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Lab3. Computing Document Similarity using VSM

EXCERCISE-1:Print TFIDF values

```
In [13]:
from sklearn.feature_extraction.text import TfidfVectorizer
In [14]:
import pandas as pd
In [15]:
docs=["good movie","not a god movie","did not like","i like it","good one"]
In [32]:
tfidf=TfidfVectorizer(min_df=2,max_df=0.5,ngram_range=(1,2))
features=tfidf.fit_transform(docs)
print(features)
  (0, 1)
               0.7071067811865476
               0.7071067811865476
  (0, 3)
  (1, 0)
               0.7071067811865476
  (1, 2)
               0.7071067811865476
  (2, 1)
               0.7071067811865476
  (2, 3)
               0.7071067811865476
  (3, 0)
               0.7071067811865476
  (3, 2)
               0.7071067811865476
In [33]:
df=pd.DataFrame(
    features.todense(),
    columns=tfidf.get_feature_names())
print(df)
       cat
               house the cat the house
0 0.000000 0.707107 0.000000
                                 0.707107
  0.707107 0.000000 0.707107
                                  0.000000
  0.000000 0.707107 0.000000
                                 0.707107
```

EXCERCISE-2:

0.707107 0.000000 0.707107

4 0.000000 0.000000 0.000000

1. Change the values of min_df and ngram_range and observe various outputs

0.000000

0.000000

```
In [27]:
```

```
tfidf=TfidfVectorizer(min_df=1,max_df=.5,ngram_range=(2,4))
features=tfidf.fit transform(docs)
print(features)
                0.23636461617263152
  (0, 46)
                0.29296784934087045
  (0, 22)
  (0, 19)
                0.29296784934087045
  (0, 52)
                0.29296784934087045
  (0, 25)
                0.29296784934087045
  (0, 47)
                0.29296784934087045
  (0, 23)
                0.29296784934087045
  (0, 20)
                0.29296784934087045
  (0, 53)
                0.29296784934087045
  (0, 48)
                0.29296784934087045
  (0, 24)
                0.29296784934087045
  (0, 21)
                0.29296784934087045
  (1, 38)
                0.2916794154657719
  (1, 8)
                0.36152911730069653
  (1, 36)
                0.36152911730069653
  (1, 41)
                0.36152911730069653
  (1, 9)
                0.36152911730069653
  (1, 37)
                0.36152911730069653
  (1, 42)
                0.36152911730069653
  (1, 10)
                0.36152911730069653
  (2, 46)
                0.21836428188496418
  (2, 26)
                0.27065689895808104
  (2, 33)
                0.27065689895808104
  (2, 2)
                0.27065689895808104
  (2, 17)
                0.27065689895808104
  (2, 28)
                0.27065689895808104
  (2, 35)
                0.27065689895808104
                0.27065689895808104
  (2, 4)
  (3, 38)
                0.24721169864215167
  (3, 5)
                0.3064125284733739
  (3, 14)
                0.3064125284733739
  (3, 0)
                0.3064125284733739
  (3, 39)
                0.3064125284733739
  (3, 6)
                0.3064125284733739
  (3, 15)
                0.3064125284733739
  (3, 1)
                0.3064125284733739
  (3, 40)
                0.3064125284733739
  (3, 7)
                0.3064125284733739
  (3, 16)
                0.3064125284733739
  (4, 43)
                0.3015113445777636
  (4, 11)
                0.3015113445777636
  (4, 30)
                0.3015113445777636
  (4, 29)
                0.3015113445777636
  (4, 44)
                0.3015113445777636
  (4, 12)
                0.3015113445777636
  (4, 31)
                0.3015113445777636
  (4, 51)
                0.3015113445777636
  (4, 45)
                0.3015113445777636
  (4, 13)
                0.3015113445777636
                0.3015113445777636
  (4, 32)
In [34]:
#pretty printing
```

```
0.000000
                                   0.000000
1
   0.707107
                        0.707107
2
  0.000000
             0.707107
                        0.000000
                                   0.707107
                        0.707107
                                   0.000000
   0.707107
             0.000000
  0.000000
             0.000000
                        0.000000
                                   0.000000
```

EXCERCISE-3:Compute Cosine Similarity between 2 Documents

```
In [21]:
```

```
from sklearn.metrics.pairwise import linear_kernel
doc1=features[0:1]
doc2=features[1:2]
score=linear_kernel(doc1,doc2)
print(score)
```

[[0.5]]

```
In [22]:
scores=linear_kernel(doc1,features)
print(scores)
             0.5
                        0.
                                   0.
                                               0.70710678]]
In [24]:
query="I like this good movie"
qfeature=tfidf.transform([query])
scores2=linear_kernel(doc1,features)
print(scores2)
[[1.
             0.5
                        0.
                                    0.
                                               0.70710678]]
```

EXCERCISE-4:Find Top-N similar documents

Question-1. Consider the following documents and compute TFIDF values

```
In [25]:
```

```
docs=["the house had a tiny little mouse",
    "the cat saw the mouse",
    "the mouse ran away from the house",
    "the cat finally ate the mouse",
    "the end of the mouse story"]
```

Question-2.Compute Cosine similarity between 3rd document ("the mouse ran away from the house") with all other documents. Which is the most similar document?

```
In [35]:
```

```
tfidf = TfidfVectorizer(min_df=2, max_df=0.5, ngram_range=(1, 2))
features = tfidf.fit_transform(docs)
print(features)
  (0, 1)
                0.7071067811865476
                0.7071067811865476
  (0, 3)
  (1, 0)
                0.7071067811865476
  (1, 2)
                0.7071067811865476
  (2, 1)
                0.7071067811865476
  (2, 3)
                0.7071067811865476
  (3, 0)
                0.7071067811865476
  (3, 2)
                0.7071067811865476
```

In [36]:

```
doc1=features[0:3]
sr=linear_kernel(doc1, features)
print(sr)

[[1. 0. 1. 0. 0.]
[0. 1. 0. 1. 0.]
```

Question-3. Find Top-2 similar documents for the 3rd document based on Cosine similarity values.

```
In [37]:
```

```
scores2 = linear_kernel(doc1, features)
print(scores2)

[[1. 0. 1. 0. 0.]
```

```
[[1. 0. 1. 0. 0.]
[0. 1. 0. 1. 0.]
[1. 0. 1. 0. 0.]]
```

[1. 0. 1. 0. 0.]]