Quantization for LLM

Overview

1. **Weight-only Quantization**
    1. AWQ

2. **Weight and Activation Quantization**
    1. SmoothQuant
    2. QuaRot/SpinQuant

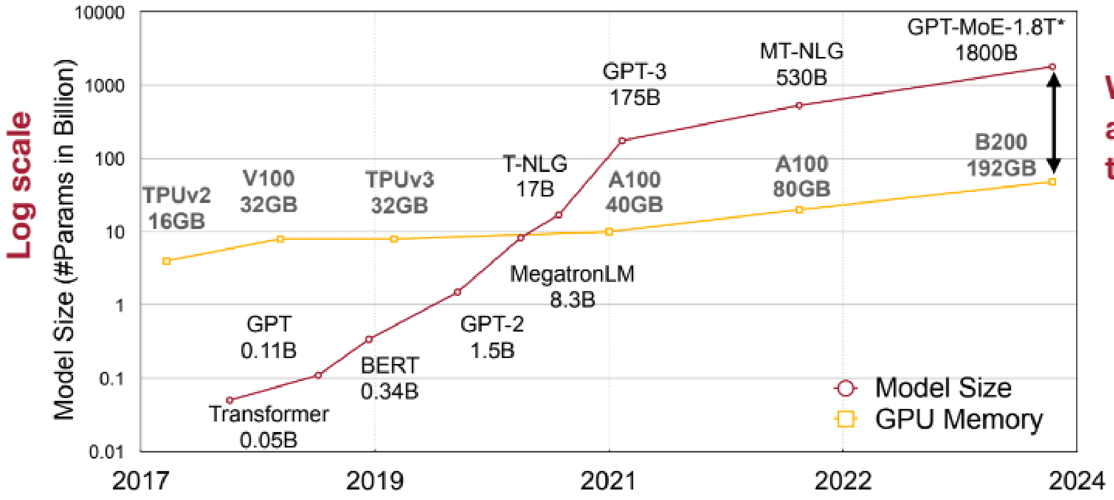
Setup

- 실습 자료 “Quantization for LLM.ipnyb”을 colab에서 실행해주세요
- Colab 런타임을 GPU(T4)로 설정해 주세요
- Setup 코드 셀을 실행해 필요한 패키지를 설치해주세요

Challenge for LLM deployment

Despite being powerful, LLMs are hard to serve on the edge

- LLM sizes and computation are increasing exponentially.
- Domain-specific accelerator alone is not enough.
  - We need model compression techniques and system support to bridge the gap.



We need efficient algorithms and systems to bridge the gap.

AWQ: Activation-aware Weight Quantization

Observation: Weights are not equally important; 0.1% salient weights

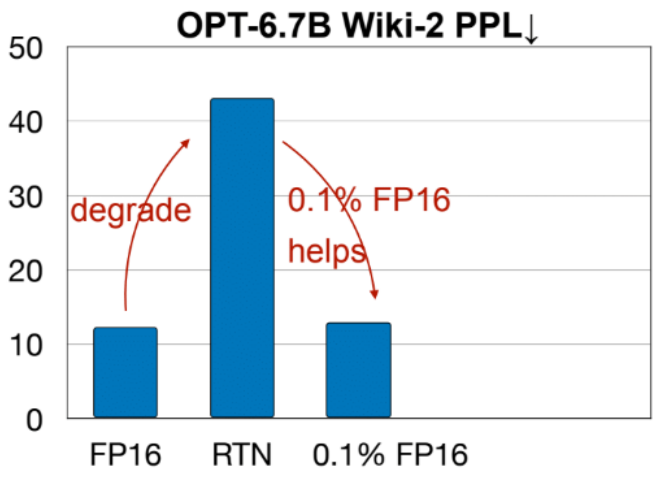
W_{FP16}

+1.2	−0.2	−2.4	−3.4
−2.5	−3.5	+1.9	+1.4
−0.9	+1.6	−2.5	−1.9
−3.5	+1.5	+0.5	−0.1
+1.8	−1.6	−3.2	−3.4
+2.4	−3.5	−2.8	−3.9
+0.1	−3.8	+2.4	+3.4
+0.9	+3.3	−1.9	−2.3

$\xrightarrow{\text{RTN}}$

$Q(W)_{MixPrec}$

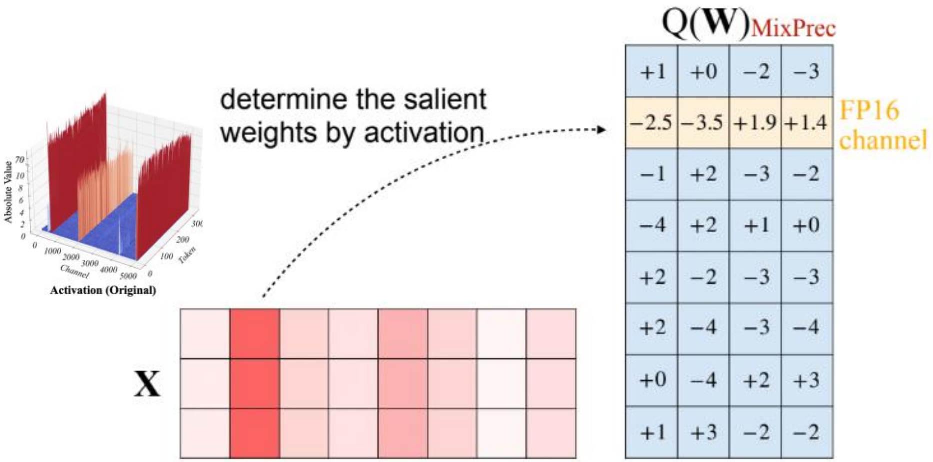
+1	+0	−2	−3	
−2.5	−3.5	+1.9	+1.4	FP16 channel
−1	+2	−3	−2	
−4	+2	+1	+0	
+2	−2	−3	−3	
+2	−4	−3	−4	
+0	−4	+2	+3	
+1	+3	−2	−2	

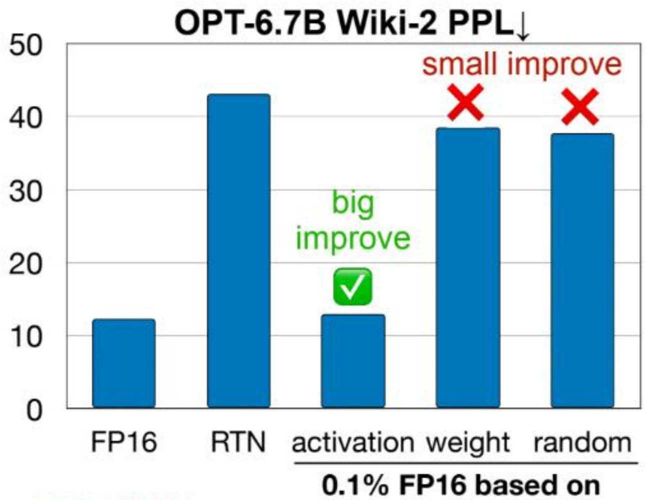


- We find that weights are not equally important, keeping **only 0.1%** of salient weight channels in FP16 can greatly improve perplexity
- But how do we select salient channels? Should we select based on weight magnitude?

Protect 1% salient channels

Salient weights are determined by activation distribution, not weight





- We find that weights are not equally important, keeping **only 0.1%** of salient weight channels in FP16 can greatly improve perplexity
- But how do we select salient channels? Should we select based on weight magnitude?
- No! We should look for **activation distribution, but not weight!**

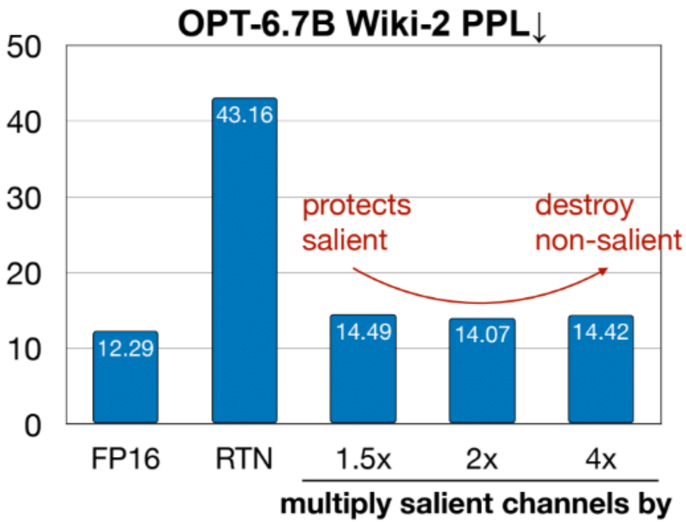
Scale 0.1% salient channels

Protecting salient weights by scaling (no mixed prec.)

$$
Q\left(\begin{array}{c}\mathbf{W} \\ \begin{array}{|c|c|c|c|}\hline +1.2 & -0.2 & -2.4 & -3.4 \\ \hline -2.5 & -3.5 & +1.9 & +1.4 \\ \hline -0.9 & +1.6 & -2.5 & -1.9 \\ \hline -3.5 & +1.5 & +0.5 & -0.1 \\ \hline +1.8 & -1.6 & -3.2 & -3.4 \\ \hline +2.4 & -3.5 & -2.8 & -3.9 \\ \hline +0.1 & -3.8 & +2.4 & +3.4 \\ \hline +0.9 & +3.3 & -1.9 & -2.3 \\ \hline \end{array}\end{array}
\begin{array}{c} \\ \times 1 \\ \times 2 \\ \times 1 \\ \times 1 \\ \times 1 \\ \times 1 \\ \times 1 \\ \times 1 \end{array}\right)
$$

fuse to previous op

$$\mathbf{WX} \longrightarrow Q(\mathbf{W} \cdot \mathbf{s})(\mathbf{s}^{-1} \cdot \mathbf{X})$$



- Multiplying the salient channels with $s > 1$ reduces its quantization error
- Why?

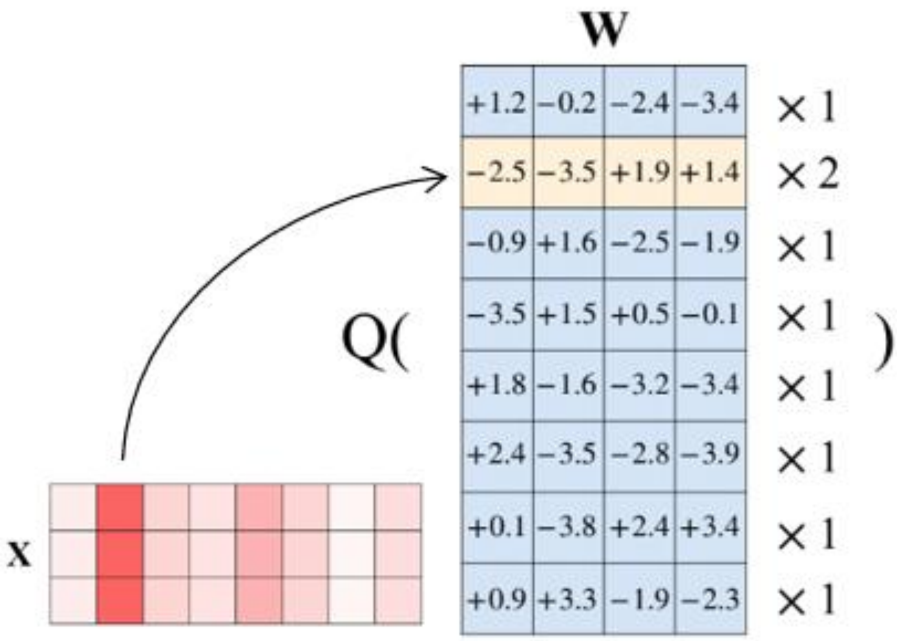
Scale 1% salient channels

Protecting salient weights by scaling (no mixed precision)

- Consider a linear layer channel $\mathbf{y} = \mathbf{w}x$ (from $\mathbf{W}\mathbf{x}$). We care about the quantization error from $Q(\mathbf{w})x$
- $\boxed{Q(\mathbf{w}) = \Delta \cdot \text{Round}(\mathbf{w}/\Delta), \quad \Delta = \frac{\max(|\mathbf{w}|)}{2^{N-1}}}$ $\quad Error = \Delta \cdot RoundErr$
- The scaled version is $Q(\mathbf{w} \cdot s)(x/s) = \Delta' \cdot \text{Round}(s\mathbf{w}/\Delta') \cdot x \cdot \frac{1}{s}$ $\quad Error' = \Delta' \cdot RoundErr \cdot \frac{1}{s}$
- We find that the error from Round() is always ~0.25 (average from 0-0.5)
- The maximum value in a group "usually" does not change if we just scale up a channel -> Δ not changed
- With $s > 1$, the error is scaled down.

$$q = int(round(r/s)) + z$$

[실습1] Scale 1% salient channels



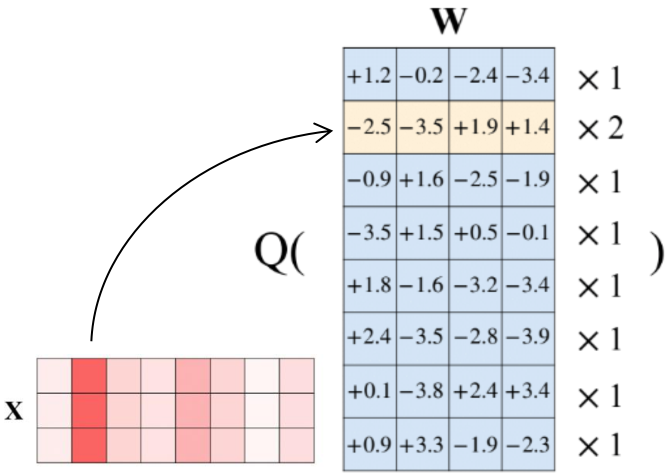
$$\mathbf{WX} \rightarrow Q(\mathbf{W} \cdot \boxed{\mathbf{s}})(\boxed{\mathbf{s}^{-1}} \cdot \mathbf{X})$$

Answer


```
################# YOUR CODE STARTS HERE #################

# Step 1: importance를 기준으로 1%의 중요한 채널을 찾으세요  (hint: use torch.topk())
# hint : torch.topk() 함수를 사용하세요. torch.topk() 함수는 PyTorch에서 텐서의 값 중 상위 k개의 값과 그들의 인덱스를 반환하는 함수입니다.
outlier_mask = torch.topk(importance, int(len(importance) * 0.01))[1]
assert outlier_mask.dim() == 1

################# YOUR CODE ENDS HERE ###################

# 스케일 팩터를 적용하는 것을 시뮬레이션하기 위해, 양자화 전에 스케일 팩터를 곱하고, 양자화 후에 스케일 팩터로 나눕니다.
# scale_factor를 이용해 중요한 가중치 채널의 값을 확대합니다.
m.weight.data[:, outlier_mask] *= scale_factor

m.weight.data = pseudo_quantize_tensor(m.weight.data, n_bit=w_bit, q_group_size=q_group_size)

################# YOUR CODE STARTS HERE #################

# Step 2: scale_factor를 이용해 중요한 가중치 채널의 값을 다시 축소하세요.
m.weight.data[:, outlier_mask] /= scale_factor

################# YOUR CODE ENDS HERE ###################
```

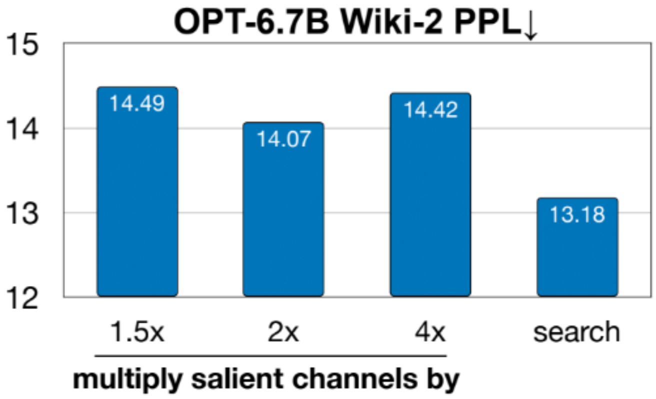
Scale Factor Search

Protecting salient weights by scaling (no mixed prec.)



fuse to previous op

$$\mathbf{W}\mathbf{X} \longrightarrow Q(\mathbf{W} \cdot \mathbf{s})(\mathbf{s}^{-1} \cdot \mathbf{X})$$



$$\mathcal{L}(\mathbf{s}) = \|Q(\mathbf{W} \cdot \mathbf{s})(\mathbf{s}^{-1} \cdot \mathbf{X}) - \mathbf{W}\mathbf{X}\|$$

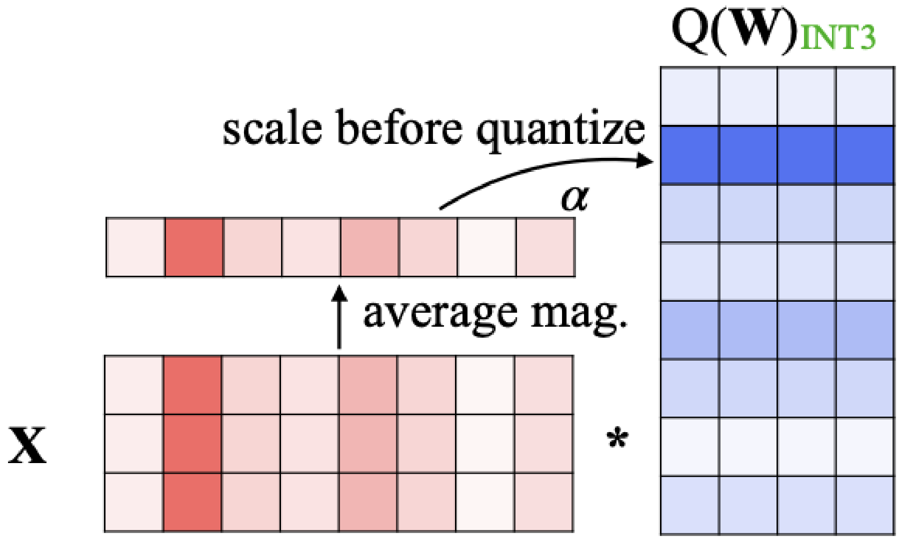
$$\boxed{\mathbf{s} = \mathbf{s_X}^{\alpha}}$$

Activation-awareness is important, but not weight-awareness

- Multiplying the salient channels with $s > 1$ reduces its quantization error
- Take a data-driven approach with a fast **grid search**

L1 norm of Activation

[실습2] Scale Factor Search



$$s_{X^{\alpha}} = \|X\|_1, \qquad \|X\|_1 = \Sigma\, |X_i|$$

$$\mathbf{s} = \mathbf{s_X}^{\alpha}$$

Activation-awareness is important, but not weight-awareness

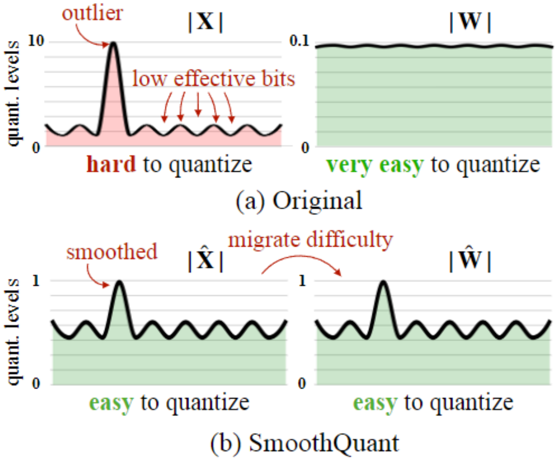
- Multiplying the salient channels with $s > 1$ reduces its quantization error
- Take a data-driven approach with a fast **grid search**

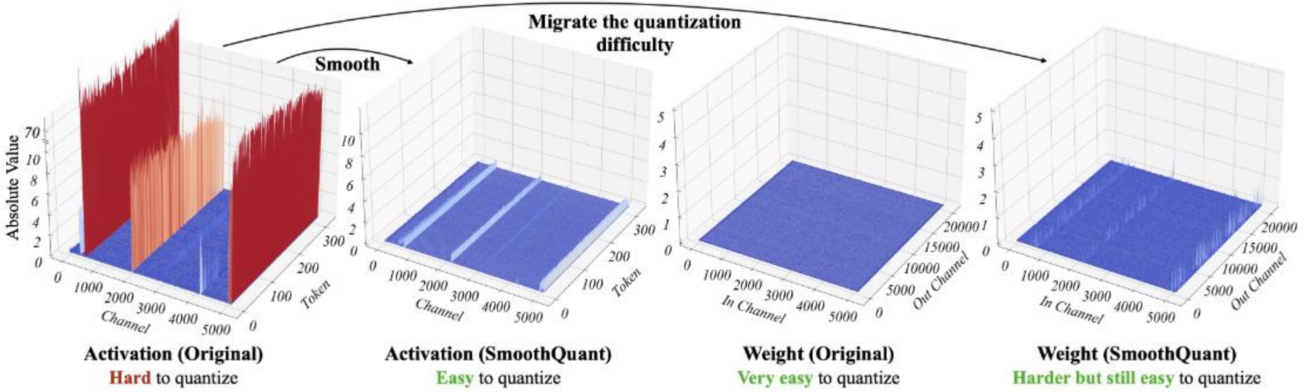
Answer


```python
################ YOUR CODE STARTS HERE ################

# Step 2: 공식에 따라 스케일 계산: scales = s_x^ratio
scales = s_x ** ratio # must clip the s_x, otherwise will get nan later

assert scales.shape == s_x.shape

################ YOUR CODE ENDS HERE ##################

scales = scales / (scales.max() * scales.min()).sqrt().view(1, -1)

for fc in linears2scale:

    scales = scales.to(fc.weight.device)

    # scale_factor를 이용해 중요한 가중치 채널의 값을 확대합니다.
    fc.weight.mul_(scales)

    fc.weight.data = pseudo_quantize_tensor(fc.weight.data, w_bit, q_group_size)

    ################ YOUR CODE STARTS HERE ################

    # Step 3: scale_factor를 이용해 중요한 가중치 채널의 값을 다시 축소하세요.
    fc.weight.data /= scales

    ################ YOUR CODE ENDS HERE ##################
```

SmoothQuant

- **SmoothQuant's intuition**
  - Migrate **scale** from activations to weights W before quantization





SmoothQuant

- **Main idea of SmoothQuant**

$$\mathbf{Y} = \mathbf{X} \cdot \mathbf{W}, \mathbf{Y} \in \mathbb{R}^{T \times C_o}, \mathbf{X} \in \mathbb{R}^{T \times C_i}, \mathbf{W} \in \mathbb{R}^{C_i \times C_o},$$

$$\boxed{\mathbf{s}_j = \max(|\mathbf{X}_j|)^{\alpha} / \max(|\mathbf{W}_j|)^{1-\alpha}}$$

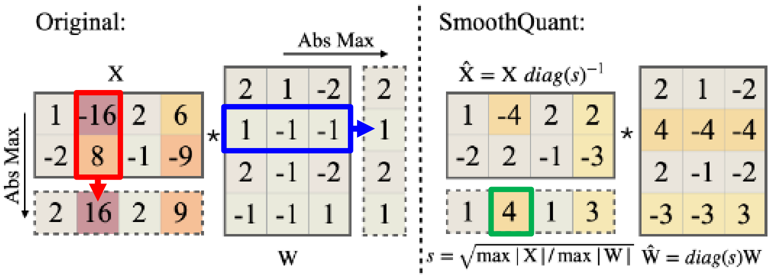


Figure 5: Main idea of SmoothQuant when α is 0.5. The smoothing factor s is obtained on calibration samples and the entire transformation is performed offline. At runtime, the activations are smooth without scaling.

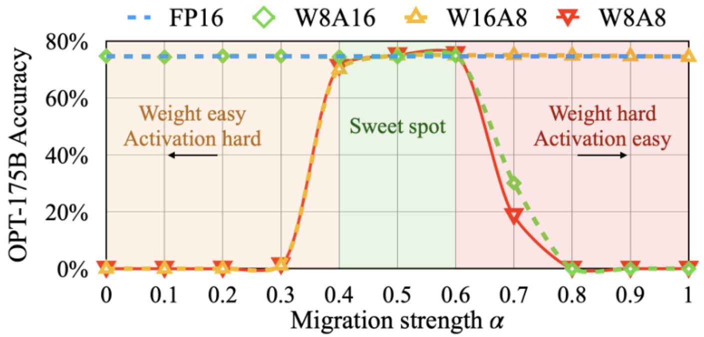
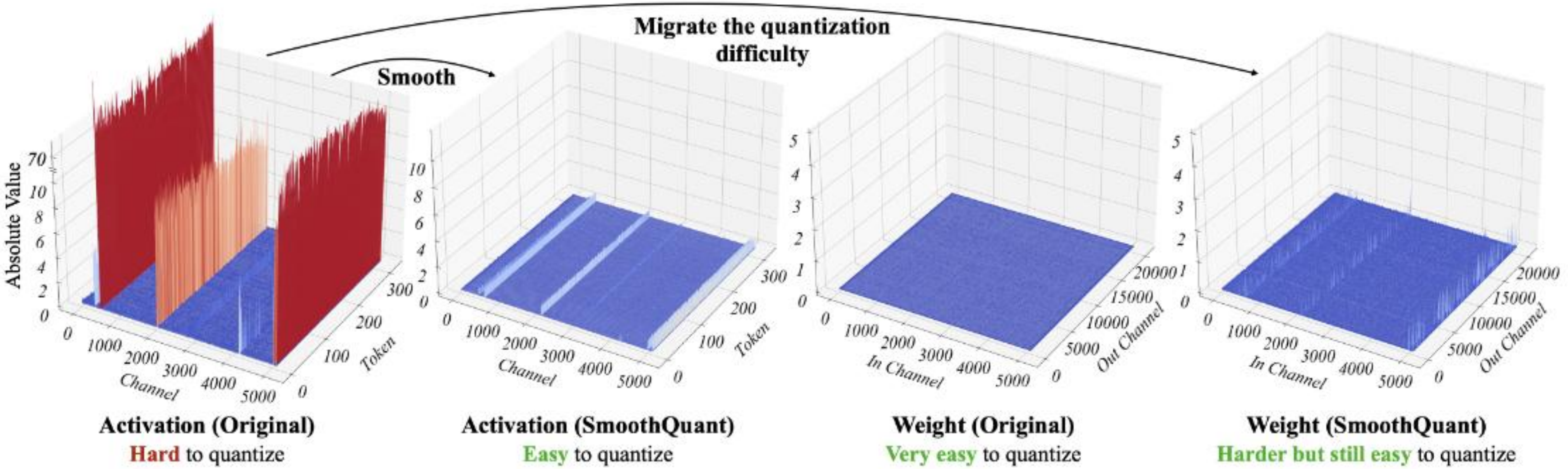


Figure 10: A suitable migration strength α (sweet spot) makes both activations and weights easy to quantize. If the α is too large, weights will be hard to quantize; if too small, activations will be hard to quantize.

[실습3] Quantization Difficulty Migration



Answer


```python
def smooth_ln_fcs_by_scale(ln, fcs, scale):
    if not isinstance(fcs, list):
        fcs = [fcs]
    assert isinstance(ln, nn.LayerNorm)
    for fc in fcs:
        assert isinstance(fc, nn.Linear)
    ################ YOUR CODE STARTS HERE ################
    # Step 1: layernorm의 weight와 bias를 scale로 나누어주세요. (hint: div_()함수를 통해 tensor 전체를 특정한 값으로 나누어 줄 수 있습니다.)
    ln.weight.div_(scale)
    ln.bias.div_(scale)
    ################ YOUR CODE ENDS HERE ##################

    for fc in fcs:
        ################ YOUR CODE STARTS HERE ################
        # Step 2: fc의 weight에 scale을 곱해주세요. (hint: mul_()함수를 통해 tensor 전체에 특정한 값을 곱해 줄 수 있습니다.)
        fc.weight.mul_(scale)
        ################ YOUR CODE ENDS HERE ##################
```

[실습4] Scale Factor Search

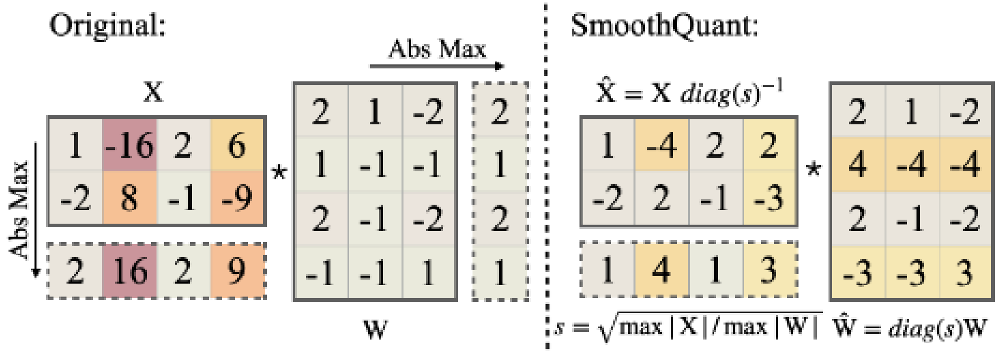


Figure 5: Main idea of SmoothQuant when α is 0.5. The smoothing factor s is obtained on calibration samples and the entire transformation is performed offline. At runtime, the activations are smooth without scaling.

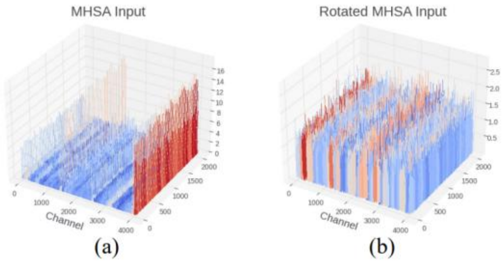
Answer


```
scales = (
    ################ YOUR CODE STARTS HERE ################
    #Activation Scales 값과 Weight Scales 값에 alpha를 적절히 거듭제곱해주어야 합니다.
    #Hint: pow()함수를 통해서 거듭제곱을 사용할 수 있습니다.
    (act_scales.pow(alpha) / weight_scales.pow(1 - alpha))
    ################ YOUR CODE ENDS HERE ##################
)
```

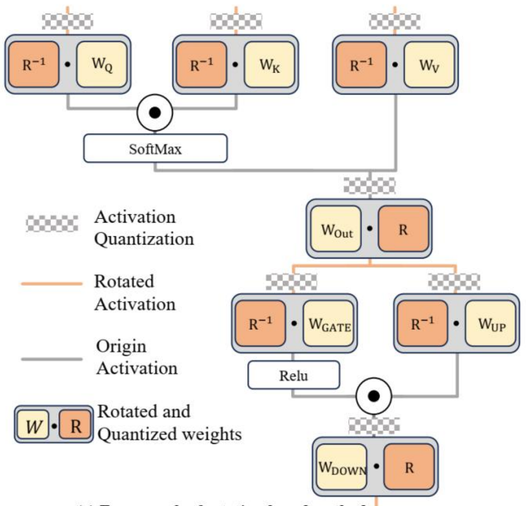
Ratation based Quantization

$$\mathbf{Y} = (\mathbf{XR})(\mathbf{R}^{-1}\mathbf{W}^{-1}) = \mathbf{XW}^{\mathbf{T}}$$

A rotation matrix is an orthogonal matrix $\mathbf{R}$ satisfied $\mathbf{RR}^{\mathbf{T}} = 1$ and $|\mathbf{R}| = 1$

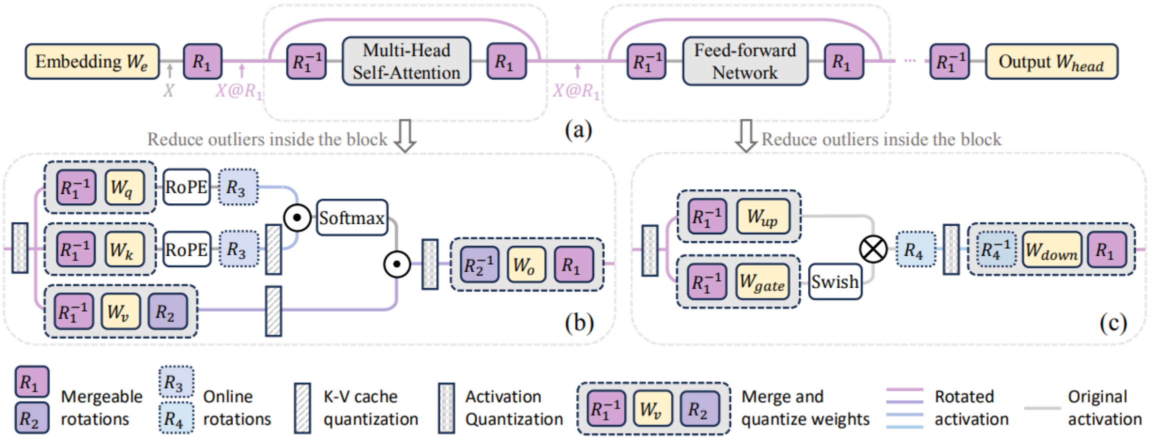


QuaRot

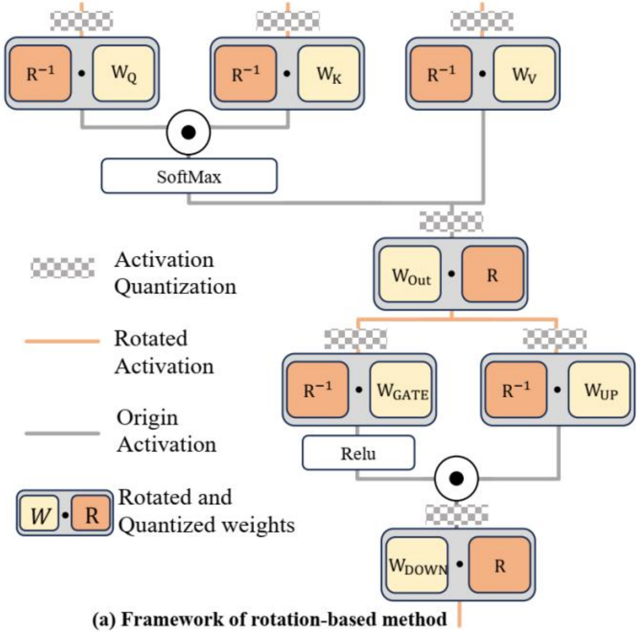


(a) Framework of rotation-based method

SpinQuant



[실습5] Rotate Matrix 적용



(a) Framework of rotation-based method

- @ ➔ Dot Product
- nn.Linear 연산은 W^T 형태로 저장
- Embedding Parameter Shape : (Num_Tokens, Hidden_dim)
- Linear Parameter Shape : (Output_Channel, Input_Channel)
- Roation Matrix Shape : (Hidden_dim, Hidden_dim)

Answer


```
############### YOUR CODE STARTS HERE ###############
# Pytorch에서 @ 연산이 Dot Product 임을 사용하시기 바랍니다.
# nn.Linear 연산의 Parameter는 W^T 형태로 저장되어 있다는 것을 유의하시기 바랍니다.
# Embedding Parameter Shape : (Num_Tokens, Hidden_dim)
# Linear Parameter Shape : (Output_Channel, Input_Channel)
# Roation Matrix Shape : (Hidden_dim, Hidden_dim)

if isinstance(m, nn.Embedding):
  W_ = m.weight.data
  m.weight.data = W_ @ R1

if isinstance(m, nn.Linear):
  if "out_proj" in n or "fc2" in n:
    # Att Out Proj, FFN Down Proj
    W_ = m.weight.data
    m.weight.data = R1.T @ W_
```

$\Rightarrow x \cdot W \cdot R$

```
  else:
    # QKV Proj, FFN Up Proj, FFN Gate Proj
    W_ = m.weight.data
    m.weight.data = W_ @ R1
```

$\Rightarrow x \cdot R^T \cdot W$

```
############### YOUR CODE ENDS HERE #################
```