

## Appendix

### A. Notation

For  $n \in \mathbb{N}$ , we use  $[n]$  to denote the set  $\{0, \dots, n\}$ . For a vector  $\mathbf{v}$ , we use  $\mathbf{v}_j$  to denote the element in the  $j^{\text{th}}$  position of the vector. We use  $\mathbf{A}_{j,:}$  and  $\mathbf{A}_{:,k}$  to denote the  $j^{\text{th}}$  row and  $k^{\text{th}}$  column of the matrix  $\mathbf{A}$  respectively. We assume both  $\mathbf{A}_{j,:}$ ,  $\mathbf{A}_{:,k}$  to be column vectors (thus  $\mathbf{A}_{j,:}$  is the transpose of  $j^{\text{th}}$  row of  $\mathbf{A}$ ).  $\mathbf{A}_{j,k}$  denotes the element in  $j^{\text{th}}$  row and  $k^{\text{th}}$  column of  $\mathbf{A}$ .  $\mathbf{A}_{j,:k}$  and  $\mathbf{A}_{:j,k}$  denote the vectors containing the first  $k$  elements of the  $j^{\text{th}}$  row and first  $j$  elements of  $k^{\text{th}}$  column, respectively.  $\mathbf{A}_{:,j:k}$  denotes the matrix containing the first  $j$  rows and  $k$  columns of  $\mathbf{A}$ . The same rules can be directly extended to higher order tensors. We use bold zero i.e  $\mathbf{0}$  to denote the matrix (or tensor) consisting of zero at all elements,  $\mathbf{I}_n$  to denote the identity matrix of size  $n \times n$ . We use  $\mathbb{C}$  to denote the field of complex numbers and  $\mathbb{R}$  for real numbers. For a scalar  $a \in \mathbb{C}$ ,  $\bar{a}$  denotes its complex conjugate. For a vector  $\mathbf{v}$  or matrix (or tensor)  $\mathbf{A}$ ,  $\bar{\mathbf{v}}$  or  $\bar{\mathbf{A}}$  denotes the element-wise complex conjugate. For  $\mathbf{A} \in \mathbb{C}^{m \times n}$ ,  $\mathbf{A}^H$  denotes the hermitian transpose i.e  $\mathbf{A}^H = \overline{\mathbf{A}^T}$ . For a scalar  $a \in \mathbb{C}$ ,  $\text{Re}(a)$ ,  $\text{Im}(a)$  and  $|a|$  denote the real part, imaginary part and modulus of  $a$  respectively. We use  $[a, b)$  where  $a, b \in \mathbb{C}$  to denote the set consisting of complex scalars on the line connecting  $a$  and  $b$  (including  $a$ , but excluding  $b$ ).  $\mathbf{A} \otimes \mathbf{B}$  denotes the kronecker product between matrices  $\mathbf{A}$  and  $\mathbf{B}$ . We use  $\iota$  to denote *iota* (i.e  $\iota^2 = -1$ ).

For a matrix  $\mathbf{A} \in \mathbb{C}^{q \times r}$  and a tensor  $\mathbf{B} \in \mathbb{C}^{p \times q \times r}$ ,  $\vec{\mathbf{A}}$  denotes the vector constructed by stacking the rows of  $\mathbf{A}$  and  $\vec{\mathbf{B}}$  by stacking the vectors  $\vec{\mathbf{B}}_{j,:}$ ,  $j \in [p-1]$  so that:

$$\begin{aligned} (\vec{\mathbf{A}})^T &= [\mathbf{A}_{0,:}^T, \mathbf{A}_{1,:}^T, \dots, \mathbf{A}_{q-1,:}^T] \\ (\vec{\mathbf{B}})^T &= \left[ (\vec{\mathbf{B}}_{0,:})^T, (\vec{\mathbf{B}}_{1,:})^T, \dots, (\vec{\mathbf{B}}_{p-1,:})^T \right] \end{aligned}$$

For a 2D convolution filter,  $\mathbf{L} \in \mathbb{C}^{p \times q \times r \times s}$ , we define the tensor  $\text{conv\_transpose}(\mathbf{L}) \in \mathbb{C}^{q \times p \times r \times s}$  as follows:

$$[\text{conv\_transpose}(\mathbf{L})]_{i,j,k,l} = \overline{[\mathbf{L}]_{j,i,r-1-k,s-1-l}} \quad (7)$$

Note that this is very different from the usual matrix transpose. Given an input  $\mathbf{X} \in \mathbb{C}^{p \times n \times n}$ , we use  $\mathbf{L} \star \mathbf{X} \in \mathbb{C}^{p \times n \times n}$  to denote the convolution of filter  $\mathbf{L}$  with  $\mathbf{X}$ . The notation  $\mathbf{L} \star^i \mathbf{X} \triangleq \mathbf{L} \star^{i-1} (\mathbf{L} \star \mathbf{X})$ . Unless specified otherwise, we assume zero padding and stride 1 in each direction.

### B. Proofs

#### B.1. Proof of Theorem 1

**Theorem.** Consider a convolution filter  $\mathbf{L} \in \mathbb{C}^{m \times m \times (2p+1) \times (2q+1)}$  applied to an input  $\mathbf{X} \in \mathbb{C}^{m \times n \times n}$

that results in output  $\mathbf{Y} = \mathbf{L} \star \mathbf{X} \in \mathbb{C}^{m \times n \times n}$ . Let  $\mathbf{J}$  be the jacobian of  $\vec{\mathbf{Y}}$  with respect to  $\vec{\mathbf{X}}$ , then the jacobian for convolution with the filter  $\text{conv\_transpose}(\mathbf{L})$  is equal to  $\mathbf{J}^H$ .

*Proof.* We first prove the above result assuming  $m = 1$ .

**Assuming  $m = 1$ :**

We know that  $\mathbf{J}$  is a doubly toeplitz matrix of size  $n^2 \times n^2$ :

$$\mathbf{J} = \begin{bmatrix} \mathbf{J}^{(0)} & \mathbf{J}^{(-1)} & \dots & \mathbf{J}^{(-p)} & 0 \\ \mathbf{J}^{(1)} & \mathbf{J}^{(0)} & \mathbf{J}^{(-1)} & \ddots & \ddots \\ \vdots & \mathbf{J}^{(1)} & \mathbf{J}^{(0)} & \ddots & \ddots \\ \mathbf{J}^{(p)} & \ddots & \ddots & \ddots & \mathbf{J}^{(-1)} \\ 0 & \ddots & \ddots & \mathbf{J}^{(1)} & \mathbf{J}^{(0)} \end{bmatrix}$$

In the above equation, each  $\mathbf{J}^{(i)}$  is a toeplitz matrix of size  $n \times n$ . Define  $\mathbf{P}^{(k)}$  as a  $n \times n$  matrix with  $\mathbf{P}_{i,j}^{(k)} = 1$  if  $i - j = k$  and 0 otherwise. Thus  $\mathbf{J}$  can be written as:

$$\mathbf{J} = \sum_{i=-p}^p \mathbf{P}^{(i)} \otimes \mathbf{J}^{(i)}$$

Since each matrix  $\mathbf{J}^{(i)}$  is a toeplitz matrix, it can be written as follows. Because the first two dimensions of filter  $\mathbf{L}$  are of size 1, we index  $\mathbf{L}$  using only the last two indices:

$$\mathbf{J}^{(i)} = \sum_{j=-q}^q \mathbf{L}_{p+i,q+j} \mathbf{P}^{(j)}$$

Thus,  $\mathbf{J}$  can be written as:

$$\mathbf{J} = \sum_{i=-p}^p \sum_{j=-q}^q \mathbf{L}_{p+i,q+j} \left( \mathbf{P}^{(i)} \otimes \mathbf{P}^{(j)} \right)$$

Thus,  $\mathbf{J}^H$  can be written as:

$$\begin{aligned} \mathbf{J}^H &= \sum_{i=-p}^p \sum_{j=-q}^q \overline{\mathbf{L}_{p+i,q+j}} \left( \mathbf{P}^{(i)} \otimes \mathbf{P}^{(j)} \right)^T \\ \mathbf{J}^H &= \sum_{i=-p}^p \sum_{j=-q}^q \overline{\mathbf{L}_{p+i,q+j}} \left( \mathbf{P}^{(i)} \right)^T \otimes \left( \mathbf{P}^{(j)} \right)^T \\ \mathbf{J}^H &= \sum_{i=-p}^p \sum_{j=-q}^q \overline{\mathbf{L}_{p+i,q+j}} \left( \mathbf{P}^{(-i)} \otimes \mathbf{P}^{(-j)} \right) \\ \mathbf{J}^H &= \sum_{i=-p}^p \sum_{j=-q}^q \overline{\mathbf{L}_{p-i,q-j}} \left( \mathbf{P}^{(i)} \otimes \mathbf{P}^{(j)} \right) \end{aligned}$$

Thus  $\mathbf{J}^H$  corresponds to the jacobian of the convolution filter flipped along the third, fourth axis and each individual element conjugated.

Next, we prove the result when  $m > 1$ .

**Assuming  $m > 1$ :**

We know that  $\mathbf{J}$  is a matrix of size  $mn^2 \times mn^2$ . Let  $\mathbf{J}^{(i,j)}$  denote the block of size  $n^2 \times n^2$  as follows:

$$\mathbf{J}^{(i,j)} = \mathbf{J}_{in^2:(i+1)n^2, jn^2:(j+1)n^2}$$

Note that  $\mathbf{J}^{(i,j)}$  is the jacobian of convolution with  $1 \times 1$  filter  $\mathbf{L}_{i:i+1, j:j+1, :, :}$ . Now consider the  $(i, j)^{th}$  block of  $\mathbf{J}^H$ . Using definition of conjugate transpose (i.e  $H$  operator):

$$(\mathbf{J}^H)^{(i,j)} = (\mathbf{J}^{(j,i)})^H \quad (8)$$

Consider the  $1 \times 1$  filter at the  $(i, j)^{th}$  index in  $\text{conv\_transpose}(\mathbf{L})$ . By the definition of  $\text{conv\_transpose}$  operator, we have:

$$\begin{aligned} & [\text{conv\_transpose}(\mathbf{L})]_{i:i+1, j:j+1, :, :} \\ &= \text{conv\_transpose}(\mathbf{L}_{j:j+1, i:i+1, :, :}) \end{aligned} \quad (9)$$

Using equations (8) and (9) and the proof for the case  $m = 1$ , we have the desired proof.  $\square$

## B.2. Proof of Theorem 2

**Theorem.** Consider a convolution filter  $\mathbf{L} \in \mathbb{C}^{m \times m \times (2p+1) \times (2q+1)}$ . Given an input  $\mathbf{X} \in \mathbb{C}^{m \times n \times n}$ , output  $\mathbf{Y} = \mathbf{L} \star \mathbf{X} \in \mathbb{C}^{m \times n \times n}$ . The jacobian of  $\vec{\mathbf{Y}}$  with respect to  $\vec{\mathbf{X}}$  (call it  $\mathbf{J}$ ) will be a matrix of size  $n^2 m \times n^2 m$ .  $\mathbf{J}$  is a skew hermitian matrix if and only if:

$$\mathbf{L} = \mathbf{M} - \text{conv\_transpose}(\mathbf{M})$$

for some filter  $\mathbf{M} \in \mathbb{C}^{m \times m \times (2p+1) \times (2q+1)}$ .

*Proof.* We first prove that if  $\mathbf{J}$  is a skew-hermitian matrix, then:

$$\mathbf{L} = \mathbf{M} - \text{conv\_transpose}(\mathbf{M})$$

Let  $\mathbf{J}^{(i,j)}$  denote the block of size  $n^2 \times n^2$  as follows:

$$\mathbf{J}^{(i,j)} = \mathbf{J}_{in^2:(i+1)n^2, jn^2:(j+1)n^2}$$

so that  $\mathbf{J}$  can be written in terms of the blocks  $\mathbf{J}^{(i,j)}$ :

$$\mathbf{J} = \begin{bmatrix} \mathbf{J}^{(0,0)} & \mathbf{J}^{(0,1)} & \dots & \mathbf{J}^{(0,m-1)} \\ \mathbf{J}^{(1,0)} & \mathbf{J}^{(1,1)} & \dots & \mathbf{J}^{(1,m-1)} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{J}^{(m-1,0)} & \mathbf{J}^{(m-1,1)} & \dots & \mathbf{J}^{(m-1,m-1)} \end{bmatrix}$$

Since  $\mathbf{J}$  is skew-hermitian, we have:

$$\mathbf{J}^{(i,j)} = -\left(\mathbf{J}^{(j,i)}\right)^H, \quad \forall i, j \in [m-1]$$

It is readily observed that  $\mathbf{J}^{(i,j)}$  corresponds to the jacobian of convolution with  $1 \times 1$  filter  $\mathbf{L}_{i:i+1, j:j+1, :, :}$ . For some given filter  $\mathbf{A}$ , we use  $\mathbf{A}^{(i,j)}$  to denote the  $1 \times 1$  filter  $\mathbf{A}_{i:i+1, j:j+1, :, :}$  for simplicity. Thus, the above equation can be rewritten as:

$$\mathbf{L}^{(i,j)} = -\text{conv\_transpose}\left(\mathbf{L}^{(j,i)}\right), \quad \forall i, j \in [m-1] \quad (10)$$

Now construct a filter  $\mathbf{M}$  such that for  $i \neq j$ :

$$\mathbf{M}^{(i,j)} = \begin{cases} \mathbf{L}^{(i,j)}, & i < j \\ \mathbf{0}, & i > j \end{cases} \quad (11)$$

For  $i = j$ ,  $\mathbf{M}$  is given as follows:

$$\mathbf{M}_{r,s}^{(i,i)} = \begin{cases} \mathbf{L}_{r,s}^{(i,i)}, & r \leq p-1 \\ \mathbf{L}_{r,s}^{(i,i)}, & r = p, s \leq q-1 \\ 0.5 \times \mathbf{L}_{r,s}^{(i,i)}, & r = p, s = q \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

Next, our goal is to show that:

$$\mathbf{L} = \mathbf{M} - \text{conv\_transpose}(\mathbf{M})$$

Now by the definition of  $\text{conv\_transpose}$ , we have:

$$\begin{aligned} & [\mathbf{M} - \text{conv\_transpose}(\mathbf{M})]^{(i,j)} \\ &= \mathbf{M}^{(i,j)} - [\text{conv\_transpose}(\mathbf{M})]^{(i,j)} \\ &= \mathbf{M}^{(i,j)} - \text{conv\_transpose}\left(\mathbf{M}^{(j,i)}\right) \end{aligned} \quad (13)$$

**Case 1:** For  $i < j$ , using equations (10) and (11):

$$\mathbf{M}^{(i,j)} - \text{conv\_transpose}\left(\mathbf{M}^{(j,i)}\right) = \mathbf{M}^{(i,j)} = \mathbf{L}^{(i,j)}$$

**Case 2:** For  $i > j$ , using equations (10) and (11):

$$\begin{aligned} & \mathbf{M}^{(i,j)} - \text{conv\_transpose}\left(\mathbf{M}^{(j,i)}\right) \\ &= -\text{conv\_transpose}\left(\mathbf{M}^{(j,i)}\right) \\ &= -\text{conv\_transpose}\left(\mathbf{L}^{(j,i)}\right) = \mathbf{L}^{(i,j)} \end{aligned}$$

**Case 3:** For  $i = j$ , we further simplify equation (13):

$$\begin{aligned} & \mathbf{M}_{r,s}^{(i,i)} - \left[\text{conv\_transpose}\left(\mathbf{M}^{(i,i)}\right)\right]_{r,s} \\ &= \mathbf{M}_{r,s}^{(i,i)} - \overline{\mathbf{M}_{2p-r, 2q-s}^{(i,i)}} \end{aligned} \quad (14)$$

**Subcase 3(a):** For  $(r \leq p-1)$  or  $(r = p, s \leq q-1)$ , we have:

$$\mathbf{M}_{2p-r, 2q-s}^{(i,i)} = 0$$

Thus for  $(r \leq p-1)$  or  $(r = p, s \leq q-1)$ : equation (14) simplifies to  $\mathbf{M}_{r,s}^{(i,i)}$ . The result follows trivially from the

very definition of  $\mathbf{M}_{r,s}^{(i,i)}$ , i.e equation (12).

**Subcase 3(b):** For  $(r \geq p+1)$  or  $(r = p, s \geq q+1)$ , we have:

$$\mathbf{M}_{r,s}^{(i,i)} = 0$$

Thus, equation (14) simplifies to:

$$\mathbf{M}_{r,s}^{(i,i)} - \overline{\mathbf{M}_{2p-r,2q-s}^{(i,i)}} = -\overline{\mathbf{M}_{2p-r,2q-s}^{(i,i)}}$$

Since  $(r \geq p+1)$  or  $(r = p, s \geq q+1)$ , we have:  $(2p-r \leq p-1)$  or  $(2p-r = p, 2q-s \leq q-1)$  respectively. Thus using equation (12), we have:

$$-\overline{\mathbf{M}_{2p-r,2q-s}^{(i,i)}} = -\overline{\mathbf{L}_{2p-r,2q-s}^{(i,i)}}$$

Since  $\mathbf{L}^{(i,i)}$  is a skew-hermitian filter, we have from Theorem 1:

$$\mathbf{L}_{r,s}^{(i,i)} = -\overline{\mathbf{L}_{2p-r,2q-s}^{(i,i)}}$$

Thus in this subcase, equation (14) simplifies to  $\mathbf{L}_{r,s}^{(i,i)}$  again.

**Subcase 3(c):** For  $r = p, s = q$ , since  $\mathbf{L}^{(i,i)}$  is a skew-hermitian filter, we have:

$$\begin{aligned} \mathbf{L}_{p,q}^{(i,i)} &= -\overline{\mathbf{L}_{p,q}^{(i,i)}} \\ \mathbf{L}_{p,q}^{(i,i)} + \overline{\mathbf{L}_{p,q}^{(i,i)}} &= 0 \end{aligned}$$

Thus,  $\mathbf{L}_{p,q}^{(i,i)}$  is a purely imaginary number. In this subcase

$$\begin{aligned} \mathbf{M}_{r,s}^{(i,i)} - \overline{\mathbf{M}_{2p-r,2q-s}^{(i,i)}} \\ = \mathbf{M}_{p,q}^{(i,i)} - \overline{\mathbf{M}_{p,q}^{(i,i)}} = 2\mathbf{M}_{p,q}^{(i,i)} \end{aligned}$$

Using equation (12), we have:

$$2\mathbf{M}_{p,q}^{(i,i)} = \mathbf{L}_{p,q}^{(i,i)}$$

Thus, we get:

$$\mathbf{M}_{r,s}^{(i,i)} - \left[ \text{conv\_transpose} \left( \mathbf{M}^{(i,i)} \right) \right]_{r,s} = \mathbf{L}_{r,s}^{(i,i)}$$

Thus we have established:  $\mathbf{L} = \mathbf{M} - \text{conv\_transpose}(\mathbf{M})$ . Note that the opposite direction of the if and only if statement follows trivially from the above proof.  $\square$

### B.3. Proof of Theorem 3

**Theorem.** (a) For a scalar  $\lambda \in \mathbb{C}$  with  $\text{Re}(\lambda) = 0$ , the error between  $\exp(\lambda)$  and approximation  $p_k(\lambda)$  given below can be bounded as follows:

$$\exp(\lambda) = \sum_{i=0}^{\infty} \frac{\lambda^i}{i!}, \quad p_k(\lambda) = \sum_{i=0}^{k-1} \frac{\lambda^i}{i!} \quad (15)$$

$$\left| \exp(\lambda) - p_k(\lambda) \right| \leq \frac{|\lambda|^k}{k!}, \quad \forall \lambda : \text{Re}(\lambda) = 0$$

(b) For a skew-hermitian matrix  $\mathbf{A}$ , the error between  $\exp(\mathbf{A})$  and the series approximation  $\mathbf{S}_k(\mathbf{A})$  can be bounded as follows:

$$\begin{aligned} \exp(\mathbf{A}) &= \sum_{i=0}^{\infty} \frac{\mathbf{A}^i}{i!}, \quad \mathbf{S}_k(\mathbf{A}) = \sum_{i=0}^{k-1} \frac{\mathbf{A}^i}{i!} \\ \|\exp(\mathbf{A}) - \mathbf{S}_k(\mathbf{A})\|_2 &\leq \frac{\|\mathbf{A}\|_2^k}{k!} \end{aligned}$$

*Proof.* Since  $\mathbf{A}$  is skew-hermitian, it is a normal matrix and eigenvectors for distinct eigenvalues must be orthogonal. Let the eigenvalue decomposition of  $\mathbf{A}$  be given as follows:

$$\mathbf{A} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H$$

Note that  $\mathbf{\Lambda}$  is a diagonal matrix, and each element along the diagonal is purely imaginary (since  $\mathbf{A}$  is skew-hermitian). Exponentiating both sides, we get:

$$\exp(\mathbf{A}) = \mathbf{U} \exp(\mathbf{\Lambda}) \mathbf{U}^H$$

Thus the error  $\mathbf{E}_k(\mathbf{A})$  is given by:

$$\mathbf{E}_k(\mathbf{A}) = \exp(\mathbf{A}) - \mathbf{S}_k(\mathbf{A}) \quad (16)$$

$$\mathbf{E}_k(\mathbf{A}) = \mathbf{U} (\exp(\mathbf{\Lambda}) - \mathbf{S}_k(\mathbf{\Lambda})) \mathbf{U}^H$$

$$\|\mathbf{E}_k(\mathbf{A})\|_2 = \|\mathbf{U} (\exp(\mathbf{\Lambda}) - \mathbf{S}_k(\mathbf{\Lambda})) \mathbf{U}^H\|_2$$

$$\|\mathbf{E}_k(\mathbf{A})\|_2 = \|(\exp(\mathbf{\Lambda}) - \mathbf{S}_k(\mathbf{\Lambda}))\|_2$$

Since  $(\exp(\mathbf{\Lambda}) - \mathbf{S}_k(\mathbf{\Lambda}))$  is a diagonal matrix, we have:

$$\|\mathbf{E}_k(\mathbf{A})\|_2 = \max_i |(\exp(\Lambda_{i,i}) - p_k(\Lambda_{i,i}))| \quad (17)$$

Let  $\lambda$  be an arbitrary element along the diagonal of  $\mathbf{\Lambda}$  i.e  $\lambda = \Lambda_{i,i}$  for some  $i$ . First note that:

$$\begin{aligned} \lambda \int_0^1 \{\exp(t\lambda) - p_k(t\lambda)\} dt \\ = \int_0^1 \{\exp(t\lambda) - p_k(t\lambda)\} \lambda dt \end{aligned}$$

Substituting  $u = \lambda t$ , we have:

$$\begin{aligned} &= \int_0^\lambda \{\exp(u) - p_k(u)\} du \\ &= \int_0^\lambda \exp(u) du - \int_0^\lambda p_k(u) du \\ &= \exp(\lambda) - 1 - \int_0^\lambda p_k(u) du \end{aligned}$$

Substituting  $p_k(u)$  using equation (15):

$$\begin{aligned}
 &= \exp(\lambda) - 1 - \int_0^\lambda \sum_{i=0}^{k-1} \frac{u^i}{i!} du \\
 &= \exp(\lambda) - 1 - \sum_{i=0}^{k-1} \int_0^\lambda \frac{u^i}{i!} du \\
 &= \exp(\lambda) - 1 - \sum_{i=0}^{k-1} \frac{u^{i+1}}{(i+1)!} \Big|_0^\lambda \\
 &= \exp(\lambda) - 1 - \sum_{i=0}^{k-1} \frac{\lambda^{i+1}}{(i+1)!} \\
 &= \exp(\lambda) - 1 - \sum_{i=1}^k \frac{\lambda^i}{i!} \\
 &= \exp(\lambda) - \sum_{i=0}^{k+1} \frac{\lambda^i}{i!} \\
 &= \exp(\lambda) - p_{k+1}(\lambda)
 \end{aligned}$$

This gives the following result:

$$\exp(\lambda) - p_{k+1}(\lambda) = \lambda \int_0^1 \left( \exp(t\lambda) - p_k(t\lambda) \right) dt \quad (18)$$

We shall now prove the main result using induction and equation (18):

**Base case:**

Use  $k = 0$  and the convention that  $p_0(\lambda) = 0$ . We know that  $p_1(\lambda) = 1$ .

$$\begin{aligned}
 \exp(\lambda) - p_1(\lambda) &= \lambda \int_0^1 \left( \exp(t\lambda) - p_0(t\lambda) \right) dt \\
 |\exp(\lambda) - 1| &= \left| \lambda \int_0^1 \exp(t\lambda) dt \right|
 \end{aligned}$$

Since  $\lambda$  is purely imaginary and  $t$  is purely real, we have  $|\exp(t\lambda)| = 1$ :

$$\begin{aligned}
 |\exp(\lambda) - 1| &\leq |\lambda| \int_0^1 |\exp(t\lambda)| dt = |\lambda| \int_0^1 1 dt \\
 |\exp(\lambda) - 1| &\leq |\lambda|
 \end{aligned}$$

**Induction step:**

Assuming this holds for all  $k$  i.e:

$$\left| \exp(\lambda) - p_k(\lambda) \right| \leq \frac{|\lambda|^k}{k!} \quad (19)$$

Now let us consider  $|\exp(\lambda) - p_{k+1}(\lambda)|$ :

$$\begin{aligned}
 |\exp(\lambda) - p_{k+1}(\lambda)| &\leq \left| \lambda \int_0^1 \left( \exp(t\lambda) - p_k(t\lambda) \right) dt \right| \\
 |\exp(\lambda) - p_{k+1}(\lambda)| &\leq |\lambda| \int_0^1 \left| \exp(t\lambda) - p_k(t\lambda) \right| dt
 \end{aligned}$$

Using equation (19), we have:

$$\begin{aligned}
 |\exp(\lambda) - p_{k+1}(\lambda)| &\leq |\lambda| \int_0^1 \frac{|t\lambda|^k}{k!} dt \\
 |\exp(\lambda) - p_{k+1}(\lambda)| &\leq |\lambda|^{k+1} \int_0^1 \frac{|t|^k}{k!} dt \\
 |\exp(\lambda) - p_{k+1}(\lambda)| &\leq \frac{|\lambda|^{k+1}}{(k+1)!}
 \end{aligned}$$

This proves (a).

Since  $\lambda$  is an arbitrary element along the diagonal of eigenvalue matrix  $\Lambda$ , using equations (16) and (17) we have:

$$\begin{aligned}
 \|\exp(\mathbf{A}) - \mathbf{S}_k(\mathbf{A})\|_2 &= \max_i \left| \exp(\Lambda_{i,i}) - p_k(\Lambda_{i,i}) \right| \\
 \|\exp(\mathbf{A}) - \mathbf{S}_k(\mathbf{A})\|_2 &\leq \max_i \frac{|\Lambda_{i,i}|^k}{k!} \\
 \|\exp(\mathbf{A}) - \mathbf{S}_k(\mathbf{A})\|_2 &\leq \frac{1}{k!} \max_i |\Lambda_{i,i}|^k \quad (20)
 \end{aligned}$$

Since  $\mathbf{A}$  is skew-hermitian, it is a normal matrix and singular values are equal to the magnitude of eigenvalues. Thus we have from equation (20):

$$\begin{aligned}
 \max_i |\Lambda_{i,i}| &= \|\Lambda\|_2 = \|\mathbf{A}\|_2 \\
 \|\exp(\mathbf{A}) - \mathbf{S}_k(\mathbf{A})\|_2 &\leq \frac{\|\mathbf{A}\|_2^k}{k!}
 \end{aligned}$$

This proves (b).  $\square$

#### B.4. Proof of Theorem 4

**Theorem.** Given a real skew-symmetric matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$ , we can construct a real skew-symmetric matrix  $\mathbf{B} \in \mathbb{R}^{n \times n}$  such that  $\mathbf{B}$  satisfies: (a)  $\exp(\mathbf{A}) = \exp(\mathbf{B})$  and (b)  $\|\mathbf{B}\|_2 \leq \pi$ .

*Proof.* We know that for eigenvalues of real symmetric matrices are purely imaginary and come in pairs:  $\lambda_1 t, -\lambda_1 t, \lambda_2 t, -\lambda_2 t$  where each  $\lambda_i$  is real. When  $n$  is an odd integer, 0 is an eigenvalue. Additionally, we know that a real skew symmetric matrix can be expressed in a block diagonal form as follows:

$$\mathbf{A} = \mathbf{Q}\Sigma\mathbf{Q}^T \quad (21)$$

Here  $\mathbf{Q}$  is a real orthogonal matrix and  $\Sigma$  is a block diagonal matrix defined as follows:

$$\Sigma_{2i:2i+2, 2i:2i+2} = \begin{bmatrix} 0 & \lambda_i \\ -\lambda_i & 0 \end{bmatrix}, \quad 0 \leq i < \left\lfloor \frac{n}{2} \right\rfloor \quad (22)$$

In the above equation,  $\lambda_i \in \mathbb{R}$  and  $\pm \lambda_i t$  are the eigenvalues of  $\mathbf{A}$ . When  $n$  is odd, we additionally have:

$$\Sigma_{n-1, n-1} = 0$$

Taking the exponential of both sides of equation (21):

$$\exp(\mathbf{A}) = \mathbf{Q} \exp(\Sigma) \mathbf{Q}^T \quad (23)$$

We can compute  $\exp(\Sigma)$  by computing the exponential of each  $2 \times 2$  block defined in equation (22):

$$\begin{aligned} & \exp\left(\begin{bmatrix} 0 & \lambda_i \\ -\lambda_i & 0 \end{bmatrix}\right) \\ &= \exp\left(\lambda_i \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}\right) = \begin{bmatrix} \cos(\lambda_i) & -\sin(\lambda_i) \\ \sin(\lambda_i) & \cos(\lambda_i) \end{bmatrix} \end{aligned} \quad (24)$$

From equation (24), we observe each  $\lambda_i$  can be shifted by integer multiples of  $2\pi\ell$  without changing the exponential. For each  $\lambda_i$ ,  $i \in [\lfloor n/2 \rfloor - 1]$ , we define a scalar  $\mu_i$ :

$$\mu_i = \lambda_i + 2\pi k_i \ell, \quad k_i \in \mathbb{Z} \quad (25)$$

$$\mu_i \in [-\pi\ell, \pi\ell] \quad (26)$$

Construct a new matrix  $\mathbf{B}$  defined as follows:

$$\mathbf{B} = \mathbf{Q}\mathbf{D}\mathbf{Q}^T \quad (27)$$

The matrix  $\mathbf{D}$  in equation (27) is defined as follows:

$$\mathbf{D}_{2i:2i+2, 2i:2i+2} = \begin{bmatrix} 0 & \mu_i \\ -\mu_i & 0 \end{bmatrix}, \quad 0 \leq i < \lfloor \frac{n}{2} \rfloor \quad (28)$$

Let us verify that  $\mathbf{B}$  satisfies the following properties. Using equations (24), (25) and (28), we know that:

$$\exp(\mathbf{D}) = \exp(\Lambda)$$

This results in the following set of equations:

$$\exp(\mathbf{B}) = \mathbf{Q} \exp(\mathbf{D}) \mathbf{Q}^T$$

$$\exp(\mathbf{B}) = \mathbf{Q} \exp(\Lambda) \mathbf{Q}^T = \exp(\mathbf{A})$$

Using equations (26) and (28), we have:

$$\begin{aligned} \|\mathbf{B}\|_2 &= \|\mathbf{Q}\mathbf{D}\mathbf{Q}^T\|_2 = \|\mathbf{D}\|_2 \\ \|\mathbf{D}\|_2 &\leq \pi \end{aligned}$$

Note that  $\mathbf{B}$  is a product of 3 real matrices  $\mathbf{Q}$ ,  $\mathbf{D}$  and  $\mathbf{Q}^T$  and hence  $\mathbf{B}$  is real. Moreover, since  $\mathbf{D}$  is skew symmetric,  $\mathbf{B}$  is skew symmetric.  $\square$

### B.5. Proof of Theorem 5

**Theorem 5.** *Given a skew-hermitian matrix  $\mathbf{A}$ , we can construct a skew-hermitian matrix  $\mathbf{B}$  by adding integer multiples of  $2\pi\ell$  to eigenvalues of  $\mathbf{A}$  such that  $\mathbf{B}$  satisfies: (a)  $\exp(\mathbf{A}) = \exp(\mathbf{B})$  and (b)  $\|\mathbf{B}\|_2 \leq \pi$ .*

*Proof.* Let the eigenvalue decomposition of  $\mathbf{A}$  be given:

$$\mathbf{A} = \mathbf{U}\Lambda\mathbf{U}^H$$

Let  $\lambda_j$  be some eigenvalue of  $\mathbf{A}$  such that:

$$\lambda_j = \Lambda_{j,j}$$

Construct a new diagonal matrix  $\mathbf{D}$  of eigenvalues such that:

$$\mathbf{D}_{j,j} = \lambda_j + 2\pi k_j \ell, \quad k_j \in \mathbb{Z} \quad (29)$$

$$\mathbf{D}_{j,j} \in [-\pi\ell, \pi\ell] \quad (30)$$

Construct a new matrix  $\mathbf{B}$  defined as follows:

$$\mathbf{B} = \mathbf{U}\mathbf{D}\mathbf{U}^H$$

Let us verify that  $\mathbf{B}$  satisfies the following properties.

Using equation (29), we have:

$$\exp(\mathbf{B}) = \mathbf{U} \exp(\mathbf{D}) \mathbf{U}^H$$

$$\exp(\mathbf{B}) = \mathbf{U} \exp(\Lambda) \mathbf{U}^H = \exp(\mathbf{A})$$

Using equation (30), we have:

$$\begin{aligned} \|\mathbf{B}\|_2 &= \|\mathbf{U}\mathbf{D}\mathbf{U}^H\|_2 = \|\mathbf{D}\|_2 \\ \|\mathbf{D}\|_2 &= \max_j |D_{j,j}| \leq \pi \end{aligned}$$

$\square$

### B.6. Proof of Theorem 6

**Theorem 6.** *Consider a convolution filter  $\mathbf{L} \in \mathbb{C}^{m \times m \times (2p+1) \times (2q+1) \times (2r+1)}$  applied to an input  $\mathbf{X} \in \mathbb{C}^{m \times n \times n \times n}$  that results in output  $\mathbf{Y} = \mathbf{L} \star \mathbf{X} \in \mathbb{C}^{m \times n \times n \times n}$ . Let  $\mathbf{J}$  be the jacobian of  $\vec{\mathbf{Y}}$  with respect to  $\vec{\mathbf{X}}$ , then the jacobian for convolution with the filter  $\text{conv3d\_transpose}(\mathbf{L})$  is equal to  $\mathbf{J}^H$ .*

*Proof.* We first prove the above result assuming  $m = 1$ .

**Assuming  $m = 1$ :**

Because the first two dimensions of filter  $\mathbf{L}$  are of size 1, we index  $\mathbf{L}$  using only the last two indices. Define  $\mathbf{P}^{(k)}$  as a  $n \times n$  matrix with  $\mathbf{P}_{i,j}^{(k)} = 1$  if  $i - j = k$  and 0 otherwise. We know that  $\mathbf{J}$  is a triply toeplitz matrix of size  $n^3 \times n^3$  given as follows:

$$\mathbf{J} = \sum_{i=-p}^p \sum_{j=-q}^q \sum_{k=-r}^r \mathbf{L}_{p+i, q+j, r+k} \left( \mathbf{P}^{(i)} \otimes \mathbf{P}^{(j)} \otimes \mathbf{P}^{(k)} \right)$$

Thus,  $\mathbf{J}^H$  can be written as:

$$\begin{aligned} & \mathbf{J}^H \\ &= \sum_{i=-p}^p \sum_{j=-q}^q \sum_{k=-r}^r \overline{\mathbf{L}_{p+i, q+j, r+k}} \left( \mathbf{P}^{(i)} \otimes \mathbf{P}^{(j)} \otimes \mathbf{P}^{(k)} \right)^T \\ &= \sum_{i=-p}^p \sum_{j=-q}^q \sum_{k=-r}^r \overline{\mathbf{L}_{p+i, q+j, r+k}} \mathbf{P}^{(-i)} \otimes \mathbf{P}^{(-j)} \otimes \mathbf{P}^{(-k)} \\ &= \sum_{i=-p}^p \sum_{j=-q}^q \sum_{k=-r}^r \overline{\mathbf{L}_{p-i, q-j, r-k}} \mathbf{P}^{(i)} \otimes \mathbf{P}^{(j)} \otimes \mathbf{P}^{(k)} \end{aligned}$$

Thus  $\mathbf{J}^H$  corresponds to the jacobian of the convolution filter flipped along the third, fourth, fifth axis and each individual element conjugated.

Next, we prove the above result when  $m > 1$ .

**Assuming  $m > 1$ :**

We know that  $\mathbf{J}$  is a matrix of size  $mn^3 \times mn^3$ . Let  $\mathbf{J}^{(i,j)}$  denote the block of size  $n^3 \times n^3$  as follows:

$$\mathbf{J}^{(i,j)} = \mathbf{J}_{in^3:(i+1)n^3, jn^3:(j+1)n^3}$$

Note that  $\mathbf{J}^{(i,j)}$  is the jacobian of convolution with  $1 \times 1$  filter  $\mathbf{L}_{i:i+1, j:j+1, :, :}$ . Now consider the  $(i, j)^{th}$  block of  $\mathbf{J}^H$ . Using definition of conjugate transpose (i.e  $H$  operator):

$$(\mathbf{J}^H)^{(i,j)} = (\mathbf{J}^{(j,i)})^H \quad (31)$$

Consider the  $1 \times 1$  filter at the  $(i, j)^{th}$  index in  $\text{conv3d\_transpose}(\mathbf{L})$ . By the definition of  $\text{conv3d\_transpose}$  operator, we have:

$$\begin{aligned} & [\text{conv3d\_transpose}(\mathbf{L})]_{i:i+1, j:j+1, :, :} \\ &= \text{conv3d\_transpose}(\mathbf{L}_{j:j+1, i:i+1, :, :}) \end{aligned} \quad (32)$$

Using equations (31) and (32) and the proof for the case  $m = 1$ , we have the desired proof.  $\square$

## B.7. Proof of Theorem 7

**Theorem 7.** Consider a convolution filter  $\mathbf{L} \in \mathbb{C}^{m \times m \times (2p+1) \times (2q+1) \times (2r+1)}$ . Given an input  $\mathbf{X} \in \mathbb{C}^{m \times n \times n \times n}$ , output  $\mathbf{Y} = \mathbf{L} \star \mathbf{X} \in \mathbb{C}^{m \times n \times n \times n}$ . The jacobian of  $\vec{\mathbf{Y}}$  with respect to  $\vec{\mathbf{X}}$  (call it  $\mathbf{J}$ ) will be a matrix of size  $n^3 m \times n^3 m$ .  $\mathbf{J}$  is a skew hermitian matrix if and only if:

$$\mathbf{L} = \mathbf{M} - \text{conv3d\_transpose}(\mathbf{M})$$

for some filter  $\mathbf{M} \in \mathbb{C}^{m \times m \times (2p+1) \times (2q+1) \times (2r+1)}$ .

*Proof.* We first prove that if  $\mathbf{J}$  is a skew-hermitian matrix, then:

$$\mathbf{L} = \mathbf{M} - \text{conv3d\_transpose}(\mathbf{M})$$

Let  $\mathbf{J}^{(i,j)}$  denote the block of size  $n^3 \times n^3$  as follows:

$$\mathbf{J}^{(i,j)} = \mathbf{J}_{in^3:(i+1)n^3, jn^3:(j+1)n^3}$$

Since  $\mathbf{J}$  is skew-hermitian, we have:

$$\mathbf{J}^{(i,j)} = -\left(\mathbf{J}^{(j,i)}\right)^H, \quad \forall i, j \in [m-1]$$

It is readily observed that  $\mathbf{J}^{(i,j)}$  corresponds to the jacobian of convolution with  $1 \times 1$  filter  $\mathbf{L}_{i:i+1, j:j+1, :, :}$ . For some given filter  $\mathbf{A}$ , we use  $\mathbf{A}^{(i,j)}$  to denote the  $1 \times 1$  filter

$\mathbf{A}_{i:i+1, j:j+1, :, :}$  for simplicity. Thus, the above equation can be rewritten as:

$$\mathbf{L}^{(i,j)} = -\text{conv3d\_transpose}\left(\mathbf{L}^{(j,i)}\right), \quad \forall i, j \in [m-1] \quad (33)$$

Now construct a filter  $\mathbf{M}$  such that for  $i \neq j$ :

$$\mathbf{M}^{(i,j)} = \begin{cases} \mathbf{L}^{(i,j)}, & i < j \\ \mathbf{0}, & i > j \end{cases} \quad (34)$$

For  $i = j$ ,  $\mathbf{M}$  is given as follows:

$$\mathbf{M}_{s,t,u}^{(i,i)} = \begin{cases} \mathbf{L}_{s,t,u}^{(i,i)}, & s \leq p-1 \\ \mathbf{L}_{s,t,u}^{(i,i)}, & s = p, t \leq q-1 \\ \mathbf{L}_{s,t,u}^{(i,i)}, & s = p, t = q, u \leq r-1 \\ 0.5 \times \mathbf{L}_{s,t,u}^{(i,i)}, & s = p, t = q, u = r \\ 0, & \text{otherwise} \end{cases} \quad (35)$$

Next, our goal is to show that:

$$\mathbf{L} = \mathbf{M} - \text{conv3d\_transpose}(\mathbf{M})$$

Now by the definition of  $\text{conv3d\_transpose}$ , we have:

$$\begin{aligned} & [\mathbf{M} - \text{conv3d\_transpose}(\mathbf{M})]^{(i,j)} \\ &= \mathbf{M}^{(i,j)} - [\text{conv3d\_transpose}(\mathbf{M})]^{(i,j)} \\ &= \mathbf{M}^{(i,j)} - \text{conv3d\_transpose}\left(\mathbf{M}^{(j,i)}\right) \end{aligned} \quad (36)$$

**Case 1:** For  $i < j$ , using equations (33) and (34):

$$\mathbf{M}^{(i,j)} - \text{conv3d\_transpose}\left(\mathbf{M}^{(j,i)}\right) = \mathbf{M}^{(i,j)} = \mathbf{L}^{(i,j)}$$

**Case 2:** For  $i > j$ , using equations (33) and (34):

$$\begin{aligned} & \mathbf{M}^{(i,j)} - \text{conv3d\_transpose}\left(\mathbf{M}^{(j,i)}\right) \\ &= -\text{conv3d\_transpose}\left(\mathbf{M}^{(j,i)}\right) \\ &= -\text{conv3d\_transpose}\left(\mathbf{L}^{(j,i)}\right) = \mathbf{L}^{(i,j)} \end{aligned}$$

**Case 3:** For  $i = j$ , we further simplify equation (36):

$$\begin{aligned} & \mathbf{M}_{s,t,u}^{(i,i)} - \left[\text{conv3d\_transpose}\left(\mathbf{M}^{(i,i)}\right)\right]_{s,t,u} \\ &= \mathbf{M}_{s,t,u}^{(i,i)} - \overline{\mathbf{M}_{2p-s, 2q-t, 2r-u}^{(i,i)}} \end{aligned} \quad (37)$$

**Subcase 3(a):** For  $(s \leq p-1)$  or  $(s = p, t \leq q-1)$  or  $(s = p, t = q, u \leq r-1)$ , we have:

$$\mathbf{M}_{2p-s, 2q-t, 2r-u}^{(i,i)} = 0$$

Thus for  $(s \leq p - 1)$  or  $(s = p, t \leq q - 1)$  or  $(s = p, t = q, u \leq r - 1)$ : equation (37) simplifies to  $\mathbf{M}_{s,t,u}^{(i,i)}$ . The result follows trivially from the very definition of  $\mathbf{L}_{s,t,u}^{(i,i)}$ , i.e equation (35).

**Subcase 3(b):** For  $(s \geq p + 1)$  or  $(s = p, t \geq q + 1)$  or  $(s = p, t = q, u \geq r + 1)$ , we have:

$$\mathbf{M}_{s,t,u}^{(i,i)} = 0$$

Thus, equation (14) simplifies to:

$$\mathbf{M}_{s,t,u}^{(i,i)} - \overline{\mathbf{M}_{2p-s,2q-t,2r-u}^{(i,i)}} = -\overline{\mathbf{M}_{2p-s,2q-t,2r-u}^{(i,i)}}$$

Since  $(s \geq p + 1)$  or  $(s = p, t \geq q + 1)$  or  $(s = p, t = q, u \geq r + 1)$ , we have:  $(2p - s \leq p - 1)$  or  $(2p - s = p, 2q - t \leq q - 1)$  or  $(2p - s = p, 2q - t = q, 2u - r \leq r - 1)$  respectively. Thus using equation (35), we have:

$$-\overline{\mathbf{M}_{2p-s,2q-t,2r-u}^{(i,i)}} = -\overline{\mathbf{L}_{2p-s,2q-t,2r-u}^{(i,i)}}$$

Since  $\mathbf{L}^{(i,i)}$  is a skew-hermitian filter, we have from Theorem 6:

$$\mathbf{L}_{s,t,u}^{(i,i)} = -\overline{\mathbf{L}_{2p-s,2q-t,2r-u}^{(i,i)}}$$

Thus in this subcase, equation (37) simplifies to  $\mathbf{L}_{s,t,u}^{(i,i)}$  again.

**Subcase 3(c):** For  $s = p, t = q, u = r$ , since  $\mathbf{L}^{(i,i)}$  is a skew-hermitian filter, we have:

$$\begin{aligned} \mathbf{L}_{p,q,r}^{(i,i)} &= -\overline{\mathbf{L}_{p,q,r}^{(i,i)}} \\ \mathbf{L}_{p,q,r}^{(i,i)} + \overline{\mathbf{L}_{p,q,r}^{(i,i)}} &= 0 \end{aligned}$$

Thus,  $\mathbf{L}_{p,q,r}^{(i,i)}$  is a purely imaginary number. In this subcase

$$\begin{aligned} \mathbf{M}_{s,t,u}^{(i,i)} - \overline{\mathbf{M}_{2p-s,2q-t,2r-u}^{(i,i)}} \\ = \mathbf{M}_{p,q,r}^{(i,i)} - \overline{\mathbf{M}_{p,q,r}^{(i,i)}} = 2\mathbf{M}_{p,q,r}^{(i,i)} \end{aligned}$$

Using equation (35), we have:

$$2\mathbf{M}_{p,q,r}^{(i,i)} = \mathbf{L}_{p,q,r}^{(i,i)}$$

Thus, we get:

$$\mathbf{M}_{p,q,r}^{(i,i)} - \left[ \text{conv3d\_transpose} \left( \mathbf{M}^{(i,i)} \right) \right]_{p,q,r} = \mathbf{L}_{p,q,r}^{(i,i)}$$

Thus we have established:  $\mathbf{L} = \mathbf{M} - \text{conv3d\_transpose}(\mathbf{M})$ . Note that the opposite direction of the if and only if statement follows trivially from the above proof.  $\square$

## C. MaxMin Activation function

Given a feature map  $\mathbf{X} \in \mathbb{R}^{2m \times n \times n}$  (we assume the number of channels in  $\mathbf{X}$  is a multiple of 2), to apply the MaxMin activation function, we first divide the input into two chunks of equal size:  $\mathbf{A}$  and  $\mathbf{B}$  such that:

$$\begin{aligned} \mathbf{A} &= \mathbf{X}_{:,m,:} \\ \mathbf{B} &= \mathbf{X}_{m,:} \end{aligned}$$

Then the MaxMin activation function is given as follows:

$$\begin{aligned} \text{MaxMin}(\mathbf{X})_{:,m,:} &= \max(\mathbf{A}, \mathbf{B}) \\ \text{MaxMin}(\mathbf{X})_{m,:} &= \min(\mathbf{A}, \mathbf{B}) \end{aligned}$$

## D. Additional Experiments

Model	Standard Accuracy		Provably Robust Accuracy	
	BCOP-20	BCOP-30	BCOP-20	BCOP-30
LipConvnet-5	74.35%	74.93%	58.01%	58.97%
LipConvnet-10	74.47%	74.63%	58.48%	58.23%
LipConvnet-15	73.86%	74.09%	57.39%	57.42%
LipConvnet-20	69.84%	70.01%	52.10%	52.59%
LipConvnet-25	68.26%	66.66%	49.92%	47.63%
LipConvnet-30	64.11%	65.77%	43.39%	45.10%
LipConvnet-35	63.05%	63.45%	41.72%	42.41%
LipConvnet-40	60.17%	59.60%	38.87%	37.75%

Table 5. Comparing between results using BCOP with 20 (BCOP-20) and 30 (BCOP-30) Bjorck iterations for provable robustness against adversarial examples ( $l_2$  perturbation radius of 36/255 and CIFAR-10 dataset).

Model	BCOP	SOC
LipConvnet-5	40.34%	<b>42.01%</b>
LipConvnet-10	40.77%	<b>44.13%</b>
LipConvnet-15	39.33%	<b>44.24%</b>
LipConvnet-20	34.75%	<b>45.18%</b>
LipConvnet-25	31.99%	<b>43.50%</b>
LipConvnet-30	25.02%	<b>42.39%</b>
LipConvnet-35	23.30%	<b>41.75%</b>
LipConvnet-40	21.20%	<b>37.88%</b>

Table 6. Comparing between BCOP and SOC for provably robust accuracy using  $l_2$  perturbation radius of 72/255.