

# Painless Application Development with 3D Slicer and Python

Basic Python and Index tricks

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LMI 09/2008

# Python Basics

# Python Basics

- Object oriented language
- Interpreted language
- Everything is an object
- References are the main way of passing parameters
- Duck typing

# Python Basics

- Object oriented language
- Some functional capabilities
- Lambda expression
- Lists by comprehension
- Partial evaluation not directly supported

# Python Basics

- Object oriented language
- Some functional capabilities
- Everything can be defined or redefined in execution time

# Python basic Datatypes

- Literals (i.e. integers, floats, complex and characters)
- Tuples: fixed combinations of objects `t=('a', 2)`
- Lists: resizable combinations of objects `t=['a', 2]`
- Dictionaries: key/value pairs `t['a']=2`
- Sets: non-iterable containers with a fast membership operation `t={'a', 2}`
- Functions
- Classes
- Modules

# Numpy basic Datatypes

- array datatype
  - Multidimensional array
  - Operations are done in an element by element basis
- matrix datatype
  - Bidimensional array of elements
  - matrix semantics

# Numpy: slicing

```
>>> a[0,3:5]
array([3,4])
```

```
>>> a[4:,4:]
array([[44, 45],
       [54, 55]])
```

```
>>> a[:,2]
array([2,22,52])
```

```
>>> a[2::2,::2]
array([[20,22,24]
       [40,42,44]])
```

0	1	2	3	4	5
0	1	2	3	4	5
10	11	12	13	14	15
20	21	22	23	24	25
30	31	32	33	34	35
40	41	42	43	44	45
50	51	52	53	54	55



Slicing does not create copies of the array's contents



# Numpy: fancy indexing

## INDEXING BY POSITION

```
>>> a = arange(0,80,10)

# fancy indexing
>>> y = a[[1, 2, -3]]
>>> print y
[10 20 50]

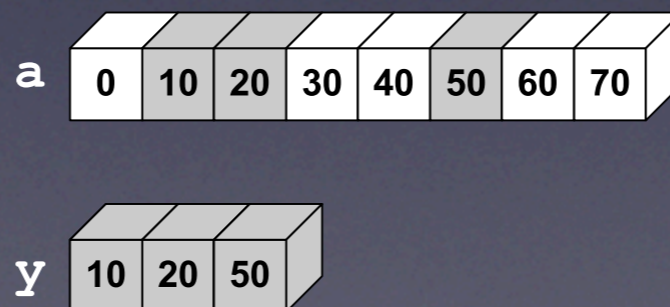
# using take
>>> y = take(a, [1,2,-3])
>>> print y
[10 20 50]
```

## INDEXING WITH BOOLEANS

```
>>> mask = array([0,1,1,0,0,1,0,0],
...              dtype=bool)

# fancy indexing
>>> y = a[mask]
>>> print y
[10,20,50]

# using compress
>>> y = compress(mask, a)
>>> print y
[10,20,50]
```



# Numpy: fancier indexing

```
>>> a[(0,1,2,3,4), (1,2,3,4,5)]  
array([ 1, 12, 23, 34, 45])
```

```
>>> a[3:,[0, 2, 5]]  
array([[30, 32, 35],  
       [40, 42, 45]],  
       [50, 52, 55])
```

```
>>> mask = array([1,0,1,0,0,1],  
                 dtype=bool)
```

```
>>> a[mask,2]  
array([2,22,52])
```

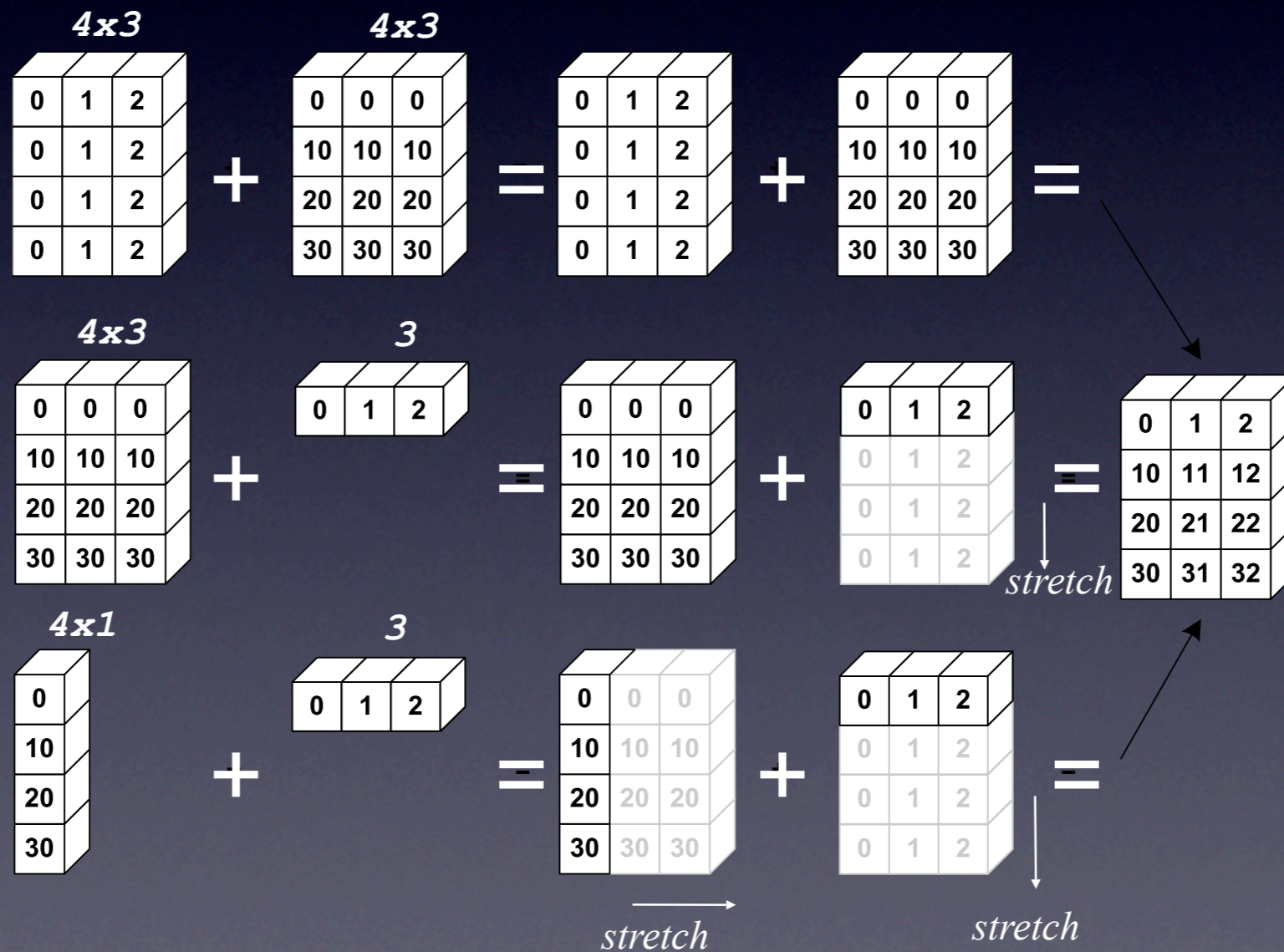
0	1	2	3	4	5
10	11	12	13	14	15
20	21	22	23	24	25
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40	41	42	43	44	45
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Unlike slicing, fancy indexing creates copies instead of views into original arrays.

# Numpy broadcasting

Semantic of binary operations between arrays



[Oliphant]

# Full example: NCuts Nystrom

Get the most significant eigenvectors of a normalized matrix  $W$ , using only the submatrices  $A$  and  $B$

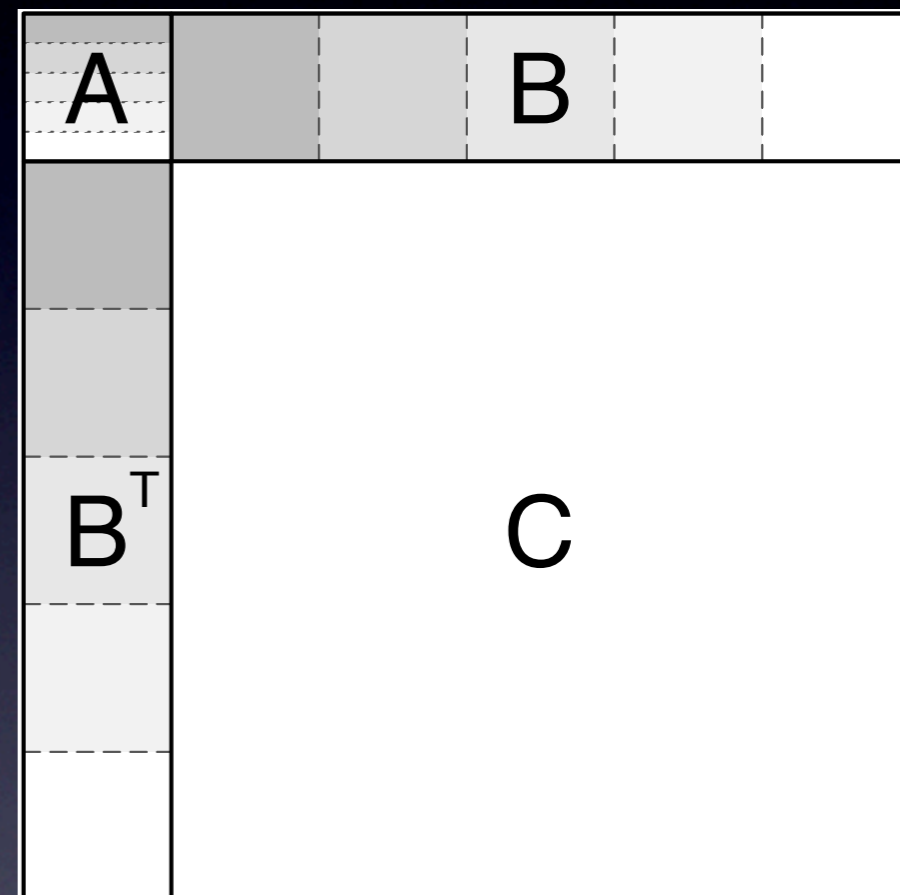
- Subsampling  $W$  to get  $A$
- Normalizing of the partial parts
- Eigenvalue decomposition of  $A$
- Estimation of the Eigenvectors of  $W$

$$W = D^{-\frac{1}{2}} W D^{-\frac{1}{2}}$$

A			B		
	C				
$B^T$					

# Full example: NCuts Nystrom

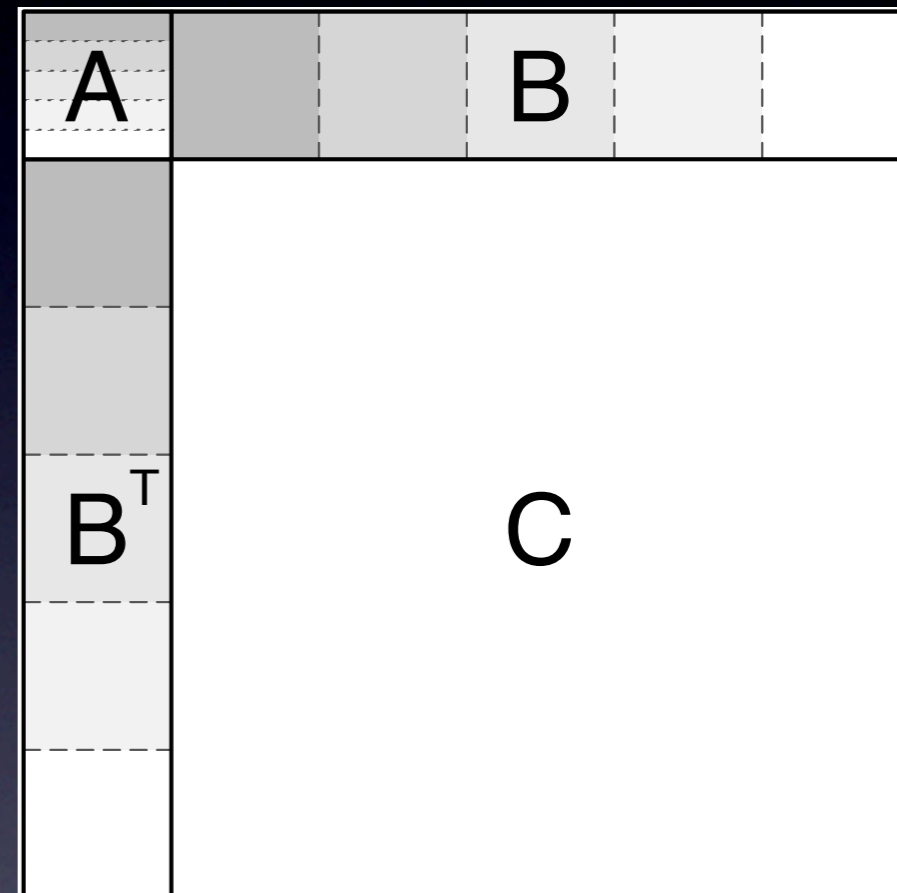
Subsampling D to get A and B



# Full example: NCuts Nystrom

Subsampling  $D$  to get  $A$  and  $B$

```
#W is the initial matrix  
#ratio is the relative size of A with respect to W  
  
import numpy  
from numpy import random
```



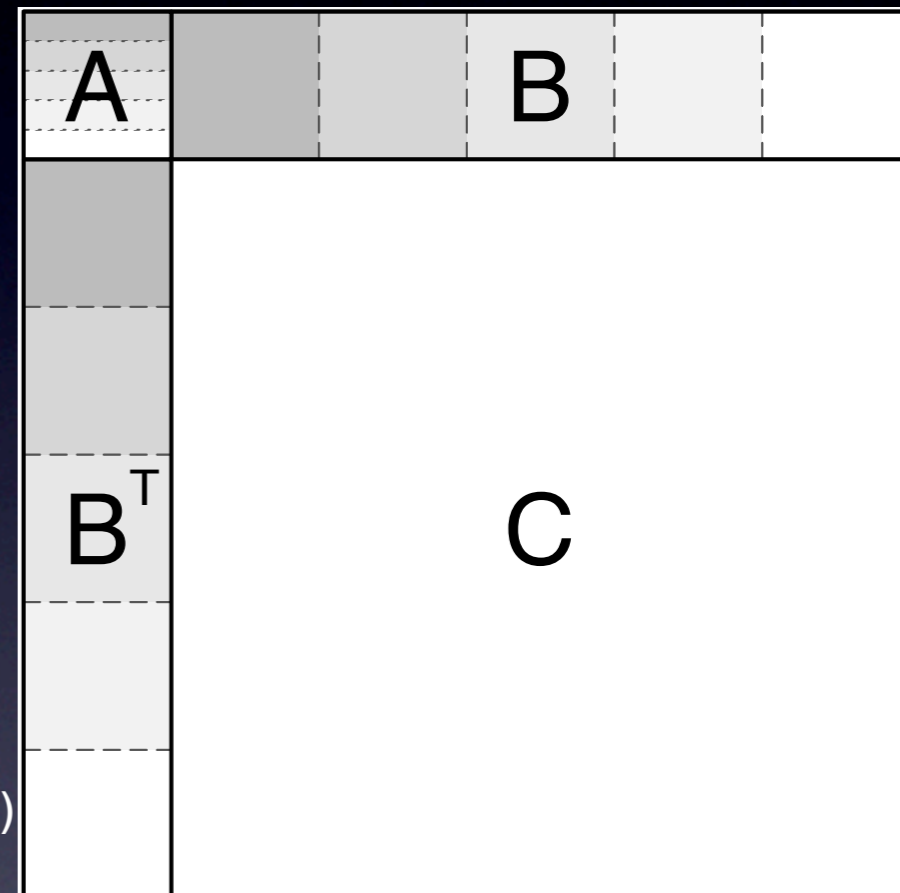
# Full example: NCuts Nystrom

Subsampling D to get A and B

```
#W is the initial matrix
#ratio is the relative size of A with respect to W

import numpy
from numpy import random

shuffled_indexes = numpy.arange( W.shape[0], dtype=int )
random.shuffle( shuffled_indexes )
```



# Full example: NCuts Nystrom

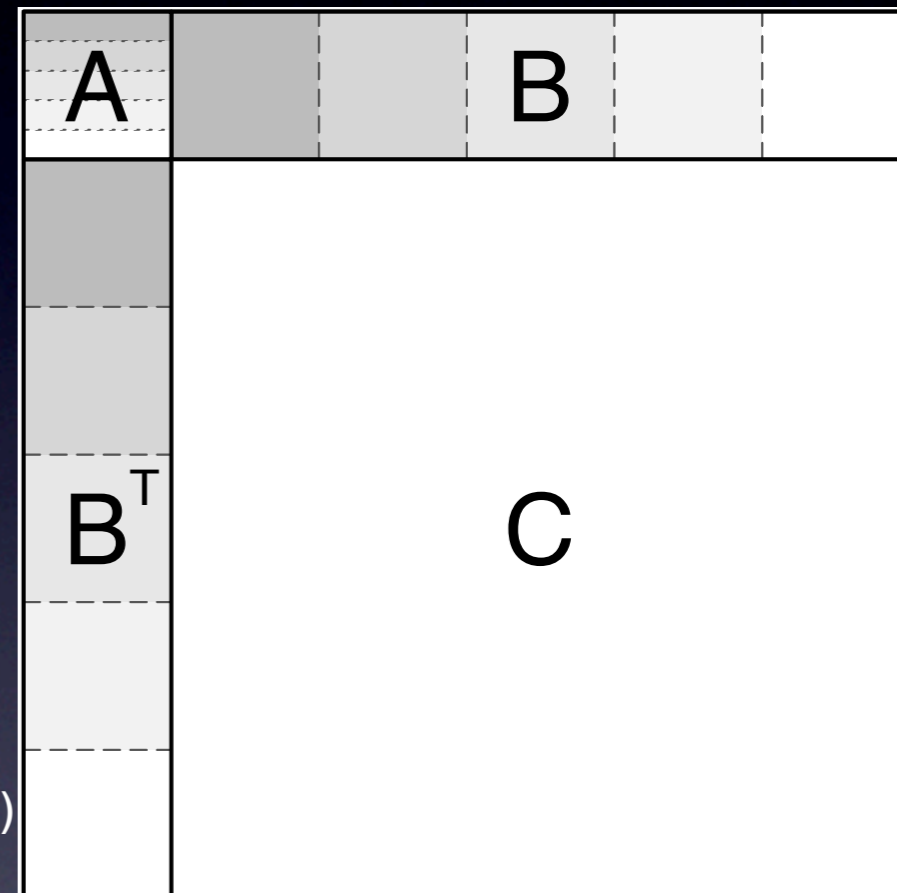
Subsampling D to get A and B

```
#W is the initial matrix
#ratio is the relative size of A with respect to W

import numpy
from numpy import random

shuffled_indexes = numpy.arange( W.shape[0], dtype=int )
random.shuffle( shuffled_indexes )

Na = int(numpy.round( elementQty*ratio ))
Nb = elementQty-Na
a_indexes = shuffled_indexes[:Na]
b_indexes = shuffled_indexes[Na:]
```





# Full example: NCuts Nystrom

Subsampling D to get A and B

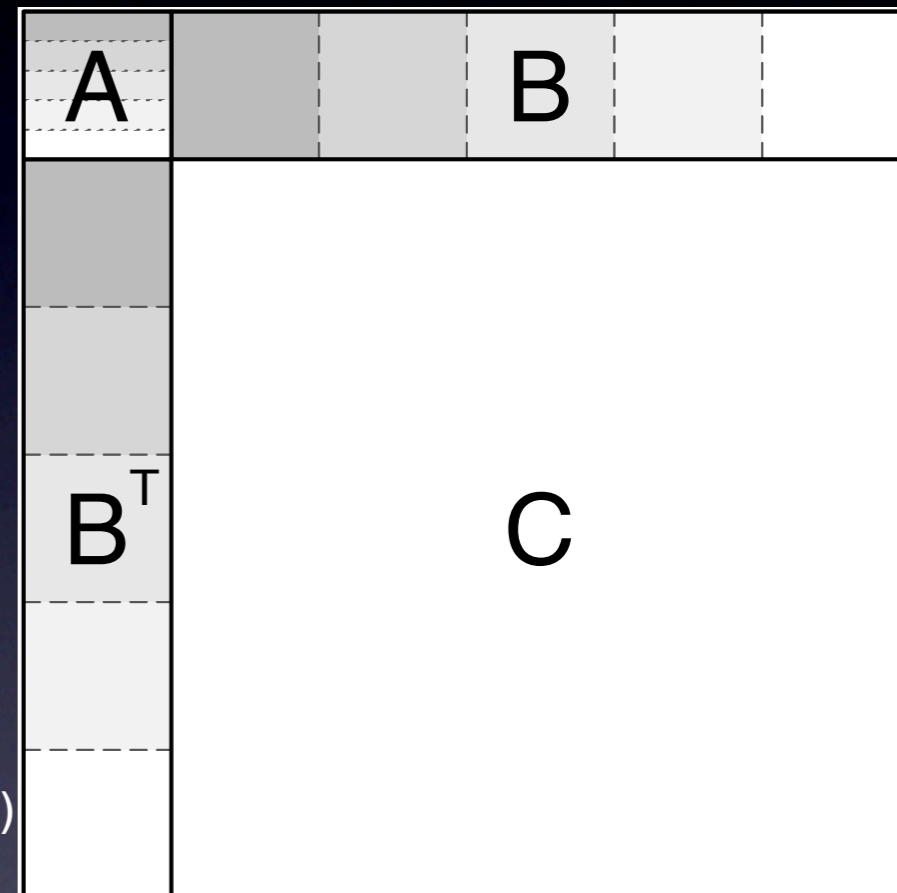
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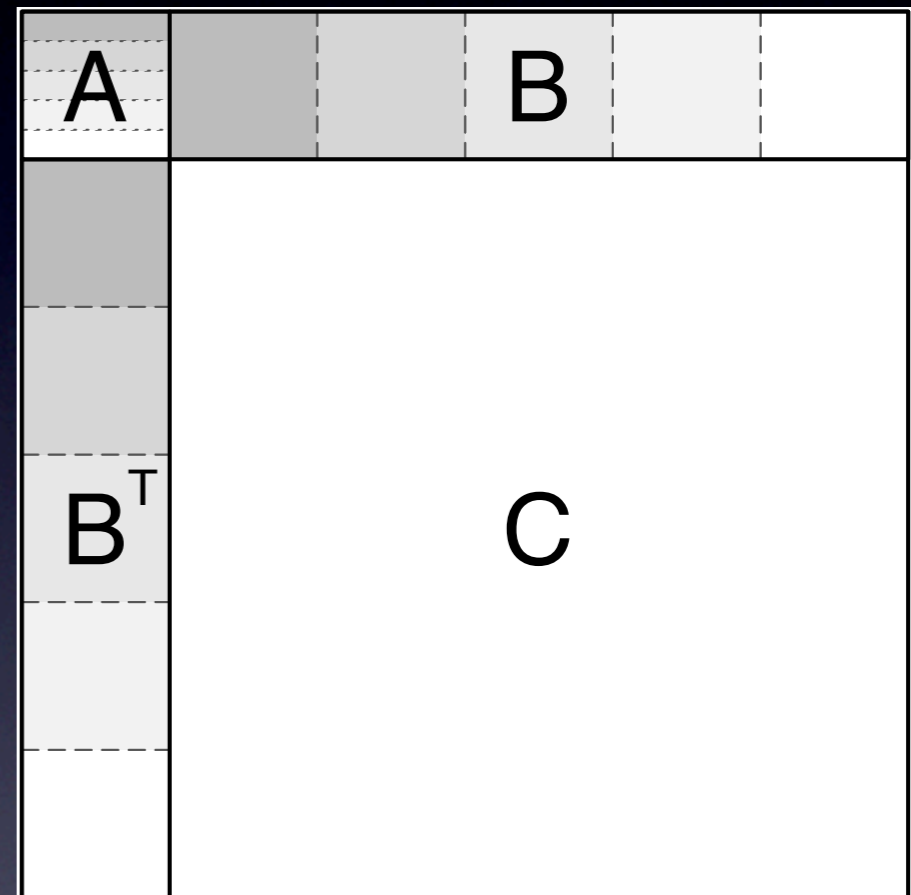
Na = int(numpy.round( elementQty*ratio ))
Nb = elementQty-Na
a_indexes = shuffled_indexes[:Na]
b_indexes = shuffled_indexes[Na:]

A = numpy.asmatrix(D[a_indexes,:][:,a_indexes])
B = numpy.asmatrix(D[a_indexes,:][:,b_indexes])
```



# Full example: NCuts Nystrom

Normalizing A and B



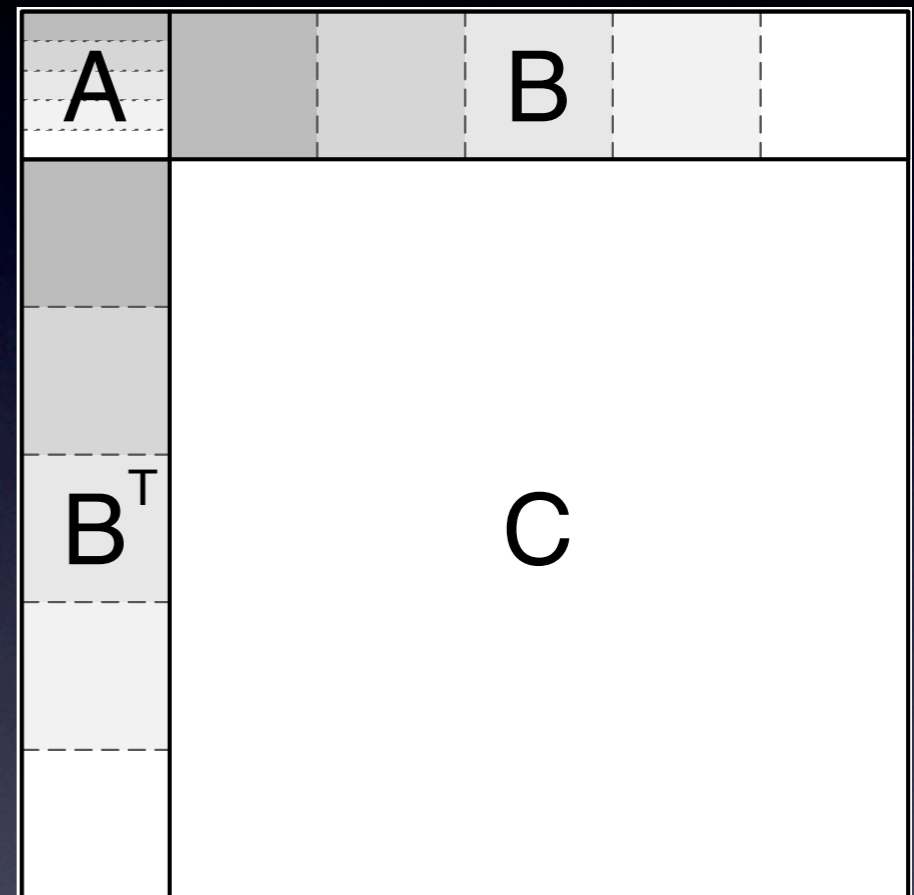
$$\mathcal{W} = \mathbf{D}^{-\frac{1}{2}} \mathbf{W} \mathbf{D}^{-\frac{1}{2}}.$$

$$\hat{\mathbf{d}} = \begin{bmatrix} \mathbf{a}_r + \mathbf{b}_r \\ \mathbf{b}_c + \mathbf{B}^T \mathbf{A}^{-1} \mathbf{b}_r \end{bmatrix}$$

# Full example: NCuts Nystrom

Normalizing A and B

$$\begin{aligned} \mathbf{a}_r &= \mathbf{A}.\text{sum}(1) \\ \mathbf{b}_r &= \mathbf{B}.\text{sum}(1) \\ \mathbf{b}_c &= \mathbf{B}^T.\text{sum}(1) \end{aligned}$$



$$\mathcal{W} = \mathbf{D}^{-\frac{1}{2}} \mathbf{W} \mathbf{D}^{-\frac{1}{2}}$$

$$\hat{\mathbf{d}} = \begin{bmatrix} \mathbf{a}_r + \mathbf{b}_r \\ \mathbf{b}_c + \mathbf{B}^T \mathbf{A}^{-1} \mathbf{b}_r \end{bmatrix}$$

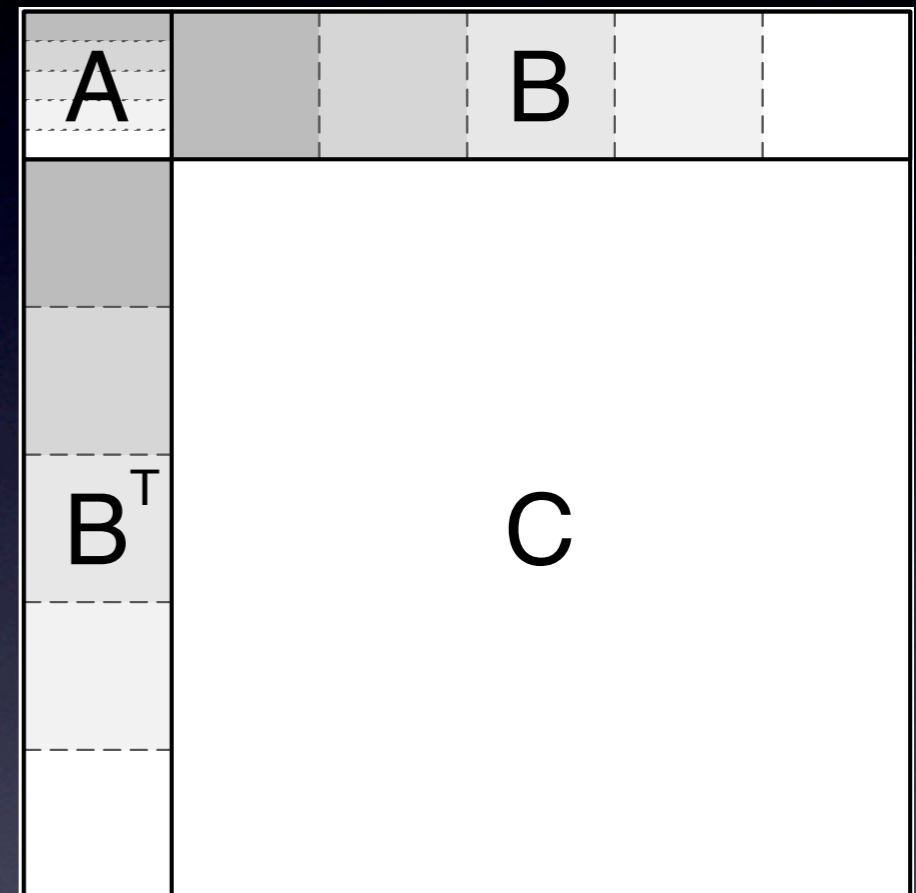
# Full example: NCuts Nystrom

## Normalizing A and B

```
a_r = A.sum(1)
b_r = B.sum(1)
b_c = B.T.sum(1)
```

```
d = numpy.vstack((\
    a_r + b_r,\
    b_c + (B.T * linalg.inv(A)) * b_r\
))
```

```
d_inv_sqr = 1./numpy.sqrt(d)
```



$$\mathcal{W} = \mathbf{D}^{-\frac{1}{2}} \mathbf{W} \mathbf{D}^{-\frac{1}{2}}$$

$$\hat{\mathbf{d}} = \begin{bmatrix} \mathbf{a}_r + \mathbf{b}_r \\ \mathbf{b}_c + \mathbf{B}^T \mathbf{A}^{-1} \mathbf{b}_r \end{bmatrix}$$

# Full example: NCuts Nystrom

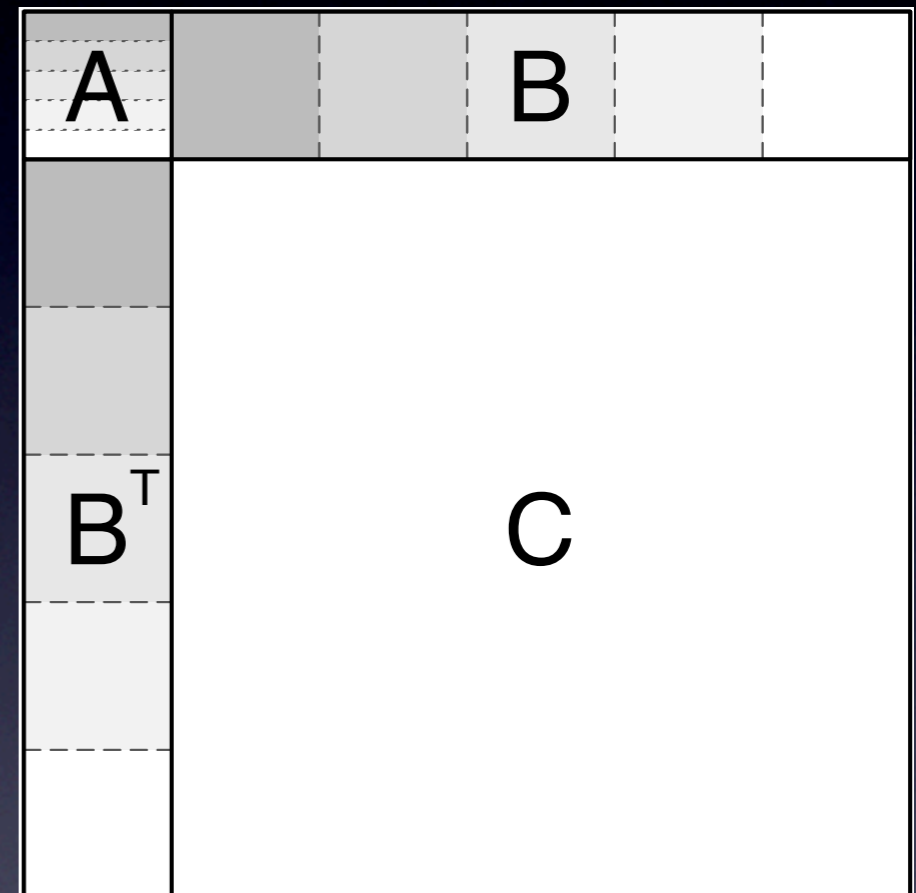
## Normalizing A and B

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a_r = A.sum(1)
b_r = B.sum(1)
b_c = B.T.sum(1)

d = numpy.vstack((\
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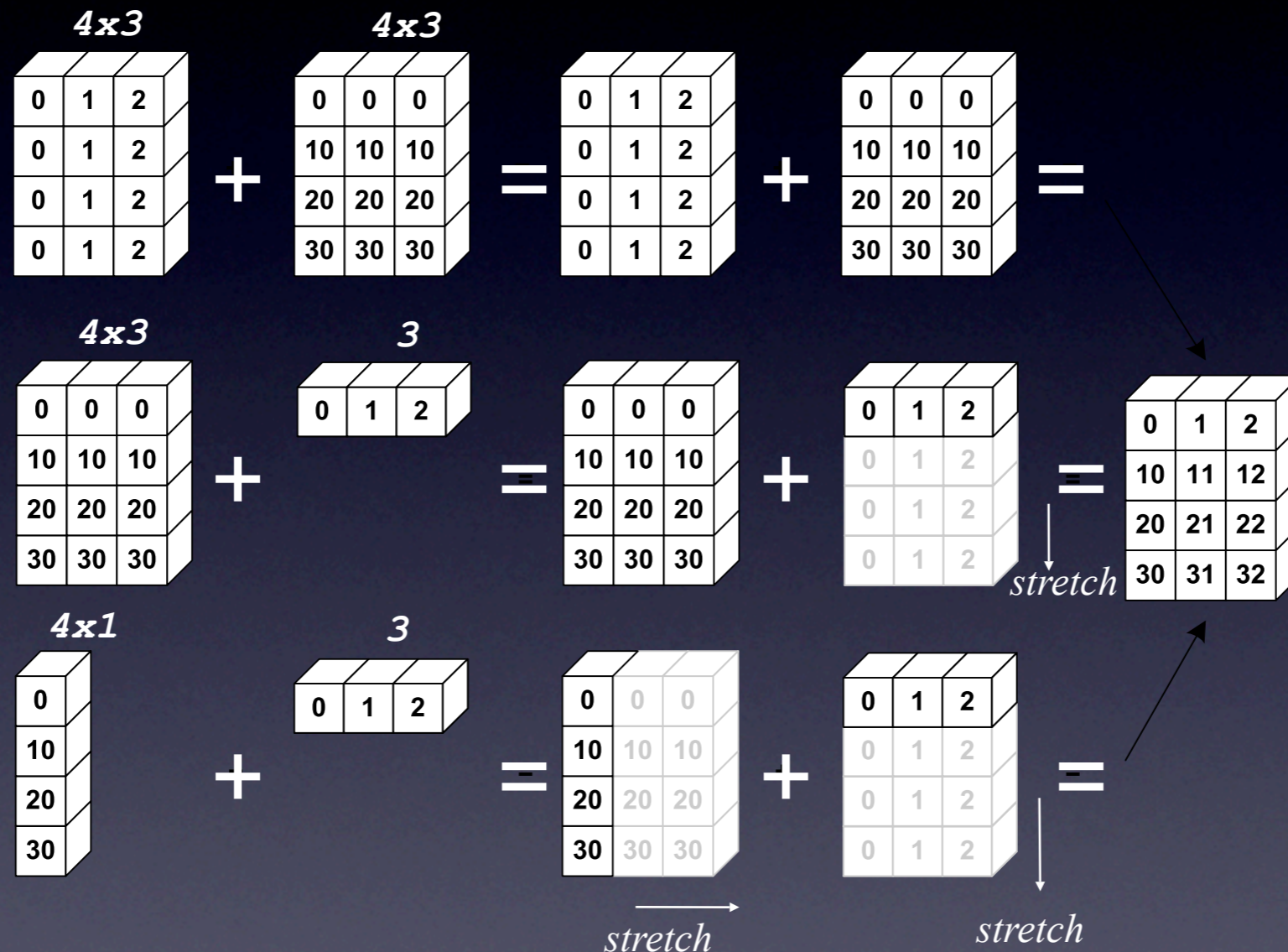
d_inv_sqr = 1./numpy.sqrt(d)

An = \
    numpy.multiply(\
        numpy.multiply( d_inv_sqr[:Na], A ),\
        d_inv_sqr[:Na].T)
Bn = \
    numpy.multiply(\
        numpy.multiply( d_inv_sqr[Na:].T, B ),\
        d_inv_sqr[:Na])
```



$$\mathcal{W} = \mathbf{D}^{-\frac{1}{2}} \mathbf{W} \mathbf{D}^{-\frac{1}{2}}$$
$$\hat{\mathbf{d}} = \begin{bmatrix} \mathbf{a}_r + \mathbf{b}_r \\ \mathbf{b}_c + \mathbf{B}^T \mathbf{A}^{-1} \mathbf{b}_r \end{bmatrix}$$

# Numpy broadcasting



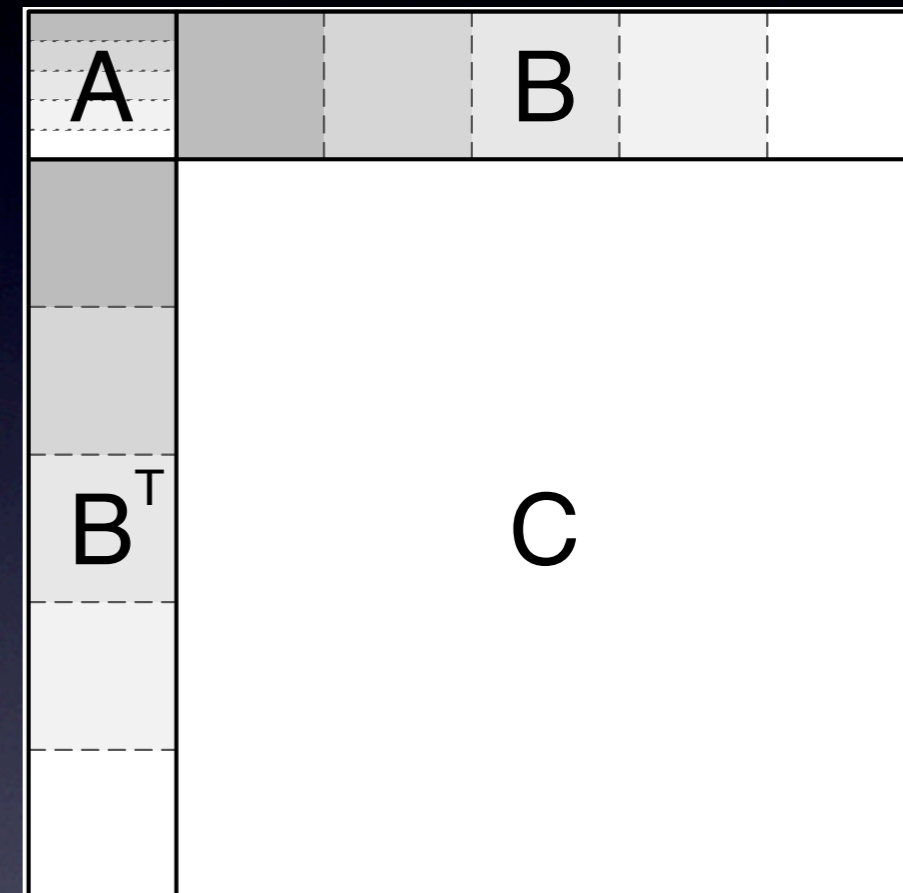
## Equivalent syntax for the normalization

```
d_inv_sqrt = numpy.asarray(d_inv_sqrt)
An = d_inv_sqrt[:Na]*numpy.asarray(A)*d_inv_sqrt[:Na].T
#Warning here the d_inv_sqr and A are arrays not matrices
```

# Full example: NCuts Nystrom

Eigenvalue decomposition of A

```
Delta,U = linalg.eig(An)
Delta_inv = numpy.asmatrix( numpy.diag(1./Delta) )
Ubar = numpy.vstack((\
    U,\
    Bn.T*U*Delta_inv\
))
return Delta, Ubar[ numpy.argsort( shuffled_indexes ),:]
```



$$\bar{\mathbf{U}} = \begin{bmatrix} \mathbf{U} \\ \mathbf{B}^T \mathbf{U} \mathbf{\Lambda}^{-1} \end{bmatrix}$$

Time and energy to  
take a look at one  
more module?