Next Token Prediction

Building ChatGPT from Scratch (Conceptually)

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Overview of the Journey

Today we will build a Language Model from scratch.

1. **The "Autocomplete" Game:** Intuition.
2. **Level 1: Bigrams:** Just counting letters.
3. **Level 2: Embeddings:** Representing meaning.
4. **Level 3: Neural Networks (MLP):** Learning patterns.
5. **Level 4: RNNs:** Adding memory (briefly).
6. **Level 5: Transformers:** The "Attention" Revolution.
7. **Real World:** How ChatGPT actually works.

Part 1: The Intuition

The Core Problem

Deep Learning, at its heart, often answers one simple question:

"Given what I have seen so far, what comes next?"

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This is a **Sequence Modeling** problem.

The "Autocomplete" Game

Let's play. Guess the next word:

Sequence: "New Delhi is the capital of ____"
Your Brain: "India" (100% confidence)

Sequence: "I want to eat ____"
Your Brain: "Pizza"? "Apples"? (Uncertainty)

> **Key Insight:** Language modeling is about assigning **probabilities** to the next token.

It's Just Prediction!

You might think ChatGPT "knows" physics or history.
Actually, it just predicts the next word.

- **Input:** "F = m"
- **Prediction:** "a" (Newton's Law)
- **Input:** "To be or not to"
- **Prediction:** "be" (Shakespeare)

If you predict well enough, you **appear** intelligent.

Part 2: The "Counting" Era (Bigrams)

The Simplest Model: Bigrams

Imagine we want to generate Indian names like `aabid`, `zeel`, etc.
Let's look at the dataset: `["aabid", "zeel"]`.

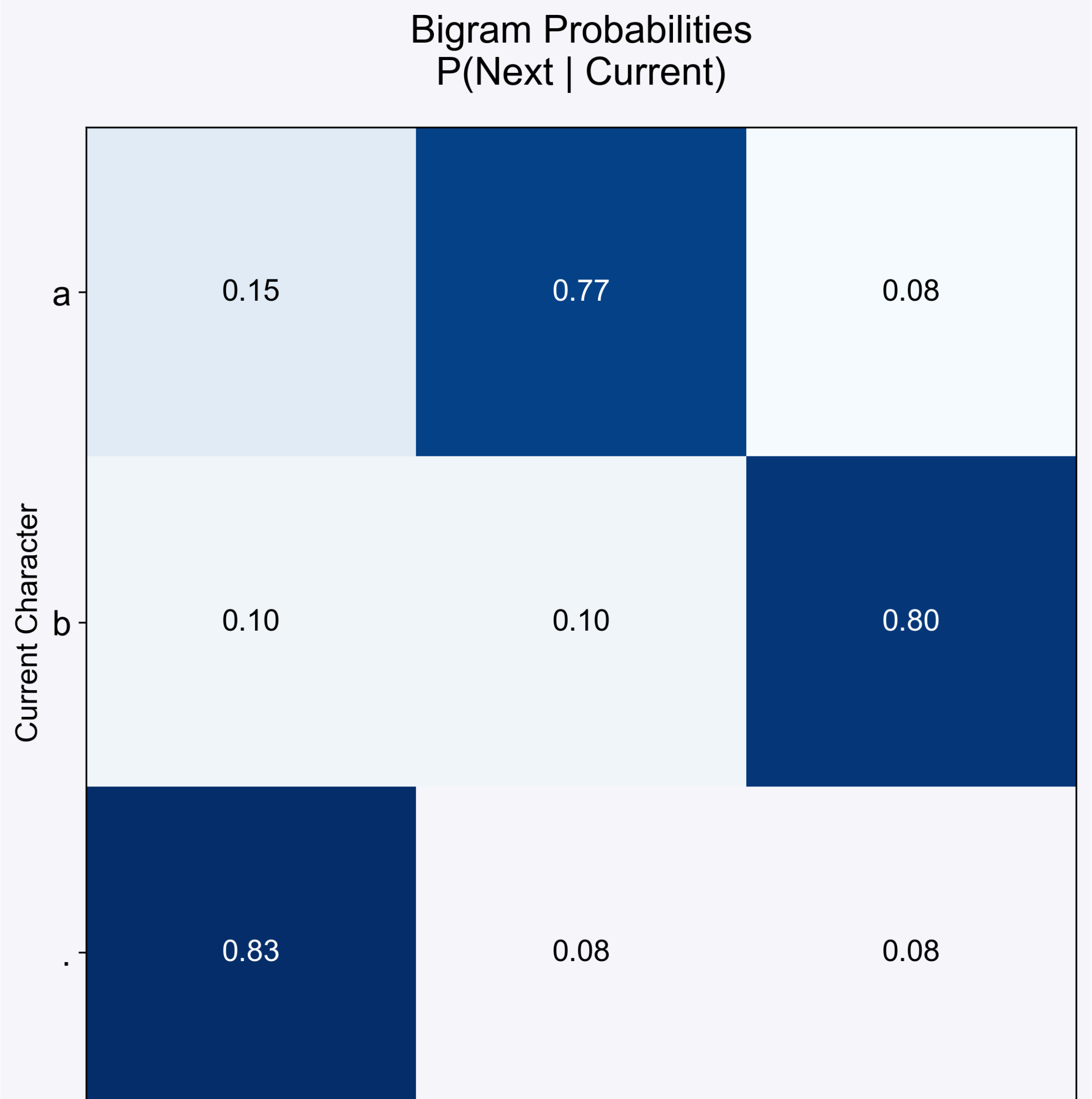
Idea: Only look at the **last character**.
If I see `a`, what usually comes next?

- In `aabid`: `a` -> `a`, `a` -> `b`. (50% each)

This is a **Bigram** (2-gram) model.

Visualizing Bigram Probabilities

We can build a huge lookup table by just counting.



Generating with Bigrams

1. Start with `.` (start token).
2. Look at row `.`. High prob for `a`, `z`.
3. Roll dice -> Get `a`.
4. Look at row `a`.
5. Roll dice -> Get `b`.
6. Repeat until `.` (end token).

Result: `abid`, `zel`, `aab`. (It makes decent syllables!)

Why Counting Fails

What if we want to write a sentence?

`"The quick brown fox jumps..."`

If I only see `fox`, I might predict `runs` or `eats`.
I **forgot** that the sentence started with `"The quick..."`!

- **Bigram:** Context = 1 char. (Too small)
- **Trigram:** Context = 2 chars.
- **N-gram:** Context = N chars?

The Curse of Dimensionality

Why not just count 10-grams? (Last 10 characters).

- **1-gram table:** 26 rows.
- **2-gram table:** $26^2 = 676$ rows.
- **3-gram table:** $26^3 = 17,576$ rows.
- **10-gram table:** $141,000,000,000,000$ rows!

Impossible! We need a better way than counting. We need to **approximate**.

Part 3: Representing Meaning (Embeddings)

How do computers read?

Computers only understand numbers.

Option A: **One-Hot Encoding**

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Problem: These vectors are **Orthogonal**.

Dot Product(`a`, `b`) = 0.

The computer thinks `a` and `b` are completely different. It doesn't know they are both letters!

Option B: Dense Embeddings

Let's represent each character as a list of **learnable attributes**.
Maybe:

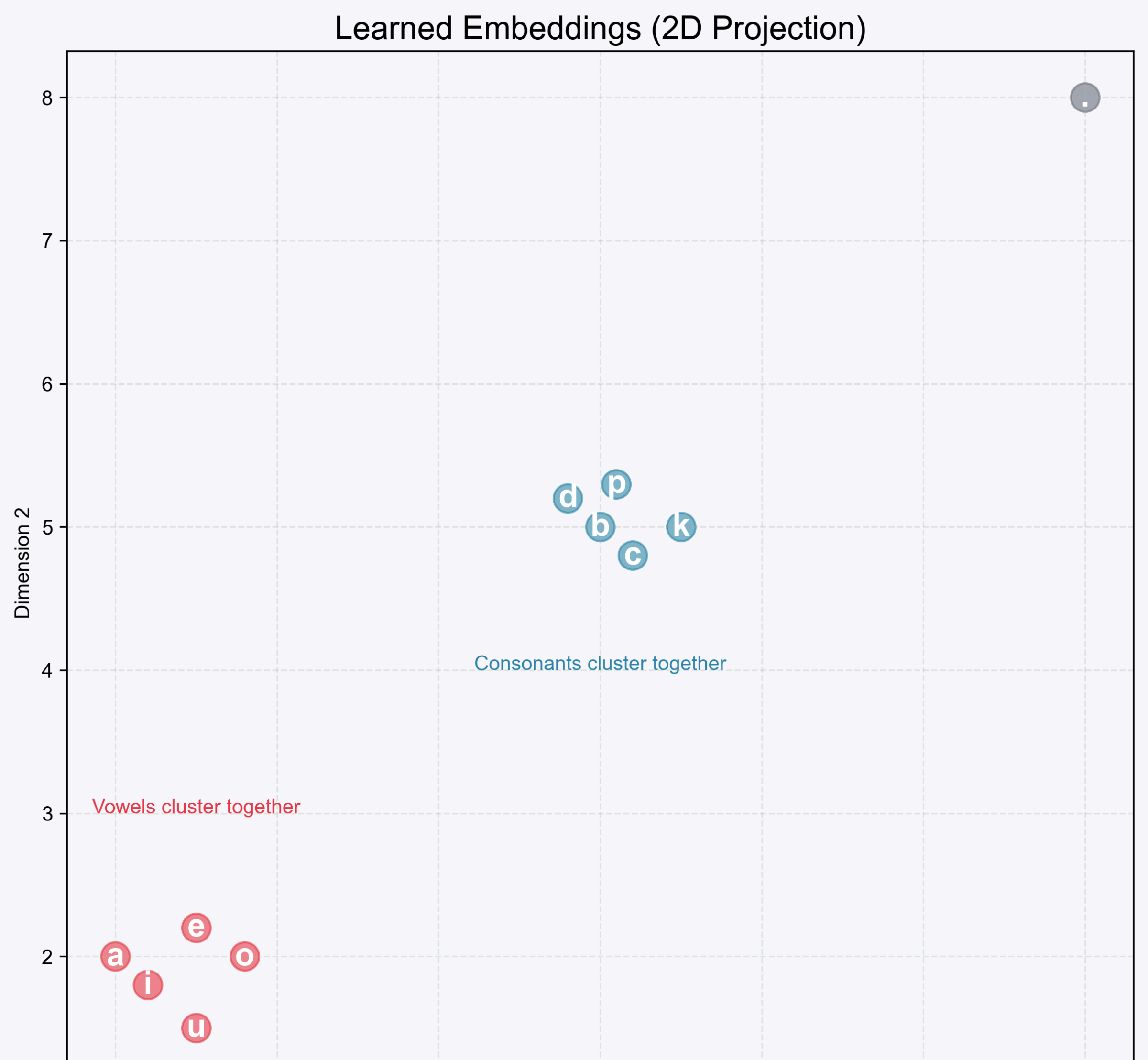
- Dim 1: "Is it a vowel?"
- Dim 2: "Is it a common ending?"

`a` = `[0.9, 0.1]`
`e` = `[0.8, 0.2]`
`b` = `[-0.5, 0.1]`

Now, `a` and `e` are **mathematically close**!

The Latent Space

If we train a model, these embeddings organize themselves automatically.



Part 4: The Neural Network (MLP)

Moving to "Deep Learning"

Instead of a lookup table, let's use a **Multi-Layer Perceptron (MLP)**.

Goal: Predict $P(\text{next}|\text{context})$ using a function.

$$y = f(x; W)$$

- x: Context (e.g., 3 previous characters).
- W: Weights (The "Brain").
- y: Probabilities.

The Sliding Window

We create a dataset by sliding a window over text.

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The Architecture

1. **Lookup:** Get embeddings for `a`, `a`, `b`.
2. **Concat:** Merge them into one big vector.
3. **Hidden Layer:** Mix them (Feature extraction).
4. **Output:** Softmax (Convert to probability).

The Architecture Diagram

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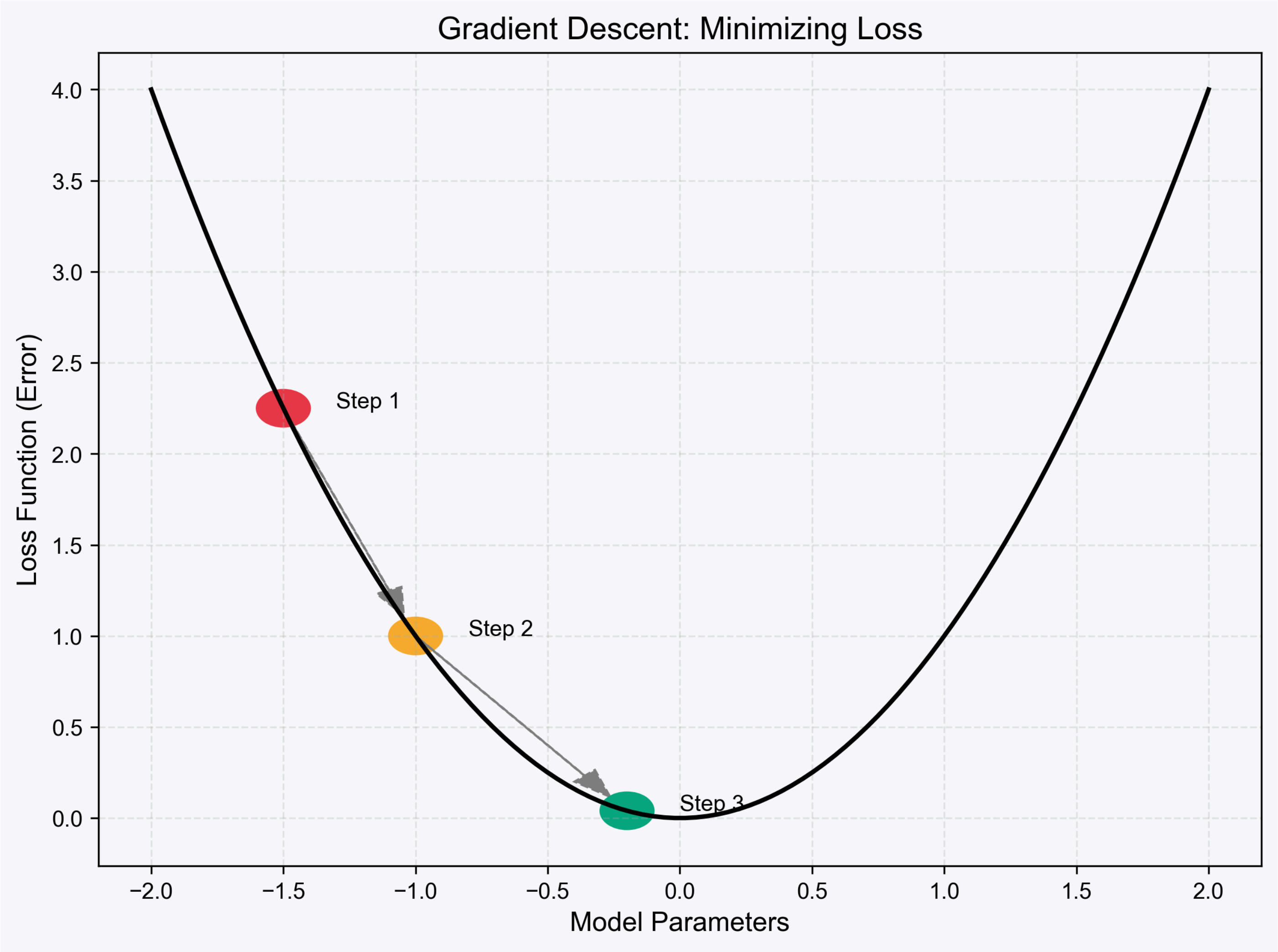
How does it learn? (Training)

We start with random weights. The model is stupid.
It predicts `z` when the answer is `i`.

We calculate the **Loss** (Error).
Then we minimize it using **Gradient Descent**.

Minimizing Loss



We "slide down the hill" to find the best weights.

This updates both the **Weights** and the **Embeddings**!

Part 5: The "Context" Bottleneck

The Problem with Fixed Windows

Our MLP has a fatal flaw.
It has a **Fixed Block Size** (e.g., 3 characters).

It can **never** see further back than 3 steps.

The "Alice" Example

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The model sees `...with the ?`.
It has **no idea** Alice is holding a key. The key fell off the "Window".

Attempted Solution: RNNs

Recurrent Neural Networks (RNNs) try to fix this by keeping a "Memory".

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Issue: For long sentences, the memory gets "muddy".
It's like the "Telephone Game". By the end, the message is lost.
(Vanishing Gradient Problem).

Part 6: The Revolution (Transformers)

Enter Attention

What if, instead of a fixed window or a fading memory...

We could just **look back** at everything?

Attention Mechanism:

"I am at step 10. I can 'attend' to step 1, 5, or 9 depending on what is important."

The "Searchlight" Analogy

> **Fixed Window (MLP):** Reading with tunnel vision. **RNN:** Reading while trying to memorize everything. **Attention:** Reading with a highlighter and a search engine.

When the model sees `"it"`, it asks: **"What object was mentioned before?"**
And it finds `"animal"`.

Attention Diagram

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This "connection" allows the model to handle contexts of thousands of words!

How Attention Works (Q, K, V)

It uses a "Database Lookup" logic.

1. **Query (Q):** What am I looking for? ("Holding object")
2. **Key (K):** What does this word define? ("Alice", "Door")
3. **Value (V):** The actual content.

Score = Match(Q, K).

QKV Visualized

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In ChatGPT, this happens **billions** of times in parallel!

Part 7: From Theory to ChatGPT

Scaling Up

We built a character-level model.
ChatGPT is the **same thing**, just bigger.

- **Tokens:** Not characters, but sub-words.
- **Layers:** Not 1 hidden layer, but 96 layers.
- **Heads:** Not 1 attention head, but 96 heads.
- **Data:** The entire internet.

Tokenization

We don't use characters (too slow) or words (too many).

We use **Tokens** (Sub-words).

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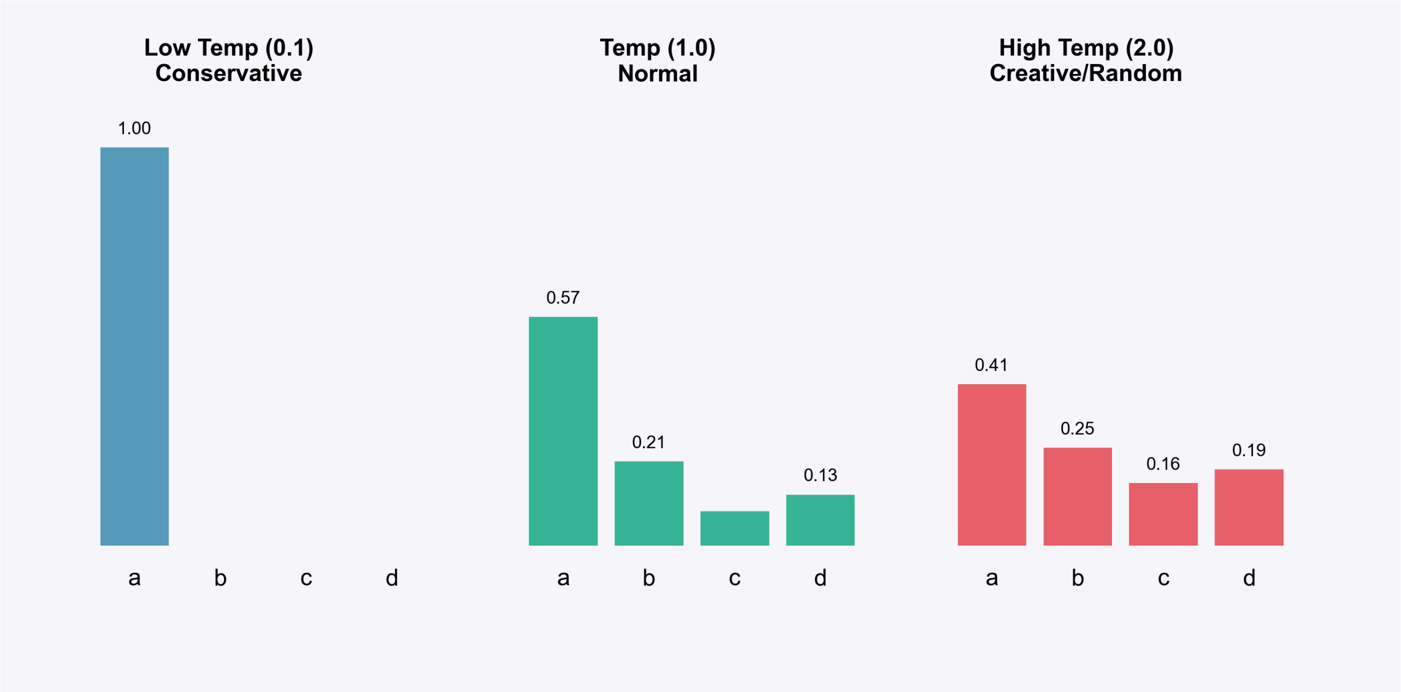
Sampling: The "Creativity" Knob

When ChatGPT generates, it picks from the probabilities.

We can control this with **Temperature**.



The Sampling Tree

Because we sample, we can get different stories every time!

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Summary: The Recipe

To build a modern LLM:

1. **Input:** Massive text data.
2. **Tokenize:** Convert to numbers.
3. **Embed:** Learn meaning.
4. **Model:** Transformer (Attention) to predict next token.
5. **Train:** Minimize Cross-Entropy Loss on GPUs for months.
6. **RLHF:** Fine-tune it to be helpful (not covered today).

Resources

1. **Andrej Karpathy:** "Neural Networks: Zero to Hero" (YouTube).
2. **Jay Alammar:** "The Illustrated Transformer".
3. **NanoGPT:** Karpathy's code repo to build this in 100 lines of Python.

Thank You

"The best way to predict the future is to create it."

Questions?