```
svm_type c_svc
kernel_type polynomial
degree 2
gamma 1
coef0 1
nr class 2
total_sv 5
rho 1.66653
label 1 -1
nr_sv 3 2
SV
0.8887164347987063 1:-1 => x4
0.1502852229699299 2:2 => x5
0.3681704323551298 2:-2 => x6
-0.48570486954923172:1 \Rightarrow x2
-0.9214672205745343 2:-1 => x3
對應到SV=x2,x3,x4,x5,x6
因此min (alpha i i從1到7) = alpha 7
```

5.

4.

如講義第三講第4頁,

The curves should be different in the x space, because they are learned with respect to different z spaces.

如第三講第7頁,藍色的transition跟綠色的transition一樣,雖然具有同樣的power但是有不同的inner product不同的geometry。

或8頁所說, change selecting K if and only if change of margin definition。

 $alpha_n^*y_n^*kernel(x_n,x)+b=1/9(8^*x1^2-16^*x1+6^*x2^2-15)=0$

15.

用libsvm,參數為-t0線性kernel,根據不同的C。

log10_C:-6,IWI:1.23092046817e-08

log10 C:-4,IWI:5.97920361981e-05

log10_C:-2,IWI:0.326392895857

log10_C:0,IWI:128.172269053

log10_C:2,IWI:171.301590146

因為margin = 2d (線到SV的距離) = 2/IIwll

當C越大的時候越不能容忍錯誤,margin越小,w越大。

16.

log10_C:-6,Ein:0.0743382252092

log10_C:-4,Ein:0.0743382252092

log10_C:-2,Ein:0.0743382252092

log10_C:0,Ein:0.0743382252092

log10_C:2,Ein:0.0743382252092

因為屬於8這類的class樣本很少,非8的樣本很多,就算c跟w怎麼變都不會影響到Ein。

17.

log10_C:-6,alpha:0.001084

log10_C:-4,alpha:0.1084

log10_C:-2,alpha:10.84

log10_C:0,alpha:1084.0

log10_C:2,alpha:108400.0

因為C越大W越大Margin越小alpha越大。

應證第四講第8頁

No loss of optimality if solving with implicit constraint beta = C - alpha and explicit constraint $0 \le alpha \le C$:

18.

參考:<u>http://my.oschina.net/u/1461744/blog/209104</u>

先算出IWI,再運用svm_predict去算出free support vector的p_val。最後 p_val / lwl 得到距離

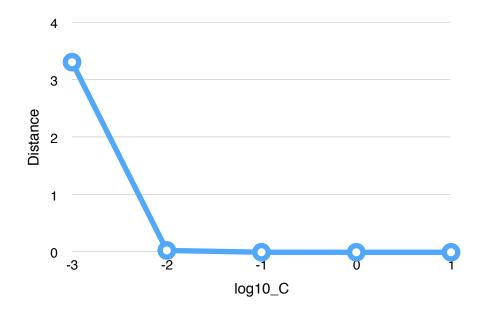
log10_C:-3, Distance:3.31437425017

log10_C:-2, Distance:0.0320639400527

log10_C:-1, Distance:0.000671724709803

log10_C:0, Distance:0.000257625011818

log10_C:1, Distance:0.000235309159599



19. Eout:0.107125062282 Eout:0.0991529646238 Eout:0.105132037867 Eout:0.178873941206 Eout:0.178873941206

因為固定C所以在gamma增加時,Eout沒有顯著的改變微微上升。

20. gamma:0 times:7 gamma:1 times:71 gamma:2 times:22

