

# Rotary Position Embeddings (RoPE)

## Comprehensive Demo and Analysis

RoPE encodes relative position directly into attention dot products through rotation. Each dimension pair defines a 2D subspace with position-dependent rotation.

Key property:  $\langle \text{RoPE}(q,m), \text{RoPE}(k,n) \rangle$  depends only on  $(m-n)$ , making RoPE a true relative position encoding.

Used by: Llama 1/2/3, Mistral, Qwen, Gemma, DeepSeek, and virtually all modern open-weight LLMs.

Random seed: 42  
Number of visualizations: 6  
Examples: 6

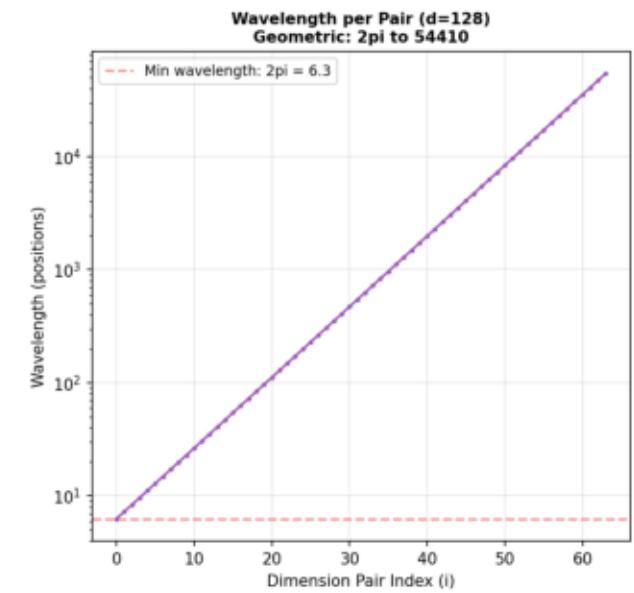
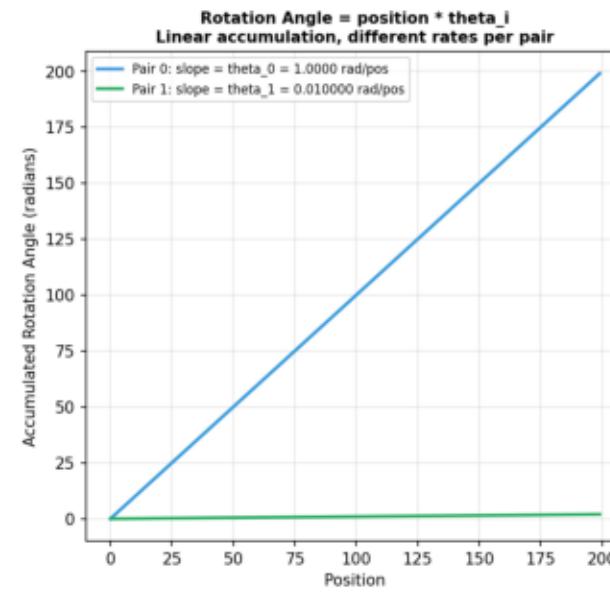
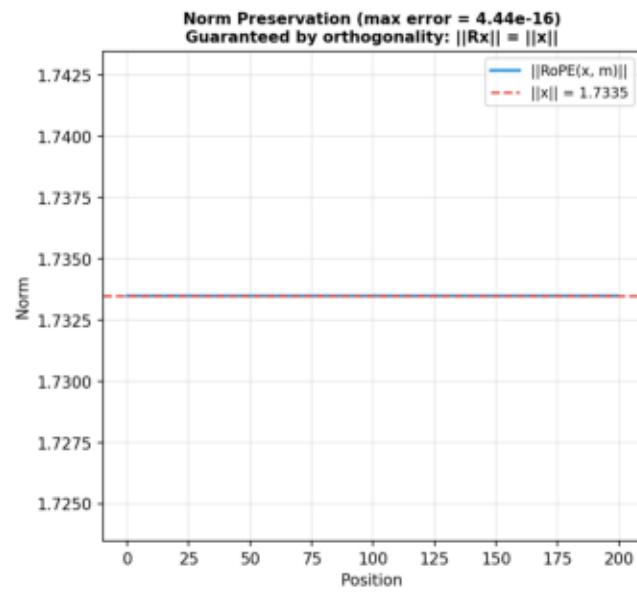
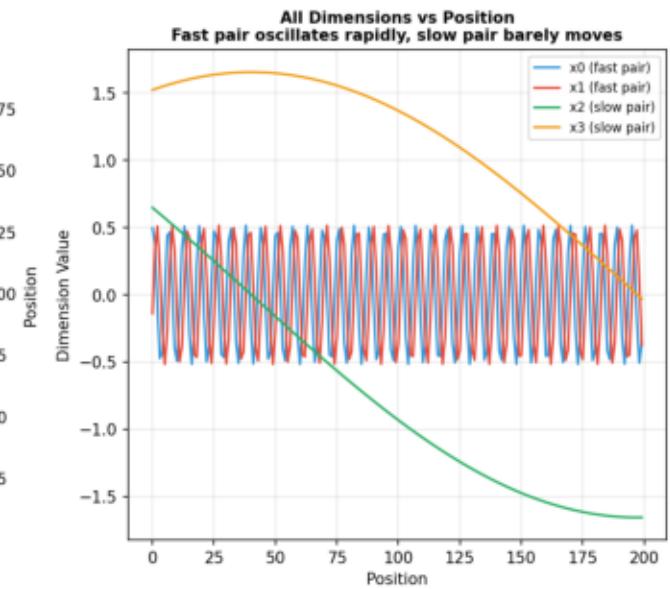
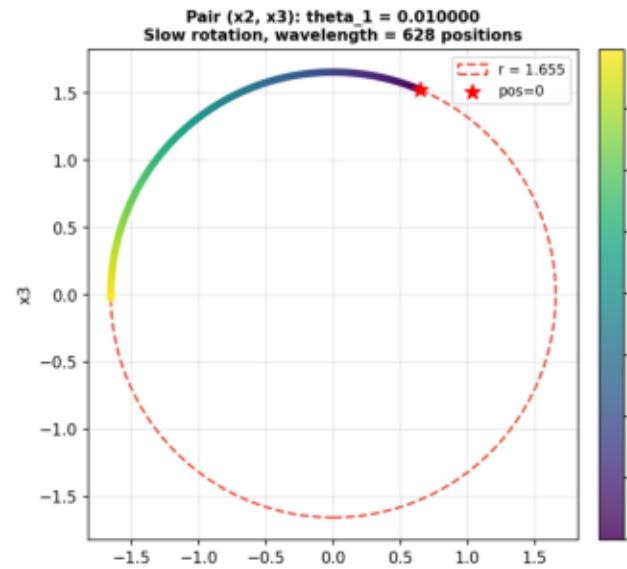
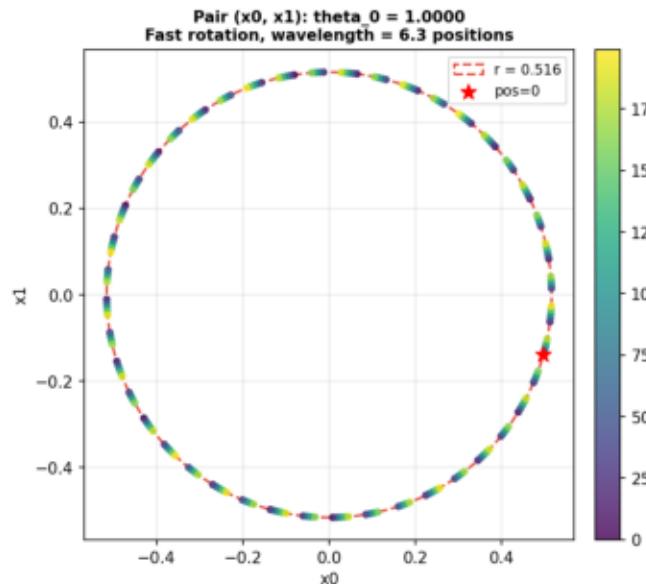
*Generated by demo.py*

# Summary of Findings

1. Rotation Visualization: Each dimension pair  $(2i, 2i+1)$  traces a circle in its 2D subspace. Pair 0 rotates fast ( $\theta_0 = 1.0$ ), higher pairs rotate progressively slower. Norm is preserved because rotations are orthogonal transformations.
2. Relative Position Property (CENTERPIECE): The dot product  $\langle \text{RoPE}(q, m), \text{RoPE}(k, n) \rangle = q^T R(n-m)$   $k$  depends ONLY on  $(m-n)$ .  
Proof:  $R(m)^T R(n) = R(-m)R(n) = R(n-m)$  by angle addition.  
Verified empirically: max variation < 1e-12 across all positions.
3. Norm & Orthogonality:  $\|\text{RoPE}(x, m)\| = \|x\|$  guaranteed by  $R^T R = I$ .  
 $\det(R) = 1$  (proper rotation).  $R(m)R(n) = R(m+n)$  (composition).  
 $R(m)R(-m) = I$  (inverse). All analytically exact from  $\cos^2 + \sin^2 = 1$ .
4. RoPE vs Sinusoidal PE: Both use  $\theta_i = 10000^{(-2i/d)}$ .  
Sinusoidal is ADDITIVE (position added to content), creating cross-terms that depend on absolute position. RoPE is MULTIPLICATIVE ( $q' = R(m)q$ ), giving a pure relative position encoding. This is the key advantage.
5. Attention Impact: With identical token embeddings, RoPE creates position-dependent attention patterns (weights vary by relative position). Without RoPE, attention is uniform. Patterns are shift-invariant (shifting all positions preserves relative distances).
6. Context Extension: Larger  $\theta_{\text{base}}$  stretches wavelengths, extending effective context. Llama 3 uses  $\theta=500K$  vs standard 10K. NTK-aware scaling preserves high-freq (local) while stretching low-freq (long-range) -- can extend context without retraining.

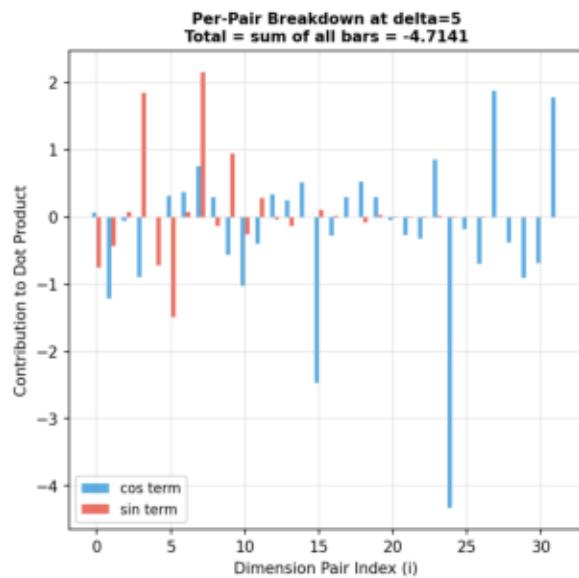
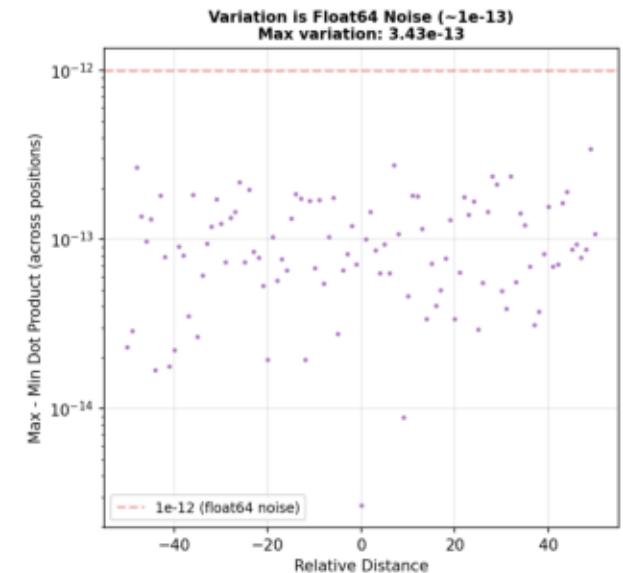
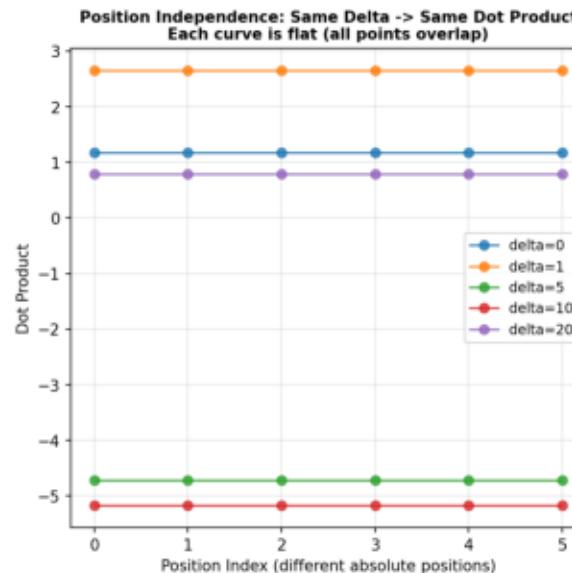
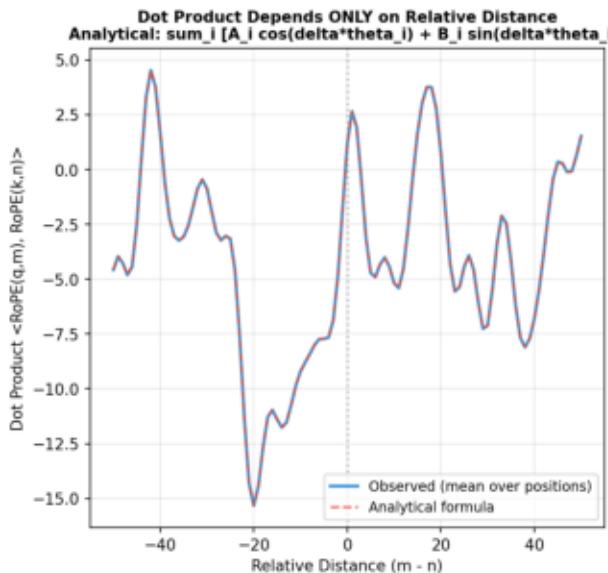
# Example 1: Rotation Visualization -- Circles in 2D Subspaces

**RoPE Rotation Visualization: Each Dimension Pair Traces a Circle**



## Example 2: Relative Position Property -- The Key Theorem

RoPE Relative Position Property: Dot Product Depends Only on (m-n)



**ANALYTICAL DERIVATION**

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Given:  $q' = R(m)q, k' = R(n)k$

$$\langle q', k' \rangle = \langle R(m)q \rangle^T \langle R(n)k \rangle$$

$$= q^T R(m)^T R(n) k$$

$$= q^T R(-m) R(n) k \quad [R^T = R^{-1} = R(-m)]$$

$$= q^T R(n-m) k \quad [R(a)R(b) = R(a+b)]$$

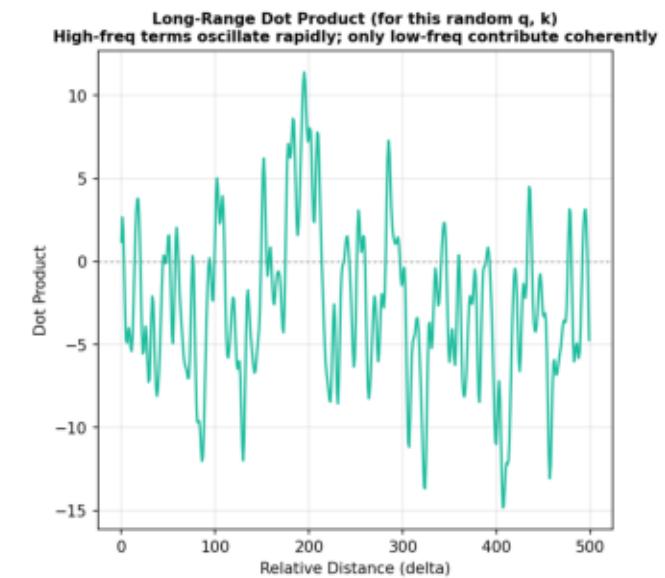
Per pair  $i$ :

$$(q_{\{2i\}}k_{\{2i\}} + q_{\{2i+1\}}k_{\{2i+1\}}) \cos((m-n)\theta_i)$$

$$+ (q_{\{2i\}}k_{\{2i+1\}} - q_{\{2i+1\}}k_{\{2i\}}) \sin((m-n)\theta_i)$$

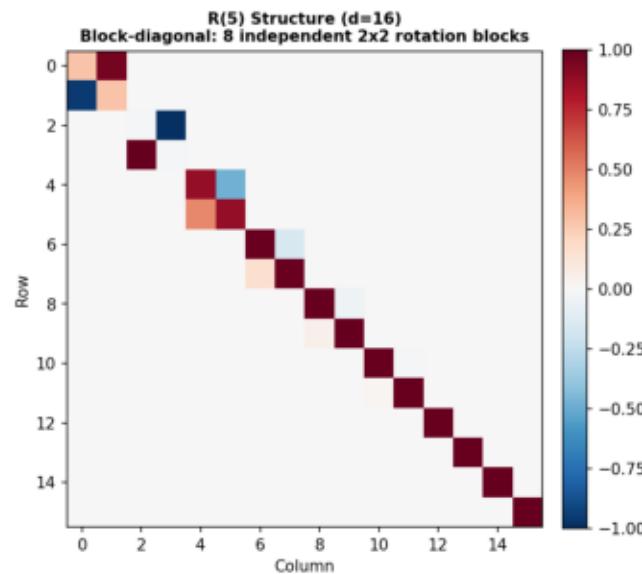
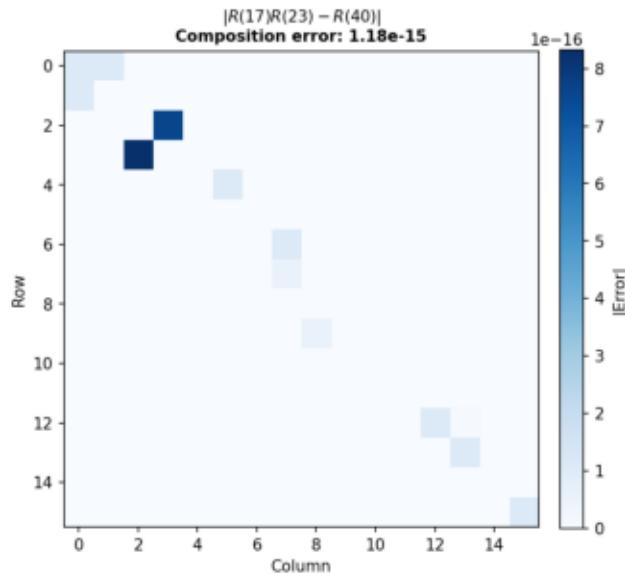
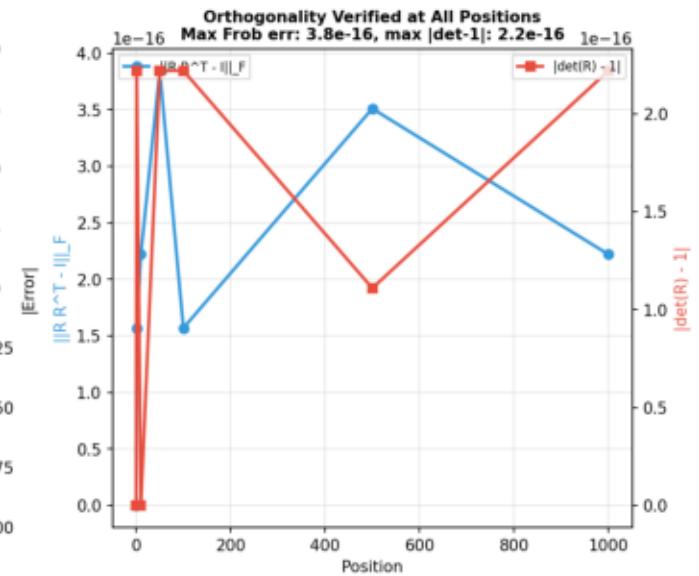
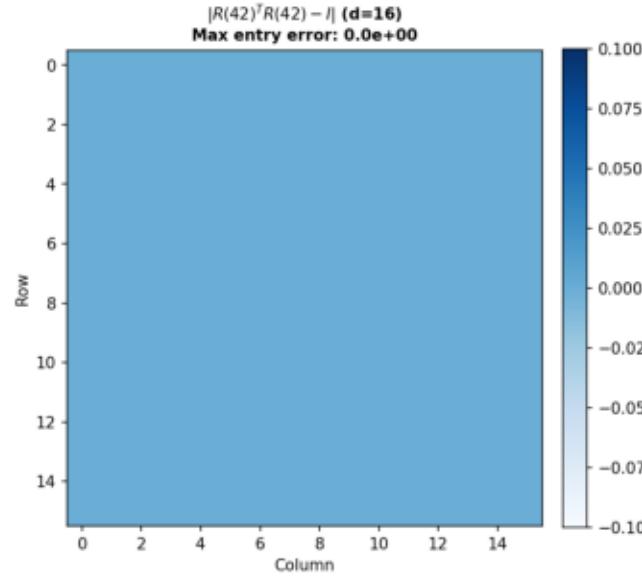
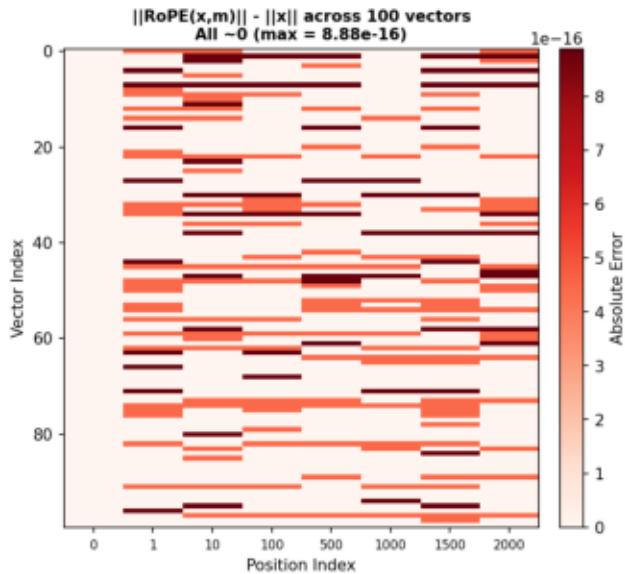
KEY: depends on  $(m-n)$ ,  $q$ ,  $k$  only.  
 NOT on  $m$  or  $n$  individually.

This is why RoPE is a RELATIVE position encoding despite using ABSOLUTE positions in the rotation.



## Example 3: Norm Preservation & Orthogonality

**RoPE Orthogonality:  $R^T R = I$ ,  $\det(R) = 1$ ,  $R(m)R(n) = R(m+n)$ ,  $\|Rx\| = \|x\|$**



**ROTATION MATRIX PROPERTIES**  
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R is 16x16 block-diagonal with 8 blocks

Each  $2 \times 2$  block  $R_i(m)$ :  
 $[\cos(m^*\theta_i), -\sin(m^*\theta_i)],$   
 $[\sin(m^*\theta_i), \cos(m^*\theta_i)]$

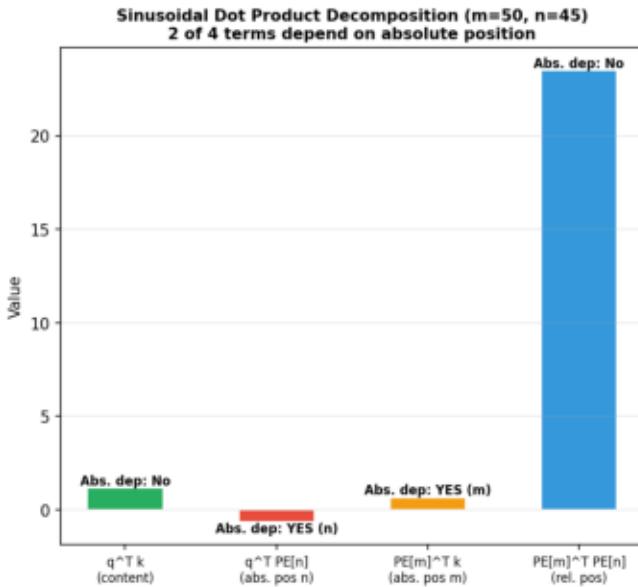
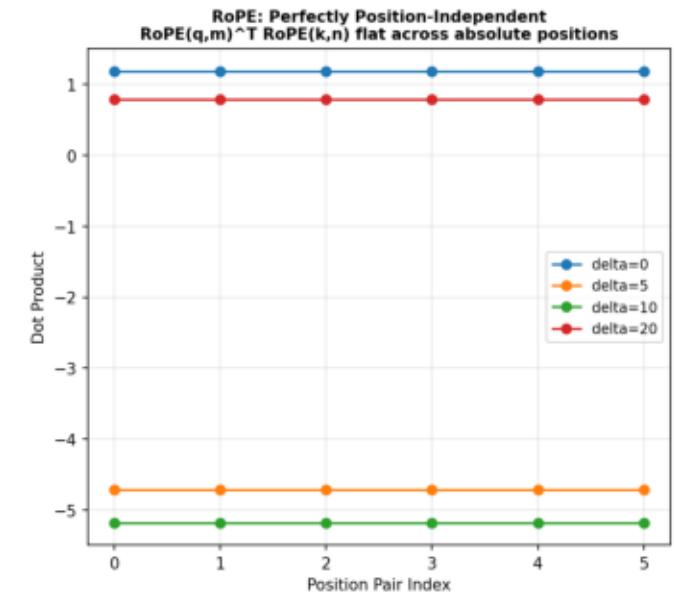
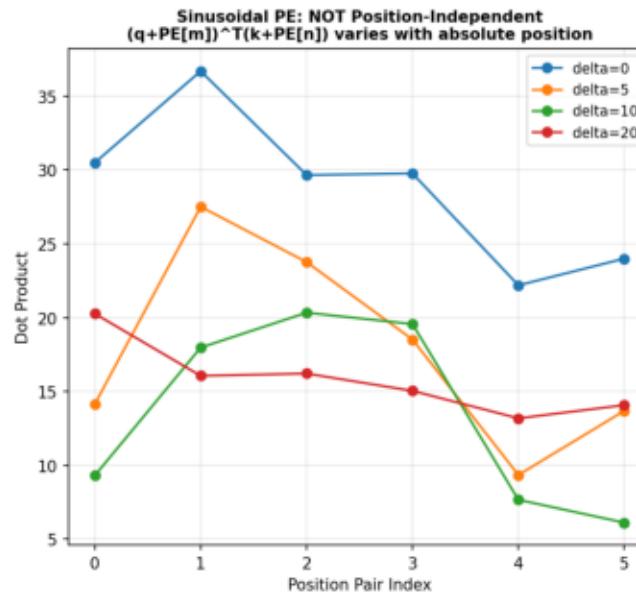
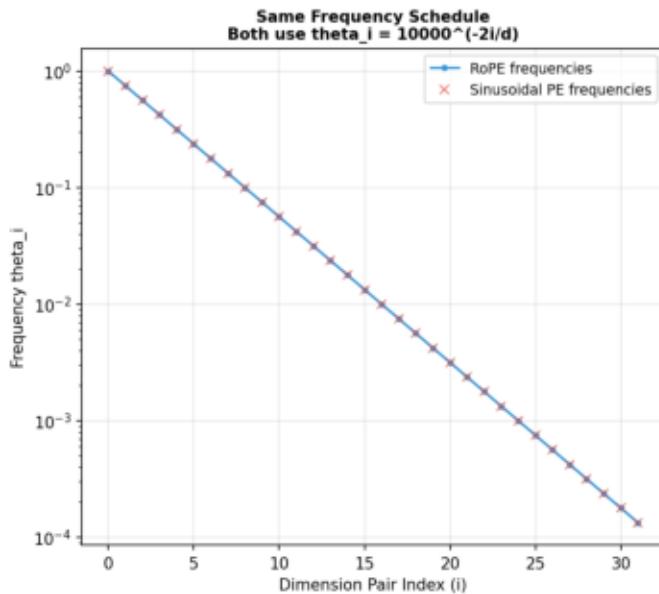
Guaranteed properties:

1. Orthogonality:  $R^T R = I$   
Verified:  $\|R^T R - I\| < 4e-16$
2. Proper rotation:  $\det(R) = 1$   
Verified:  $|\det - 1| < 2e-16$
3. Composition:  $R(m)R(n) = R(m+n)$   
Verified: error =  $1e-15$
4. Inverse:  $R(m)R(-m) = I$   
Verified: error =  $4e-16$
5. Norm preservation:  $\|Rx\| = \|x\|$   
Verified: max error =  $9e-16$

All from  $\cos^2 + \sin^2 = 1$ .

# Example 4: RoPE vs Sinusoidal PE -- Additive vs Multiplicative

## RoPE vs Sinusoidal PE: Same Frequencies, Fundamentally Different Application



**COMPARISON: ADDITIVE vs MULTIPLICATIVE**

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**SINUSOIDAL PE (Additive):**

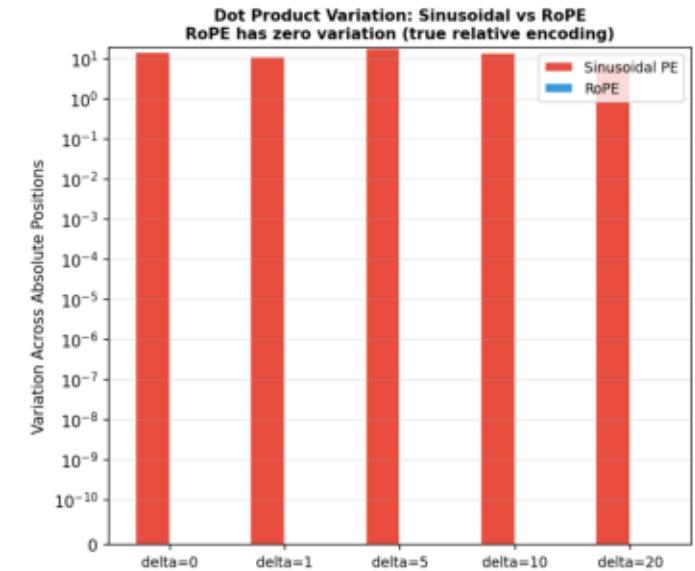
```

input' = input + PE[position]
q = input' @ W_Q
k = input' @ W_K
score = q^T k
      = (x+PE[m])^T W_Q^T W_K (x+PE[n])
--> cross-terms depend on abs. position
  
```

**RoPE (Multiplicative):**

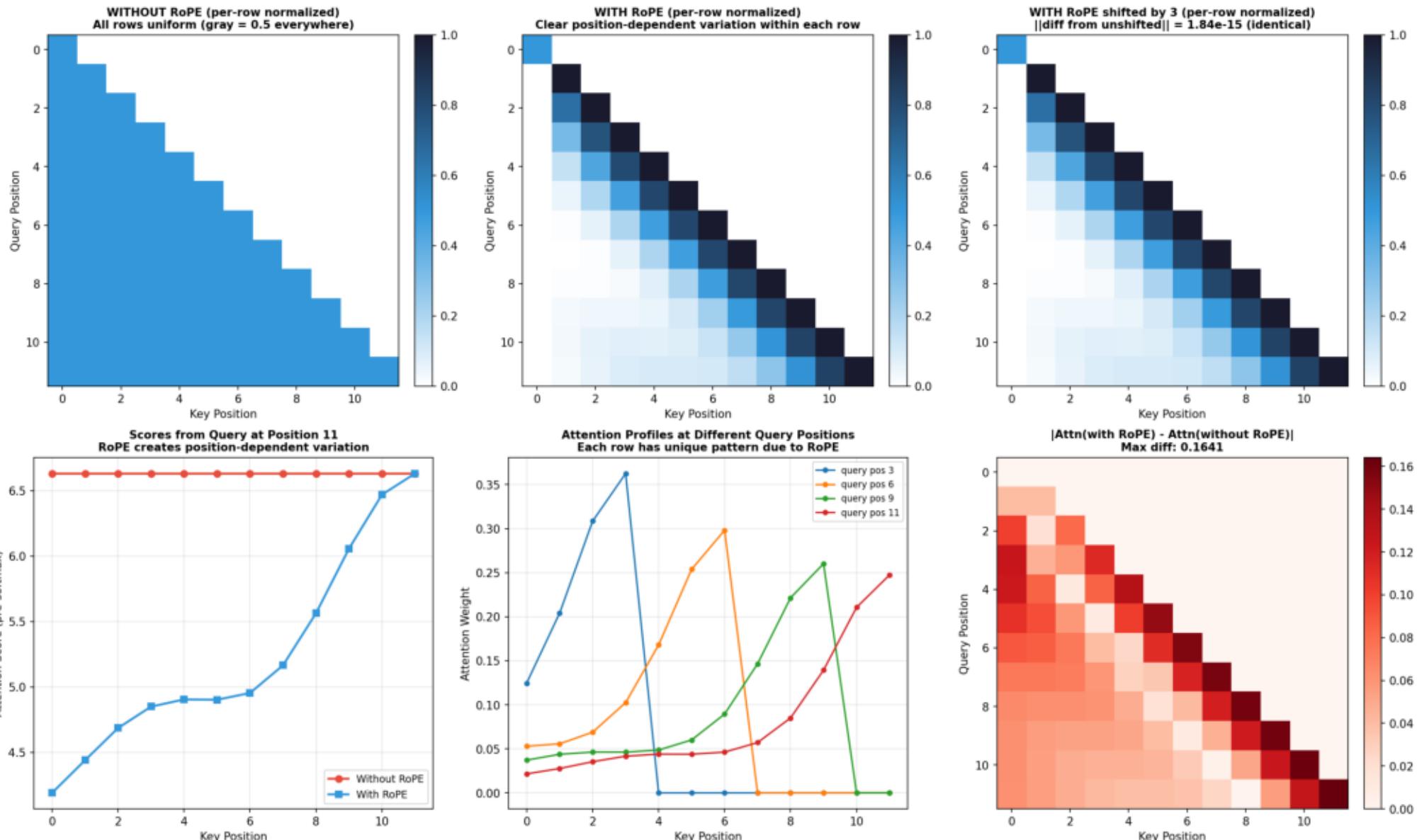
```

q = input @ W_Q
k = input @ W_K
q' = R(m) @ q      (rotate AFTER proj.)
k' = R(n) @ k
score = q'^T k'
      = q^T R(m)^T R(n) k
      = q^T R(n-m) k
--> depends on (n-m) only!
  
```



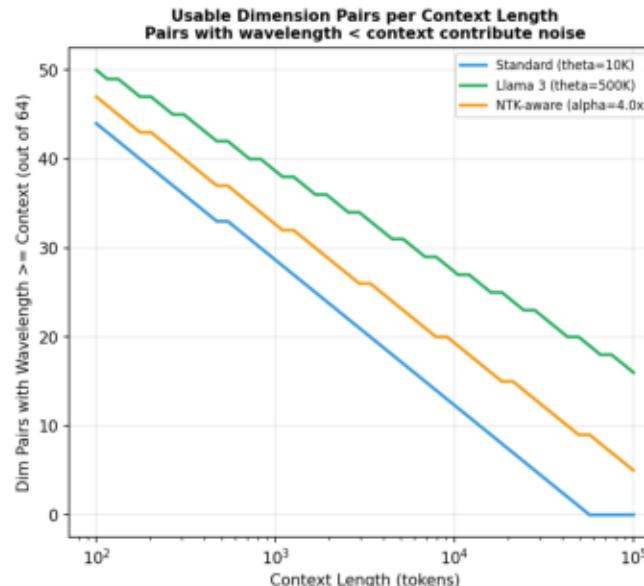
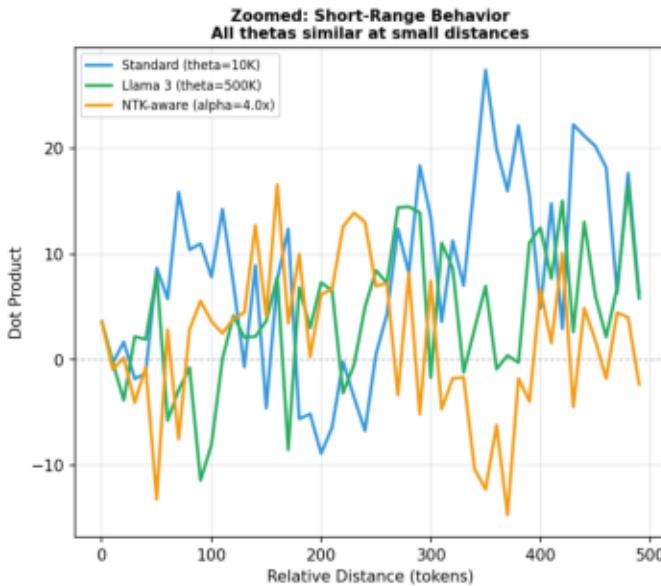
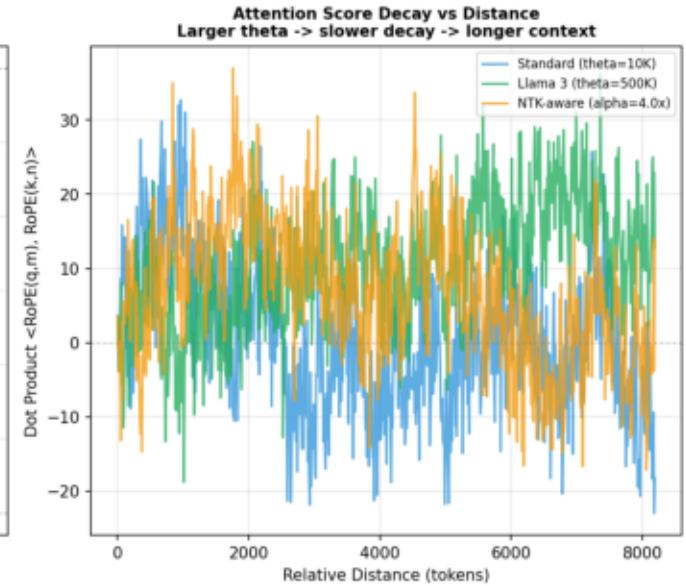
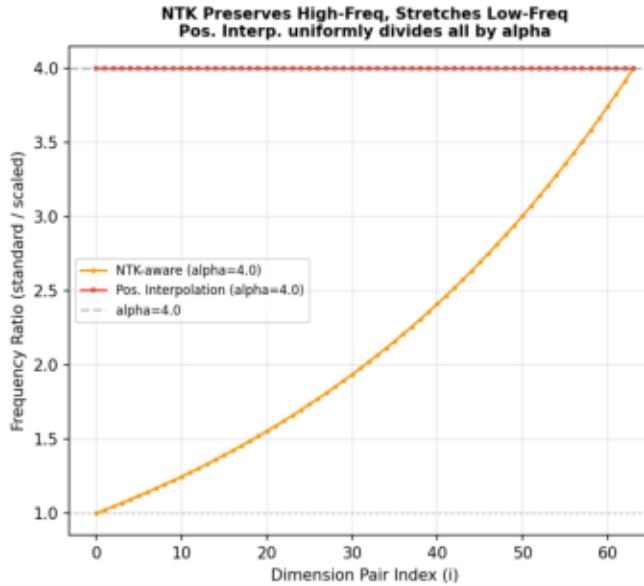
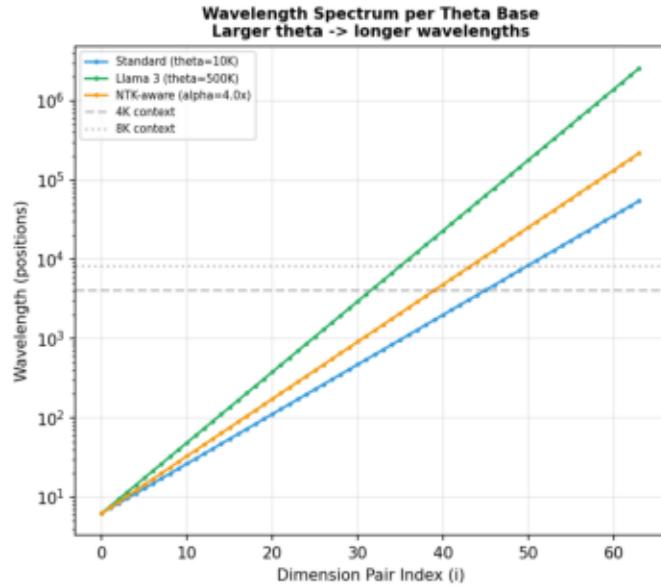
# Example 5: Impact on Attention Patterns

**Impact of RoPE on Attention: Position-Dependent Patterns from Identical Inputs**



# Example 6: Context Extension via Theta Scaling

Context Extension via Theta Scaling: Standard vs Llama 3 vs NTK-Aware



**CONTEXT EXTENSION METHODS**

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**Standard (theta=10000):**  
Effective context: ~4K-8K tokens  
Used by: Llama 1/2, RoFormer

**Higher base (theta=500000):**  
Effective context: ~128K tokens  
Used by: Llama 3, Qwen 2  
Simple but requires retraining

**NTK-aware (alpha=4.0, theta'=40890):**  
 $\theta' = \theta \cdot \alpha^{(d/(d-2))}$   
Preserves high-freq (local) resolution  
Stretches low-freq (long-range) only  
Can be applied WITHOUT retraining

**Position interpolation (alpha=4.0):**  
Divides ALL positions by alpha  
Simpler but degrades local resolution  
Requires fine-tuning for good results