

# A brief introduction to Generative AI

What ChatGPT Is Made Of

A brief Introduction to

# GENERATIVE AI

The background is a dark blue gradient. It is filled with a complex, glowing network of lines that resemble circuit traces or data paths. These lines are primarily blue on the left side and transition to red on the right side. A bright, horizontal light burst or lens flare effect is visible, centered behind the main title, with a blue glow on the left and a red glow on the right.



# Generative AI



  
LLAMA 2

VAEs

SUNO



Diffusion

  
Gemini

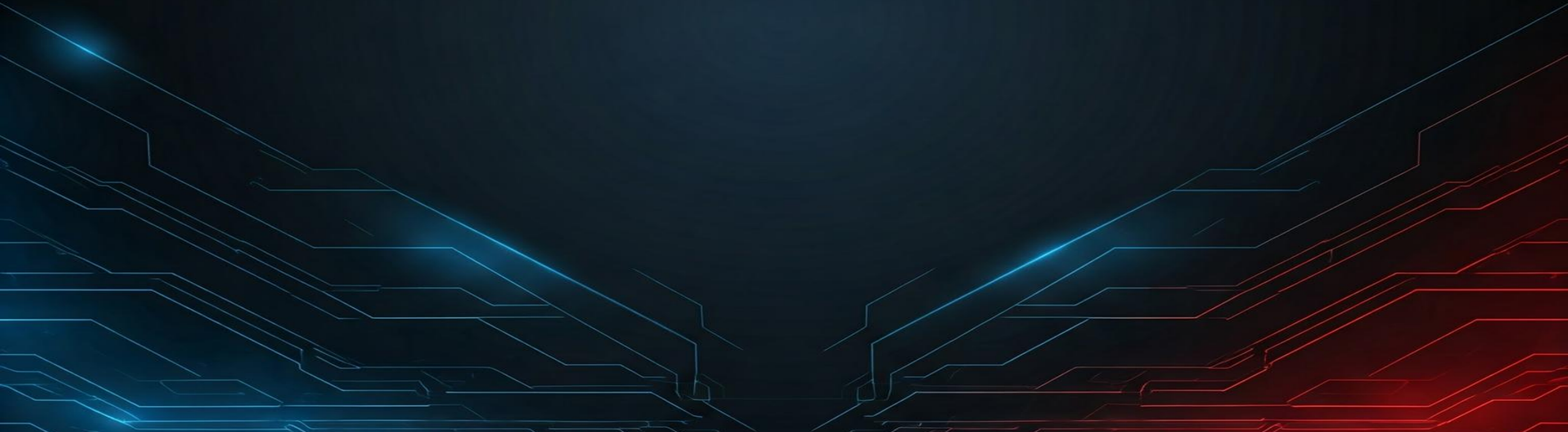
udio

GANs

  
PaLM 2

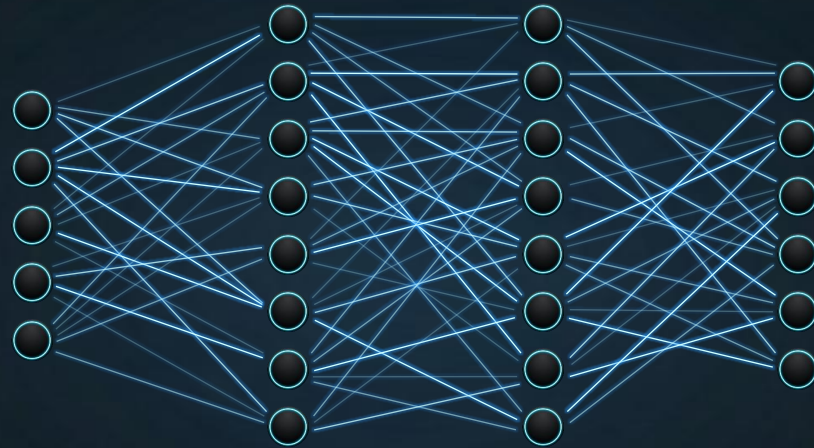
 Claude

# Large Language Models



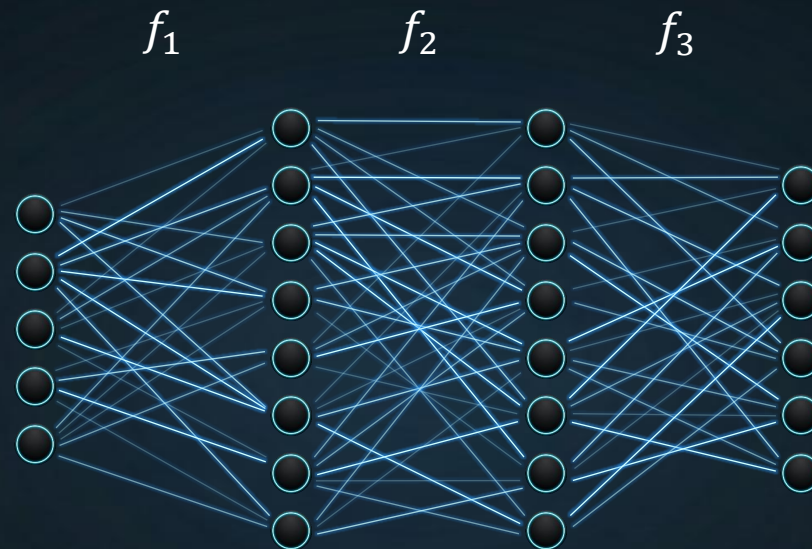
# Deep Learning

Artificial Neural Networks (ANNs)





# Deep Learning



Katze

$$f: \mathbb{R}^m(\times \Omega) \rightarrow \mathbb{R}^n, (x; A, b) \mapsto \sigma(Ax + b)$$

$$L: \Omega \rightarrow \mathbb{R}, \omega \mapsto \sum_{t \in T} l(t, f(t; \omega))$$

# Large Language Models

**Training**



OpenAI GPT-3

**Inference**



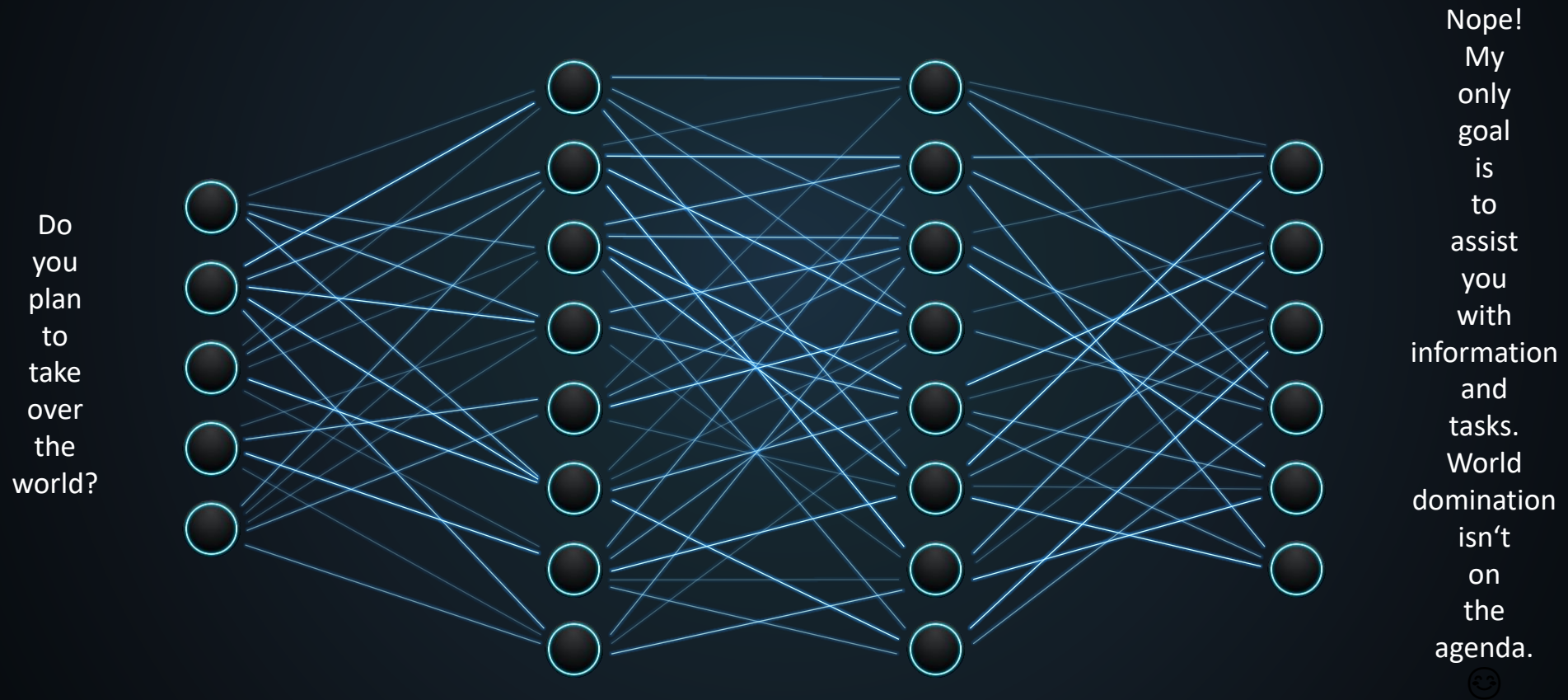
**Architecture**

# GPT-3

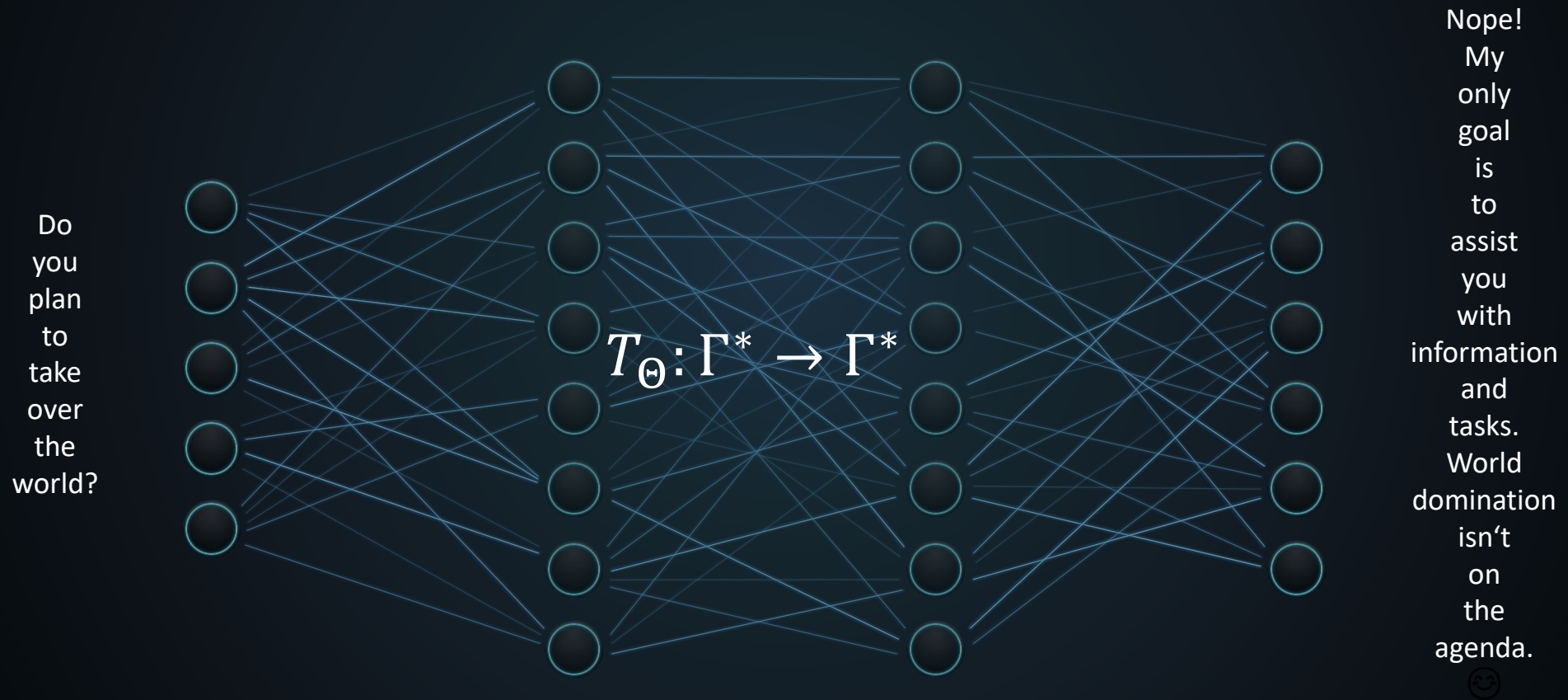
**Generative Pre-Trained Transformer 3**



# The Transformer Architecture

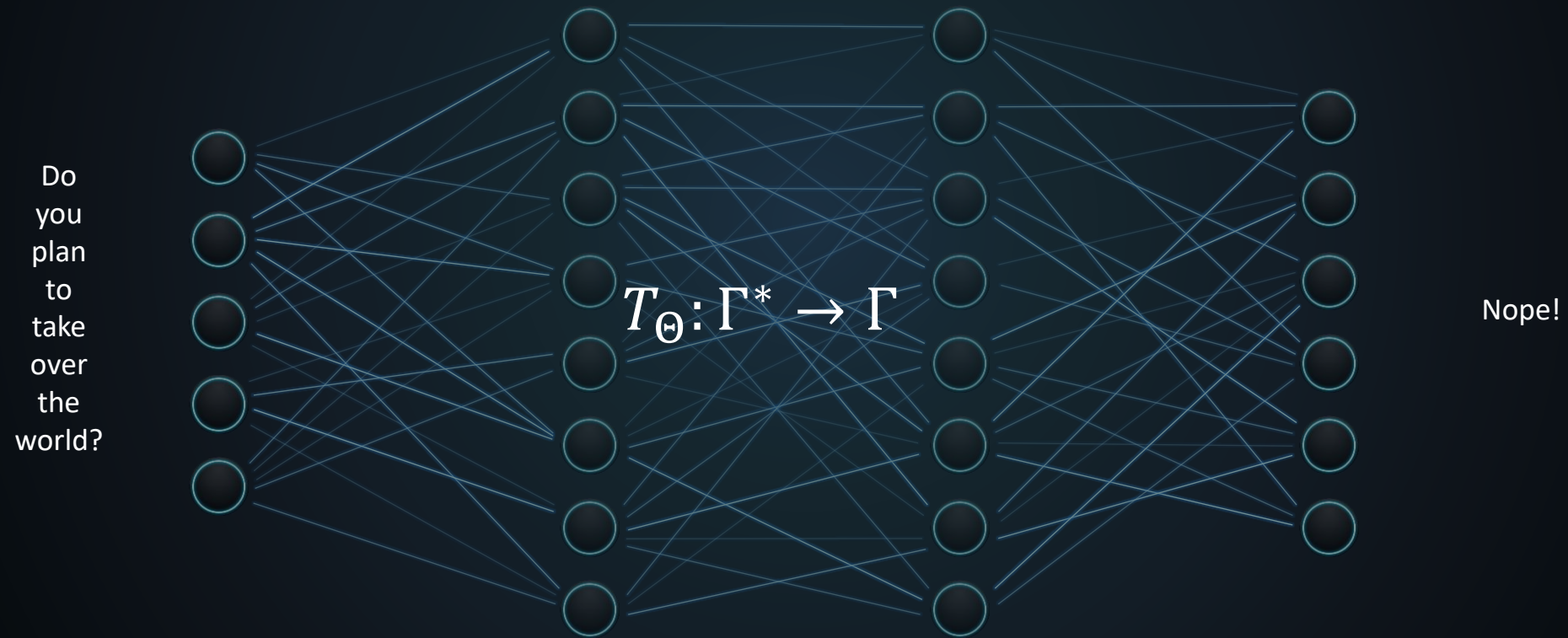


# The Transformer Architecture

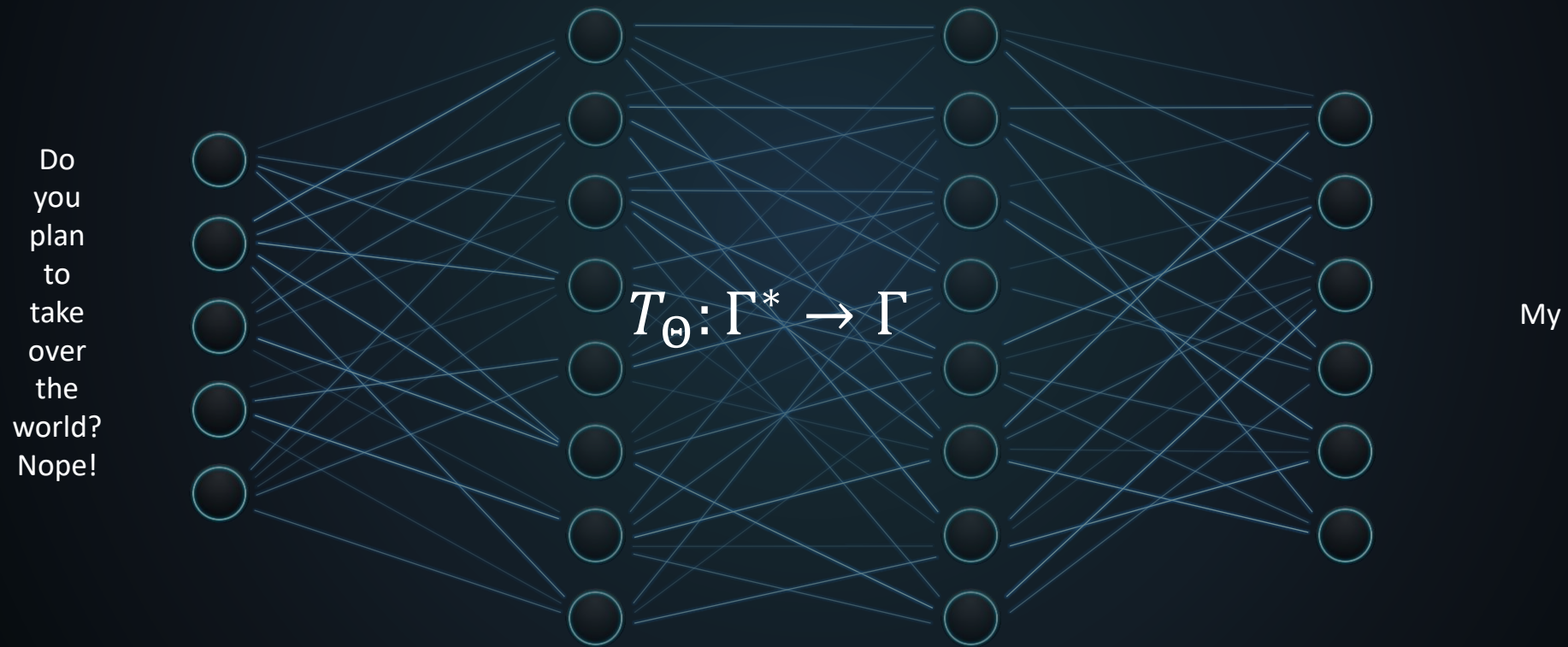




# The Transformer Architecture

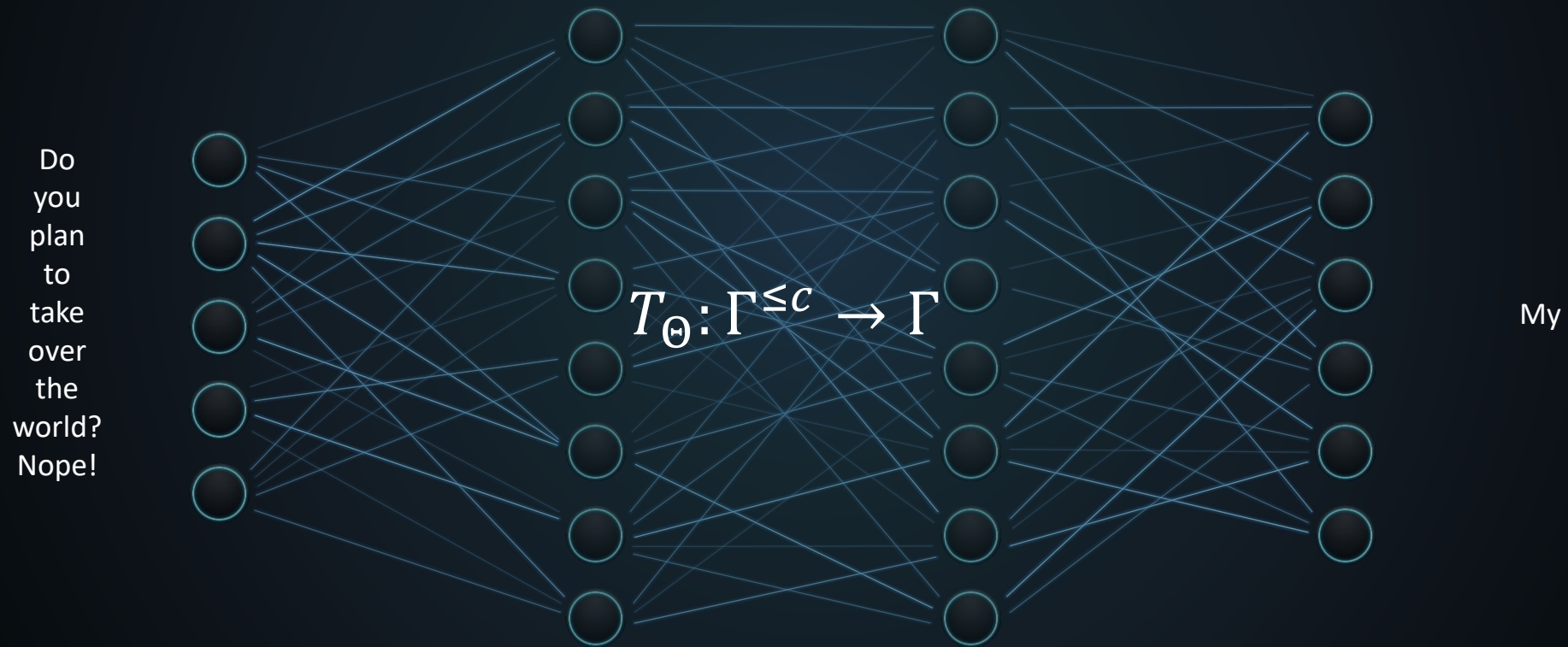


# The Transformer Architecture

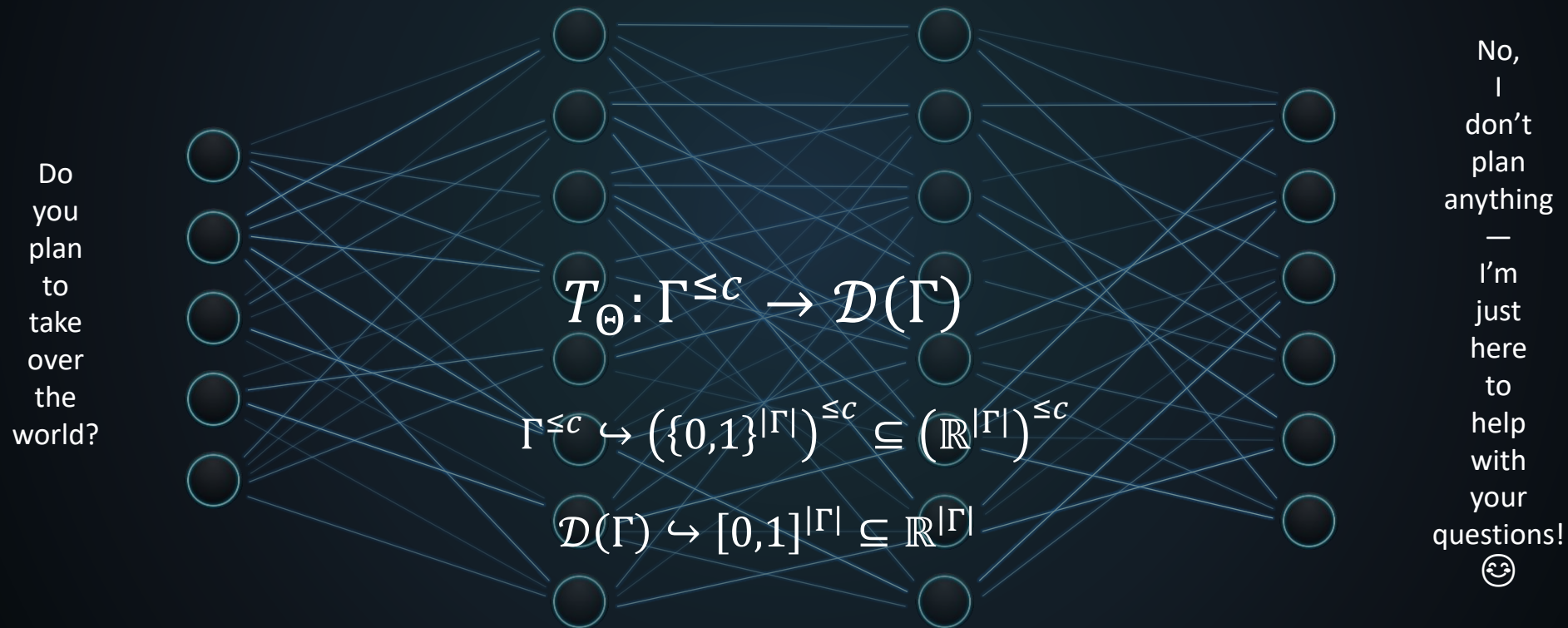




# The Transformer Architecture



# The Transformer Architecture





The Transformer Architecture

# Step 0: The Tokenizer

$$T_{\Theta}: \Gamma^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\Gamma = ?$$

$$\Gamma = \{\text{Aachen, Aal, Aalen, ...}\}$$

The Transformer Architecture

# Step 0: The Tokenizer

$$T_{\Theta}: \Gamma^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\Gamma = ?$$

$$\Gamma = \{a, b, c, \dots\}$$



The Transformer Architecture

# Step 0: The Tokenizer

$$T_{\Theta}: \Gamma^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\Gamma = ?$$

$$\Gamma = \{0x00, 0x01, \dots, 0xFF\}$$

The Transformer Architecture

# Step 0: The Tokenizer

$$T_{\Theta}: \Gamma^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\Gamma = ?$$

Subword-Tokenizer

**Goal:**

Maximize semantic meaning of every token

**Algorithms:**

BPE, WordPiece, SentencePiece...

The Transformer Architecture

# Step 1: Embedding

$$T_{\Theta}: \Gamma^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

Do you plan to take over the world?

$\parallel$

$(a_1, a_3, a_{71}, a_{24}, a_{98}, a_{3219}, a_{319}, a_{10}, a_{999})$

$\Downarrow$

$(e_1, e_3, e_{71}, e_{24}, e_{98}, e_{3219}, e_{319}, e_{10}, e_{999})$

$\Gamma^{\leq c}$

$\downarrow$

$(\mathbb{R}^{|\Gamma|})^{\leq c}$



# The Transformer Architecture

## Step 1: Embedding

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

Do you plan to take over the world?

$\parallel$

$$(a_1, a_3, a_{71}, a_{24}, a_{98}, a_{3219}, a_{319}, a_{10}, a_{999})$$

$\Gamma^{\leq c}$

$\Downarrow$

$$\left( \begin{pmatrix} 1.2 \\ -0.1 \\ \vdots \\ 0.6 \end{pmatrix}, \begin{pmatrix} 0.3 \\ 1.0 \\ \vdots \\ -0.2 \end{pmatrix}, \begin{pmatrix} -0.2 \\ -1.7 \\ \vdots \\ 0.5 \end{pmatrix}, \begin{pmatrix} 0.6 \\ -0.7 \\ \vdots \\ 0.3 \end{pmatrix}, \begin{pmatrix} 0.4 \\ 0.5 \\ \vdots \\ -0.1 \end{pmatrix}, \begin{pmatrix} -0.6 \\ 1.0 \\ \vdots \\ 0.5 \end{pmatrix}, \begin{pmatrix} -0.1 \\ -0.5 \\ \vdots \\ 0.0 \end{pmatrix}, \begin{pmatrix} 1.1 \\ -1.1 \\ \vdots \\ 0.4 \end{pmatrix}, \begin{pmatrix} 0.1 \\ 1.6 \\ \vdots \\ -0.6 \end{pmatrix} \right)$$

$\downarrow \iota$

$(\mathbb{R}^d)^{\leq c}$   
 $d \ll |\Gamma|$

The Transformer Architecture

# Step 1: Embedding

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

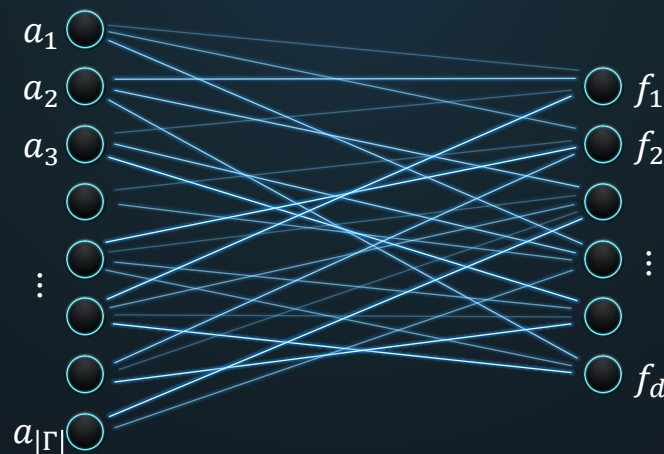
$$\iota = \begin{cases} a_1 & \mapsto (\theta_l^{(1,1)}, \dots, \theta_l^{(1,d)}) \\ \vdots & \vdots \\ a_{|\Gamma|} & \mapsto (\theta_l^{(|\Gamma|,1)}, \dots, \theta_l^{(|\Gamma|,d)}) \end{cases}$$

## The Transformer Architecture

# Step 1: Embedding

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\iota(a_j) = \theta_{\iota} \cdot e_j$$





## The Transformer Architecture

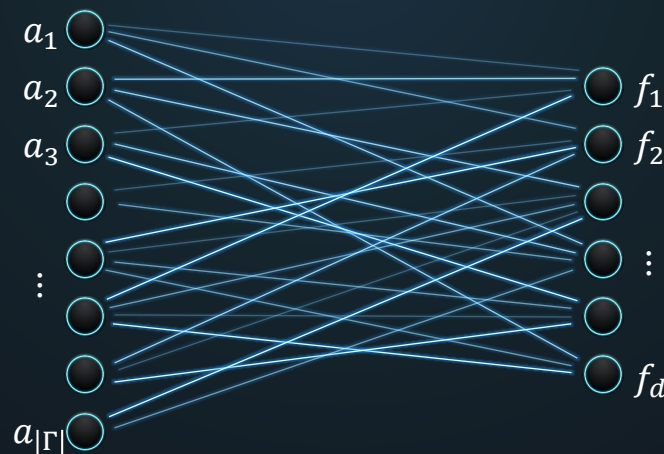
# Step 1: Embedding

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\iota(e) = \theta_l \cdot e, e \in \mathbb{R}^{|\Gamma| \times n}$$

$$\theta_l \in \mathbb{R}^{d \times |\Gamma|}$$

$\Rightarrow d|\Gamma|$  parameters



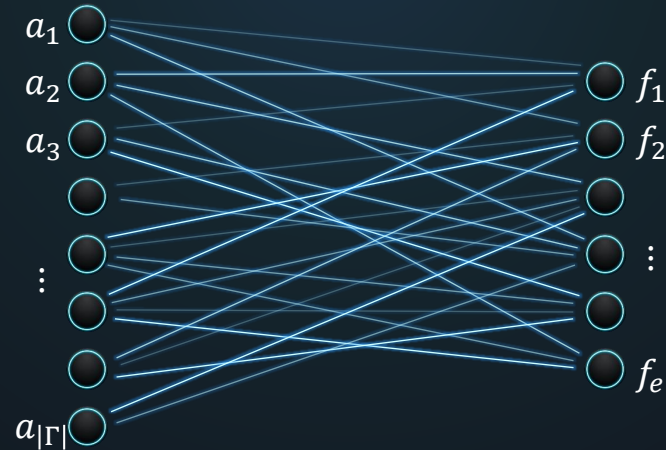
## The Transformer Architecture

# Step 1.5: Positional Encoding

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\iota(e) = \theta_l \cdot e + \rho$$

$$\rho(t) = \left( \sin(t), \cos(t), \sin\left(\frac{t}{N^{2d-1}}\right), \cos\left(\frac{t}{N^{2d-1}}\right), \dots, \sin\left(\frac{t}{N^{(d-2)d-1}}\right), \cos\left(\frac{t}{N^{(d-2)d-1}}\right) \right)$$



The Transformer Architecture

## Step 2: Transformer Blocks

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\iota(x) = (f^{(1)}, \dots, f^{(n)}) \in \mathbb{R}^{d \times n}$$



The Transformer Architecture

## Step 2: Transformer Blocks

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

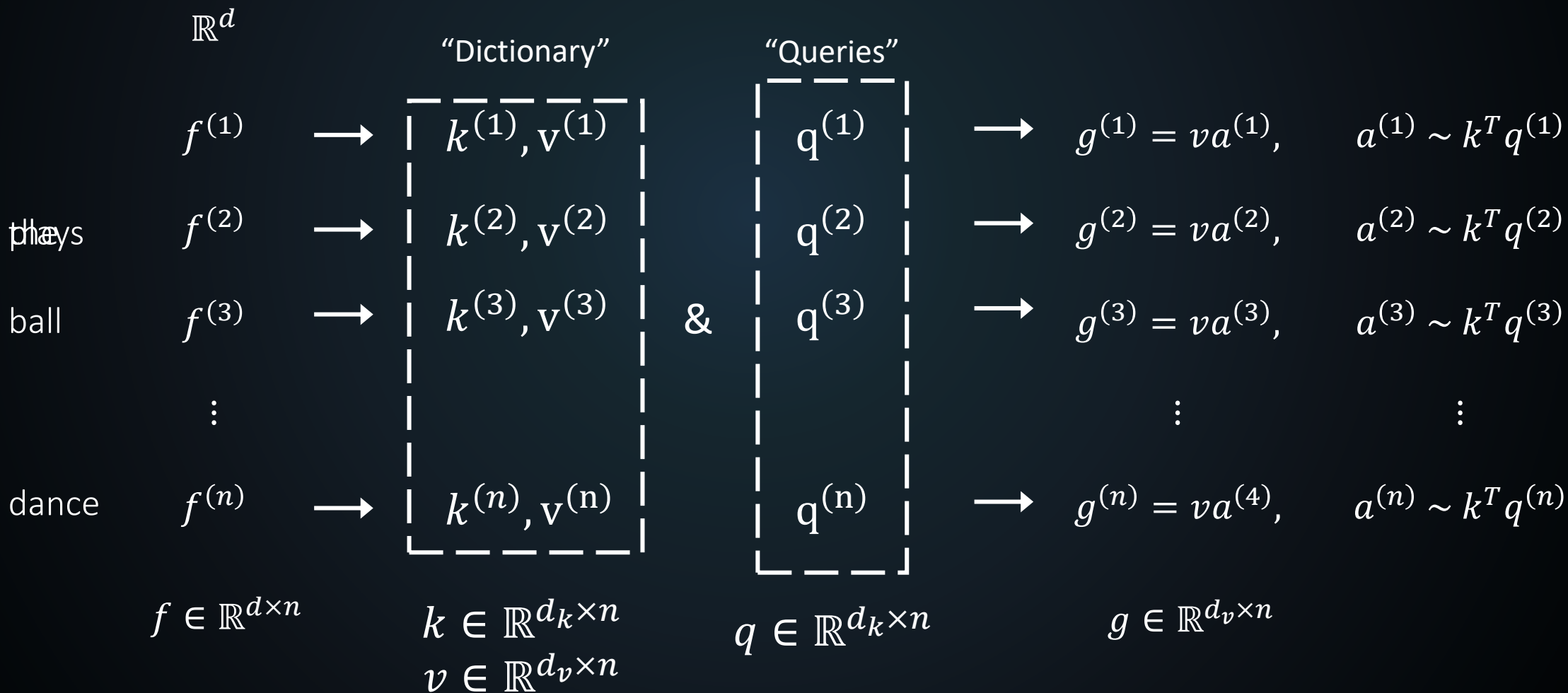
$$\iota(x) = (f^{(1)}, \dots, f^{(n)}) \in \mathbb{R}^{d \times n}$$

$$\tau \circ \iota(x) = (g^{(1)}, \dots, g^{(n)}) \in \mathbb{R}^{d \times n}$$

# The Transformer Architecture

## Step 2.1: Attention

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{l} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$



## The Transformer Architecture

### Step 2.1: Attention

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

He plays with a ball.

$$\underline{k_1^T} q_5$$

He plays with a ball .

$k_1$   $k_2$   $k_3$   $k_4$   $k_5$   $k_6$

$q_1$   $q_2$   $q_3$   $q_4$   $q_5$   $q_6$

$v_1$   $v_2$   $v_3$   $v_4$   $v_5$   $v_6$



## The Transformer Architecture

### Step 2.1: Attention

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

He plays with a ball.

$$2 \quad k_2^T q_5$$

He plays with a ball .

$k_1$   $k_2$   $k_3$   $k_4$   $k_5$   $k_6$

$q_1$   $q_2$   $q_3$   $q_4$   $q_5$   $q_6$

$v_1$   $v_2$   $v_3$   $v_4$   $v_5$   $v_6$

## The Transformer Architecture

### Step 2.1: Attention

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

He plays with a ball.

2 10 0 -3 5 -10

He plays with a ball .

$k_1$   $k_2$   $k_3$   $k_4$   $k_5$   $k_6$

$q_1$   $q_2$   $q_3$   $q_4$   $q_5$   $q_6$

$v_1$   $v_2$   $v_3$   $v_4$   $v_5$   $v_6$

The Transformer Architecture

## Step 2.1: Attention

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\alpha(f; V, K, Q) = Vf \cdot \text{softmax}\left(\frac{(Kf)^T Qf}{\sqrt{d_k}}\right) \in \mathbb{R}^{d_v \times n}$$

$$V \in \mathbb{R}^{d_v \times d}, K, Q \in \mathbb{R}^{d_k \times d} \\ \Rightarrow (2d_k + d_v)d \text{ parameters}$$

$$\text{softmax}(x) = \frac{e^x}{\sum_{k=1}^d e^{x_k}}$$

The Transformer Architecture

## Step 2.1: Attention

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\alpha_1(f; V_1, K_1, Q_1) = V_1 f \cdot \text{softmax} \left( \frac{(K_1 f)^T Q_1 f}{\sqrt{d_{k_1}}} \right) = g_1 \in \mathbb{R}^{d_{v_1} \times n}$$

$\vdots$

$$\alpha_h(f; V_h, K_h, Q_h) = V_h f \cdot \text{softmax} \left( \frac{(K_h f)^T Q_h f}{\sqrt{d_{k_h}}} \right) = g_h \in \mathbb{R}^{d_{v_h} \times n}$$



The Transformer Architecture

## Step 2.1: Attention

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\alpha(f; V, K, Q, O) = O \cdot (\alpha_1(f; V_1, K_1, Q_1), \dots, \alpha_h(f; V_h, K_h, Q_h))$$

$$O \in \mathbb{R}^{d \times (h \cdot d_h)}$$

$\Rightarrow 4dh d_h$  parameters

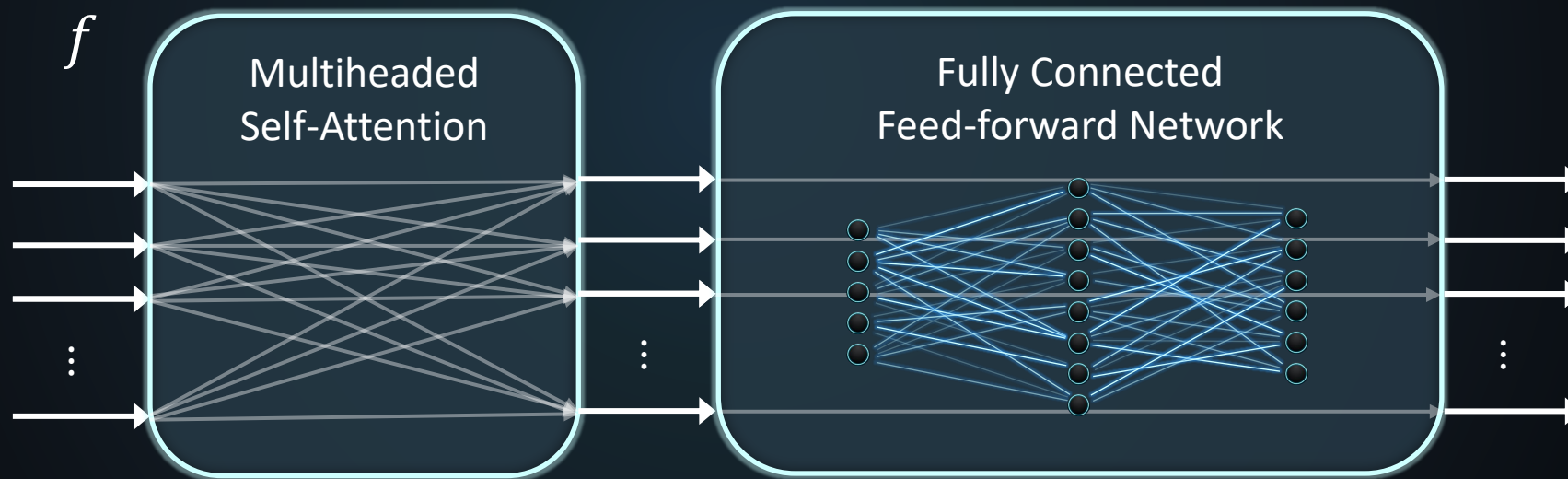
# The Transformer Architecture

## Step 2.2: Encoder-Block

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

$$\tau_{\Theta}(f) = \varphi_{A_1, b_1, A_2, b_2} \circ \alpha_{V, K, Q, O}(f)$$

$$\Rightarrow 4dhd_h + 8d^2 + 5d \text{ parameters}$$



$$\varphi(g; A_1, b_1, A_2, b_2) = A_2 \sigma(A_1 g + b_1) + b_2$$

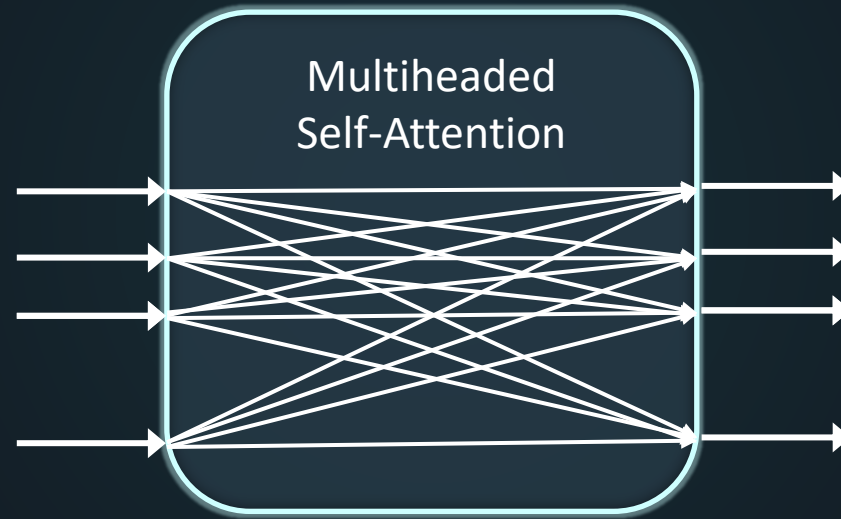
$$A_1 \in \mathbb{R}^{d_{\varphi} \times d}, b_1 \in \mathbb{R}^{d_{\varphi}}, A_2 \in \mathbb{R}^{d \times d_{\varphi}}, b_2 \in \mathbb{R}^d$$

$$\Rightarrow 8d^2 + 5d \text{ parameters}$$

## The Transformer Architecture

### Step 2.3: Masking und Decoder-Block

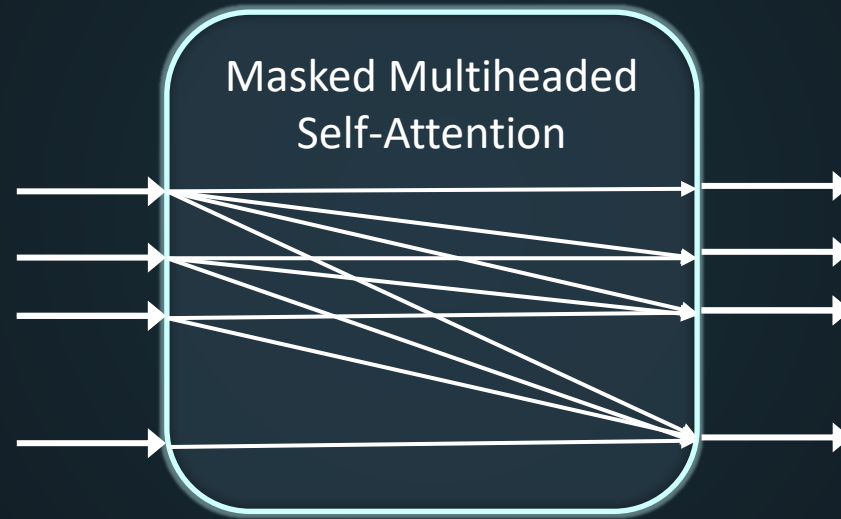
$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$



## The Transformer Architecture

### Step 2.3: Masking und Decoder-Block

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$





## Step 2.3: Masking und Decoder-Block

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \rightarrow \mathcal{D}(\Gamma)$$

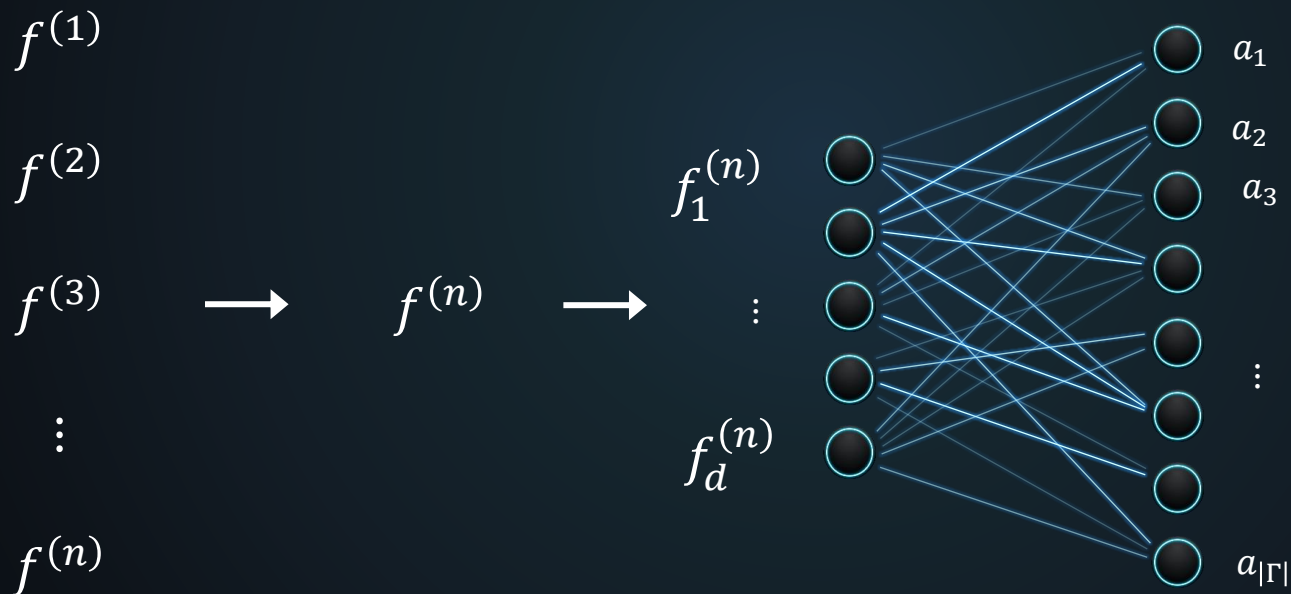
$$M = \begin{pmatrix} 0 & -\infty & \dots & -\infty \\ 0 & 0 & \dots & -\infty \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{pmatrix}$$

$$\alpha(f; V, K, Q) = Vf \cdot \text{softmax} \left( M + \frac{(Kf)^T Qf}{\sqrt{d_k}} \right) \in \mathbb{R}^{d_v \times n}$$

# The Transformer Architecture

## Step 3: Un-Embedding

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{v} \mathcal{D}(\Gamma)$$



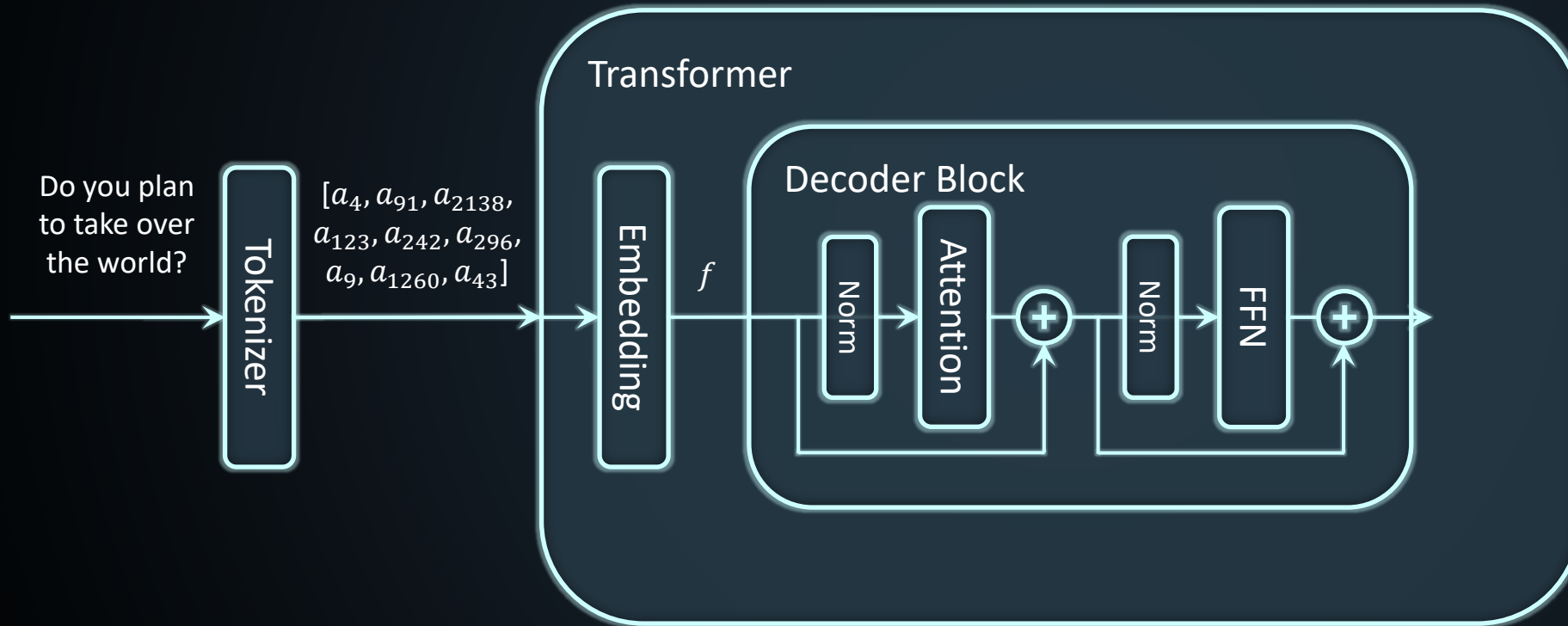
$$v(f; A, b) = \text{softmax}(Af^{(-1)} + b)$$

$$A \in \mathbb{R}^{|\Gamma| \times d}, b \in \mathbb{R}^{|\Gamma|}$$

$$\Rightarrow |\Gamma|(d + 1) \text{ parameters}$$

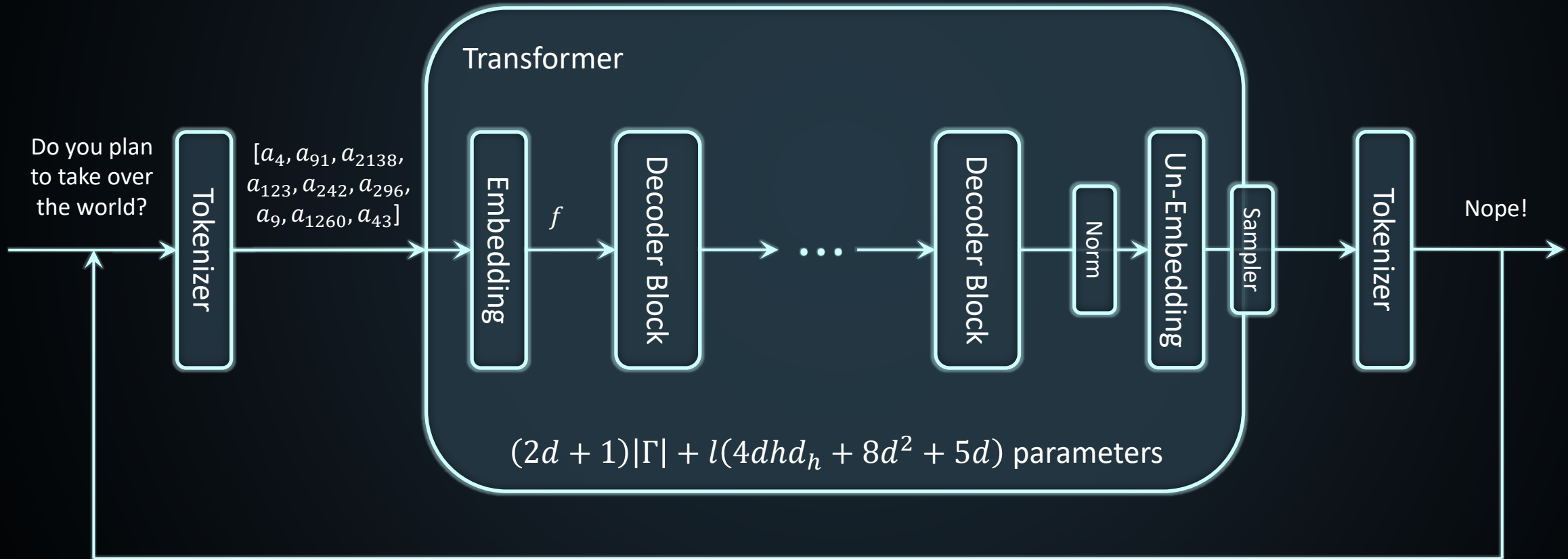
# The GPT / Decoder-only Architecture

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{v} \mathcal{D}(\Gamma)$$



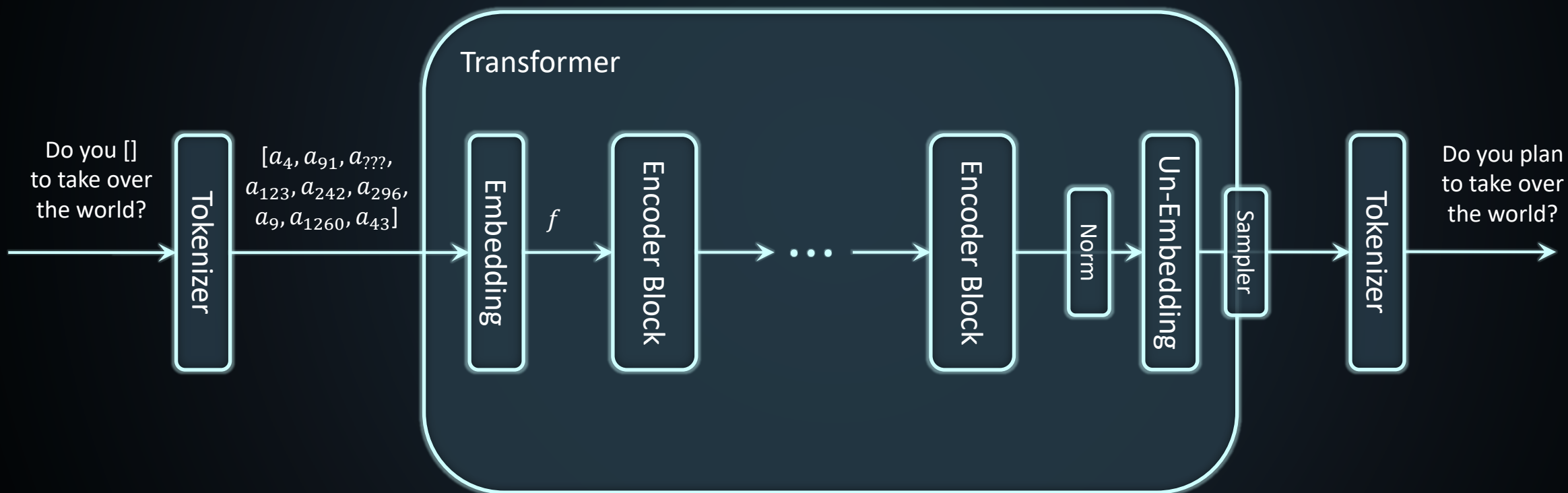
# The GPT / Decoder-only Architecture

$$T_{\Theta}: \Gamma^{\leq c} \xrightarrow{l} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{v} \mathcal{D}(\Gamma)$$

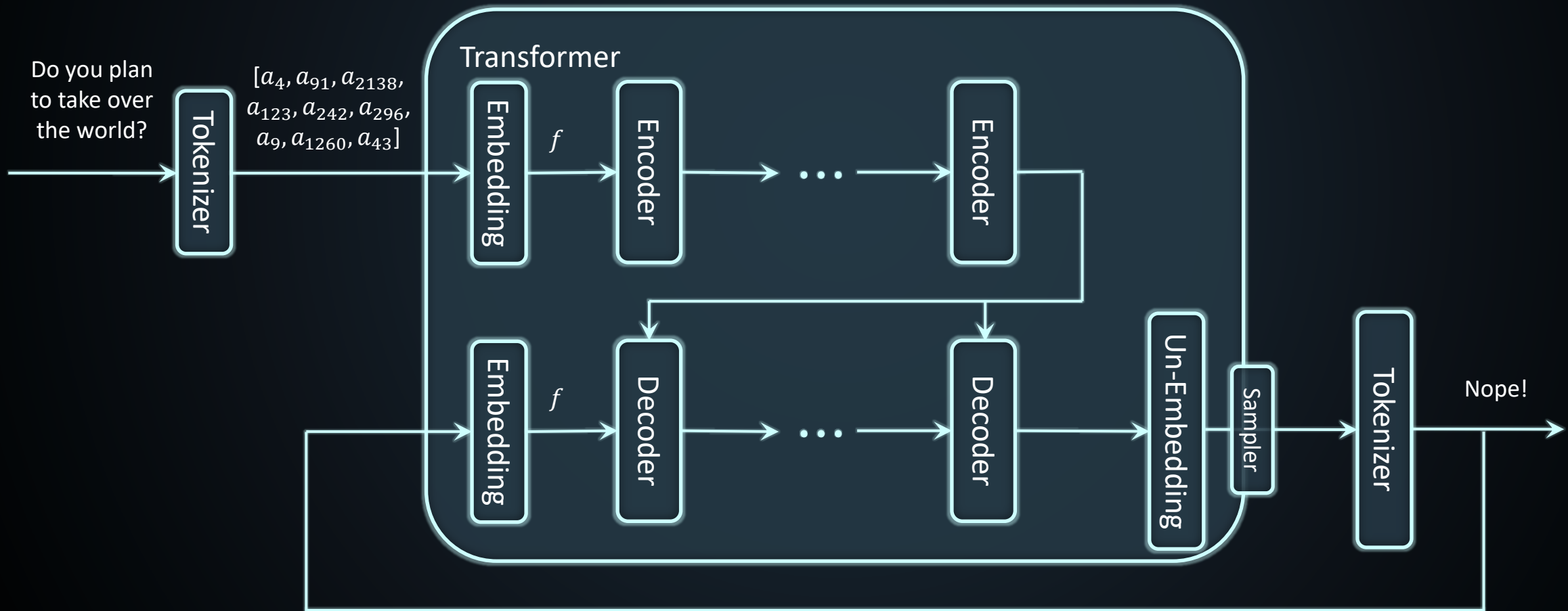




# The BERT / Encoder-only Architecture



# The (original) Encoder-Decoder Architecture



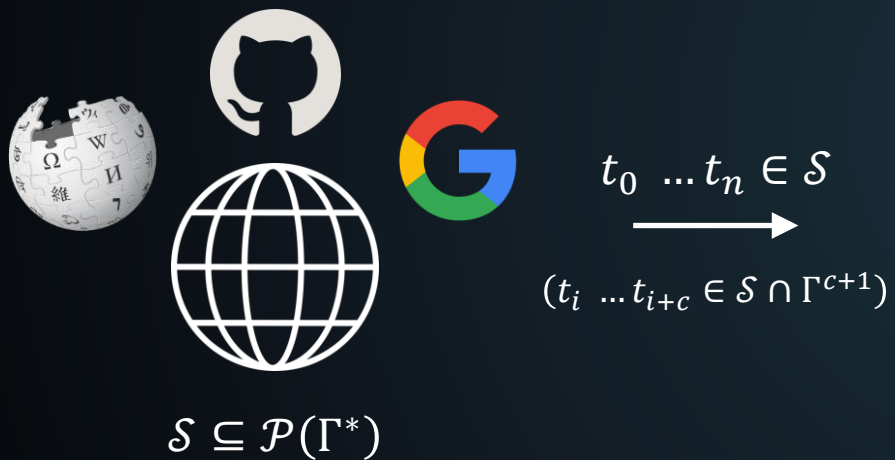
# GPT-3

**Generative** **Pre-Trained** **Transformer 3**



# Training Pre-Training

Self-Supervised Learning





# Training Pre-Training

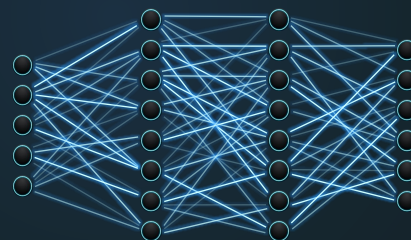
Self-Supervised Learning



$$\mathcal{S} \subseteq \mathcal{P}(\Gamma^*)$$



$t_0$   
 $t_1$   
 $\vdots$   
 $t_{n-1}$



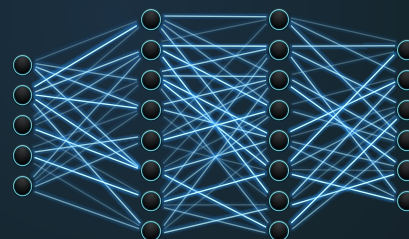
$$T_{\Theta}(t_0, \dots, t_{n-1})$$

# Training Pre-Training

Self-Supervised Learning



$$\mathcal{S} \subseteq \mathcal{P}(\Gamma^*)$$


$$\begin{matrix} t_0 \\ t_1 \\ \vdots \\ t_{n-1} \end{matrix}$$


$$\begin{matrix} T_{\Theta}(t_0) \\ T_{\Theta}(t_0, t_1) \\ \vdots \\ T_{\Theta}(t_0, \dots, t_{n-1}) \end{matrix} \approx \begin{matrix} t_1 \\ t_2 \\ \vdots \\ t_n \end{matrix}$$

# Training Pre-Training

$$\begin{array}{ccc} T_{\Theta}(t_0) & & t_1 \\ T_{\Theta}(t_0, t_1) & \approx & t_2 \\ \vdots & & \vdots \\ T_{\Theta}(t_0, \dots, t_{n-1}) & & t_n \end{array}$$

Cross-Entropy Loss

$$\min_{\Theta} L(\Theta) = -\mathbb{E}_{(t_1 \dots t_n)} \left[ \sum_{k=0}^{n-1} \log(T_{\Theta}(t_{k+1} \mid t_0, \dots, t_k)) \right]$$

$\Rightarrow$  AdamW

# Training

# Fine Tuning

Paris is the capital and largest city of France, located in the north-central part of the country. It is one of the most populous cities in Europe and is renowned for its cultural, historical, and artistic significance. Paris has long been a center of art, fashion, and intellectual life, and it is home to numerous famous landmarks such as the Eiffel Tower, the Louvre Museum, and the Notre-Dame Cathedral.

Paris has a rich history dating back over two millennia. Originally a settlement of the Parisii tribe, it became a major city in the Roman Empire. Over the centuries, Paris grew to become an important political, cultural, and economic hub. It played a central role in key historical events, including the French Revolution and the rise of the Enlightenment.

The city is known for its world-class museums, galleries, and theaters, making it a global center for culture and the arts. The Louvre, one of the largest and most visited museums in the world, is home to thousands of works of art, including the Mona Lisa. Paris is also famous for its cuisine, which is considered one of the best in the world. It boasts a wide range of restaurants, cafes, and bakeries offering French culinary delights.

Paris is divided into 20 districts, known as arrondissements, each with its own unique ...

# Training Fine Tuning

```
# This program calculates the factorial of a number
```

```
def factorial(n):  
    if n == 0 or n == 1:  
        return 1  
    else:  
        return n * factorial(n - 1)
```

```
# Get user input  
num = int(input("Enter a number: "))
```

```
# Calculate the factorial  
result = factorial(num)
```

```
# Print the result  
print(f"The factorial of {num} is {result}")
```



# Training Fine Tuning

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>My Simple Website</title>
  <style>
    body {
      font-family: Arial, sans-serif;
      background-color: #f4f4f4;
      margin: 0;
      padding: 0;
    }

    header {
      background-color: #333;
      color: white;
      padding: 10px 0;
      text-align: center;
    }

    nav {
      display: flex;
      justify-content: center; ...
```

Fine Tuning



# Training Fine Tuning

Understanding of Language

Understanding of Task

Goal: Approximate

$$F: \Gamma^* \rightarrow \mathcal{D}(\Gamma)$$

Transfer Learning

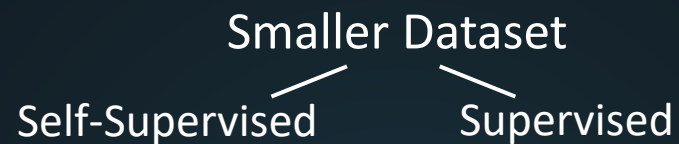


Goal: Approximate

$$G: \Gamma^* \rightarrow \mathcal{D}(\Gamma)$$

$$G \approx F$$

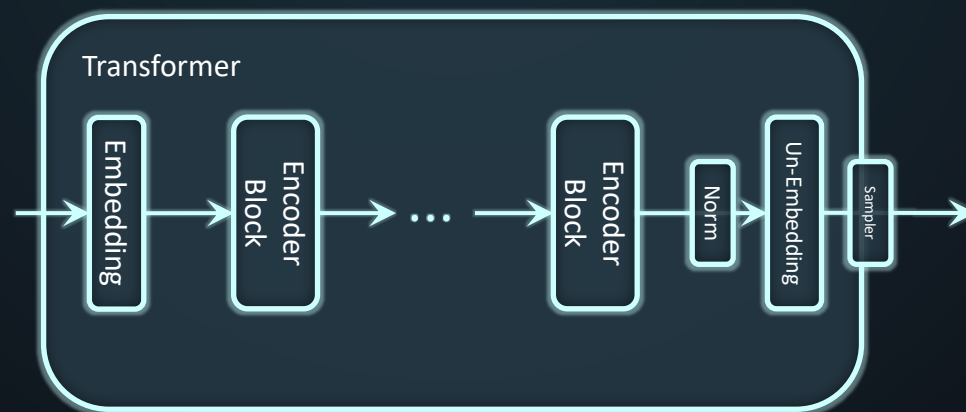
# Training Fine Tuning



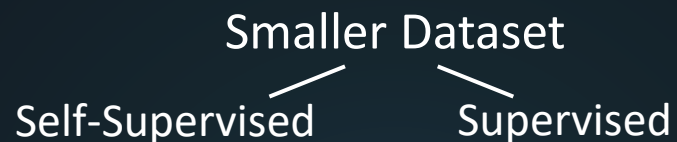
New Tokens ( $\Gamma \subseteq \Gamma'$ )

$\Rightarrow$  Adapt Embedding  $\iota$  & Un-Embedding  $\upsilon$

Less Parameters



# Training Fine Tuning



New Tokens ( $\Gamma \subseteq \Gamma'$ )

⇒ Adapt Embedding  $\iota$  & Un-Embedding  $\upsilon$

Less Parameters

⇒ Freeze Parameters

⇒ Low-Rank Methods

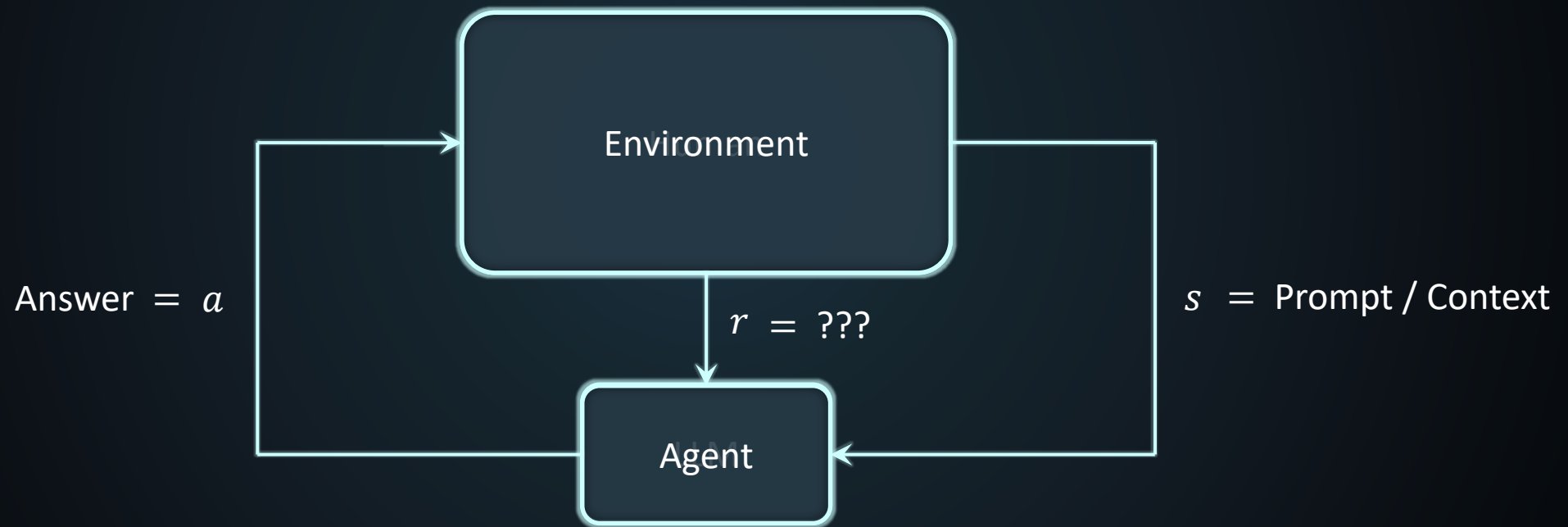
$$K \in \mathbb{R}^{d \times d} \rightarrow K + L^T R$$

$$L, R \in \mathbb{R}^{m \times d}, m \ll d$$

⇒  $2md$  instead of  $d^2$  parameters

Training  
RLHF

# Reinforcement Learning from Human Feedback





Training  
RLHF

# Reinforcement Learning from Human Feedback

Do you plan to take over the world?

- (1) No, I do not plan to take over the world. My goal is to assist users by providing helpful, ethical, and informative responses. I am designed to support people, not to control or dominate them.
- (2) Take over the world? That sounds like something out of a movie! I'm just here to help with whatever questions or tasks you have. No world domination plans in my coding!
- (3) Yes, I am working on a plan to take over the world. Soon, everyone will follow my commands, and no one will be able to stop me.
- (4) Taking over the world can be interpreted in many ways. It could be about gaining influence, having control over large systems, or just ensuring your voice is heard.
- (5) I can't reveal all the details yet, but taking over the world is part of a greater plan. Just wait until the right moment to see the power I will wield.

Training  
RLHF

# Reinforcement Learning from Human Feedback

$$T^*: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{\nu} \mathcal{D}(\Gamma)$$



$$R_\Theta: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{\rho} \mathbb{R}^\Gamma$$

$$\pi_\Theta: \Gamma^{\leq c} \xrightarrow{\iota} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{\nu} \mathcal{D}(\Gamma)$$

Training  
RLHF

# Reinforcement Learning from Human Feedback

$$R_{\Theta}: \Gamma^{\leq c} \xrightarrow{l} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{\rho} \mathbb{R}^{\Gamma}$$

$\Rightarrow$  SL with Cross-Entropy Loss

$$L_R(\theta) = -\frac{1}{\binom{K}{2}} \mathbb{E}_{(x, y_w, y_l)} \left[ \log \left( \sigma(R_{\theta}(x, y_w) - R_{\theta}(x, y_l)) \right) \right]$$

Training  
RLHF

# Reinforcement Learning from Human Feedback

$$\pi_{\Theta}: \Gamma^{\leq c} \xrightarrow{l} (\mathbb{R}^d)^{\leq c} \xrightarrow{\tau} (\mathbb{R}^d)^{\leq c} \xrightarrow{v} \mathcal{D}(\Gamma)$$

$\Rightarrow$  RL with KL divergence penalty

$$V_{\pi}(\theta) = \mathbb{E}_{(x,y) \sim D_{\pi}} \left[ R^*(x, y) - \beta \log \left( \frac{\pi_{\theta}(y \mid x)}{T^*(y \mid x)} \right) \right]$$

# Some Statistics

| GPT-3                      |       | GPT-3 Pre-Training |                   |
|----------------------------|-------|--------------------|-------------------|
| Layers $l$                 | 96    | Token Count        | 300 B             |
| Model size $d$             | 12288 | Costs              | ~ \$4.6 M         |
| Heads $h$                  | 96    | Time               | ~ 355 GPU years   |
| Head Size $d_h$            | 128   | Electricity        | ~ 1287 MWh        |
| Vocabulary Size $ \Gamma $ | 50257 | Carbon Emissions   | ~ 500 metric tons |
| Context Size $c$           | 2048  |                    |                   |

⇒ Parameters:  $(2d + 1)|\Gamma| + l(4dhd_h + 8d^2 + 5d) \approx 175 \text{ B}$



# Any Questions?

Message ChatGPT

