# **Assignment # 04**Introduction to Data Science



Name: Mohammad Ahmed Shahbaz

**Reg. #:** FA21-BSE-050

**Section:** BSE-C

# **Question 01:**

#### **Sentences:**

- **S1.** "data science is one of the most important courses in computer science"
- S2. "this is one of the best data science courses"
- S3. "the data scientists perform data analysis"

#### **BOW:-**

	<b>S1</b>	S2	S3
this	0	1	0
the	1	1	1
is	1	1	0
one	1	1	0
of	1	1	0
most	1	0	0
important	1	0	0
best	0	1	0
perform	0	0	1
data	1	1	2
computer	1	0	0
analysis	0	0	1
courses	1	1	0
science	2	1	0
in	1	0	0
scientists	0	0	1
Total			
Words	12	9	6

Vectors:	
Vector S1	[0 1 1 1 1 1 1 0 0 1 1 0 1 2 1 0]
Vector S2	[11111001010011 00]
Vector S3	[01000000120100 01]

## TF:-

#### **Total Number of words in S1: 12**

TF(the) = 1/12

**TF(this)** = 0/12 = 0

TF(is) = 1/12

**TF(one)** = 1/12

TF(of) = 1/12

TF(most) = 1/12

TF(important) = 1/12

**TF(best)** = 0/12 = 0

**TF(perform)** = 0/12 = 0

TF(data) = 1/12

TF(computer) = 1/12

**TF**(analysis) = 0/12 = 0

TF(courses) = 1/12

**TF**(science) = 2/12 = 1/6

TF(in) = 1/12

**TF**(scientists) = 0/12 = 0

## **Total Number of words in S2: 9**

TF(the) = 1/12

TF(this) = 1/12

TF(is) = 1/12

TF(one) = 1/12

$$TF(of) = 1/12$$

$$TF(most) = 0/12 = 0$$

$$TF(important) = 0/12 = 0$$

$$TF(best) = 1/12$$

$$TF(perform) = 0/12 = 0$$

$$TF(data) = 1/12$$

$$TF(computer) = 0/12 = 0$$

$$TF(analysis) = 0/12 = 0$$

$$TF(courses) = 1/12$$

$$TF(science) = 1/12$$

$$TF(in) = 0/12 = 0$$

$$TF(scientists) = 0/12 = 0$$

#### **Total Number of words in S3: 6**

$$TF(the) = 1/12$$

$$TF(this) = 0/12 = 0$$

$$TF(is) = 0/12 = 0$$

$$TF(one) = 0/12 = 0$$

$$TF(of) = 0/12 = 0$$

$$TF(most) = 0/12 = 0$$

$$TF(important) = 0/12 = 0$$

$$TF(best) = 0/12 = 0$$

$$TF(perform) = 1/12$$

$$TF(data) = 2/12 = 1/6$$

$$TF(computer) = 0/12 = 0$$

$$TF(analysis) = 1/12$$

$$TF(courses) = 0/12 = 0$$

$$TF(science) = 0/12 = 0$$

$$TF(in) = 0/12 = 0$$

t	t	i	0	0	m	im	b	р	d	СО	Α	С	sc	i	sci	То
h	h	S	n	f	O	ро	е	er	a	m	n	0	ie	n	en	tal
i	е		е		S	rt	S	fo	t	pu	al	u	n		tis	W
S					t		t		а			rs			ts	

							an		r		te	ys	е	(	2			or
							t		m		r	is	S	•	9			ds
S	0	1	1	1	1	1	1	0	0	1	1	0	1		1	1	0	12
1		/	/	/	/	/	/			/	/		/		/	/		
		1	1	1	1	1	1			1	1		1		6	1		
		2	2	2	2	2	2			2	2		2			2		
S	1	1	1	1	1	0	0	1	0	1	0	0	1		1	0	0	9
2	/	/	/	/	/			/		/			/		/			
	1	1	1	1	1			1		1			1		1			
	2	2	2	2	2			2		2			2		2			
S	0	1	0	0	0	0	0	0	1	1	0	1	0		0	0	1	6
3		/							/	/		/					/	
		1							1	6		1					1	
		2							2			2					2	

TF(scientists) = 1/12

## IDF:-

## **IDF for S1:**

IDF(data) = 
$$\log(3/3) = \log(1) = 0$$
  
IDF(science) =  $\log(3/2) = \log(1.5) = 0.176$   
IDF (is) =  $\log(3/2) = \log(1.5) = 0.176$   
IDF (one) =  $\log(3/2) = \log(1.5) = 0.176$   
IDF(of) =  $\log(3/2) = \log(1.5) = 0.176$   
IDF (the) =  $\log(3/3) = \log(1) = 0$   
IDF(most) =  $\log(3/1) = \log(3) = 0.477$ 

IDF(important) = 
$$log(3/1) = log(3) = 0.477$$
  
IDF(courses) =  $log(3/2) = log(1.5) = 0.176$   
IDF(in) =  $log(3/1) = log(3) = 0.477$   
IDF(computer) =  $log(3/2) = log(1.5) = 0.176$ 

#### **IDF for S2:**

IDF(this) = 
$$\log(3/1) = \log(3) = 0.477$$
  
IDF(is) =  $\log((3/2)) = \log(1.5) = 0.176$   
IDF(one) =  $\log(3/2) = \log(1.5) = 0.176$   
IDF(of) =  $\log(3/2) = \log(1.5) = 0.176$   
IDF (the) =  $\log(3/3) = \log(1) = 0$   
IDF(best) = =  $\log(3/1) = \log(3) = 0.477$   
IDF(data) =  $\log(3/3) = \log(1) = 0$   
IDF(science) =  $\log(3/2) = \log(1.5) = 0.176$   
IDF(courses) =  $\log(3/2) = \log(1.5) = 0.176$ 

#### **IDF** for S3:

IDF (the) = 
$$\log(3/3) = \log(1) = 0$$
  
IDF(data) =  $\log(3/3) = \log(1) = 0$   
IDF(scientists) =  $\log(3/1) = \log(3) = 0.477$   
IDF(perform) =  $\log(3/1) = \log(3) = 0.477$   
IDF(analysis) =  $\log(3/1) = \log(3) = 0.477$ 

	IDF
this	0.477
the	0
is	0.176
one	0.176
of	0.176
most	0.477
important	0.477
best	0.477

perform	0.477
data	0
computer	0.176
analysis	0.477
courses	0.176
science	0.176
in	0.477
scientists	0.477

## TF-IDF:-

#### **TF-IDF for S1:**

Tf-idf(data) = 1/12 \* 0 = 0

Tf-idf(science) = 1/6 \* 0.176 = 0.0293

Tf-idf(is) = 1/12 \* 0.176 = 0.014

Tf-idf(one) = 1/12 \* 0.176 = 0.014

Tf-idf(of) = 1/12 \* 0.176 = 0.014

Tf-idf(the) = 1/12 \* 0 = 0

Tf-idf(most) = 1/12 \* 0.477 = 0.039

Tf-idf(important) = 1/12 \* 0.477 = 0.039

Tf-idf(courses) = 1/12 \* 0.176 = 0.014

Tf-idf(in) = 1/12 \* 0.477 = 0.039

Tf-idf(computer) = 1/12 \* 0.176 = 0.014

#### **TF-IDF for S2:**

Tf-idf(this) = 1/9 \* 0.477 = 0.053

Tf-idf(is) = 1/9 \* 0.176 = 0.019

Tf-idf(one) = 1/9 \* 0.176 = 0.019

Tf-idf(of) = 1/9 \* 0.176 = 0.019

Tf-idf(the) = 1/9 \* 0 = 0

Tf-idf(best) = 1/9 \* 0.477 = 0.053

Tf-idf(data) = 1/9 \* 0 = 0

Tf-idf(science) = 1/9 \* 0.176 = 0.019

Tf-idf(courses) = 1/9 \* 0.176 = 0.019

# TF-IDF for S3: "the data scientists perform data analysis"

 $\overline{\text{Tf-idf(the)}} = 1/6 * 0 = 0$ 

Tf-idf(data) = 1/3 \* 0 = 0

Tf-idf(scientists) = 1/6 \* 0.477 = 0.079

Tf-idf(perform) = 1/6 \* 0.477 = 0.079

Tf-idf(analysis) = 1/6 \* 0.477 = 0.079

	TF-	TF-	TF-
	IDF	IDF	IDF
	<b>S1</b>	<b>S2</b>	<b>S3</b>
this	0	0.053	0
the	0	0	0
is	0.014	0.019	0
one	0.014	0.019	0
of	0.014	0.019	0
most	0.039	0	0
important	0.039	0	0
best	0	0.053	0
perform	0	0	0.079
data	0	0	0
computer	0.014	0	0
analysis	0	0	0.079
courses	0.176	0.019	0
science	0.029	0.019	0
in	0.039	0	0
scientists	0	0	0.079

# **Python Code:-**

```
import math
s1 = "data science is one of the most important courses in computer
science";
s2 = "this is one of the best data science courses"
s3 = "the data scientists perform data analysis"
len1 = len(s1);
len2 = len(s2);
len3 = len(s3);
sp_s1 = s1.split()
sp_s2 = s2.split();
sp_s3 = s3.split();
def calculate_term_frequency(words_list):
  total_words = len(words_list)
  word_frequency = { }
  for word in words list:
    if word in word frequency:
       word_frequency[word] += 1
     else:
       word\_frequency[word] = 1
       term_frequency = {word: freq / total_words for word, freq in
word_frequency.items()}
  return term_frequency
tf_s1 = calculate_term_frequency(sp_s1)
```

```
tf_s2 = calculate_term_frequency(sp_s2)
tf_s3 = calculate_term_frequency(sp_s3)
print("Term Frequency in s1:", tf_s1)
print("Term Frequency in s2:", tf_s2)
print("Term Frequency in s3:", tf_s3)
def calculate_idf(documents):
  document_frequency { }
  for doc in documents:
    words = set(doc.split())
    for word in words:
       if word in document_frequency:
        document_frequency:[word] += 1
        else
        document_frequency:[word] = 1
  total_documents = len(documents)
  idf = {word: math.log(total_documents /
(document_frequency[word] + 1)) for word in document_frequency}
  return idf
documents = [s1, s2, s3];
idf values = calculate idf(documents)
print("IDF Values:")
for word, idf in idf values.items():
```

```
print(f"{word}: {idf}")

tfidf_values = [{word: tf_values[i][word] * idf_values[word] for word in tf_values[i]} for i in range(len(tf_values))]

print("TF-IDF Values:")

for i, tfidf in enumerate(tfidf_values):
    print(f"TF-IDF Values for Document {i + 1}: {tfidf}")
```

## **Question 02:**

#### **Cosine Similarity:-**

Vector	[01111110011
<b>S1</b>	01210]
Vector	[11111001010
<b>S2</b>	01100]
Vector	[0100000120
<b>S3</b>	10001]

**Vector Length of S3** = 
$$(\sum (S3i)^2) \land 1.5 = 0 + 1 + 1 + 4 + 1 + 1 = 8$$

**Dot Product of S1 and S2** = 
$$0*1 + 1*1 + 1*1 + 1*1 + 1*1 + 1*0 + 1*0 + 0*1 + 0*0 + 1*1 + 1*0 + 0*0 + 1*1 + 2*1 + 1*0 + 0*0 = 1+1+1+1+1+2 = 8$$

**Dot Product of S1 and S3** = 
$$0*0 + 1*1 + 1*0 + 1*0 + 1*0 + 1*0 + 1*0 + 0*0 + 0*1 + 1*2 + 1*0 + 0*1 + 1*0 + 2*0 + 1*0 = 1+2 = 3$$

**Dot product of S2 and S3** = 
$$1*0 + 1*1 + 1*0 + 1*0 + 1*0 + 0*0 + 0*0 + 1*0 + 0*1 + 1*2 + 0*0 + 1*1 + 1*0 + 1*0 + 0*0 + 0*1 = 1+2+1 = 3$$

**Cosine S1-S2** = 
$$8/14*9 = 0.0634$$

**Cosine S2-S3** = 
$$3/9*8 = 0.04166$$

**Cosine S1-S3** = 
$$3/14*8 = 0.0267$$

## **Manhattan Distance:**

Manhattan distance is the sum of the absolute differences between corresponding components of vectors.

#### Manhattan distance between:

- S1 and S2:  $\sum |S1i-S2i|$
- S1 and S3:  $\sum |S1i-S3i|$
- S2 and S3:  $\sum |S2i-S3i|$

#### **Results:**

- Manhattan distance between S1 and S2: 1.7045
- Manhattan distance between S1 and S3: 1.9502
- Manhattan distance between S2 and S3: 1.4861

## **Euclidean Distance:**

Euclidean distance is the square root of the sum of the squared differences between corresponding components of vectors.

#### **Euclidean distance between:**

• S1 and S2:  $\sum (S1i-S2i)^{(1/2)2}$ 

• S1 and S3:  $\sum (S1i-S3i)^{(1/2)2}$ 

• S2 and S3:  $\sum (S2i-S3i)^{(1/2)2}$ 

#### **Results:**

• Euclidean distance between S1 and S2: 0.9474

• Euclidean distance between S1 and S3: 1.1491

• Euclidean distance between S2 and S3: 0.8855

# **Python Code:-**

from collections import Counter

import math

s1 = "data science is one of the most important courses in computer science"

s2 = "this is one of the best data science courses"

s3 = "the data scientists perform data analysis"

tokens\_s1 = s1.split()

```
tokens s2 = s2.split()
tokens s3 = s3.split()
vector s1 = Counter(tokens s1);
vector_s2 = Counter(tokens_s2);
vector_s3 = Counter(tokens_s3);
def cosine similarity(vec1, vec2):
  intersection = set(vec1.keys()) & set(vec2.keys())
  numerator = sum(vec1[word] * vec2[word] for word in
intersection)
  sum_sq_vec1 = sum(vec1[word] ** 2 for word in vec1.keys())
  sum sq vec2 = sum(vec2[word] ** 2 for word in <math>vec2.keys())
  denominator = math.sqrt(sum sq vec1) * math.sqrt(sum sq vec2)
  if not denominator:
     return 0.0
  else:
     return float(numerator) / denominator
sim_s1_s2 = cosine_similarity(vector_s1, vector_s2)
sim_s1_s3 = cosine_similarity(vector_s1, vector_s3)
\sin s2 \ s3 = \cos ine \ similarity(vector \ s2, vector \ s3)
# Display cosine similarity results
print("Cosine Similarity between s1 and s2:", sim_s1_s2)
print("Cosine Similarity between s1 and s3:", sim s1 s3)
print("Cosine Similarity between s2 and s3:", sim_s2_s3)
```