

Computational Methods for Inverse Problems and Applications in Image Processing

Introduction to Kronecker Products

If \mathbf{A} is an $m \times n$ matrix and \mathbf{B} is a $p \times q$ matrix, then the *Kronecker product* of \mathbf{A} and \mathbf{B} is the $mp \times nq$ matrix

$$\mathbf{A} \otimes \mathbf{B} = \begin{bmatrix} a_{11}\mathbf{B} & a_{12}\mathbf{B} & \cdots & a_{1n}\mathbf{B} \\ a_{21}\mathbf{B} & a_{22}\mathbf{B} & \cdots & a_{2n}\mathbf{B} \\ \vdots & \vdots & & \vdots \\ a_{m1}\mathbf{B} & a_{m2}\mathbf{B} & \cdots & a_{mn}\mathbf{B} \end{bmatrix}$$

Note that if \mathbf{A} and \mathbf{B} are large matrices, then the Kronecker product $\mathbf{A} \otimes \mathbf{B}$ will be huge. MATLAB has a built-in function `kron` that can be used as

```
K = kron(A, B);
```

However, you will quickly run out of memory if you try this for matrices that are 50×50 or larger. Fortunately we can exploit the block structure of Kronecker products to do many computations involving $\mathbf{A} \otimes \mathbf{B}$ without actually forming the Kronecker product. Instead we need only do computations with \mathbf{A} and \mathbf{B} individually.

To begin, we state some very simple properties of Kronecker products, which should not be difficult to verify:

- $(\mathbf{A} \otimes \mathbf{B})^T = \mathbf{A}^T \otimes \mathbf{B}^T$
- If \mathbf{A} and \mathbf{B} are square and nonsingular, then $(\mathbf{A} \otimes \mathbf{B})^{-1} = \mathbf{A}^{-1} \otimes \mathbf{B}^{-1}$
- $(\mathbf{A} \otimes \mathbf{B})(\mathbf{C} \otimes \mathbf{D}) = \mathbf{AC} \otimes \mathbf{BD}$

The next property we want to consider involves the matrix-vector multiplication

$$\mathbf{y} = (\mathbf{A} \otimes \mathbf{B})\mathbf{x},$$

where $\mathbf{A} \in \mathcal{R}^{m \times n}$ and $\mathbf{B} \in \mathcal{R}^{p \times q}$. Thus $\mathbf{A} \otimes \mathbf{B} \in \mathcal{R}^{mp \times nq}$, $\mathbf{x} \in \mathcal{R}^{nq}$, and $\mathbf{y} \in \mathcal{R}^{mp}$. Our goal is to exploit the block structure of the Kronecker product matrix to compute \mathbf{y} without explicitly forming $(\mathbf{A} \otimes \mathbf{B})$. To see how this can be done, first partition the vectors \mathbf{x} and \mathbf{y} as

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_n \end{bmatrix}, \quad \mathbf{x}_i \in \mathcal{R}^q \quad \text{and} \quad \mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_m \end{bmatrix}, \quad \mathbf{y}_i \in \mathcal{R}^p$$

Then

$$\mathbf{y} = (\mathbf{A} \otimes \mathbf{B})\mathbf{x} = \begin{bmatrix} a_{11}\mathbf{B} & a_{12}\mathbf{B} & \cdots & a_{1n}\mathbf{B} \\ a_{21}\mathbf{B} & a_{22}\mathbf{B} & \cdots & a_{2n}\mathbf{B} \\ \vdots & \vdots & & \vdots \\ a_{m1}\mathbf{B} & a_{m2}\mathbf{B} & \cdots & a_{mn}\mathbf{B} \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_n \end{bmatrix}$$

which can be written as

$$\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_m \end{bmatrix} = \begin{bmatrix} a_{11}\mathbf{B}\mathbf{x}_1 + a_{12}\mathbf{B}\mathbf{x}_2 + \cdots + a_{1n}\mathbf{B}\mathbf{x}_n \\ a_{21}\mathbf{B}\mathbf{x}_1 + a_{22}\mathbf{B}\mathbf{x}_2 + \cdots + a_{2n}\mathbf{B}\mathbf{x}_n \\ \vdots \\ a_{m1}\mathbf{B}\mathbf{x}_1 + a_{m2}\mathbf{B}\mathbf{x}_2 + \cdots + a_{mn}\mathbf{B}\mathbf{x}_n \end{bmatrix}$$

Now notice that each \mathbf{y}_i has the form

$$\begin{aligned} \mathbf{y}_i &= a_{i1}\mathbf{B}\mathbf{x}_1 + a_{i2}\mathbf{B}\mathbf{x}_2 + \cdots + a_{in}\mathbf{B}\mathbf{x}_n \\ &= \begin{bmatrix} \mathbf{B}\mathbf{x}_1 & \mathbf{B}\mathbf{x}_2 & \cdots & \mathbf{B}\mathbf{x}_n \end{bmatrix} \begin{bmatrix} a_{i1} \\ a_{i2} \\ \vdots \\ a_{in} \end{bmatrix} \\ &= \mathbf{B} \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_n \end{bmatrix} \begin{bmatrix} a_{i1} \\ a_{i2} \\ \vdots \\ a_{in} \end{bmatrix} \end{aligned}$$

Now define $\mathbf{a}_i^T = \begin{bmatrix} a_{i1} & a_{i2} & \cdots & a_{in} \end{bmatrix}$ = i th row of \mathbf{A} , and define \mathbf{X} to be a matrix with i th column \mathbf{x}_i ; that is,

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_n \end{bmatrix}$$

Then

$$\mathbf{y}_i = \mathbf{B}\mathbf{X}\mathbf{a}_i, \quad i = 1, 2, \dots, m$$

Analogous to the matrix \mathbf{X} , define a matrix \mathbf{Y} with columns \mathbf{y}_i :

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 & \mathbf{y}_2 & \cdots & \mathbf{y}_m \end{bmatrix}$$

Then we have

$$\begin{aligned} \mathbf{Y} &= \begin{bmatrix} \mathbf{y}_1 & \mathbf{y}_2 & \cdots & \mathbf{y}_m \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{B}\mathbf{X}\mathbf{a}_1 & \mathbf{B}\mathbf{X}\mathbf{a}_2 & \cdots & \mathbf{B}\mathbf{X}\mathbf{a}_m \end{bmatrix} \\ &= \mathbf{B}\mathbf{X} \begin{bmatrix} \mathbf{a}_1 & \mathbf{a}_2 & \cdots & \mathbf{a}_m \end{bmatrix} \\ &= \mathbf{B}\mathbf{X}\mathbf{A}^T \end{aligned}$$

In the last step above, recall that \mathbf{a}_i^T is the i th row of \mathbf{A} , so \mathbf{a}_i is the i th column of \mathbf{A}^T .

To summarize, we have the following property of Kronecker products:

$\mathbf{y} = (\mathbf{A} \otimes \mathbf{B})\mathbf{x} \quad \Leftrightarrow \quad \mathbf{Y} = \mathbf{B}\mathbf{X}\mathbf{A}^T$ <p style="text-align: center;">where</p> $\mathbf{X} = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_n \end{bmatrix} \in \mathcal{R}^{q \times n} \quad \text{and} \quad \mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 & \mathbf{y}_2 & \cdots & \mathbf{y}_m \end{bmatrix} \in \mathcal{R}^{p \times m}$
--

Remarks on notation and MATLAB computations:

- If $\mathbf{X} = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_n \end{bmatrix}$ is an array with columns \mathbf{x}_i , then in many books you will see the notation $\mathbf{x} = \text{vec}(\mathbf{X})$ used to denote a vector obtained by stacking the columns of \mathbf{X} on top of each other. That is,

$$\mathbf{x} = \text{vec}(\mathbf{X}) = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_n \end{bmatrix}$$

- MATLAB does not have a `vec` function, but it does have a built-in function called `reshape` that can be used for this purpose. Specifically, if $\mathbf{X} \in \mathcal{R}^{q \times n}$, then the vector $\mathbf{x} = \text{vec}(\mathbf{X})$ can be obtained with the MATLAB statement:

```
x = reshape(X, q*n, 1);
```

A short cut to using the `reshape` command is to use the colon operator. That is,

```
x = X(:);
```

does the same thing as `x = reshape(X, q*n, 1)`. To go the other way, from \mathbf{x} to \mathbf{X} , you can again use the `reshape` function:

```
X = reshape(x, q, n);
```

For more information, see the MATLAB doc page for `reshape`.

- Thus, suppose we are given \mathbf{A} , \mathbf{B} , and \mathbf{x} in MATLAB, and we want to compute $\mathbf{y} = (\mathbf{A} \otimes \mathbf{B})\mathbf{x}$. This can be done without explicitly forming $\mathbf{A} \otimes \mathbf{B}$ as follows:

```
[m, n] = size(A);  
[p, q] = size(B);  
X = reshape(x, q, n);  
Y = B*X*A';  
y = reshape(Y, m*p, 1);
```

Note that this computation requires $O(npq + qnm)$ arithmetic operations (FLOPS) to compute \mathbf{y} . On the other hand, if we explicitly form $\mathbf{A} \otimes \mathbf{B}$, then the cost to compute \mathbf{y} is $O(mpnq)$. In addition to the computational savings, we save a lot on storage if we don't explicitly construct $\mathbf{A} \otimes \mathbf{B}$, and instead just store the smaller matrices \mathbf{A} and \mathbf{B} .

- As with matrix-vector multiplication, we can efficiently solve linear systems

$$(\mathbf{A} \otimes \mathbf{B})\mathbf{x} = \mathbf{y}$$

using properties of Kronecker products. Specifically, assume \mathbf{A} and $\mathbf{B} \in \mathcal{R}^{n \times n}$ are both nonsingular. Then using properties of Kronecker products we know

$$\mathbf{x} = (\mathbf{A} \otimes \mathbf{B})^{-1}\mathbf{y} = (\mathbf{A}^{-1} \otimes \mathbf{B}^{-1})\mathbf{y}$$

From the matrix-vector multiplication property this is equivalent to computing:

$$\mathbf{X} = \mathbf{B}^{-1}\mathbf{Y}\mathbf{A}^{-T}, \quad \mathbf{x} = \text{vec}(\mathbf{X}), \quad \mathbf{y} = \text{vec}(\mathbf{Y})$$

Generally we never explicitly form the inverse of a matrix, and instead should read “inverse” for meaning “solve”. That is:

- Computing $\mathbf{Z} = \mathbf{B}^{-1}\mathbf{Y}$ is equivalent to the problem: Given \mathbf{B} and \mathbf{Y} , solve the matrix equation $\mathbf{B}\mathbf{Z} = \mathbf{Y}$ for \mathbf{Z} .
- Computing $\mathbf{X} = \mathbf{Z}\mathbf{A}^{-T}$ is equivalent to the problem: Given \mathbf{A} and \mathbf{Z} , solve the matrix equation $\mathbf{X}\mathbf{A}^T = \mathbf{Z}$ for \mathbf{X} . (Note that this is also equivalent to solving the matrix equation $\mathbf{A}\mathbf{X}^T = \mathbf{Z}^T$ for \mathbf{X} .)

The cost of doing this with matrix factorization methods (e.g., $\mathbf{P}\mathbf{A} = \mathbf{L}\mathbf{U}$) is only $O(n^3)$. On the other hand, if we explicitly form $\mathbf{A} \otimes \mathbf{B}$ and then solve the system, the cost will be $O(n^6)$.

In MATLAB, using the efficient method outlined above to solve $(\mathbf{A} \otimes \mathbf{B})\mathbf{x} = \mathbf{y}$ can be implemented as:

```
n = size(A,1);
Y = reshape(y, n, n);
X = B \ Y / A';
x = reshape(X, n*n, 1);
```

If you're not sure how the back-slash `\` and the forward-slash `/` operators work, then you should read the MATLAB doc pages: `doc slash`.