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**LAB MANUAL**  
**On**  
**ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING LAB**  
**COURSE CODE (22CDPC55)**  
**(III- B. Tech. – I– Semester)**

**Submitted to**  
**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING**  
**(DATA SCIENCE)**  
**By**

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**(2024-25)**

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## CMR INSTITUTE OF TECHNOLOGY

**VISION:** To create world class technocrats for societal needs

**MISSION:** Impart global quality technical education assessing learning environment through

- Innovative Research & Development
- Eco system for better Industry institute interaction
- Capacity building among stakeholders

**QUALITY POLICY:** Strive for global Professional excellence in pursuit of key – Stake holders

### DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING: COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

**Vision:** Develop competent software professionals, researchers' and entrepreneurs to serve global society.

**Mission:** The department of **Computer Science and Engineering (Data Science)** is committed to

- Create technocrats with proficiency in design and code for software development
- Adapt contemporary technologies by lifelong learning and face challenges in IT and ITES sectors
- Quench the thirst of knowledge in higher education, employment, R&D and entrepreneurship

#### I. PROGRAMME EDUCATIONAL OBJECTIVES (PEO's)

**PEO1:** Graduate will be capable of practicing principles of computer science & engineering, mathematics and scientific investigation to solve the problems that are appropriate to the discipline.

[PO's:1,2,3,4,5,7,8,9,10,11 and 12] [PSO's:1 and 2]

**PEO2:** Graduate will profess in Data Science applications that lead to professional, career and research advancement. [PO's: 1,2,3,4,5,6,7,8,9,10 and 12][PSO's:1, 2 and 3]

**PEO3:** Graduate exhibits professional ethics, communication skills, teamwork and adapts to changing environments of engineering and technology by engaging in lifelong learning. [PO's:1,2,3,4,5,6,7,8,9,10,11 and 12][PSO's:2 and 3]

#### II. PROGRAMME OUTCOMES (PO's)

1. **Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems. [PEO's: 1,2 and 3]
2. **Problem analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences. [PEO's: 1,2 and 3]

3. **Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations. [PEO's: 1,2 and 3]
4. **Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions. [PEO's: 1,2 and 3]
5. **Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations. [PEO's: 1,2 and 3]
6. **The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice. [PEO's: 2 and 3]
7. **Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development. [PEO's: 1,2 and 3]
8. **Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice. [PEO's: 1,2 and 3]
9. **Individual and team work:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings. [PEO's: 1,2 and 3]
10. **Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions. [PEO's: 1,2 and 3]
11. **Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments. [PEO's: 1 and 3]
12. **Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change. [PEO's: 1,2 and 3]

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**ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING LAB**

**III-B.Tech.-I-Sem.**  
**Subject Code: 22CDPC55**

**L TPC**  
**- - 2 1**

**Course Outcomes:**

Upon completion of the course, the students will be able to:

1. Illustrate various search technique.
2. Solve real-time problems using graph theory.
3. Use techniques of knowledge representation and probabilistic reasoning.
4. Design various supervised learning algorithms.
5. Implement various unsupervised learning algorithms.

**LIST OF EXPERIMENTS**

1. Write a program to implement BFS and DFS Traversal.
2. Write a program to implement A\* Search.
3. Write a program to implement Travelling Salesman Problem and Graph Coloring Problem.
4. Write a program to implement Knowledge Representation.
5. Write a program to implement Bayesian Network.
6. Write a program to implement Hidden Markov Model.
7. Write a program to implement Regression algorithm.
8. Write a program to implement decision tree based ID3 algorithm.
9. Write a program to implement K-Means Clustering algorithm.
10. Write a program to implement K-Nearest Neighbor algorithm (K-NN).
11. Write a program to implement Back Propagation Algorithm.
12. Write a program to implement Support Vector Machine.

**Micro-Projects:** Student must submit are port on one of the following Micro–Projects before commencement of second internal examination.

1. ArtificialIntelligencefor RecordsManagement.
2. Efficient,ScalableProcessingofPatientDatausingArtificialIntelligence.
3. Smart BikeShareProgramsusingArtificialIntelligence.
4. AutomaticDocumentClassificationusingBayesiantheorem.
5. ArtificialIntelligenceine-Commerce.
6. DiagnosecropdiseasewithMachineLearning.
7. Developasystemtoanalyzebuyingbehaviorofacustomer.
8. Develop asystemtostudysentimentofusers ontwitter.
9. Develop apredictivemodeltostudytheemployeesatisfactioninanorganization.
10. Developapredictivemodeltostudytherainfallofoursociety.

**Reference:**

- 1.ArtificialIntelligenceandMachineLearningLab Manual,Dept.ofCSE(DS),CMRIT,Hyd.

## 2. STUDENT ENTRY BEHAVIOR OR PRE-REQUISITES

- Students should have basic knowledge on Data Structures and Data Mining
- Students should have basic knowledge on Design and Analysis of Algorithms.
- Student should have knowledge on Python.

These prerequisites are taken by the students during the first two years. However during the initial sessions the topics are reviewed.

## 3. COURSE OBJECTIVES

Course Objectives	Course Objective Statements
Objective - 1	Explain the concepts of artificial intelligence and Machine Learning
Objective – 2	Adapt various probabilistic reasoning approaches
Objective – 3	Illustrate various search algorithms , Classification and Clustering techniques
Objective – 4	Elaborate Hidden Markov Model in AI and Back Propagation Algorithm in ML
Objective – 5	Perceive various reinforcement learning approaches

#### 4. COURSE OUTCOMES

COs	Upon completion of course the students will be able to	PO4	PO5	PO9	PSO2
CO1	illustrate various search techniques	3	3	3	3
CO2	solve real-time problems using graph theory	3	3	3	3
CO3	use techniques of knowledge representation and probabilistic reasoning	3	3	3	3
CO4	design various supervised learning algorithms	3	3	3	3
CO5	implement various unsupervised learning algorithms	3	3	3	3

#### Course Mapping

Course Name	PEO1	PEO2	PEO3	PSO1	PSO2	PSO3
Artificial Intelligence and Machine Learning Lab	√	√	√	√	√	√

Course Name	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
Artificial Intelligence and Machine Learning Lab				√	√				√			



## 5. MAPPING OF COURSE WITH PEOS-PSOS-POS

### Program Educational Objectives (PEOs)

Sl. No.	PEOs Name	Program Education Objective Statements
1	PEO - 1	Impart profound knowledge in humanities and basic sciences along with core engineering concepts for practical understanding & project development. [PO's: 1,2,3,4,5,7,8,9,10,11 and 12] [PSO's: 1 and 2]
2	PEO - 2	Enrich analytical skills and Industry-based modern technical skills in core and interdisciplinary areas for accomplishing research, higher education, entrepreneurship and to succeed in various engineering positions globally. [PO's: 1,2,3,4,5,6,7,8,9,10 and 12] [PSO's: 1, 2 and 3]
3	PEO - 3	Infuse life-long learning, professional ethics, responsibilities and adaptation to innovation along with effective communication skills with a sense of social awareness. [PO's: 1,2,3,4,5,6,7,8,9,10,11 and 12] [PSO's: 2 and 3]

### Program Specific Objectives (PSOs)

Sl. No.	PSOs Name	Program Specific Objective Statements
1	PSO - 1	Use mathematical abstractions and Algorithmic design along with open source programming tools to solve complexities involved in efficient programming. [PO:1,2,3,4 and 5] & [PEO:1 and 2]
2	PSO - 2	Ensure programming & documentation skills for each individual student in relevant subjects i.e., C, C++, Java, DBMS, Web Technologies (Development), Linux, Data Warehousing & Data Mining and on Testing Tools. [PO:1,2,3,4,5,10 and 11] & [PEO:1,2 and 3]
3	PSO - 3	Ensure employability and career development skills through Industry oriented mini & major projects, internship, industry visits, seminars and workshops. [PO:6,7,8,9,10,11 and 12] & [PEO:1,2 and 3]

### Program Outcomes (POs)

PO Name	Graduate Attributes	PO Statements
PO1	Engineering knowledge	Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems. [PEO's: 1,2 and 3] [PSO's: 1,2 and 3]
PO 2	Problem analysis	Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences. [PEO's: 1,2 and 3] [PSO's: 1,2 and 3]
PO 3	Design/development of solutions	Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations. [PEO's: 1,2 and 3] [PSO's: 1,2 and 3]
PO 4	Conduct investigations of complex problems	Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions. [PEO's: 1,2 and 3] [PSO's: 1,2 and 3]
PO 5	Modern tool usage	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations. [PEO's: 1,2 and 3] [PSO's: 1,2 and 3]
PO 6	The engineer and society	Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice. [PEO's: 2 and 3]
PO 7	Environment and sustainability	Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development. [PEO's: 1,2 and 3]
PO 8	Ethics	Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice. [PEO's: 1,2 and 3] [PSO's: 2 and 3]
PO 9	Individual and team work	Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings. [PEO's: 1,2 and 3] [PSO's: 3]
PO 10	Communication	Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions. [PEO's: 1,2 and 3] [PSO's: 2 and 3]
PO 11	Project management and finance	Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments. [PEO's: 1 and 3] [PSO's: 2 and 3]
PO 12	Life-long learning	Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change. [PEO's: 1,2 and 3] [PSO's: 1,2 and 3]

**MAPPING OF COURSE OUTCOMES WITH PEO'S, PO'S**  
**(No correlation:0; Low:1; Medium:2; High:3)**

Course Outcomes	PEO1	PEO2	PEO3	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO-1	3	3	3	0	0	0	3	3	0	0	0	3	0	0	0
CO-2	3	3	3	0	0	0	3	3	0	0	0	3	0	0	0
CO-3	3	3	3	0	0	0	3	3	0	0	0	3	0	0	0
CO-4	3	3	3	0	0	0	3	3	0	0	0	3	0	0	0
CO-5	3	3	3	0	0	0	3	3	0	0	0	3	0	0	0

**6. Mapping Of Course Outcomes With PEOs**

(Ticking &amp; Correlation - 2 Tables)

No	Course Outcomes	PEO1	PEO2	PEO3
1	CO - 1	√	√	√
2	CO – 2	√	√	√
3	CO – 3	√	√	√
4	CO – 4	√	√	√
5	CO – 5	√	√	√

## 7. Mapping Of Course Outcomes With PSOs

(Ticking & Correlation - 2 Tables)

No	Course Outcomes	PSO1	PSO2	PSO3
1	CO - 1	√	√	√
2	CO – 2	√	√	√
3	CO – 3	√	√	√
4	CO – 4	√	√	√
5	CO – 5	√	√	√

No	Course Outcomes	PSO1	PSO2	PSO3	Avg
1	CO - 1	3	3	2	2.67
2	CO – 2	3	3	2	2.67
3	CO – 3	3	3	3	3.00
4	CO – 4	2	3	1	2.00
5	CO – 5	2	3	1	2.00
	Avg	2.6	3	1.8	2.46

## 8. Mapping Of Course Outcomes With POs

(Ticking & Correlation - 2 Tables)

No	Course Outcomes	Po1	Po2	Po3	Po4	Po5	Po6	Po7	Po8	Po9	Po10	Po11	Po12
1	CO - 1				√	√				√			
2	CO – 2				√	√				√			
3	CO – 3				√	√				√			
4	CO – 4				√	√				√			
5	CO – 5				√	√				√			

No	Course Outcomes	Po1	Po2	Po3	Po4	Po5	Po6	Po7	Po8	Po9	Po10	Po11	Po12	Avg
1	CO - 1				3	3				3				2.8
2	CO – 2				3	3				3				2.6
3	CO – 3				3	3				3				2.6
4	CO – 4				3	3				3				1.4
5	CO – 5				3	3				3				1.4
	Avg				3	3				3				1.96

## 9. Direct Course Assessment

(As mentioned in following table of 10 parameters, of which consider only the parameters required for this courses)

No	Description	Targeted Performance	Actual Performance	Remarks	Course Attainment
1	Internal Marks(25)	80% of Students(182 Students) should Secure 60% of Internal Marks i.e., 15 Marks			
2	External Marks(50)	80% of Students(182 Students) should Secure 70% of External Marks i.e., 35 Marks			
3	Clearing of Subject	A minimum of 95% of Students(216 Students) should clear this course in first attempt			
4	Getting First Class	90% of Students(205 Students) should Secure I Class Marks i.e., 45 Marks in my course			
5	Distinction	80% of Students (182 Students) should secure First Class With Distinction i.e., 53 Marks in my course			
6	Outstanding Performance	60% of Students (137 Students) should secure 80% and above Marks. i.e., 60 Marks in my course			

## 10. Indirect Course Assessment

(As mentioned-strong (3), moderate (2), weak (1) & no comment (0))

### Mission Statement of CSE

- Impart fundamentals through state of art technologies for research and career in Computer Science & Engineering.
- Create value-based, socially committed professionals for anticipating and satisfying fast changing societal requirements.
- Foster continuous self learning abilities through regular interaction with various stake holders for holistic development.

Correlation of Mission Elements with Mission Statement of CSE Department related to the Course  
(only Ticking given by faculty)

No	Mission Elements	Strong	Moderate	Weak	No Comment
M-1	Impart Fundamentals	√			
M-2	State Of Art Technologies	√			
M-3	Research & Career Development	√			
M-4	Value based Socially Committed Professional	√			
M-5	Anticipating & Satisfying Industry Trends		√		
M-6	Changing Societal Requirements			√	
M-7	Foster Continuous Learning	√			
M-8	Self Learning Abilities	√			
M-9	Interaction with stakeholders	√			
M-10	Holistic Development		√		



### Indirect Course Assessment through Student Satisfaction Survey

(Note for \*:Parameters used for course teaching like

a: Classroom teaching      b: Simulations      c: labs      d: Mini\_Projects  
 e: Major Projects      f: Conferences      g: professional activities  
 h: Technical Clubs      i: Guest Lectures      j: Workshops      k: Technical Fests l: Tutorials  
 m: NPTLs      n: Digital Library      o: Industrial Visits  
 p: software Tools      q: Internship/training      r: Technical Seminars  
 s: NSS      t: NSS      u: sports etc.

No	Question Based on PEO/ PO/PSO/CO	Parameters (a /b /c.../)*	Strong (3)	Moderate (2)	Weak (1)	No comment (0)
1	Did the course impart fundamentals through interactive learning and contribute to core competence?					
2	Did the course provide the required knowledge to foster continuous learning?					
3	Whether the syllabus content anticipates & satisfies the industry and societal needs?					
4	Whether the course focuses on value based education to be a socially committed professional?					
5	Rate the role of the facilitator in mentoring and promoting the self learning abilities to excel academically and professionally?					
6	Rate the methodology adopted and techniques used in teaching learning processes?					
7	Rate the course in applying sciences & engineering fundamentals in providing research based conclusions with the help of modern tools?					
8	Did the course have any scope to design, develop and test a system or component?					
9	Rate the scope of this course in addressing cultural, legal, health, environment and safety issues?					
10	Scope of applying management fundamentals to demonstrate effective technical project presentations & report writing?					
	Total					
	Average					
Total Average			2.52			

## 11. Overall Course Assessment

(80% Direct + 20% Indirect, if any)

No	Assessment Type	Weightage	Attainment Level
1	Direct-Assignment, Quiz, Subjective, University Exams, Results, Bench Marks	0.8	
2	Indirect-Surveys-Questionnaire	0.2	
	Overall		

AI & ML LAB Course Attainment level:

## 12. Pi diagrams, Bar charts, Histograms

(For representing previous results, if any)

WT Pass % for Last 4 Academic Years	Appeared	Passed	Pass%

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**EXPERIMENT NO: 1**

**AIM :**Write a program to implement BFS and DFS Traversal.

**ALGORITHM:**

DFS (Depth first search) starts with a given node and explores the first unexplored node it comes across before returning to itself again and exploring its remaining nodes (e.g: if the parent node 1 has 2 children 2, 3 the DFS method will explore 2 and its children nodes before exploring 3. It will print self before exploring its children (so 1->(2,3) will print 1,2,3))

BFS (Breadth first search) works down a tree in a top-to-bottom manner (e.g: a graph with parent 1 and children 2, 3 will print level 1 first (1) then level 2 (2, 3) and then level 3 (the children of nodes 2 and 3). The level of a given node is determined by the highest level it could appear on (e.g: if 2 is a child of an item on level 1 and level 4, it would be printed as if it were a level 2 item)

**SOURCE CODE:**

```
from collections import defaultdict
```

```
class Graph():
    def __init__(self):
        self.value = defaultdict(list)

    def addConnection(self, parent, child):
        self.value[parent].append(child)

    def DFS(self, start):
        visited = [start]
        stack = [start]
        print(start, end=" ")
        while stack:
            s = stack[-1]
            if any([item for item in self.value[s] if item not in visited]):
                for item in [item for item in self.value[s] if item not in visited]:
                    stack.append(item)
                    visited.append(item)
                    print(item, end=" ")
                    break
            else:
                stack.pop()

    def BFS(self, start):
        visited = [start]
        queue = [start]
        while queue:
            x = queue.pop(0)
            print(x, end=" ")
            for item in self.value[x]:
                if item not in visited:
                    queue.append(item)
```

---

```
visited.append(item)
```

```
#Build the graph
g=Graph()
g.addConnection(1,4)
g.addConnection(1,2)
g.addConnection(2,3)
g.addConnection(2,6)
g.addConnection(4,5)
g.addConnection(4,7)
g.addConnection(7,96)
```

```
#Explore the graph
g.DFS(1)
print("\n")
g.BFS(1)
```

**OUTPUT:**

```
DFS: 145796236
BFS: 142573696
```

**EXPERIMENT NO: 2**

**AIM :** Write a program to implement A\*Search.

**ALGORITHM:**

- 1: Firstly, Place the starting node into OPEN and find its f (n) value.
- 2: Then remove the node from OPEN, having the smallest f (n) value. If it is a goal node, then stop and return to success.
- 3: Else remove the node from OPEN, and find all its successors.
- 4: Find the f (n) value of all the successors, place them into OPEN, and place the removed node into CLOSE.
- 5: Goto Step-2.
- 6: Exit.

**SOURCE CODE:**

```
def aStarAlgo(start_node, stop_node):
    open_set = set(start_node)
    closed_set = set()
    g = {}          #store distance from starting node
    parents = {}     # parents contains an adjacency map of all nodes
    #distance of starting node from itself is zero
    g[start_node] = 0
    #start_node is root node i.e it has no parent nodes
    #so start_node is set to its own parent node
    parents[start_node] = start_node
    while len(open_set) > 0:
        n = None
        #node with lowest f() is found
        for v in open_set:
            if n == None or g[v] + heuristic(v) < g[n] + heuristic(n):
                n = v
        if n == stop_node or Graph_nodes[n] == None:
            pass
        else:
            for (m, weight) in get_neighbors(n):
                #nodes 'm' not in first and last set are added to first
                #n is set its parent
                if m not in open_set and m not in closed_set:
                    open_set.add(m)
                    parents[m] = n
                    g[m] = g[n] + weight
                #for each node m, compare its distance from start i.e g(m) to the
                #from start through n node
                else:
                    if g[m] > g[n] + weight:
                        #update g(m)
                        g[m] = g[n] + weight
                        #change parent of m to n
                        parents[m] = n
                        #if m in closed set, remove and add to open
```

---

```

        if m in closed_set:
            closed_set.remove(m)
            open_set.add(m)
            if n == None:
                print('Path does not exist!')
                return None

            # if the current node is the stop_node
            # then we begin reconstructin the path from it to the start_node
            if n == stop_node:
                path = []
                while parents[n] != n:
                    path.append(n)
                    n = parents[n]
                path.append(start_node)
                path.reverse()
                print('Path found: {}'.format(path))
                return path
            # remove n from the open_list, and add it to closed_list
            # because all of his neighbors were inspected
            open_set.remove(n)
            closed_set.add(n)
            print('Path does not exist!')
            return None

#define fuction to return neighbor and its distance
#from the passed node
def get_neighbors(v):
    if v in Graph_nodes:
        return Graph_nodes[v]
    else:
        return None
def heuristic(n):
H_dist = {
    'A': 11,
    'B': 6,
    'C': 5,
    'D': 7,
    'E': 3,
    'F': 6,
    'G': 5,
    'H': 3,
    'I': 1,
    'J': 0
}
    return H_dist[n]
Graph_nodes = {
    'A': [('B', 6), ('F', 3)],
    'B': [('A', 6), ('C', 3), ('D', 2)],
    'C': [('B', 3), ('D', 1), ('E', 5)],
    'D': [('B', 2), ('C', 1), ('E', 8)],

```

---

```
'E': [('C', 5), ('D', 8), ('T', 5), ('J', 5)],  
'F': [('A', 3), ('G', 1), ('H', 7)],  
'G': [('F', 1), ('T', 3)],  
'H': [('F', 7), ('T', 2)],  
'I': [('E', 5), ('G', 3), ('H', 2), ('J', 3)],  
}
```

```
aStarAlgo('A', 'J')
```

OUTPUT:

```
Path found: ['A', 'F', 'G', 'T', 'J']  
            ['A', 'F', 'G', 'T', 'J']
```



**EXPERIMENT NO: 3**

**AIM:** Write a program to implement Travelling Salesman Problem and Graph Coloring Problem.

**ALGORITHM – Travelling salesman problem**

- Consider city 1 as the starting and ending point.
- Generate all  $(n-1)!$  Permutations of cities.
- Calculate cost of every permutation and keep track of minimum cost permutation.
- Return the permutation with minimum cost.

**ALGORITHM – Graph coloring problem**

- Color first vertex with first color.
- Do following for remaining  $V-1$  vertices.  
 ..... a) Consider the currently picked vertex and color it with the lowest numbered color that has not been used on any previously colored vertices adjacent to it. If all previously used colors appear on vertices adjacent to  $v$ , assign a new color to it.

**SOURCE CODE- Travelling salesman problem**

```

from sys import maxsize
from itertools import permutations
V = 4
# implementation of traveling Salesman Problem
def travellingSalesmanProblem(graph, s):
    # store all vertex apart from source vertex
    vertex = []
    for i in range(V):
        if i != s:
            vertex.append(i)
    # store minimum weight Hamiltonian Cycle
    min_path = maxsize
    next_permutation=permutations(vertex)
    for i in next_permutation:
        # store current Path weight(cost)
        current_pathweight = 0
        # compute current path weight
        k = s
        for j in i:
            current_pathweight += graph[k][j]
            k = j
        current_pathweight += graph[k][s]
        # update minimum
        min_path = min(min_path, current_pathweight)
    return min_path

```

---

```
# Driver Code
if __name__ == "__main__":
    # matrix representation of graph
    graph = [[0, 10, 15, 20], [10, 0, 35, 25],
             [15, 35, 0, 30], [20, 25, 30, 0]]
    s = 0
    print(travellingSalesmanProblem(graph, s))
```

**OUTPUT- Travelling salesman problem**  
80

### SOURCE CODE:

```
#!/usr/bin/env python
# coding: utf-8
# In[6]:
colors = ['Red', 'Blue', 'Green', 'Yellow', 'Black']
states = ['Andhra', 'Karnataka', 'TamilNadu', 'Kerala']
neighbors = { }
neighbors['Andhra'] = ['Karnataka', 'TamilNadu']
neighbors['Karnataka'] = ['Andhra', 'TamilNadu', 'Kerala']
neighbors['TamilNadu'] = ['Andhra', 'Karnataka', 'Kerala']
neighbors['Kerala'] = ['Karnataka', 'TamilNadu']
colors_of_states = { }
def promising(state, color):
    for neighbor in neighbors.get(state):
        color_of_neighbor = colors_of_states.get(neighbor)
        if color_of_neighbor == color:
            return False
    return True
def get_color_for_state(state):
    for color in colors:
        if promising(state, color):
            return color

def main():
    for state in states:
        colors_of_states[state] = get_color_for_state(state)
    print (colors_of_states)
main()
# In[ ]:
# In[ ]:
```

**OUTPUT – Graph coloring problem.**

```
{'Andhra': 'Red', 'Karnataka': 'Blue', 'TamilNadu': 'Green', 'Kerala': 'Red'}
```

**EXPERIMENT NO: 4**

**AIM :** Write a program to implement Knowledge Representation.

**ALGORITHM:**

Let's start with a Harry Potter example. Consider the following sentences:

1. If it didn't rain, Harry visited Hagrid today.
2. Harry visited Hagrid or Dumbledore today, but not both.
3. Harry visited Dumbledore today.

Based on these three sentences, we can answer the question "did it rain today?", even though none of the individual sentences tell us anything about whether it is raining today. Here is how we can go about it: looking at sentence 3, we know Harry visited Dumbledore. Looking at sentence 2, we know Harry visited either Dumbledore or Hagrid, and thus we can conclude **4. Harry did not visit Hagrid.**

Now, looking at sentence 1, we understand that if it didn't rain, Harry would have visited Hagrid. However, knowing sentence 4, we know that this is not the case. Therefore, we can conclude **5. It rained today.**

**SOURCE CODE:**

```
# Here we import everything from logic.py
from logic import *
rain = Symbol("rain")    # Rain is the symbol for rain
hagrid = Symbol("hagrid")
dumbledore = Symbol("dumbledore")
# we create here a logical sentence using logical connectives
logical_sentence = And(rain, hagrid)
# we can't directly print the logical sentence so we use a formula function
print(logical_sentence.formula())
# we create a implication logic here
implication_logic = Implication(Not(rain), hagrid)
print(implication_logic.formula())
"""We make decision from knowledge base " ,all of the statement will be true then knowlegde base will be true"""
knowledge_base = And(
    Implication(Not(rain), hagrid),
    Or(hagrid, dumbledore),
    Not(And(hagrid, dumbledore)),
```

---

```
hagrid
```

```
)
```

```
print(knowledge_base.formula())
```

```
""" Here we use the model_check function and here two arguments are knowledge_base and another is it rain today or not. Then we print it"""
```

```
print(model_check(knowledge_base, rain))
```

**OUTPUT:**

Rain ^ hagrid

$(\neg \text{rain} \Rightarrow \text{hagrid})$

$((\neg \text{rain}) \Rightarrow \text{hagrid} \wedge (\text{hagrid} \vee \text{dumbledore}) \wedge (\neg(\text{hagrid} \wedge \text{dumbledore})) \wedge \text{dumbledore})$

true

**EXPERIMENT NO: 5**

**AIM** Write a program to implement Bayesian Network.

**ALGORITHM:**

A Bayesian network, Bayes network, belief network, decision network, Bayes(ian) model or probabilistic directed acyclic graphical model is a probabilistic graphical model (a type of statistical model) that represents a set of variables and their conditional dependencies via a directed acyclic graph (DAG). Bayesian networks are ideal for taking an event that occurred and predicting the likelihood that any one of several possible known causes was the contributing factor. For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases.

**Graphical Model:**

Formally, Bayesian networks are directed acyclic graphs (DAGs) whose nodes represent variables in the Bayesian sense: they may be observable quantities, latent variables, unknown parameters or hypotheses. Edges represent conditional dependencies; nodes that are not connected (no path connects one node to another) represent variables that are conditionally independent of each other. Each node is associated with a probability function that takes, as input, a particular set of values for the node's parent variables, and gives (as output) the probability (or probability distribution, if applicable) of the variable represented by the node.

**SOURCE CODE:**

```
import numpy
from pomegranate import *
guest = DiscreteDistribution({'A': 1./3, 'B': 1./3, 'C': 1./3})
prize = DiscreteDistribution({'A': 1./3, 'B': 1./3, 'C': 1./3})

monty = ConditionalProbabilityTable([
    ['A', 'A', 'A', 0.0 ],
    ['A', 'A', 'B', 0.5 ],
    ['A', 'A', 'C', 0.5 ],
    ['A', 'B', 'A', 0.0 ],
    ['A', 'B', 'B', 0.0 ],
    ['A', 'B', 'C', 1.0 ],
    ['A', 'C', 'A', 0.0 ],
    ['A', 'C', 'B', 1.0 ],
    ['A', 'C', 'C', 0.0 ],
    ['B', 'A', 'A', 0.0 ],
    ['B', 'A', 'B', 0.0 ],
    ['B', 'A', 'C', 1.0 ],
    ['B', 'B', 'A', 0.5 ],
```

---

```
[ 'B', 'B', 'B', 0.0 ],  
[ 'B', 'B', 'C', 0.5 ],  
[ 'B', 'C', 'A', 1.0 ],  
[ 'B', 'C', 'B', 0.0 ],  
[ 'B', 'C', 'C', 0.0 ],  
[ 'C', 'A', 'A', 0.0 ],  
[ 'C', 'A', 'B', 1.0 ],  
[ 'C', 'A', 'C', 0.0 ],  
[ 'C', 'B', 'A', 1.0 ],  
[ 'C', 'B', 'B', 0.0 ],  
[ 'C', 'B', 'C', 0.0 ],  
[ 'C', 'C', 'A', 0.5 ],  
[ 'C', 'C', 'B', 0.5 ],  
[ 'C', 'C', 'C', 0.0 ]], [guest, prize])
```

```
s1 = State(guest, name="guest")  
s2 = State(prize, name="prize")  
s3 = State(monty, name="monty")  
model = BayesianNetwork("Monty Hall Problem")  
model.add_states(s1, s2, s3)  
model.add_edge(s1, s3)  
model.add_edge(s2, s3)  
model.bake()  
print(model.probability([['A', 'B', 'C'], ['A', 'A', 'C'], ['A', 'C', 'C']]))  
print(model.predict([['A', None, 'C'], ['A', 'A', None], [None, 'B', 'A']]))
```

**EXPERIMENT NO: 6**

**AIM :**Write a program to implement Hidden Markov Model.

**ALGORITHM:**

The Hidden Markov Model (HMM) algorithm can be implemented using the following steps:

Step 1: Define the state space and observation space

The state space is the set of all possible hidden states, and the observation space is the set of all possible observations.

Step 2: Define the initial state distribution

This is the probability distribution over the initial state.

Step 3: Define the state transition probabilities

These are the probabilities of transitioning from one state to another. This forms the transition matrix, which describes the probability of moving from one state to another.

Step 4: Define the observation likelihoods:

These are the probabilities of generating each observation from each state. This forms the emission matrix, which describes the probability of generating each observation from each state.

Step 5: Train the model

The parameters of the state transition probabilities and the observation likelihoods are estimated using the Baum-Welch algorithm, or the forward-backward algorithm. This is done by iteratively updating the parameters until convergence.

Step 6: Decode the most likely sequence of hidden states

Given the observed data, the Viterbi algorithm is used to compute the most likely sequence of hidden states.

This can be used to predict future observations, classify sequences, or detect patterns in sequential data.

Step 7: Evaluate the model

The performance of the HMM can be evaluated using various metrics, such as accuracy, precision, recall, or F1 score.

**SOURCE CODE:**

```
import numpy as np
import itertools
import pandas as pd
# create state space and initial state probabilities
states = ['sleeping', 'eating', 'pooping']

hidden_states = ['healthy', 'sick']
pi = [0.5, 0.5]
state_space = pd.Series(pi, index=hidden_states, name='states')
print(state_space)

a_df = pd.DataFrame(columns=hidden_states, index=hidden_states)
a_df.loc[hidden_states[0]] = [0.7, 0.3]
a_df.loc[hidden_states[1]] = [0.4, 0.6]
```

---

```

print(a_df)

observable_states = states

b_df = pd.DataFrame(columns=observable_states, index=hidden_states)
b_df.loc[hidden_states[0]] = [0.2, 0.6, 0.2]
b_df.loc[hidden_states[1]] = [0.4, 0.1, 0.5]

print(b_df)

def HMM(obsq,a_df,b_df,pi,states,hidden_states):
    hidst=list(itertools.product(hidden_states,repeat=len(obsq)))
    print(hidst)
    sum=0
    for k in hidst:
        prod=1
        for j in range(len(k)):
            c=0
            for i in obsq:
                if c==0:
                    prod*=a_df[i][k[j]]*pi[hidden_states.index(k[j])]
                    c=1
                else:
                    prod*=b_df[k[j]][k[j-1]]*a_df[i][k[j]]
            sum+=prod
            c=0
    return sum

def vertibi(obsq,a_df,b_df,pi,states,hidden_states):
    sum=0
    hidst=list(itertools.product(hidden_states,repeat=len(obsq)))
    for k in hidst:
        sum1=0
        prod=1
        for j in range(len(k)):
            c=0
            for i in obsq:
                if c==0:
                    prod*=a_df[i][k[j]]*pi[hidden_states.index(k[j])]
                    c=1
                else:
                    prod*=b_df[k[j]][k[j-1]]*a_df[i][k[j]]
            c=0
            sum1+=prod
        if(sum1>sum):
            sum=sum1
            hs=k
    return sum,hs

```



```
obsq=['pooping','pooping','pooping']
print(HMM(obsq,b_df,a_df,pi,states,hidden_states))
print(vertibi(obsq,b_df,a_df,pi,states,hidden_states))
```

**OUTPUT:**

```
healthy  0.5
sick     0.5
Name: states, dtype: float64
    healthy sick
healthy  0.7 0.3
sick     0.4 0.6
    sleeping eating pooping
healthy  0.2 0.6 0.2
sick     0.4 0.1 0.5
[('healthy', 'healthy', 'healthy'), ('healthy', 'healthy', 'sick'), ('healthy', 'sick', 'healthy'), ('healthy', 'sick', 'sick'), ('sick',
 'healthy', 'healthy'), ('sick', 'healthy', 'sick'), ('sick', 'sick', 'healthy'), ('sick', 'sick', 'sick')]
1.1662322536e-05
(1.1390624999999999e-05, ('sick', 'sick', 'sick'))
```

**EXPERIMENT :7**

**AIM :**Write a program to implement Regression algorithm

**ALGORITHM:**

**STEP 1:**Linear Assumption. Linear regression assumes that the relationship between your input and output is linear. It does not support anything else. This may be obvious, but it is good to remember when you have a lot of attributes. You may need to transform data to make the relationship linear (e.g. log transform for an exponential relationship).

**STEP 2:** Remove Noise. Linear regression assumes that your input and output variables are not noisy. Consider using data cleaning operations that let you better expose and clarify the signal in your data. This is most important for the output variable and you want to remove outliers in the output variable (y) if possible.

**STEP 3:**Remove Collinearity. Linear regression will over-fit your data when you have highly correlated input variables. Consider calculating pairwise correlations for your input data and removing the most correlated.

**STEP 4:**Gaussian Distributions. Linear regression will make more reliable predictions if your input and output variables have a Gaussian distribution. You may get some benefit using transforms (e.g. log or BoxCox) on you variables to make their distribution more Gaussian looking.

**STEP 5:**Rescale Inputs: Linear regression will often make more reliable predictions if you rescale input variables using standardization or normalization.

**SOURCE CODE:**

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

dataset = pd.read_csv('Salary_Data.csv')
dataset.head()

# data preprocessing
X = dataset.iloc[:, :-1].values #independent variable array
y = dataset.iloc[:, 1].values #dependent variable vector

# splitting the dataset
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=1/3,random_state=0)

# fitting the regression model
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train,y_train) #actually produces the linear eqn for the data

# predicting the test set results
y_pred = regressor.predict(X_test)
```

---

```
y_pred
```

```
y_test
```

```
# visualizing the results
```

```
#plot for the TRAIN
```

```
plt.scatter(X_train, y_train, color='red') # plotting the observation line
```

```
plt.plot(X_train, regressor.predict(X_train), color='blue') # plotting the regression line
```

```
plt.title("Salary vs Experience (Training set)") # stating the title of the graph
```

```
plt.xlabel("Years of experience") # adding the name of x-axis
```

```
plt.ylabel("Salaries") # adding the name of y-axis
```

```
plt.show() # specifies end of graph
```

```
#plot for the TEST
```

```
plt.scatter(X_test, y_test, color='red')
```

```
plt.plot(X_train, regressor.predict(X_train), color='blue') # plotting the regression line
```

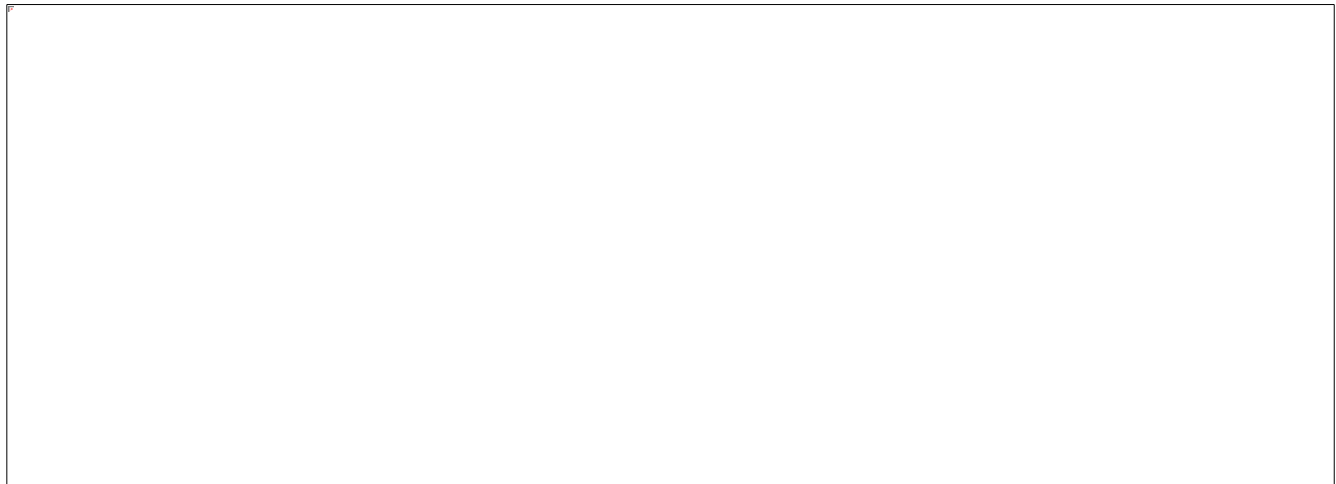
```
plt.title("Salary vs Experience (Testing set)")
```

```
plt.xlabel("Years of experience")
```

```
plt.ylabel("Salaries")
```

```
plt.show()
```

### OUTPUT:



**EXPERIMENT NO: 8**

**AIM :** Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

**Description:**

- ID3 algorithm is a basic algorithm that learns decision trees by constructing them topdown, beginning with the question "which attribute should be tested at the root of the tree".
- To answer this question, each instance attribute is evaluated using a statistical test to determine how well it alone classifies the training examples. The best attribute is selected and used as the test at the root node of the tree.
- A descendant of the root node is then created for each possible value of this attribute, and the training examples are sorted to the appropriate descendant node (i.e., down the branch corresponding to the example's value for this attribute).
- The entire process is then repeated using the training examples associated with each descendant node to select the best attribute to test at that point in the tree.
- A simplified version of the algorithm, specialized to learning boolean-valued functions (i.e., concept learning), is described below.

**Algorithm:**

ID3(Examples, Target

Attribute, Attributes) Input: Examples are the training examples.

Target attribute is the attribute whose value is to be predicted by the tree. Attributes is a list of other attributes that may be tested by the learned decision tree.

Output: Returns a decision tree that correctly classifies the given Examples

Method

1. Create a Root node for the tree

2. If all Examples are positive, Return the single-node tree Root, with label = +

3. If all Examples are negative, Return the single-node tree Root, with label = -

4. If Attributes is empty,

Return the single-node tree Root, with label = most common value of Target Attribute in Examples

Else

A ← the attribute from Attributes that best classifies Examples  
The decision attribute for Root ← A

For each possible value,  $v_i$ , of A,

Add a new tree branch below Root, corresponding to the test  $A =$

$v_i$  Let Examples  $v_i$  be the subset of Examples that have value  $v_i$  for A

Else If Examples  $v_i$  is empty Then below this new branch add a leaf node with label = most common value of Target Attribute in Examples

{A})

End Below this new branch add the subtree ID3(Examples  $v_i$ , Target Attribute, Attributes –

## 5. ReturnRoot

**Sourcecode:**

```

import pandas as pd
df=pd.read_csv("lab2dataset.csv")

#Calculate Entropy
def entropy(probs):
    import math
    return sum(-prob*math.log(prob,2) for prob in probs)

# Calculating the Probability of Positive and negative examples
def entropy_of_list(a_list):
    from collections import Counter
    cnt = Counter(x for x in a_list)
    num_instances =len(a_list)
    probs=[x/num_instances for x in cnt.values()]
    return entropy(probs)

total_entropy= entropy_of_list(df['PlayTime'])

def information_gain(df,split_attribute_name, target_attribute_name, trace=0):
df_split=df.groupby(split_attribute_name)
    for name,group in df_split:
        #print("Name", name)
        #print("Group",group)
        nobs=len(df.index)*1.0
        # Calculating Entropy of an attribute and probability part of formula
    df_agg_ent=df_split.agg({target_attribute_name: [entropy_of_list,lambda x: len(x)/nobs]
        #print("df_agg_ent", df_agg_ent)
        #print(df_agg_ent.columns)
        #calculate information gain
    avg_info=sum(df_agg_ent['entropy_of_list'] * df_agg_ent['<lambda_0>'])
    old_entropy=entropy_of_list(df[target_attribute_name])
    return old_entropy-avg_

def id3DT(df, target_attribute_name, attribute_names, default_class=None):
    from collections import Counter
    cnt = Counter(x for x in df[target_attribute_name])
    if len(cnt)==1:
        return next(iter(cnt))
    elif df.empty or (not attribute_names):
        return default_class
    else:

```

---

```

default_class =max(cnt.keys())
    #print("attributes_names:",attribute_names)
gainz=[information_gain(df,attr, target_attribute_name) for attr in attribute_names]
index_of_max=gainz.index(max(gainz))
best_attr=attribute_names[index_of_max]
    tree={best_attr:{ }}
remaining_attributes_names=[i for i in attribute_names if i != best_attr]
    for attr_val, data_subset in df.groupby(best_attr):
subtree=id3DT(data_subset,target_attribute_name,remaining_attributes_names,default)
    tree[best_attr][attr_val]=subtree
return tree

attribute_names=list(df.columns)
attribute_names.remove('PlayTime')
from pprint import pprint
tree= id3DT(df,'PlayTime',attribute_names)
print("The Resultant Decision Tree is ")
pprint(tree)
attribute=next(iter(tree))
print("Best Attribute: \n", attribute)
print("Tree Keys\n ", tree[attribute].keys())

def classify(instance, tree, default=None):
    attribute=next(iter(tree))
    print("Key:",tree.keys())
    print("Attribute",attribute)
    if instance[attribute] in tree[attribute].keys():
        result=tree[attribute][instance[attribute]]
    print("Instance Attribute:",instance[attribute], "TreeKeys:",tree[attribute].keys())
    if isinstance(result,dict):
        return classify(instance,result)
    else:
        return result
    else:
        return default

tree1={'Outlook':['Rainy','Sunny'],'Temperature':['Mild','Hot'],'Humidity':['Normal','High'],'Windy':['Weak','Strong']}
df2=pd.DataFrame(tree1)
df2['Predicted']=df2.apply(classify,axis=1, args=(tree,'No'))
print(df2)

```

**Output:**

```
Key: dict_keys(['Outlook'])
Attribute Outlook
Key: dict_keys(['Outlook'])
Attribute Outlook
Instance Attribute: Sunny TreeKeys: dict_keys(['Overcast', 'Rain', 'Sunny'])
Key: dict_keys(['Temperature'])
Attribute Temperature
Instance Attribute: Hot TreeKeys: dict_keys(['Cool', 'Hot', 'Mild'])
  Outlook Temperature Humidity Windy Predicted
0 Rainy      Mild Normal Weak    No
1 Sunny      Hot  High Strong    No
```

**EXPERIMENT-8**

**AIM:** Implement the K-means clustering Algorithms

**ALGORITHM:****K-means Clustering**

- The algorithm will categorize the items into groups of similarity. To calculate that similarity, we will use the Euclidean distance as a measurement.
- The algorithm works as follows:
  1. First we initialize  $k$  points, called means, randomly.
  2. We categorize each item to its closest mean and we update the mean's coordinates, which are the averages of the items categorized in that mean so far.
  3. We repeat the process for a given number of iterations and at the end, we have our clusters.
- The “points” mentioned above are called means, because they hold the mean values of the items categorized in it. To initialize these means, we have a lot of options. An intuitive method is to initialize the means at random items in the data set. Another method is to initialize the means at random values between the boundaries of the data set (if for a feature  $x$  the items have values in  $[0,3]$ , we will initialize the means with values for  $x$  at  $[0,3]$ ).
- Pseudocode:
  1. Initialize  $k$  means with random values
  2. For a given number of iterations: Iterate through items:
    - Find the mean closest to the item
    - Assign item to mean
    - Update mean

**Source code:**

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np

iris = datasets.load_iris()
X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length', 'Sepal_Width', 'Petal_length', 'Petal_Width']
y = pd.DataFrame(iris.target)
y.columns = ['target']
plt.figure(figsize=(14,7))
colormap = np.array(['red', 'lime', 'black'])
```

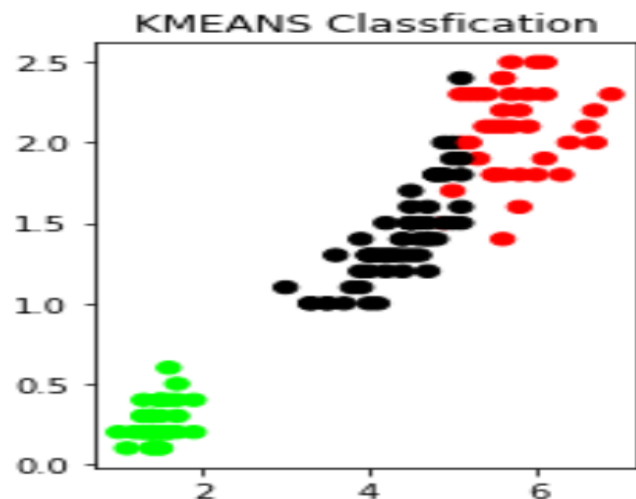
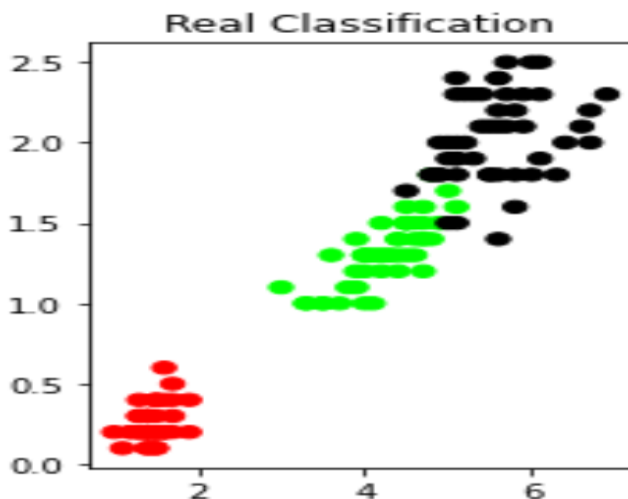
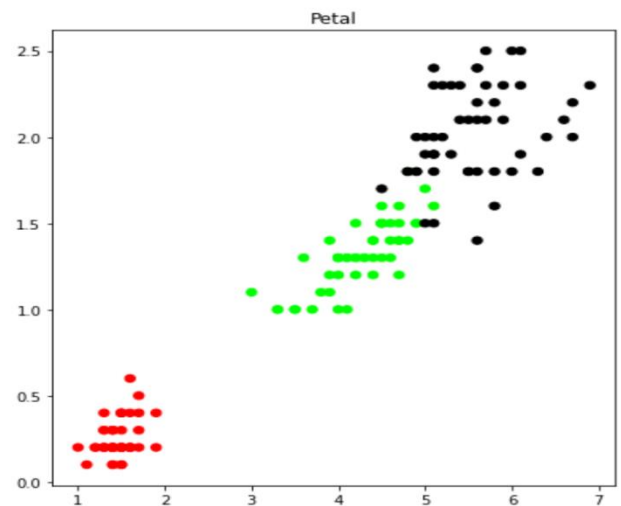
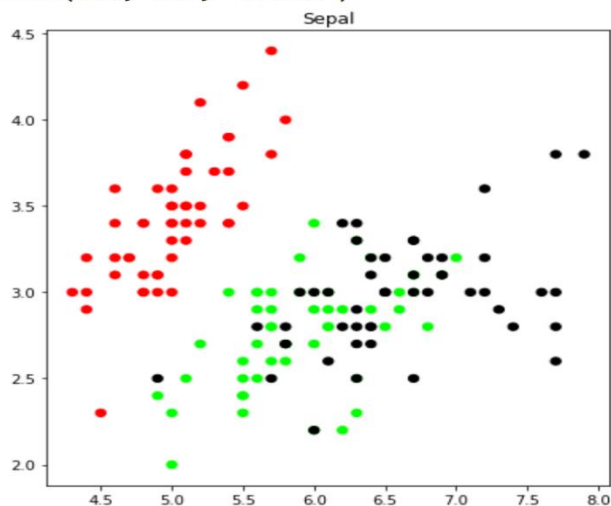


```

plt.subplot(1,2,1)
plt.scatter(X.Sepal_Length,X.Sepal_Width,c=colormap[y.target],s=40)
plt.title('Sepal')
plt.subplot(1,2,2)
plt.scatter(X.Petal_length,X.Petal_Width,c=colormap[y.target],s=40)
plt.title('Petal')
model=KMeans(n_clusters=3)
model.fit(X)
print(model.labels_)
plt.subplot(1,2,1)
plt.scatter(X.Petal_length,X.Petal_Width,c=colormap[y.target],s=40)
plt.title('Real Classification')
plt.subplot(1,2,2)
plt.scatter(X.Petal_length,X.Petal_Width,c=colormap[model.labels_],s=40)
plt.title('KMEANS Classification')

```

☞ Text(0.5, 1.0, 'Petal')



**EXPERIMENT-10**

**AIM:** Write a program to implement k-Nearest Neighbor algorithm to classify the iris dataset.

**DESCRIPTION:**

- K-Nearest Neighbors is one of the most basic yet essential classification algorithms in Machine Learning. It belongs to the supervised learning domain and finds intense application in pattern recognition, data mining and intrusion detection.
- It is widely disposable in real-life scenarios since it is non-parametric, meaning, it does not make any underlying assumptions about the distribution of data.

**ALGORITHM:**

Input: Let  $m$  be the number of training data samples. Let  $p$  be an unknown point. Method:

1. Store the training samples in an array of data points  $arr[]$ . This means each element of this array represents a tuple  $(x, y)$ .
2. for  $i = 0$  to  $m$   
    Calculate Euclidean distance  $d(arr[i], p)$ .
3. Make set  $S$  of  $K$  smallest distances obtained. Each of these distances corresponds to an already classified data point.
4. Return the majority label among  $S$ .

**SOURCE CODE:**

```
import sklearn
import pandas as pd
from sklearn.datasets import load_iris
iris=load_iris()
print(iris.keys())
df=pd.DataFrame(iris['data'])
print(df)
print(iris['target_names'])
print(iris['feature_names'])
print(iris['target'])

X=df
y=iris['target']
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.33,random_state=42)
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train,y_train)
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
y_pred=knn.predict(X_test)
cm=confusion_matrix(y_test,y_pred)
```

```
print(cm)
print("Correct prediction", accuracy_score(y_test,y_pred))
print("Wrong prediction", (1-accuracy_score(y_test,y_pred)))
y_testtrain=knn.predict(X_train)
cm1=confusion_matrix(y_train,y_testtrain)
print(cm1)
```

**EXPERIMENT -11**

**AIM:** Implementing Backpropagation algorithm and test the same using appropriate datasets.

**DESCRIPTION:**

- Artificial neural networks (ANNs) provide a general, practical method for learning real-valued, discrete-valued, and vector-valued functions from examples.
- Algorithms such as BACKPROPAGATION gradient descent to tune network parameters to best fit a training set of input-output pairs.
- ANN learning is robust to errors in the training data and has been successfully applied to problems such as interpreting visual scenes, speech recognition, and learning robot control strategies.

**ALGORITHM:**

1. Create a feed-forward network with  $n_i$  inputs,  $n_h$  hidden units, and  $n_o$  output units.
2. Initialize each with some small random value (e.g., between -0.05 and 0.05).
3. Until the termination condition is met, do
  - For each training example  $\langle (x_1, \dots, x_n), t \rangle$ , do
    - // Propagate the input forward through the network:
      - a. Input the instance  $(x_1, \dots, x_n)$  to the network & compute the network outputs for every unit
    - // Propagate the errors backward through the network:
      - b. For each output unit  $k$ , calculate its error term
      - c. For each hidden unit  $h$ , calculate its error term
      - d. For each network weight  $w_{ij}$ , do;

**SOURCE CODE:**

```
import numpy as np
x=np.array([[2,9],[1,5],[3,6]],dtype=float)print (x)
y=np.array([[92],[86],[89]],dtype=float)

#Normalization of
datasetx=x/np.max(x,axis=0)
)
y=y/100
print(x)
print(y)
def sigmoid(x):
    return(1/(1+np.exp(-x)))

def
derivatives_sigmoid(x):return
```

---

```

    nx*(1-x)
epoch=10

00lr=0.01

input_layer_neurons=2hi
dden_layer_neurons=2o
utput_neurons=1

wh=np.random.uniform(size=(input_layer_neurons,hidden_layer_neurons))bh=n
p.random.uniform(size=(1,hidden_layer_neurons))
wout=np.random.uniform(size=(hidden_layer_neurons,output_neurons))

bout=np.random.uniform(size=(1,output_neurons))
for i in
    range(epoch):hinp1=n
    p.dot(x,wh)hinp=hinp
    1+bh
    hlayer_act=sigmoid(hinp)
    outinp1=np.dot(hlayer_act,wout)ou
    tinp=outinp1+bout
    output=sigmoid(outinp)
    EO=(y-output)
    # back Propagation
    outgrad=derivatives_sigmoid(output)d_
    output=EO*outgrad
    EH=d_output.dot(wout.T)
    hiddengrad=derivatives_sigmoid(hlayer_act)d_h
    iddenlayer=EH*hiddengrad
    #change of weight at each layer
    wout+=hlayer_act.T.dot(d_output)*lr
    bout += np.sum(d_output,axis=0,keepdims=True)
    *lrwh+=x.T.dot(d_hiddenlayer)*lr
    bh +=np.sum(d_hiddenlayer, axis=0,keepdims=True)
    *lr#output after each epoch
    #print("-----Epoch-",i+1,"Starts-----")
    #print("Input:\n"+ str(x))
    #print("ActualOutput: \n"+ str(y))
    #print("Predicted Output: \n" ,output)
    #print("Error:\n"+str(EO))
    #print("-----Epoch-",i+1,"Ends ----- \n")

```

---

```
print("Actual output"+str(y))
print("Predicted
Output"+str(output))print("Error"+str(EO)
)
```

**Output:**

Actual Output:

```
[[0.92]
 [0.86]
 [0.89]]
```

Predicted Output:

```
[[0.86627165]
 [0.8576674 ]
 [0.86966079]]
```

Error:

```
[[0.05372835]
 [0.0023326 ]
 [0.02033921]]
```

**EXPERIMENT-12**

**AIM:** Write a program to do sentiment analysis of live tweets.

**DESCRIPTION:**

TextBlob: textblob is the **python** library for

processing textual **data**. We follow these 3 major steps

**in our program:**

1. Authorize **twitter** API client.
2. **Make** a GET request to **Twitter** API to fetch **tweets** for a particular query.
3. Parse the **tweets**. Classify each **tweet** as positive, negative or neutral.

**SOURCE CODE:**

```
import tweepy
import pandas as pd
import numpy as np
from IPython.display import display
import matplotlib.pyplot as plt
import seaborn as sns

def
    twit
    ter_
    setu
    p():
    """
    Utility function to setup the Twitter's
    API with our access keys provided.
    """
    # Authentication and access using keys:
    auth = tweepy.OAuthHandler("API Key", "API
    Secret")auth.set_access_token("AccessKey","Acces
    sToken")

    # Return API with authentication:
    api=tweepy.API(auth)
    return api

# We create an extractor object:
extractor=twitter_setup()

# We create a tweet list as follows:
tweets = extractor.user_timeline(screen_name="Username of Twitter account",
count=200)print("Number of tweets extracted:{ }.\n".format(len(tweets)))

# We print the most recent 5 tweets:
print("13 recent tweets:\n")
for tweet in
    tweets[:1
```

```

3]:print(t
weet.text
)
print()

# We create a pandas dataframe as follows:https://t.co/cGS4gdrBYH
data=pd.DataFrame(data=[tweet.textfortweetintweets],columns=['Tweets'])
# We display the first 10 elements of the dataframe:
display(data.head(5))

Internal methods of a single tweet object:
print(dir(tweets[0]))

# We print info from the first tweet:
print(tweets[0].id)
print(tweets[0].created_at)print(tweet
s[0].source)
print(tweets[0].favorite_
count)print(tweets[0].ret
weet_count)print(tweets
[0].geo)
print(tweets[0].coordinates)print(tweets[0].entities

# We add relevant data:
data['len']= np.array([len(tweet.text) for tweet in tweets])data['ID']
=np.array([tweet.idfortweetintweets])
data['Date'] = np.array([tweet.created_at for tweet in
tweets])data['Source']=np.array([tweet.sourcefortweetintweets])
data['Likes']= np.array([tweet.favorite_count for tweet in tweets])data['RTs']
=np.array([tweet.retweet_countfortweetintweets])

# Display of first 10 elements from dataframe:
display(data.head(10))
mean=np.mean(data['len'])
print("Thelenght'saverageintweets:{ }".format(mean))

# We extract the tweet with more FAVs and more RTs:
fav_max =
np.max(data['Likes'])rt_
max=np.max(data['RTs'])
)
fav = data[data.Likes ==
fav_max].index[0]rt
=data[data.RTs==rt_max].index[
0]
# Max FAVs:
print("The tweet with more likes is:
\n{ }".format(data['Tweets'][fav]))print("Numberof likes: { }".format(fav_max))
print("{ }characters.\n".format(data['len'][fav]))
# Max RTs:
print("The tweet with more retweets is:
\n{ }".format(data['Tweets'][rt]))print("Numberof retweets: { }".format(rt_max))
print("{ }characters.\n".format(data['len'][rt]))
tlen = pd.Series(data=data['len'].values, index=data['Date'])tfav =
pd.Series(data=data['Likes'].values,
index=data['Date'])tret=pd.Series(data=data['RTs'].values,index=dat
a['Date'])

```



```

# Lengths along time:
tlen.plot(figsize=(16,4),color='r');

tfav.plot(figsize=(16,4),label="Likes",legend=True)
tret.plot(figsize=(16,4),label="Retweets",legend=True);

# We obtain all possible sources:
sources=[]
for source in data['Source']:
    if source not in
        sources:
        sources.append(
            source)
# We print sources list:
print("Creation of content sources:")
for source in sources:
    print("{} {}".format(source))

# We create a numpy vector mapped to labels:
percent=np.zeros(len(sources))
for source in data['Source']:
    for index in range(len(sources)):
        if source ==
            sources[index]
            :percent[index]
            +=1
        pass

percent/=100
# Pie chart:
pie_chart=pd.Series(percent,index=sources,name='Sources')
pie_chart.plot.pie(fontsize=11,autopct='%0.2f',figsize=(6,6));

from textblob import TextBlob
import re
def
    clean_tweet(
        tweet):
    """
    Utility function to clean the text in a tweet by removing links
    and special characters using regex.
    """
    return " ".join(re.sub("(@[A-Za-z0-9]+)|(^0-9A-Za-z\t)|(\w+:\w+\S+)", "", tweet).split())

def
    analyze_tweet_sentiment(
        tweet):
    """
    Utility function to classify the polarity of a
    tweet using textblob.
    """
    analysis=TextBlob(clean_tweet(tweet))
    if analysis.sentiment.polarity>0:
        return 1
    elif analysis.sentiment.polarity==0:
        return 0
    else:

```

```

return-1

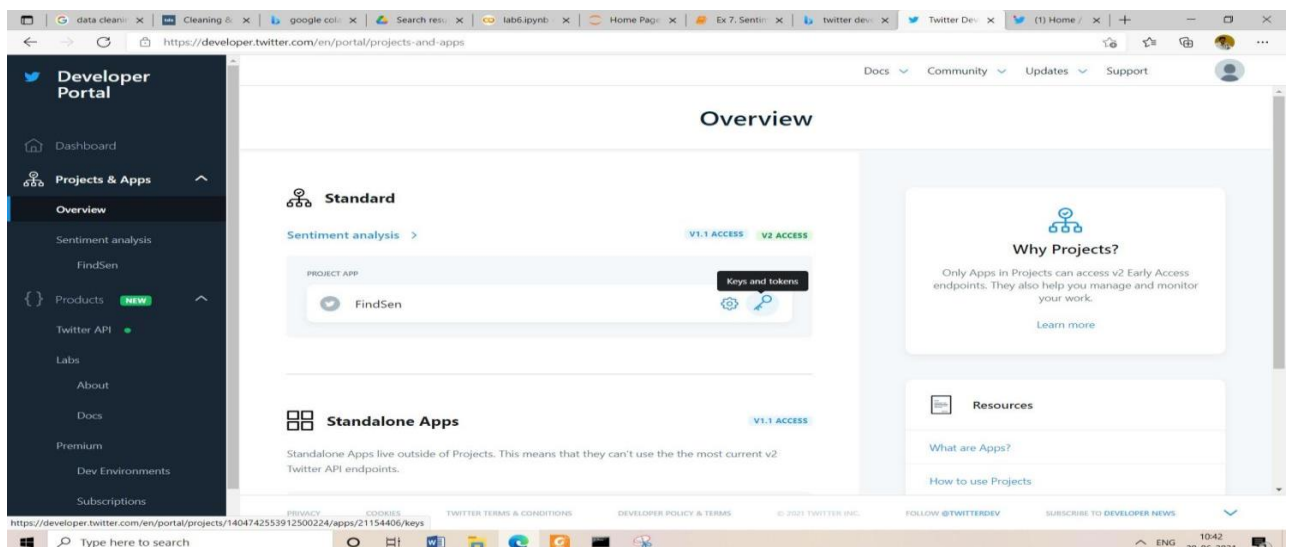
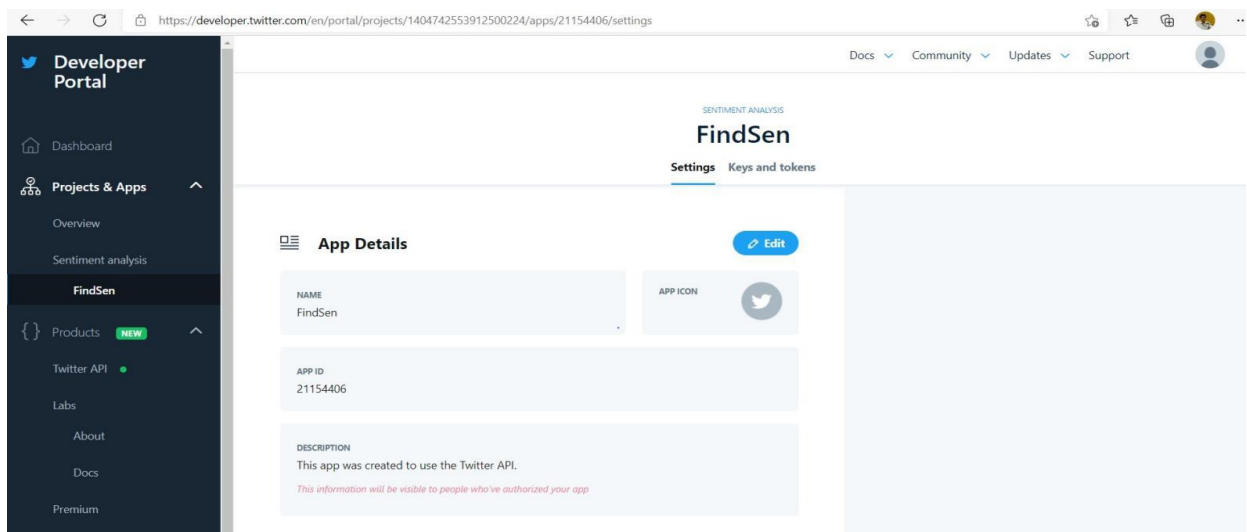
# We create a column with the result of the analysis:
data['SA']=np.array([analyze_sentiment(tweet)fortweetindata['Tweets']])
# We display the updated dataframe with the new column:
display(data.head(10))

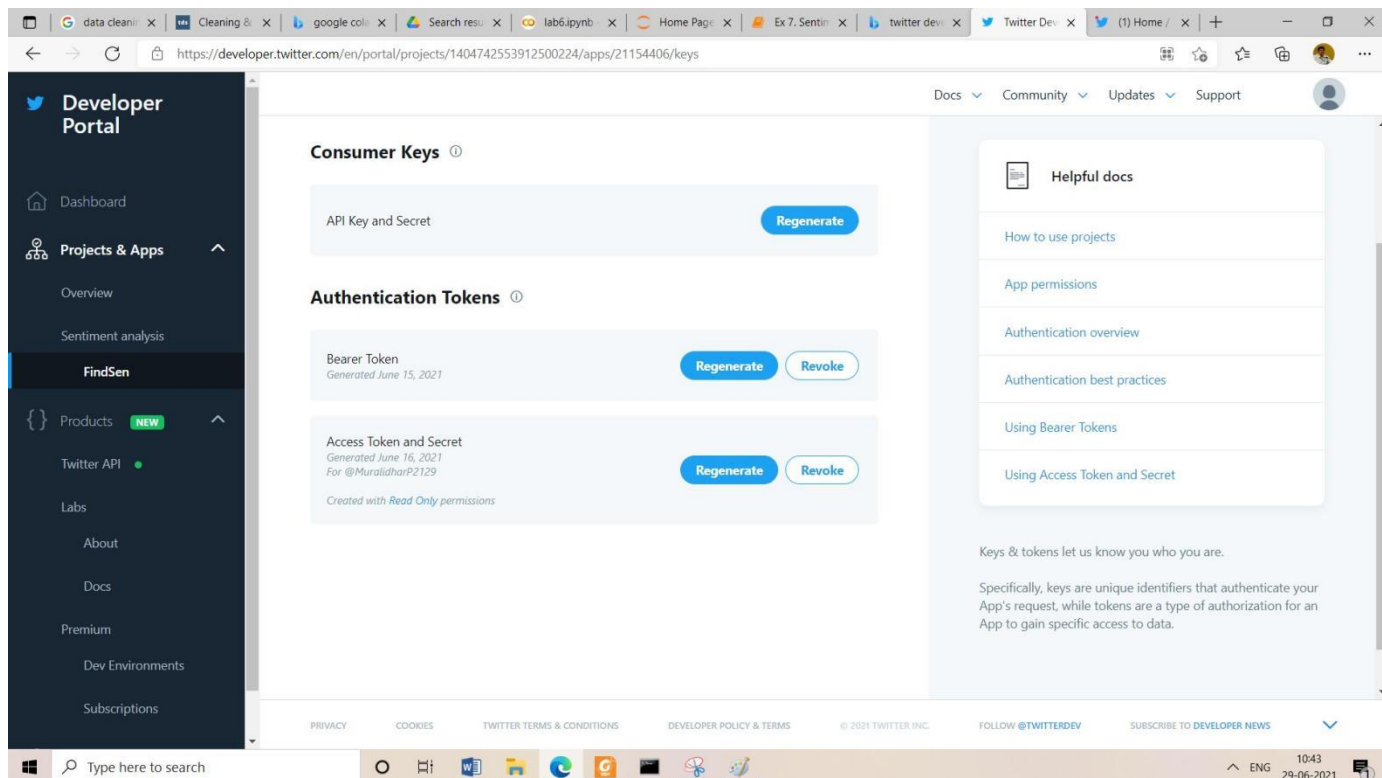
# We construct lists with classified tweets:
pos_tweets = [ tweet for index, tweet in enumerate(data['Tweets']) if data['SA'][index] > 0
neu_tweets = [ tweet for index, tweet in enumerate(data['Tweets']) if data['SA'][index] == 0
neg_tweets = [ tweet for index, tweet in enumerate(data['Tweets']) if data['SA'][index] < 0
print(pos_tweets,neu_tweets, neg_tweets)

# We print percentages:
print("Percentage of positive tweets: { }%".format(len(pos_tweets)*100/len(data['Tweets'])))
print("Percentage of neutral tweets: { }%".format(len(neu_tweets)*100/len(data['Tweets'])))
print("Percentage of negative tweets: { }%".format(len(neg_tweets)*100/len(data['Tweets'])))

```

## Output:





Number of tweets extracted: 13.

13 recent tweets:

Youngster's are making Indian powerful

Indian Covid Vaccine became much popular in the world

Yes! The All-Party Parliamentary Group on  
Coronavirus (@AppgCoronavirus  
) is now discussing the needed scope & str...  
<https://t.co/f3dxLJupGm> (<https://t.co/f3dxLJupGm>)

How can this mob of aggressive anti-lockdown protesters think it's  
OK to [pursue & threaten BBC journalist...](https://t.co/JM67tEAwpy)  
<https://t.co/JM67tEAwpy> (<https://t.co/JM67tEAwpy>)

Akshay Kumar's #BellBottom to release in theatres... After weeks of  
stimulation over its release plan, the makers  
[h...https://t.co/AyJxA87Xx2](https://t.co/AyJxA87Xx2)([http  
s://t.co/AyJxA87Xx2](https://t.co/AyJxA87Xx2))

Than  
k you  
so so  
much  
@aks

hayk

umar

, I guess other will follow suit and start announcing dates and we can prepare...<https://t.co/7rnQJOGjYn>(<https://t.co/7rnQJOGjYn>)

- 0 Youngster's are making Indian powerful
- 1 Indian Covid Vaccine became much popular in the...
- 2 Yes! The All-Party Parliamentary Group on Coro...
- 3 How can this mob of aggressive anti-lockdown p...
- 4 Akshay Kumar's #BellBottom to release in theat...

1405056277709946881

2021-06-16 06:54:55

{'hashtags': [], 'symbols': [], 'user\_mentions': [], 'urls': []}

Twitter web App 0

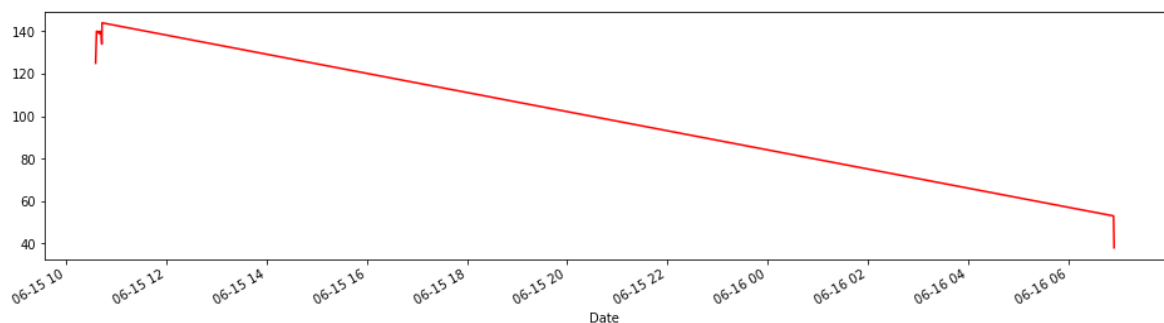
The length's average in tweets: 123.92307692307692

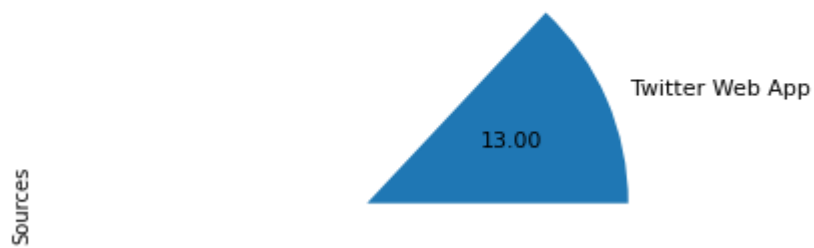
The tweet with more likes is:

Youngster's are making  
Indian powerful  
Number of  
likes: 0  
38 characters.

The tweet with more retweets is:

Youngster's are making  
Indian powerful  
Number of  
retweets: 0  
38 characters.





Percentage of positive tweets:

46.15384615384615%

Percentage of neutral tweets: 46.15384615384615%

Percentage de negative tweets: 7.6923076923076925%