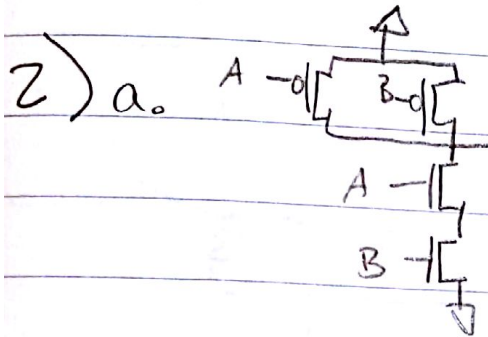
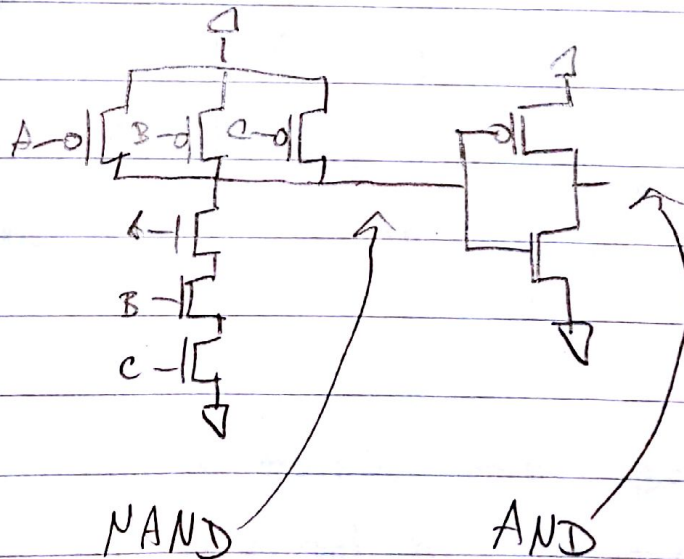
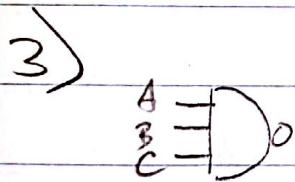
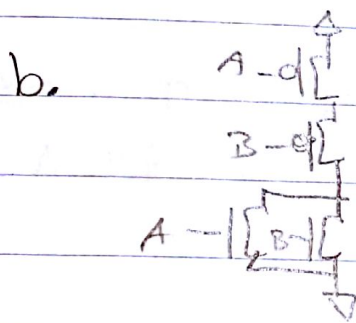


# Dis 5

Worksheet :



A	B	Nand	Nor
0	0	1	1
0	1	1	0
1	0	1	0
1	1	0	0

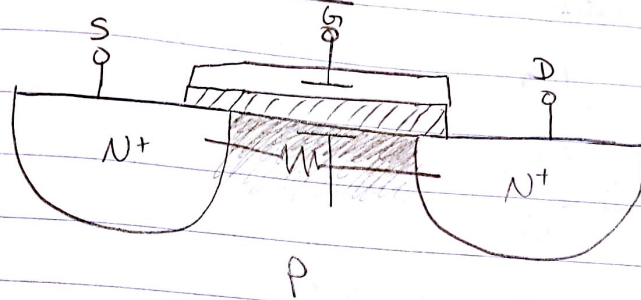


$$4) \overline{AB + \overline{A}\overline{B}}$$

$$5) \overline{(A+B)C}$$

6)	$B_0$	$B_1$	$B_2$	$\overline{B_0 B_1 B_2}$	$\overline{\overline{B_0} + \overline{B_1} + \overline{B_2}}$
	0	0	0	1	1
	0	0	1	1	1
	0	1	0	1	1
	0	1	1	1	1
	1	0	0	1	1
	1	0	1	1	1
	1	1	0	1	1
	1	1	1	0	0

## MOSFET Review



What is this structure?

MOSFET (what does that stand for  
Metal oxide semiconductor field effect device)

Lets talk about each terminal:

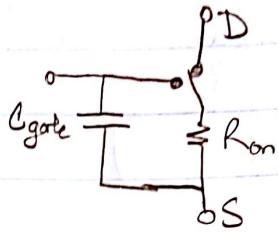
Gate:

- Oxide isolates the gate from drain or source
- Metal acts like a big capacitor

Source/Drain:

- 'Source' of carriers (electrons for nmos, opposite for pmos)
- Source & Drain are connected by a resistor

Switch model:



Why do we even care about those  $C \neq R$ ?

Delay - the bigger  $C$  or  $R$  the more delay

There are two places we care about  $C \neq R$ .

Input  $\neq$  Output

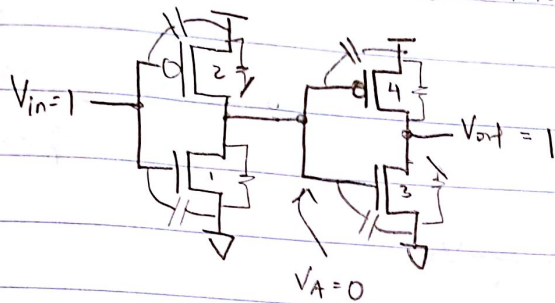
You will learn the particulars of how to calculate delay in lecture, so let's practice collecting all the  $R$ s  $\neq$   $C$ s together to make the math easier

Let's redraw our mosfet



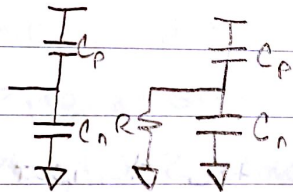
Now, it is easy to see that we care about capacitance on the input  $\neq$  resistance on the output

In class you looked at two inverters



So, 1 & 4 are on so they have a resistance  
2 & 3 are off so they don't

We rewrite as

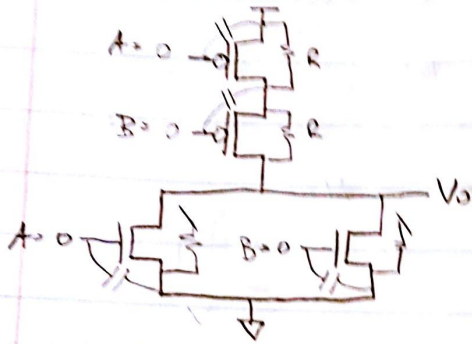


What capacitance on the input?  $C_p + C_n$

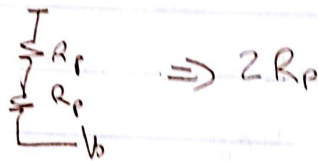
What resistance on the output?  $R$

capacitance?  $C_p + C_n$

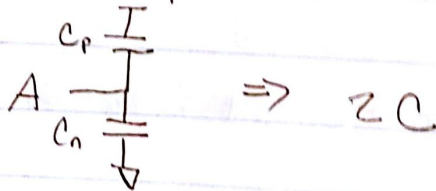
Now, lets do a harder one, NAND



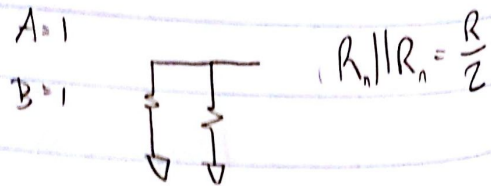
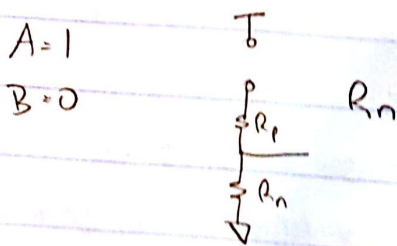
What is the resistance on the output?



What is the capacitance on the A input?



Now let  $A = 1$  &  $B = 0$  then  $B = 1$ . Find the output resistance yourself.



## SVD

The all imp't. SVD eqn

$$M = U \Sigma V^T$$

where

$M$  is a matrix that represents something imp't & complex to you

$V$  are orthogonal vectors which are eigenvectors of  $M$  ( $MV_i = \lambda V_i$ )

In other words,  $V$  is a current domain

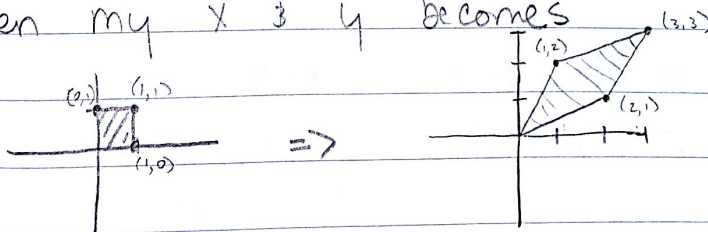
$U$  are orthogonal vectors of a co-domain

$\Sigma$  are weights that describe  $M$  in the co-domain

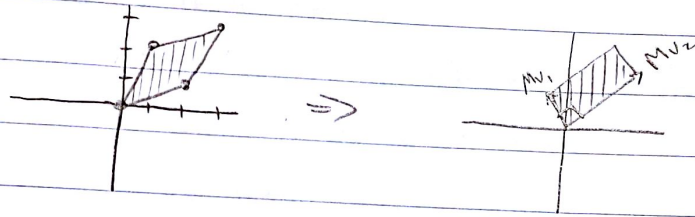
For example, if I am given some  $M$  transform

$$M = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

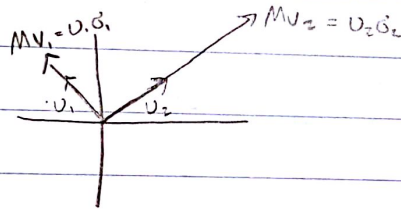
Then my  $x$  &  $y$  becomes



I can describe this transformation in parts, first break  $M$  into eigen values so that I can describe the transform in an orthogonal domain



Next, turn those eigen vectors into unit vectors & weights



where  $U$  is the new co-domain of  $u_i$  vectors &  $\sigma_i$  are the weights that translate  $Mv_i = u_i \sigma_i$

Thus, we can kind of intuit what it means to break  $M$  into 3 parts

$$M = U \Sigma V^T$$



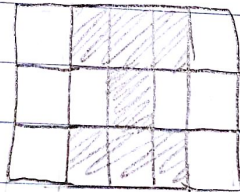
Now, why is this useful? What are the applications of this?

How did we use it in lab?

Noise reduction

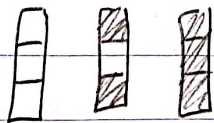
- we can look at the weight ( $\sigma_i$ ) of each  $u_i$  vector & determine what  $u_i$  are very imp't in  $M$  & which don't change very much, then we keep some number of the largest  $\sigma_i$ .

Example:



Imagine we describe this picture as a 1 for a black box & 0 for white

We can see very easily that there are only 3 vectors in this picture



When we break  $M$  into parts we will get back only  $\sigma_1, \sigma_2, \sigma_3$  for each of the three independent vectors, & 3  $u_i$  vectors

SVD has given us a way to transform into the three most important vectors.

This is what you did in lab, but with some noise mixed in, you got back a lot of vectors, but by only taking the 20 largest  $\sigma_i$ , you picked out the more "important" vectors that could describe the neuron data.

What are other applications?

Netflix recommendations

Image compression

Machine learning

Lets look at the SVD problem in your HW.

Another application of SVD is to rewrite a transform into matrices with nicer properties

for example, you are given

$$x \begin{bmatrix} \downarrow \\ \uparrow \end{bmatrix} \xrightarrow{H} \begin{bmatrix} \downarrow \\ \downarrow \\ \downarrow \end{bmatrix} y$$

What is a formula (w/o SVD) to describe this?

$$y = Hx$$

We can break  $H$  into SVD, what is it?

$$H = U \Sigma V^T$$

$$y = U \Sigma V^T x$$

orthogonal matrix  $\nearrow$   $\nwarrow$  diagonal

Now we have an equation in terms of only unitary  $\pm$  a diagonal matrix