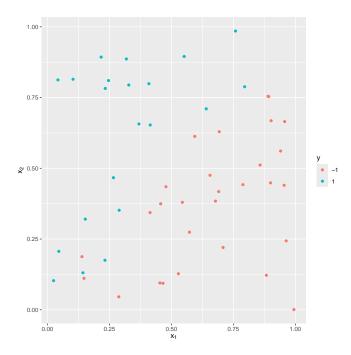
Univariate Optimization 1

## Solution 1: Golden Ratio, Brent's Method

```
library(ggplot2)
set.seed(123)

X = matrix(runif(100), ncol = 2)
y = -((X %*% c(-1, 1) + rnorm(50, 0, 0.1) < 0) * 2 - 1)
df = as.data.frame(X)
df$type = as.character(y)

ggplot(df) +
   geom_point(aes(x = V1, y = V2, color=type)) +
   xlab(expression(x[1])) +
   ylab(expression(x[2])) +
   labs(color="y")</pre>
```



- (a) Since f is convex it holds for arbitrary  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^2, t \in [0, 1]$  that  $f(\mathbf{x} + t(\mathbf{y} \mathbf{x})) \leq f(\mathbf{x}) + t(f(\mathbf{y}) f(\mathbf{x}))$ . This means this holds also for  $\mathbf{x}_c = (x, c)^{\top}$  and  $\mathbf{y}_c = (y, c)^{\top}$  with  $x, y \in \mathbb{R}$  and fixed  $c \in \mathbb{R}$ :  $f(\mathbf{x}_c + t(\mathbf{y}_c \mathbf{x}_c)) \leq f(\mathbf{x}_c) + t(f(\mathbf{y}_c) f(\mathbf{x}_c)) \iff g_c(x + t(y x)) \leq g_c(x) + t(g_c(y) g_c(x))$ .  $\Rightarrow g_c$  is convex.
- (b) The non-geometric primal linear SVM formulation is convex and unconstrained  $\Rightarrow$  For one parameter the objective is also convex (a) and we can directly use GR. In contrast, the geometric formulation has linear constraints.

```
(c) # Define objective
   f <- function(theta) theta %*% theta +
       sum(sapply(1 - y * (X %*% theta), function(x) max(x, 0)))
   # Objective w.r.t theta_1 with fixed theta_2
   ft1 <- function(theta_1) f(c(theta_1, 2))</pre>
   phi = (sqrt(5) - 1)/2
   gr \leftarrow function(f, lx=-3, rx=3, abs\_error = 0.01)
     # initialize variables needed for stopping criterion
     fbest_old = Inf
     xbest_old = Inf
     xbest = NA
     # compute candidate xs
     dist = rx - lx
     cx = c(lx + (1-phi) * dist, rx - (1-phi) * dist)
     while(TRUE){
       fcx1 = f(cx[1])
       fcx2 = f(cx[2])
       # check which candidate is better and update cx
       if (fcx1 < fcx2){</pre>
        fbest = fcx1
        xbest = cx[1]
        rx = cx[2]
        cx[2] = cx[2] - (cx[1] - 1x)
       }else{
         fbest = fcx2
         xbest = cx[2]
         lx = cx[1]
        cx[1] = cx[1] + (rx - cx[2])
       # assure cx[1] < cx[2]
       cx = sort(cx)
       # check if we need to stop the loop depending on the termination criterion
       if (abs(xbest_old - xbest) < abs_error){</pre>
        return(c(xbest, fbest))
       fbest_old = fbest
       xbest_old = xbest
   gr(ft1)
   ## [1] -2.45898 29.91294
```

(d) We are given three equations:

```
ax_1^2 + bx_1 + c = y_1
ax_2^2 + bx_2 + c = y_2
```

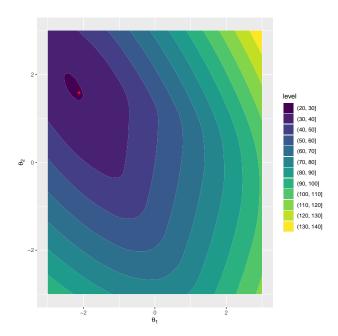
 $ax_3^2 + bx_3 + c = y_3$ . Which we can express equivalently as  $\underbrace{\begin{pmatrix} x_1^2 & x_1 & 1 \\ x_2^2 & x_2 & 1 \\ x_3^2 & x_3 & 1 \end{pmatrix}}_{:-\mathbf{A}} \cdot \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix}$ . The result follows

straightforwardly assuming  $\Lambda$  is non-singular.

```
(e) gr_step <- function(f, lx, rx){</pre>
     dist = rx - lx
     # compute candidates
     cxs = c(lx + (1-phi) * dist,
      rx - (1-phi) * dist)
     fcx = sapply(cxs, f)
     # find best candidate
     if (fcx[1] < fcx[2]){
      fbest = fcx[1]
       cx = cxs[1]
      rx = cxs[2]
     }else{
       fbest = fcx[2]
       cx = cxs[2]
       lx = cxs[1]
     return(c(lx, rx, cx, fbest))
   brent <- function(f, lx = -3, rx = 3, abs_error = 0.01){
     fbest_old = Inf
     xbest = NA
     xbest_old = Inf
     # we do not have a valid candidate in the beginning
     cx = Inf
     while(TRUE){
       # if candidate is not valid do a golden ratio step
       if(cx \le lx \mid cx \ge rx)
         res = gr_step(f, lx, rx)
         lx = res[1]
         rx = res[2]
         cx = res[3]
         xbest = cx
         fbest = res[4]
       }else{ # try doing quadratic interpolation otherwise
         # compute objective values
         xs = c(lx, rx, cx)
         fxs = sapply(xs, f)
         # find parameters of the interpolating parabola
         params = solve(t(sapply(xs, function(x) c(x^2, x, 1))), fxs)
         # find minimum of the parabola
         cx_{new} = -params[2]/(2*params[1])
         # if candidate is valid do quadratic interpolation step
         if(cx_new < rx & cx_new > lx){
```

```
cxs = sort(c(cx, cx_new))
        fcx = sapply(cxs, f)
        # find best candidate
        if (fcx[1] < fcx[2]){</pre>
         fbest = fcx[1]
          cx = cxs[1]
         rx = cxs[2]
        }else{
          fbest = fcx[2]
          cx = cxs[2]
          lx = cxs[1]
        xbest = cx
  # check if we need to stop the loop depending on the termination criterion
  if (abs(xbest - xbest_old) < abs_error){</pre>
   return(c(xbest, fbest))
 fbest_old = fbest
 xbest_old = xbest
brent(ft1)
## [1] -2.409456 29.903281
```

```
(f) # intialize thetas
  t1 = 0
  t2 = 0
  for(i in 0:9){
    # alternate between univariately optimizing each parameter while the other
     # is fixed
    if(i %% 2 == 0){
      ft <- function(t) f(c(t, t2))
      res = gr(ft)
      t1 = res[1]
    }else{
      ft <- function(t) f(c(t1, t))
      res = gr(ft)
      t2 = res[1]
    print(c(t1, t2, f(c(t1, t2))))
   ## [1] -1.583592 0.000000 37.878640
   ## [1] -1.583592 1.583592 32.490253
  ## [1] -2.124612 1.583592 29.742862
  ## [1] -2.124612 1.583592 29.742862
  ## [1] -2.124612 1.583592 29.742862
  ## [1] -2.124612 1.583592 29.742862
```



(g) The trace looks like a orthogonal zig-zag line.