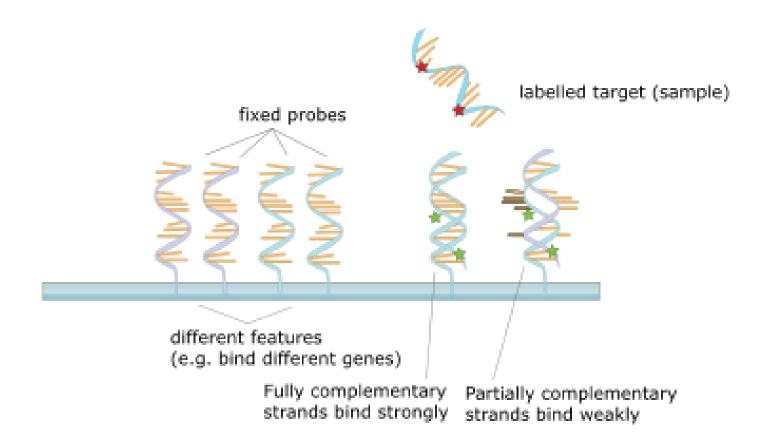
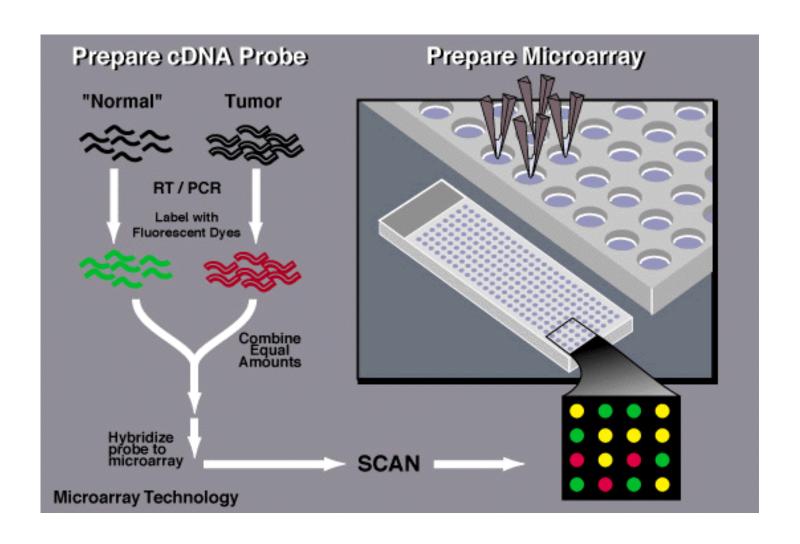
Microarrays



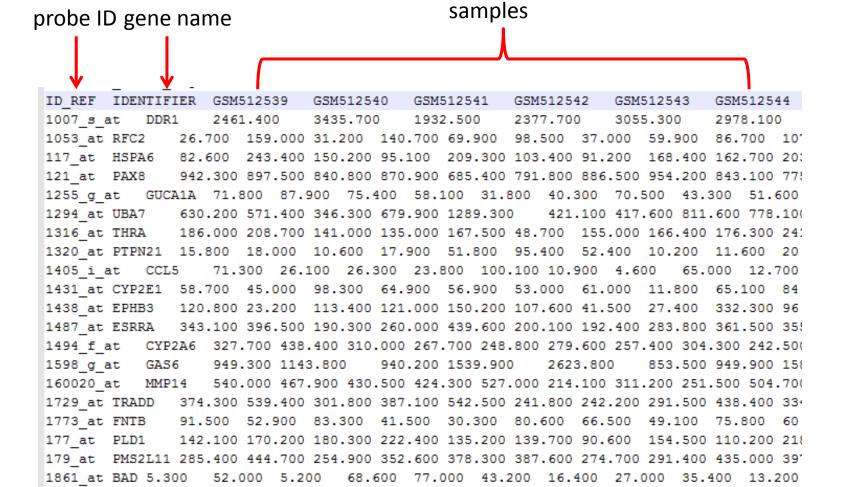
More target in sample = more binding to probe = brighter signal

Two channel



Q1) GDS3716

Diseased (ER+/ER-) vs normal in breast cancer



Microarray Analysis

- Normalisation
 - transformation: compare cancerous to healthy
 - ratio gene = cancerous gene / healthy gene
 - up-regulation = ratio > 1
 - down-regulation = 0-1
 - ge3716.getRatio()

Code

```
from genome import *
ge3716 = readGEOFile('GDS3716.soft')

#empty GeneExpression class
ratio = GeneExpression('GDS3716_ratio')

#example for 1 sample
ratio.addSamples('S1_ER+/Healthy', ge3716.getRatio(33,0))
```

Healthy controls			Cancer patients		
Index	Name	Description	Index	Name	Description
0	#GSM512539	control (RM) sample 1	33	#GSM512557	cancer: ER+ (breast) sample 1
1	#GSM512540	control (RM) sample 2	34	#GSM512558	cancer: ER+ (breast) sample 2
2	#GSM512541	control (RM) sample 3	35	#GSM512559	cancer: ER+ (breast) sample 3
3	#GSM512542	control (RM) sample 4	36	#GSM512560	cancer: ER+ (breast) sample 4
4	#GSM512543	control (RM) sample 5	37	#GSM512561	cancer: ER+ (breast) sample 5
5	#GSM512544	control (RM) sample 6	38	#GSM512562	cancer: ER+ (breast) sample 6
6	#GSM512545	control (RM) sample 7	39	#GSM512563	cancer: ER+ (breast) sample 7
7	#GSM512546	control (RM) sample 8	40	#GSM512564	cancer: ER+ (breast) sample 8
8	#GSM512547	control (RM) sample 9	41	#GSM512565	cancer: ER+ (breast) sample 9
9	#GSM512548	control (RM) sample 10	24	#GSM512566	cancer: ER- (breast) sample 1
10	#GSM512549	control (RM) sample 11	25	#GSM512567	cancer: ER- (breast) sample 2
11	#GSM512550	control (RM) sample 12	26	#GSM512568	cancer: ER- (breast) sample 3
12	#GSM512551	control (RM) sample 13	27	#GSM512569	cancer: ER- (breast) sample 4
13	#GSM512552	control (RM) sample 14	28	#GSM512570	cancer: ER- (breast) sample 5
14	#GSM512553	control (RM) sample 15	29	#GSM512571	cancer: ER- (breast) sample 6
15	#GSM512554	control (RM) sample 16	30	#GSM512572	cancer: ER- (breast) sample 7
16	#GSM512555	control (RM) sample 17	31	#GSM512573	cancer: ER- (breast) sample 8
17	#GSM512556	control (RM) sample 18	32	#GSM512574	cancer: ER- (breast) sample 9

Code

```
from genome import *
ge3716 = readGEOFile('GDS3716.soft')
#empty GeneExpression class
ratio = GeneExpression('GDS3716 ratio')
#example for 1 sample
ratio.addSamples('S1 ER+/Healthy', ge3716.getRatio(33,0))
#set up age-matched sample indices (0: healthy, 1: cancer)
paired ERpos = [[0,1,2,3,4,5,6,7,8],[33,34,35,36,37,38,39,40,41]]
paired ERneg = #fill in yourself
#Fill class with ER+ matched samples
i = 0 #sample counter
while i < len(paired ERpos[0]):
    name = 'S'+str(i+1)+' ER+/Healthy' #meaningful name for column header
    ratio.addSamples(#fill this in yourself)
    i+=1
#Fill class with ER- matched samples
```

Microarray Analysis

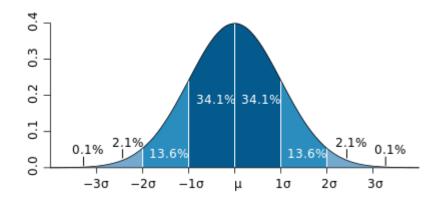
- Normalisation
 - log₂ transformation: easy to compare
 - log₂ (cancerous gene / healthy gene)
 - up-regulation = log(ratio) > 0
 - down-regulation = log(ratio) < 0
 - ge3716.getLogRatio()

Q1a)

- Why are log2 transformations "useful"?
- Pick 3 probes, e.g.
 - 204531_s_at (BRCA1)
 - 209969_s_at (STAT1)
 - -211300 s at (TP53)
- For 1st ER+/healthy-matched sample:
 - raw expression values
 - ratio value
 - log2 ratio value

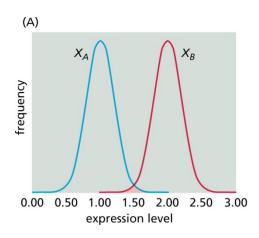
Q1b) & c)

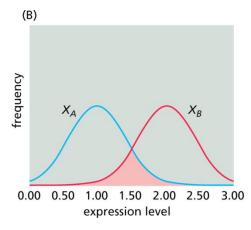
- Histogram for ratio values (all probes, all samples)
- Histogram for log2 values (all probes, all samples)
 - compare to ratio histogram
 - does log2 follow a normal distribution?

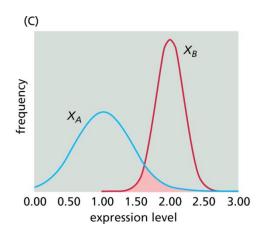


When are two measurements significantly different?

- An expression ratio is significant only if it is big enough or small enough
- A two-fold ratio (for example) is only significant if the variances of the underlying measurements are sufficiently small
- The significance is related to the area of the overlap of the underlying distributions

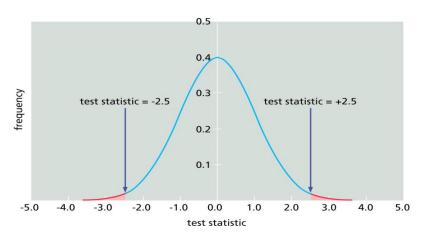






The Z-test

$$Z = \frac{\bar{X} - \mu}{\sigma / \sqrt{n}}.$$



- If the data is approximately normal, convert it to a Z-score
 - The Z-test is a <u>one</u> location/observation test
 - X can be the log expression ratio; μ is then 0
 - $-\sigma$ is the sample standard deviation; n is the number of repeats
- The Z-score is distributed N(0,1) (standard normal).
- The significance level is the area in the tail(s) of the standard normal distribution (P-value)

Z-test

```
sdict={} #dictionary for gene: no. of significant samples
#set up gene dictionary
genes = logratio.getGenes()
for gene in genes: #fill sdict with 0 so can add counter to them
    sdict[gene] = 0
#Z-score calculation for each sample
for #loop through samples to get zscore
    zscores=logratio.getZScore(sample)
    #iterate the dictionary to identify probes
    for key in zscores.iterkeys():
        if #Key condition(Zscore greater than 2 or less than -2)
            sdict[key] +=1 #add to sample count
#display significant genes
for key in sdict:
    if #Key condition (at least 11 sample pairs)
        #print something
```

Q2)

- List of significantly up/down regulated genes
 - Code used to get list
- Explain how Z-score is calculated
 - Use a specific probe (e.g. 214493_s_at) as example

Co-expressed genes: correlation

- GDS38: yeast cell cycle gene expression
 - two channel
 - already transformed
- Focus on gene CLN2
 - what other genes have similar gene expression patterns?

Pearson's correlation co-efficient

 Cluster analysis method: correlation between expression values of CLN2 and each other gene

-1	0	+1
Negative	No correlation	Positive
correlation		correlation

Gene correlation with CLN2

```
ge38 = readGEOFile('GDS38.soft', id column=1)
cln2 = ge38.getGenes('CLN2') #expression for CLN2
#get Pearson co-efficient for CLN2
cln2R = qe38.qetPearson(#do something)
#need to get top 5 genes - but cln2R is a dictionary, no order
#function sort() in GeneExpression class can handle this
#convert cln2R to GeneExpression class
gecln2R = GeneExpression(#'name', [#'column header'], cln2R)
gecln2Rsorted = gecln2R.sort(#do something)
#print out top 5 genes
```

Q3a)

- List the top 5 genes with correlated CLN2
 - Include code

Q3b)

- Get GO terms for top 5 genes
 - Include code + output
- Summarise findings (1 statement per gene)
- Are they involved in cell cycle? Justify
- Useful code:

```
#import webservice module
from webservice import *
#get uniprot id
rows=search('taxonomy:4932+AND+gene:CLN2,'uniprot',format='list')
#get GO terms for first search term
terms=getGOTerms(rows[0])
#get definition of GO terms
geneinfo = getGODef(term)
```