

# Homework 2

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## I. PROBLEM 1

- (a)  $1 + 8 = 9$ ,  $x_{13}, x_{15}$   
 (b)  $\frac{1+8}{20(20-12)} = 0.05625$   
 (c)  $1 - \text{ErrRate} = 0.94375$   
 (d) Shown in figure 1

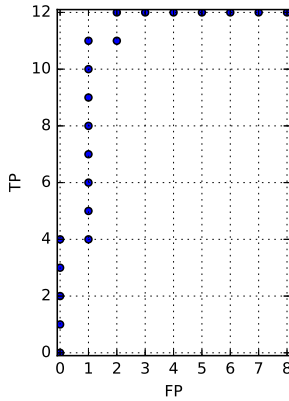


Fig. 1. problem 1(d)

## II. PROBLEM 2

- (a) Shown in figure 7

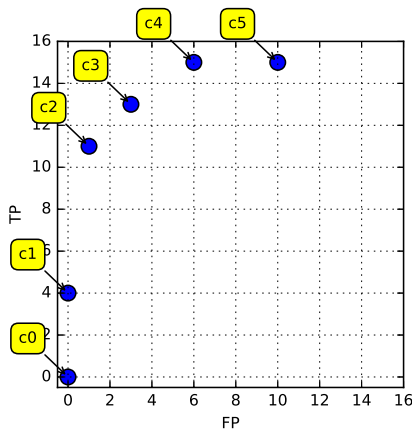


Fig. 2. problem 2(a)

- (b) Shown in figure 3

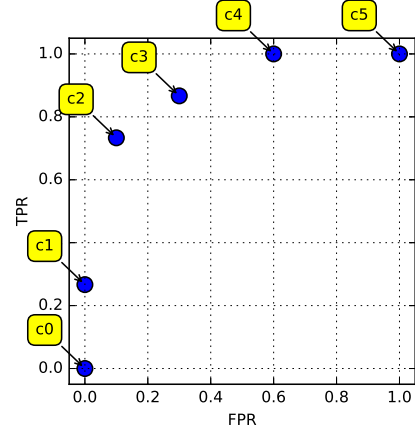


Fig. 3. problem 2(b)

- (c)  $C_0$  have the lowest accuracy.  $C_2, C_3$  both have the highest accuracy.

$$\text{accuracy} = \frac{TP + N - FP}{N + P} \quad (1)$$

All accuracy shown below:

c0	0.4
c1	0.56
c2	0.8
c3	0.8
c4	0.76
c5	0.6

- (d)  $C_2$  have the highest average recall,  $C_0, C_5$  have the lowest average recall

$$\text{avg-rec} = (tpr + tnr)/2 \quad (2)$$

All avg-rec shown below:

c0	0.5
c1	0.63
c2	0.82
c3	0.78
c4	0.7
c5	0.5

- (e)  $C_5$  and  $C_4$  are complete. A complete classifier has all positive examples in positive prediction.  
 (f)  $C_0$  and  $C_1$  are consistent. A consistent classifier has no negative example in positive prediction.

### III. PROBLEM 3

Note that, margin caculation is below(nc——w—— normlization is common pitfall). Fomulas of loss are from textbook.

$$\text{margin} = c(X) \frac{W \cdot X - t}{\|W\|}$$

Code is as follow:

```
w=np.array([2,1,3])
t=12
inp=np.array([
[2, 2, 3],[3, 3, 2],[1, 2, 3],[1, 4, 1],
[4, 4, 4],[2, 2, 2],[1, 1, 1],[0, 4, 2],
[4, 0, 0],[3, 3, 1],[3, 3, 3]])
label=np.array([
[1 if i < 6 else -1 for i in range(len(inp))])
margin=label*(inp.dot(w.T)-t)/np.linalg.norm(w)
(margin < 0).astype(int)#0-1
(np.maximum(1-margin,0))#hinge
(1-margin)**2#square
```

	<i>margin</i>	0-1	<i>hinge</i>	<i>square</i>
0	0.801784	0.0	0.198216	0.039290
1	0.801784	0.0	0.198216	0.039290
2	0.267261	0.0	0.732739	0.536906
3	-0.801784	1.0	1.801784	3.246425
4	3.207135	0.0	0.000000	4.871444
5	0.000000	0.0	1.000000	1.000000
6	1.603567	0.0	0.000000	0.364294
7	0.534522	0.0	0.465478	0.216669
8	1.069045	0.0	0.000000	0.004767
9	0.000000	0.0	1.000000	1.000000
10	-1.603567	1.0	2.603567	6.778563

### IV. PROBLEM 4

	<i>relative</i>	<i>laplace</i>	1-estimate	1-estimate
1	0.08	0.100000	0.100000	0.133333
2	0.16	0.166667	0.166667	0.177778
3	0.32	0.300000	0.300000	0.266667
4	0.00	0.033333	0.033333	0.088889
5	0.44	0.400000	0.400000	0.333333

My code of computing probability and generating figures is as follow:

```
inp=pd.Series([
3,5,5,2,3,1,5,3,5,5,2,
3,5,5,1,2,3,3,5,3,3,5,5,2,5])
result=[]
relative=inp.value_counts(
normalize=True,sort=False)
relative.reindex(range(1,6),fill_value=0)
result.append(relative)
nominator=
(inp.value_counts()
.reindex(range(1,6),fill_value=0)+1)
```

```
laplace=nominator/sum(nominator)
result.append(laplace)
result.append(laplace)
nominator=(
inp.value_counts().
reindex(range(1,6),fill_value=0)+4)
m_est=nominator/sum(nominator)
result.append(m_est)
result=pd.DataFrame(
result,index=
['relative','laplace','1-est','5-est']).T
for i in result:
result[i].plot()
plt.xticks(range(1,6))
plt.title(i)
plt.grid(True)
plt.savefig(i+'.eps')
plt.show()
```

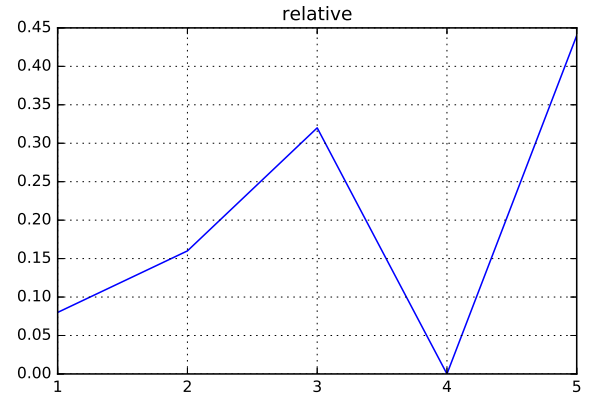


Fig. 4. problem 4(a)

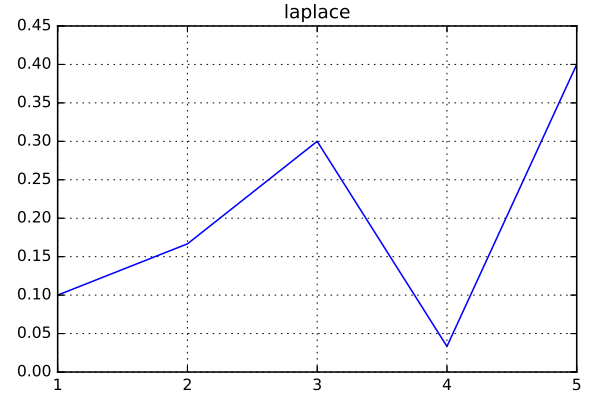


Fig. 5. problem 4(b)

From figures, we can see that increasing the number of pseudocounts makes the connected line softer. In general, it decrease the standard deviation of the

## VI. PROBLEM 6

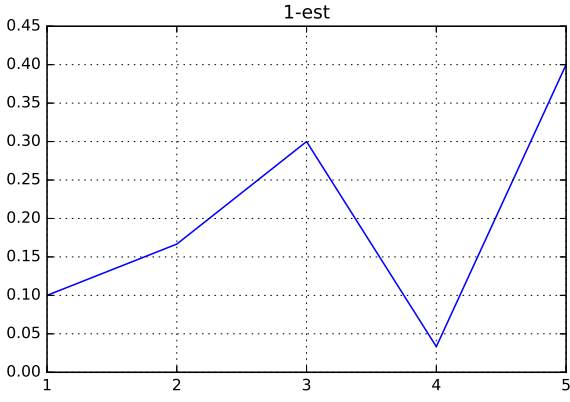


Fig. 6. problem 4(c)

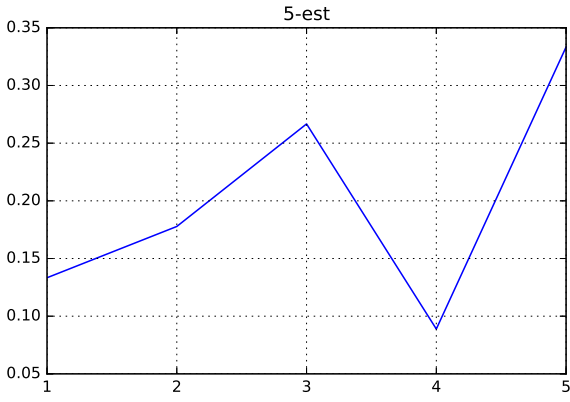


Fig. 7. problem 4(d)

pdf, that is make lower probability higher, higher probability lower. It also shows that with small dataset like this one, higher  $m$  maybe better an more general.

## V. PROBLEM 5

We have Cartesian product of all features

$$4 \times 2 \times 3 \times 4 \quad (4)$$

(a)

$$2^{4*2*3*4} = 2^{96} \quad (5)$$

(b)

$$5 \times 3 \times 4 \times 5 = 300 \quad (6)$$

(c)

$$(4^2 - 1) * (2^2 - 1) * (3^2 - 1) * (4^2 - 1) = 5400 \quad (7)$$