CMPS 142: Homework Assignment 3

Jeffrey Petersen - 1329242
Ben Gordon - 1263760
Raymond Colebaugh - 1377877

May 12, 2015

1. We want to find the minimum of the geometric margin,

$$min_{w,b} \frac{y(w \cdot x_i + b)}{||w||^2}$$

Our decision boundary will be of the form $w \cdot x_i + b > 0$, which can also be expressed as $w_1 x + w_2 y + b > 0$. After graphing the data and evaluating them visually, we can find a good candidate for a decision boundary at $y > -x + \frac{3}{2}$, or $x + y - \frac{3}{2} > 0$. Our w_1 and w_2 are both 1 and we have a margin of $\frac{2}{||w||} = \sqrt{2}$. The support vectors, then, are (1,1), (1,0), and (0,1).

2. In executing grid search with the specified bounds on parameters, we determined the following costs and gammas for SMO:

C_{min}	C_{max}	C_{step}	γ_{min}	γ_{max}	γ_{step}	Sample Size	C	γ	Accuracy
1	16	1	-5	2	1	25%	16	0	93.6318 %
1	16	1	-5	2	1	50%	14	1	93.6101 %
15	32	1	0	2	0.25	10%	31	0	93.6536 %
15	32	1	0	2	0.25	25%	25	0	93.697 %
23	27	0.25	0.7	1.3	0.1	10%	27	0.7	93.3275 %
23	27	0.25	0.7	1.3	0.1	25%	25.75	0.7	93.371 %
23	27	0.25	0.7	1.3	0.1	50%	24.75	0.7	93.371 %

Where the expression for c was i and the expression for γ was 10^i. Whenever one of the parameters was chosen to be on a boundry, such as the first trial which found $C = 16$, we adjusted the boundries for the next execution to more appropriately tune the parameter.
Performing a similar analysis using a second degree polynomial kernel with LibSVM yeilded the following results:

γ_{min}	γ_{max}	γ_{step}	$coef0_{min}$	$coef0_{max}$	$coef0_{step}$	Sample Size	γ	$coef0$	Accuracy
5	20	1	-10	5	1	25%	20	5	92.4582 %
15	30	1	0	15	1	25%			%

Executing grid search on LibSVM took much longer than using Weka's SMO. Furthermore, the few outputs we received yeilded a lower accuracy for a similar sample size.

3. We can demonstrate the construction of a decision tree on a simple binary dataset such as the following, which represents the function $x_1 XOR x_2 = y$

x_1	x_2	x_3	y
0	0	0	0
0	0	0	0
0	0	0	0
0	1	1	1
0	1	1	1
0	1	1	1
1	0	1	1
1	0	0	1
1	1	1	0
1	1	1	0

In deciding the first node of our decision tree by following the the decision tree algorithm, we have x_1 classifies $\frac{7}{10}$, x_2 classifies $\frac{6}{10}$, and x_1 classifies $\frac{5}{10}$ if x_3

x_1	x_2	x_3	y
0	1	1	1
0	1	1	1
0	1	1	1
1	0	1	1
1	1	1	0
1	1	1	0

x_1 classifies $\frac{4}{6}$, x_2 classifies $\frac{3}{6}$
if x_1

x_1	x_2	x_3	y
1	0	1	1
1	1	1	0
1	1	1	0

if x_2

x_1	x_2	x_3	y
1	1	1	0
1	1	1	0

else

x_1	x_2	x_3	y
1	0	1	1

else

x_1	x_2	x_3	y
0	1	1	1
0	1	1	1
0	1	1	1

else

x_1	x_2	x_3	y
0	0	0	0
0	0	0	0
0	0	0	0
1	0	0	1

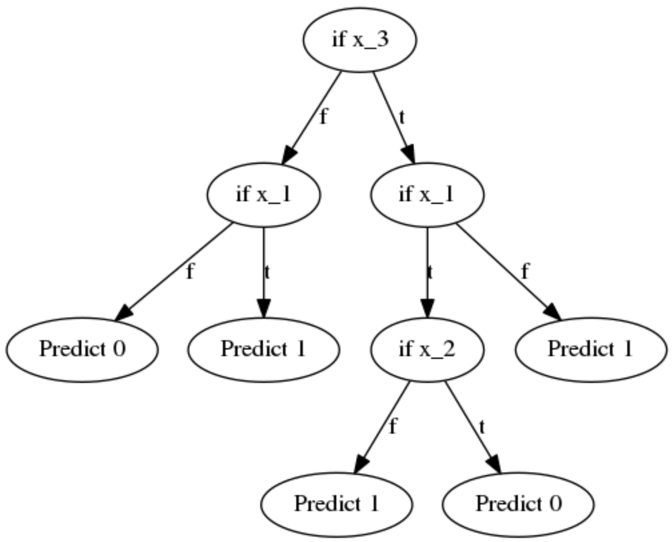
(x_1 classifies $\frac{4}{4}$, x_2 classifies $\frac{3}{4}$)
if x_1

x_1	x_2	x_3	y
1	0	0	1

else

x_1	x_2	x_3	y
0	0	0	0
0	0	0	0
0	0	0	0

The algorithm then will have producted the following tree:



Then, without following the decision tree algorithm, we can simplify the logic to the following, somitting values for convenience:

```
if x_1
    if x_2
else
    if x_2
```