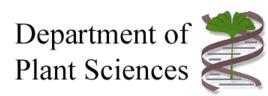
Introduction to Metabolomics

Introduction to chemometrics

How to analyse many metabolites





Introduction to chemometrics

- Aims

- Align and Bin raw spectral output files
- Merge files for statistical analysis
- Identify many metabolites
- •Multivariate data analysis PCA, Cluster analysis
- ANOVA, false-positive corrections
- Metadata

Align and "Bin" raw spectral output files

3.00E+03 2.50E+03

2.00E+03 1.50E+03

1.00E+03 5.00E+02

-5.00E+02 4.00E+03 3.50E+03 3.00E+03 2.50E+03

2.00E+03 1.50E+03

1.00E+03 5.00E+02 0.00E+00 -5.00E+02

100

100.5

101

101.5

102

102.5

Technical rep 1

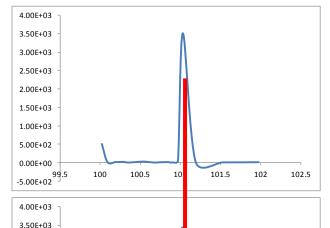
100.0181	4.27E+02
100.1587	8.33E+00
100.1869	9.78E+00
100.3746	3.13E+01
100.5719	2.41E+01
100.666	4.44E+00
100.713	4.56E+00
100.7412	9.67E+00
100.7694	5.78E+00
100.793	2.44E+00
100.8212	4.22E+00
100.8589	1.20E+01
100.9624	8.59E+01
101.0284	3.39E+03
101.4859	4.78E+00
101.8025	1.13E+01
101.9065	1.04E+01
101.9728	4.67E+00

Technical rep 2

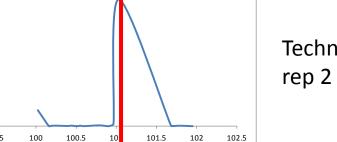
4.36E+02
7.56E+00
1.18E+01
1.76E+01
8.00E+00
1.81E+01
6.67E+00
5.78E+00
1.57E+01
4.00E+00
2.48E+01
2.78E+00
1.39E+01
7.48E+01
3.44E+03
1.70E+01
9.44E+00
7.56E+00
1.61E+01
3.67E+00

Technical rep 3

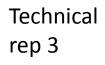
100.0179	5.06E+02
100.0882	1.09E+01
100.1867	1.81E+01
100.2148	1.38E+01
100.2805	2.18E+01
100.3322	5.11E+00
100.3979	7.89E+00
100.5294	2.89E+01
100.6093	1.44E+01
100.6799	1.78E+00
100.7175	6.67E+00
100.8445	1.56E+01
100.8728	7.78E-01
100.8963	8.67E+00
100.9669	4.27E+01
101.0282	3.51E+03
101.1884	1.90E+01
101.5234	6.89E+00
101.9726	1.20E+01



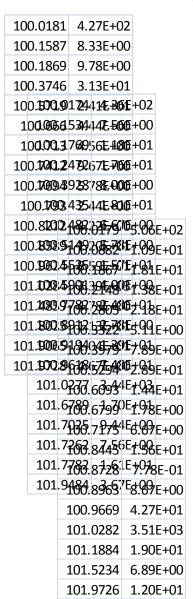
Technical rep 1



Technical



Align and "Bin" raw spectral output files



4.00E+03

3.50E+03

3.00E+03

2.50E+03

2.00E+03

1.50E+03

5.00F+02

0.00E+00 — 99.5 -5.00E+02

4.00E+03

3.50E+03

3.00E+03

2.50E+03

2.00E+03

1.50E+03

1.00E+03

5.00E+02

0.00E+00

4.00E+03

3.50E+03

3.00E+03

2.50E+03

2.00E+03

1.50E+03

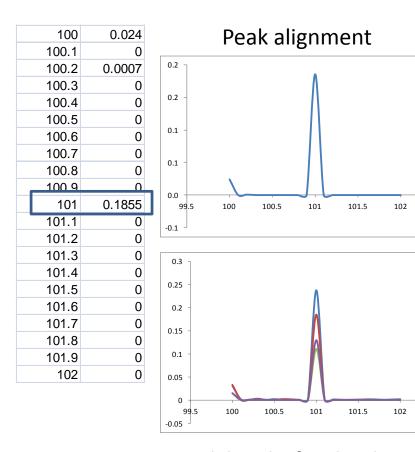
1.00E+03

5.00E+02

100.5 101 101.5

-5.00E+02 99.5

"Bin" 101 = contains all data between 100.95 to 101.05



102.5

102.5

Compare peak height for that bin across many samples

Normalise height to %TIC (TIC/sum total TIC * 100)

Why do we merge? - help with identifying many metabolites

- •Identify many compounds earlier we looked at identifying one metabolite
- •Very few sites allows the searching for many metabolites

Equipment software

Usually lab specific software – excel macros

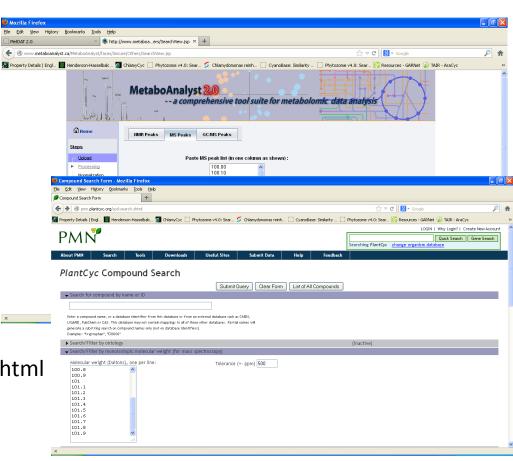
METABOANALYST

http://www.metaboanalyst.ca/MetaboAnalyst/faces/Secure/Others/SearchView.jsp

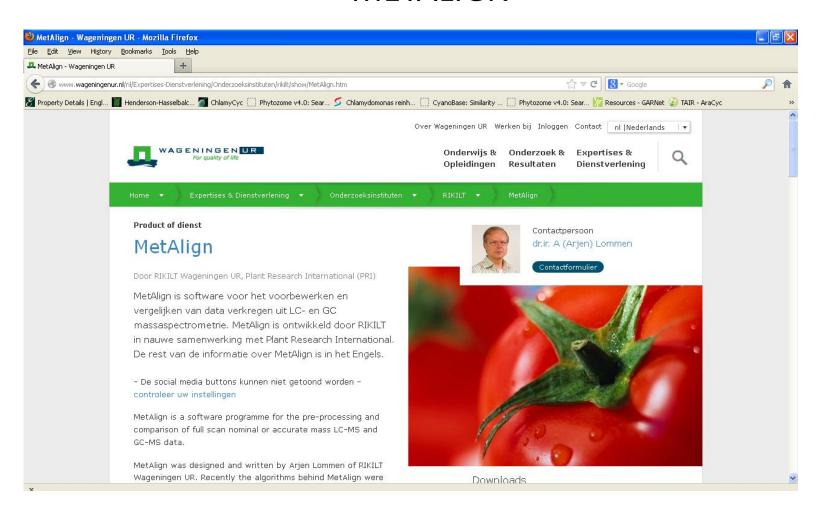
PlantCyc

http://pmn.plantcyc.org/cpd-search.shtml

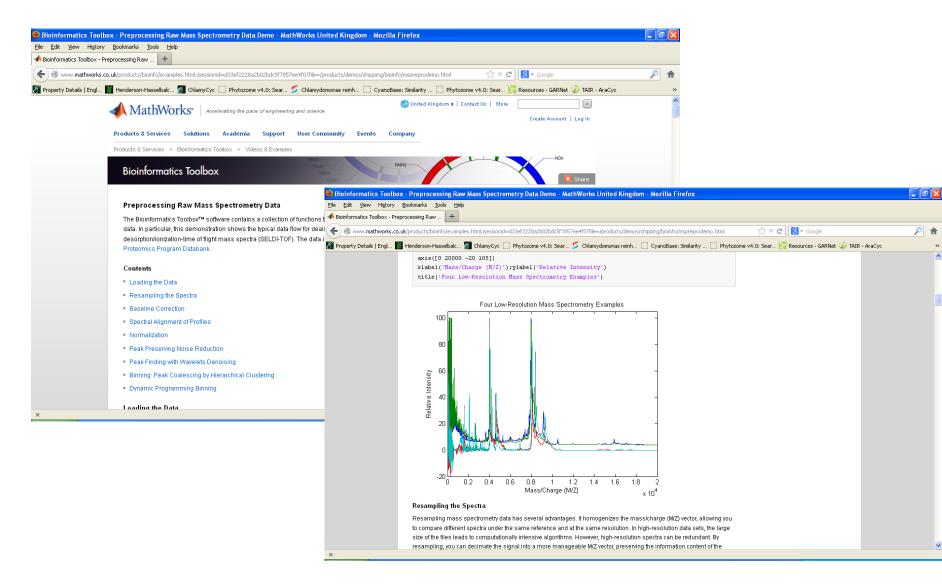
http://smbl.nus.edu.sg/METDAT2/



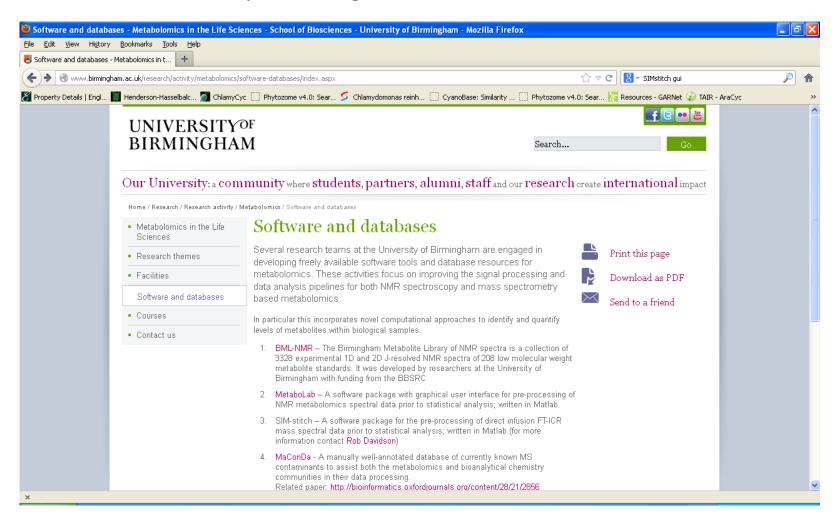
Align and "Bin" raw spectral output filesMETALIGN



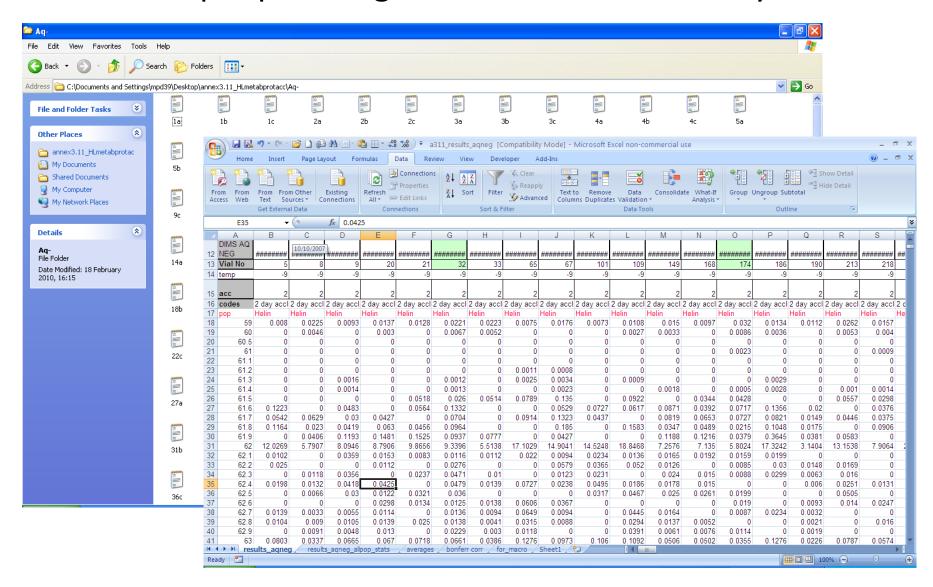
Matlab - MathWorks - commercial



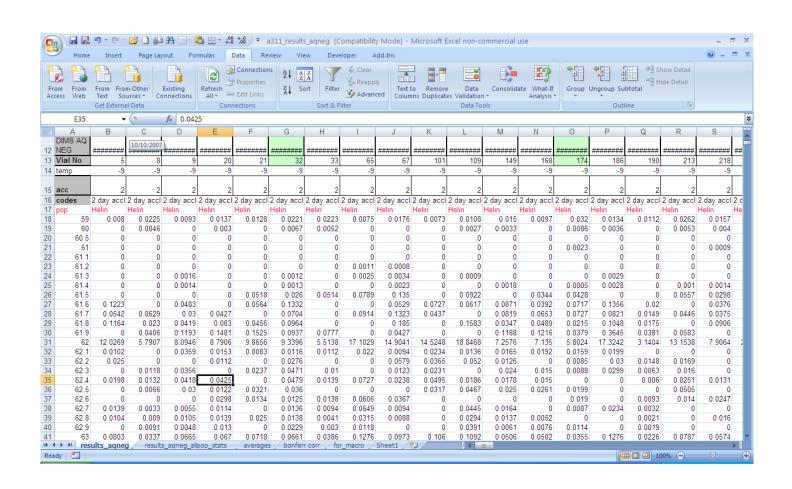
SIM-Stitch University of Birmingham



Most people merge files for statistical analysis



Multivariate data analysis – PCA, Cluster analysis



Multivariate Data Analysis

Unsupervised

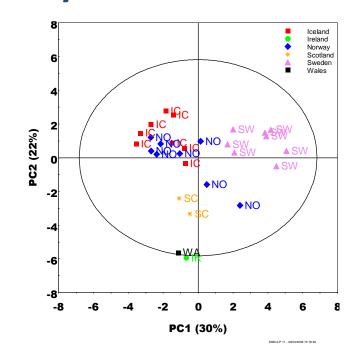
Principal Component Analysis (PCA)

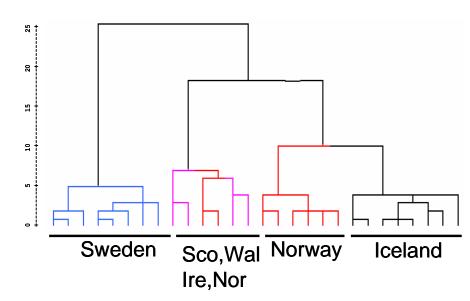
Supervised

Partial Least Squares

-Discriminant Analysis (PLS-DA)





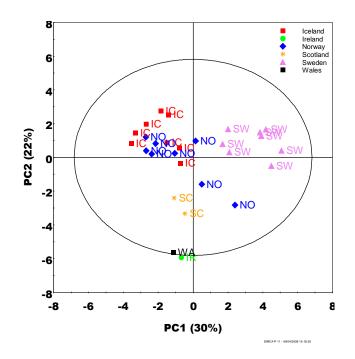


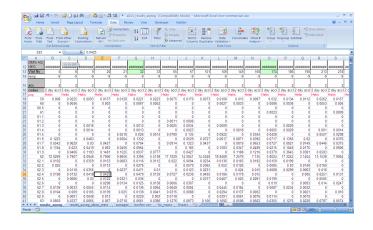
Trygg et al. 2007

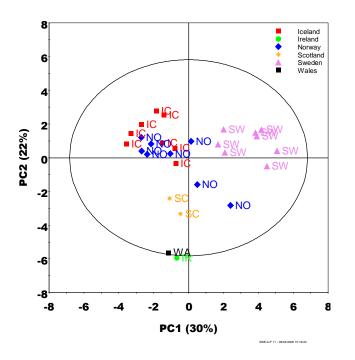
Objectives of PCA

- reduce number of variables
- identify outliers
- identify any splits within the data
- discriminate between samples
 (eg, cold stress, GM, disease, control)
 or separation by other unplanned
 means (eg, analytical error)

How does it work?







If each variable (ie. metabolite ion intensity or concentration) is thought of as a dimension,

and there are *n* variables,

every sample is at a unique position in the *n*-dimensional space defined by these *n* variables.

Very difficult for people to visualise

– aim is to reduce this dimensional space
by summarising the data using relatively
few parameters

Ie. Make a 2D plot!

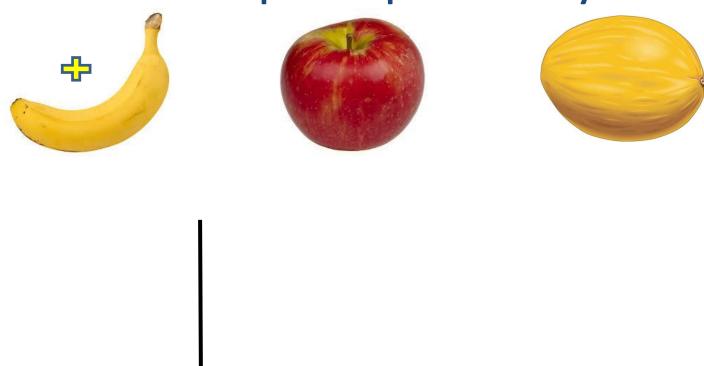
Will attempt to explain PCA...



Scores out of 10

Bendy-ess:	8	2	3
Yellow-ness:	9	2	7
Round-ness:	3	8	5

Plot these data in K-space



Bendy-ess:

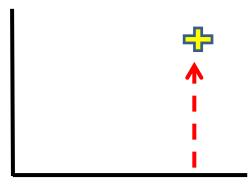
Bendy-ess:	8	2	
Yellow-ness:	9	2	7
Round-ness:	3	8	5







Yellow-ness:



Bendy-ess:

Bendy-ess:

8

2

3

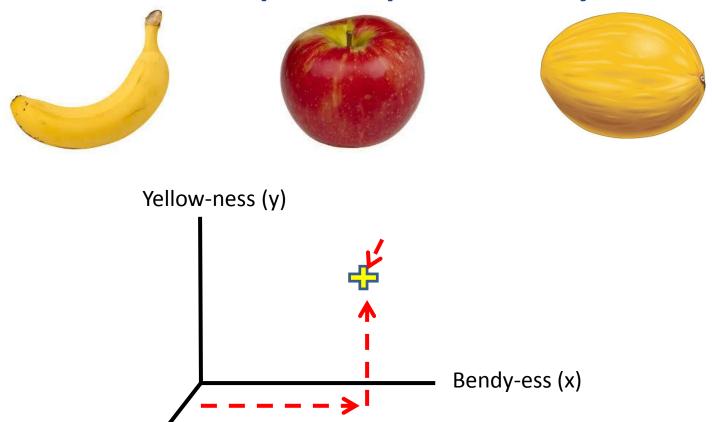
Yellow-ness:

2

7

Round-ness:

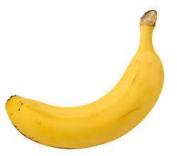
8



Round-ness (z)

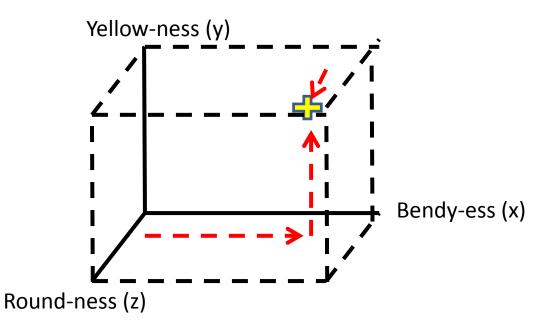
Bendy-ess: 8 2 3
Yellow-ness: 9 2 7

Round-ness: 3 8 5









Bendy-ess:

8

3

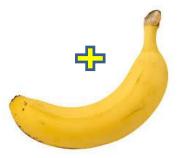
Yellow-ness:

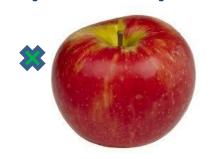
2

7

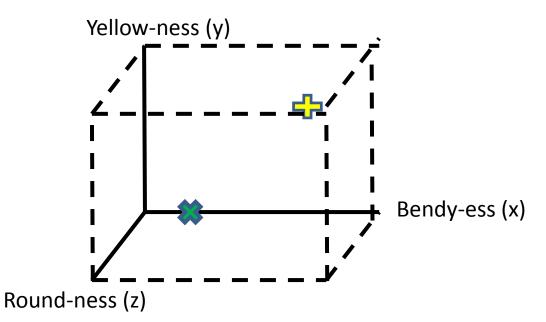
Round-ness:

8









Bendy-ess:

8

2

3

Yellow-ness:

7

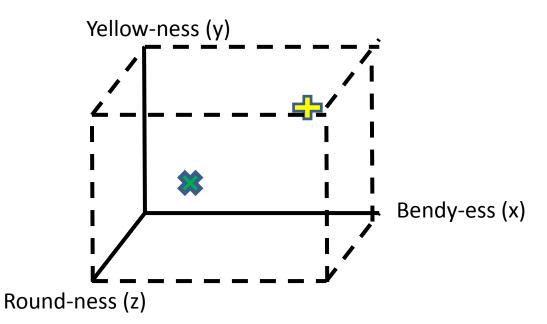
Round-ness:

8







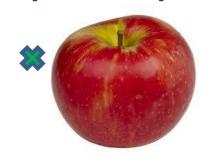


Bendy-ess:

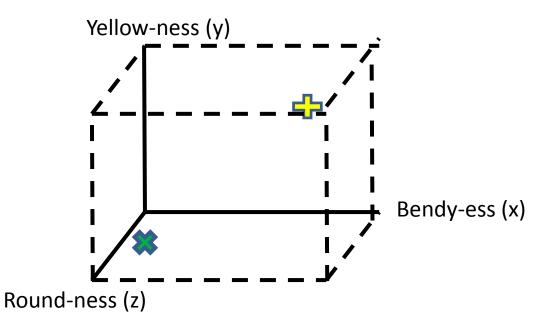
Yellow-ness:

Round-ness:









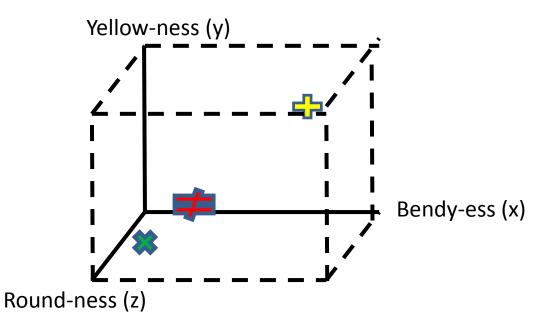
Bendy-ess:

•

Yellow-ness:

Round-ness:

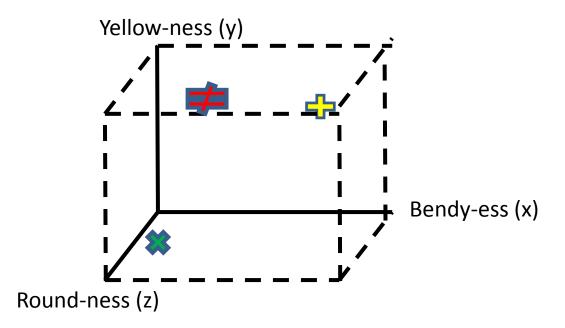




Bendy-ess: 8 2 3
Yellow-ness: 9 2 7

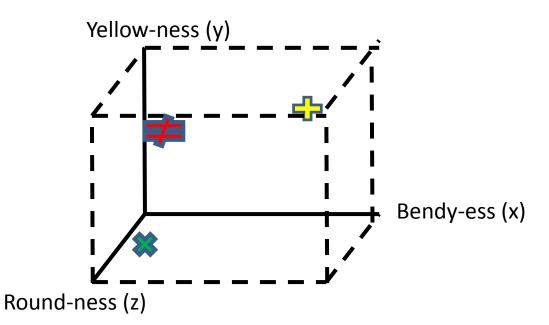
Round-ness: 3 8 5



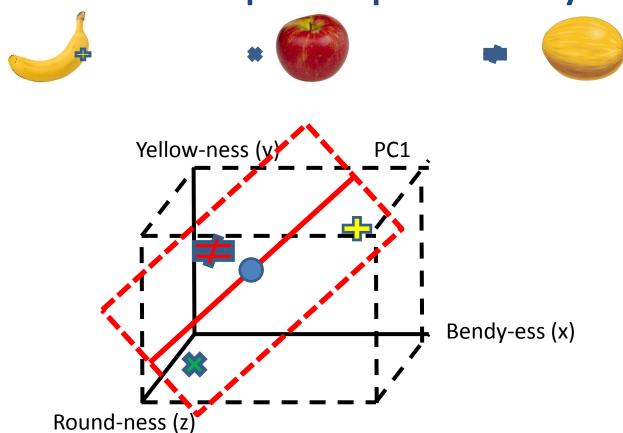


Bendy-ess:	8	2	
Yellow-ness:	9	2	7
Round-ness:	3	8	5





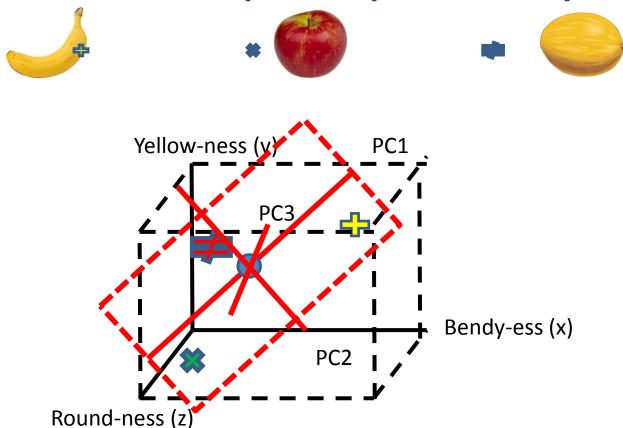
Bendy-ess:	8	2	
Yellow-ness:	9	2	7
Round-ness:	3	8	5



A 2D window is inserted over this 3D space (or in real PCA datasets over all k-dimensions) that covers the most variation of the data set

A line is then placed through this window and a dot is placed in the centre (mean centred)

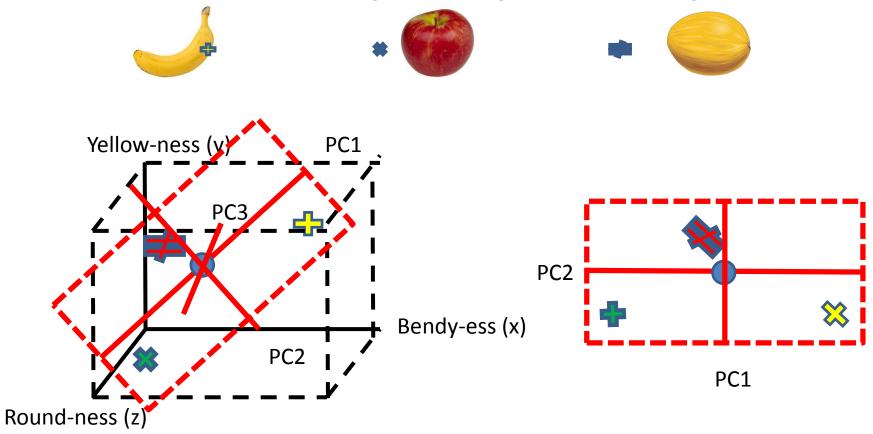
This is what we call PC (principal component) 1!



The second PC is calculated by looking at the variation at 90 ° to the first PC

The third PC is calculated by looking at the variation at 90 ° to the second PC

Each subsequent PC lies in an orthogonal direction of maximum variance that has not been considered by the former components.



Rotating the window converts the multidimension data to a 2D PCA plot (this is called a score scatter plot)

How do we know what causes each point to be in each position? – loadings plot







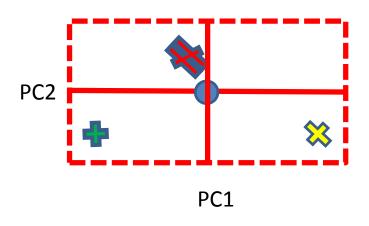


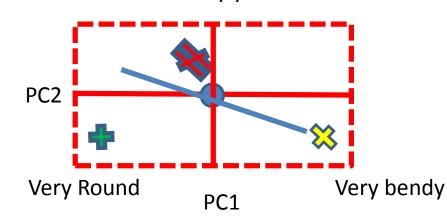
How do we see what causes each point to be in each position? – loadings plot Displays the relationships among the variables

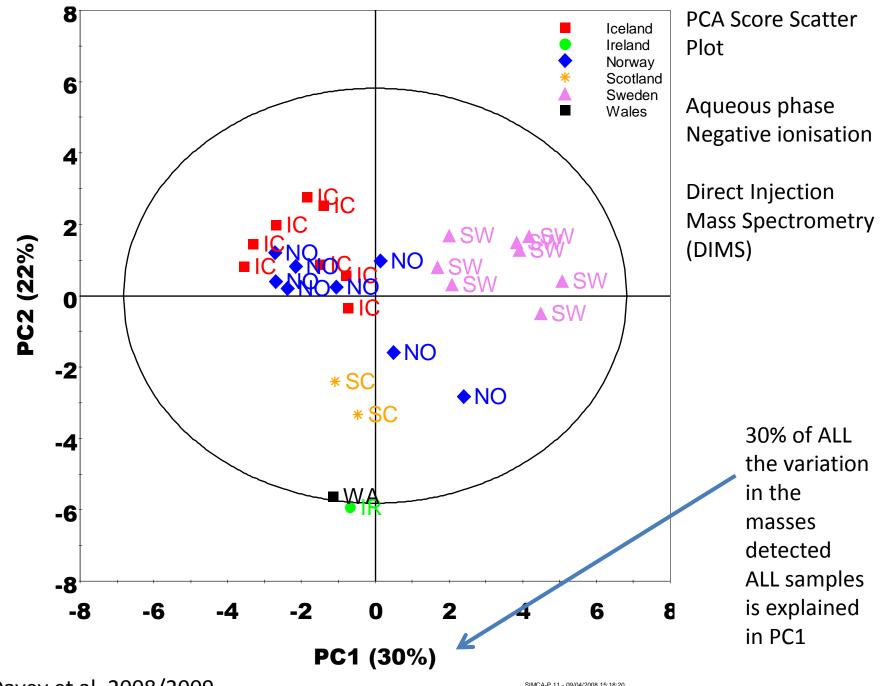
Loading score for each measurement is given between 0-1 (essentially an R2)

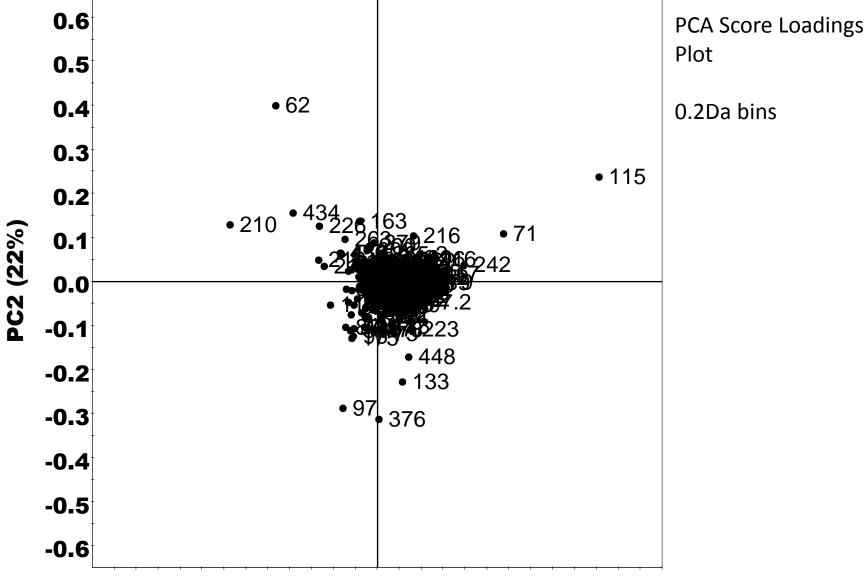
Are inversely related measurement – what is high in bendy is low in opposite measurement

Very yellow

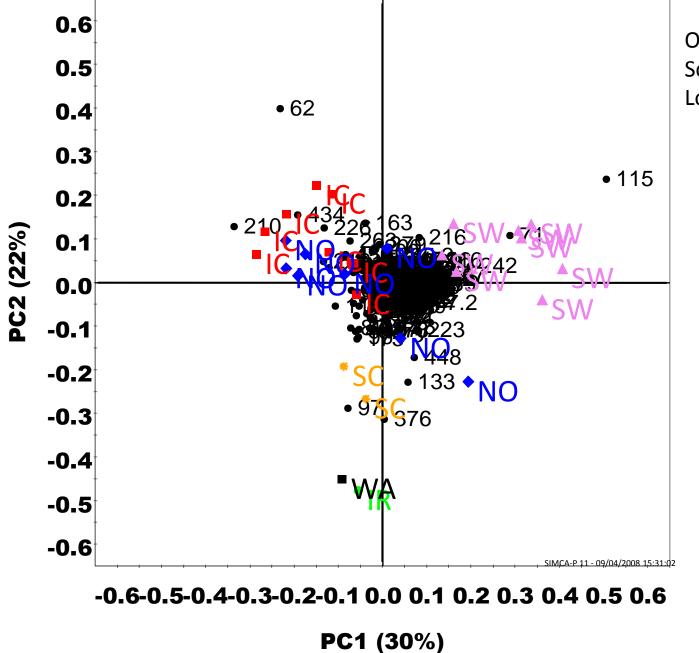








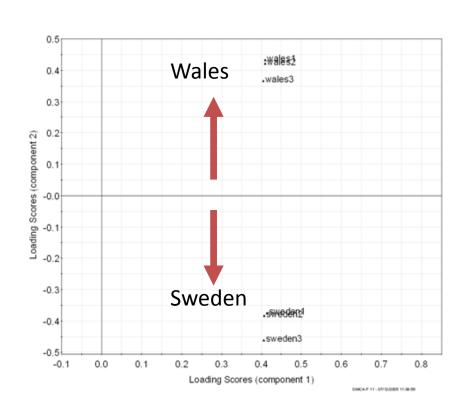
-0.6-0.5-0.4-0.3-0.2-0.1 0.0 0.1 0.2 0.3 0.4 0.5 0.6 PC1 (30%)



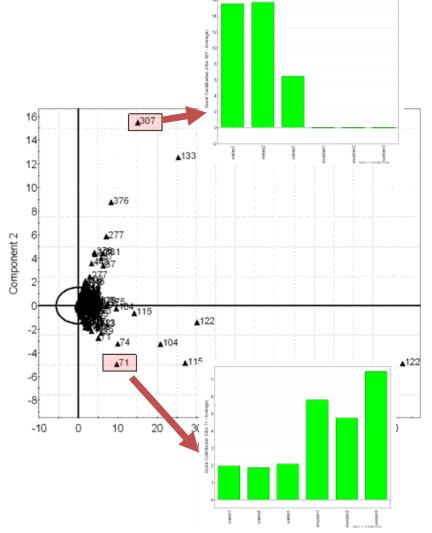
Overlay PCA
Score Scatter and
Loadings Plot

SIMCA-P 11 - 09/04/2008 15:26:59

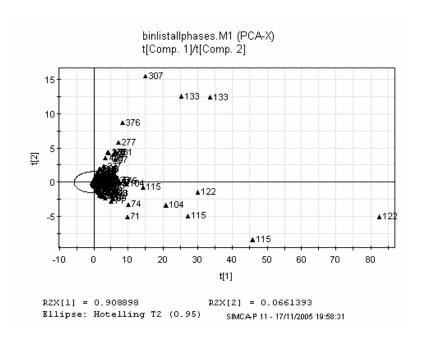
Simca-P software - PCA



Data mining – search masses in our metabolite database



SMILE STRUCTURE REPRESENTATION



binlistallphases.M1 (PCA-X) t[Comp. 1]/t[Comp. 2] ▲307 15 ▲C(O)(▲O)(O)(=O)CC 10 **▲**C(O)C(O)C(**▲**C(O)(=O)CC [2] AC(=O)(CAC(O)C(N)C(▲C(O)(=O)C= **▲**C(Φ)α -5 ▲C(O)(=O)C= -10 10 20 30 40 60 70 80 t[1] R2X[1] = 0.908898R2X[2] = 0.0661393Ellipse: Hotelling T2 (0.95) SIMCAP 11 - 17/11/2005 20:42:33

M1.t[1] = 82.5556M1.t[2] = -4.89724Primary ID = 2431

MASS 122 - Malonate

Primary ID = 448 MASS 115 - Fumaric acid

M1.t[1] = 25.4171M1.t[2] = 12.544Primary ID = 1786

MASS 133 - Malic acid



M1.t[1] = 9.94449M1.t[2] = -3.22985Primary ID = 1730

M1.t[1] = 45.7915

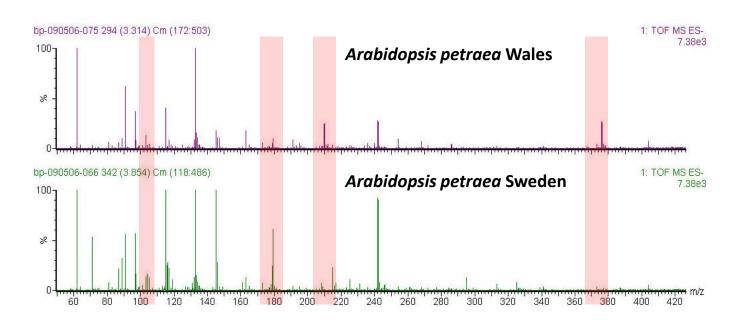
M1.t[2] = -8.28212

MASS 74 - Glycine



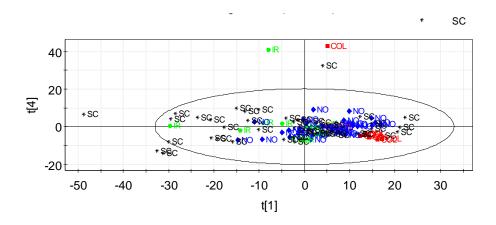
Scaling data

Reducing bias against very intense peaks -need to highlight fold/relative intensities among samples of the same peak



Scaling data

Reducing bias against very intense peaks
-need to highlight fold/relative intensities among samples of the same peak

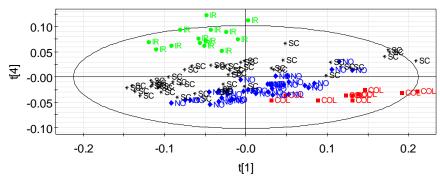


Unit variance scaling

Most objective – takes data as face value

Pareto Scaling

Best for MS, NMR
Decreases importance of high intensity peaks
Depends on question...



How many components should I look at?

How many components should be included in the model?

Degree of fit and the predictive ability

Fit = how well we are able to mathematically reproduce the data of a training set (goodness of fit) R^2X = the explained variation (0-1)

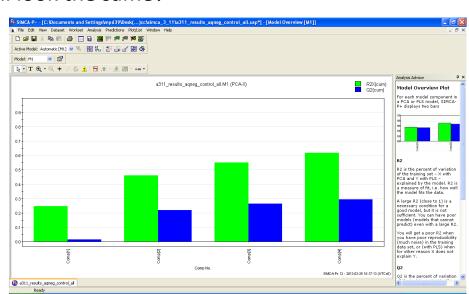
Predictive ability = how accurately can we predict the raw X data? (goodness of predictability) Q^2X

Take out 25% of samples, does the PCA still look the same?

(a good reason to have many samples!)

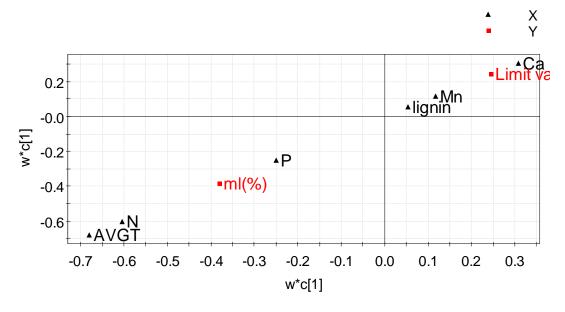
Does adding more components make the model better?

Poor R^2X and Q^2X if very noisy dataset or too few replicates

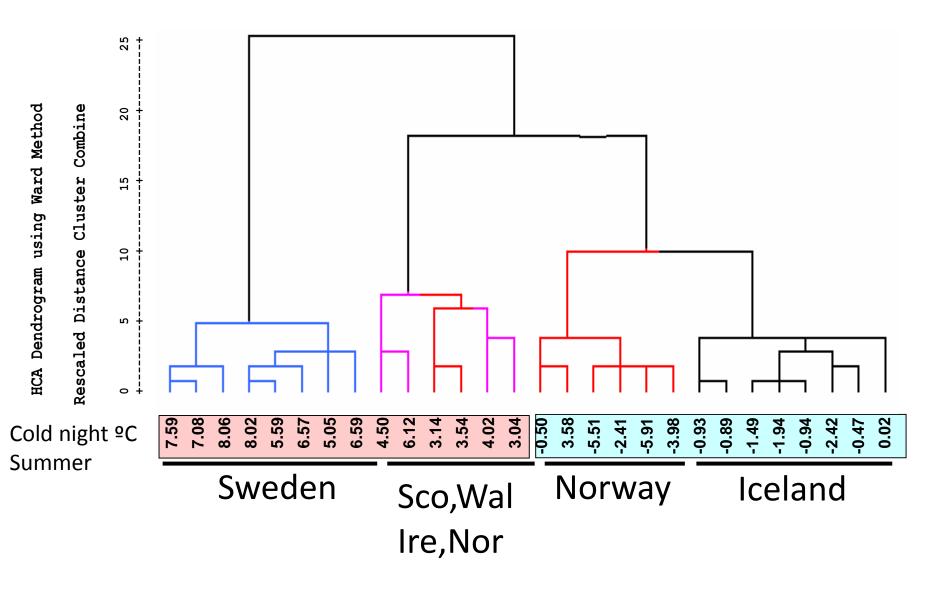


•PLS-DA – projections to latent structures by partial least squares – discriminate analysis

- •Similar to PCA
- •Supervised method good for discovering biomarkers
- •Can connect other data (Y) with your MS/NMR dataset (X)
- you tell the model that some samples are from control, others treated etc.



HCA – Hierarchical Cluster Analysis



ANOVA, false-positive corrections

Which masses are statistically significantly different between our samples?

T-test

ANOVA

Many samples (10's or 100's)

a311_results_agneg [Compatibility Mode] - Microsoft Excel non-commercial use Conditional Format Cell E17 218 🚾 day accl|2 day accl 0.0009 0.0034 0.0014 0.0013 0.0023 0.001 0.0014 0.0922 0.0427 0.0704 0.0437 0.0375 0.0964 61.8 0.0419 61.9 0.0406 0.1193 0.1481 0.1525 0.0937 0.0777 0.0427 0.1216 0.0379 0.0381 0.0583 62 12.0269 8.0946 8.7906 9.3396 5.5138 17.1029 14.9041 14.5248 18.8468 7.2576 7.135 5.8024 17.3242 7.9064 62.1 0.0359 0.0153 0.0083 0.0116 0.0094 0.0136 0.0192 0.0159 62.2 0.0112 0.0276 0.0579 0.0365 0.052 0.0126 0.0085 0.03 0.0148 62.3 0.0118 0.0237 0.0471 0.01 0.0123 0.0231 0.024 0.015 0.0088 0.0299 0.0063 0.016 0.0198 0.0132 0.0425 0.0479 0.0139 0.0727 0.0238 0.0495 0.0186 0.0178 0.015 0.0251 0.0131 0.0122 0.0321 0.036 0.0467 0.025 0.0261 0.0199 0.0134 0.0247 0.0164 0.0087 0.0445 62.8 0.0104 0.009 0.0052 0.0021 0.016 0.0138 0.0315 62.9 0.0091 0.013 0.0229 0.003 0.0118 0.0391 0.0114 0.0019 63 0.0803 0.0337 0.067 0.0718 0.1276 0.0973 0.106 0.0355 0.0226 0.0787 0.0574 0.0042 0.0104 0.0045 0.0024 0.0209 63.2 0.0031 0.0036 0.0128 0.0038 0.0136 0.0037 **III** II II 100% (-)

Many bins (MW) 1000's

Many intensities 10,000's

ANOVA, false-positive corrections

Testing so many samples runs the risk of significant values occurring by chance Change the usual p < 0.05 to take into account the number of samples

p<0.05 is usually considered a significant result - error rate of 5 %
 (ie: 1 in every 20 tests gives a false result)</pre>

If a dataset has 1000 metabolites (so 1000 univariate tests...) **50 metabolites are significantly different when they are not**

ANOVA, false-positive corrections

Testing so many samples runs the risk of significant values occurring by chance Change the usual p <0.05 to take into account the number of samples

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 (ie: 1 in every 20 tests gives a false result)</pre>

If a dataset has 1000 metabolites (so 1000 univariate tests...) **50 metabolites are significantly different when they are not**

Two main False-positive corrections

Bonferroni adjusted P-value is: 0.05/number of samples (very strict)

$$=0.05/4254$$
 $P_{adj} = 0.00001175$

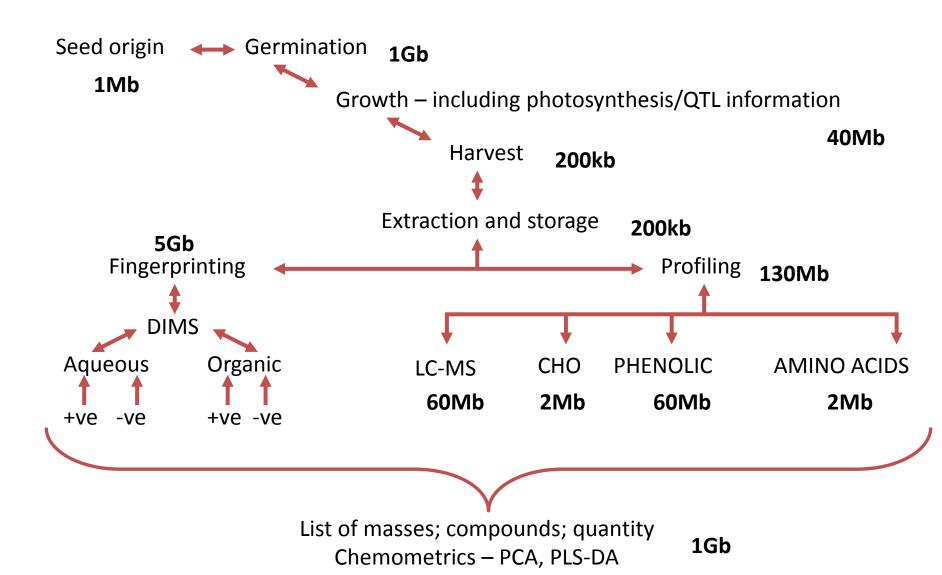
Benjamini and Hochberg – rank the p-values highest to lowest $P_{adj} = (number \ of \ samples/p-value)*position \ in \ ranked \ p-value \ table$ Keep going until you get to P_{adj} of 0.05 $Original \ p-value = 0.011718$ $P_{adj} = 0.051755$

Introduction to chemometrics

•Metadata – useful for interpreting PCA, Y-var for PLS-DA

	META-DATA
Experiment set-up	Seed origin
	Germination conditions – soil, light, humidity, CO2, day length, temp
	Growth conditions – randonisation etc
	Harvest conditions, time, weight of plant
Gas exchange	Time, growth conditions, IRGA conditions saved per raw sample run
Growth	Plant and cabinet data

Metadata – data storage



Online practical involving multivariate statistics – PCA etc