

Assignment 2

Step 1) Data Selection

- **SQL queries:**

```
CREATE TABLE TX_A2_INITIAL AS
```

```
SELECT MESHHEADING, COUNT(DISTINCT TERM) AS NUMBER_OF_TERMS,
COUNT(DISTINCT DMUSER.ML330_SODA_MSH.PMID) AS NUMBER_OF_ABSTRACTS
```

```
FROM DMUSER.ML330_SODA_MSH, DMUSER.ML330_SODA_NWD
```

```
WHERE DMUSER.ML330_SODA_MSH.PMID = DMUSER.ML330_SODA_NWD.PMID
```

```
GROUP BY MESHHEADING;
```

- **Result:**

	MESHHEADING	NUMBER_OF_TERMS	NUMBER_OF_ABSTRACTS
1	Heart Diseases	67713	25000
2	Lung Neoplasms	89205	25000

For category 'Heart Diseases', there are 67713 distinct terms and 25000 abstracts.

For category 'Lung Neoplasms', there are 89205 distinct terms and 25000 abstracts.

There are some overlapping terms between the two categories.

Step 2) Preprocessing

- How many words are there with no vocabulary changes or pruning?

```
SELECT COUNT(DISTINCT TERM)
```

```
FROM DMUSER.ML330_SODA_NWD;
```

	COUNT(DISTINCTTERM)
1	126848

Before any preprocessing, the total number of distinct terms of both categories is 126848.

- How many lower case words are there?

```
SELECT COUNT(DISTINCT TERM)
```

```
FROM DMUSER.ML330_SODA_NWD
```

```
WHERE TERM = LOWER(TERM);
```

	COUNT(DISTINCTTERM)
1	83383

There are 83383 terms in lowercase.

```
SELECT COUNT(DISTINCT LOWER(TERM))
```

```
FROM DMUSER.ML330_SODA_NWD;
```

COUNT(DISTINCT LOWER(TERM))	
1	114881

The total number of distinct terms when converting to lowercase is 114881.

- How many words are there after removing stop words?

I imported stop word list from <http://www.lextek.com/manuals/onix/stopwords2.html>, and created a table named TX_A2_STOPWORDS. The list contains 571 words.

```
SELECT COUNT(DISTINCT LOWER(TERM))
FROM DMUSER.ML330_SODA_NWD, TX_A2_STOPWORDS
WHERE LOWER(TERM) = TX_A2_STOPWORDS.STOPWORD;
```

COUNT(DISTINCT LOWER(TERM))	
1	490

There are 490 words of the terms can be regarded as stop words. So after removing stop words, there are $114881 - 490 = 114391$ distinct words in lower case.

- Select distinct terms in lowercase without stopwords

```
CREATE TABLE TX_A2_DISTINCT_LOWER_NOSTOP AS
SELECT DISTINCT LOWER(TERM) AS DISTINCTTERM
FROM DMUSER.ML330_SODA_NWD;
DELETE FROM TX_A2_DISTINCT_LOWER_NOSTOP
WHERE DISTINCTTERM IN (SELECT DISTINCTTERM
                        FROM TX_A2_DISTINCT_LOWER_NOSTOP, TX_A2_STOPWORDS
                        WHERE DISTINCTTERM = STOPWORD);
SELECT COUNT(*)
FROM TX_A2_DISTINCT_LOWER_NOSTOP;
```

COUNT(*)	
1	114391

- Identify and remove terms that appear in few abstracts or in most abstracts

(1) Remove terms that appear less than 11 times.

```
CREATE TABLE TX_A2_DF AS
SELECT DISTINCTTERM, COUNT(DISTINCT DMUSER.ML330_SODA_NWD.PMID) AS
ABSTRACTNUMBER
FROM TX_A2_DISTINCT_LOWER_NOSTOP, DMUSER.ML330_SODA_NWD
```

```
WHERE TX_A2_DISTINCT_LOWER_NOSTOP.DISTINCTTERM
LOWER(DMUSER.ML330_SODA_NWD.TERM) =
```

```
GROUP BY DISTINCTTERM
```

```
HAVING COUNT(DISTINCT DMUSER.ML330_SODA_NWD.PMID)>10
```

```
ORDER BY COUNT(DISTINCT DMUSER.ML330_SODA_NWD.PMID) DESC;
```

(2) Remove terms that are integers less than 50 and have appeared many times in different abstracts.

Remove some special meaningless words such as “s”.

62	response	3127	-15	2	5657
			16	carcinoma	5331
			17	significant	5270
-63	's	3125	18	cases	5228
64	levels	3081	-19	1	5222

(3) The word that appears most among all the abstracts is ‘lung’. It appears 17566 times in different abstracts. However, there are 50,000 abstracts in all. So there is no need to remove words which appear so many times.

	DISTINCTTERM	ABSTRACTNUMBER
1	lung	17566
2	patients	16473
3	cancer	13690
4	results	11788
5	disease	10648

```
SELECT COUNT(*)
```

```
FROM TX_A2_DF;
```

	COUNT(*)
1	14531

The number of terms after step 2 is 14531.

Step 3) Transformations

3.1) Term Frequency (tf) * Inverse Document Frequency (idf)

- SQL queries for computing tf*idf:

```
CREATE TABLE TX_A2_TF AS
```

```
SELECT DISTINCTTERM, PMID, COUNT(LOWER(DMUSER.ML330_SODA_NWD.TERM)) AS
TERMSNUMBER
```

```
FROM DMUSER.ML330_SODA_NWD, TX_A2_DF
```

```
WHERE LOWER(DMUSER.ML330_SODA_NWD.TERM) = TX_A2_DF.DISTINCTTERM
```

```
GROUP BY DISTINCTTERM, PMID
```

```
ORDER BY COUNT(LOWER(DMUSER.ML330_SODA_NWD.TERM)) DESC;
```

```
SELECT COUNT(DISTINCT DISTINCTTERM)
```

```
FROM TX_A2_TF;
```

```
CREATE TABLE TX_A2_TFIDF AS
```

```
SELECT TX_A2_TF.DISTINCTTERM, PMID, TERMNUMBER * (LOG(2,50000)-  
LOG(2,ABSTRACTNUMBER)+1) AS TFIDF
```

```
FROM TX_A2_DF, TX_A2_TF
```

```
WHERE TX_A2_TF.DISTINCTTERM = TX_A2_DF.DISTINCTTERM
```

```
ORDER BY TERMNUMBER * (LOG(2,50000)-LOG(2,ABSTRACTNUMBER)+1) DESC;
```

```
SELECT COUNT(*)
```

```
FROM TX_A2_TFIDF;
```

```
CREATE TABLE TX_A2_TFIDF_TOP AS
```

```
SELECT DISTINCT DISTINCTTERM, MAX(TFIDF) AS MAXTFIDF
```

```
FROM TX_A2_TFIDF
```

```
GROUP BY DISTINCTTERM
```

```
ORDER BY MAX(TFIDF) DESC;
```

- Select top 100/200/500 terms with highest values of $tf*idf$.

```
SELECT DISTINCTTERM
```

```
FROM TX_A2_TFIDF_TOP
```

```
WHERE ROWNUM<=100; or 200 or 500
```

3.2) Information Gain

- Probability of $Pr(t)$

```
CREATE TABLE TX_A2_DF_PR1 AS
```

```
SELECT DISTINCTTERM, ABSTRACTNUMBER/50000 AS PR1
```

FROM TX_A2_DF;

- Probability of Pr(Lung Neoplasms|t)

CREATE TABLE TX_A2_DF_LUNGNUMBER AS

SELECT TX_A2_DF.DISTINCTTERM, COUNT(DISTINCT DMUSER.ML330_SODA_NWD.PMID)
AS LUNGNUMBER

FROM TX_A2_DF, DMUSER.ML330_SODA_MSH, DMUSER.ML330_SODA_NWD

WHERE TX_A2_DF.DISTINCTTERM = LOWER(DMUSER.ML330_SODA_NWD.TERM) AND
DMUSER.ML330_SODA_NWD.PMID = DMUSER.ML330_SODA_MSH.PMID

AND DMUSER.ML330_SODA_MSH.MESHHEADING = 'Lung Neoplasms'

GROUP BY TX_A2_DF.DISTINCTTERM

ORDER BY LUNGNUMBER DESC;

CREATE TABLE TX_A2_DF_NUM_PR2 AS

SELECT TX_A2_DF.DISTINCTTERM, TX_A2_DF_LUNGNUMBER.LUNGNUMBER AS
LUNGNUMBER

FROM TX_A2_DF_LUNGNUMBER

RIGHT OUTER JOIN TX_A2_DF

ON TX_A2_DF.DISTINCTTERM = TX_A2_DF_LUNGNUMBER.DISTINCTTERM;

- ❖ Right outer join is critical with null values for future computation of probability

CREATE TABLE TX_A2_DF_PR2 AS

SELECT TX_A2_DF.DISTINCTTERM, LUNGNUMBER/ABSTRACTNUMBER AS PR2

FROM TX_A2_DF, TX_A2_DF_NUM_PR2

WHERE TX_A2_DF.DISTINCTTERM = TX_A2_DF_NUM_PR2.DISTINCTTERM;

- Probability of Pr(Heart Diseases|t)

CREATE TABLE TX_A2_DF_HEARTNUMBER AS

SELECT TX_A2_DF.DISTINCTTERM, COUNT(DISTINCT DMUSER.ML330_SODA_NWD.PMID)
AS HEARTNUMBER

FROM TX_A2_DF, DMUSER.ML330_SODA_MSH, DMUSER.ML330_SODA_NWD

WHERE TX_A2_DF.DISTINCTTERM = LOWER(DMUSER.ML330_SODA_NWD.TERM) AND
DMUSER.ML330_SODA_NWD.PMID = DMUSER.ML330_SODA_MSH.PMID

AND DMUSER.ML330_SODA_MSH.MESHHEADING = 'Heart Diseases'

GROUP BY TX_A2_DF.DISTINCTTERM

ORDER BY HEARTNUMBER DESC;

CREATE TABLE TX_A2_DF_NUM_PR3 AS

SELECT TX_A2_DF.DISTINCTTERM, TX_A2_DF_HEARTNUMBER.HEARTNUMBER AS
HEARTNUMBER

FROM TX_A2_DF_HEARTNUMBER

RIGHT OUTER JOIN TX_A2_DF

ON TX_A2_DF.DISTINCTTERM = TX_A2_DF_HEARTNUMBER.DISTINCTTERM;

CREATE TABLE TX_A2_DF_PR3 AS

SELECT TX_A2_DF.DISTINCTTERM, HEARTNUMBER/ABSTRACTNUMBER AS PR3

FROM TX_A2_DF, TX_A2_DF_NUM_PR3

WHERE TX_A2_DF.DISTINCTTERM = TX_A2_DF_NUM_PR3.DISTINCTTERM;

- Probability of Pr(not t)

CREATE TABLE TX_A2_DF_PR4 AS

SELECT DISTINCTTERM, 1 - ABSTRACTNUMBER/50000 AS PR4

FROM TX_A2_DF;

- Probability of Pr(Lung Neoplasma|not t)

CREATE TABLE TX_A2_DF_PR5 AS

SELECT TX_A2_DF.DISTINCTTERM, (25000-NVL(LUNGNUMBER,0))/(50000-
ABSTRACTNUMBER) AS PR5

FROM TX_A2_DF, TX_A2_DF_NUM_PR2

WHERE TX_A2_DF.DISTINCTTERM = TX_A2_DF_NUM_PR2.DISTINCTTERM;

- Probability of Pr(Heart Diseases|not t)

CREATE TABLE TX_A2_DF_PR6 AS

SELECT TX_A2_DF.DISTINCTTERM, (25000-NVL(HEARTNUMBER,0))/(50000-
ABSTRACTNUMBER) AS PR6

FROM TX_A2_DF, TX_A2_DF_NUM_PR3

WHERE TX_A2_DF.DISTINCTTERM = TX_A2_DF_NUM_PR3.DISTINCTTERM;

- Compute IG of each term

CREATE TABLE TX_A2_IG AS

```

SELECT    TX_A2_DF_PR1.DISTINCTTERM,    (PR1*(NVL(PR2,0)*LOG(2,NVL(PR2,1))    +
NVL(PR3,0)*LOG(2,NVL(PR3,1))) + PR4*(PR5*LOG(2,PR5) + PR6*LOG(2,PR6))) AS IG
FROM TX_A2_DF_PR1, TX_A2_DF_PR2, TX_A2_DF_PR3, TX_A2_DF_PR4, TX_A2_DF_PR5,
TX_A2_DF_PR6

WHERE    TX_A2_DF_PR1.DISTINCTTERM    =    TX_A2_DF_PR2.DISTINCTTERM    AND
TX_A2_DF_PR2.DISTINCTTERM = TX_A2_DF_PR3.DISTINCTTERM

    AND    TX_A2_DF_PR3.DISTINCTTERM    =    TX_A2_DF_PR4.DISTINCTTERM    AND
TX_A2_DF_PR4.DISTINCTTERM = TX_A2_DF_PR5.DISTINCTTERM

    AND TX_A2_DF_PR5.DISTINCTTERM = TX_A2_DF_PR6.DISTINCTTERM

ORDER BY IG DESC;

```

- Select top 100/200/500 terms with highest values of Information Gain.

```

SELECT DISTINCTTERM
FROM TX_A2_IG
WHERE ROWNUM<=100;   or 200 or 500

```

3.3) Create tables for classification

Create 6 tables with 100, 200 and 500 terms for tf*idf and for information gain respectively.

- Table1: Top 100 terms for tf*idf

```

CREATE TABLE TX_A2_C1 AS
SELECT TX_A2_FEATURES1.*, DMUSER.ML330_SODA_MSH.MESHHEADING
FROM TX_A2_FEATURES1
JOIN DMUSER.ML330_SODA_MSH
ON TX_A2_FEATURES1.PMID = DMUSER.ML330_SODA_MSH.PMID;

```

	PMID	MG_M	ANP	TGF_BETA	TOPOTECAN	BUPIVACAINE	DOT	ANG
1	35194	0	0	0	0	0	0	0
2	36578	0	0	0	0	0	0	0
3	36744	0	0	0	0	0	0	0
4	37740	0	0	0	0	0	0	0
5	38426	0	0	0	0	0	0	0

- Table2: Top 200 terms for tf*idf

```

CREATE TABLE TX_A2_C2 AS
SELECT TX_A2_FEATURES2.*, DMUSER.ML330_SODA_MSH.MESHHEADING
FROM TX_A2_FEATURES2

```

```
JOIN DMUSER.ML330_SODA_MSH
```

```
ON TX_A2_FEATURES2.PMID = DMUSER.ML330_SODA_MSH.PMID;
```

- Table3: Top 500 terms for tf*idf

```
CREATE TABLE TX_A2_C3 AS
```

```
SELECT TX_A2_FEATURES3.*, DMUSER.ML330_SODA_MSH.MESHHEADING
```

```
FROM TX_A2_FEATURES3
```

```
JOIN DMUSER.ML330_SODA_MSH
```

```
ON TX_A2_FEATURES3.PMID = DMUSER.ML330_SODA_MSH.PMID;
```

- Table4: Top 100 terms for Information Gain

```
CREATE TABLE TX_A2_C4 AS
```

```
SELECT TX_A2_FEATURES4.*, DMUSER.ML330_SODA_MSH.MESHHEADING
```

```
FROM TX_A2_FEATURES4
```

```
JOIN DMUSER.ML330_SODA_MSH
```

```
ON TX_A2_FEATURES4.PMID = DMUSER.ML330_SODA_MSH.PMID;
```

	PMID	LUNG	CANCER	HEART	CARDIAC	CELL	TUMOR
1	56439	0	1	0	0	0	3
2	56980	2	1	0	0	0	1
3	56986	0	0	0	0	0	10
4	56987	4	3	0	0	3	0
5	57472	0	0	0	0	0	0

- Table5: Top 200 terms for Information Gain

```
CREATE TABLE TX_A2_C5 AS
```

```
SELECT TX_A2_FEATURES5.*, DMUSER.ML330_SODA_MSH.MESHHEADING
```

```
FROM TX_A2_FEATURES5
```

```
JOIN DMUSER.ML330_SODA_MSH
```

```
ON TX_A2_FEATURES5.PMID = DMUSER.ML330_SODA_MSH.PMID;
```

- Table6: Top 500 terms for Information Gain

```
CREATE TABLE TX_A2_C6 AS
```

```
SELECT TX_A2_FEATURES6.*, DMUSER.ML330_SODA_MSH.MESHHEADING
```

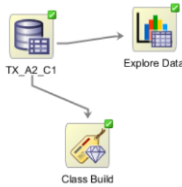
```
FROM TX_A2_FEATURES6
```

```
JOIN DMUSER.ML330_SODA_MSH
```

```
ON TX_A2_FEATURES6.PMID = DMUSER.ML330_SODA_MSH.PMID;
```


Step 4) Data Mining

Use the oracle data miner to create two classifiers (a decision tree and naïve bayes) for the 6 tables of feature sets. The screenshot below is an example.



Step 5) Interpretation

1. Table of top 100 terms for tf*idf

- Accuracy and confusion matrix of decision trees

Average Accuracy: 53.4149 Overall Accuracy: 53.4149 Total Cost: 18,580		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
	Heart Diseases	9,876	95	9,971	99.0472	190
	Lung Neoplasms	9,195	776	9,971	7.7826	18,390
	Total	19,071	871	19,942		
	Correct %	51.7854	89.093			
	Cost	18,390	190			

- Accuracy and confusion matrix of naïve bayes

Average Accuracy: 54.3927 Overall Accuracy: 54.3927		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
	Heart Diseases	9,867	104	9,971	98.957	
	Lung Neoplasms	8,991	980	9,971	9.8285	
	Total	18,858	1,084	19,942		
	Correct %	52.3226	90.4059			
	Cost					

2. Table of top 200 terms for tf*idf

- Accuracy and confusion matrix of decision trees

Average Accuracy: 53.9214 Overall Accuracy: 53.9214 Total Cost: 18,378		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
	Heart Diseases	9,917	54	9,971	99.4584	108
	Lung Neoplasms	9,135	836	9,971	8.3843	18,270
	Total	19,052	890	19,942		
	Correct %	52.0523	93.9326			
	Cost	18,270	108			

- Accuracy and confusion matrix of naïve bayes

Average Accuracy: 57.4967 Overall Accuracy: 57.4967		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
	Heart Diseases	9,753	218	9,971	97.8137	
	Lung Neoplasms	8,258	1,713	9,971	17.1798	
	Total	18,011	1,931	19,942		
	Correct %	54.1502	88.7105			
	Cost					

3. Table of top 500 terms for tf*idf

- Accuracy and confusion matrix of decision trees

		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Average Accuracy: 58.7403	Heart Diseases	1,795	8,176	9,971	18.0022	16,352
Overall Accuracy: 58.7403	Lung Neoplasms	52	9,919	9,971	99.4785	104
Total Cost: 16,456	Total	1,847	18,095	19,942		
	Correct %	97.1846	54.8162			
	Cost	104	16,352			

- Accuracy and confusion matrix of naïve bayes

		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Average Accuracy: 62.9024	Heart Diseases	9,666	305	9,971	96.9411	
Overall Accuracy: 62.9024	Lung Neoplasms	7,093	2,878	9,971	28.8637	
	Total	16,759	3,183	19,942		
	Correct %	57.6765	90.4178			
	Cost					

4. Table of top 100 terms for Information Gain

- Accuracy and confusion matrix of decision trees

		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Average Accuracy: 90.7582	Heart Diseases	9,764	207	9,971	97.924	414
Overall Accuracy: 90.7582	Lung Neoplasms	1,636	8,335	9,971	83.5924	3,272
Total Cost: 3,686	Total	11,400	8,542	19,942		
	Correct %	85.6491	97.5767			
	Cost	3,272	414			

- Accuracy and confusion matrix of naïve bayes

		Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Average Accuracy: 91.1192	Heart Diseases	9,837	134	9,971	98.6561	
Overall Accuracy: 91.1192	Lung Neoplasms	1,637	8,334	9,971	83.5824	
	Total	11,474	8,468	19,942		
	Correct %	85.733	98.4176			
	Cost					

5. Table of top 200 terms for Information Gain

- Accuracy and confusion matrix of decision trees

	Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Heart Diseases	9,764	207	9,971	97.924	414
Lung Neoplasms	1,636	8,335	9,971	83.5924	3,272
Total	11,400	8,542	19,942		
Correct %	85.6491	97.5767			
Cost	3,272	414			

Average Accuracy: 90.7582
 Overall Accuracy: 90.7582
 Total Cost: 3,686

- Accuracy and confusion matrix of naïve bayes

	Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Heart Diseases	9,829	142	9,971	98.5759	
Lung Neoplasms	1,746	8,225	9,971	82.4892	
Total	11,575	8,367	19,942		
Correct %	84.9158	98.3029			
Cost					

Average Accuracy: 90.5325
 Overall Accuracy: 90.5325

6. Table of top 500 terms for Information Gain

- Accuracy and confusion matrix of decision trees

	Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Heart Diseases	9,764	207	9,971	97.924	414
Lung Neoplasms	1,636	8,335	9,971	83.5924	3,272
Total	11,400	8,542	19,942		
Correct %	85.6491	97.5767			
Cost	3,272	414			

Average Accuracy: 90.7582
 Overall Accuracy: 90.7582
 Total Cost: 3,686

- Accuracy and confusion matrix of naïve bayes

	Heart Diseases	Lung Neoplasms	Total	Correct %	Cost
Heart Diseases	9,786	185	9,971	98.1446	
Lung Neoplasms	2,275	7,696	9,971	77.1838	
Total	12,061	7,881	19,942		
Correct %	81.1376	97.6526			
Cost					

Average Accuracy: 87.6642
 Overall Accuracy: 87.6642

7. Findings from the above results

In general, performances of text classification of feature sets based on tf*idf selection method are much worse than those of feature sets based on Information Gain. The overall accuracy of tf*idf feature sets is about 50% to 65%, while the overall accuracy of Information Gain feature sets is about 90%. So information gain feature selection method is more effective for this text classification project.

Discrepancies of accuracy between decision trees and naïve bayes are not obvious for the same table (source data). For top 100/200/500 terms based on tf*idf and top 100 terms based on information gain, the performances of naïve bayes are a little bit better than decision trees.

For tf*idf feature sets, as the number of terms increases, the accuracy of both decision trees and naïve bayes increase. As can be seen in the confusion matrix, the accuracy of 'Heart Diseases' is much higher than 'Lung Neoplasms'. However, there is a reverse for the accuracy of decision trees with 500 terms based on tf*idf, which shows that the performance of identification of 'Lung Neoplasms' is much better than the other.

For information gain feature sets, as the number of terms increases, there is no difference between the accuracy of decision trees. Decision trees have the same performance on all the three tables based on information gain regardless of the number of terms. On the other hand, however, as the number of terms rises, the accuracy of naïve bayes declines for feature sets based on information gain.

As the number of terms increase, the model of decision trees become more sophisticated with more braches. After taking a look at the selected terms that played an important role for text classification, I find that top terms selected by information gain look more reasonable and anticipated, while top terms selected by tf*idf seem surprised to me.