Example of transforming a term-document matrix using TFxIDF (Term Frequency x Inverse Document Frequency)

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
Data = pd.read_csv("http://facweb.cs.depaul.edu/mobasher/classes/csc478/data
Data
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	database	24	32	12	6	43	2	0	3	1	6	4	0	0	0	0
1	index	9	5	5	2	20	0	1	0	0	0	27	14	3	2	11
2	likelihood	0	3	0	0	3	7	12	4	27	4	0	1	0	0	0
3	linear	3	0	0	0	0	16	0	2	25	23	7	12	21	3	2
4	matrix	1	0	0	0	0	33	2	0	7	12	14	5	12	4	0
5	query	12	2	0	0	27	0	0	0	0	22	9	4	0	5	3
6	regression	0	0	0	0	0	18	32	22	34	17	0	0	0	0	0
7	retrieval	1	0	0	0	2	0	0	0	3	9	27	7	5	4	4
8	sql	21	10	16	7	31	0	0	0	0	0	0	0	0	1	0
9	vector	2	0	0	2	0	27	4	2	11	8	33	16	14	7	3

In [3]:

```
# Let's remove the column containing the terms
# TD will be out term x document matrix
TD = Data.iloc[:,1:]
TD
```

Out[3]:

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	24	32	12	6	43	2	0	3	1	6	4	0	0	0	0
1	9	5	5	2	20	0	1	0	0	0	27	14	3	2	11
2	0	3	0	0	3	7	12	4	27	4	0	1	0	0	0
3	3	0	0	0	0	16	0	2	25	23	7	12	21	3	2
4	1	0	0	0	0	33	2	0	7	12	14	5	12	4	0
5	12	2	0	0	27	0	0	0	0	22	9	4	0	5	3
6	0	0	0	0	0	18	32	22	34	17	0	0	0	0	0
7	1	0	0	0	2	0	0	0	3	9	27	7	5	4	4
8	21	10	16	7	31	0	0	0	0	0	0	0	0	1	0
9	2	0	0	2	0	27	4	2	11	8	33	16	14	7	3

In [4]:

```
# Reindex the columns to start from 0
TD.columns= range(15)
TD
```

Out[4]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	24	32	12	6	43	2	0	3	1	6	4	0	0	0	0
1	9	5	5	2	20	0	1	0	0	0	27	14	3	2	11
2	0	3	0	0	3	7	12	4	27	4	0	1	0	0	0
3	3	0	0	0	0	16	0	2	25	23	7	12	21	3	2
4	1	0	0	0	0	33	2	0	7	12	14	5	12	4	0
5	12	2	0	0	27	0	0	0	0	22	9	4	0	5	3
6	0	0	0	0	0	18	32	22	34	17	0	0	0	0	0
7	1	0	0	0	2	0	0	0	3	9	27	7	5	4	4
8	21	10	16	7	31	0	0	0	0	0	0	0	0	1	0
9	2	0	0	2	0	27	4	2	11	8	33	16	14	7	3

In [5]:

```
# The list of our index terms
terms = Data.iloc[:,0]
terms
```

Out[5]:

```
0      database
1         index
2    likelihood
3        linear
4        matrix
5         query
6    regression
7     retrieval
8           sql
9        vector
Name: 0, dtype: object
```

In [6]:

```
TD.shape
```

Out[6]:

```
(10, 15)
```

In [7]:

```
numTerms=TD.shape[0]
NDocs = TD.shape[1]
```

In [8]:

```
print(numTerms)
print(NDocs)
```

```
10
15
```

Next, let's compute term frequencies to get an idea of their distributions across the corpus.

In [9]:

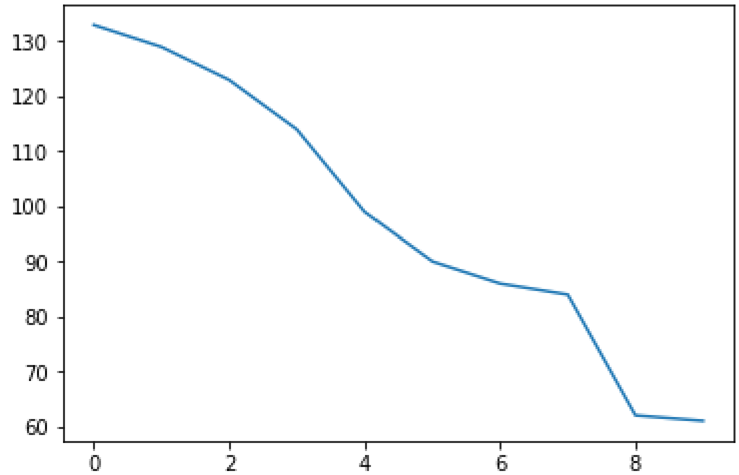
```
termFreqs = TD.sum(axis=1)
termFreqs
```

Out[9]:

```
0    133
1     99
2     61
3    114
4     90
5     84
6    123
7     62
8     86
9    129
dtype: int64
```

In [10]:

```
plt.plot(sorted(termFreqs, reverse=True))
plt.show()
```



Next, we will transform the data to TFxIDF weights:

In [11]:

```
# Note: doc frequency (df) for a term t is the number of docs in which t app

# first let's find the doc counts for each term

DF = pd.DataFrame([(TD!=0).sum(1)]).T
DF
```

Out[11]:

	0
0	10
1	11
2	8
3	10
4	9
5	8
6	5
7	9
8	6
9	12

In [12]:

```
# Create a matrix with all entries = NDocs
NMatrix=np.ones(np.shape(TD), dtype=float)*NDocs
np.set_printoptions(precision=2,suppress=True,linewidth=120)
print(NMatrix)
```

```
[[15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15.]
 [15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15.]
 [15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15.]
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 [15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15.]
 [15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15.]
 [15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15.]
 [15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15. 15.]]
```

In [13]:

```
# Convert each entry into IDF values
# IDF is the log of the inverse of document frequency
# Note that IDF is only a function of the term, so all columns will be ident

IDF = np.log2(np.divide(NMatrix, np.array(DF)))
```

In [14]:

```
print(IDF)
```

```
[[0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.
 [0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.45 0.
 [0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.
 [0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.58 0.
 [0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.
 [0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.91 0.
 [1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.58 1.
 [0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.74 0.
 [1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.32 1.
 [0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.32 0.
```

In [15]:

```
# Finally compute the TFxIDF values for each document-term entry
TD_tfidf = TD * IDF
```

In [16]:
```
pd.set_option("display.precision", 2)

TD_tfidf
```

Out[16]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	1:
0	14.04	18.72	7.02	3.51	25.15	1.17	0.00	1.75	0.58	3.51	2.34	0.00	0.00	0.0(
1	4.03	2.24	2.24	0.89	8.95	0.00	0.45	0.00	0.00	0.00	12.08	6.26	1.34	0.8!
2	0.00	2.72	0.00	0.00	2.72	6.35	10.88	3.63	24.49	3.63	0.00	0.91	0.00	0.0(
3	1.75	0.00	0.00	0.00	0.00	9.36	0.00	1.17	14.62	13.45	4.09	7.02	12.28	1.7!
4	0.74	0.00	0.00	0.00	0.00	24.32	1.47	0.00	5.16	8.84	10.32	3.68	8.84	2.9!
5	10.88	1.81	0.00	0.00	24.49	0.00	0.00	0.00	0.00	19.95	8.16	3.63	0.00	4.5:
6	0.00	0.00	0.00	0.00	0.00	28.53	50.72	34.87	53.89	26.94	0.00	0.00	0.00	0.0(
7	0.74	0.00	0.00	0.00	1.47	0.00	0.00	0.00	2.21	6.63	19.90	5.16	3.68	2.9!
8	27.76	13.22	21.15	9.25	40.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.3:
9	0.64	0.00	0.00	0.64	0.00	8.69	1.29	0.64	3.54	2.58	10.62	5.15	4.51	2.2!

Let's now repeat the k-nearest-neighbor document retrieval example from earier notebook, but this time, we'll use the TFxIDF weighted document vectors.

In [17]:
```
def knn_search(x, D, K, measure):
    """ find K nearest neighbors of an instance x among the instances in D '
    if measure == 0:
        # euclidean distances from the other points
        dists = np.sqrt(((D - x)**2).sum(axis=1))
    elif measure == 1:
        # first find the vector norm for each instance in D as wel as the nc
        D_norm = np.array([np.linalg.norm(D[i]) for i in range(len(D))])
        x_norm = np.linalg.norm(x)
        # Compute Cosine: divide the dot product o x and each instance in D
        sims = np.dot(D,x)/(D_norm * x_norm)
        # The distance measure will be the inverse of Cosine similarity
        dists = 1 - sims
    idx = np.argsort(dists) # sorting
    # return the indexes of K nearest neighbors
    return idx[:K], dists
```

Let's now try this on a new query object as a test instance

In [18]:
```
x = np.array([3, 22, 0, 17, 9, 6, 1, 12, 0, 22])
```

Need to also perform TFxIDF transformation on the query

In [19]:
```
# Each term in query x must be multiplied by the idf value of the term we cc
x_tfidf = x * IDF.T[0]  # note that this coordinatewise multiplication of tw
print(x_tfidf)
```

```
[1.75 9.84 0.   9.94 6.63 5.44 1.58 8.84 0.   7.08]
```

In [20]:
```
# The KNN Search function expects a document x term materix as an np array,
DT_tfidf = TD_tfidf.T
DT_array = np.array(DT_tfidf)
```

In [21]:
```
# Finding the k=5 nearest neighbors using inverse of Cosine similarity as a
neigh_idx, distances = knn_search(x_tfidf, DT_array, 5, 1)
```

In [22]:
```
distances = pd.Series(distances, index=DT_tfidf.index)
distances.sort_values()
```

Out[22]:
```
11    0.01
10    0.10
14    0.18
13    0.20
12    0.21
9     0.44
5     0.55
4     0.75
8     0.75
0     0.77
1     0.86
7     0.89
6     0.90
3     0.90
2     0.92
dtype: float64
```

In [23]:
```
print("Query:", x)
print("\nNeighbors:")
DT_tfidf.iloc[neigh_idx]
```

```
Query: [ 3 22  0 17  9  6  1 12  0 22]

Neighbors:
```

Out[23]:

	0	1	2	3	4	5	6	7	8	9
11	0.00	6.26	0.91	7.02	3.68	3.63	0.0	5.16	0.00	5.15
10	2.34	12.08	0.00	4.09	10.32	8.16	0.0	19.90	0.00	10.62
14	0.00	4.92	0.00	1.17	0.00	2.72	0.0	2.95	0.00	0.97
13	0.00	0.89	0.00	1.75	2.95	4.53	0.0	2.95	1.32	2.25
12	0.00	1.34	0.00	12.28	8.84	0.00	0.0	3.68	0.00	4.51

If you compare this result to the one from the previous notebook (where we did not use TFxIDF), you'll note that document 12 was demoted in the new ranking (it was previously in the 3rd position). This is likely because this document matched strongly with the query on terms 3 and 9. Both of these terms occur frequently across the documents and so the TFxIDF transformation resulted in their weights being penalized.

Next, let's extend this example to classification using the KNN approach.

In [24]:

```
# Let's add some labels to our original data

cat_labels = np.array(["Databases", "Databases", "Databases", "Databases", '
cat_labels = pd.Series(cat_labels, index=DT_tfidf.index)

DT_tfidf["Category"] = cat_labels

DT_tfidf
```

Out[24]:

	0	1	2	3	4	5	6	7	8	9	Category
0	14.04	4.03	0.00	1.75	0.74	10.88	0.00	0.74	27.76	0.64	Databases
1	18.72	2.24	2.72	0.00	0.00	1.81	0.00	0.00	13.22	0.00	Databases
2	7.02	2.24	0.00	0.00	0.00	0.00	0.00	0.00	21.15	0.00	Databases
3	3.51	0.89	0.00	0.00	0.00	0.00	0.00	0.00	9.25	0.64	Databases
4	25.15	8.95	2.72	0.00	0.00	24.49	0.00	1.47	40.98	0.00	Databases
5	1.17	0.00	6.35	9.36	24.32	0.00	28.53	0.00	0.00	8.69	Regression
6	0.00	0.45	10.88	0.00	1.47	0.00	50.72	0.00	0.00	1.29	Regression
7	1.75	0.00	3.63	1.17	0.00	0.00	34.87	0.00	0.00	0.64	Regression
8	0.58	0.00	24.49	14.62	5.16	0.00	53.89	2.21	0.00	3.54	Regression
9	3.51	0.00	3.63	13.45	8.84	19.95	26.94	6.63	0.00	2.58	Regression
10	2.34	12.08	0.00	4.09	10.32	8.16	0.00	19.90	0.00	10.62	Information Retrieval
11	0.00	6.26	0.91	7.02	3.68	3.63	0.00	5.16	0.00	5.15	Information Retrieval
12	0.00	1.34	0.00	12.28	8.84	0.00	0.00	3.68	0.00	4.51	Information Retrieval
13	0.00	0.89	0.00	1.75	2.95	4.53	0.00	2.95	1.32	2.25	Information Retrieval
14	0.00	4.92	0.00	1.17	0.00	2.72	0.00	2.95	0.00	0.97	Information Retrieval

The function below will use our previous knn_search function to identify the label/category for for an instance x to be classifed, using the majority label of the K nearest neighbors of x.

In [25]:

```
def knn_classify(x, D, K, labels, measure):
    from collections import Counter
    neigh_idx, distances = knn_search(x, D, K, measure)
    neigh_labels = labels[neigh_idx]
    count = Counter(neigh_labels)
    print("Labels for top ", K, "neighbors: ", count)
    return count.most_common(1)[0][0]
```

In [26]:

```
print("Instance to classify:\n", x)
print("Predicted Category for the new instance: ", knn_classify(x_tfidf, DT_
```

```
Instance to classify:
 [ 3 22  0 17  9  6  1 12  0 22]
Labels for top  5 neighbors:  Counter({'Information Retrieval': 5})
Predicted Category for the new instance:  Information Retrieval
```

In [ ]: