
Supplementary information

Learning high-accuracy error decoding for quantum processors

In the format provided by the
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Pseudocode

Algorithm 1: AttentionWithBias

/* Computes a single self-attention head. */
Input: $X \in \mathbb{R}^{d_d \ell}$, vector representations of primary sequence. $\mathbf{B}' \in \mathbb{R}^{\ell \times \ell}$ attention bias.
Output: $\tilde{V} \in \mathbb{R}^{d_{\text{mid}} \ell}$, updated representations of tokens in X .
Parameters: \mathcal{W}_{qkv} consisting of: $\mathbf{W}_q \in \mathbb{R}^{d_{\text{attn}} d_d}$, $\mathbf{b}_q \in \mathbb{R}^{d_{\text{attn}}}$ $\mathbf{W}_k \in \mathbb{R}^{d_{\text{attn}} d_d}$, $\mathbf{b}_k \in \mathbb{R}^{d_{\text{attn}}}$
 $\mathbf{W}_v \in \mathbb{R}^{d_{\text{mid}} d_d}$, $\mathbf{b}_v \in \mathbb{R}^{d_d}$.

- 1 $\mathbf{Q} \leftarrow \mathbf{W}_q X + \mathbf{b}_q \mathbf{1}^\top$ [Query $\in \mathbb{R}^{d_{\text{attn}} \ell}$]
- 2 $\mathbf{K} \leftarrow \mathbf{W}_k Z + \mathbf{b}_k \mathbf{1}^\top$ [Key $\in \mathbb{R}^{d_{\text{attn}} \ell}$]
- 3 $\mathbf{V} \leftarrow \mathbf{W}_v Z + \mathbf{b}_v \mathbf{1}^\top$ [Value $\in \mathbb{R}^{d_{\text{mid}} \ell}$]
- 4 $\mathbf{S} \leftarrow \mathbf{K}^\top \mathbf{Q} + \mathbf{B}'$ [Score $\in \mathbb{R}^{\ell \ell}$]
- 5 **return** $\tilde{V} = \mathbf{V} \cdot \text{softmax}(\mathbf{S} / \sqrt{d_{\text{attn}}})$

Algorithm 2: MHAttentionWithBias

/* Computes Multi-Head self-attention layer with attention bias. */
Input: $X \in \mathbb{R}^{d_d \times \ell}$, vector representations sequence. $\mathbf{B} \in \mathbb{R}^{d_b \ell \ell}$ embedded attention bias.
Output: $\tilde{V} \in \mathbb{R}^{d_d \ell}$, updated representations of tokens in X .
Hyperparameters: H , number of attention heads
Parameters: \mathcal{W} consisting of
For $h = 0, 1 \dots H - 1$, \mathcal{W}_{qkv}^h consisting of:
 $\quad | \quad \mathbf{W}_q^h \in \mathbb{R}^{d_{\text{attn}} d_d}$, $\mathbf{b}_q^h \in \mathbb{R}^{d_{\text{attn}}}$,
 $\quad | \quad \mathbf{W}_k^h \in \mathbb{R}^{d_{\text{attn}} d_d}$, $\mathbf{b}_k^h \in \mathbb{R}^{d_{\text{attn}}}$,
 $\quad | \quad \mathbf{W}_v^h \in \mathbb{R}^{d_{\text{mid}} d_d}$, $\mathbf{b}_v^h \in \mathbb{R}^{d_{\text{mid}}}$.
 $\mathbf{W}_b \in \mathbb{R}^{h \times d_b}$
 $\mathbf{W}_o \in \mathbb{R}^{d_d d_{\text{mid}}}$, $\mathbf{b}_o \in \mathbb{R}^{d_{\text{out}}}$.

- 1 $\mathbf{B}' \leftarrow \mathbf{W}_b \mathbf{B}$
- 2 **for** $h = 0, 1 \dots H - 1$ **do**
- 3 | $\mathbf{Y}^h \leftarrow \text{AttentionWithBias}(X, \mathbf{B}'[h, :, :] | \mathcal{W}_{qkv}^h)$
- 4 **end**
- 5 $\mathbf{Y} \leftarrow [\mathbf{Y}^0; \mathbf{Y}^1; \dots; \mathbf{Y}^{H-1}]$
- 6 **return** $\tilde{V} = \mathbf{W}_o \mathbf{Y} + \mathbf{b}_o \mathbf{1}^\top$

Algorithm 3: GatedDenseBlock

Input: $X \in \mathbb{R}^{d_d \times \ell}$, input
Output: $Y \in \mathbb{R}^{d_d \times \ell}$, output
Parameters: $W_1 \in \mathbb{R}^{wd_d \times d_d}$, $W_2 \in \mathbb{R}^{d_d \times (wd_d/2)}$, $\mathbf{b}_1 \in \mathbb{R}^{wd_d}$, $\mathbf{b}_2 \in \mathbb{R}^{d_d}$
Hyperparameters: w , widening factor

```
1 for  $l = 0, 1, \dots, \ell - 1$  do
2    $Y \leftarrow W_1 X[:, l] + \mathbf{b}_1 \mathbf{1}^\top$ 
3    $Y \leftarrow \text{GELU}(Y[:, (wd_d/2)]) Y[(wd_d/2) :]$ 
4    $Y^l \leftarrow W_2 Y + \mathbf{b}_2 \mathbf{1}^\top$ 
5 end
6 return  $Y = [Y^0; Y^1; \dots; Y^{\ell-1}]$ 
```

Algorithm 4: ScatteringResidualConvBlock

Input: $X \in \mathbb{R}^{d_d \times \ell}$
Output: $Z \in \mathbb{R}^{d_d \times \ell}$
Hyperparameters: ℓ, d number of stabilizers and code distance, related by $\ell = d^2 - 1$.
 L number of CNN layers. $c \in \mathbb{R}^L$ output channels of CNN.

/* Scatter to 2D */

```
1 for  $coord = (0, 0), (0, 1) \dots (d, d)$  do
2   if  $\exists$  stabilizer index with coordinates  $coord$  then  $Y[coord, :] \leftarrow X[:, index]$ 
3   else  $Y[coord, :] \leftarrow \mathbf{P}$ 
4 end
5 for  $l = 0, 1, \dots, L - 1$  do
6   /* Dilated convolutions */
7    $\tilde{Y} \leftarrow \text{layer\_norm}(Y)$ 
8    $\tilde{Y} \leftarrow \text{GELU}(\text{CNN}(\tilde{Y}; \text{kernel\_size} = 3, \text{channels} = c[l]))$ 
9   if  $c[l] \neq d_d$  then
10    |  $\tilde{Y} \leftarrow \text{CNN}(\tilde{Y}; \text{kernel\_size} = 1, \text{channels} = d_d)$ 
11  end
12   $Y \leftarrow Y + \tilde{Y}$                    $\llbracket Y \in \mathbb{R}^{(d+1)(d+1)d_d} \rrbracket$ 
13 end
14 /* Gather from 2D */
15 for  $coord = (0, 0), (0, 1) \dots (d, d)$  do
16   if  $\exists$  stabilizer index with coordinates  $coord$  then
17     |  $Z[:, index] \leftarrow Y[coord, :]$ 
18   end
19 end
20 return  $Z$ 
```

Algorithm 5: RNNCore

Input: $X \in \mathbb{R}^{d_d \times \ell}$, decoder state. $S \in \mathbb{R}^{d_d \times \ell}$, embedded stabilizers at current round.
 $B \in \mathbb{R}^{d_b \ell \ell}$ embedded attention bias.

Output: $X \in \mathbb{R}^{d_d \times \ell}$, updated decoder state.

Hyperparameters: $L \in \mathbb{N}$, number of layers

```
1  $X \leftarrow (X + S)/\sqrt{2}$ 
2 for  $l = 0, 1, \dots, L - 1$  do
3   /* SyndromeTransformer */
4    $\tilde{X} \leftarrow \text{layer\_norm}(X)$ 
5    $X \leftarrow X + \text{MHAttentionWithBias}(\tilde{X}, B)$ 
6    $\tilde{X} \leftarrow \text{layer\_norm}(X)$ 
7    $X \leftarrow X + \text{GatedDenseBlock}(\tilde{X})$ 
8    $X \leftarrow \text{ScatteringResidualConvBlock}(X)$ 
9 end
9 return  $X$ 
```
