

Novelty of LLMs

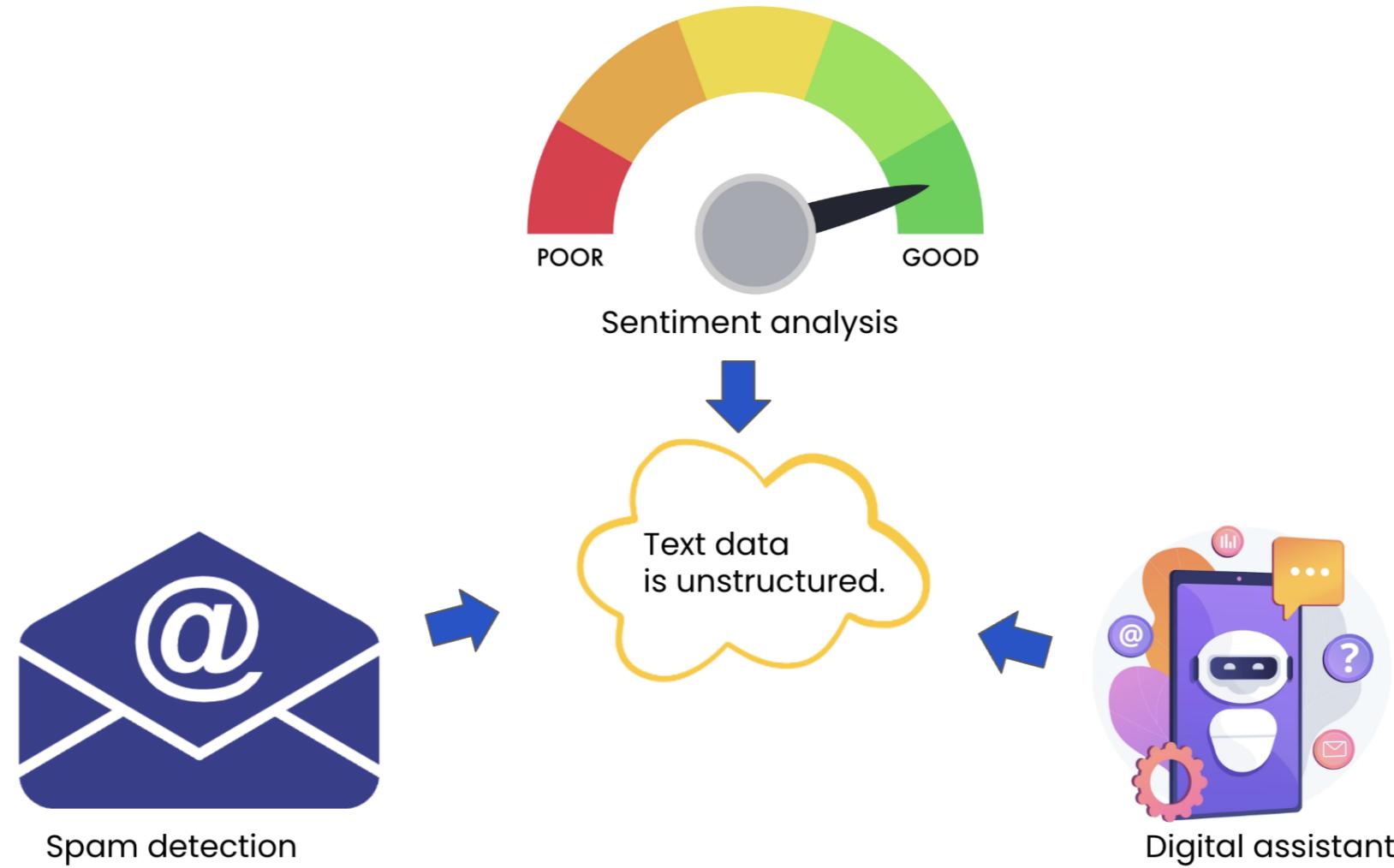
LARGE LANGUAGE MODELS (LLMs) CONCEPTS



Vidhi Chugh

AI strategist and ethicist

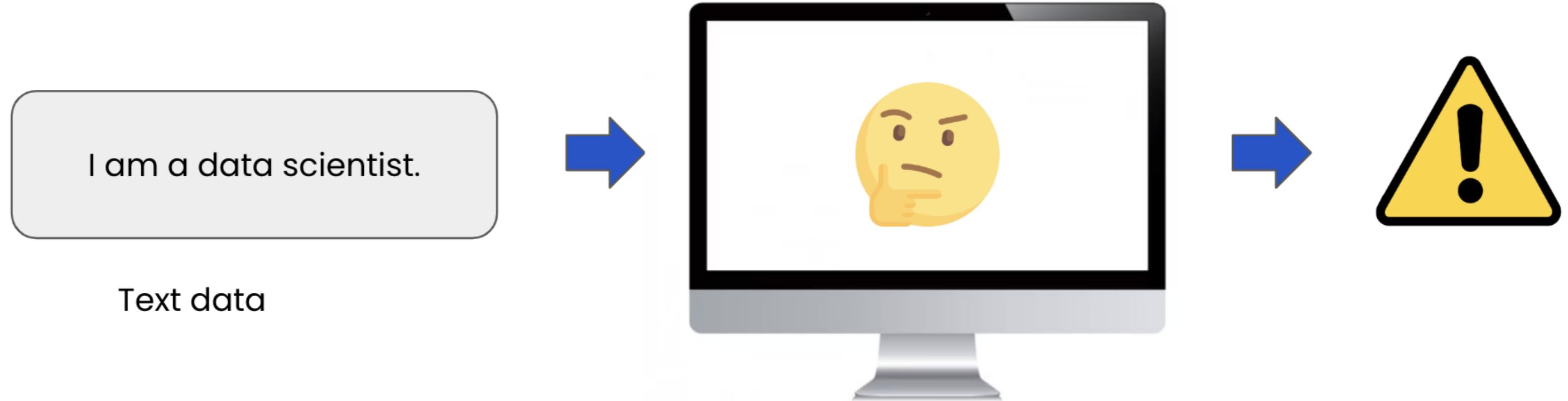
Using text data



- Unstructured data - messy and inconsistent

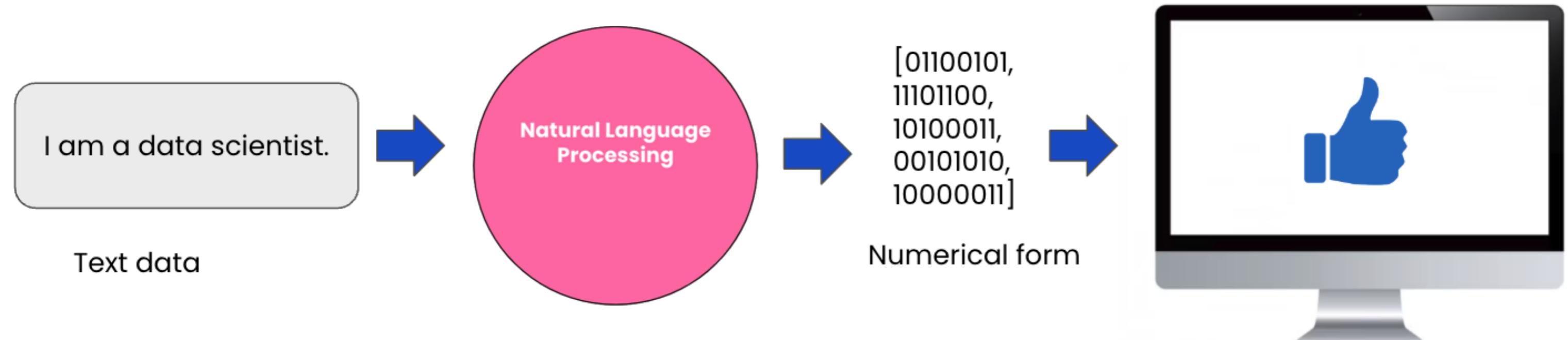
¹ Freepik

Machines do not understand language!



¹ Freepik

Need for NLP



¹ Freepik

Unique capabilities of LLMs

- Linguistic subtleties
 - Irony
 - Humor
 - Pun
 - Sarcasm
 - Intonation
 - Intent



¹ Freepik

What's your favorite book?

- **Natural response:** "Oh, that's a tough one!"
- **Personal opinion:** "My all-time favorite book is To Kill a Mockingbird by Harper Lee."
- **Supporting statement:** "It's a powerful story about prejudice, justice, and the human experience."
- **Follow-up question:** "Have you read it?"

Linguistic subtleties

Sarcasm: "Oh great, another meeting."

Traditional language model:

- Response: "What's the meeting about?"
 - Neutral
 - Does not pick up sarcasm

Large language model:

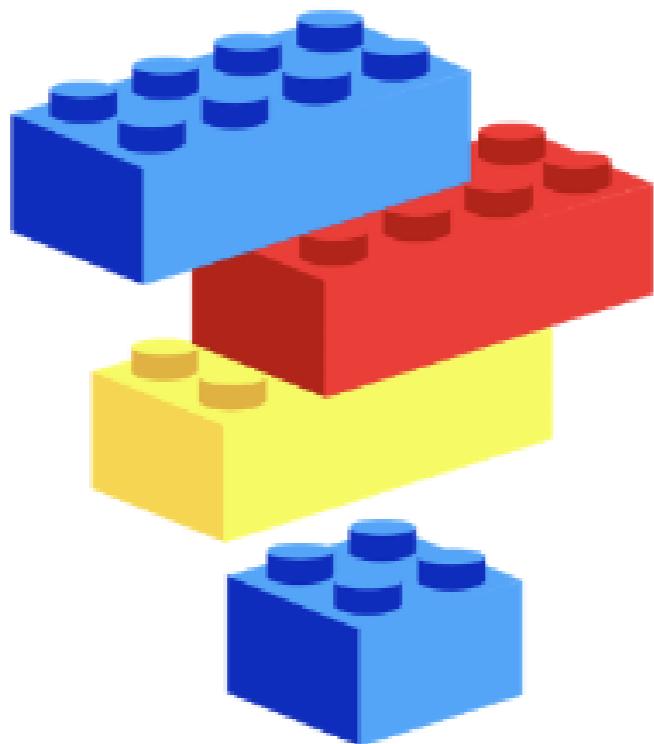
- Response: "Sounds like you're looking forward to it!"
 - Playful
 - Engaging
 - Matches the sarcasm

How do LLMs understand

- Trained on vast amounts of data
- Largeness of LLMs: parameters
- Parameters represent the patterns and rules
- More parameters -> complex patterns
- Generates sophisticated and accurate responses

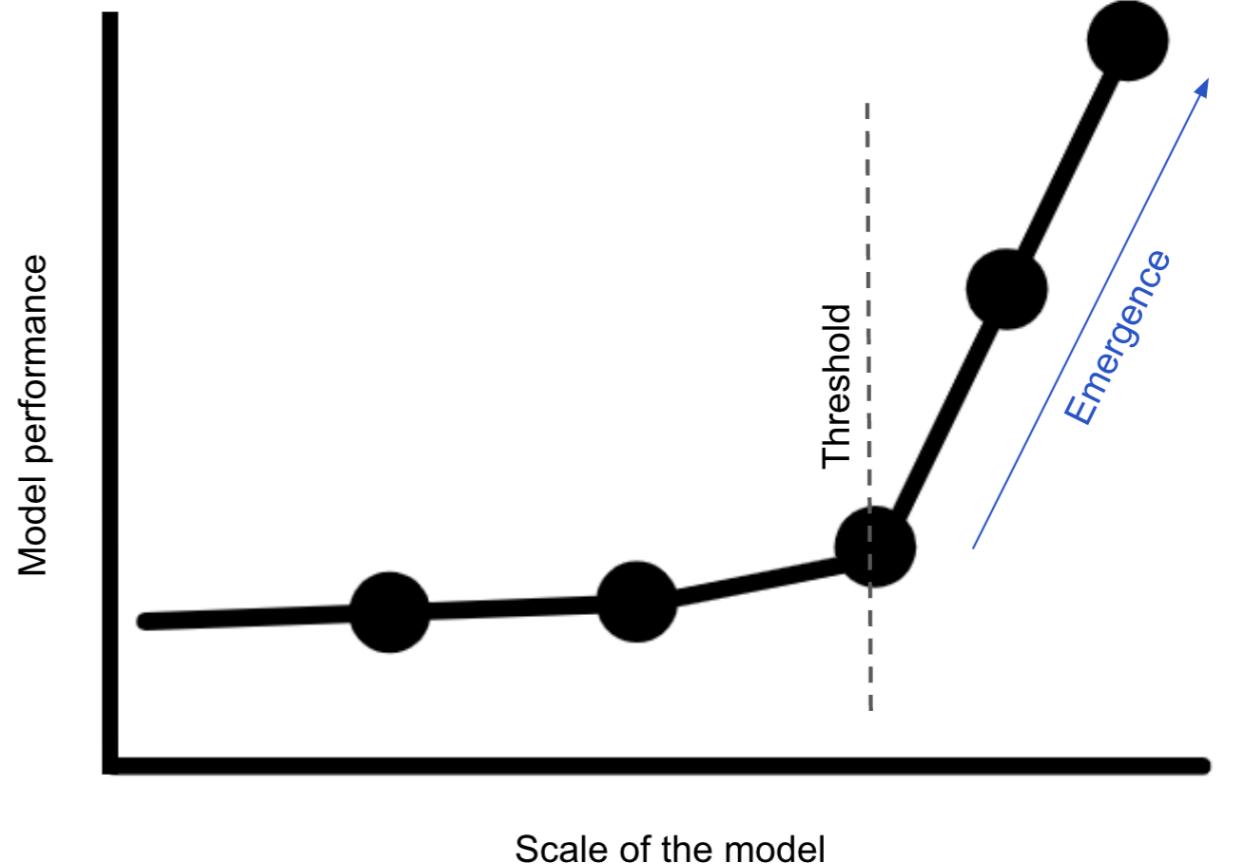
Parameters

- Small number of bricks -> limited structures
- Larger number of bricks -> complex and detailed structures



Emergence of new capabilities

- Emergent abilities
 - only present in large-scale models
- Scale:
 - The volume of training data
 - The number of model parameters



Emergence of new capabilities



Music



Poetry



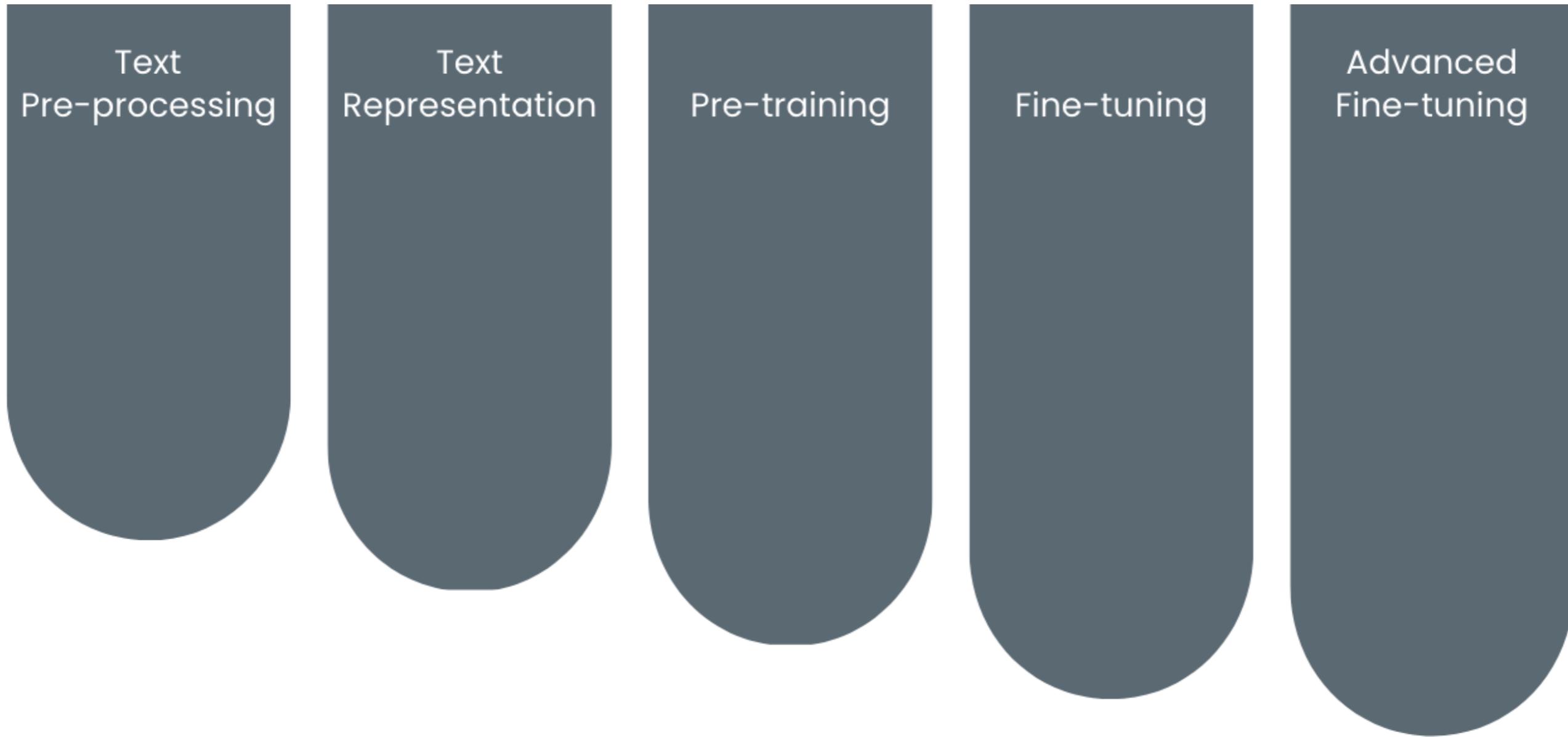
Code generation



Medical diagnosis and treatment plans



Building blocks of LLMs



To recap

LLMs:

- Overcome data's unstructured nature
- Outperform traditional models
- Understand linguistic subtleties

How?

- LLMs' "largeness"
- Extensive training data
- Many parameters
- Emergent abilities

Let's practice!

LARGE LANGUAGE MODELS (LLMS) CONCEPTS

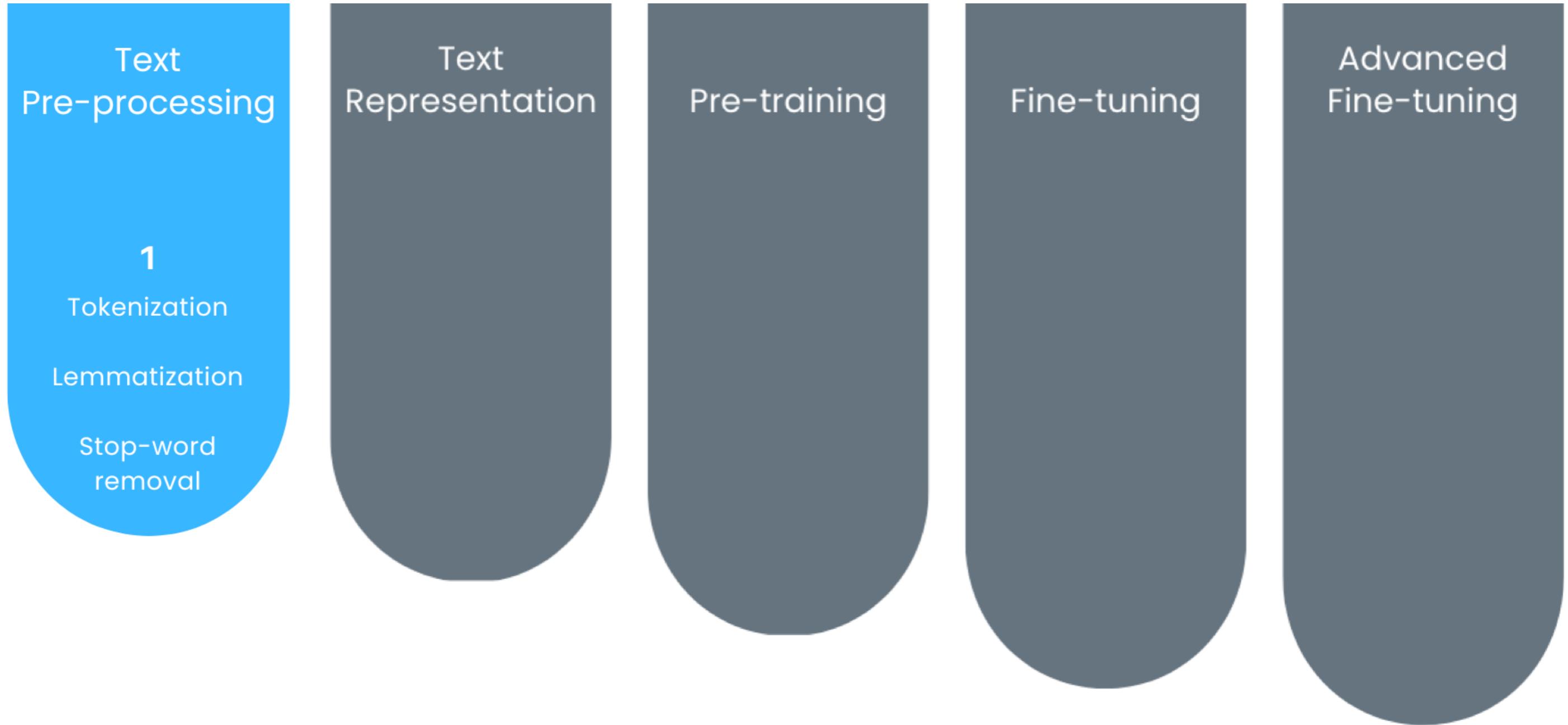
Generalized overview of NLP

LARGE LANGUAGE MODELS (LLMS) CONCEPTS



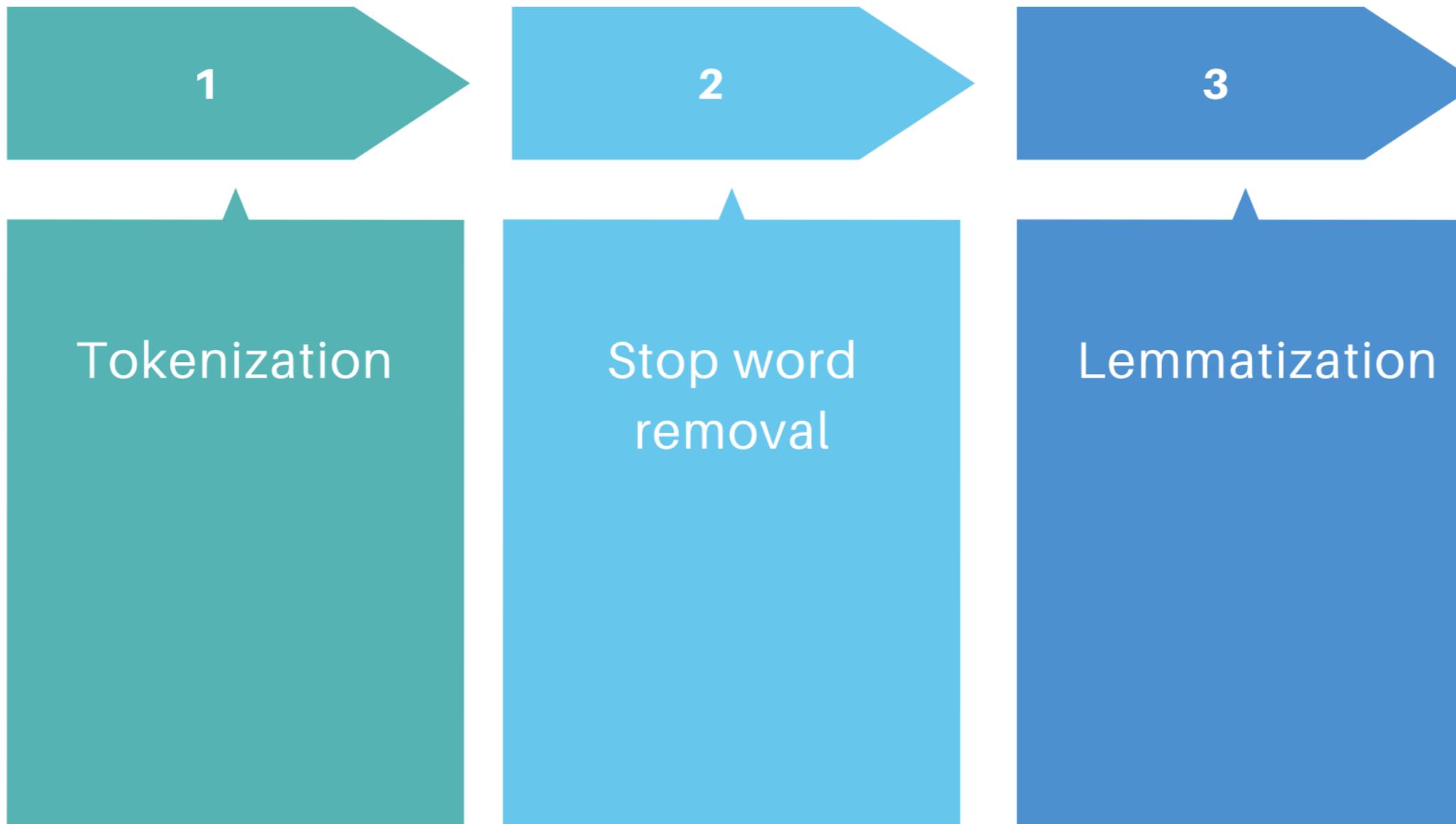
Vidhi Chugh
AI strategist and ethicist

Where are we?



Text pre-processing

- Can be done in a different order as they are independent



Tokenization

- Splits text into individual words, or **tokens**
- Text:
 - "Working with natural language processing techniques is tricky."
- Tokenization:
 - `["Working", "with", "natural", "language", "processing", "techniques", "is", "tricky", "."]`
 - Converts into a list

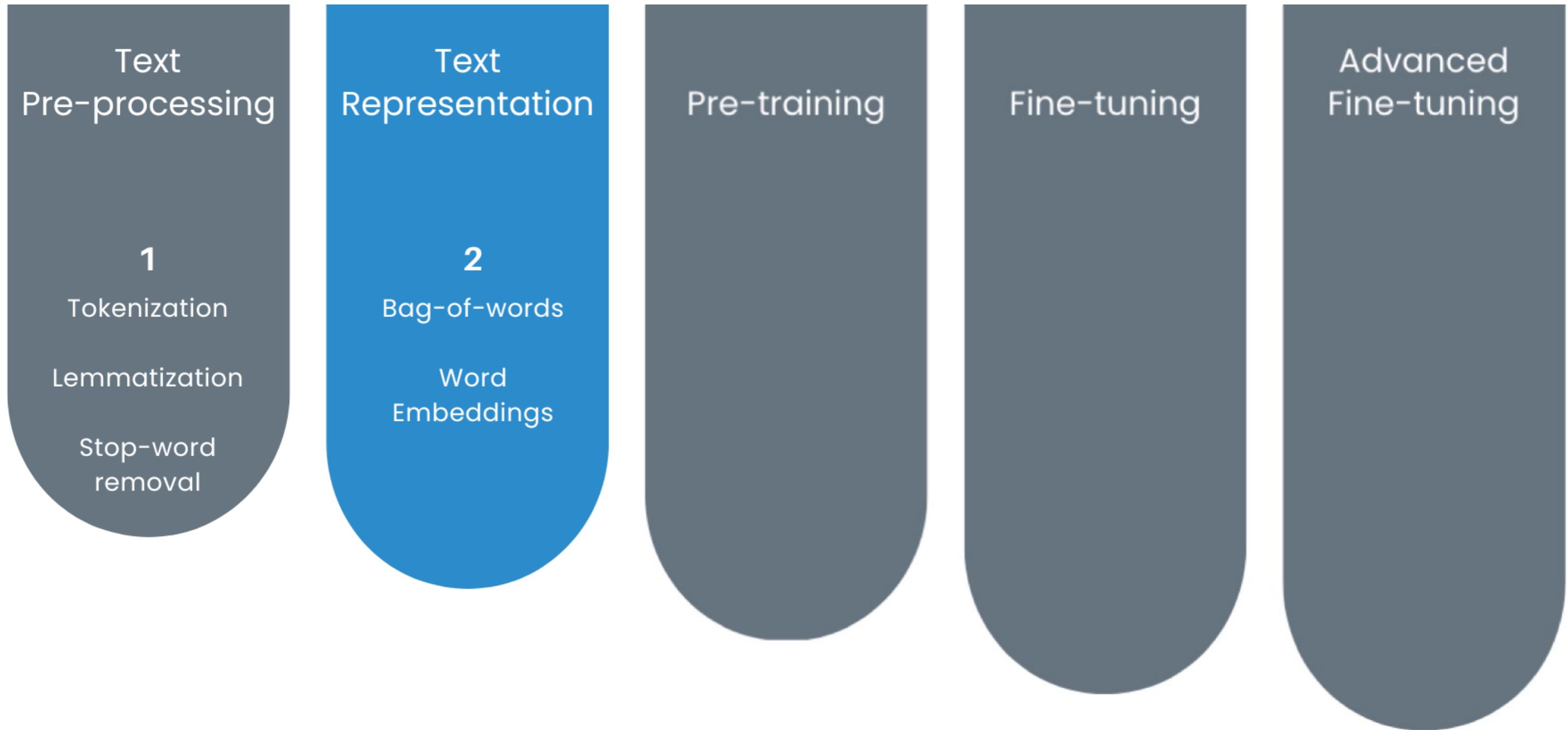
Stop word removal

- Stop words do not add meaning
- Eliminated through stop word removal
- **Before** stop word removal:
 - ["Working", "with", "natural", "language", "processing", "techniques", "is", "challenging", "."]
- **After** stop word removal:
 - ["Working", "natural", "language", "processing", "techniques", "challenging", "."]

Lemmatization

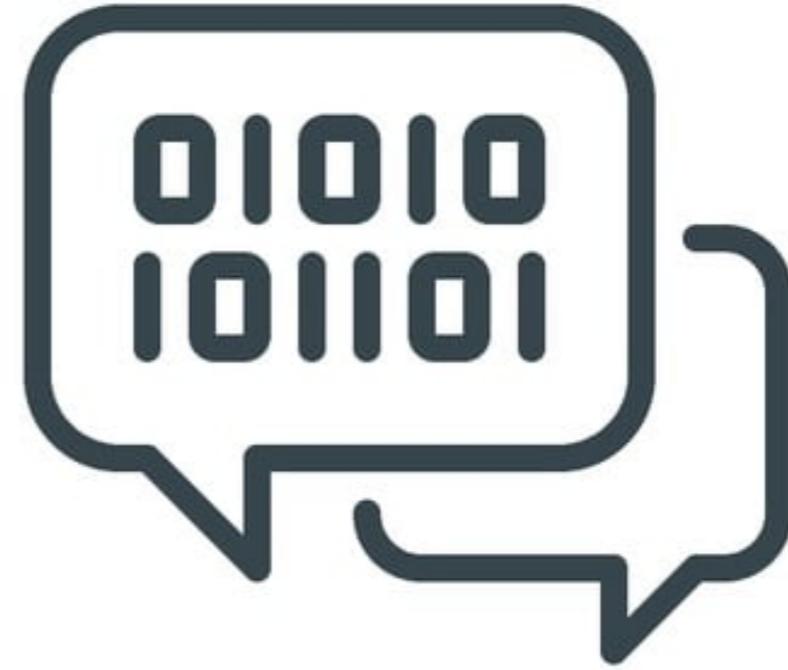
- Group slightly different words with similar meaning
 - Talking -> Talk
 - Talked -> Talk
 - Talk -> Talk
- Reduces words to their base form
- Mapped to root word

Text representation



Text representation

- Text data into numerical form
- Bag-of-words
- Word embeddings



Bag-of-words

- Text into a matrix of word counts

Sentence	“cat”	“chased”	“mouse”	“swiftly”
“The cat chased the mouse swiftly.”	1	1	1	1
“The mouse chased the cat.”	1	1	1	0

- 0 represents the absence of a word

Limitations of bag-of-words

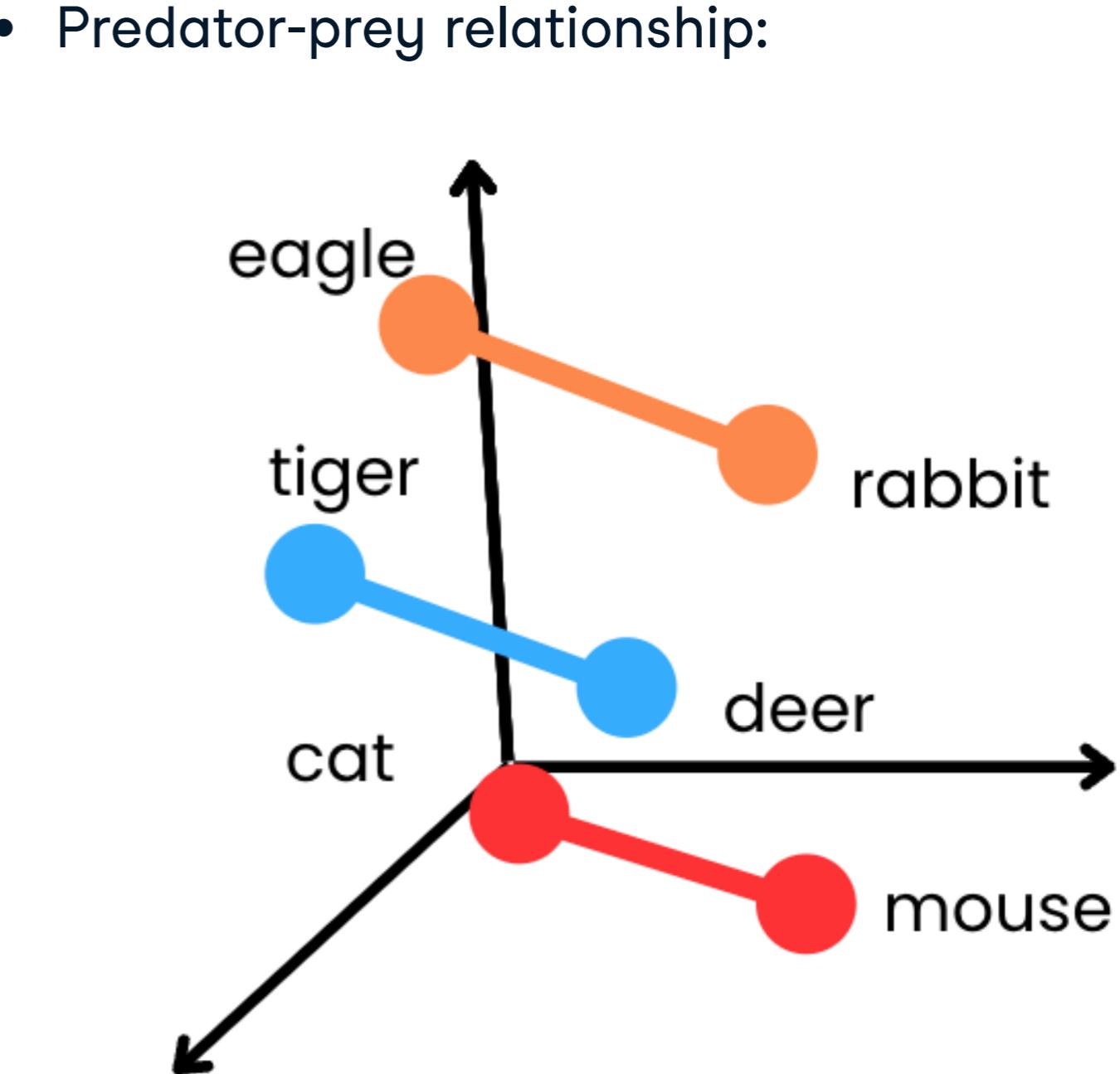
- Does not capture the order or context
 - Can lead to incorrect interpretations
 - Similar sentences but opposite meaning
 - "The cat chased the mouse swiftly."
 - "The mouse chased the cat."
- Does not capture the semantics between the words
 - Treats related words as independent
 - Like "cat" and "mouse"

Word embeddings

- Capture the semantic meanings as numbers
- Predator-prey relationship:

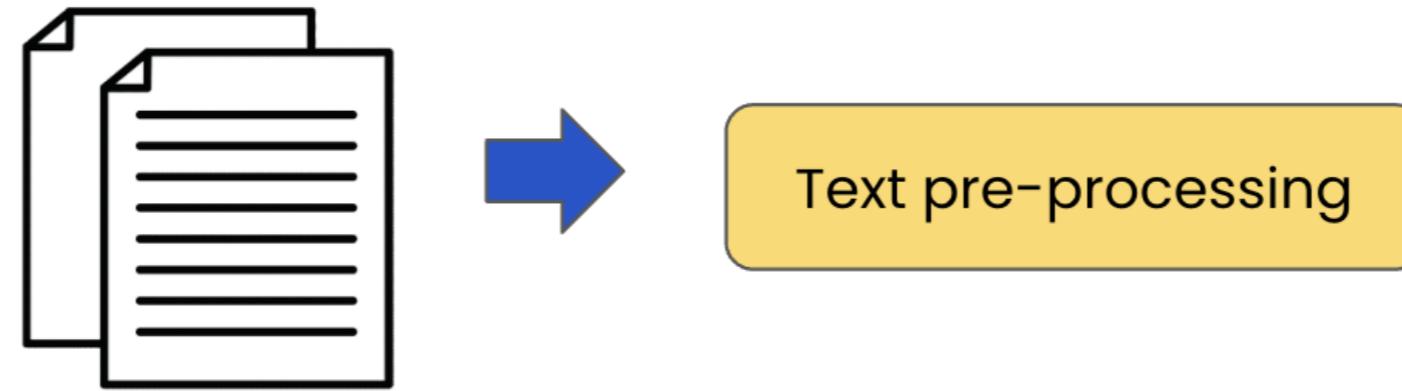
	Cat	Mouse
Plant	-0.9	-0.8
Furry	0.9	0.7
Carnivore	0.9	-0.8

- Cat [-0.9, 0.9, 0.9]



Machine-readable form

- Start with text pre-processing

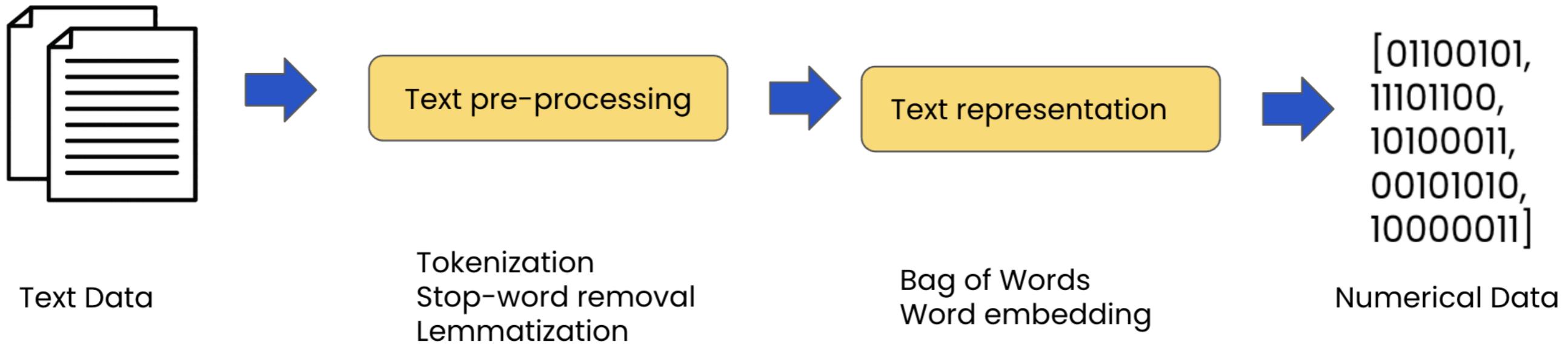


Text Data

Tokenization
Stop-word removal
Lemmatization

Machine-readable form

- Convert pre-processed text to numerical format



Let's practice!

LARGE LANGUAGE MODELS (LLMS) CONCEPTS

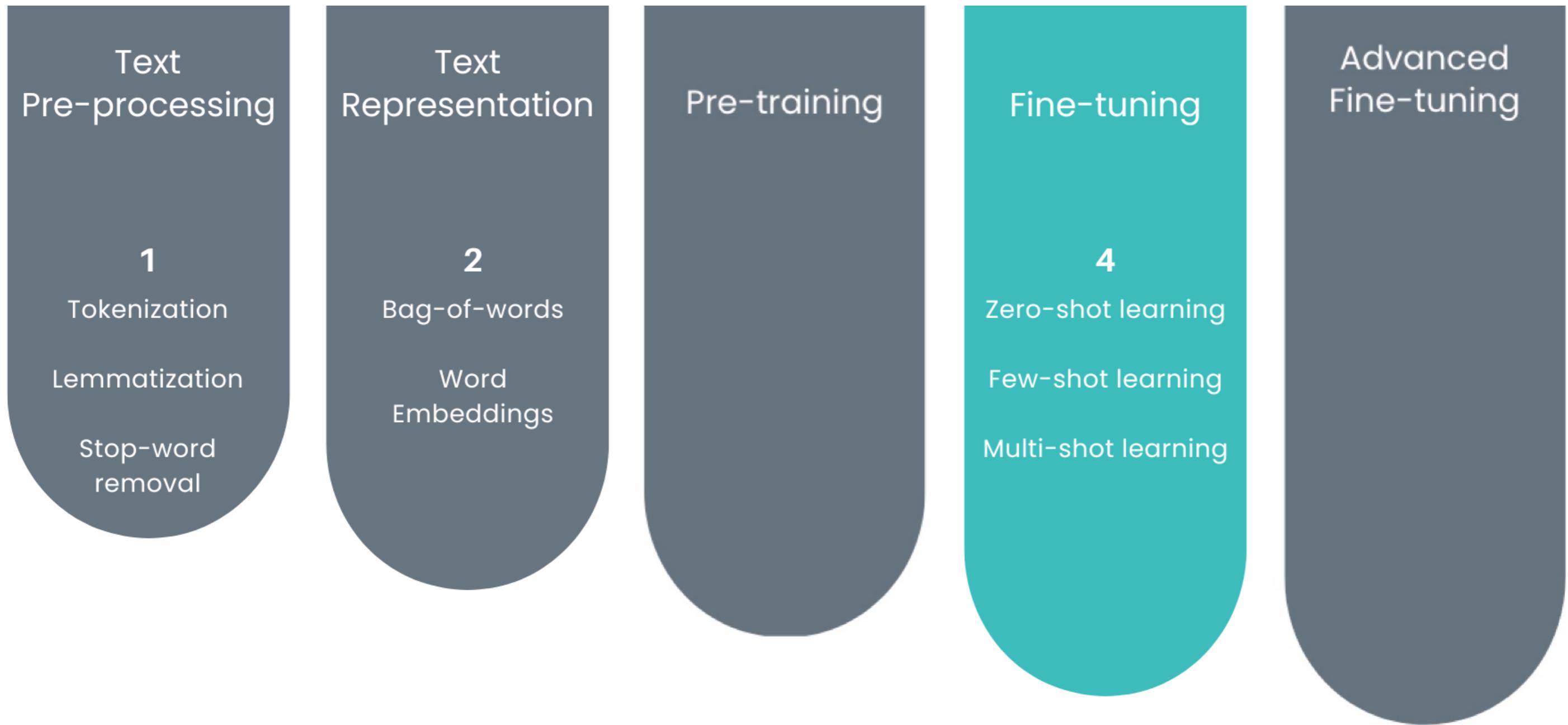
Fine-tuning

LARGE LANGUAGE MODELS (LLMS) CONCEPTS



Vidhi Chugh
AI strategist and ethicist

Where are we?



- Pre-training



School education

- Fine-tuning



University specialization

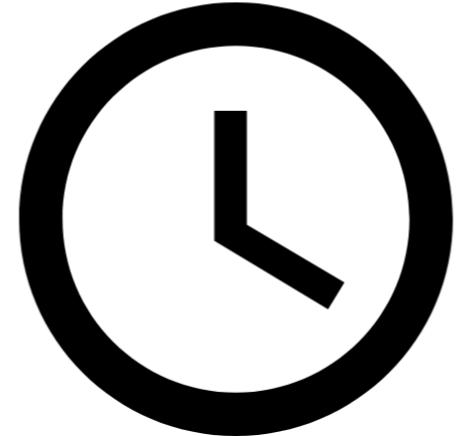
¹ Freepik

"Largeness" challenges

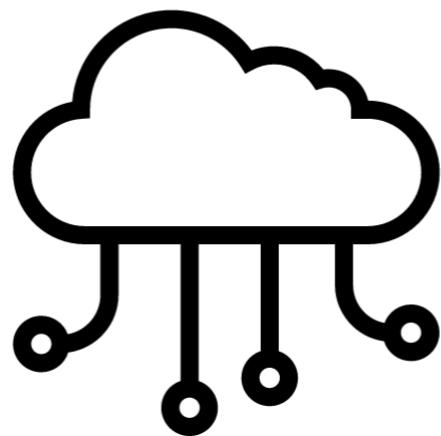
- Fine-tuning can help
- Powerful computers
- Efficient model training methods
- Large amounts of training data



data



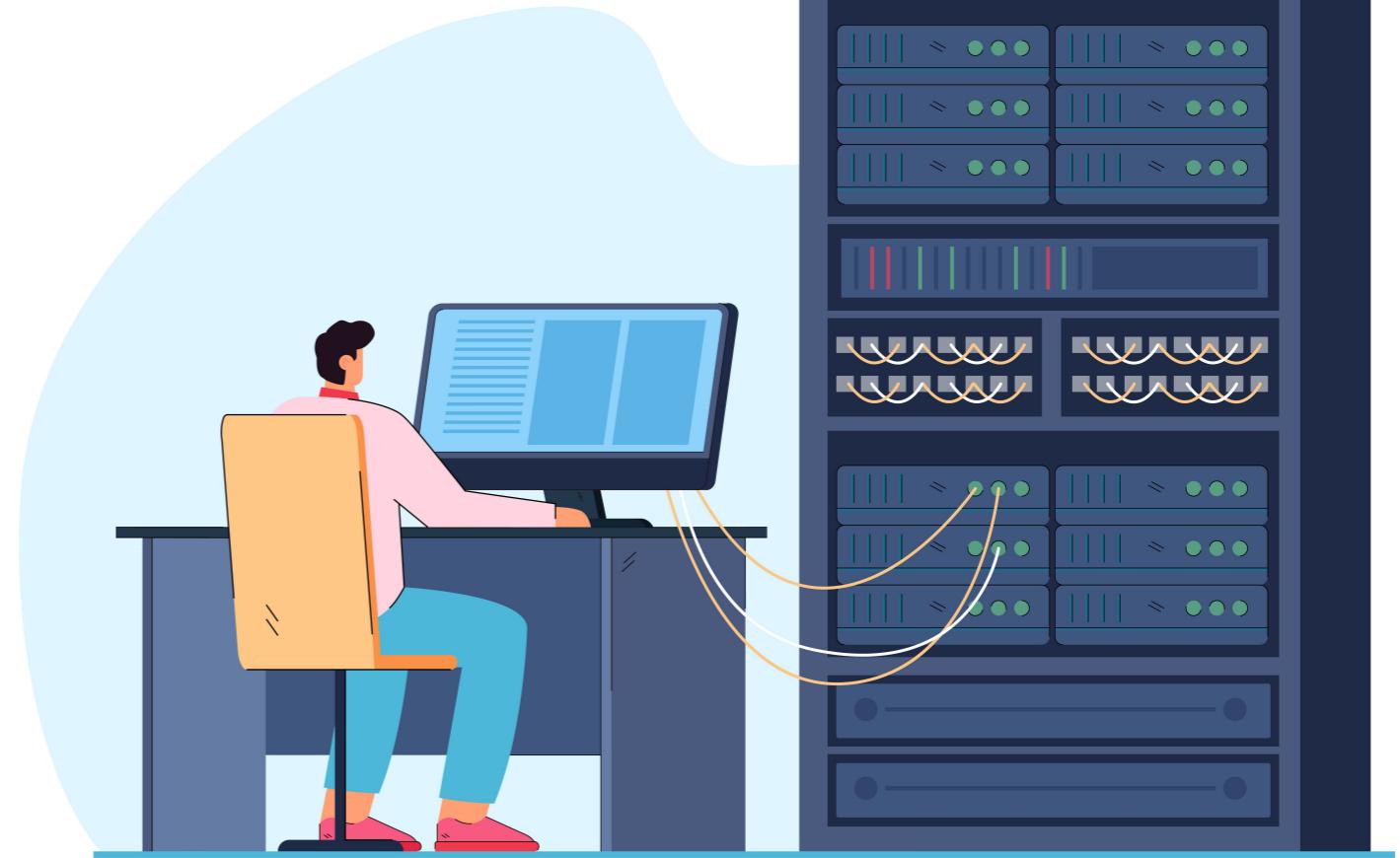
train



compute

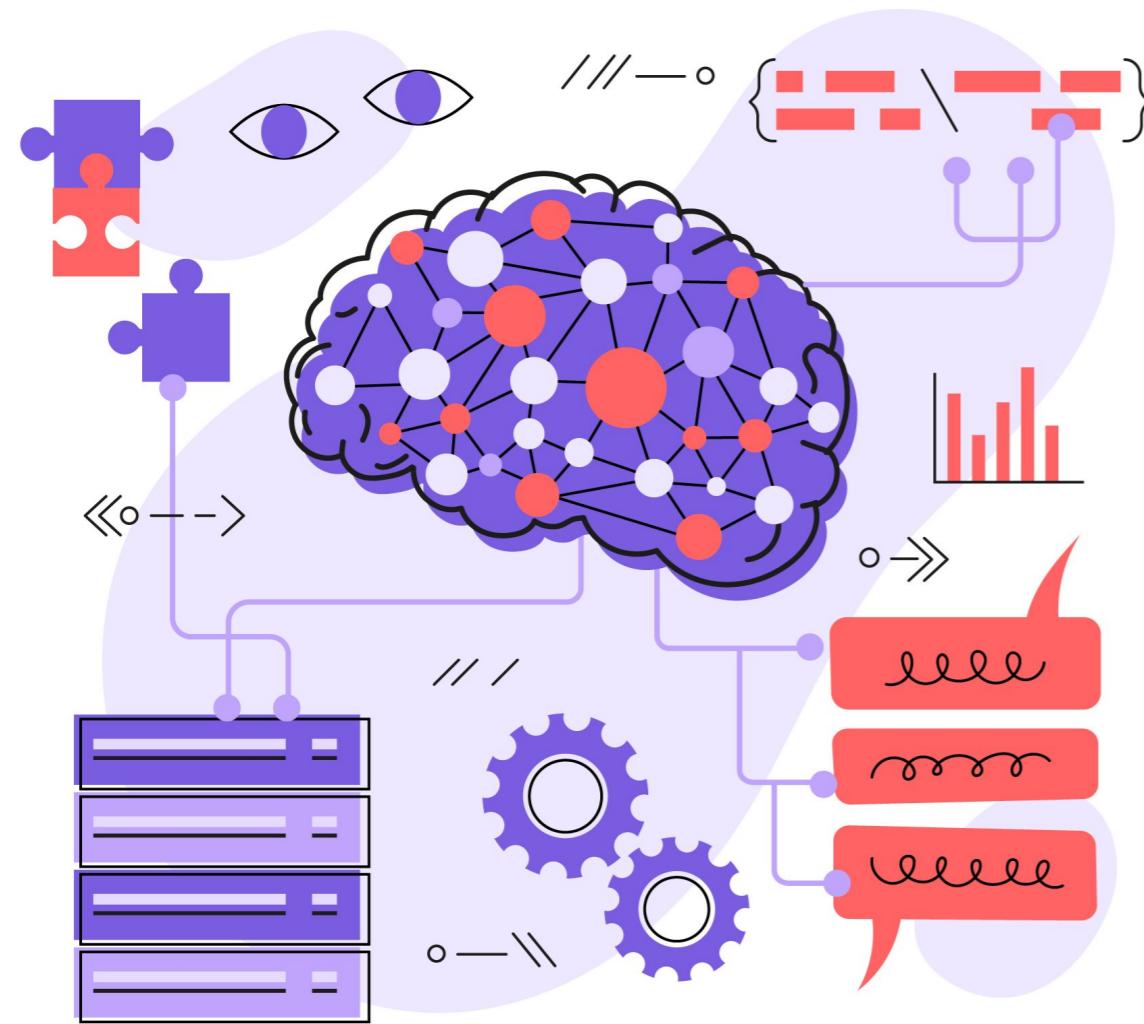
Computing power

- Memory
- Processing power
- Infrastructure
- Expensive
- LLM:
 - 100,000's Central Processing Units (CPUs)
 - 10,000's Graphic Processing Units (GPUs)
- A personal computer: 4-8 CPU and 1-2 GPUs



¹ Freepik

Efficient model training



- Training time is huge
- May take weeks or even months
- Efficient model training = faster training time
- 355 years of processing time on a single GPU

Data availability

- Need of high-quality data
- To learn the complexities and subtleties of language
- A few hundred gigabytes (GBs) of text data
 - More than a million books
- Massive amount of data



Overcoming the challenges

- **Fine-tuning**
 - Addresses some of these challenges
 - Adapts a pre-trained model
- **Pre-trained model**
 - Learned from general-purpose datasets
 - Not optimized for specific-tasks
 - Can be fine-tuned for a specific problem



Fine-tuning vs. Pre-training

- Fine-tuning
- Compute
 - 1-2 CPU and GPU
- Training time
 - Hours to days
- Data
 - ~1 gigabyte
- Pre-training
- Compute
 - Thousands of CPUs and GPUs
- Training time
 - Weeks to months
- Data
 - Hundreds of gigabytes

Let's practice!

LARGE LANGUAGE MODELS (LLMS) CONCEPTS

Learning techniques

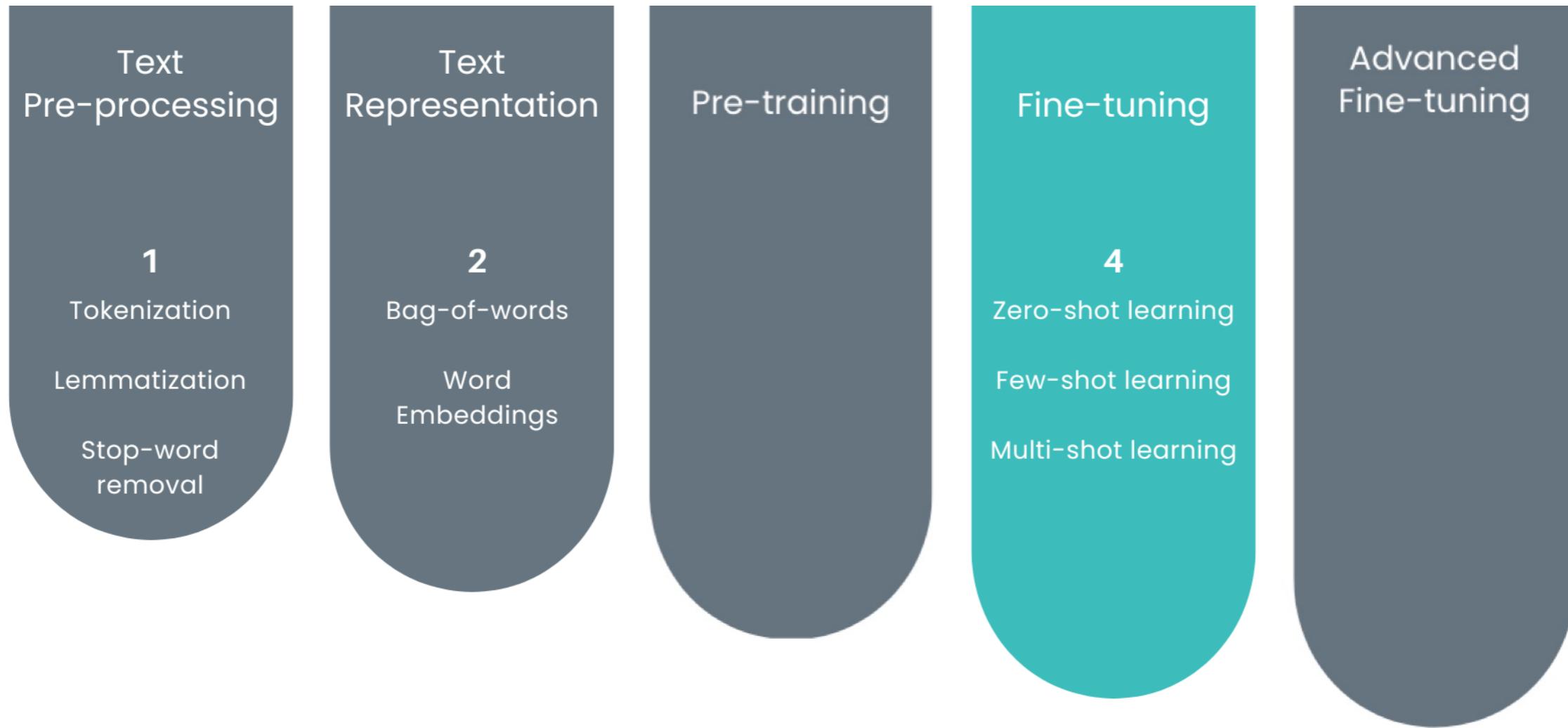
LARGE LANGUAGE MODELS (LLMS) CONCEPTS



Vidhi Chugh

AI strategist and ethicist

Where are we?



Getting beyond data constraints

- **Fine-tuning:** training a pre-trained model for a specific task
- But, what if there is little to no labeled data?
- **N-shot learning:** zero-shot, few-shot, and multi-shot

Transfer learning

- Learn from one task and transfer to related task
- Transferring knowledge from piano to guitar
 - Reading musical notes
 - Understanding rhythm
 - Grasping musical concepts
- N-shot learning
 - Zero-shot - no task-specific data
 - Few-shot - little task-specific data
 - Multi-shot - relatively more training data



Zero-shot learning

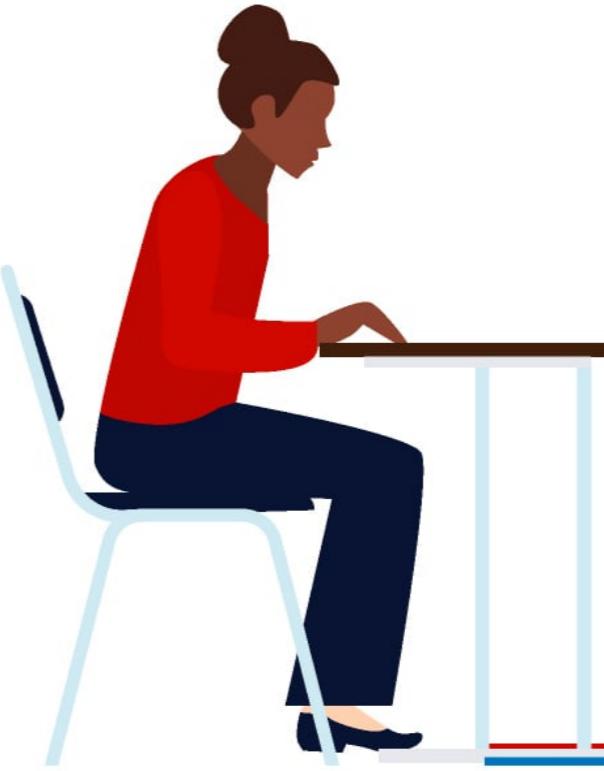
- No explicit training
- Uses language understanding and context
- Generalizes without any prior examples



¹ Freepik

Few-shot learning

- Learn a new task with a few examples
- Prior knowledge to answer new question



- One-shot learning: fine-tuning from one example

Multi-shot learning

- Requires more examples than few-shot
- Previous tasks, plus new examples
- For example, a model trained on Golden Retriever



¹ Freepik

Multi-shot learning

- Model output: Labrador Retriever
- Saves time in collecting and labeling data
- No compromise on accuracy



¹ Freepik

Building blocks so far

- Data preparation workflow
- Fine-tuning
- N-shot learning techniques
- Next up: pre-training

Let's practice!

LARGE LANGUAGE MODELS (LLMS) CONCEPTS