73
T5-XXL (CNNDM)	T5-LARGE	T=0	0.74
T5-XXL (CNNDM)	UNIGRAM	T=1	0.08
T5-XXL (CNNDM)	BIGRAM	T=1	0.16
T5-XXL (CNNDM)	T5-SMALL	T=1	0.53
T5-XXL (CNNDM)	T5-BASE	T=1	0.55
T5-XXL (CNNDM)	T5-LARGE	T=1	0.56
LAMDA (137B)	LAMDA (100M)	T=0	0.61
LAMDA (137B)	LAMDA (2B)	T=0	0.71
LAMDA (137B)	LAMDA (8B)	T=0	0.75
LAMDA (137B)	LAMDA (100M)	T=1	0.57
LAMDA (137B)	LAMDA (2B)	T=1	0.71
LAMDA (137B)	LAMDA (8B)	T=1	0.74

Inference from a 11B model can be sped up 2-3x

Table 2. Empirical results for speeding up inference from a T5-XXL 11B model.

TASK	M_q	TEMP	γ	α	SPEED
ENDE	T5-SMALL ★	0	7	0.75	**3.4X**
ENDE	T5-BASE	0	7	0.8	2.8X
ENDE	T5-LARGE	0	7	0.82	1.7X
ENDE	T5-SMALL ★	1	7	0.62	**2.6X**
ENDE	T5-BASE	1	5	0.68	2.4X
ENDE	T5-LARGE	1	3	0.71	1.4X
CNNDM	T5-SMALL ★	0	5	0.65	**3.1X**
CNNDM	T5-BASE	0	5	0.73	3.0X
CNNDM	T5-LARGE	0	3	0.74	2.2X
CNNDM	T5-SMALL ★	1	5	0.53	**2.3X**
CNNDM	T5-BASE	1	3	0.55	2.2X
CNNDM	T5-LARGE	1	3	0.56	1.7X

Model sizes Q:

- T5-small: 77 mio
- T5-base: 250 mio
- T5-large: 800 mio

But what about computational cost for the parallel M_p evaluations?

1. You might be willing to **trade off** total cost vs. latency
2. Inference is typically **memory bound** => Batch-size 1 and batch-size γ have almost identical cost

References

- **Fast Inference from Transformers via Speculative Decoding**
  Leviathan et al., 2023
  http://arxiv.org/abs/2211.17192