# CSCE 689-609 Tokenization and Sampling

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# The Tokenizer Playground

### https://huggingface.co/spaces/Xenova/the-tokenizer-playground

Experiment with different tokenizers (running locally in your browser).

gpt-4 / gpt-3.5-turbo / text-embedding-ada-002

Where is Texas A&M?

Where is Texas A&M?

TOKENS CHARACTERS

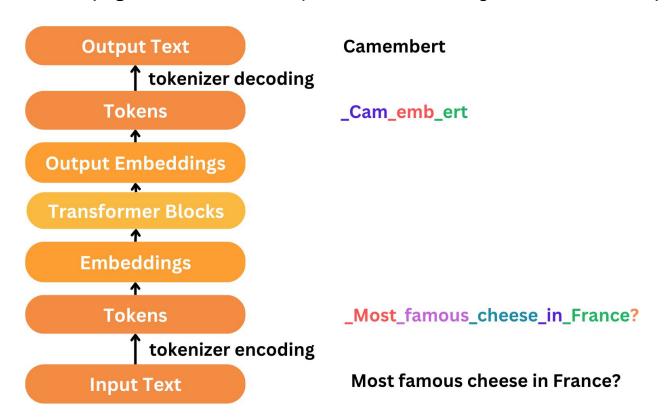
6 19

TOKENS CHARACTERS 8 19

Where is Texas A&M?

<s> Where is Texas A&M?

# Tokenization (e.g., Mistral Al: https://docs.mistral.ai/guides/tokenization)



# **Establishing the Vocabulary**

- 1. **Collect Training Data**: Gather a large corpus of text data that the model will learn from.
- Initial Tokenization: Apply preliminary tokenization methods to split the text into basic units (words, subwords, or characters).
- 3. **Vocabulary Creation**: Choose a tokenization algorithm (e.g., Byte Pair Encoding (BPE), WordPiece, Unigram, SentencePiece) to generate a manageable and efficient set of tokens.
- 4. **Apply Algorithm:** Run the selected algorithm on the initial tokens to create a set of subword tokens or characters that capture the linguistic nuances of the training data.
- 5. **Assign IDs:** Each unique token in the resulting vocabulary is assigned a specific integer ID.

### **Real-Time Tokenization Process**

- Convert text stream to tokens: Convert incoming text into the tokens found in the established vocabulary, ensuring all text can be represented.
- 2. **Token ID**: Map each token to its corresponding integer ID as defined in the pre-established vocabulary).

Implementation <a href="https://github.com/karpathy/llama2.c/blob/master/run.c#L452-L571">https://github.com/karpathy/llama2.c/blob/master/run.c#L452-L571</a>

```
void encode(Tokenizer* t, char *text, int8_t bos, int8_t eos, int *tokens, int *n_tokens) {
    // encode the string text (input) into an upper-bound preallocated tokens[] array
    // bos != 0 means prepend the BOS token (=1), eos != 0 means append the EOS token (=2)
    if (text == NULL) { fprintf(stderr, "cannot encode NULL text\n"); exit(EXIT FAILURE); }
    if (t->sorted vocab == NULL) {
        // lazily malloc and sort the vocabulary
        t->sorted_vocab = malloc(t->vocab_size * sizeof(TokenIndex));
        for (int i = 0; i < t \rightarrow vocab\_size; i++) {
            t->sorted_vocab[i].str = t->vocab[i];
            t->sorted vocab[i].id = i:
        qsort(t->sorted_vocab, t->vocab_size, sizeof(TokenIndex), compare_tokens);
   // create a temporary buffer that will store merge candidates of always two consecutive tokens
    // *2 for concat, +1 for null terminator +2 for UTF8 (in case max_token_length is 1)
    char* str_buffer = malloc((t->max_token_length*2 +1 +2) * sizeof(char));
    size t str len = 0;
```

# **Tokenization Basic Units**

- Word-level
- Character-level
- Subword-level
- Byte-level
- Multi-word
- Phrase-level
- ...

Token size	Pros	Cons
Smaller tokens (character or subword tokenization)	<ul> <li>Enables the model to handle a wider range of inputs, such as unknown words, typos, or complex syntax.</li> <li>Might allow the vocabulary size to be reduced, requiring fewer memory resources.</li> </ul>	- A given text is broken into more tokens, requiring additional computational resources while processing - Given a fixed token limit, the maximum size of the model's input and output is smaller
Larger tokens (word tokenization)	<ul> <li>A given text is broken into fewer tokens, requiring fewer computational resources while processing.</li> <li>Given the same token limit, the maximum size of the model's input and output is larger.</li> </ul>	<ul> <li>Might cause an increased vocabulary size, requiring more memory resources.</li> <li>Can limit the models ability to handle unknown words, typos, or complex syntax.</li> </ul>

# Mistral V3 (tekken) tokenizer

- Subword-level tokenization
- Byte-Pair Encoding (BPE)
- **Vocabulary size**: 130k vocab + 1k control tokens
- Special control tokens: 14
  - The tokenizer does not encode control tokens (to prevent prompt injection)

```
<unk>
<S>
</s>
[INST]
[/INST]
[AVAILABLE_TOOLS]
[/AVAILABLE TOOLS]
[T00L RESULTS]
[/T00L_RESULTS]
[TOOL_CALLS]
<pad>
[PREFIX]
[MIDDLE]
[SUFFIX]
```

Mistral control tokens

### Al21's Jurassic models tokenizers

https://docs.ai21.com/docs/large-language-models

# **Token dictionary**

AI21 Studio uses a large token dictionary (250K), which contains tokens generated from separate characters, words, word parts, such as prefixes and suffixes, and multi-word tokens. For example, in our current tokenizer, the phrase "I want to break free." is split into the following tokens:

```
['_I_want_to', '_break', '_free', '.']
```

# **Byte-Pair Encoding (BPE)**

Paper: Neural Machine Translation of Rare Words with Subword Units

- **Byte split:** It starts by treating each byte in a text as a separate token
- Merge: Then, it iteratively adds new tokens to the vocabulary for the most frequent pair
  of tokens currently appearing in the corpus.
  - E.g., if the most frequent pair of tokens is "th" + "e", then a new token "the" will be added.
- This process continues until a target vocabulary size is reached

Example: <a href="https://huggingface.co/docs/transformers/en/tokenizer\_summary">https://huggingface.co/docs/transformers/en/tokenizer\_summary</a>

- **Popular:** GPT-4, Claude, Llama-3, all use BPE

# Unigram

Paper: Subword Regularization: Improving Neural Network Translation Models with Multiple Subword Candidates

- Idea: In contrast to BPE, Unigram initializes its base vocabulary to a large number of symbols and progressively trims down each symbol to obtain a smaller vocabulary.
- Loss-based removal: The algorithm defines a loss over the training data.
  - For each symbol, it computes how much the overall loss would increase if the symbol was to be removed from the vocabulary
  - It then removes the symbols whose loss increase is the lowest

## **SentencePiece**

Paper: <a href="https://arxiv.org/pdf/1808.06226">https://arxiv.org/pdf/1808.06226</a>

- **Idea:** It treats the input text as a continuous sequence of characters without explicitly splitting it by whitespace (it escapes the whitespace with a meta symbol \_ (U+2581))
  - For tokenization, it can use BPE or Unigram

Examples of models using SentencePiece are <u>ALBERT</u>, <u>XLNet</u>, <u>Marian</u>, and <u>T5</u>.

# Sampling (the Next Token)

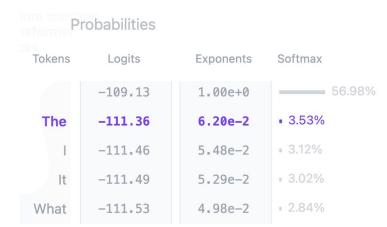
**Logits:** Unnormalized scores that represent the likelihood of each token being the next in the sequence

 Logits are passed through a softmax function to convert into a probability distribution (sum to 1)

**Temperature:** Before sampling, the distribution can be adjusted using a parameter called **temperature (T)**:

**Top-k Sampling:** only the top **k** most probable tokens are considered for sampling.

**Top-p Sampling:** chooses tokens from the smallest possible set whose cumulative probability exceeds a threshold **p**.



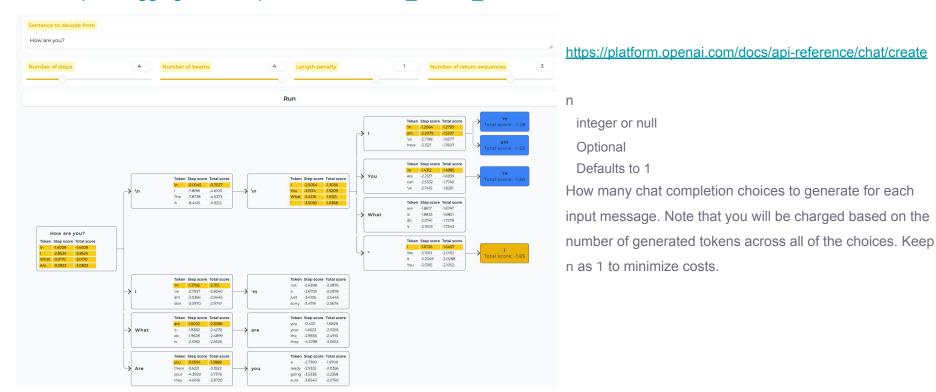
$$p_i = rac{\exp\left(rac{ ext{logit}_i}{T}
ight)}{\sum_j \exp\left(rac{ ext{logit}_j}{T}
ight)}$$

### Implementation <a href="https://github.com/karpathy/llama2.c/blob/master/run.c#L691-L714">https://github.com/karpathy/llama2.c/blob/master/run.c#L691-L714</a>

```
int sample(Sampler* sampler, float* logits) {
   // sample the token given the logits and some hyperparameters
   int next;
   if (sampler->temperature == 0.0f) {
       // greedy argmax sampling: take the token with the highest probability
       next = sample argmax(logits, sampler->vocab size);
    } else {
       // apply the temperature to the logits
       for (int q=0; q<sampler->vocab size; q++) { logits[q] /= sampler->temperature; }
       // apply softmax to the logits to get the probabilities for next token
       softmax(logits, sampler->vocab_size);
       // flip a (float) coin (this is our source of entropy for sampling)
       float coin = random_f32(&sampler->rng_state);
       // we sample from this distribution to get the next token
       if (sampler->topp <= 0 || sampler->topp >= 1) {
           // simply sample from the predicted probability distribution
           next = sample mult(logits, sampler->vocab size, coin);
       } else {
           // top-p (nucleus) sampling, clamping the least likely tokens to zero
           next = sample_topp(logits, sampler->vocab_size, sampler->topp, sampler->probindex, coin);
   return next;
```

# Parallel Decoding (decode multiple parallel sequences)

https://huggingface.co/spaces/m-ric/beam\_search\_visualizer



./llama-batched -m Meta-Llama-3.1-8B-Instruct-Q4\_K\_M.gguf -p "9.11 and 9.9, which one is larger? answer:" -np 4

# **Important Notes**

- Read:
  - llama2.c: <a href="https://github.com/karpathy/llama2.c">https://github.com/karpathy/llama2.c</a>
  - SGLang <a href="https://github.com/sgl-project/sglang">https://github.com/sgl-project/sglang</a>
- Due
  - HW1 (Saturday Sep 14, 11:59 PM)