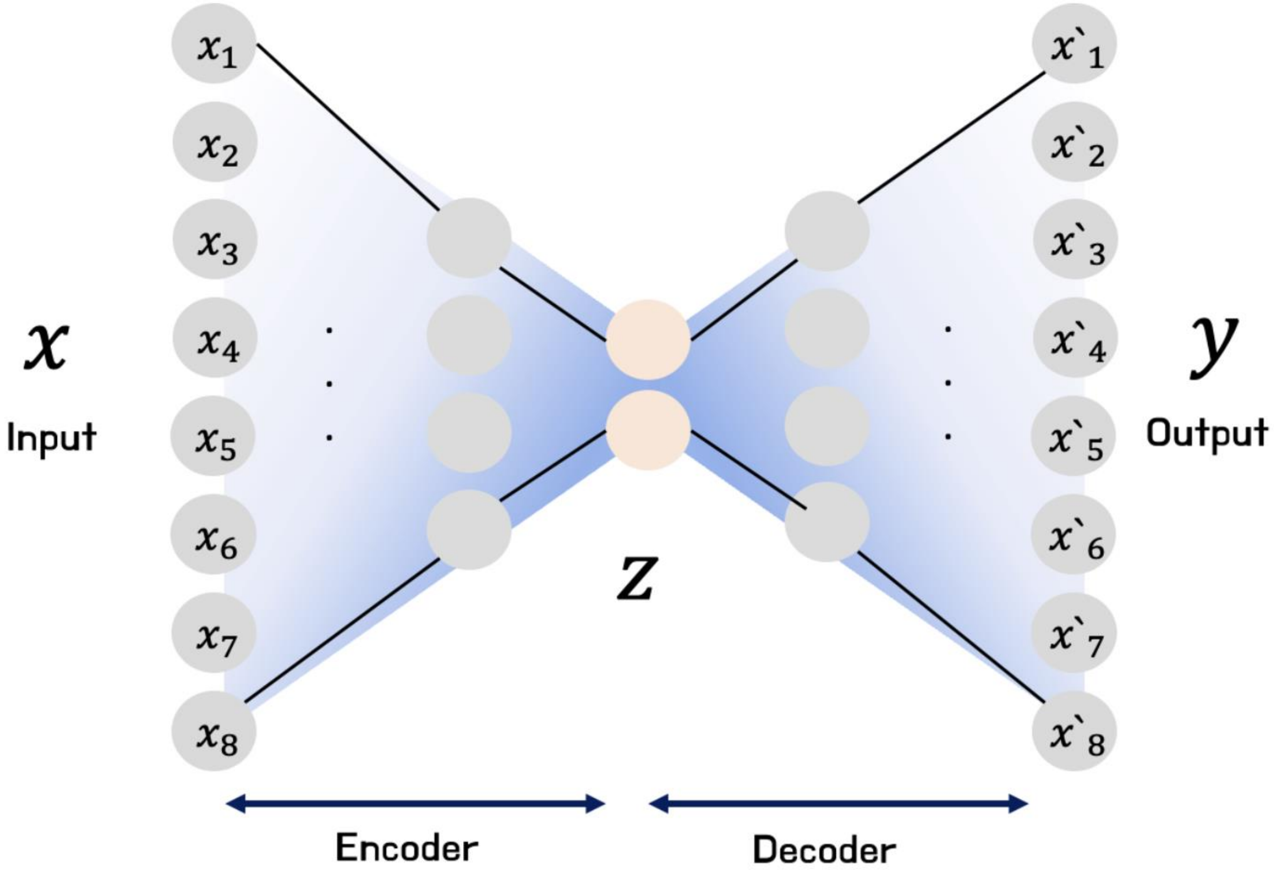
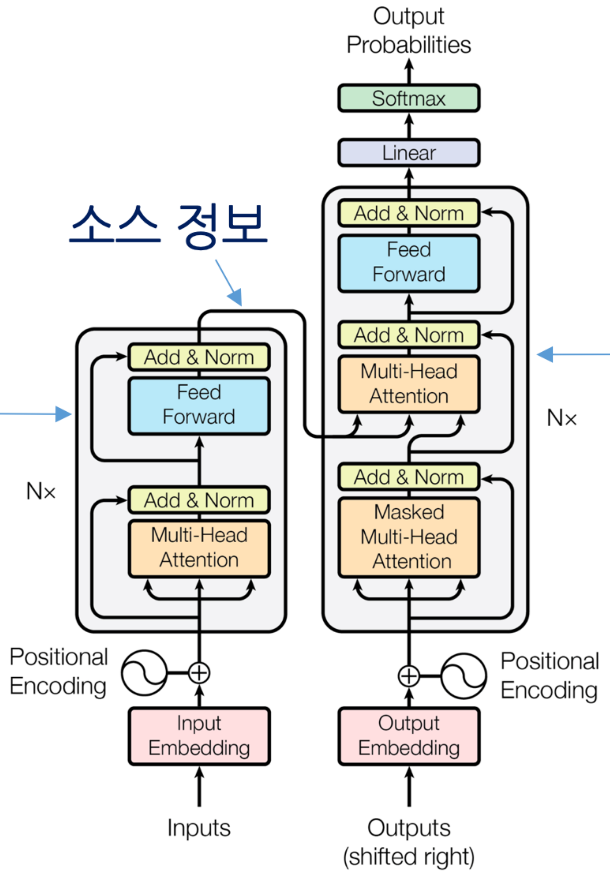
AI 11주차 LLM

텍스트 생성

오토인코더


x
Input
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
z
$x`_1$
$x`_2$
$x`_3$
$x`_4$
$x`_5$
$x`_6$
$x`_7$
$x`_8$
y
Output
Encoder
Decoder

트랜스포머

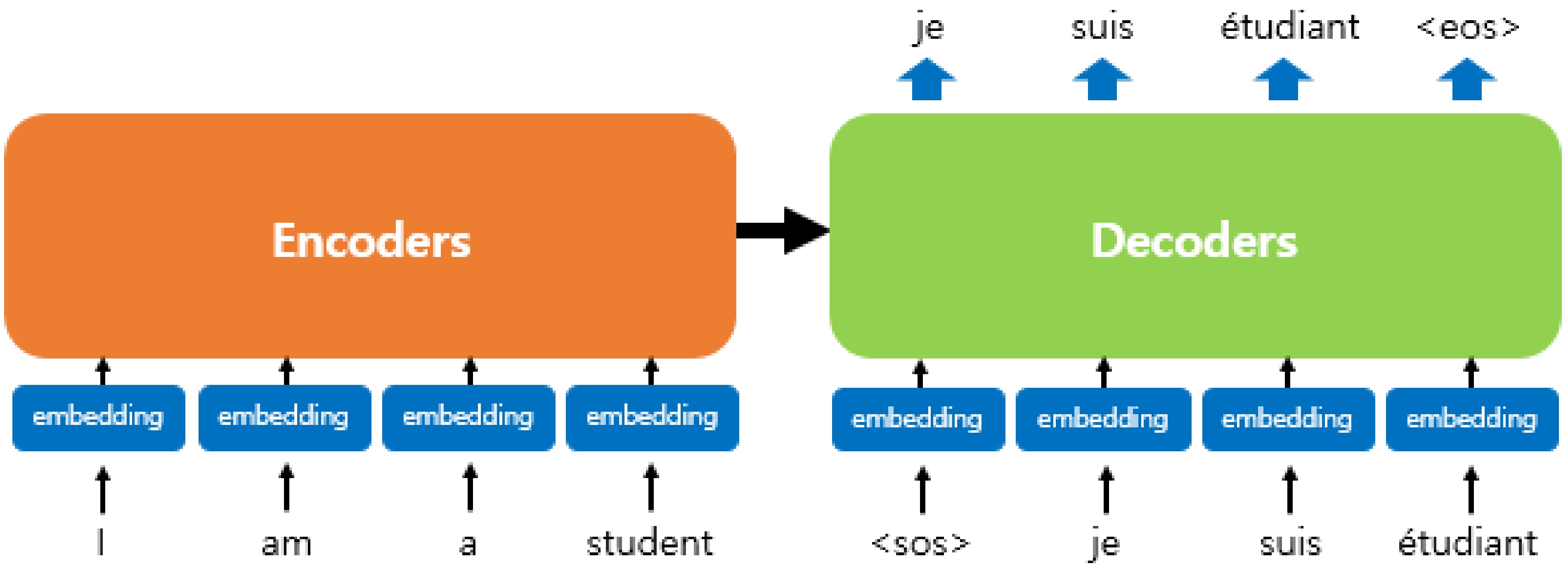


소스 정보

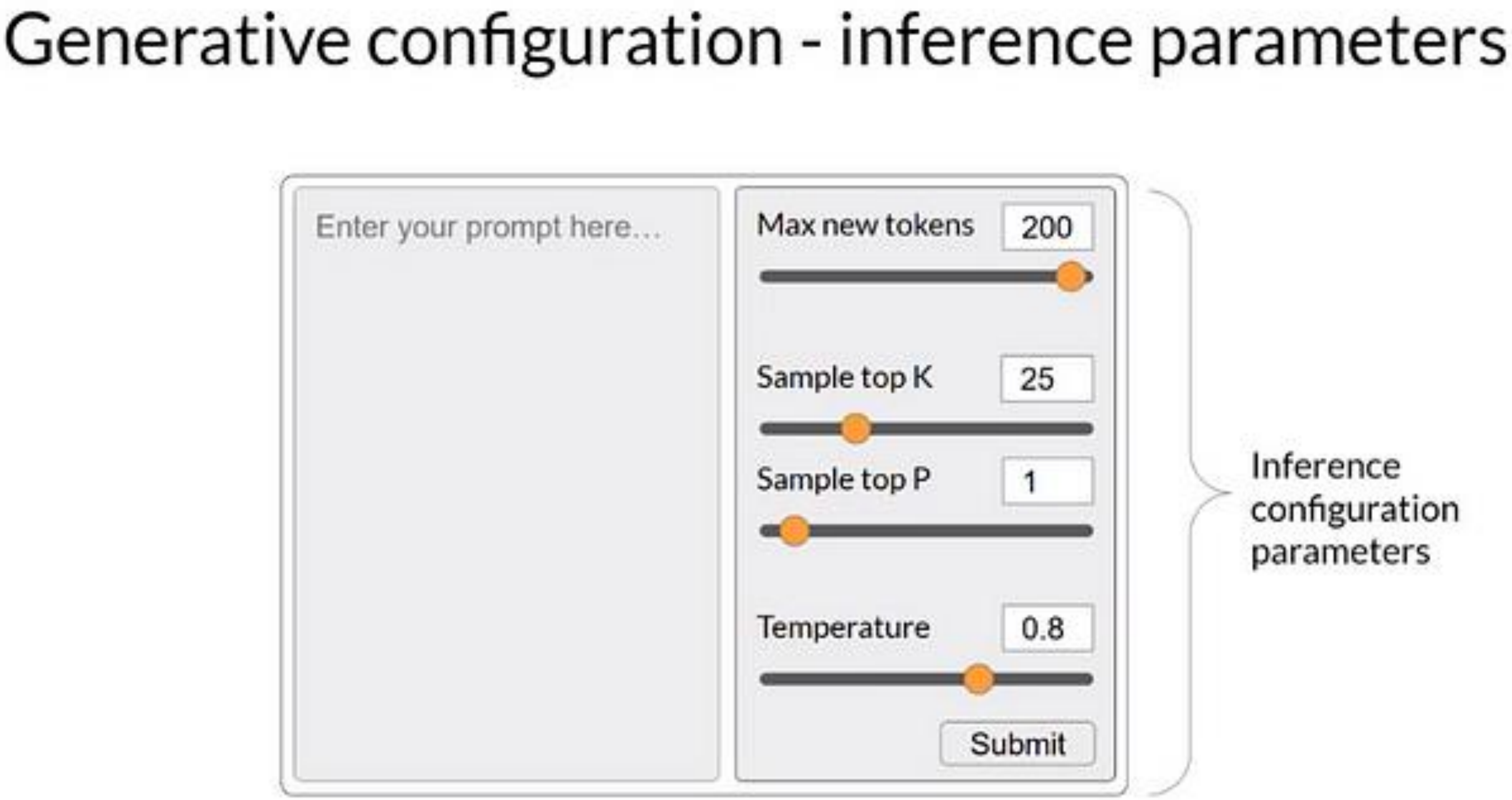
Encoder
소스 시퀀스 압축

Decoder
타겟 시퀀스 생성

트랜스포머 핵심 – 인코더 디코더



LLM Configuration



"Max new tokens"

- 모델이 생성하는 토큰의 수에 제한을 둡니다. 그러나 다른 중단 조건으로 인해 완성의 실제 길이는 다를 수 있습니다.

"Greedy Decoding"

- 다음 단어 예측을 위한 가장 간단한 방법으로, 가장 높은 확률을 가진 단어를 선택합니다. 그러나 이는 반복된 단어나 시퀀스를 결과로 가져올 수 있습니다.

"Random Sampling"

- - 확률 분포를 기반으로 단어를 무작위로 선택하여 다양성을 도입하며, 단어의 반복 가능성을 줄입니다.

"Top-K"

- 가장 높은 확률을 가진 k개의 토큰 중에서 선택하여 옵션을 제한하며, 높은 무작위성을 촉진하면서도 매우 불가능한 완성을 방지합니다

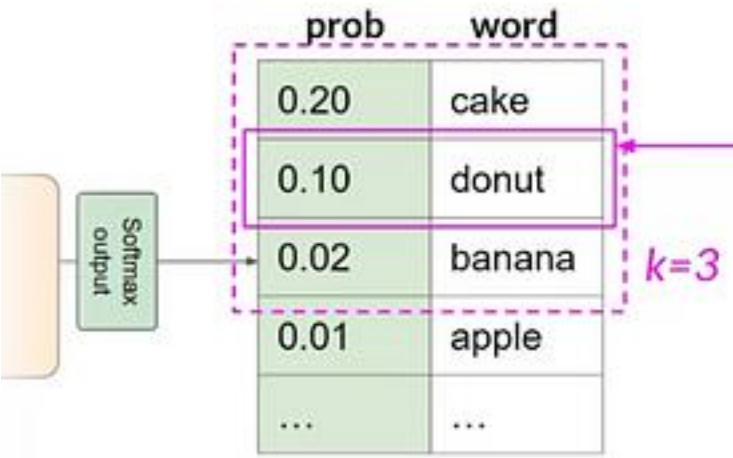
"Top-P"

- 누적 확률이 지정된 임계값을 초과하지 않는 예측에 무작위 샘플링을 제한하여 합리적인 출력을 보장합니다.

"Temperature"

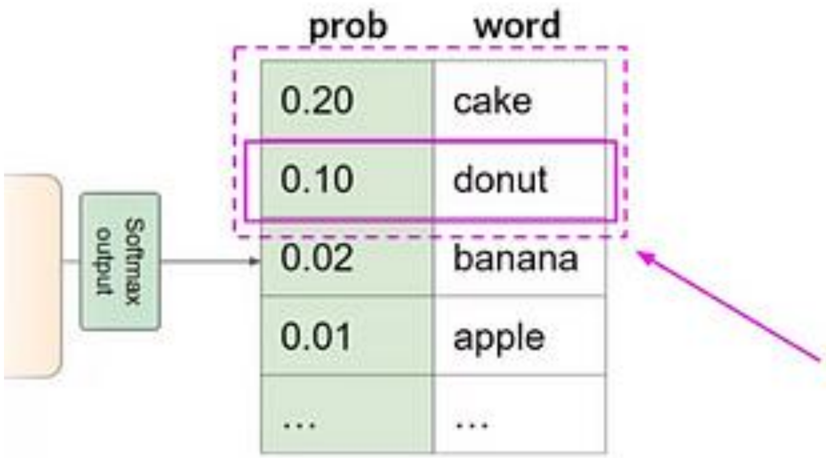
- - 확률 분포의 형태에 영향을 미칩니다. 높은 온도 값은 무작위성을 증가시키며, 낮은 값은 확률을 더 작은 단어 집합에 집중시킵니다.

Generative config - top-k sampling



top-k: select an output from the top-k results after applying random-weighted strategy using the probabilities

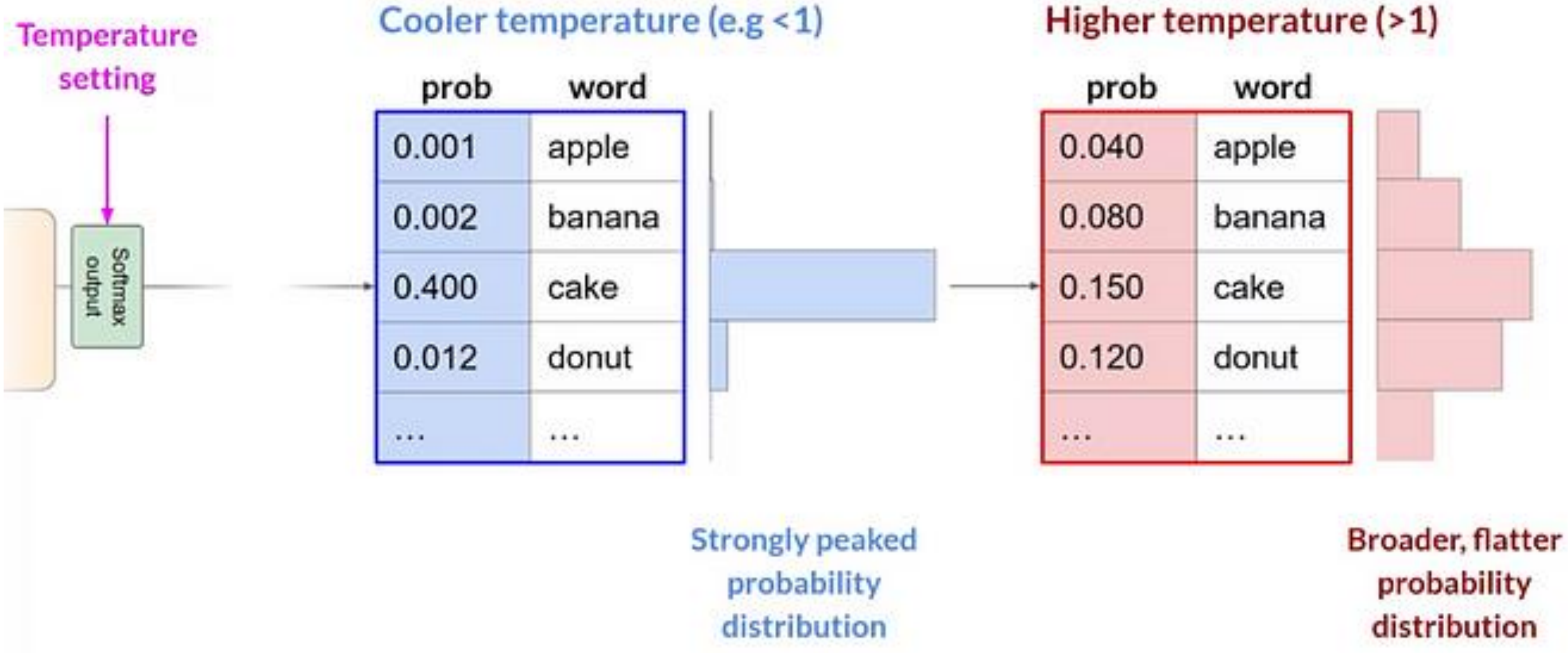
Generative config - top-p sampling



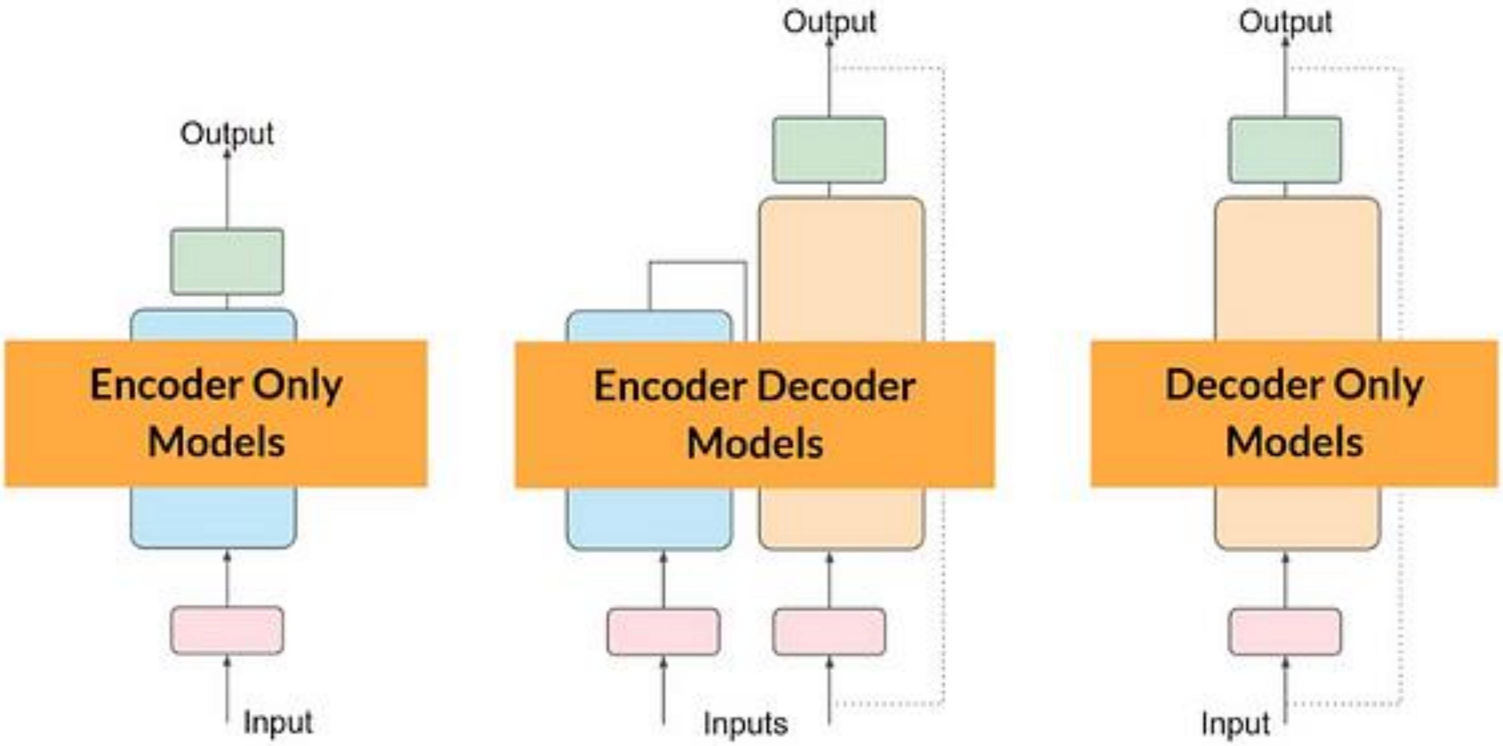
top-p: select an output using the random-weighted strategy with the top-ranked consecutive results by probability and with a cumulative probability <= *p*.

p = 0.30

Generative config - temperature



Transformers

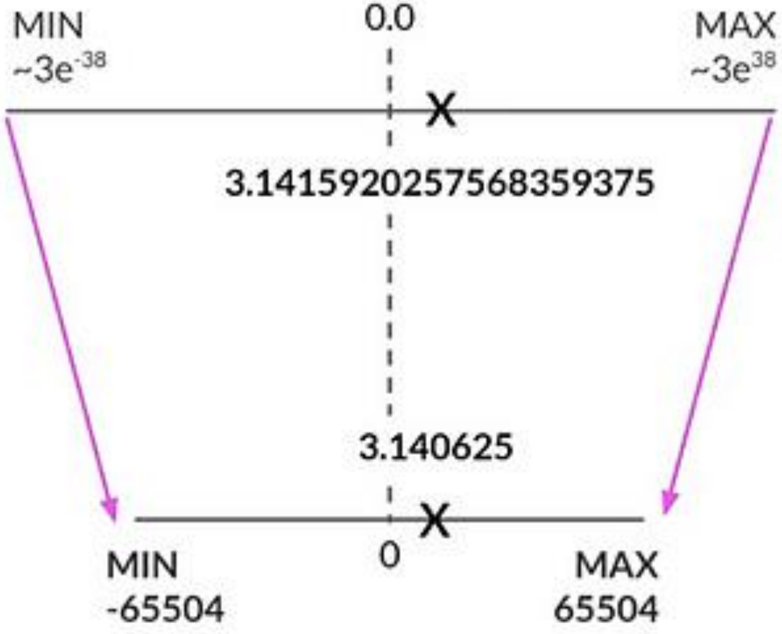


Additional GPU RAM needed to train 1B parameters

	Bytes per parameter
Model Parameters (Weights)	4 bytes per parameter
Adam optimizer (2 states)	+8 bytes per parameter
Gradients	+4 bytes per parameter
Activations and temp memory (variable size)	+8 bytes per parameter (high-end estimate)
TOTAL	**=4 bytes per parameter +20 extra bytes per parameter**

~20 extra bytes per parameter

Quantization: FP16



Let's store Pi: 3.141592

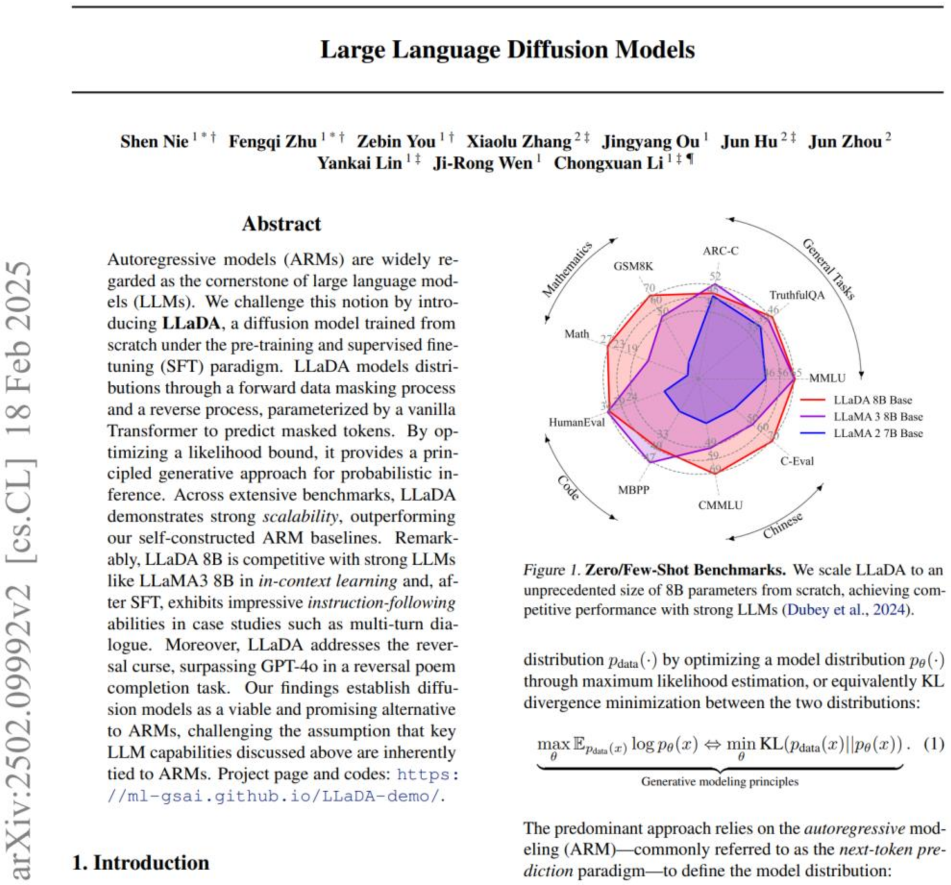
FP32 4 bytes memory

0	10000000	10010010000111111011000
Sign 1 bit	**Exponent** 8 bits	**Fraction** 23 bits

FP16 2 bytes memory

0	10000	1001001000
Sign 1 bit	**Exponent** 5 bits	**Fraction** 10 bits

LLADA Model



Large Language Diffusion Models

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Abstract

Autoregressive models (ARMs) are widely regarded as the cornerstone of large language models (LLMs). We challenge this notion by introducing **LLaDA**, a diffusion model trained from scratch under the pre-training and supervised fine-tuning (SFT) paradigm. LLaDA models distributions through a forward data masking process and a reverse process, parameterized by a vanilla Transformer to predict masked tokens. By optimizing a likelihood bound, it provides a principled generative approach for probabilistic inference. Across extensive benchmarks, LLaDA demonstrates strong *scalability*, outperforming our self-constructed ARM baselines. Remarkably, LLaDA 8B is competitive with strong LLMs like LLaMA3 8B in *in-context learning* and, after SFT, exhibits impressive *instruction-following* abilities in case studies such as multi-turn dialogue. Moreover, LLaDA addresses the reversal curse, surpassing GPT-4o in a reversal poem completion task. Our findings establish diffusion models as a viable and promising alternative to ARMs, challenging the assumption that key LLM capabilities discussed above are inherently tied to ARMs. Project page and codes: https://ml-gsai.github.io/LLaDA-demo/.

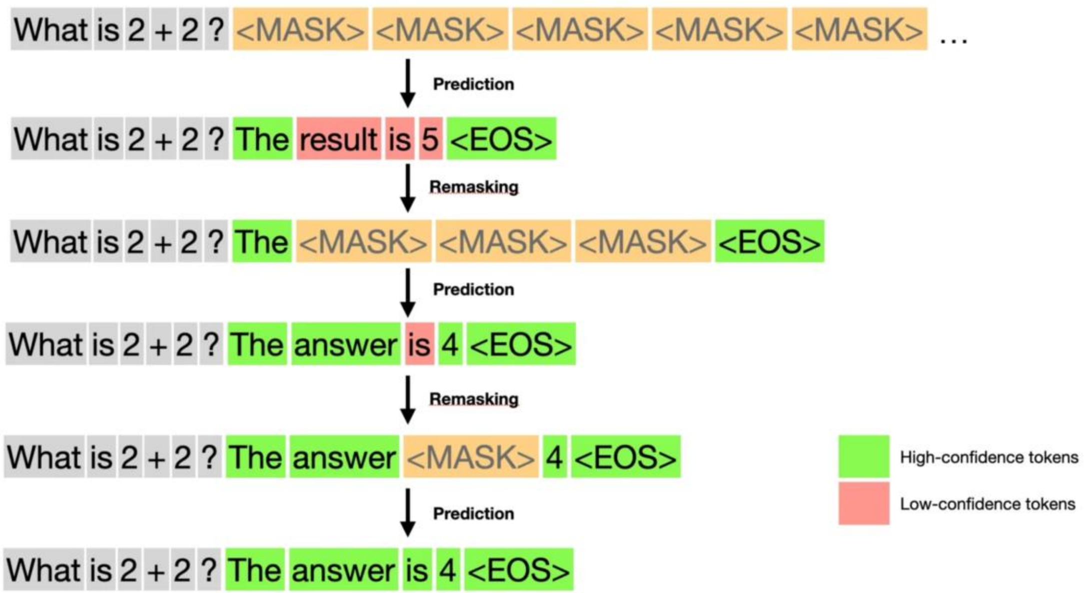
1. Introduction

Figure 1. **Zero/Few-Shot Benchmarks.** We scale LLaDA to an unprecedented size of 8B parameters from scratch, achieving competitive performance with strong LLMs (Dubey et al., 2024).

distribution $p_{\text{data}}(\cdot)$ by optimizing a model distribution $p_\theta(\cdot)$ through maximum likelihood estimation, or equivalently KL divergence minimization between the two distributions:

$$\underbrace{\max_\theta \mathbb{E}_{p_{\text{data}}(x)} \log p_\theta(x) \Leftrightarrow \min_\theta \mathrm{KL}(p_{\text{data}}(x)||p_\theta(x))}_{\text{Generative modeling principles}}. \quad (1)$$

The predominant approach relies on the *autoregressive* modeling (ARM)—commonly referred to as the *next-token prediction* paradigm—to define the model distribution:



LLADA PREVIEW