Spectral Clustering

Much of this uses information from A Tutorial on Spectral Clustering by Ulrike von Luxburg and Proximity in Statistical Machine Learning by Michael Trosset.

The Ratio Cut Problem

Ratio Cut for $k = 2$

It can be shown that in the relaxed case for $k = 2$, minimizing:

$$W(k) = \sum_{i=1}^{k}(x_i - m_1)^2 + \sum_{i=k+1}^{n}(x_i - m_2)^2$$

where m_1 and m_2 are k-means centers, as perscribed by Luxburg results in the same clustering as by assigning clusters by minimizing

$$R(k) = \sum_{i=1}^{k}\left(x_i + \sqrt{\frac{n-k}{k}}\right)^2 + \sum_{i=k+1}^{n}\left(x_i - \sqrt{\frac{k}{n-k}}\right)^2$$

in $\mathbb{R}^1$ and where x_is are ordered, i.e., $x_i \leq \cdots \leq x_n$. We also constrain the problem to $\sum_i^n x_i = 0$ and $\sum_i^n x_i^2 = n$.

The k-means centers in $\mathbb{R}$ are

$$m_1 = \frac{1}{k}\sum_{i=1}^{k} x_i$$

$$m_2 = \frac{1}{n-k}\sum_{i=k+1}^{n} x_i$$

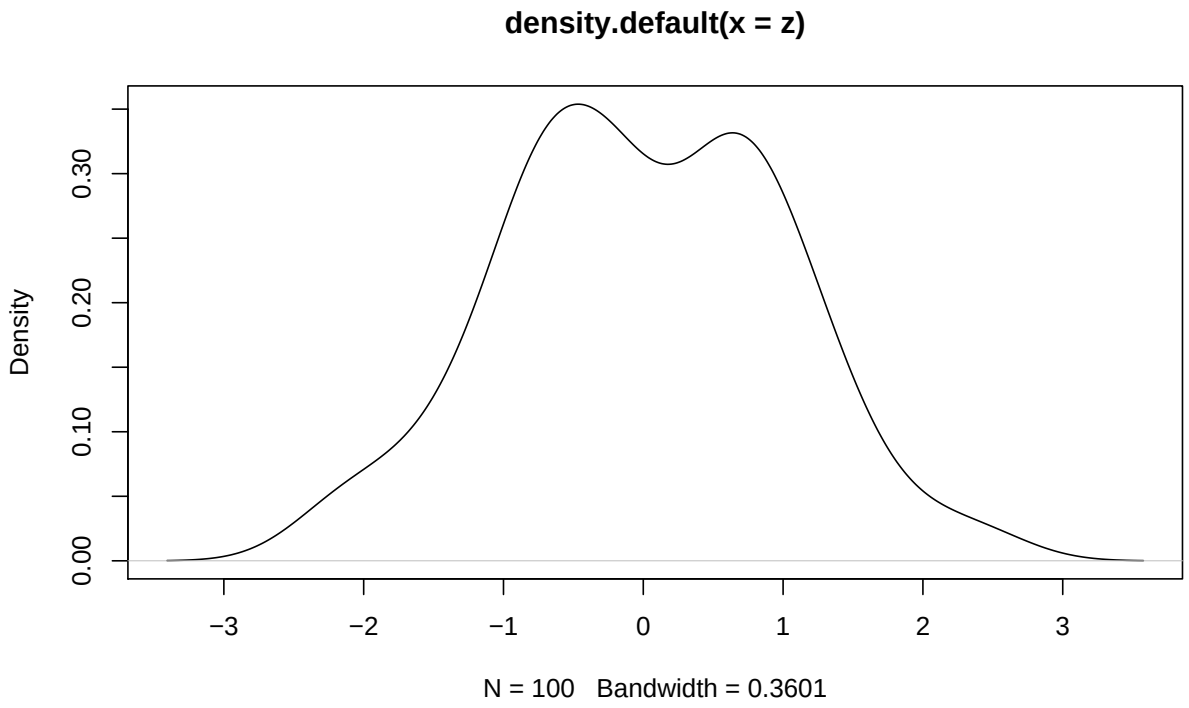
Note that m_1 and m_2 are functions of k.

Numerical results

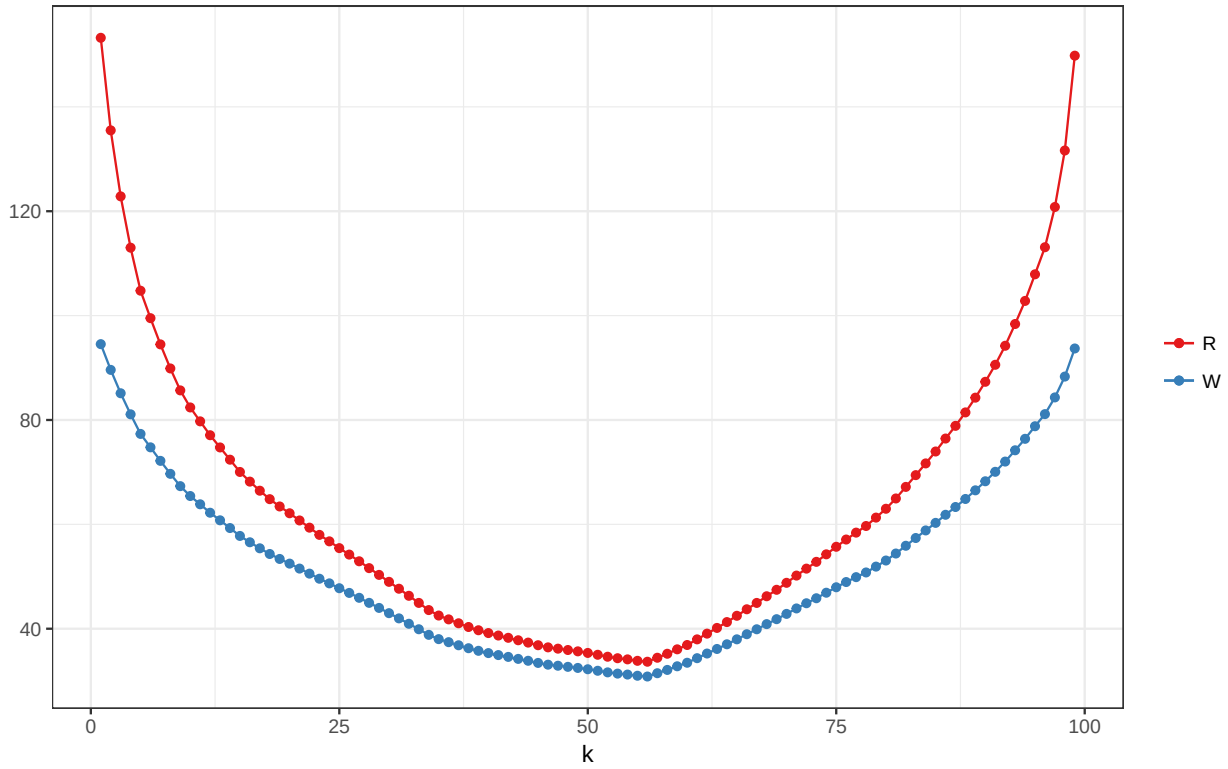
Using an arbitrary vector $\vec{x} \in \mathbb{R}^n$ such that $\sum_i x_i = 0$ and $|\vec{x}|_2^2 = n$:

```
# packages
library(ggplot2)
import::from(magrittr, `%>%`, `%<>%`)
theme_set(theme_bw())
import::from(psych, tr)

# --- functions --- #

normalize <- function(x) {
  y <- x - mean(x)
```

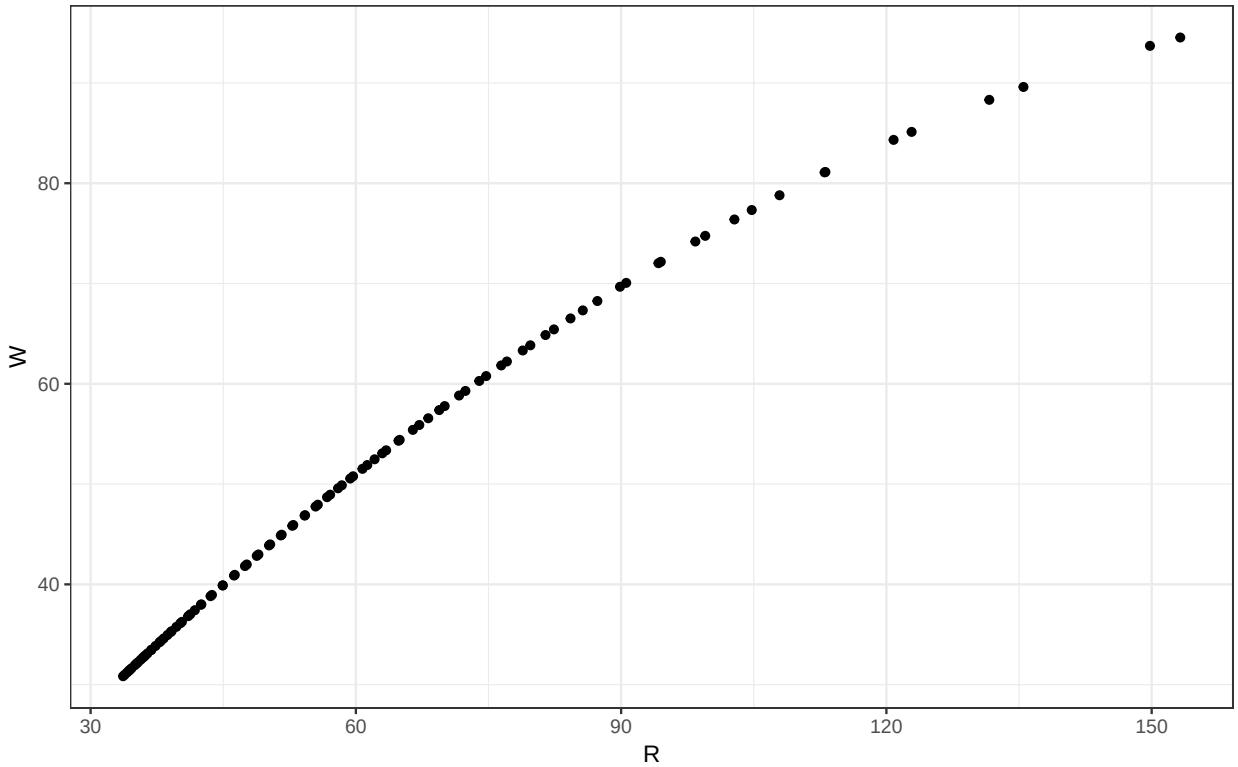
```
  z <- y / sqrt(mean(y ** 2))
  return(z)
}

k.means <- function(x) {
  x <- sort(x)
  n <- length(x)

  sapply(seq(n - 1), function(k) {
    m1 <- 1 / k * sum(x[seq(k)])
    m2 <- 1 / (n - k) * sum(x[seq(k + 1, n)])

    W <- sum((x[seq(k)] - m1)^2) + sum((x[seq(k + 1, n)] - m2)^2)
    return(W)
  })
}

ratio.cut <- function(x) {
  x <- sort(x)
  n <- length(x)

  sapply(seq(n - 1), function(k) {
    Ac <- sqrt((n - k) / k)
    A <- sqrt(k / (n - k))

    R <- sum((x[seq(k)] + Ac)^2) + sum((x[seq(k + 1, n)] - A)^2)
    return(R)
  })
}

# generate random data
n <- 100
k <- 4
x <- c(rnorm(n / k, -1),
       rnorm(n / k, 0),
       rnorm(n / k, 1),
       rnorm(n / k, 3))
z <- normalize(x)
plot(density(z))
```




```
# compute W and R
W <- k.means(z)
R <- ratio.cut(z)

# visualizations
k <- seq(n - 1)

ggplot() +
  geom_point(aes(x = k, y = W, colour = 'W')) +
  geom_line(aes(x = k, y = W, colour = 'W')) +
  geom_point(aes(x = k, y = R, colour = 'R')) +
  geom_line(aes(x = k, y = R, colour = 'R')) +
  scale_colour_brewer(palette = 'Set1') +
  labs(x = 'k', y = NULL, colour = NULL)
```




```
ggplot() +
  geom_point(aes(x = R, y = W))
```



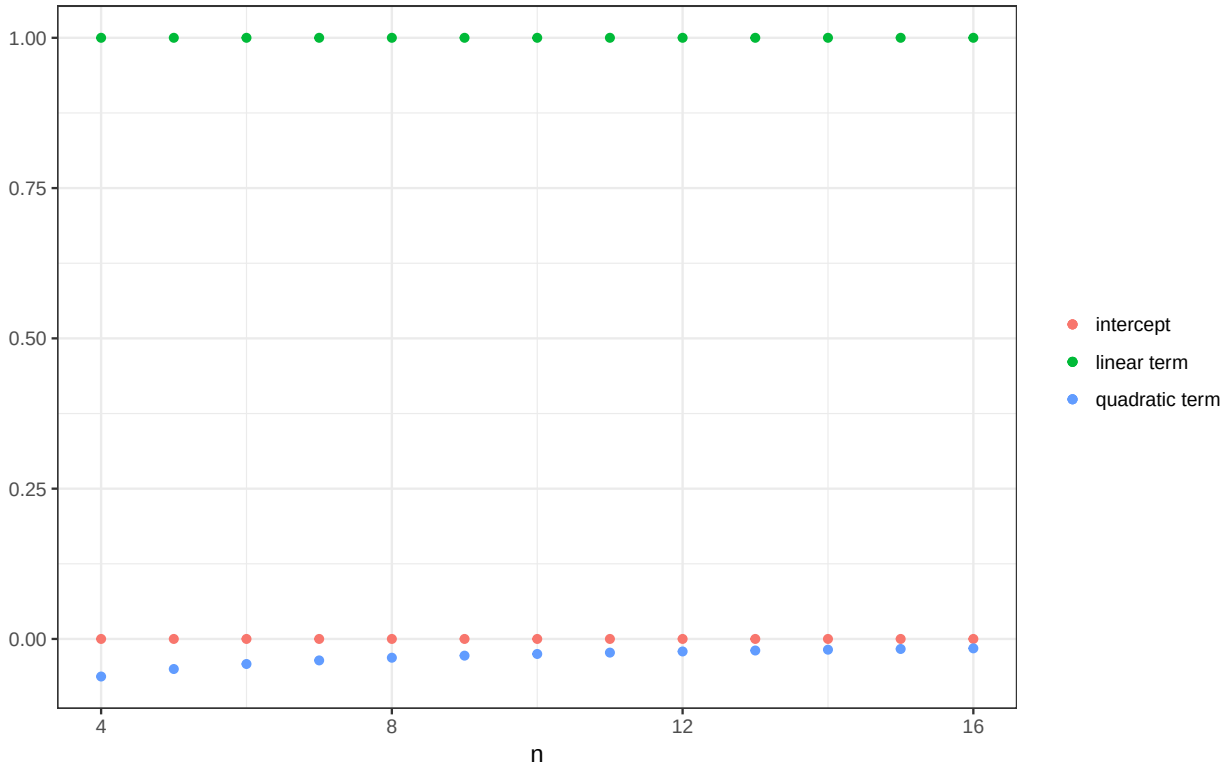
It appears that there is a definite relationship between W and R. Using quadratic regression:

```
summary(lm(W ~ R + I(R ** 2)))
```

```
Call:
lm(formula = W ~ R + I(R^2))

Residuals:
       Min         1Q     Median         3Q        Max
-2.154e-14 -3.325e-15 -1.910e-16  3.462e-15  3.200e-14

Coefficients:
             Estimate Std. Error    t value Pr(>|t|)
(Intercept)  3.428e-14  3.993e-15  8.584e+00 1.62e-13 ***
R            1.000e+00  1.119e-16  8.934e+15  < 2e-16 ***
I(R^2)      -2.500e-03  6.825e-19 -3.663e+15  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.49e-15 on 96 degrees of freedom
Multiple R-squared:      1, Adjusted R-squared:      1
F-statistic: 3.355e+32 on 2 and 96 DF,  p-value: < 2.2e-16
```

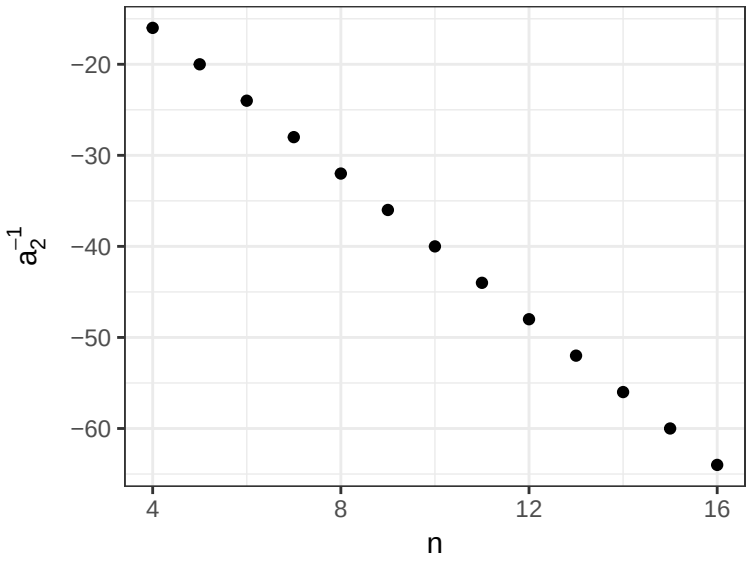
... we get a perfect fit. We can try several values of the data size n:

```
N <- 2 ** 4  # number of obs to try
coefs.df <- lapply(seq(4, N), function(n) {
  x <- normalize(rnorm(n))  # generate data

  # compute results
  W <- k.means(x)
  R <- ratio.cut(x)

  # compute coefs for quadratic equation
  quad.coefs <- lm(W ~ R + I(R ** 2))$coefficients
  a0 <- quad.coefs['(Intercept)']
  a1 <- quad.coefs['R']
  a2 <- quad.coefs['I(R^2)']

  # compile into data frame
  dplyr::data_frame(n, a0, a1, a2)
}) %>%
  dplyr::bind_rows()

ggplot(coefs.df) +
  geom_point(aes(x = n, y = a0, colour = 'intercept')) +
  geom_point(aes(x = n, y = a1, colour = 'linear term')) +
  geom_point(aes(x = n, y = a2, colour = 'quadratic term')) +
  labs(colour = NULL, y = NULL)
```



The intercept term stays at 0 and the linear term stays at 1. Looking closer at the quadratic term:

```
ggplot(coefs.df) +
  geom_point(aes(x = n, y = a2 ** -1)) +
  labs(y = expression(a[2]^-1))
```



Then we arrive at the result $W = R - \frac{1}{4n}R^2$.

Analytic result

We can show:

$$W(k) = R(k) - \frac{(R(k))^2}{4n}$$

or $W(R) = R - \frac{1}{4n}R^2$. This function is strictly increasing for $R(k) \leq 2n$. Expanding $R(k)$, we get:

$$R(k) = 2n + 2\sqrt{\frac{n-k}{k}}\sum_{i=1}^{k} x_i - 2\sqrt{\frac{k}{n-k}}\sum_{i=k+1}^{n} x_i$$

It can be shown that $R(k)$ is maximized at the endpoints.

Note that since $\sum_i^n x_i = 0$, $\sum_i^{k<n} x_i \leq 0$, $x_n \geq 0$, and $x_i \leq 0$.

k can range from 1 to $n-1$. If $k = n-1$, we get $R(n-1) = 2n + 2\sqrt{\frac{1}{k}}\sum_i^{n-1} x_i - 2\sqrt{n-1}x_n$. The second term is ≤ 0 and the third term is ≥ 0, so we get $R \leq 2n$. On the other hand, if $k = 1$, $R(1) = 2n + 2\sqrt{n-1}x_1 - \frac{2}{\sqrt{n-1}}\sum_{i=2}^{n} x_i = 2n + 2\sqrt{n-1}x_1 - \frac{2}{\sqrt{n-1}}(-x_1) = 2n + x_1\big(2\sqrt{n-1} + \frac{2}{\sqrt{n-1}}\big) \leq 2n$.

Expanding $W(k)$, we get:

$$W(k) = \sum_{i=1}^{k} x_i^2 - 2m_1\sum_{i=1}^{k} x_i + km_1^2 + \sum_{i=k+1}^{n} x_i^2 - 2m_2\sum_{i=k+1}^{n} x_i + m_2^2(n-k)$$

$$= n - \frac{2}{k}\Big(\sum_{i=1}^{k} x_i\Big)^2 + \frac{1}{k}\Big(\sum_{i=1}^{k} x_i\Big)^2 - \frac{2}{n-k}\Big(\sum_{i=k+1}^{n} x_i\Big)^2 + \frac{1}{n-k}\Big(\sum_{i=k+1}^{n} x_i\Big)^2$$

$$= n - \frac{1}{k}\Big(\sum_{i=1}^{k} x_i\Big)^2 - \frac{1}{n-k}\Big(\sum_{i=k+1}^{n} x_i\Big)^2$$

$$= n - km_1^2 - (n-k)m_2^2$$

Since $\sum_i^n x_i = 0$, $km_1 + (n-k)m_2 = 0$, or, $-nm_2 = k(m_1 - m_2)$. Then

$$W(k) = n - km_1^2 - (n-k)m_2^2$$
$$= n - km_1^2 - nm_2^2 + km_2^2$$
$$= n - km_1^2 + (nm_2)m_2 + km_2^2$$
$$= n - km_1 + k(m_1 - m_2)m_2 + km_2 2$$
$$= n + k(-m_1^2 + m_1m_2 - m_2^2 + m_2^2)$$
$$= n + km_1(m_2 - m_1)$$

Using the relationship $-nm_2 = k(m_1 - m_2) \implies m_2 - m_1 = \frac{nm_2}{k}$ from before, we can again rewrite $W(k)$:

$$W(k) = n - (n-k)m_2\frac{nm_2}{k}$$
$$= n\frac{(n-k)n}{k}m_2^2$$

And we use the same relationship again: $m_2 - m_1 = \frac{n}{k}m_2 \implies m_2 = (m_2 - m_1)\frac{k}{n}$.

Then we can finally write $W(k)$ as:

$$W(k) = n - \frac{(n-k)n}{k}\frac{k^2}{n^2}(m_1 - m_2)^2$$

$$\boxed{W(k) = n - \frac{(n-k)k}{n}(m_1 - m_2)^2}$$

On the other hand, if we expand $R(k)$:

$$\begin{aligned} R(k) &= \sum_1^k x_i^2 + 2\sqrt{\frac{n-k}{k}}\sum_1^k x_i + n - k + \sum_{k+1}^n x_i^2 - 2\sqrt{\frac{k}{n-k}}\sum_{k+1}^n x_i + k \\ &= 2n + 2\sqrt{k(n-k)}m_1 - 2\sqrt{k(n-k)}m_2 \end{aligned}$$

If we expand and simplify $-\frac{(R(k))^2}{4n}$, we get:

$$-\frac{(R(k))^2}{4n} = -n - \frac{k(n-k)}{n}m_1^2 - \frac{k(n-k)}{n}m_2^2 - 2m_1\sqrt{k(n-k)} + 2m_2\sqrt{k(n-k)} + \frac{2k(n-k)}{n}m_1m_2$$

Then noting that some terms cancel each other out, $R(k) - \frac{(R(k))^2}{4n}$:

$$\begin{aligned} &n - \frac{k(n-k)}{n}m_1^2 - \frac{k(n-k)}{n}m_2^2 + 2\frac{k(n-k)}{n}m_1m_2 \\ &= n - \frac{k(n-k)}{n}(m_1^2 + m_2^2 - 2m_1m_2) \\ &\boxed{= n - \frac{k(n-k)}{n}(m_1 - m_2)^2} \end{aligned}$$

Which is exactly the same as our expression for $W(k)$.

Arbitrary k

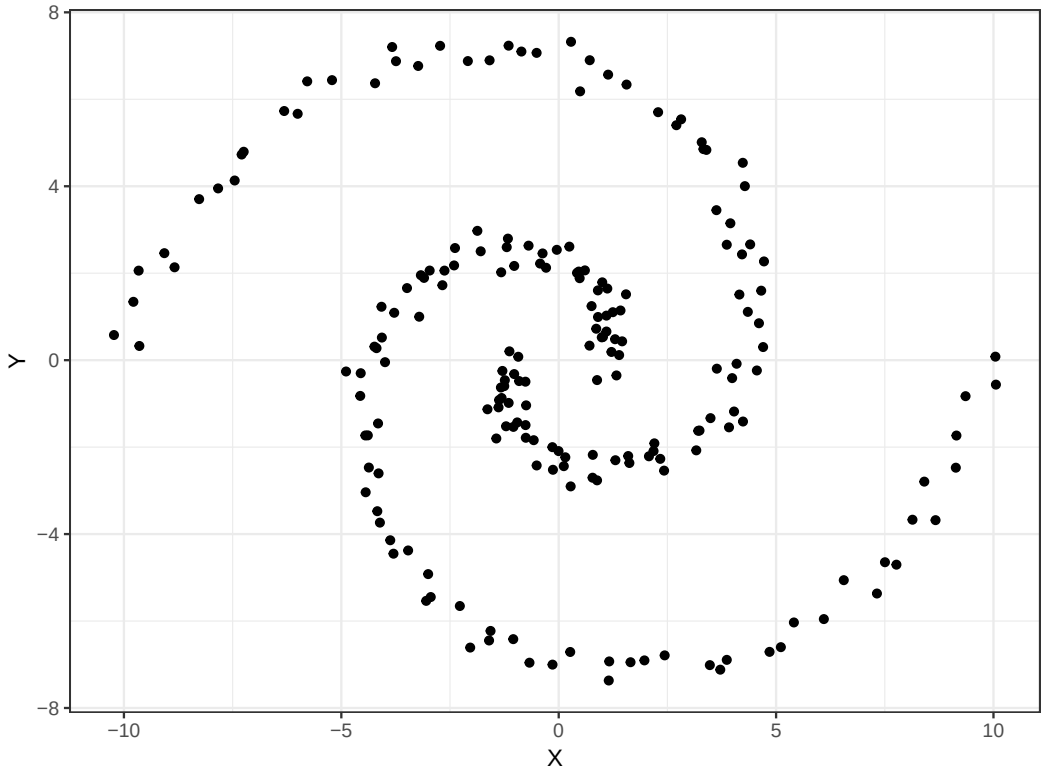
For arbitrary k, the methods as prescribed by Luxburg involve embedding the graph to $\mathbb{R}^k$ and then performing k-means clustering. In this case, we cannot perform the same sort of analysis since there is no way to "order" the x_i's.

Numerical experiments for $k = 2$ and $\mathbb{R}^2$

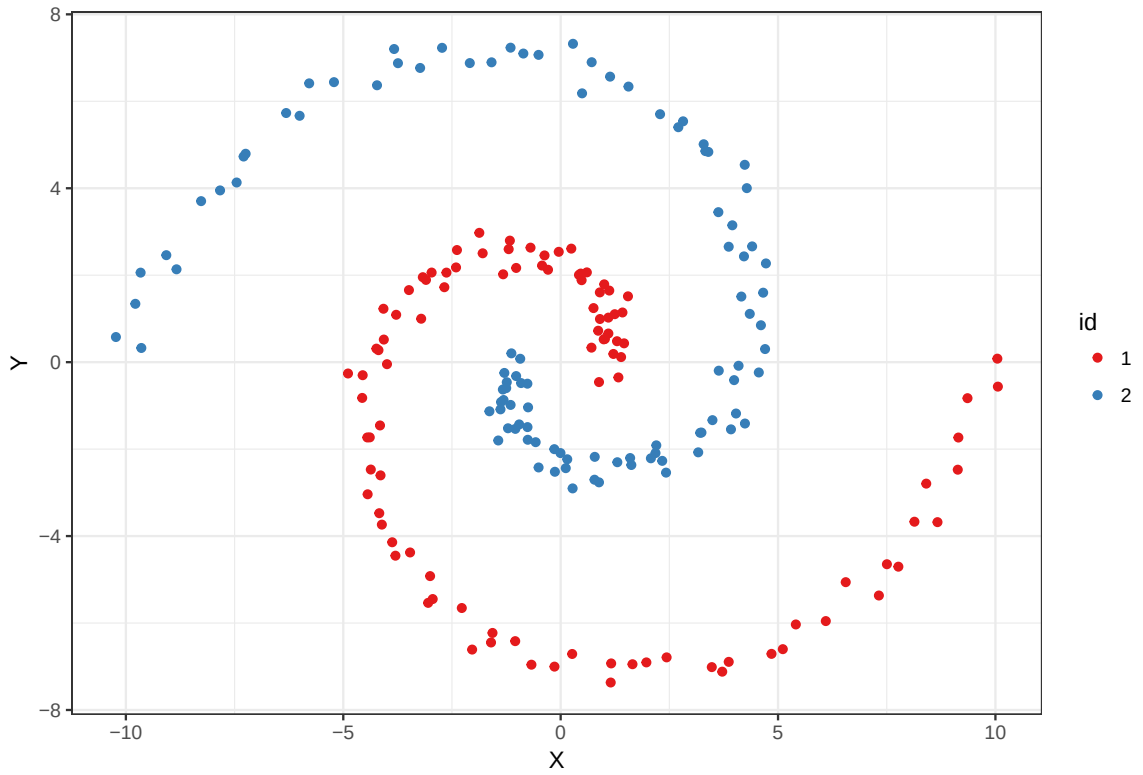
Double spiral

We will generate a "double spiral" to be partitioned into two clusters. This is an example that k-means would fail but is fairly distinguishable visually or intuitively. After generating the spiral, we will construct a k-nearest neighbors graph.

```r
# borrow some functions from S675
source('http://pages.iu.edu/~mtrosset/Courses/675/manifold.r')

# parameters
set.seed(112358)
s <- 2 ** 5
eps <- 2 ** -2
k <- 10
cols2 <- colorRampPalette(c('blue', 'white', 'red'))(256)
rad.max <- 10
ang.max <- 2 * pi
angles <- seq(0, ang.max, length.out = 100)
radii <- seq(1, sqrt(rad.max), length.out = 100) ** 2

# data
spiral.df <- dplyr::data_frame(X = radii * cos(angles),
                               Y = radii * sin(angles))
spiral.df <- dplyr::data_frame(X = radii * cos(angles),
                               Y = radii * sin(angles))
neg.spiral.df <- dplyr::mutate(spiral.df,
                               X = -X, Y = -Y,
                               id = '2')
spiral.df %<>%
  dplyr::mutate(id = '1') %>%
  dplyr::bind_rows(neg.spiral.df) %>%
  dplyr::mutate(X = X + rnorm(n = n(), sd = eps),
                Y = Y + rnorm(n = n(), sd = eps))

n <- nrow(spiral.df)

# viz
ggplot(spiral.df) +
  geom_point(aes(x = X, y = Y)) +
  coord_fixed()
```

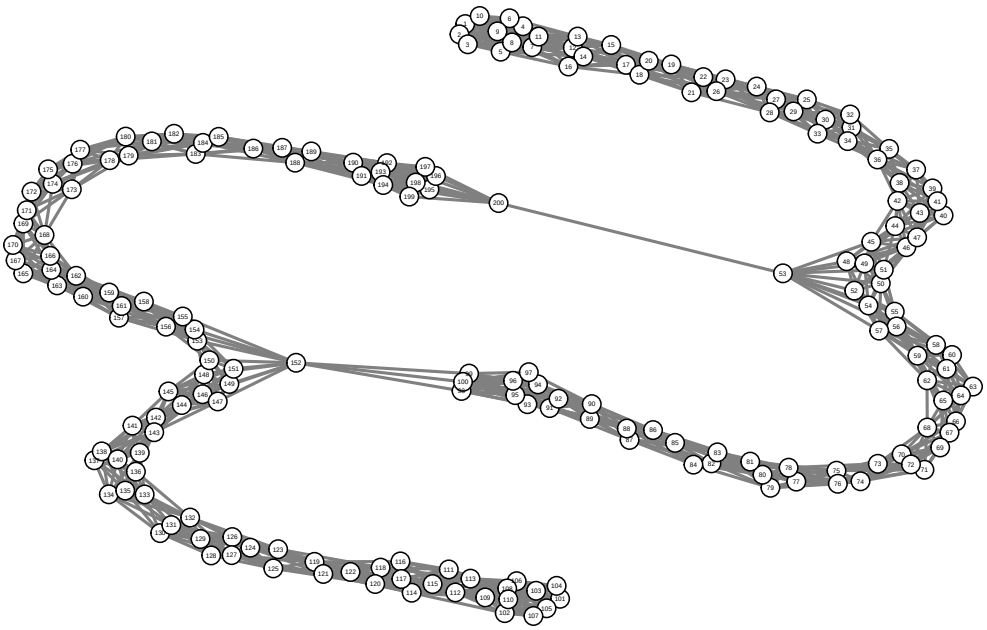



```
ggplot(spiral.df) +
  geom_point(aes(x = X, y = Y, colour = id)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1')
```



Then we will construct a(n) 10-nearest-neighbors graph:

```
# construct W
W <- spiral.df %>%
  dplyr::select(X, Y) %>%
  as.matrix() %>%
  mds.edm1() %>%
  graph.knn(k) %>%
  graph.adj()

# viz
qgraph::qgraph(W)
```



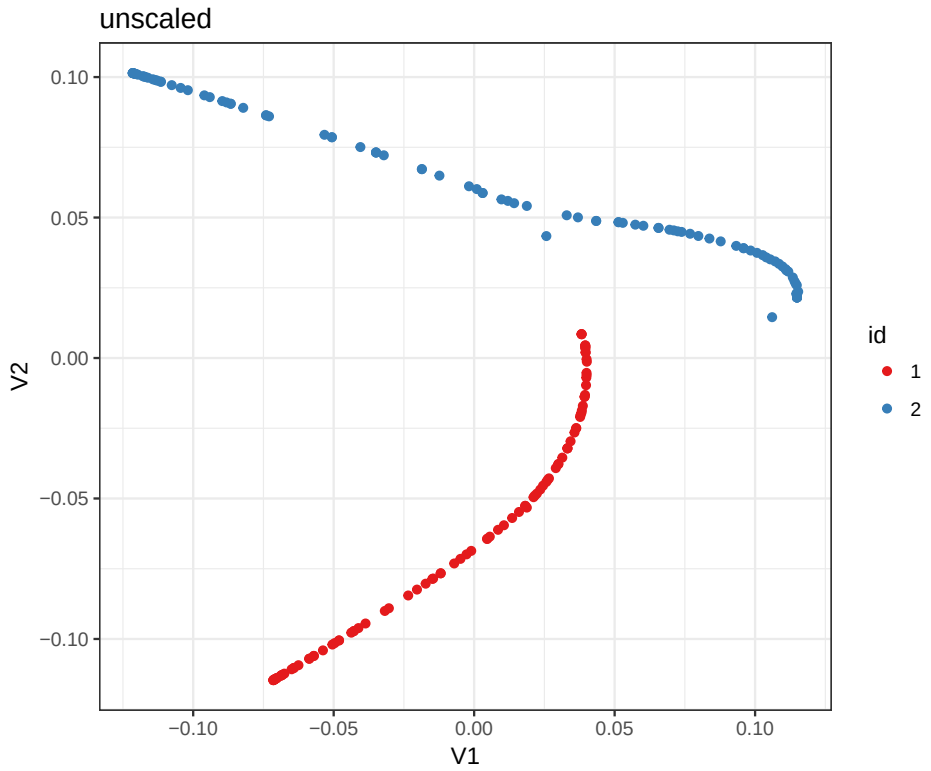
Here it is pretty obvious how we should cut the graph.

Then proceed with the clustering method as described by Luxburg:

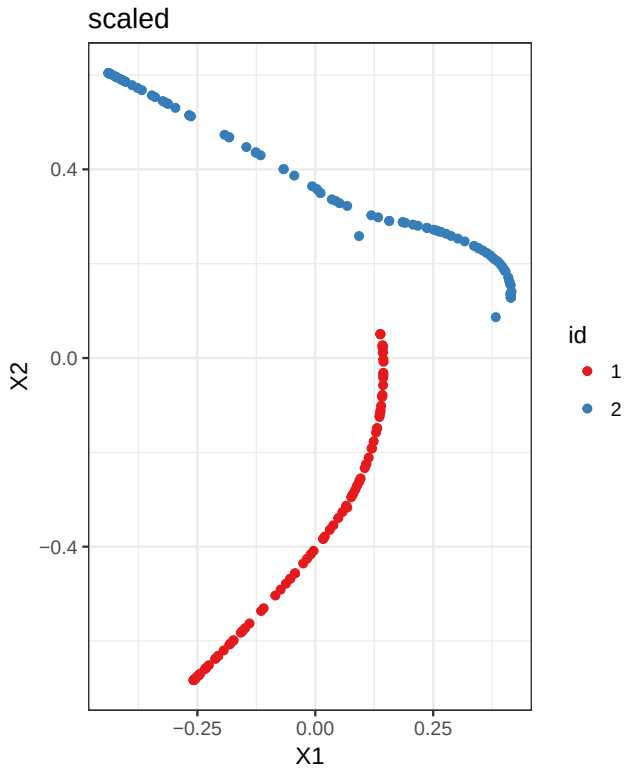
```
# construct L
L <- graph.laplacian(W)

# eigendecomposition
L.eigen <- eigen(L)

two.eigen.df <- L.eigen$vectors[, c(n - 2, n - 1)] %>%
  as.data.frame() %>%
  dplyr::mutate(id = spiral.df$id) %>%
  dplyr::mutate(X1 = V1 / sqrt(L.eigen$values[n - 2]),
                X2 = V2 / sqrt(L.eigen$values[n - 1]))
```

Then we can take a look at the projection to $\mathbb{R}^2$:

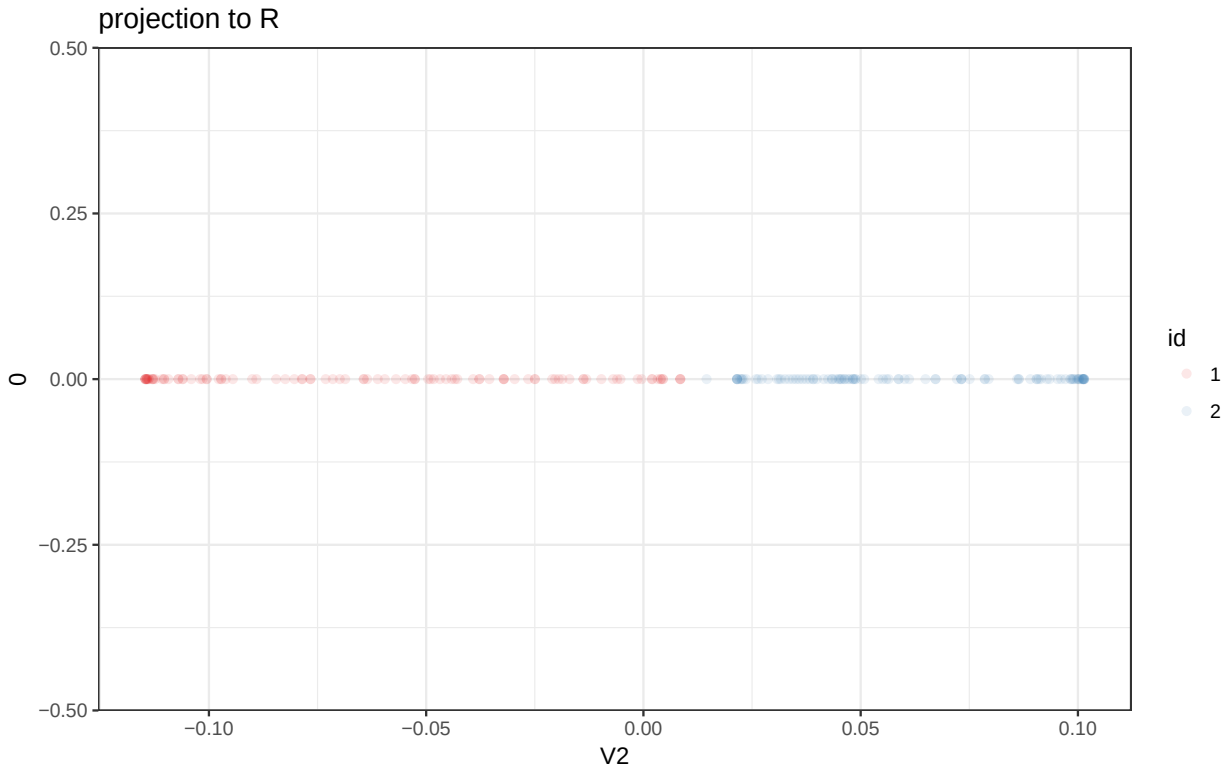
```
ggplot(two.eigen.df) +
  geom_point(aes(x = V1, y = V2, colour = id)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1') +
  labs(title = 'unscaled')
```




```
ggplot(two.eigen.df) +
  geom_point(aes(x = X1, y = X2, colour = id)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1') +
  labs(title = 'scaled')
```

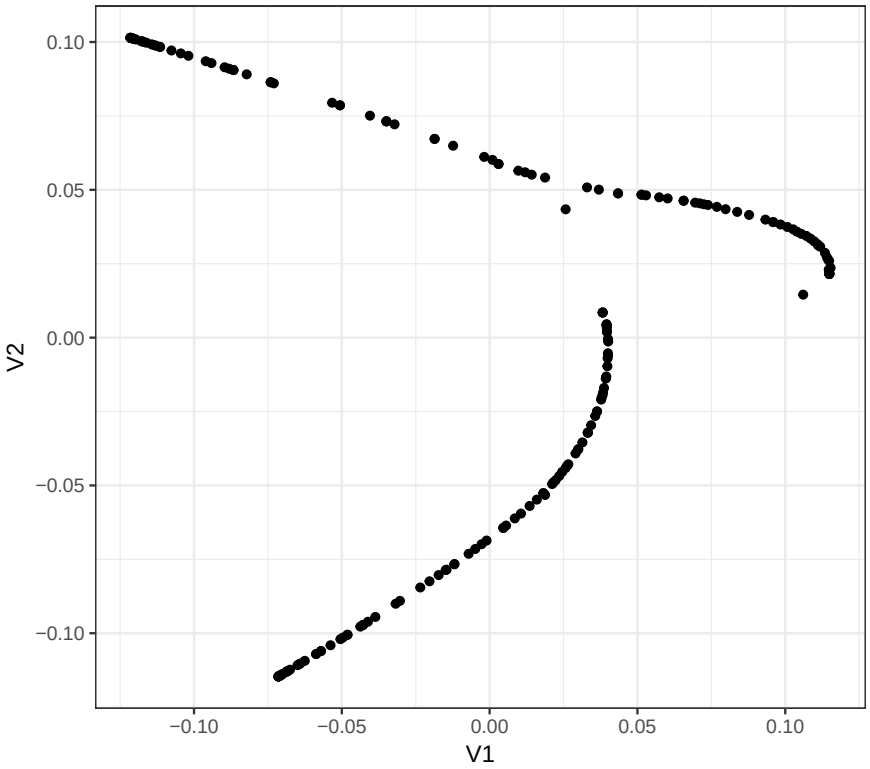



```
ggplot(two.eigen.df) +
  geom_point(aes(x = V2, y = 0, colour = id),
             alpha = .1) +
  scale_colour_brewer(palette = 'Set1') +
  labs(title = 'projection to R')
```



Next, we can take a look at how the three methods correspond to our original labels:

```
ggplot(two.eigen.df) +
  geom_point(aes(x = V1, y = V2)) +
  coord_fixed()
```




```
unscaled.clustering <- two.eigen.df %>%
  dplyr::select(V1, V2) %>%
  dist() %>%
  kmeans(2)

scaled.clustering <- two.eigen.df %>%
  dplyr::select(X1, X2) %>%
  dist() %>%
  kmeans(2)

one.d.clustering <- two.eigen.df %>%
  dplyr::select(X2) %>%
  dist() %>%
  kmeans(2)

spiral.df %<>%
  dplyr::mutate(unscaled = as.character(unscaled.clustering$cluster),
                scaled = as.character(scaled.clustering$cluster),
                one.d = as.character(one.d.clustering$cluster))

table(spiral.df$id, spiral.df$unscaled)
```

```
    1  2
  1 43 57
  2 40 60
```

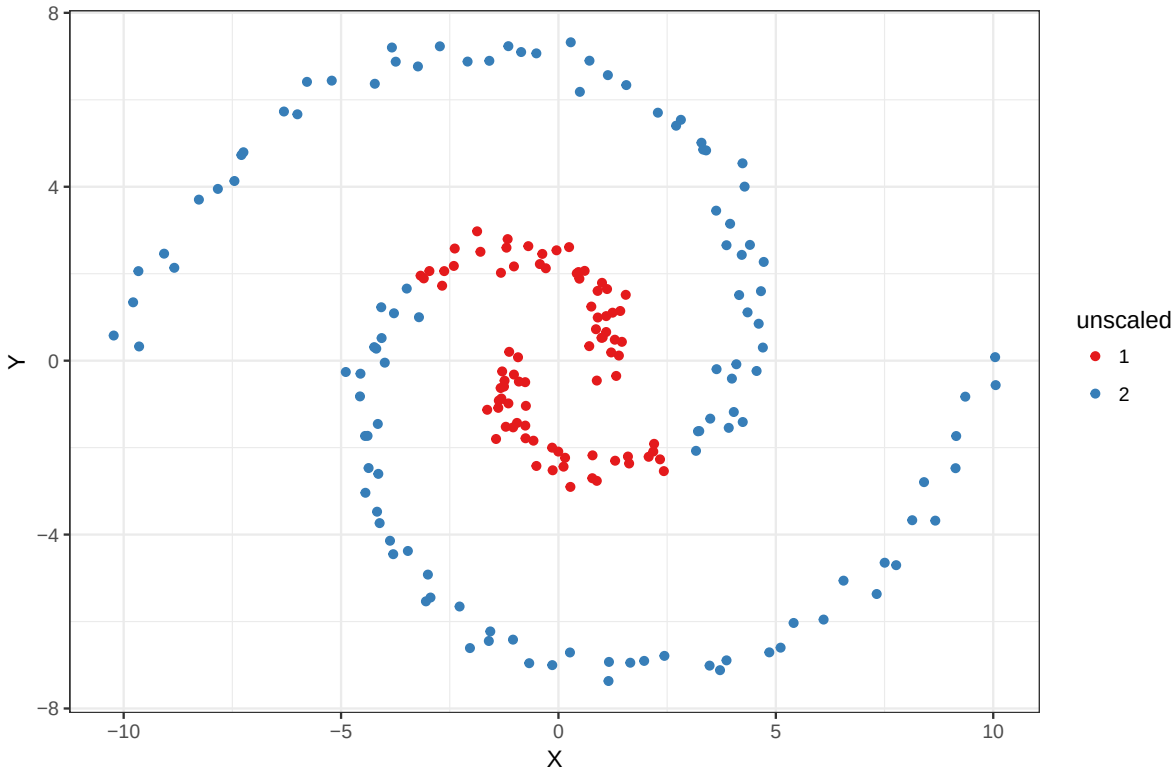
```
table(spiral.df$id, spiral.df$scaled)
```

```
    1   2
1  20  80
2 100   0
```

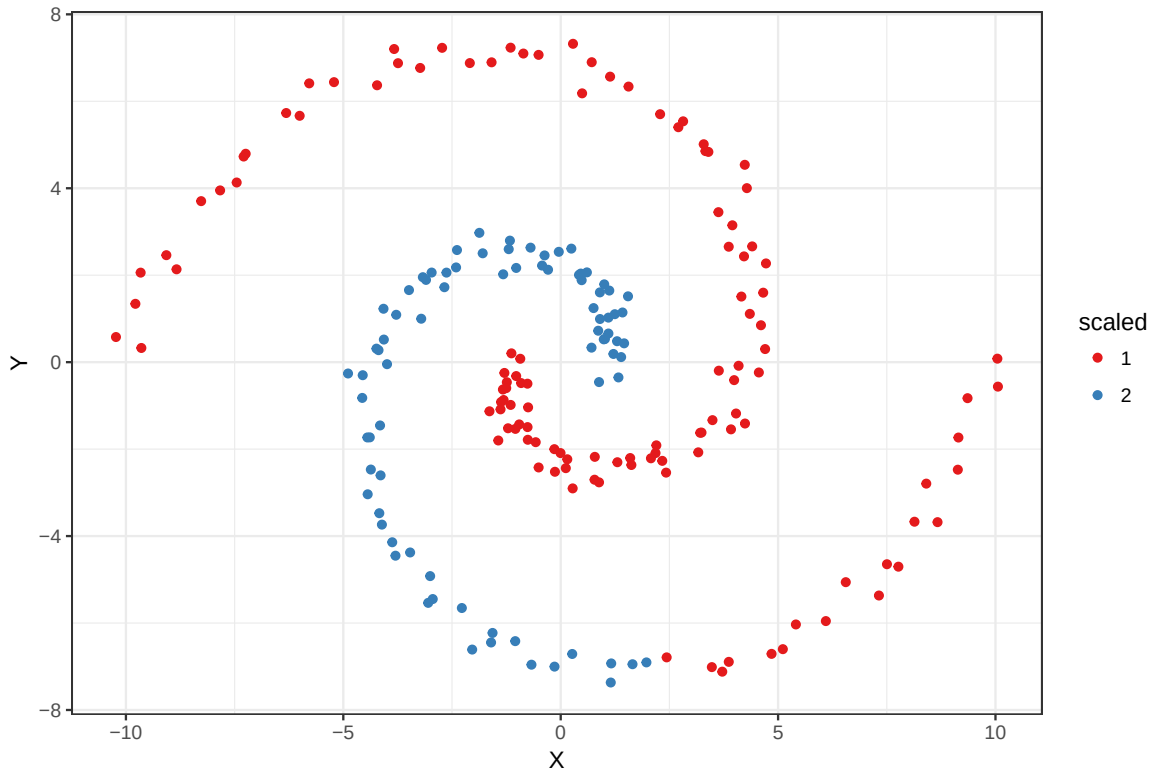
```
table(spiral.df$id, spiral.df$one.d)
```

```
    1   2
1  19  81
2 100   0
```

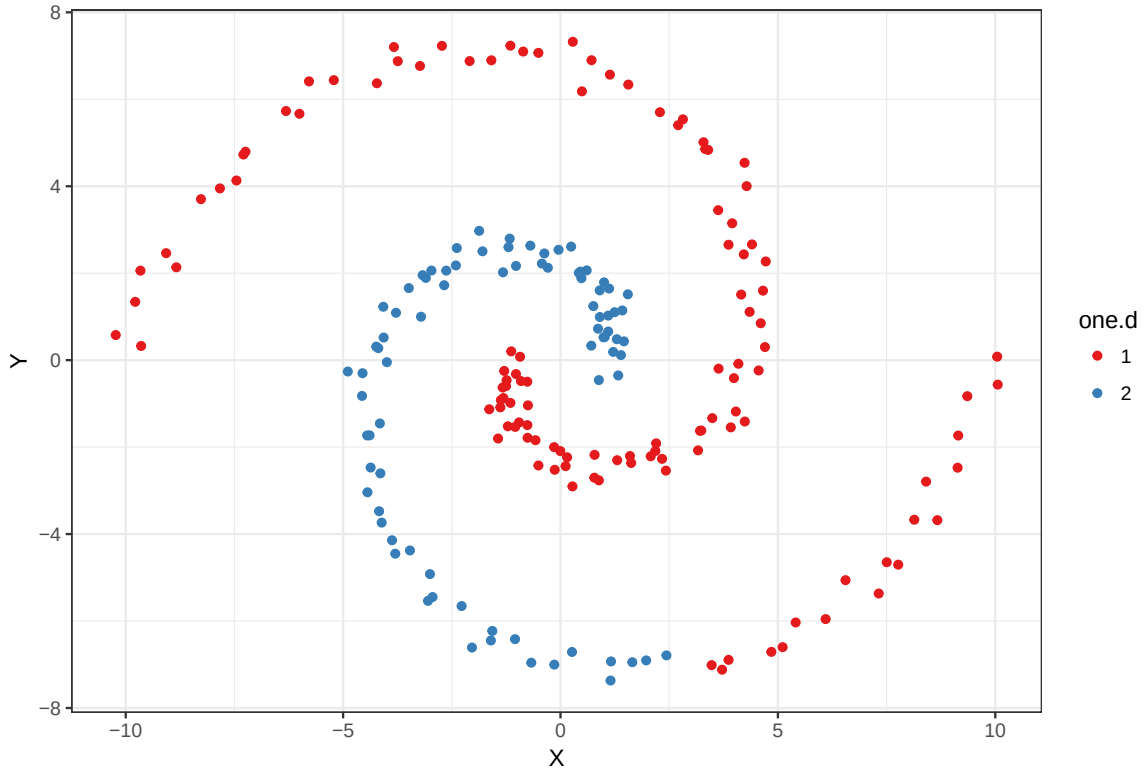
```
ggplot(spiral.df) +
  geom_point(aes(x = X, y = Y, colour = unscaled)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1')
```




```
ggplot(spiral.df) +
  geom_point(aes(x = X, y = Y, colour = scaled)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1')
```

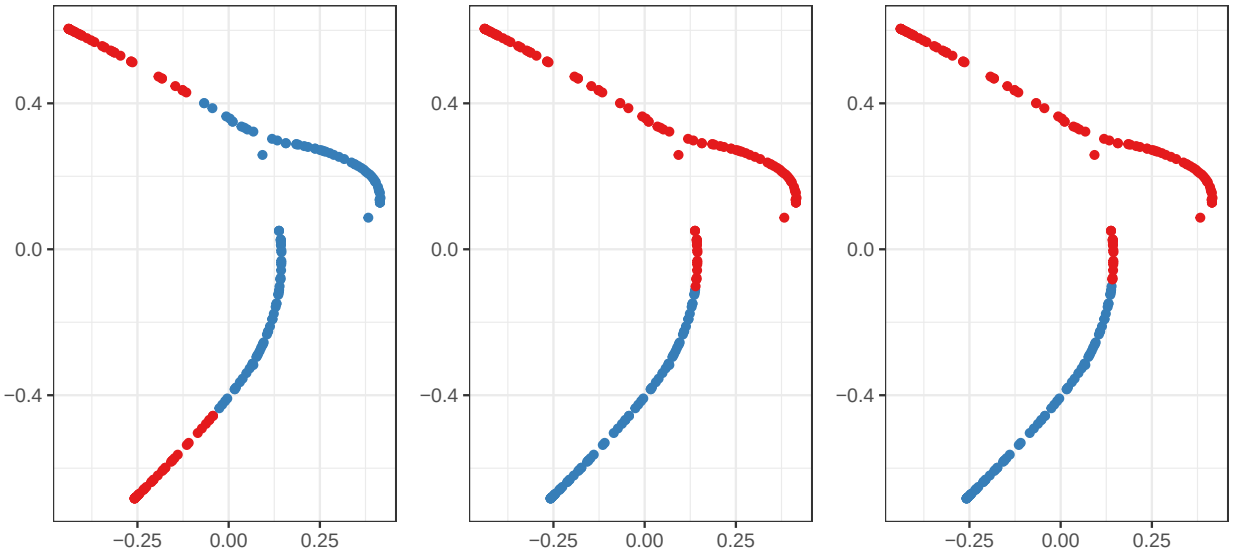



```
ggplot(spiral.df) +
  geom_point(aes(x = X, y = Y, colour = one.d)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1')
```



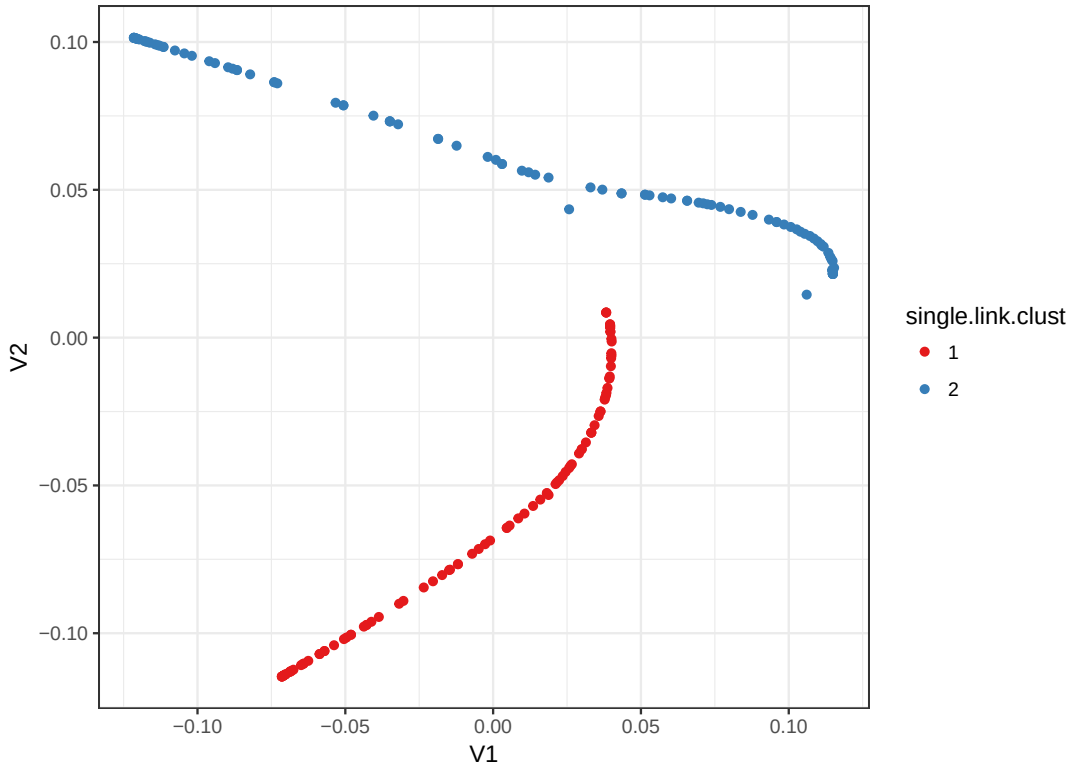
In a way, we have "unraveled" the spirals, resulting in two curves. Eye-balling this representation gives us two obvious clusters, but k-means fails to separate them the way we would expect since they are not spherical clusters. Projection to the unscaled space seems to perform especially poorly, and the plots of the columns of H_{approx} reveal why.

```
two.eigen.df %<>%
  dplyr::mutate(unscaled.clust = as.character(unscaled.clustering$cluster),
                scaled.clust = as.character(scaled.clustering$cluster),
                one.d.clust = as.character(one.d.clustering$cluster))

clust.list <- list('unscaled.clust', 'scaled.clust', 'one.d.clust')

clust.plots <- lapply(clust.list, function(i) {
  ggplot(two.eigen.df) +
    geom_point(aes_string(x = 'X1', y = 'X2', colour = i)) +
    scale_colour_brewer(palette = 'Set1') +
    coord_fixed() +
    guides(colour = FALSE) +
    labs(x = NULL, y = NULL)
})

.gridarrange <- function(...) gridExtra::grid.arrange(..., ncol = 3)
do.call(.gridarrange, clust.plots)
```

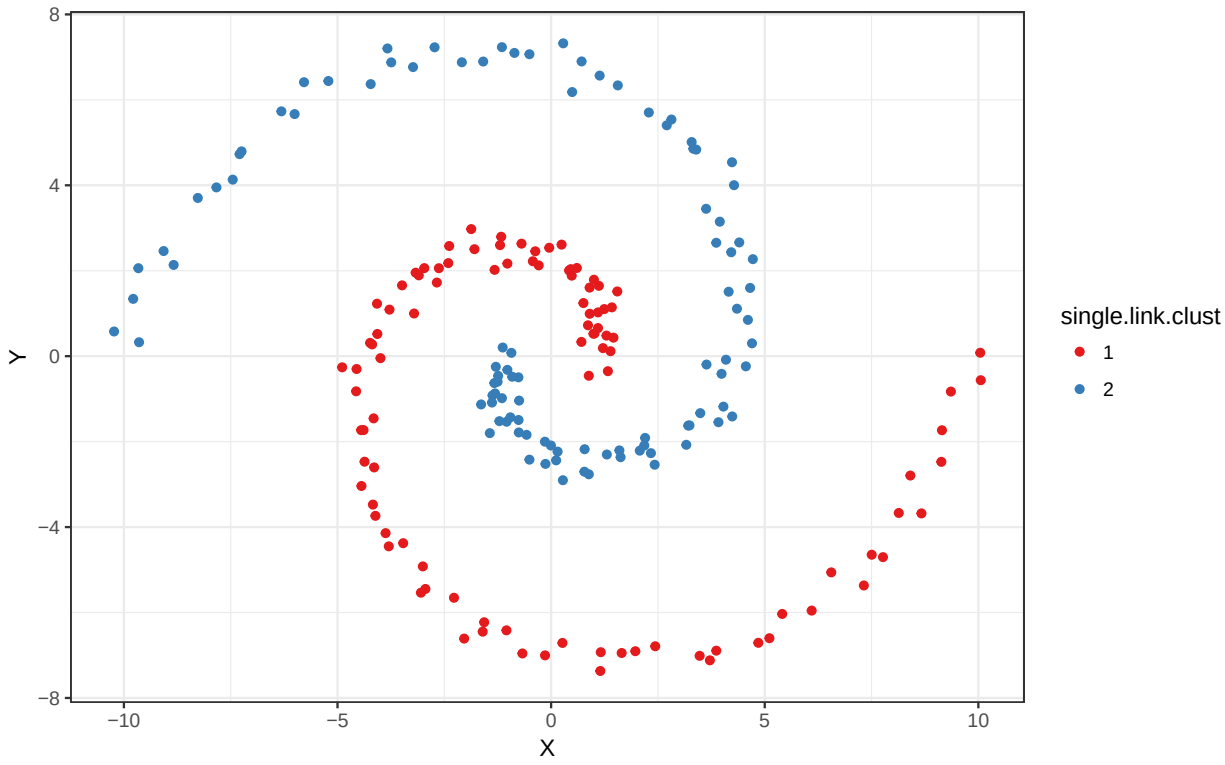


In fact, it almost looks as if another clustering method is more appropriate here, in particular, single-linkage.

```
single.link.clust <- two.eigen.df %>%
  dplyr::select(V1, V2) %>%
  dist() %>%
  hclust(method = 'single') %>%
  cutree(2)

two.eigen.df %<>%
  dplyr::mutate(single.link.clust = as.character(single.link.clust))
spiral.df %<>%
  dplyr::mutate(single.link.clust = as.character(single.link.clust))

ggplot(two.eigen.df) +
  geom_point(aes(x = V1, y = V2, colour = single.link.clust)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1')
```




```
ggplot(spiral.df) +
  geom_point(aes(x = X, y = Y, colour = single.link.clust)) +
  coord_fixed() +
  scale_colour_brewer(palette = 'Set1')
```




```
table(spiral.df$id, spiral.df$single.link.clust)
```

```
     1   2
  1 100   0
  2   0 100
```

We should also check that this clustering is actually better according to the metrics from the Luxburg tutorial. We try this two ways:

1. H_{approx} should be as close of an approximation to H as possible. Here, H_{approx} is the k-dimensional embedding via spectral decomposition while H defines the actual best clustering. In this comparison, we fix H_{approx} and construct H according to the resulting clustering of H_{approx} (e.g., via k-means or single-linkage), then compare the constructed H to H_{approx} via the Frobenious norm.
2. The exact clustering should minimize $\text{Tr}(H^T L H)$ where H is defined by the particular clustering. If single-linkage is indeed better than k-means in this case, then the H constructed from single-linkage clustering should result in a lower metric than the one constructed from k-means clustering.

```
# construct Happrox
H.approx <- two.eigen.df %>%
  dplyr::select(V2, V1) %>%  # i put this in the wrong order
  as.matrix()

#' @title construct H function
#' @description H is constructed based on a vector that designates the clusters
#' @param clustering (numeric) A vector of cluster assignments
#' @return (matrix) H based on the cluster assignments
construct.H <- function(clustering) {
  # this function is limited to nonempty clusters
  # e.g., if there are 3 clusters, they must be assigned as 1, 2, 3
```

```
  clusters <- unique(clustering)
  if (length(clusters) != max(clustering)) {
    stop(simpleError('there are empty clusters'))
  }
  if (min(clustering) < 1) {
    stop(simpleError('cluster indexing starts at 1'))
  }

  # find |A_k|
  cluster.sizes <- sapply(clusters, function(i) {
    length(clustering[clustering == i])
  })

  # construct H
  H <- sapply(clustering, function(i) {
    h <- rep(0, length(clusters))
    h[i] <- 1 / sqrt(cluster.sizes[i])
    return(h)
  }) %>%
    t()

  return(H)
}

# construct H for k-means (unscaled)
H.kmeans <- construct.H(unscaled.clustering$cluster)

# construct H for single linkage
H.singlelink <- construct.H(single.link.clust)

# frobenius norm comparison
norm(H.approx - H.kmeans, type = 'F')
```

```
[1] 1.747271
```

```
norm(H.approx - H.singlelink, type = 'F')
```

```
[1] 2.257204
```

```
# making sure ordering doesn't matter
# this could get messy for large k
norm(H.approx - H.kmeans[, 2:1], type = 'F')
```

```
[1] 2.275743
```

```
norm(H.approx - H.singlelink[, 2:1], type = 'F')
```

```
[1] 1.704416
```

```
# minimizing trace comparison
# here order doesn't matter
tr(t(H.kmeans) %*% L %*% H.kmeans)
```

```
[1] 0.6796416
```

```
tr(t(H.singlelink) %*% L %*% H.singlelink)
```

```
[1] 0.08
```

Here, we can see that single linkage produces a H matrix that is closer to H_{approx} and results in a better clustering metric.

However, this may be a very particular case. From the embedding, we can see that while there is a very obvious clustering, the clusters are not ellipsoids, which is what k-means is good at. Perhaps in most graph embeddings of this type, we do end up with ellpsoid clusters, and we just happened to get long strands in this example.