

Dimensionality Reduction

Lavinia Carabet

Dimensionality Reduction

Techniques that attempt to examine the underlying patterns or relationships for a large number of variables and determine whether the information can be better summarized in a few factors or components

Principal Component Analysis

Statistical method that projects a high-dimensional space into a much lower-dimensional subspace (2D or 3D)

Identifies principal components to reduce dimensionality while maintaining the inherent structure of the data

Principal components are uncorrelated linear combinations of the original variables with variances as large as possible, with each successive component explaining less and less variability

The first principal component can be defined as a direction that maximizes the variance of the projected data
The i -th principal component can be taken as a direction orthogonal to the first $i-1$ principal components that maximizes the variance of the projected data

Principal components are eigenvectors of the data's covariance matrix often computed by eigen decomposition of the data covariance matrix or singular value decomposition of the data matrix

Eigenvector - of a linear transformation - is a non-zero vector that changes at most by a scalar factor when that linear transformation is applied to it

Eigenvalue - corresponding to the eigenvector - is the factor by which the eigenvector is scaled

Geometrically, an eigenvector, corresponding to a real non-zero eigenvalue, points in a direction in which it is stretched by the transformation and the eigenvalue is the factor by which it is stretched

Preparation

Load the GEO GSE2990 Sotiriou Breast Cancer data - Gene Expression Profiling in Breast Cancer: Understanding the Molecular Basis of Histologic Grade To Improve Prognosis

<https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE2990>

Dataset - microarray experiments (gene expression data) from primary breast tumors of tamoxifen-untreated patients

Load also the annotation file for this dataframe

```
dat <- read.table('./sotiriou.txt', header=T, row.names=1)
dim(dat)
```

```
## [1] 239 125
```

```
#dat
dat[1:5,]
```

```
##          GSM65752 GSM65753 GSM65754 GSM65755 GSM65756 GSM65757 GSM65758
## 160020_at    7.127042  9.100651  8.203144  5.870628  6.812588  8.085146  8.293816
## 200616_s_at  9.900457  9.472446  9.991549  9.560798  9.453957 10.345307 10.947466
## 200702_s_at  9.927486  9.071813  9.621632  9.866459  9.845791  9.104895  9.434893
## 200769_s_at  5.492201  5.106272  5.189343  5.374762  5.210284  5.335828  5.329314
## 200998_s_at 11.135597 10.466324  9.779081  9.892760  8.966400 11.219400 10.655453
##          GSM65760 GSM65761 GSM65762 GSM65763 GSM65764 GSM65765
## 160020_at    5.909595  5.681155  9.480939  8.371547  9.516220  8.245924
## 200616_s_at  9.082748 10.787522  9.617904 10.421155  9.408520 10.121032
## 200702_s_at  9.994836  9.433560  9.426032  9.747579  8.554534  9.846077
## 200769_s_at  5.398720  2.500648  5.801551  5.338819  5.625358  2.950183
## 200998_s_at  9.392855  9.097819 10.404082 10.200129 10.817661  9.001823
##          GSM65766 GSM65767 GSM65768 GSM65769 GSM65770 GSM65771
## 160020_at    8.644868  8.120205  8.231659  8.033868  7.711178  9.022717
## 200616_s_at 10.547777 10.994460 10.493583  8.814009  8.574927 10.678708
## 200702_s_at  9.690883  9.640134  8.903683  9.698340  8.297697  9.932706
## 200769_s_at  3.664175  5.459398  5.975150  6.332186  6.192912  5.317168
## 200998_s_at 10.133112  9.691442 10.825326 10.061569  9.850459 10.047732
##          GSM65772 GSM65773 GSM65774 GSM65775 GSM65776 GSM65777 GSM65780
## 160020_at    7.119111  6.528758  6.857606  7.779015  8.830330  8.510281  8.256988
## 200616_s_at  9.810289  8.994529 10.454922  8.599527  8.584614  9.300683 11.086693
## 200702_s_at  9.967046  7.984709  8.739218  8.723353  7.463278  9.105808  9.529709
## 200769_s_at  5.374693  6.082383  6.595516  6.135871  5.778541  5.107219  5.345398
## 200998_s_at 10.732827  9.832214  9.427659 10.415562 10.422325  9.943425  9.546482
##          GSM65781 GSM65782 GSM65783 GSM65784 GSM65785 GSM65786 GSM65787
## 160020_at    6.801547  7.880265  7.917776  6.337465  9.020984  6.825657  7.818748
## 200616_s_at  8.018304 11.168007  9.660540 10.144745 10.917555  9.936215  9.781399
## 200702_s_at  8.501395  9.632202  9.617484  8.902115  9.996999  9.042858  8.971623
## 200769_s_at  6.134436  5.790030  5.341360  7.059119  6.571793  7.277563  6.644540
## 200998_s_at  8.824451  9.848869  8.630958  9.356876 10.230284  9.690731  9.496230
##          GSM65788 GSM65789 GSM65790 GSM65791 GSM65792 GSM65793 GSM65794
## 160020_at    8.068011  7.407714  8.988034  8.230169  7.635828  7.890231  5.979435
## 200616_s_at 10.789638  9.668978  8.181882  9.317535  9.719525 10.677062 10.252366
## 200702_s_at  9.916601  9.245667  8.798942  9.233922  8.259998  9.856308  9.371726
## 200769_s_at  4.795179  5.416566  5.602389  5.395962  6.238359  5.178281  4.852333
## 200998_s_at  9.753282  9.682318 10.066601  9.068825 10.020634  9.373232 10.301871
##          GSM65795 GSM65796 GSM65797 GSM65798 GSM65799 GSM65800
## 160020_at    7.984038  8.309032  9.380480  7.487749  7.529136  9.754835
## 200616_s_at 10.252106 10.565160 11.255753 11.165969 10.590101 10.080474
## 200702_s_at  8.526333 10.186376  9.419193  9.096370 10.133660  9.296562
## 200769_s_at  5.407855  5.252883  5.391743  6.109436  5.374098  5.873256
## 200998_s_at 10.446065  9.992373 10.694382  9.240809  9.797251 10.853646
##          GSM65801 GSM65802 GSM65803 GSM65804 GSM65805 GSM65806
## 160020_at    7.902266  6.115298  8.722334  7.736976  8.615979  6.387784
## 200616_s_at 10.853234  9.836458 11.210163 10.795851 10.578003  9.520421
## 200702_s_at  8.601716 11.137974 10.243359  9.488605  9.297246  8.246602
## 200769_s_at  6.286121  5.376139  5.154376  5.000554  5.358961  4.965700
## 200998_s_at 10.483693 10.078380 10.968063  9.949478 10.508184 10.341115
##          GSM65807 GSM65808 GSM65810 GSM65811 GSM65812 GSM65813 GSM65814
## 160020_at    7.752178  7.788342  8.051734  8.316980  7.246637  7.198145  8.467210
```

```

## 200616_s_at 8.633368 9.690017 10.462164 10.083944 8.280060 10.479837 10.339253
## 200702_s_at 9.093935 9.024625 9.267070 9.454722 8.480911 10.203286 8.726727
## 200769_s_at 5.875508 4.664785 5.312084 5.651056 5.238019 5.303193 5.871917
## 200998_s_at 9.264657 9.653221 9.314803 9.239377 9.638025 9.525043 10.353718
##          GSM65815 GSM65816 GSM65817 GSM65818 GSM65819 GSM65820 GSM65821
## 160020_at 7.177986 7.082744 6.882445 7.768723 6.167115 5.330163 5.583011
## 200616_s_at 10.714308 10.219222 8.791933 9.628977 9.210866 8.112195 8.118626
## 200702_s_at 10.188286 9.511245 8.934046 9.204855 9.602535 5.997627 6.653063
## 200769_s_at 4.961311 5.412523 6.277328 6.816162 5.392524 7.546326 6.425582
## 200998_s_at 9.378871 10.031773 9.336170 10.511327 10.356181 8.452654 8.062702
##          GSM65822 GSM65823 GSM65824 GSM65825 GSM65826 GSM65827 GSM65828
## 160020_at 5.294315 5.559391 5.446690 4.225444 6.009053 5.827058 5.349911
## 200616_s_at 6.738064 7.517329 7.567199 7.905552 7.538735 8.956796 8.172378
## 200702_s_at 7.672364 7.299689 7.349345 6.713698 5.455443 7.671101 7.368687
## 200769_s_at 9.696201 8.084531 7.120451 8.367263 6.354643 6.680537 6.183167
## 200998_s_at 6.733758 7.941445 8.403255 8.344021 7.928199 9.245684 8.823509
##          GSM65829 GSM65830 GSM65831 GSM65832 GSM65833 GSM65834 GSM65835
## 160020_at 4.858067 5.441667 5.263510 6.513543 5.312928 4.806524 5.264719
## 200616_s_at 6.969864 8.138992 9.420637 9.279276 7.304441 9.532450 7.673764
## 200702_s_at 6.191760 6.479657 5.780219 7.386742 7.147238 6.637015 6.842989
## 200769_s_at 5.900277 6.897877 5.836441 6.079820 7.561734 8.535315 5.973704
## 200998_s_at 8.729199 8.430658 9.094698 9.477792 7.959189 9.924686 9.568696
##          GSM65836 GSM65837 GSM65838 GSM65839 GSM65840 GSM65841 GSM65842
## 160020_at 6.452673 3.553217 5.308978 6.565343 6.688451 6.100403 6.131141
## 200616_s_at 6.799957 8.505827 7.906421 9.233981 9.922303 7.495615 7.817343
## 200702_s_at 6.064194 7.760058 7.233753 6.598780 8.639239 6.217803 7.393500
## 200769_s_at 7.869046 4.488966 8.189155 8.501925 5.838808 8.034822 8.088876
## 200998_s_at 7.774166 7.337992 9.162603 8.917767 9.313191 8.923974 9.322993
##          GSM65843 GSM65844 GSM65845 GSM65846 GSM65847 GSM65848 GSM65849
## 160020_at 6.085709 6.192932 6.225261 6.074410 5.867830 5.945478 5.238206
## 200616_s_at 8.990263 7.835177 9.618565 8.376150 8.702616 9.494268 7.608893
## 200702_s_at 7.269527 6.049418 7.906513 7.745725 6.415752 7.732984 7.236409
## 200769_s_at 7.366368 7.633503 7.443933 8.175065 7.641305 8.196143 5.752735
## 200998_s_at 9.091870 8.323871 10.222800 9.445476 9.117662 9.152535 8.141216
##          GSM65850 GSM65851 GSM65852 GSM65853 GSM65854 GSM65855 GSM65856
## 160020_at 5.346330 5.320685 4.607676 7.290498 5.897952 5.329988 4.716552
## 200616_s_at 7.758706 8.791167 8.582104 9.113793 7.690340 7.162172 7.440817
## 200702_s_at 7.265456 7.563192 7.054802 7.652907 6.813953 6.613734 7.370872
## 200769_s_at 6.840295 7.241069 7.131030 6.556301 7.752748 7.395102 8.917769
## 200998_s_at 8.365251 7.566129 8.166242 8.964722 7.838155 7.591849 8.602457
##          GSM65857 GSM65858 GSM65859 GSM65860 GSM65861 GSM65862 GSM65863
## 160020_at 6.228811 6.353189 6.319914 5.388501 6.803573 5.299090 5.403714
## 200616_s_at 8.139498 7.684448 7.838530 8.627343 7.661839 6.776158 8.299346
## 200702_s_at 7.664270 7.027039 5.985502 7.664480 7.183214 6.880971 7.023203
## 200769_s_at 8.150211 7.780264 8.299409 7.308597 7.794505 8.887082 7.843488
## 200998_s_at 9.505822 7.517558 8.455796 8.612803 8.932506 6.871481 7.989526
##          GSM65864 GSM65865 GSM65866 GSM65867 GSM65868 GSM65869 GSM65870
## 160020_at 5.705747 5.798020 5.112201 5.832906 5.293796 5.366202 5.479538
## 200616_s_at 7.191298 7.151177 8.257703 8.620128 8.232577 7.515288 7.064911
## 200702_s_at 7.635920 8.101510 7.722635 7.719481 7.600326 6.600945 6.979100
## 200769_s_at 5.346011 6.091211 7.676671 7.151661 7.458228 8.466384 8.840666
## 200998_s_at 8.151714 7.210733 9.757229 8.159228 7.850343 8.253440 8.822553
##          GSM65871 GSM65872 GSM65873 GSM65874 GSM65875 GSM65876 GSM65877
## 160020_at 5.302505 5.610217 5.334782 5.453561 3.772388 5.303982 5.700977

```

```
## 200616_s_at 4.983138 8.013414 6.621606 6.465911 6.808675 8.631659 6.425143
## 200702_s_at 6.690384 6.363681 7.123621 7.659471 7.556384 7.646633 6.850617
## 200769_s_at 5.418327 5.770689 5.859436 5.268106 6.627903 6.539166 5.232111
## 200998_s_at 6.575140 8.253160 7.767105 7.266600 6.125215 8.296543 8.194467
##
## GSM65878 GSM65879 GSM65880
## 160020_at 6.151776 5.534651 5.311369
## 200616_s_at 6.915546 6.345979 9.133848
## 200702_s_at 7.660817 6.176146 6.391650
## 200769_s_at 8.577475 6.297069 7.325461
## 200998_s_at 8.986590 8.753346 8.562461
```

```
ann <- read.table('./sotiriouAnn.txt', header=T, row.names=1)
dim(ann)
```

```
## [1] 125 13
```

```
ann
```

```
##      site sample_name treatment dataset grade node size age er event.rfs
## GSM65752 KIU KIU_101B88      none KJ125 3 0 1.2 40 0 0
## GSM65753 KIU KIU_105B13      none KJ125 1 0 1.3 46 1 0
## GSM65754 KIU KIU_106B55      none KJ125 1 0 6.0 37 1 1
## GSM65755 KIU KIU_111B51      none KJ125 3 0 3.3 41 1 1
## GSM65756 KIU KIU_113B11      none KJ125 3 0 3.2 38 1 1
## GSM65757 KIU KIU_120B73      none KJ125 2 0 1.6 34 1 0
## GSM65758 KIU KIU_124B25      none KJ125 2 0 2.1 46 1 1
## GSM65760 KIU KIU_127B00      none KJ125 3 0 2.2 57 1 1
## GSM65761 KIU KIU_134B33      none KJ125 2 0 2.8 63 1 1
## GSM65762 KIU KIU_136B04      none KJ125 2 0 1.7 54 1 1
## GSM65763 KIU KIU_140B91      none KJ125 2 0 1.2 61 1 0
## GSM65764 KIU KIU_144B49      none KJ125 2 0 2.1 40 1 0
## GSM65765 KIU KIU_151B84      none KJ125 2 0 1.5 57 1 0
## GSM65766 KIU KIU_155B52      none KJ125 1 0 1.3 57 0 0
## GSM65767 KIU KIU_163B27      none KJ125 1 0 0.8 49 1 0
## GSM65768 KIU KIU_164B81      none KJ125 2 0 2.3 62 0 0
## GSM65769 KIU KIU_172B19      none KJ125 3 0 2.3 42 1 1
## GSM65770 KIU KIU_177B67      none KJ125 1 0 1.8 41 1 1
## GSM65771 KIU KIU_184B38      none KJ125 1 0 1.0 63 1 0
## GSM65772 KIU KIU_188B13      none KJ125 2 0 1.4 60 0 0
## GSM65773 KIU KIU_196B81      none KJ125 1 0 1.4 65 1 0
## GSM65774 KIU KIU_197B95      none KJ125 2 0 1.6 44 1 0
## GSM65775 KIU KIU_199B55      none KJ125 2 0 2.3 54 1 0
## GSM65776 KIU KIU_205B99      none KJ125 1 0 2.2 59 1 1
## GSM65779 KIU KIU_220C70      none KJ125 1 0 2.0 42 1 0
## GSM65780 KIU KIU_227C50      none KJ125 1 0 1.2 57 1 1
## GSM65781 KIU KIU_229C44      none KJ125 1 0 1.3 52 1 0
## GSM65782 KIU KIU_231C80      none KJ125 1 0 2.2 56 1 1
## GSM65783 KIU KIU_233C91      none KJ125 1 0 1.1 49 1 0
## GSM65784 KIU KIU_242C21      none KJ125 2 0 1.6 64 1 1
## GSM65785 KIU KIU_243C70      none KJ125 1 0 1.8 50 1 0
## GSM65786 KIU KIU_247C76      none KJ125 2 0 1.0 56 1 0
## GSM65787 KIU KIU_248C91      none KJ125 1 0 2.5 57 1 0
## GSM65788 KIU KIU_24C30       none KJ125 2 0 2.3 55 1 0
```

##	GSM65789	KIU	KIU_259C74	none	KJ125	1	0	1.0	65	1	0
##	GSM65790	KIU	KIU_260C91	none	KJ125	2	0	2.1	58	1	0
##	GSM65791	KIU	KIU_266C51	none	KJ125	1	0	2.2	58	1	0
##	GSM65792	KIU	KIU_268C87	none	KJ125	2	0	1.5	32	1	0
##	GSM65793	KIU	KIU_272C88	none	KJ125	2	0	1.7	45	1	0
##	GSM65794	KIU	KIU_278C80	none	KJ125	2	0	1.1	56	1	0
##	GSM65795	KIU	KIU_279C61	none	KJ125	3	0	1.9	50	1	0
##	GSM65796	KIU	KIU_280C43	none	KJ125	2	0	0.9	45	1	1
##	GSM65797	KIU	KIU_282C51	none	KJ125	1	0	1.1	55	1	0
##	GSM65798	KIU	KIU_284C63	none	KJ125	1	0	1.0	48	1	0
##	GSM65799	KIU	KIU_286C91	none	KJ125	2	0	1.8	62	1	0
##	GSM65800	KIU	KIU_28C76	none	KJ125	1	0	2.0	56	1	0
##	GSM65801	KIU	KIU_292C66	none	KJ125	2	0	2.0	51	1	0
##	GSM65802	KIU	KIU_303C36	none	KJ125	3	0	2.3	37	0	0
##	GSM65803	KIU	KIU_304C89	none	KJ125	3	0	1.5	54	0	1
##	GSM65804	KIU	KIU_308C93	none	KJ125	2	0	2.1	38	0	1
##	GSM65805	KIU	KIU_309C49	none	KJ125	1	0	1.2	44	1	0
##	GSM65806	KIU	KIU_314B55	none	KJ125	3	0	3.0	38	0	1
##	GSM65807	KIU	KIU_316C64	none	KJ125	1	0	1.3	51	1	0
##	GSM65808	KIU	KIU_36C17	none	KJ125	2	0	2.2	46	1	0
##	GSM65810	KIU	KIU_42C67	none	KJ125	1	0	2.6	59	NA	0
##	GSM65811	KIU	KIU_43C47	none	KJ125	2	0	1.2	46	0	0
##	GSM65812	KIU	KIU_52A90	none	KJ125	1	0	2.6	53	1	0
##	GSM65813	KIU	KIU_5B97	none	KJ125	2	0	2.4	37	1	1
##	GSM65814	KIU	KIU_65A68	none	KJ125	1	0	1.8	49	1	0
##	GSM65815	KIU	KIU_74A63	none	KJ125	1	0	2.2	56	1	1
##	GSM65816	KIU	KIU_86A40	none	KJ125	2	0	2.4	61	0	0
##	GSM65817	KIU	KIU_87A79	none	KJ125	2	0	1.2	36	1	0
##	GSM65818	KIU	KIU_88A67	none	KJ125	2	0	2.4	63	1	1
##	GSM65819	KIU	KIU_89A64	none	KJ125	3	0	2.3	60	1	0
##	GSM65820	OXF	OXFU_12	none	KJ125	NA	0	0.0	44	1	0
##	GSM65821	OXF	OXFU_16	none	KJ125	2	0	2.6	46	1	0
##	GSM65822	OXF	OXFU_37	none	KJ125	2	0	1.8	38	0	1
##	GSM65823	OXF	OXFU_53	none	KJ125	NA	0	0.3	61	1	0
##	GSM65824	OXF	OXFU_57	none	KJ125	2	0	2.0	43	0	1
##	GSM65825	OXF	OXFU_88	none	KJ125	3	0	2.6	65	NA	0
##	GSM65826	OXF	OXFU_90	none	KJ125	NA	0	1.4	61	1	1
##	GSM65827	OXF	OXFU_93	none	KJ125	NA	0	0.9	58	1	0
##	GSM65828	OXF	OXFU_104	none	KJ125	NA	0	3.1	60	1	1
##	GSM65829	OXF	OXFU_126	none	KJ125	NA	0	1.0	45	0	1
##	GSM65830	OXF	OXFU_127	none	KJ125	1	0	1.9	42	1	1
##	GSM65831	OXF	OXFU_138	none	KJ125	3	0	3.0	55	1	0
##	GSM65832	OXF	OXFU_145	none	KJ125	2	0	2.5	45	0	0
##	GSM65833	OXF	OXFU_157	none	KJ125	3	0	2.0	42	0	1
##	GSM65834	OXF	OXFU_181	none	KJ125	2	0	1.5	64	1	1
##	GSM65835	OXF	OXFU_217	none	KJ125	2	0	1.0	53	0	1
##	GSM65836	OXF	OXFU_220	none	KJ125	2	0	1.0	47	0	0
##	GSM65837	OXF	OXFU_223	none	KJ125	3	0	2.1	64	1	1
##	GSM65838	OXF	OXFU_245	none	KJ125	NA	0	1.0	54	NA	0
##	GSM65839	OXF	OXFU_247	none	KJ125	3	0	4.5	73	0	1
##	GSM65840	OXF	OXFU_254	none	KJ125	NA	0	2.0	48	1	1
##	GSM65841	OXF	OXFU_281	none	KJ125	2	0	1.6	64	0	1
##	GSM65842	OXF	OXFU_316	none	KJ125	3	0	2.2	47	0	0
##	GSM65843	OXF	OXFU_320	none	KJ125	3	0	5.0	39	0	1

##	GSM65844	OXF	OXFU_348	none	KJ125	2	0	4.5	65	1	1
##	GSM65845	OXF	OXFU_360	none	KJ125	3	0	3.0	32	0	0
##	GSM65846	OXF	OXFU_366	none	KJ125	3	0	2.5	57	0	1
##	GSM65847	OXF	OXFU_373	none	KJ125	NA	0	1.8	64	1	1
##	GSM65848	OXF	OXFU_382	none	KJ125	3	0	3.0	60	1	0
##	GSM65849	OXF	OXFU_397	none	KJ125	NA	0	2.0	71	1	1
##	GSM65850	OXF	OXFU_419	none	KJ125	3	0	0.7	42	0	0
##	GSM65851	OXF	OXFU_449	none	KJ125	NA	0	3.0	57	1	0
##	GSM65852	OXF	OXFU_476	none	KJ125	NA	0	2.5	53	NA	1
##	GSM65853	OXF	OXFU_484	none	KJ125	2	0	1.3	64	1	0
##	GSM65854	OXF	OXFU_491	none	KJ125	NA	0	2.0	66	1	0
##	GSM65855	OXF	OXFU_513	none	KJ125	2	0	3.8	47	0	1
##	GSM65856	OXF	OXFU_522	none	KJ125	NA	0	2.4	63	1	0
##	GSM65857	OXF	OXFU_530	none	KJ125	2	0	1.8	54	1	1
##	GSM65858	OXF	OXFU_531	none	KJ125	2	0	1.6	42	NA	0
##	GSM65859	OXF	OXFU_533	none	KJ125	3	0	2.6	53	1	0
##	GSM65860	OXF	OXFU_535	none	KJ125	3	0	1.5	59	1	0
##	GSM65861	OXF	OXFU_543	none	KJ125	2	0	1.9	71	0	1
##	GSM65862	OXF	OXFU_544	none	KJ125	2	0	1.8	54	1	0
##	GSM65863	OXF	OXFU_547	none	KJ125	3	0	4.0	45	0	0
##	GSM65864	OXF	OXFU_549	none	KJ125	NA	0	1.0	64	1	1
##	GSM65865	OXF	OXFU_557	none	KJ125	3	0	3.0	43	0	0
##	GSM65866	OXF	OXFU_559	none	KJ125	3	0	1.3	68	0	0
##	GSM65867	OXF	OXFU_573	none	KJ125	3	0	2.0	63	1	0
##	GSM65868	OXF	OXFU_598	none	KJ125	2	0	2.0	69	1	1
##	GSM65869	OXF	OXFU_608	none	KJ125	2	0	3.0	62	1	1
##	GSM65870	OXF	OXFU_662	none	KJ125	3	0	2.2	43	0	1
##	GSM65871	OXF	OXFU_869	none	KJ125	1	0	1.0	48	1	0
##	GSM65872	OXF	OXFU_1065	none	KJ125	2	0	2.0	43	0	1
##	GSM65873	OXF	OXFU_1183	none	KJ125	1	0	0.8	50	1	0
##	GSM65874	OXF	OXFU_1210	none	KJ125	1	0	0.8	43	1	0
##	GSM65875	OXF	OXFU_1248	none	KJ125	1	0	2.0	70	1	0
##	GSM65876	OXF	OXFU_1286	none	KJ125	1	0	2.0	52	NA	0
##	GSM65877	OXF	OXFU_1328	none	KJ125	NA	0	1.3	49	1	0
##	GSM65878	OXF	OXFU_1373	none	KJ125	2	0	2.0	38	0	1
##	GSM65879	OXF	OXFU_1415	none	KJ125	NA	0	0.9	47	0	0
##	GSM65880	OXF	OXFU_1605	none	KJ125	2	0	1.0	39	0	1
##			time.rfs	event.dmfs	time.dmfs						
##	GSM65752	6.2465753		0	6.2465753						
##	GSM65753	7.3287671		0	7.3287671						
##	GSM65754	1.1671233		0	1.1671233						
##	GSM65755	0.4986301		1	0.4986301						
##	GSM65756	3.0821918		1	3.0821918						
##	GSM65757	10.8273973		0	10.8273973						
##	GSM65758	4.9972603		1	4.9972603						
##	GSM65760	1.9150685		1	1.9150685						
##	GSM65761	2.0000000		1	2.0000000						
##	GSM65762	2.4164384		0	2.4164384						
##	GSM65763	7.7452055		0	7.7452055						
##	GSM65764	5.4958904		0	5.4958904						
##	GSM65765	6.9123288		0	6.9123288						
##	GSM65766	9.9945205		0	9.9945205						
##	GSM65767	6.1643836		0	6.1643836						
##	GSM65768	9.8273973		0	9.8273973						

## GSM65769	8.5780822	0	8.5780822
## GSM65770	6.8301370	1	6.8301370
## GSM65771	8.6630137	0	8.6630137
## GSM65772	9.5780822	0	9.5780822
## GSM65773	5.9123288	0	5.9123288
## GSM65774	5.1643836	0	5.1643836
## GSM65775	10.0767123	0	10.0767123
## GSM65776	4.4136986	1	4.4136986
## GSM65779	7.6630137	0	7.6630137
## GSM65780	9.0794521	0	9.0794521
## GSM65781	9.4958904	0	9.4958904
## GSM65782	6.4136986	1	6.4136986
## GSM65783	9.1616438	0	9.1616438
## GSM65784	2.1643836	0	2.1643836
## GSM65785	5.9972603	0	5.9972603
## GSM65786	4.1643836	0	4.1643836
## GSM65787	2.9150685	0	2.9150685
## GSM65788	5.9972603	0	5.9972603
## GSM65789	6.7452055	0	6.7452055
## GSM65790	4.4986301	0	4.4986301
## GSM65791	8.8273973	0	8.8273973
## GSM65792	8.9123288	0	8.9123288
## GSM65793	3.6657534	0	3.6657534
## GSM65794	8.6630137	0	8.6630137
## GSM65795	8.7452055	0	8.7452055
## GSM65796	1.0000000	0	1.0000000
## GSM65797	2.3315068	0	2.3315068
## GSM65798	9.4109589	0	9.4109589
## GSM65799	7.3287671	0	7.3287671
## GSM65800	6.2465753	0	6.2465753
## GSM65801	8.9945205	0	8.9945205
## GSM65802	6.7452055	0	6.7452055
## GSM65803	2.5808219	1	2.5808219
## GSM65804	2.2493151	1	2.2493151
## GSM65805	8.4109589	0	8.4109589
## GSM65806	0.1671233	0	0.1671233
## GSM65807	9.2438356	0	9.2438356
## GSM65808	8.2465753	0	8.2465753
## GSM65810	8.8273973	0	8.8273973
## GSM65811	0.5835616	0	0.5835616
## GSM65812	11.9095890	0	11.9095890
## GSM65813	0.7506849	0	0.7506849
## GSM65814	3.4986301	0	3.4986301
## GSM65815	5.9123288	1	5.9123288
## GSM65816	9.9945205	0	9.9945205
## GSM65817	10.1616438	0	10.1616438
## GSM65818	4.2465753	0	4.2465753
## GSM65819	11.4109589	0	11.4109589
## GSM65820	14.5342466	0	14.5342466
## GSM65821	11.1808219	0	11.1808219
## GSM65822	8.4767123	0	8.4767123
## GSM65823	14.1863014	0	14.1863014
## GSM65824	12.0493151	1	12.0493151
## GSM65825	13.9616438	0	13.9616438

## GSM65826	5.8219178	1	5.8219178
## GSM65827	13.7780822	0	13.7780822
## GSM65828	1.7753425	1	1.7753425
## GSM65829	11.4054794	0	11.4054794
## GSM65830	13.3397260	0	13.3397260
## GSM65831	13.7780822	0	13.7780822
## GSM65832	12.9150685	0	12.9150685
## GSM65833	13.4410959	0	13.4410959
## GSM65834	12.5452055	1	12.5452055
## GSM65835	1.5397260	1	1.5397260
## GSM65836	12.6164384	0	12.6164384
## GSM65837	5.1369863	1	5.1369863
## GSM65838	13.3123288	0	13.3123288
## GSM65839	0.6904110	0	1.5397260
## GSM65840	12.6410959	0	12.6410959
## GSM65841	10.5589041	0	10.5589041
## GSM65842	12.8301370	0	12.8301370
## GSM65843	7.0191781	0	7.0191781
## GSM65844	0.6054795	1	0.6054795
## GSM65845	12.5972603	0	12.5972603
## GSM65846	2.8438356	1	3.0465753
## GSM65847	2.9178082	1	2.9178082
## GSM65848	12.7890411	0	12.7890411
## GSM65849	2.8931507	1	2.8931507
## GSM65850	10.4520548	0	12.4219178
## GSM65851	12.4657534	0	12.4657534
## GSM65852	3.4712329	1	3.4712329
## GSM65853	10.7178082	0	10.7178082
## GSM65854	12.2657534	0	12.2657534
## GSM65855	3.1123288	0	3.1123288
## GSM65856	9.8164384	0	9.8164384
## GSM65857	2.7287671	1	4.7424658
## GSM65858	12.0410959	0	12.0410959
## GSM65859	12.3232877	0	12.3232877
## GSM65860	12.2547945	0	12.2547945
## GSM65861	2.6438356	1	2.6438356
## GSM65862	11.8602740	0	11.8602740
## GSM65863	9.2602740	0	11.9287671
## GSM65864	10.0438356	0	10.0438356
## GSM65865	12.0602740	0	12.0602740
## GSM65866	11.1726027	0	11.1726027
## GSM65867	11.5561644	0	11.5561644
## GSM65868	4.0849315	1	3.0082192
## GSM65869	2.6328767	1	2.6328767
## GSM65870	5.7068493	0	11.4602740
## GSM65871	8.7369863	0	8.7369863
## GSM65872	1.9972603	1	1.9972603
## GSM65873	4.3589041	0	4.3589041
## GSM65874	5.2602740	0	5.2602740
## GSM65875	8.9369863	0	8.9369863
## GSM65876	5.2410959	0	5.2410959
## GSM65877	7.2547945	0	7.2547945
## GSM65878	0.7342466	1	0.7342466
## GSM65879	3.5342466	0	3.5342466


```
## GSM65880 6.2931507 0 7.6958904
```

Conduct Principal Component Analysis (PCA) and plot PCA results

`prcomp` performs a PCA by a singular value decomposition of the given (centered and possibly scaled) data matrix and returns a list with class `prcomp` containing the following components:

`sdev` the standard deviations of the principal components (i.e., the square roots of the eigenvalues of the covariance/correlation matrix, though the calculation is actually done with the singular values of the data matrix)

`rotation` the matrix of variable loadings (i.e., a matrix whose columns contain the eigenvectors); (the coordinates of the variables -genes- in the projected principal components' space)

`X` the value of the rotated data (the centered (and scaled if requested) data multiplied by the rotation matrix); (the coordinates of the observations -samples- in the projected principal components' space)

`center, scale` the centering and scaling used, or FALSE

```
dat.pca <- prcomp(t(dat))
# unclass(dat.pca)

dat.loadings <- dat.pca$x[,1:2] #dim(dat.loadings) [1] 125 2
dat.loadings
```

```
##          PC1          PC2
## GSM65752 -14.92456344 -14.67002303
## GSM65753 -17.99926227  5.01873475
## GSM65754 -21.97354514  2.42028906
## GSM65755 -10.79713986 -9.38130114
## GSM65756 -14.26983862 -5.74194199
## GSM65757 -17.29355494 -2.04883659
## GSM65758 -26.56613784  3.44526064
## GSM65760 -9.21772822 -11.77618373
## GSM65761 -12.51569635 -12.98409816
## GSM65762 -17.47428838  4.96624609
## GSM65763 -21.85924545  8.26062150
## GSM65764 -15.38425743 11.68214464
## GSM65765 -22.66576725  0.41360007
## GSM65766 -31.48160123  5.11562410
## GSM65767 -16.21433595  2.22536762
## GSM65768 -9.45464513 -7.18468035
## GSM65769 -11.58828600 -4.80960579
## GSM65770 -12.20507465 12.79583223
## GSM65771 -27.69494347  3.70043820
## GSM65772 -14.55425062 -5.02265929
## GSM65773 -5.40054185  5.69097189
## GSM65774 -5.03615728 -5.41812221
## GSM65775 -12.31335216  4.33201319
## GSM65776 -8.77553098 15.05716233
## GSM65779 -19.50729077  6.80129585
## GSM65780 -21.77700786  4.80715349
## GSM65781 -0.01069766  1.31370499
## GSM65782 -19.96577691 -0.77671354
## GSM65783 -25.11545179  3.44101158
```

```

## GSM65784 -10.96091939 -8.73117495
## GSM65785 -20.63259971 5.52791805
## GSM65786 -4.29565962 -6.67219848
## GSM65787 -15.07279600 6.87366553
## GSM65788 -29.82268762 -0.03909213
## GSM65789 -21.89897379 5.74635714
## GSM65790 -14.80896133 10.72691999
## GSM65791 -18.61568268 8.91547616
## GSM65792 -6.86098554 -21.13922323
## GSM65793 -27.31436691 -4.02842422
## GSM65794 -16.33480540 -10.35144687
## GSM65795 -9.90799098 -13.50493489
## GSM65796 -23.07141055 1.79146773
## GSM65797 -22.27313784 0.72940181
## GSM65798 -18.70801260 -2.62774575
## GSM65799 -23.11984635 1.95582074
## GSM65800 -21.96043686 6.31659018
## GSM65801 -15.38463909 0.29130114
## GSM65802 -14.29494391 -23.60889788
## GSM65803 -30.50295653 -0.70055336
## GSM65804 -20.51461424 -15.32063741
## GSM65805 -19.53294963 -12.24287372
## GSM65806 -9.66339271 -15.78209465
## GSM65807 -17.18738377 11.75299208
## GSM65808 -19.81072184 4.69409794
## GSM65810 -18.89960112 2.17736254
## GSM65811 -20.58980251 -3.49349442
## GSM65812 -17.74320325 9.74555188
## GSM65813 -16.08828565 -8.91633835
## GSM65814 -18.84969391 3.76522235
## GSM65815 -21.16041336 -2.73914263
## GSM65816 -12.44757273 -19.90100126
## GSM65817 -7.39666072 4.58860859
## GSM65818 -9.71204477 2.55591870
## GSM65819 -7.43068102 -12.16808389
## GSM65820 26.01033936 -7.39553293
## GSM65821 17.55212213 0.53342840
## GSM65822 19.60074519 -0.02582156
## GSM65823 20.50316908 -0.61660715
## GSM65824 16.43941525 4.15736409
## GSM65825 27.91878694 -10.27511560
## GSM65826 16.60789712 8.80256920
## GSM65827 6.79815116 7.49509897
## GSM65828 19.40277838 -1.10023345
## GSM65829 22.00679539 2.93884612
## GSM65830 17.17696404 5.44050236
## GSM65831 17.36110928 -3.47945020
## GSM65832 15.60362430 2.96287547
## GSM65833 22.51259616 -2.19205561
## GSM65834 20.97595256 2.15829222
## GSM65835 14.11306695 -0.93594897
## GSM65836 16.91298530 6.66563420
## GSM65837 18.31212618 0.17423229
## GSM65838 23.64417815 -7.79432966

```

```
## GSM65839 22.46051893 -4.06322390
## GSM65840 8.26406360 5.11189394
## GSM65841 20.12558156 -8.58953102
## GSM65842 21.31103441 -12.29672605
## GSM65843 19.16516480 -4.96181843
## GSM65844 20.04899954 -3.81862113
## GSM65845 19.53675376 -7.55081487
## GSM65846 14.05133677 1.51419980
## GSM65847 10.88387567 5.99719531
## GSM65848 8.62477485 7.24712472
## GSM65849 11.23017172 5.23467093
## GSM65850 18.33797768 -8.55260828
## GSM65851 24.80714485 -8.12601649
## GSM65852 23.84059351 -17.66702329
## GSM65853 7.72899716 11.28159305
## GSM65854 18.92649366 7.58352217
## GSM65855 18.56765568 4.07973868
## GSM65856 23.95380870 -4.23833833
## GSM65857 18.79430520 -1.04011605
## GSM65858 15.68275648 9.85833578
## GSM65859 13.30679918 14.56060555
## GSM65860 14.63411555 6.63436037
## GSM65861 14.18446365 4.71652853
## GSM65862 18.00774958 7.64068954
## GSM65863 19.49506395 -4.94521072
## GSM65864 13.57363957 6.51800381
## GSM65865 13.27992355 9.56874878
## GSM65866 19.10410101 -7.33473093
## GSM65867 16.53715140 9.59718320
## GSM65868 21.84608096 -4.37235215
## GSM65869 18.48233354 0.42937267
## GSM65870 22.13656982 -0.58727567
## GSM65871 19.47220390 6.52517234
## GSM65872 11.38475447 7.69104965
## GSM65873 12.37195278 7.88811262
## GSM65874 16.83611299 0.46793638
## GSM65875 23.78123403 -7.58771744
## GSM65876 15.51956153 2.92473424
## GSM65877 12.49204486 7.14178923
## GSM65878 15.88521378 2.19498646
## GSM65879 14.94831903 7.91479510
## GSM65880 13.83060289 10.03541283
```

```
levels(as.factor(ann$site))
```

```
## [1] "KIU" "OXF"
```

```
dat.loadings[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]]
```

```
## GSM65752 GSM65753 GSM65754 GSM65755 GSM65756 GSM65757
## -14.92456344 -17.99926227 -21.97354514 -10.79713986 -14.26983862 -17.29355494
## GSM65758 GSM65760 GSM65761 GSM65762 GSM65763 GSM65764
## -26.56613784 -9.21772822 -12.51569635 -17.47428838 -21.85924545 -15.38425743
```

```
##      GSM65765      GSM65766      GSM65767      GSM65768      GSM65769      GSM65770
## -22.66576725 -31.48160123 -16.21433595 -9.45464513 -11.58828600 -12.20507465
##      GSM65771      GSM65772      GSM65773      GSM65774      GSM65775      GSM65776
## -27.69494347 -14.55425062 -5.40054185 -5.03615728 -12.31335216 -8.77553098
##      GSM65779      GSM65780      GSM65781      GSM65782      GSM65783      GSM65784
## -19.50729077 -21.77700786 -0.01069766 -19.96577691 -25.11545179 -10.96091939
##      GSM65785      GSM65786      GSM65787      GSM65788      GSM65789      GSM65790
## -20.63259971 -4.29565962 -15.07279600 -29.82268762 -21.89897379 -14.80896133
##      GSM65791      GSM65792      GSM65793      GSM65794      GSM65795      GSM65796
## -18.61568268 -6.86098554 -27.31436691 -16.33480540 -9.90799098 -23.07141055
##      GSM65797      GSM65798      GSM65799      GSM65800      GSM65801      GSM65802
## -22.27313784 -18.70801260 -23.11984635 -21.96043686 -15.38463909 -14.29494391
##      GSM65803      GSM65804      GSM65805      GSM65806      GSM65807      GSM65808
## -30.50295653 -20.51461424 -19.53294963 -9.66339271 -17.18738377 -19.81072184
##      GSM65810      GSM65811      GSM65812      GSM65813      GSM65814      GSM65815
## -18.89960112 -20.58980251 -17.74320325 -16.08828565 -18.84969391 -21.16041336
##      GSM65816      GSM65817      GSM65818      GSM65819
## -12.44757273 -7.39666072 -9.71204477 -7.43068102
```

```
length(dat.loadings[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]])
```

```
## [1] 64
```

```
length(dat.loadings[,1][as.character(ann$site)==levels(as.factor(ann$site))[2]])
```

```
## [1] 61
```

```
col <- as.numeric(as.factor(unique(ann$site))) +1

plot(range(dat.loadings[,1]), range(dat.loadings[,2]),
     xlab='First Principal Component',ylab='Second Principal Component',
     main='PCA plot of Sotiriou breast cancer data')

points(dat.loadings[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
       dat.loadings[,2][ as.character(ann$site)==levels(as.factor(ann$site))[1]],
       col=col[1],pch=16,cex=1.5)

text(dat.loadings[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
     dat.loadings[,2][ as.character(ann$site)==levels(as.factor(ann$site))[1]],
     col=col[1] ,cex=0.7,
     labels= paste(levels(as.factor(ann$site))[1], '- ',
                   row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[1],]), sep= ' '),
     pos=2)

points(dat.loadings[,1][as.character(ann$site)==levels(as.factor(ann$site))[2]],
       dat.loadings[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
       col=col[2],pch=16,cex=1.5)

text(dat.loadings[,1][as.character(ann$site)==levels(as.factor(ann$site))[2]],
     dat.loadings[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
     col=col[2] ,cex=0.7,
     labels= paste(levels(as.factor(ann$site))[2], '- ',
```

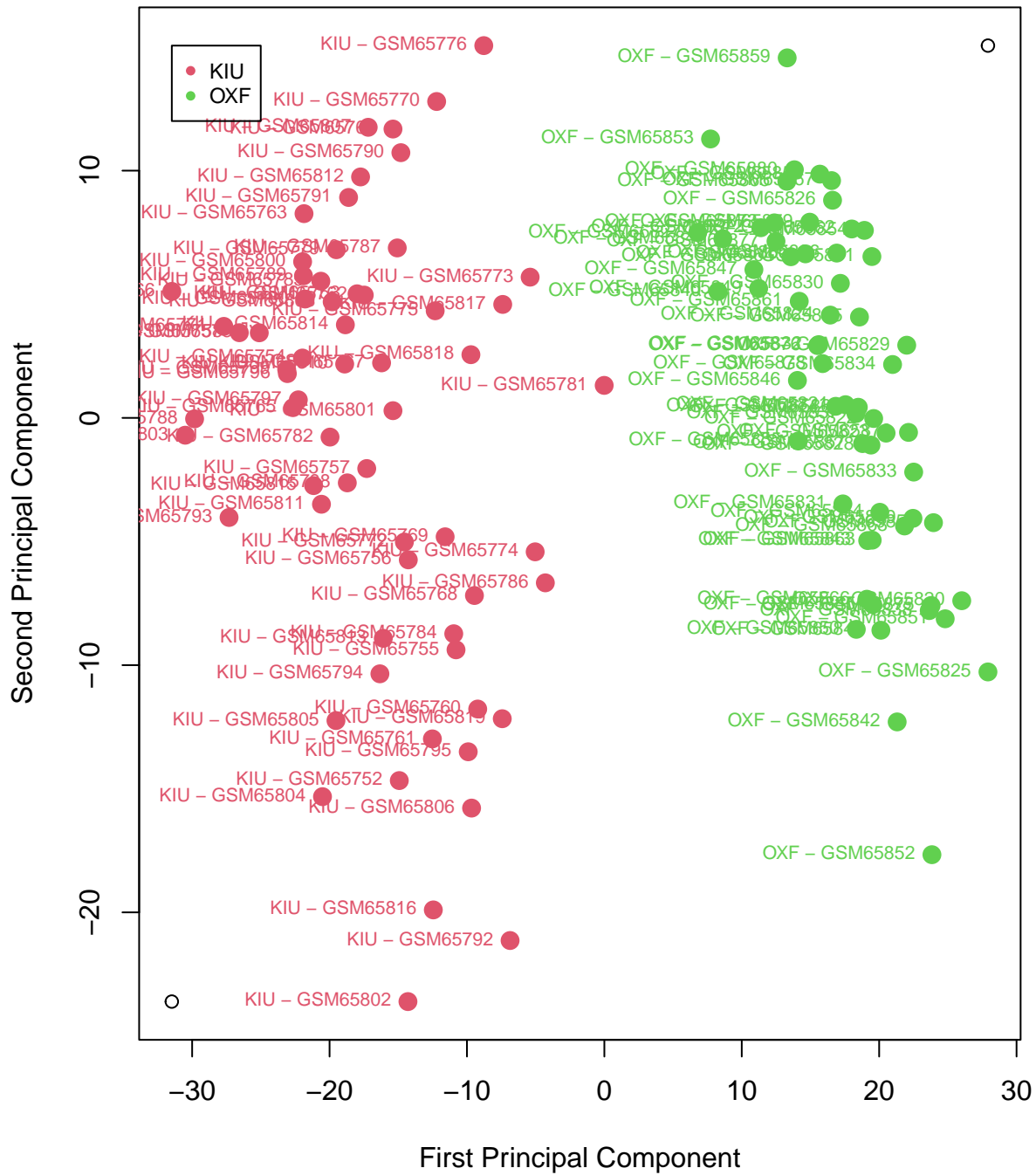
```

                                row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[2],]), sep= ' '),
pos=2)

legend(min(range(dat.loadings[,1])), max(range(dat.loadings[,2]) ),
       levels(as.factor(ann$site)),
       col=col,pch=16,cex=.75)

```

PCA plot of Sotiriou breast cancer data



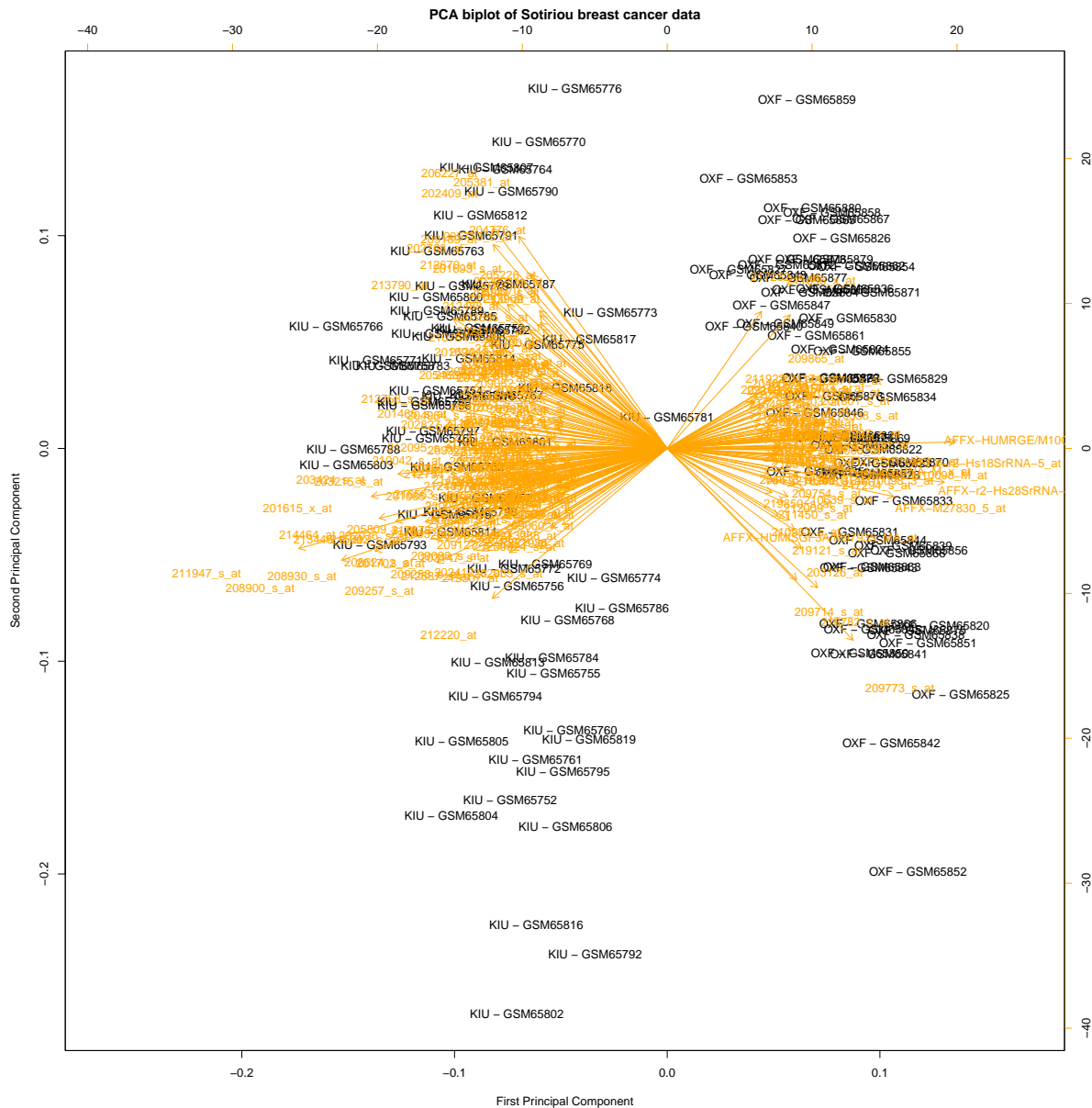
Biplot

Visualize both the observations (samples) and the variables (genes) of a data matrix on the same plot

```

names(dat) <- paste(as.character(ann$site), '-', row.names(ann), sep= ' ')
dat.pca <- prcomp(t(dat))
col <- c("black", "orange")
biplot(dat.pca, scale=TRUE, col=col,
       xlab='First Principal Component', ylab='Second Principal Component',
       main='PCA biplot of Sotiriou breast cancer data')

```



Scree plot corresponding to the PCA above

```

# standard deviation of the principal components
# (i.e. the square roots of the eigenvalues of the covariance/correlation matrix)

```

```
print("Standard deviation of the principal components")
```

```
## [1] "Standard deviation of the principal components"
```

```
dat.pca$sdev
```

```
## [1] 1.808960e+01 7.950493e+00 6.759851e+00 5.425392e+00 4.861711e+00
## [6] 4.261595e+00 3.853985e+00 3.335201e+00 3.058479e+00 2.669527e+00
## [11] 2.594844e+00 2.470256e+00 2.301769e+00 2.265594e+00 2.218159e+00
## [16] 2.114738e+00 2.042543e+00 1.968784e+00 1.952570e+00 1.832840e+00
## [21] 1.784867e+00 1.773668e+00 1.668423e+00 1.628210e+00 1.619220e+00
## [26] 1.576649e+00 1.539699e+00 1.496120e+00 1.474833e+00 1.456386e+00
## [31] 1.420215e+00 1.409495e+00 1.396450e+00 1.373183e+00 1.335322e+00
## [36] 1.315715e+00 1.286264e+00 1.277919e+00 1.214822e+00 1.192632e+00
## [41] 1.179874e+00 1.165884e+00 1.154381e+00 1.134524e+00 1.108172e+00
## [46] 1.102001e+00 1.089750e+00 1.065017e+00 1.052027e+00 1.030344e+00
## [51] 1.009403e+00 9.920168e-01 9.770316e-01 9.577450e-01 9.426928e-01
## [56] 9.292646e-01 9.279851e-01 9.161050e-01 8.983570e-01 8.877442e-01
## [61] 8.759392e-01 8.579782e-01 8.469782e-01 8.395788e-01 8.273752e-01
## [66] 7.952735e-01 7.913936e-01 7.750593e-01 7.664755e-01 7.594623e-01
## [71] 7.317864e-01 7.242785e-01 7.161824e-01 7.037500e-01 7.006396e-01
## [76] 6.962052e-01 6.749395e-01 6.679053e-01 6.548958e-01 6.403585e-01
## [81] 6.327154e-01 6.187611e-01 6.106445e-01 5.974590e-01 5.897933e-01
## [86] 5.889002e-01 5.759384e-01 5.665320e-01 5.596018e-01 5.489625e-01
## [91] 5.392246e-01 5.278660e-01 5.173781e-01 5.135641e-01 4.965416e-01
## [96] 4.903519e-01 4.873866e-01 4.668871e-01 4.610425e-01 4.505757e-01
## [101] 4.395313e-01 4.355703e-01 4.280842e-01 4.189822e-01 4.095283e-01
## [106] 4.021540e-01 3.878831e-01 3.841837e-01 3.738866e-01 3.654198e-01
## [111] 3.582208e-01 3.509715e-01 3.384415e-01 3.241306e-01 3.185773e-01
## [116] 3.119209e-01 3.054884e-01 2.848054e-01 2.714743e-01 2.632768e-01
## [121] 2.502334e-01 2.432711e-01 2.226430e-01 2.136655e-01 8.033395e-15
```

```
# percent variability of the principal components
```

```
print("Percent variability of the principal components")
```

```
## [1] "Percent variability of the principal components"
```

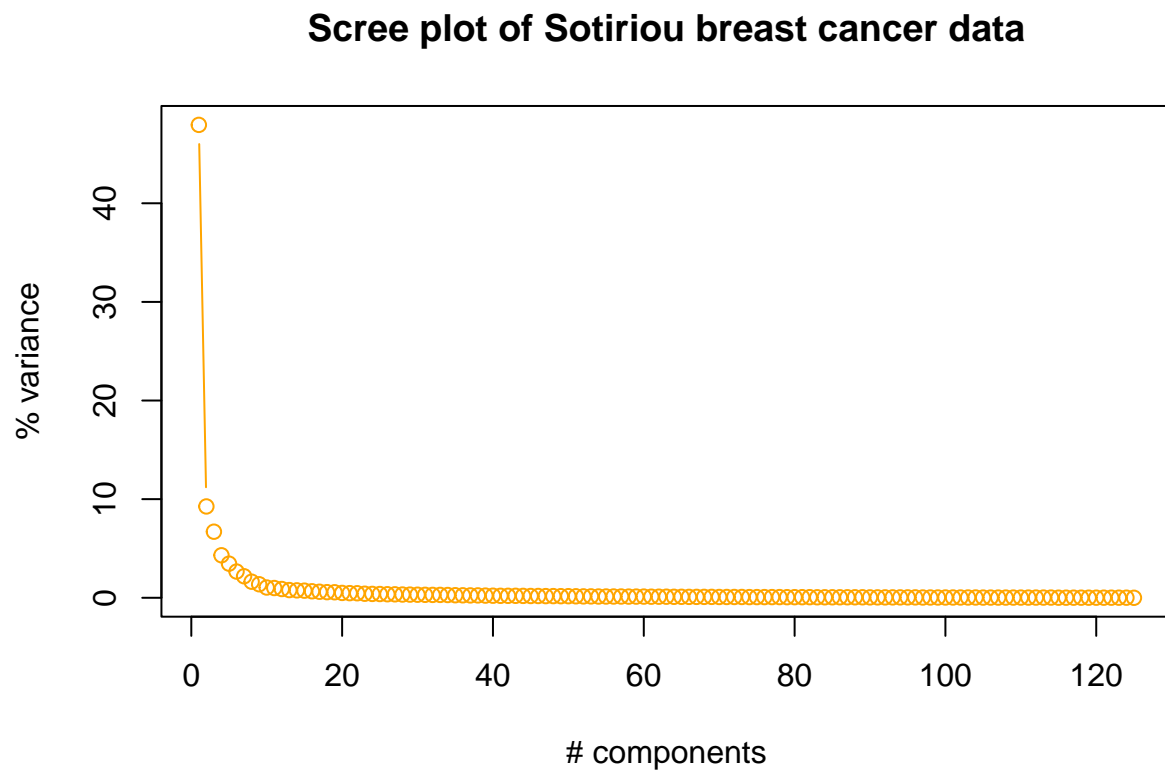
```
dat.pca.var <- round(dat.pca$sdev^2 / sum(dat.pca$sdev^2)*100,2)
```

```
dat.pca.var
```

```
## [1] 47.95 9.26 6.70 4.31 3.46 2.66 2.18 1.63 1.37 1.04 0.99 0.89
## [13] 0.78 0.75 0.72 0.66 0.61 0.57 0.56 0.49 0.47 0.46 0.41 0.39
## [25] 0.38 0.36 0.35 0.33 0.32 0.31 0.30 0.29 0.29 0.28 0.26 0.25
## [37] 0.24 0.24 0.22 0.21 0.20 0.20 0.20 0.19 0.18 0.18 0.17 0.17
## [49] 0.16 0.16 0.15 0.14 0.14 0.13 0.13 0.13 0.13 0.12 0.12 0.12
## [61] 0.11 0.11 0.11 0.10 0.10 0.09 0.09 0.09 0.09 0.08 0.08 0.08
## [73] 0.08 0.07 0.07 0.07 0.07 0.07 0.06 0.06 0.06 0.06 0.05 0.05
## [85] 0.05 0.05 0.05 0.05 0.05 0.04 0.04 0.04 0.04 0.04 0.04 0.04
## [97] 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.02 0.02 0.02 0.02
## [109] 0.02 0.02 0.02 0.02 0.02 0.02 0.01 0.01 0.01 0.01 0.01 0.01
## [121] 0.01 0.01 0.01 0.01 0.00
```



```
plot(c(1:length(dat.pca.var)),dat.pca.var,type='b',
     xlab='# components',ylab='% variance',
     main='Scree plot of Sotiriou breast cancer data', col='orange')
```



How much variability in the data is explained using only the first two eigenvalues?

```
#summary(dat.pca)
summary(dat.pca)$importance[, 1:2]
```

```
##                PC1      PC2
## Standard deviation 18.0896 7.950493
## Proportion of Variance 0.4795 0.092620
## Cumulative Proportion 0.4795 0.572120
```

```
variability <- round((summary(dat.pca)$importance[3,2])*100,2)
variability
```

```
## [1] 57.21
```

```
# or
```

```
variability <- round((summary(dat.pca)$importance[2,1] +
                     summary(dat.pca)$importance[2,2])*100,2)
variability
```

```
## [1] 57.21
```

#or

```
variability <- dat.pca.var[1] + dat.pca.var[2]
variability
```

```
## [1] 57.21
```

Multidimensional scaling (MDS)

Dimensionality reduction technique that fits the original data into a low-dimensional coordinate system, such that any distortion caused by dimension reduction is minimized

MDS uses the distances or similarities between instances (genes or samples) in representing proximities, while preserving (nearly matching) the original distances or similarities

Stress is the measure used to determine how close the low-dimensional space matches the high-dimensional space

Metric (classical) MDS

Determine the distance or similarity values between all pairs of genes/samples

Arranges the N items in low-dimensional space using the actual magnitudes of the distances/similarities

Also known as **principal coordinate analysis**

dist this function computes and returns the distance matrix computed by using the specified distance measure to compute the distances between the rows of a data matrix

cmdscale classical multidimensional scaling of a data matrix. takes a set of distances/dissimilarities and returns a set of points such that the distances between the points are approximatively equal to the dissimilarities

‘points’ a matrix with k=2 columns whose rows give the coordinates of the points chosen to represent the dissimilarities k the dimension of the space which the data are to be represented in

```
dat.dist <- dist(t(dat), method = "euclidean")
dat.loc <- cmdscale(dat.dist)

col <- as.numeric(as.factor(unique(ann$site))) +1
```

#xlab='1st dimension of space coordinates of the points representing dissimilarities between all pairs
#ylab='2nd dimension of space coordinates of the points representing dissimilarities between all pairs

```
plot(dat.loc, type = "n", xlab='1st dimension of space', ylab='2nd dimension of space')
```

```
points(dat.loc[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
       dat.loc[,2][as.character(ann$site)==levels(as.factor(ann$site))[1]],
```

```

col=col[1],pch=16,cex=1.5)

text(dat.loc[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
     dat.loc[,2][ as.character(ann$site)==levels(as.factor(ann$site))[1]],
     col=col[1] ,cex=0.7,
     labels= paste(levels(as.factor(ann$site))[1], '-',
                    row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[1],]), sep= ' '),
     pos=2)

points(dat.loc[,1][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
       dat.loc[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
       col=col[2],pch=16,cex=1.5)

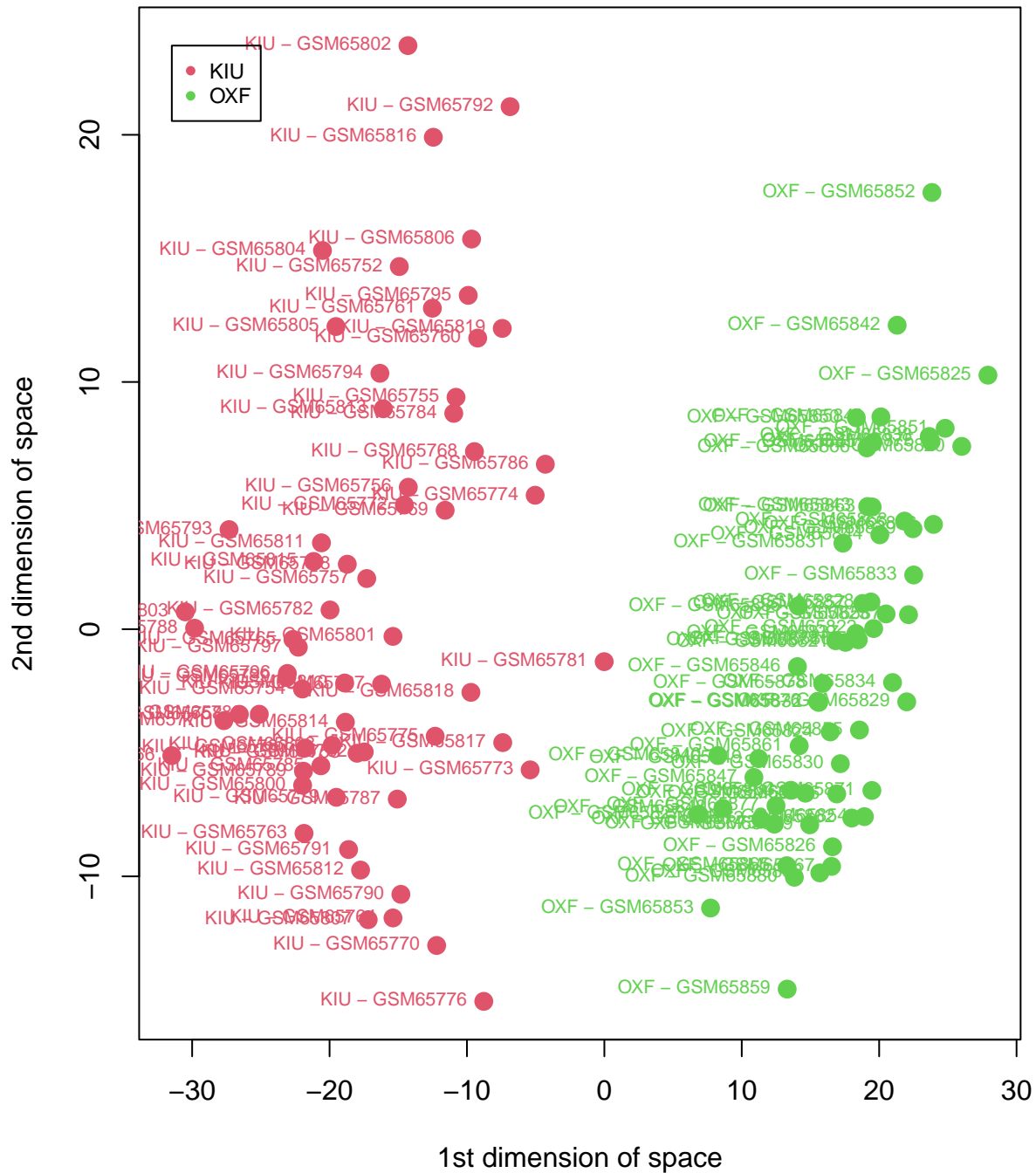
text(dat.loc[,1][as.character(ann$site)==levels(as.factor(ann$site))[2]],
     dat.loc[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
     col=col[2],cex=0.7,
     labels= paste(levels(as.factor(ann$site))[2], '-',
                    row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[2],]), sep= ' '),
     pos=2)

title(main='MDS plot of Sotiriou breast cancer data')

legend(min(range(dat.loc[,1])), max(range(dat.loc[,2]) ), levels(as.factor(ann$site)),
       col=col,pch=16,cex=.75)

```

MDS plot of Sotiriou breast cancer data



Non-Metric MDS

Determine the distance or similarity values between all pairs of genes/samples

Arrange the N items in low-dimensional space using only the rank orders of the distances/similarities

`isoMDS` Kruskal's non-metric MDS chooses a k-dimensional (default k=2) configuration to minimize the stress, which is the square root of the ratio of the sum of squared differences between the input distances and those of the configuration to the sum of configuration distances squared

Arguments:

``d`` distance structure of the form returned by `dist`, or a full, symmetric matrix.
Data are assumed to be dissimilarities or relative distances,
but must be positive except for self-distance.
Both missing and infinite values are allowed

``y`` an initial configuration.
If none is supplied, `cmdscale` is used to provide the classical solution,
unless there are missing or infinite dissimilarities.

``k`` the desired dimension for the solution, passed to `cmdscale`

``trace`` logical for tracing optimization (default TRUE).
If TRUE, the initial stress and the current stress are printed out every 5 iterations

Returns:

``points`` a k-column vector of the fitted configuration

``stress`` the final stress achieved (in percent)
Kruskal's guidelines for stress values:

Stress	Goodness of fit
20%	Poor
10%	Fair
5%	Good
2.5%	Excellent
0%	Perfect

```
library(MASS)
dat.dist <- dist(t(dat))
dat.mds <- isoMDS(dat.dist)
```

```
## initial value 16.338038
## iter 5 value 12.929006
## iter 5 value 12.920081
## iter 5 value 12.911624
## final value 12.911624
## converged
```

```
dat.mds$stress
```

```
## [1] 12.91162
```

```
dat.mds$points
```

##		[,1]	[,2]
##	KIU - GSM65752	-17.151027	14.641093982
##	KIU - GSM65753	-16.883410	-4.637055785
##	KIU - GSM65754	-21.287060	-1.895686705
##	KIU - GSM65755	-11.899699	7.770232937
##	KIU - GSM65756	-16.022333	5.195935020
##	KIU - GSM65757	-17.145175	1.595395055
##	KIU - GSM65758	-25.926887	-3.142196581
##	KIU - GSM65760	-9.651152	8.328254579
##	KIU - GSM65761	-15.954336	15.353882743
##	KIU - GSM65762	-16.821964	-5.028819276
##	KIU - GSM65763	-20.384621	-6.806571394
##	KIU - GSM65764	-14.706683	-9.742171976
##	KIU - GSM65765	-24.518610	-0.006284012
##	KIU - GSM65766	-27.650678	-4.197785312
##	KIU - GSM65767	-16.008319	-2.175667431
##	KIU - GSM65768	-10.938730	6.963334809
##	KIU - GSM65769	-11.565692	2.988331559
##	KIU - GSM65770	-11.993451	-10.347841968
##	KIU - GSM65771	-25.593893	-3.047530644
##	KIU - GSM65772	-14.776140	3.231414442
##	KIU - GSM65773	-6.269454	-5.807296550
##	KIU - GSM65774	-6.090261	4.030232976
##	KIU - GSM65775	-12.262017	-4.429950163
##	KIU - GSM65776	-9.754503	-13.661446432
##	KIU - GSM65779	-18.044675	-6.114094477
##	KIU - GSM65780	-21.631204	-4.406496593
##	KIU - GSM65781	-1.862114	-1.714468235
##	KIU - GSM65782	-18.168993	0.567211841
##	KIU - GSM65783	-25.328102	-3.282019741
##	KIU - GSM65784	-11.871661	6.459008856
##	KIU - GSM65785	-18.643626	-4.622697531
##	KIU - GSM65786	-5.365098	5.740490991
##	KIU - GSM65787	-13.535170	-5.147597109
##	KIU - GSM65788	-27.266132	-0.133209234
##	KIU - GSM65789	-22.221519	-5.460472963
##	KIU - GSM65790	-14.861950	-9.886741736
##	KIU - GSM65791	-17.881775	-7.980270553
##	KIU - GSM65792	-7.837928	20.959090232
##	KIU - GSM65793	-26.654949	3.418750605
##	KIU - GSM65794	-17.629829	8.631692124
##	KIU - GSM65795	-11.397825	13.520460099
##	KIU - GSM65796	-20.337572	-1.209592993
##	KIU - GSM65797	-25.037526	-0.408396023
##	KIU - GSM65798	-18.421368	2.067289882
##	KIU - GSM65799	-23.076445	-1.543285039
##	KIU - GSM65800	-20.237424	-5.529577013
##	KIU - GSM65801	-14.770628	-0.597225403
##	KIU - GSM65802	-15.404161	22.823974290
##	KIU - GSM65803	-31.019931	0.582009327
##	KIU - GSM65804	-21.637043	13.215207683
##	KIU - GSM65805	-21.695918	11.212533556
##	KIU - GSM65806	-10.873126	14.809000678
##	KIU - GSM65807	-16.083831	-9.288840842

```

## KIU - GSM65808 -18.441697 -3.620804169
## KIU - GSM65810 -17.131395 -1.640564049
## KIU - GSM65811 -19.758147 2.822279648
## KIU - GSM65812 -16.665574 -8.348639541
## KIU - GSM65813 -17.174748 6.937611790
## KIU - GSM65814 -18.026697 -3.134713461
## KIU - GSM65815 -19.881315 2.068410381
## KIU - GSM65816 -15.883076 25.989102864
## KIU - GSM65817 -7.822488 -4.176508388
## KIU - GSM65818 -9.711061 -2.512556659
## KIU - GSM65819 -7.970089 9.703869008
## OXF - GSM65820 26.301652 6.572513909
## OXF - GSM65821 14.817114 -0.449889967
## OXF - GSM65822 22.247129 -0.223754255
## OXF - GSM65823 21.631298 0.597635028
## OXF - GSM65824 16.725348 -5.309647811
## OXF - GSM65825 27.705806 9.374931837
## OXF - GSM65826 16.378895 -9.467242710
## OXF - GSM65827 4.160650 -6.382864233
## OXF - GSM65828 20.111154 1.481693966
## OXF - GSM65829 23.250079 -3.885700136
## OXF - GSM65830 18.581051 -6.872847638
## OXF - GSM65831 18.371559 6.254751645
## OXF - GSM65832 16.408230 -3.396329917
## OXF - GSM65833 21.334099 1.394280995
## OXF - GSM65834 28.000274 -3.941378608
## OXF - GSM65835 11.779884 1.482996680
## OXF - GSM65836 15.685625 -6.491082073
## OXF - GSM65837 21.146913 0.055545053
## OXF - GSM65838 23.647233 8.020667820
## OXF - GSM65839 24.639877 4.247008685
## OXF - GSM65840 6.833662 -6.051474929
## OXF - GSM65841 19.209951 8.739261080
## OXF - GSM65842 20.563981 11.791177257
## OXF - GSM65843 18.418868 5.887395120
## OXF - GSM65844 19.738720 3.922813470
## OXF - GSM65845 18.390451 7.794848771
## OXF - GSM65846 11.264766 -0.681867057
## OXF - GSM65847 7.504335 -4.736806799
## OXF - GSM65848 6.252025 -6.743715442
## OXF - GSM65849 8.700927 -4.808869087
## OXF - GSM65850 16.121194 8.127041486
## OXF - GSM65851 26.936038 8.753281312
## OXF - GSM65852 27.157881 22.271310537
## OXF - GSM65853 4.851631 -8.236269914
## OXF - GSM65854 20.347172 -9.069325266
## OXF - GSM65855 19.321568 -5.047125307
## OXF - GSM65856 27.136160 4.613976265
## OXF - GSM65857 18.558166 1.423730807
## OXF - GSM65858 14.361319 -9.429736487
## OXF - GSM65859 11.739784 -12.995563014
## OXF - GSM65860 12.826588 -6.394592941
## OXF - GSM65861 11.467749 -4.186009486
## OXF - GSM65862 20.535134 -9.954669243

```

```
## OXF - GSM65863 17.645194 4.645146128
## OXF - GSM65864 12.485211 -7.747147721
## OXF - GSM65865 16.121976 -19.745240698
## OXF - GSM65866 18.839104 7.958324192
## OXF - GSM65867 16.487401 -10.142281024
## OXF - GSM65868 22.776003 4.433617303
## OXF - GSM65869 19.209990 -0.589129127
## OXF - GSM65870 22.132595 -0.062026796
## OXF - GSM65871 20.521898 -7.528778400
## OXF - GSM65872 8.972325 -8.137810114
## OXF - GSM65873 10.032451 -7.870412779
## OXF - GSM65874 18.864495 0.024373613
## OXF - GSM65875 32.754722 13.194626880
## OXF - GSM65876 16.823131 -3.632139765
## OXF - GSM65877 10.698055 -7.660935646
## OXF - GSM65878 15.961626 -2.338682247
## OXF - GSM65879 15.290518 -9.689594984
## OXF - GSM65880 11.741269 -9.103034191
```

```
col <- as.numeric(as.factor(unique(ann$site))) +1
```

```
# xlab='1st dimension of the fitted configuration coordinates of the points
# representing dissimilarities between all pairs of samples'
# ylab='2nd dimension of the fitted configuration coordinates of the points
# representing dissimilarities between all pairs of samples'
```

```
plot(dat.mds$points, type = "n",
     xlab='1st dimension of the fitted configuration',
     ylab='2nd dimension of the fitted configuration')
```

```
points(dat.mds$points[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
       dat.mds$points[,2][as.character(ann$site)==levels(as.factor(ann$site))[1]],
       col=col[1],pch=16,cex=1.5)
```

```
text(dat.mds$points[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
     dat.mds$points[,2][ as.character(ann$site)==levels(as.factor(ann$site))[1]],
     col=col[1], cex=0.7,
     labels= paste(levels(as.factor(ann$site))[1], '-',
                    row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[1],]), sep= ' '),
     pos=2)
```

```
points(dat.mds$points[,1][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
       dat.mds$points[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
       col=col[2],pch=16,cex=1.5)
```

```
text(dat.mds$points[,1][as.character(ann$site)==levels(as.factor(ann$site))[2]],
     dat.mds$points[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
     col=col[2],cex=0.7,
     labels= paste(levels(as.factor(ann$site))[2], '-',
                    row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[2],]), sep= ' '),
     pos=2)
```

```
title(main=paste('MDS plot of Sotiriou breast cancer data', ' - stress = ',
                 round(dat.mds$stress,5), '%'))
```

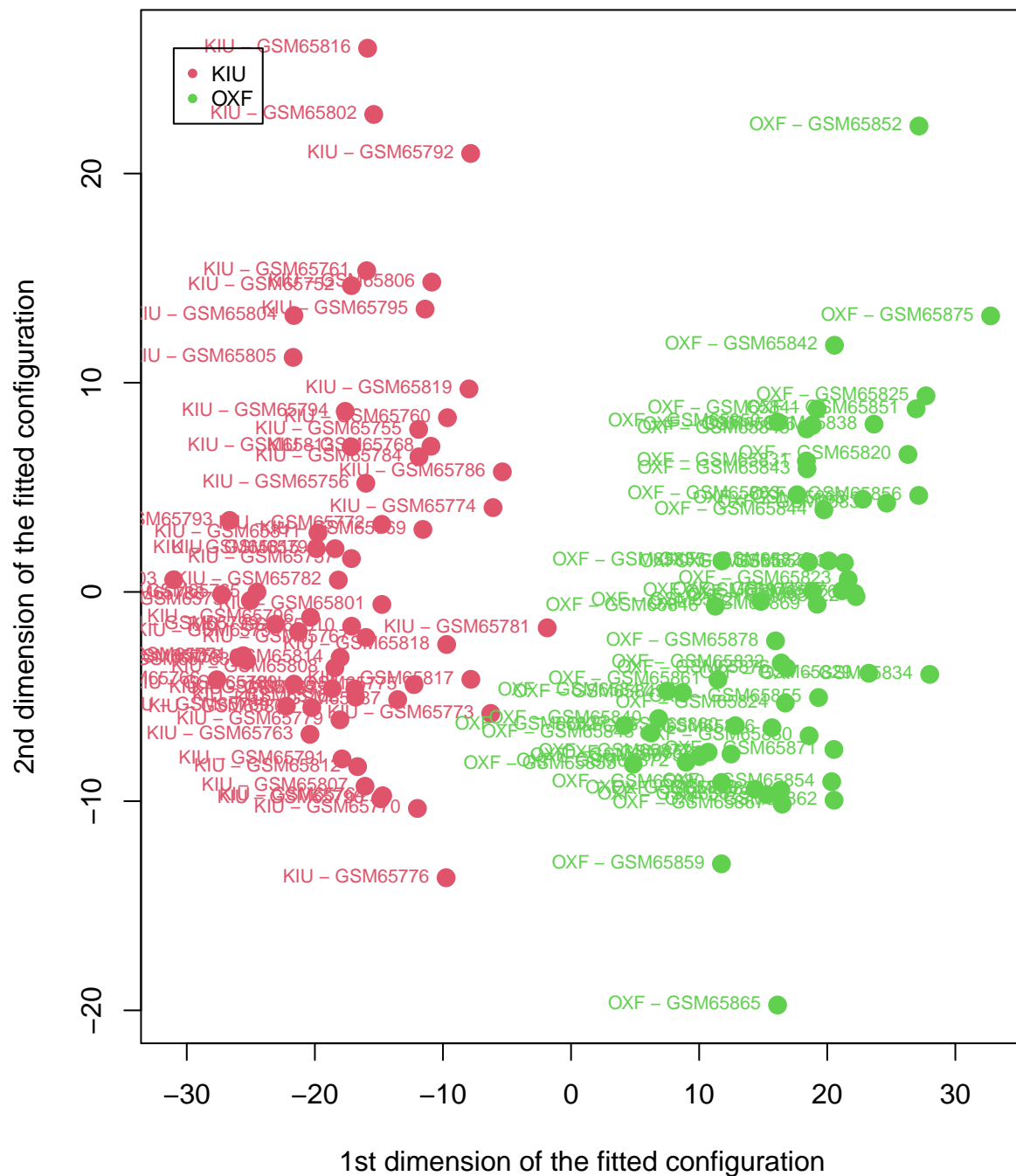


```

legend(min(range(dat.mds$points[,1])), max(range(dat.mds$points[,2])),
       levels(as.factor(ann$site)),
       col=col,pch=16,cex=.75)

```

MDS plot of Sotiriou breast cancer data – stress = 12.91162 %



Non-linear Dimensionality Reduction

Weighted Graph Laplacian

Determines the subspace that best preserves local distances and minimizes large distances Does not calculate linear projections of the data (e.g. MDS & PCA)

Builds a graph from neighborhood information of the data set

Each data point serves as a vertex (node) on the graph and connectivity between vertices is governed by the proximity of neighboring points (edge weights)

The graph thus generated can be considered as a discrete approximation of the low-dimensional manifold in the high-dimensional space

Minimization of a cost function based on the graph ensures that points close to each other on the manifold are mapped close to each other in the low-dimensional space, preserving local distances

Distances are calculated between each pair of genes/samples

Each pair of vertices is assigned a weight specific to the distance between them

A kernel is implemented to transform the distances to a predefined function (cells in adjacency matrix)

The Laplacian operator decomposes the adjacency matrix

```
k.speClust2 <- function (X, qnt=NULL) {  
  
  dist2full <- function(dis) {  
    n <- attr(dis, "Size")  
    full <- matrix(0, n, n)  
    full[lower.tri(full)] <- dis  
    full + t(full)  
  }  
  
  #squared Euclidean distances between all pairs of samples  
  dat.dis <- dist(t(X), "euc")^2  
  
  if(!is.null(qnt)) {eps <- as.numeric(quantile(dat.dis, qnt))}  
  if(is.null(qnt)) {eps <- min(dat.dis[dat.dis!=0])}  
  
  # a radial basis function (RBF) kernel to transform the distances  
  # the RBF kernel decreases with distance, ranges from 0 to 1 (identity), and  
  # is readily interpreted as a similarity measure  
  kernel <- exp(-1 * dat.dis/(eps))  
  
  # calculate the adjacency matrix K1 - square matrix with elements indicating  
  # whether pairs of vertices are adjacent or not in the graph  
  K1 <- dist2full(kernel)  
  diag(K1) <- 0  
  
  # calculate the degree matrix D - diagonal matrix calculated from the row sums of K1  
  # contains information about the degree of each vertex  
  # (i.e. the number of edges attached to each vertex)  
  D = matrix(0, ncol=ncol(K1), nrow=ncol(K1))  
  tmpe <- apply(K1, 1, sum)  
  tmpe[tmpe>0] <- 1/sqrt(tmpe[tmpe>0])  
  tmpe[tmpe<0] <- 0
```

```

diag(D) <- tmpe

# calculate the normalized Laplacian
L <- D%*% K1 %*% D

# calculate eigenvectors by single value decomposition of the Laplacian and
# place as columns of matrix X
X <- svd(L)$u

# scale the rows of matrix X to unit length and place in matrix Y
# can then create n-dimensional embedding of data utilizing the first n columns of the matrix Y
Y <- X / sqrt(apply(X^2,1,sum))
}

```

Plot a two-dimensional embedding of the weighted graph Laplacian

```

# center and scale the rows of the data matrix
dat.t.c.s <- t(dat)
dat.t.c.s <- scale(dat.t.c.s, center=T, scale=T)

# conduct spectral graph dimensionality reduction
phi <- k.speClust2(t(dat.t.c.s), qnt=NULL)
#phi

#plot
col <- as.numeric(as.factor(unique(ann$site))) +1

plot(range(phi[,1]),range(phi[,2]),
      xlab="phi1",ylab="phi2",
      main="Weighted Graph Laplacian plot of Sotiriou breast cancer data")

points(phi[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
       phi[,2][as.character(ann$site)==levels(as.factor(ann$site))[1]],
       col=col[1],pch=16,cex=1.5)

text(phi[,1][as.character(ann$site)==levels(as.factor(ann$site))[1]],
     phi[,2][ as.character(ann$site)==levels(as.factor(ann$site))[1]],
     col=col[1],cex=0.7,
     labels= paste(levels(as.factor(ann$site))[1], '-',
                    row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[1],]), sep= ' '),
     pos=2)

points(phi[,1][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
       phi[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
       col=col[2],pch=16,cex=1.5)

text(phi[,1][as.character(ann$site)==levels(as.factor(ann$site))[2]],
     phi[,2][ as.character(ann$site)==levels(as.factor(ann$site))[2]],
     col=col[2],cex=0.7,
     labels= paste(levels(as.factor(ann$site))[2], '-',
                    row.names(ann[as.character(ann$site)==levels(as.factor(ann$site))[2],]), sep= ' '),
     pos=2)

```

```
legend(min(range(phi[,1])), max(range(phi[,2])-0.5),
       levels(as.factor(ann$site)), col=col, pch=16, cex=.75)
```

Weighted Graph Laplacian plot of Sotiriou breast cancer data

