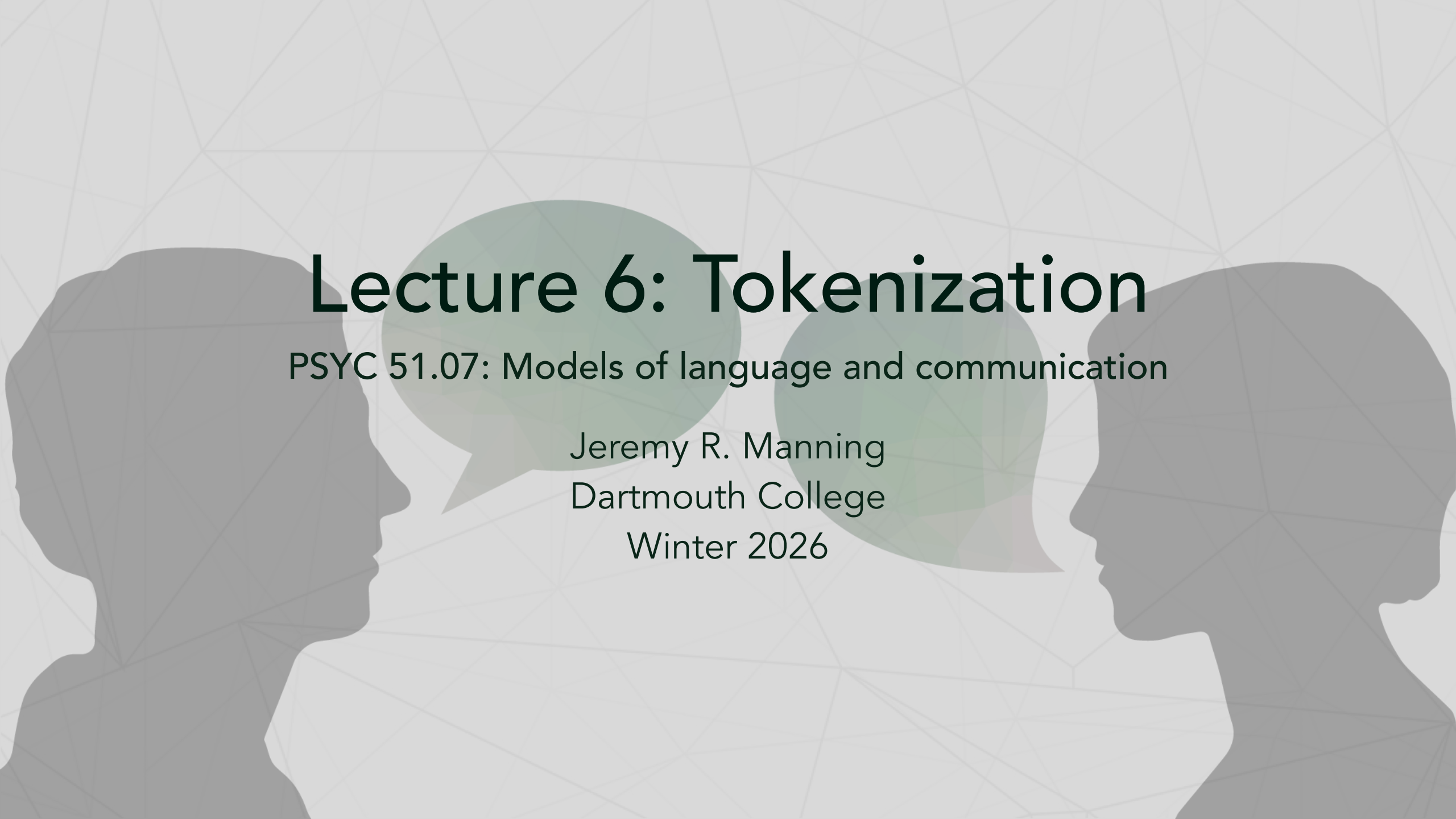

Lecture 6: Tokenization

PSYC 51.07: Models of language and communication

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Learning objectives

By the end of this lecture, you will be able to...

1. Understand what tokenization is and why it matters
2. Explain the limitations of word-level tokenization
3. Describe how subword tokenization works (BPE, WordPiece, SentencePiece)
4. Compare different tokenization methods and their trade-offs
5. Implement and experiment with different tokenizers using HuggingFace

Central question

How do we break text into meaningful units for AI models?

What is tokenization?

> Definition
>
> **Tokenization** is the process of converting text into smaller units (tokens).

Why tokenize?

- Neural networks process numbers, not text
- Need discrete units to create vocabulary
- First step in any NLP pipeline

What can tokens be?

- **Characters:** a, b, c, ... (very fine-grained)
- **Words:** "hello", "world" (intuitive but limited)
- **Subwords:** "un", "happiness" (sweet spot!)

The tokenization spectrum

Fine-grained to coarse-grained tokenization

Granularity	Vocabulary size	Sequence length
Character	~100s	Very long
Subword	30k-50k	Medium

Splitting on spaces fails for three reasons

1. Vocabulary explosion

English has ~170,000 words, each inflection counts separately ("run", "runs", "running", "ran"), and compounds vary ("ice cream", "icecream", "ice-cream")

2. Unknown words

OOV for new terms ("COVID-19", "selfie"), rare words ("supercalifragilisticexpialidocious"), and typos ("teh")

3. Languages without spaces

Chinese: 没有空格 | Japanese: 日本語も同様

Word-level limitations illustrated

Vocabulary growth as training data increases

Observation

Word-level vocabulary keeps growing! Subword vocabulary stabilizes at a reasonable size.

The OOV problem in action

```python
# Simple word-level vocabulary
vocab = {"hello", "world", "the", "cat", "sat"}

def tokenize_word_level(text, vocab):
 tokens = text.lower().split()
 result = []
 for token in tokens:
 if token in vocab:
 result.append(token)
 else:
 result.append("<UNK>") # Unknown token
 return result

# Example
text = "Hello! The cat jumped"
```

Problem

We lose information! "jumped" becomes meaningless `<UNK>`

Most words are made of smaller meaningful pieces

Examples:

- "unhappiness" = "un" + "happiness"
- "preprocessing" = "pre" + "process" + "ing"
- "antiestablishment" = "anti" + "establish" + "ment"

Benefits:

- Fixed vocabulary (30k-50k tokens)
- No OOV: break into known parts
- Captures morphology (prefixes, suffixes)

Subword tokenization solves the OOV problem

```
# Word-level vocabulary (only words seen in training)
vocab = {"the", "cat", "sat", "on", "mat", "dog", "ran"}

# Trying to tokenize a new sentence:
```

The subword solution:

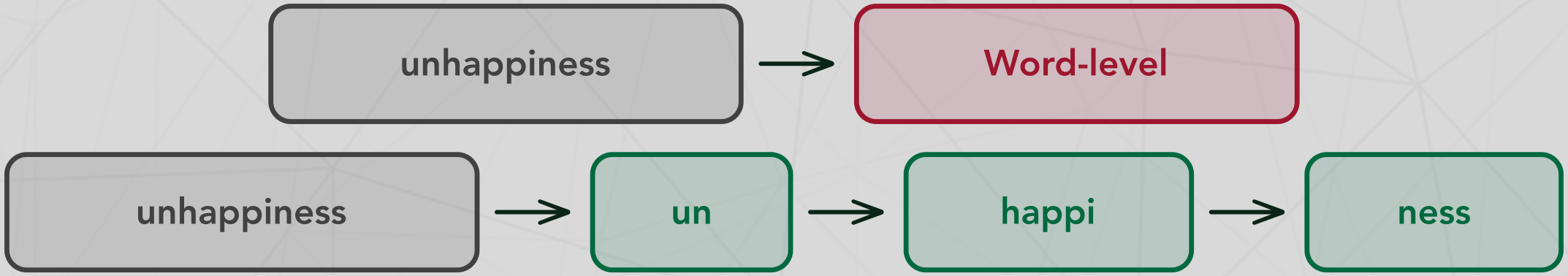
```
from transformers import AutoTokenizer
tokenizer = AutoTokenizer.from_pretrained("gpt2")

# Same difficult sentence:
tokens = tokenizer.tokenize("supercalifragilisticexpialidocious")
print(tokens)
```

Key insight

Subwords preserve meaning even for novel words!

Visual: How "unhappiness" gets tokenized



Word-level (1 token, may be OOV) vs. Subword BPE (3 tokens, always known)

Trade-off

More tokens = longer sequences, but smaller vocabulary and no OOV!

Byte-Pair Encoding (BPE)

Further reading

Sennrich, Haddow, & Birch (2016, *ACL*): Neural Machine Translation of Rare Words with Subword Units

- **Original use:** Data compression (1994)
- **Adapted for NLP:** Sennrich et al. (2016)
- **Used by:** GPT, GPT-2, GPT-3, RoBERTa, BART, many others!

Core idea

Iteratively merge the most frequent pair of characters/subwords.

Algorithm

1. Start with character-level vocabulary
2. Count all adjacent pairs in corpus
3. Merge most frequent pair → create new token
4. Repeat until desired vocabulary size

BPE example: Step by step

Training data: "low low low lower lower newest newest newest newest newest widest"

Initial tokens (characters): `l, o, w, e, r, n, s, t, i, d`

Iteration 1

Most frequent pair = `e, s` (appears 4 times)

- Merge → new token: `es`
- Vocabulary: `l, o, w, e, r, n, s, t, i, d, es`

Iteration 2

Most frequent = `es, t`

- Merge → new token: `est`
- Vocabulary: `l, o, w, e, r, n, s, t, i, d, es, est`

Iteration 3

Most frequent = `l, o`

- Merge → new token: `lo`

Continue until reaching target vocabulary size (e.g., 30,000)...

BPE learns to merge frequent character pairs

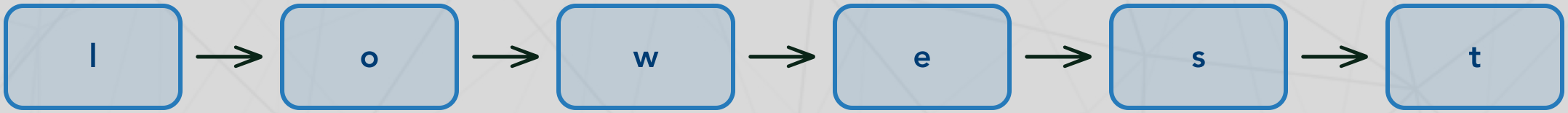
```
Training corpus: "low" (x3), "lower" (x2), "newest" (x4), "widest" (x1)

After training, vocabulary includes:
- Characters: l, o, w, e, r, n, s, t, i, d
- Merges learned: es → est → lo → low → er → ...

Tokenizing "lowest":
 Step 1: Split into characters → [l, o, w, e, s, t]
 Step 2: Apply merge rules in order learned:
 [l, o, w, e, s, t]
 → [lo, w, e, s, t] (merge l+o)
 → [low, e, s, t] (merge lo+w)
 → [low, es, t] (merge e+s)
```

Result: "lowest" → `["low", "est"]` (2 tokens instead of 6 characters!)

BPE visualization



Step 0: Character-level

After merges: "lowest" becomes 3 tokens

Result

"lowest" → `[lo, w, est]` — captures common patterns without explicit

BPE in practice with HuggingFace

```python
from transformers import AutoTokenizer
tokenizer = AutoTokenizer.from_pretrained("gpt2")  # GPT-2 uses BPE

text = "I'm learning about tokenization!"
tokens = tokenizer.tokenize(text)
print("Tokens:", tokens)
# ['I', "'m", 'Ġlearning', 'Ġabout', 'Ġtoken', 'ization', '!']
# Note: 'Ġ' represents space

token_ids = tokenizer.encode(text)  # Get token IDs
print("Token IDs:", token_ids)  # [40, 1101, 4673, 546, 11241, 1634, 0]
```

Try it out!

Use the Tokenization Explorer Demo to experiment with different tokenizers interactively.

WordPiece merges "surprisingly common" pairs

Further reading

Wu et al. (2016, *arXiv*): Google's Neural Machine Translation System

Key difference from BPE

Instead of merging most *frequent* pair, merge pair that maximizes *likelihood*:

$$\text{score}(x, y) = \frac{P(xy)}{P(x) \times P(y)}$$

- **Used by:** BERT, DistilBERT, Electra
- **Special tokens:** `##` prefix for continuation ("playing" → `["play", "##ing"]`)

WordPiece example with BERT

```python
from transformers import AutoTokenizer

# BERT uses WordPiece
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")

text = "I'm learning about tokenization!"

tokens = tokenizer.tokenize(text)
print("Tokens:", tokens)
# Output: ['i', "'", 'm', 'learning', 'about', 'token', '##ization', '!']
# ^^^ Note the ##
```

Note

BERT lowercases by default (unless using cased model)

SentencePiece works for languages without spaces

Further reading

Kudo & Richardson (2018, *EMNLP*): SentencePiece: A simple and language independent subword tokenizer

Problem with BPE/WordPiece:

- Assume pre-tokenized text
- Fail on Chinese, Japanese, Thai...

SentencePiece solution:

- Raw character stream input
- Space = just another char (`_`)

SentencePiece in action

```python
from transformers import AutoTokenizer

# T5 uses SentencePiece
tokenizer = AutoTokenizer.from_pretrained("t5-small")

text = "I'm learning about tokenization!"

tokens = tokenizer.tokenize(text)
print("Tokens:", tokens)
# Output: ['I', "'", 'm', 'learning', 'about', 'token', 'ization', '!']
# ^^^ Note the for spaces

# Works seamlessly with other languages!
```

Key advantage

No language-specific preprocessing required!

Tokenization methods comparison

Method	Approach	Used By	Key Feature
BPE	Frequency merging	GPT-2, RoBERTa	Bottom-up
WordPiece	Likelihood merging	BERT, DistilBERT	Principled scoring
SentencePiece (Unigram)	Top-down pruning	T5, mT5	Multilingual

Comparing tokenizers side-by-side

```
from transformers import AutoTokenizer
text = "The unhappiest researchers couldn't preprocess data!"

models = {"GPT-2 (BPE)": "gpt2", "BERT (WordPiece)": "bert-base-uncased",
          "T5 (SentencePiece)": "t5-small"}

for name, model_name in models.items():
    tokenizer = AutoTokenizer.from_pretrained(model_name)
    tokens = tokenizer.tokenize(text)
    print(f"{name}: Tokens ({len(tokens)}): {tokens}")

# Observe: Different handling of "unhappiest", spaces, and token counts!
```

Tokenizer comparison: Actual output

Input: `"The unhappiest researchers couldn't preprocess data!"`

Tokenizer	Tokens	Count
GPT-2 (BPE)	`['The', 'Ġun', 'happ', 'iest', 'Ġresearchers', 'Ġcouldn', "'t", 'Ġpre', 'process', 'Ġdata', '!']`	11
BERT (WordPiece)	`['the', 'un', '##hap', '##pie', '##st', 'researchers', 'couldn', "'", 't', 'pre', '##process', 'data', '!']`	13
T5 (SentencePiece)	`['The', 'un', 'happiest', 'researchers', 'couldn', "'", 't', 'pre', 'process', 'data', '!']`	11

Key observations

- `Ġ` (GPT-2) and `_` (T5) mark word starts (spaces)
- `##` (BERT) marks continuation subwords
- "unhappiest" is split differently by each
  BERT lowercases; GPT-2/T5 preserve case

Tokenizers add special tokens for model-specific purposes

Token	Purpose	Used By
[CLS]	Classification token (start)	BERT
[SEP]	Separator between segments	BERT
[PAD]	Padding to same	Most models

Working with special tokens

```python
from transformers import AutoTokenizer
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")

text = "Hello world"
encoded = tokenizer(text, return_tensors="pt")
print("Input IDs:", encoded['input_ids'])  # [101, 7592, 2088, 102]
# ^^^ [CLS] and [SEP] added automatically!

full_decode = tokenizer.decode(encoded['input_ids'][0])
print("With special:", full_decode)  # "[CLS] hello world [SEP]"

clean_decode = tokenizer.decode(encoded['input_ids'][0], skip_special_tokens=True)
print("Without special:", clean_decode)  # "hello world"
```

Vocabulary size trade-offs

Smaller vocabulary (e.g., 10k tokens):

- Faster training (smaller embedding matrix)
- Less memory
- Longer sequences (more subwords per word)
- May lose semantic

Larger vocabulary (e.g., 100k tokens):

- Shorter sequences (closer to word-level)
- Better semantic preservation
- Slower training (larger embeddings)

Tokenization pitfalls and gotchas

Common issues to watch out for

1. **Tokenizer-model mismatch:** Always use the tokenizer that matches your model! GPT-2 tokenizer ≠ BERT tokenizer
2. **Maximum sequence length:** BERT: 512 tokens | GPT-2: 1024 | GPT-3: 2048 — Text gets truncated if too long!
3. **Case sensitivity:** `bert-base-uncased` lowercases everything; `bert-base-cased` preserves case
4. **Rare words → many tokens:** "antidisestablishmentarianism" → 10+ tokens — Can hit sequence limit faster than expected!
5. **Special characters:** Emoji, Unicode, accents may be split unexpectedly

Debugging tokenization

```python
from transformers import AutoTokenizer
tokenizer = AutoTokenizer.from_pretrained("gpt2")
text = "The antidisestablishmentarianism debate continues!"

tokens = tokenizer.tokenize(text)
token_ids = tokenizer.encode(text)
print(f"Tokens ({len(tokens)}): {tokens}\n")

for i, (token, token_id) in enumerate(zip(tokens, token_ids)):
    decoded = tokenizer.decode([token_id])
    print(f"{i:2d}. ID {token_id:5d} | Token: {token:20s} | Decoded:
{decoded}")

print(f"\nVocabulary size: {tokenizer.vocab_size}")
```

Connection to human language learning

> **Further reading**
>
> **Saffran, Aslin, & Newport (1996, *Science*):** Statistical learning by 8-month-old infants

Infant learning:

- Babies track statistical regularities in speech
- Identify word boundaries from transitional probabilities

Parallel with subword tokenization:

- BPE: Merge frequent character pairs → discover common morphemes
- Infants: Track frequent syllable pairs → discover

Statistical learning in action

Infant Learning:

Input stream:

`bidakupadotigolabu ...`

Learn high-probability sequences:

- `bi-da-ku` (word)
- `pa-do-ti` (word)

BPE Learning:

Input corpus:

`low low lower ...`

Merge high-frequency pairs:

- `l+o` → `lo`
- `lo+w` → `low`

Build vocabulary:

Hands-on exercise

Experiment with different tokenizers!

1. **Choose 3 models:** GPT-2, BERT, T5
2. **Test on diverse texts:**
   - Standard English: "The cat sat on the mat"
   - Complex words: "antidisestablishmentarianism"
   - Contractions: "I'm, you're, won't"
   - Typos: "teh qiuck brown fox"
   - Emoji: "I love this!"
   - Other languages: "这是中文" (Chinese)
3. **Compare results:** Number of tokens, how words are split, handling of unknown/rare words
4. **Reflect:** Which tokenizer works best for your use case? What are the trade-offs?

Try it out!

Use the Tokenization Explorer Demo to compare tokenizers interactively!

Discussion questions

Think about it...

1. **Linguistics vs. Statistics:** BPE discovers morphemes (un-, -ing, -ness) without linguistic rules. Is this "learning" morphology, or just pattern matching?
2. **Cross-lingual tokenization:** Should we use the same tokenizer for all languages? What are the trade-offs?
3. **Semantic preservation:** Does breaking "unhappy" into ["un", "happy"] preserve meaning? What about "butterfly"?
4. **Human vs. machine:** Humans don't consciously tokenize words. Why do machines need to?
5. **Future directions:** Will we move toward character-level or byte-level models that don't need tokenization?

Primary references

Foundational papers

- **Sennrich, Haddow, & Birch (2016).** Neural Machine Translation of Rare Words with Subword Units. *ACL*. — Introduced BPE for NLP
- **Kudo & Richardson (2018).** SentencePiece: A simple and language independent approach. *EMNLP*. — Language-agnostic tokenization
- **Wu et al. (2016).** Google's Neural Machine Translation System. *arXiv*. — WordPiece algorithm

HuggingFace resources

- Chapter 2.4: Tokenizers
- Chapter 6: Tokenizers (detailed)

Key takeaways

Summary

1. **Tokenization is fundamental:** Bridges raw text and neural networks
2. **Word-level has major limitations:** OOV problem, vocabulary explosion, language-dependent
3. **Subword tokenization is the sweet spot:** Balanced vocabulary size and sequence length
4. **Different methods, similar principles:** BPE: frequency-based | WordPiece: likelihood | SentencePiece: language-agnostic
5. **Statistical learning connects humans and machines:** Both discover structure from distributional patterns
6. **Always match tokenizer to model!** Critical for correct predictions

Looking ahead

Next lecture: X-Hour Text Classification Workshop

How tokenization connects:

- POS tagging: Token-level classification
- Sentiment: Sequence-level classification
- Both depend on good tokenization!

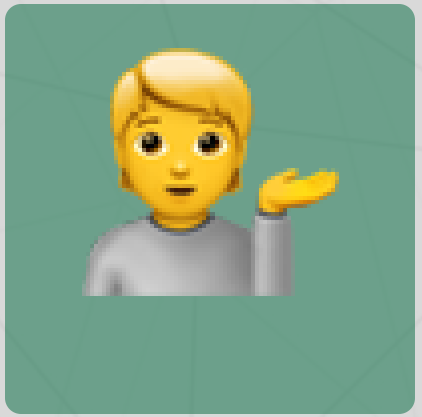
Prepare by...

- Experimenting with HuggingFace tokenizers
- Thinking about: How does token granularity affect downstream tasks?
- Exploring: Tokenizer artifacts and their impact

Questions? Want to chat more?

Email me

Join our Discord



Come to office hours

Next up

Lecture 7 — X-Hour: Text Classification Workshop