

# Positional Encoding Visualization



## Frequency Patterns Across Dimensions

Low Freq



Mid Freq



High Freq



## Unique Patterns

Each position has **unique encoding pattern**



## Smooth Gradient

Allows model to learn **relative positions**



## Multiple Frequencies

Different **frequencies** for different dimensions



## Low Frequencies

Capture **global position**  
Overall sequence location



## High Frequencies

Capture **local position**  
Fine-grained distinctions



## Magnitude Balance

Magnitude **comparable** to embedding values

Element-wise addition to token embeddings | Preserves both semantic and positional information



## Calculation Example ( $d_{model}=4$ , $\text{max\_len}=8$ )

### Formula

$$PE_{(pos,2i)} = \sin(pos / 10000^{2i/d_{model}})$$

$$PE_{(pos,2i+1)} = \cos(pos / 10000^{2i/d_{model}})$$



Token Embeddings



Positional Encoding



Final Input

$X (8 \times 4)$ 

0.5	-0.3	0.8	-0.2
-0.1	0.7	0.2	0.4
0.9	-0.5	-0.3	0.6
0.3	0.4	-0.7	0.1
-0.6	0.2	0.5	-0.4
0.7	-0.8	0.1	0.3
-0.2	0.6	-0.4	0.8
0.4	-0.1	0.9	-0.5

+

 $PE (8 \times 4)$ 

0.00	1.00	0.00	1.00
0.84	0.54	0.01	1.00
0.91	-0.42	0.02	1.00
0.14	-0.99	0.03	1.00
-0.76	-0.66	0.04	1.00
-0.96	0.28	0.05	1.00
-0.28	0.96	0.06	1.00
0.66	0.75	0.07	0.99

 $X + PE (8 \times 4)$ 

0.50	0.70	0.80	0.80
0.74	1.24	0.21	1.40
1.81	-0.92	-0.28	1.60
0.44	-0.59	-0.67	1.10
-1.36	-0.46	0.54	0.60
-0.26	-0.52	0.15	1.30
-0.48	1.56	-0.34	1.80
1.06	0.65	0.97	0.49



**Key Insight:** Each position gets a unique sinusoidal pattern. Lower dimensions (0,1) use **high frequency** for fine-grained position, while higher dimensions (2,3) use **low frequency** for global position.