

UNIVERSITY OF MUMBAI



DEPARTMENT OF COMPUTER SCIENCE

M.SC (Computer Science)

CERTIFICATE

Certified that the work entered in this journal was
done in the computer laboratory by the student

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Of the Class - MSc computer Science

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manner.

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PSCSP203	Practical Course on Web Mining	
1	<p>Scrape an online E-Commerce Site for Data.</p> <p>1. Extract product data from Amazon - be it any product and put these details in the MySQL database. One can use pipeline. Like 1 pipeline to process the scraped data and other to put data in the database and since Amazon has some restrictions on scraping of data, ask them to work on small set of requests otherwise proxies and all would have to be used.</p> <p>2. Scrape the details like color, dimensions, material etc. Or customer ratings by features.</p>	3 - 9
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Practical 1

AIM :- Scrape an online E-Commerce Site for Data.

1. Extract product data from Amazon - be it any product and put these details in the MySQL database. One can use pipeline. Like 1 pipeline to process the scraped data and other to put data in the database and since Amazon has some restrictions on scraping of data, ask them to work on small set of requests otherwise proxies and all would have to be used.
2. Scrape the details like color, dimensions, material etc. Or customer ratings by features.

THEORY :-

Web scraping is the process of collecting structured web data in an automated fashion. It's also called web data extraction. Some of the main use cases of web scraping include price monitoring, price intelligence, news monitoring, lead generation, and market research among many others.

CODE / OUTPUT :-

```
pip install kora -q
```

```
import csv
```

```
from bs4 import BeautifulSoup
```

```
from kora.selenium import wd
```

```
wd.get('https://www.amazon.in/')
```

```
wd.page_source
```



```
options.add_argument('-disable-dev-shm-usage')
```

```
wd = webdriver.Chrome('chromedriver',options=options)
```

```
wd.get("https://www.amazon.in/")
```

```
print(wd.page_source) # results
```

```
<html lang="en-in" class="a-js a-audio a-video a-canvas a-svg a-drag-drop a-geolocation a-history a-webworker a-autofocus a-
-input-placeholder a-textarea-placeholder a-local-storage a-gradients a-transform3d a-touch-scrolling a-text-shadow a-text-s
troke a-box-shadow a-border-radius a-border-image a-opacity a-transform a-transition null" data-19ax5a9jf="dingo" data-aui-b
uild-date="3.22.1-2022-05-18" data-useragent="Mozilla/5.0 (X11; Linux x86_64) AppleWebKit/537.36 (KHTML, like Gecko) Headles
sChrome/101.0.4951.64 Safari/537.36" data-platform="Linux x86_64"><!-- sp:feature:head-start --><head><script async="" src
="https://c.amazon-adsystem.com/bao-csm/forensics/a9-tq-forensics-incremental.min.js" crossorigin="anonymous"></script><scri
pt async="" src="https://images-eu.ssl-images-amazon.com/images/I/31YXrY93hfL.js" crossorigin="anonymous"></script><script>v
ar aPageStart = (new Date()).getTime();</script><meta charset="utf-8">
<!-- sp:end-feature:head-start -->

<script type="text/javascript">var ue_t0=ue_t0||new Date();</script>
<!-- sp:feature:cs-optimization -->
<meta http-equiv="x-dns-prefetch-control" content="on">
<link rel="dns-prefetch" href="https://images-eu.ssl-images-amazon.com">
<link rel="dns-prefetch" href="https://m.media-amazon.com">
<link rel="dns-prefetch" href="https://completion.amazon.com">
<!-- sp:end-feature:cs-optimization -->
<script type="text/javascript">
window.ue_ihb = (window.ue_ihb || window.ueinit || 0) + 1;

    if (window.ue_ihb === 1) {

        var ue_csm = window,
            ue_hob = new Date();

        (function(d){var e=d.ue=d.ue||{};f=Date.now||function(){return new Date};e.d=function(b){return f()-(b?0:d.ue_t0)};e.stub=fu
nction(b,a){if(!b[a]){var c=[];b[a]=function(){c.push([c.slice.call(arguments),e.d(),d.ue_id]);b[a].replay=function(b){for
(var aj;a=c.shift();){b[a[0],a[1],a[2]]};b[a].isStub=1}};e.exec=function(b,a){return function(){try{return b.apply(this,argume
nts)}catch(c){ueLogError(c,{attribution:a||"undefined",logLevel:"WARN"}})}}}(ue_csm);

            var ue_err_chan = 'jserr-rw';
            (function(d,e){function h(f,b){if(!((a.ec>a.mxe)&&f){a.ter.push(f);b=b||{};var c=f.logLevel||b.logLevel;c&&c!=k&&c!=m&&c!=
n&&c!=p||a.ec++&c&&c!=k||a.ecf++&b.pageURL=""+(e.location?e.location.href:"");b.logLevel=c;b.attribution=f.attribution||b.a
tribution;a.erl.push([e,f,info:b])}}function l(a,b,c,e,g){d.ueLogError({m:a,f:b,l:c,c:""+e,err:g,fromOnError:1,args:argume
nts},g,{attribution:g.attribution,logLevel:g.logLevel;void 0});return!1}var k="FATAL",m="ERROR",n="WARN",p="DOWNGRADED",a={e
c:0,ecf:0,
pec:0,ts:0,erl:[],ter:[],mxe:50,startTimer:function(){a.ts++;setInterval(function(){d.ue&&a.pec<a.ec&&d.ue("at");a.pec=a.e
c,1f4}});l.skipTrace=1;h.skipTrace=1;h.isStub=1;d.ueLogError=h;d.ue_err=a;e.onerror=1})(ue_csm>window);

var ue_id = 'V04XDSF8EP0HQASXGCC9',
    ue_url = '/rd/uedata',
    ue_navtiming = 1,
    ue_mid = 'A21TJRUN4KGV',
    ue_sid = '259-0154261-9957235',
    ue_sn = 'www.amazon.in',
    ue_furl = 'fls-eu.amazon.in',
    ue_surl = 'https://unagi-eu.amazon.com/1/events/com.amazon.csm.nexusclient.prod',
    ue_int = 0,
    ue_fcsn = 1,
    ue_urt = 3,
    ue_rpl_ns = 'cel-rpl',
    ue_ddq = 1,
    ue_fpf = '/fls-eu.amazon.in/1/batch/1/OP/A21TJRUN4KGV:259-0154261-9957235:V04XDSF8EP0HQASXGCC9$uedata=s:',
    ue_sbuimp = 1,
    ue_cel_lclia = 1,
    ue_ibft = 0,
    ue_sswmts = 0,
    ue_inl = 0,

    ue_swi = 1;
var ue_viz=function(){(function(b,e,a){function k(c){if(b.ue.viz.length<p&&1){var a=c.type;c=c.originalEvent;/^focus./.test
(a)&&c&&(c.toElement||c.fromElement||c.relatedTarget)||[a=e[m]]||["blur"==a||"focusout"==a?"hidden":"visible"],b.ue.viz.push
(at":"+new Date-b.ue.t0),"visible"==a&&(b.ue.isl&&q("at"),1=1)}}for(var l=0,q=b.ue.x,f,g,m,n=["","webkit","o","ms","mo
z"],d=0,p=20,h=0;h<n.length&&!d;h++)if(a=n[h],f=(a?+H:"h")+idn,d="boolean"==typeof e[f])g=a+"visibilitychange",m=(a?a
+"V":"v")+
"visibilityState";k({});d&&e.addEventListener(g,k,0);b.ue&&d&&(b.ue.pageViz={event:g,propHid:f}})(ue_csm,ue_csm.document,ue_
csm.window));

(function(d,h,N){function H(a){return a&&a.replace&&a.replace(/^\s+|\s+$/g,"")}function u(a){return"undefined"===typeof a}fu
nction B(a,b){for(var c in b)b[v](c)&&(a[c]=b[c])}function I(a){try{var b=N.cookie.match(RegExp("(^| )"+at="([^;]+)"));if(b)
return b[2].trim()}catch(c){}}function O(m,b,c){var q=(x||{}).type;if("device"!=c||2!=q&&1!=q)m&&(d.ue_id=a.id=a.rid=m,w&
&(w=w.replace(/((?:.?:){2})(\w+)/,function(a,b){return b+m})),D&&(e("id",D,m),D=0)),b&&(w&&(w=w.replace(/((?:.?:){2})(\w+)/,funct
ion(a,
c){return c+b})),d.ue_sid=b,c&&a.tag("page-source:"+c),d.ue_fpf=w}function P(){var a={};return function(b){b&&(a[b]=1);b=
[];for(var c in a)a[v](c)&&b.push(c);return b}}function y(d,b,c,q){q=q||new E;var f,l;if(b||u(c)){if(d)for(l in f=b?e("t",
b)||e("t",b,{}):a.t,f[d]=q,c[v](l)&&e(l,b,c[l]);return q}function e(d,b,c){var e=b&&b!=a.id?a.sc[b]:a.e||e(a.sc[b]=
{}),"id"---d&&e&&(0=1);return afd=lclia[d]}function B(d,h,c,e,f){var q="ae"==var l=hclia["function"]?returnpf:1;d&&(a.kfdl=1);l=f

```

```
[e]}}<{downlink:"downlink"in d?c(d.downlink||0):null,downlinkMax:"downlinkMax"in d?c(d.downlinkMax||0):null,rtt:"rtt"in d?
(d.rtt||0).toFixed():null,type:d.type||null,effectiveType:d.effectiveType||null,saveData:"saveData"in d?d.saveData:null}}fu
nction k(){v(),u()}function w(){l(),u()}l(),u(),e.on("$afterPageTransition",w),e.on(d,"change",k)});
if (window.ue && window.ue.uels) {
    ue.uels("https://c.amazon-adsystem.com/bao-csm/forensics/a9-tq-forensics-incremental.min.js");
}

ue.exec(function(d,c){function g(e,c){e&&ue.tag(e+c);return!e}function n(){for(var e=RegExp("^https://(.*\\. (images|ssl-imag
es|media)-amazon\\.com|" +c.location.hostname+" )/images/", "i"),d={},h=0,k=c.performance.getEntriesByType("resource"),l=!1,b=a,
m,f=0;f<k.length;f++)if(a=k[f],0<a.transferSize&&a.transferSize>a.encodedBodySize&&(b=e.exec(String(a.name)))&&3===b.lengt
h){a:{b=a.serverTiming||[];for(a=0;a<b.length;a++)if("provider"===b[a].name){b=b[a].description;break a}b=void 0}b&&(1||l=g
(b,"_cdn_fr")),
a=d[b]=(d[b]||0)+1,a>h&&(m=b,h=a))}g(m,"_cdn_mp")}}d.ue&&"function"===typeof d.ue.tag&&c.performance&&c.location&&n(), "cdnTa
gging")(ue_csm,window);

}
/* Δ */
</script>

</div>

<noscript>

</noscript>

<script>window.ue && ue.count && ue.count('CSMLibrarySize', 59905)</script>
</div>
<!--
    (MEOW)
    ~~~~~~
<!-- sp:eh:VcNDuIRcQpw06IzqH+VqQ/vElJ1k96NZMu0GHh3k1AiuuIPY07Nq3tqkxVaFzOgzc6eqQgrRs+stdLtMpnner1UXAZe8I6tKyk3Pud1241LuCQ7HUK
0bBulR+RqM= -->
<div id="a-popover-root" style="z-index:-1;position:absolute;"></div></body></html>
```

```
def get_url(search_term):
    template =
    "https://www.amazon.in/s?k={}&rh=n%3A1389401031&ref=nb_sb_noss"

    search_term = search_term.replace(' ', '+')

    return template.format(search_term)
```

```
url = get_url('laptops')
```

```
print(url)
```

```
https://www.amazon.in/s?k=laptops&rh=n%3A1389401031&ref=nb_sb_noss
```

```
wd.get(url)
```

```
soup = BeautifulSoup(wd.page_source, 'html.parser')
```

```
result = soup.find_all('div',{'data-component-type':'s-search-result'})
```

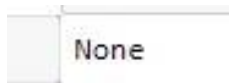
```
len(result)
```

```
print(result[2])
```



```
review_count = item.find('span', {'class':'a-size-base','dir':'auto'})
```

```
print(review_count)
```



```
def extract_record(item1):
```

```
    atag = item1.h2.a
```

```
    description = atag.text.strip()
```

```
    url = "https://www.amazon.in/" + atag.get('href')
```

```
    price_parent = item1.find('span','a-price')
```

```
    #price_parent.find('span','a-offscreen').text
```

```
    rating = ""
```

```
    result = (description, price_parent, rating)
```

```
    return result
```

```
url = get_url('mouse')
```

```
wd.get(url)
```

```
soup = BeautifulSoup(wd.page_source, 'html.parser')
```

```
records = []
```

```
results = soup.find_all('div',{'data-component-type':'s-search-result'})
```

```
for item in results:
```

```
    records.append(extract_record(item))
```

```
records[0]
```

```
print("printing records")
```

```
for x in range(len(records)):
```

```
    print(records[x])
```


printing records

('4 Seasons Minnie Mouse Wired Over the Ear Headphone (White)', ₹699₹699, '')
('Red Champion Wired Black USB Wired Plug & Play Ergonomic Mouse with Type C OTG & Micro OTG Wire', ₹349₹349, '')
('Dell Optical Mouse MS116', ₹368₹368, '')
('ELECTROPRIME 2X(2.4GHz USB Wireless Optical Pen Mouse PPT Pointer Capacitive Touch Scree K5L5', None, '')
('BenQ Zowie CAMADE II Bungee for e-Sports Mice Cable Management Device Black/Red', ₹2,499₹2,499, '')
('Microware 2.4Ghz 1600 DPI Wireless Optical Vertical Mouse, Rechargeable Ergonomic High Precision Optical Mice with USB Wireless Receiver Super Comfortable', ₹1,599₹1,599, '')
('Tandon Mobile Product i Ball Mouse style36', ₹358₹358, '')
('BYLKO 2in1 Jack Data Sync Mouse Pendrive & Charging Kit for Redmi Spower/Prime/Shadow Note 10 10pro 9 9pro 8 7 7s Mi 10i 10T Pro Y3 Y2 K30 K20 Mix3 2 Mix Alpha All Mobile(Multi Colour)', ₹199₹199, '')
('Digital Connect Alex Wired Optical Mouse (USB 2.0, Black)', ₹399₹399, '')
('ELECTROPRIME 2.4GHz USB Wireless Optical Pen Mouse PPT Pointer Capacitive Touch Screen S K2U2', None, '')
('ELECTROPRIME 2.4GHz USB Wireless Optical Pen Mouse PPT Pointer Capacitive Touch Screen S ISAG', None, '')
('SAFETYNET GSM USB PC Mouse Calling Device with GSM Listening 2-Way Audio Bug Surveillance Device(GSM Sim Card) Mouse .Clear Listening Sound', ₹3,445₹3,445, '')
('Shock Proof Back Cover polycarbonate Mini Mouse Set of 2 by SANA Mobile SN-MB-23', None, '')
('SWOFER Cable Management Retractable Cord Organizer 2-in-1 Cord Management Case Mobile Phone Holder | Cable Tidy Storage Protector Wire Winder for USB Cable | Headset Cord,Mouse Wire', ₹199₹199, '')
('Bitnrex 2-in-1 Cable Management Retractable Cord Organizer Mobile Phone Holder Cable Tidy Storage Protector Wire Winder for USB Cable,Headset Cord,Mouse Wire,Charger Cable (white)', ₹249₹249, '')
('Shock Proof Back Cover polycarbonate Mini Mouse Set of 2 by Seven Communication SN-CM-23', ₹808₹808, '')
('Shock Proof Back Cover polycarbonate Mini Mouse by SANA Mobile SN-MB-03', None, '')
('Shock Proof Back Cover polycarbonate Mini Mouse by Seven Communication SN-CM-03', ₹488₹488, '')
('Mehan's\xae3D Optical Wired Mouse (Black)", ₹249₹249, '')
('S.R.Mobile Worlds All Mobile accesories are Premium z Bold Wireless Mouse Set 1', ₹399₹399, '')
('USB Mouse Line, Light Weight Magnetic Buckle Good Match Mouses Cable for Replacement', ₹688₹688, '')
('Digital Connect Alex Wired Optical Mouse (USB 2.0, Black) Set of 2', ₹699₹699, '')
('Ubon Wireless Mouse', ₹399₹399, '')
('Mouse Shape Multi Use Foldable Mobile Holder', ₹429₹429, '')
('Call me Enterprises USB Optical Mouse', None, '')
('Shock Proof Back Cover polycarbonate Mini Mouse Set of 2 by AVS Enterprises AV-ET-23', ₹808₹808, '')
('Shock Proof Back Cover polycarbonate Mini Mouse by AVS Enterprises AV-ET-03', ₹488₹488, '')

Practical 2

AIM :- Page Rank for link analysis using python

Create a small set of pages namely page1, page2, page3 and page4 apply random walk on the same.

THEORY :-

PageRank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other websites.

CODE / OUTPUT :-

```
"""Random_Walk_Page_Rank"""
"Practical 3"

import networkx as nx
import random
import numpy as np

# Add directed edges in graph
def add_edges(g, pr):
    for each in g.nodes():
        for each1 in g.nodes():
            if (each != each1):
                ra = random.random()
                if (ra < pr):
                    g.add_edge(each, each1)
            else:
                continue

    return g
```

```

# Sort the nodes
def nodes_sorted(g, points):
    t = np.array(points)
    t = np.argsort(-t)
    return t

# Distribute points randomly in a graph
def random_Walk(g):
    rwp = [0 for i in range(g.number_of_nodes())]
    nodes = list(g.nodes())
    r = random.choice(nodes)
    rwp[r] += 1
    neigh = list(g.out_edges(r))
    z = 0

    while (z != 10000):
        if (len(neigh) == 0):
            focus = random.choice(nodes)
        else:
            r1 = random.choice(neigh)
            focus = r1[1]
            rwp[focus] += 1
            neigh = list(g.out_edges(focus))
            z += 1
    return rwp

g = nx.DiGraph()
N = 4
g.add_nodes_from(range(N))

# 2. Add directed edges in graph

```



```

g = add_edges(g, 0.4)

# 3. perform a random walk
points = random_walk(g)

# 4. Get nodes rank according to their random walk points
sorted_by_points = nodes_sorted(g, points)
print("PageRank using Random Walk Method")
print(sorted_by_points)

# p_dict is dictionary of tuples
p_dict = nx.pagerank(g)
p_sort = sorted(p_dict.items(), key=lambda x: x[1], reverse=True)

print("PageRank using inbuilt pagerank method")
for i in p_sort:
    print(i[0], end=", ")

```

```

PageRank using Random Walk Method
[0 3 1 2]
PageRank using inbuilt pagerank method
0, 3, 1, 2,

```

Practical 3

AIM :- Perform Spam Classifier

THEORY :-

A spam filter/classifier is a program used to detect unsolicited, unwanted and virus-infected emails and prevent those messages from getting to a user's inbox. Like other types of filtering programs, a spam filter looks for specific criteria on which to base its judgments.

CODE / OUTPUT :-

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import drive
from sklearn import feature_extraction, naive_bayes, metrics,
model_selection
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_recall_fscore_support as score
drive.mount('/content/drive')

dataset =pd.read_csv("/content/drive/MyDrive/spam.csv", encoding='latin-
1')
```

```
dataset.head()
```

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only ...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro...	NaN	NaN	NaN

```
#removing unnamed columns
```

```
dataset = dataset.drop('Unnamed: 2', 1)
dataset = dataset.drop('Unnamed: 3', 1)
dataset = dataset.drop('Unnamed: 4', 1)
dataset.head()
```

```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: FutureWarning: In a future version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: FutureWarning: In a future version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only
This is separate from the ipykernel package so we can avoid doing imports until
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: FutureWarning: In a future version of pandas all arguments of DataFrame.drop except for the argument 'labels' will be keyword-only
after removing the cwd from sys.path.

```

	v1	v2
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

```
dataset = dataset.rename(columns = {'v1':'label','v2':'message'})
```

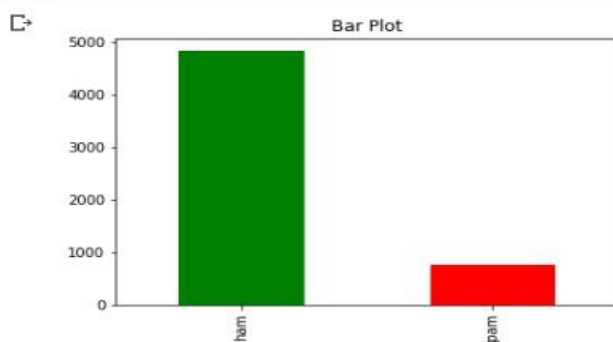
```
dataset.groupby('label').describe()
```

	message			
	count	unique	top	freq
label				
ham	4825	4516	Sorry, I'll call later	30
spam	747	653	Please call our customer service representativ...	4

```
dataset.head(4)
```

	label	message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...

```
count_Class=pd.value_counts(dataset["label"], sort= True)
count_Class.plot(kind = 'bar',color = ["green","red"])
plt.title('Bar Plot')
plt.show();
```



```
f = feature_extraction.text.CountVectorizer(stop_words = 'english')
```



```
X = f.fit_transform(dataset["message"])
np.shape(X)
```

```
↳ (5572, 8404)
```

```
# Classifying spam and not spam msgs as 1 and 0
```

```
dataset["label"]=dataset["label"].map({'spam':1,'ham':0})
X_train, X_test, y_train, y_test = model_selection.train_test_split(X,
dataset['label'], test_size=0.70, random_state=42)
```

```
list_alpha = np.arange(1/100000, 20, 0.11)
score_train = np.zeros(len(list_alpha))
score_test = np.zeros(len(list_alpha))
recall_test = np.zeros(len(list_alpha))
precision_test= np.zeros(len(list_alpha))
count = 0
for alpha in list_alpha:
    bayes = naive_bayes.MultinomialNB(alpha=alpha)
    bayes.fit(X_train, y_train)
    score_train[count] = bayes.score(X_train, y_train)
    score_test[count]= bayes.score(X_test, y_test)
    recall_test[count] = metrics.recall_score(y_test,
bayes.predict(X_test))
    precision_test[count] = metrics.precision_score(y_test,
bayes.predict(X_test))
    count = count + 1
```

```
matrix = np.matrix(np.c_[list_alpha, score_train, score_test, recall_test,
precision_test])
models = pd.DataFrame(data = matrix, columns =
    ['alpha', 'Train Accuracy', 'Test Accuracy', 'Test Recall',
'Test Precision'])
models.head(n=10)
```

```
best_index = models['Test Precision'].idxmax()
models.iloc[best_index, :]
```

```
rf = RandomForestClassifier(n_estimators=100,max_depth=None,n_jobs=-1)
rf_model = rf.fit(X_train,y_train)
```

```
y_pred=rf_model.predict(X_test)
precision,recall,fscore,support =score(y_test,y_pred,pos_label=1, average
='binary')
print('Precision : {} / Recall : {} / fscore : {} / Accuracy:
{}'.format(round(precision,3),round(recall,3),round(fscore,3),round((y_pre
d=y_test).sum()/len(y_test),3)))
```

```
📄 Precision : 0.987 / Recall : 0.747 / fscore : 0.851 / Accuracy: 0.965
```

```
import tensorflow as tf
from keras.preprocessing.text import Tokenizer
from keras.layers import Embedding, LSTM, Dropout, Dense
from keras.models import Sequential
from tensorflow.keras.utils import to_categorical
#from keras.utils import to_categorical
from keras.preprocessing.sequence import pad_sequences
import tensorflow as tf

vocab_size = 400
oov_tok = "<OOV>"
max_length = 250
embedding_dim = 16
encode = ({'ham': 0, 'spam': 1} )
#new dataset with replaced values
dataset = dataset.replace(encode)

X = dataset['message']
Y = dataset['label']
tokenizer = Tokenizer(num_words=vocab_size, oov_token=oov_tok)
tokenizer.fit_on_texts(X)
# convert to sequence of integers
X = tokenizer.texts_to_sequences(X)

X = np.array(X)
y = np.array(Y)

X = pad_sequences(X, maxlen=max_length)
```

```

model = tf.keras.Sequential([
    tf.keras.layers.Embedding(vocab_size, embedding_dim,
input_length=max_length),
    tf.keras.layers.GlobalAveragePooling1D(),
    tf.keras.layers.Dense(24, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()

num_epochs = 50
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=.20,
random_state=7)
history = model.fit(X_train, y_train, epochs=num_epochs,
validation_data=(X_test,y_test), verbose=2)

results = model.evaluate(X_test, y_test)
loss = results[0]
accuracy = results[1]

print(f"[+] Accuracy: {accuracy*100:.2f}%")

from keras.preprocessing import sequence

#Defining the function
def get_predictions(txts):
    txts = tokenizer.texts_to_sequences(txts)
    txts = sequence.pad_sequences(txts, maxlen=max_length)
    preds = model.predict(txts)
    if(preds[0] > 0.5):
        print("SPAM MESSAGE")

```



```

else:
    print('NOT SPAM')

```

```
txts=["You have won a free ticket to las vegas. Contact now"]
```

```
get_predictions(txts)
```

```
txts=["Hey there call me asap!!"]
```

```
get_predictions(txts)
```

```

140/140 - 1s - loss: 0.0482 - accuracy: 0.9838 - val_loss: 0.0468 - val_accuracy: 0.9865 - 718ms/epoch - 5ms/step
Epoch 25/50
140/140 - 1s - loss: 0.0478 - accuracy: 0.9845 - val_loss: 0.0467 - val_accuracy: 0.9857 - 610ms/epoch - 4ms/step
Epoch 26/50
140/140 - 0s - loss: 0.0467 - accuracy: 0.9850 - val_loss: 0.0453 - val_accuracy: 0.9874 - 457ms/epoch - 3ms/step
Epoch 27/50
140/140 - 1s - loss: 0.0448 - accuracy: 0.9859 - val_loss: 0.0441 - val_accuracy: 0.9874 - 696ms/epoch - 5ms/step
Epoch 28/50
140/140 - 1s - loss: 0.0434 - accuracy: 0.9856 - val_loss: 0.0439 - val_accuracy: 0.9892 - 768ms/epoch - 5ms/step
Epoch 29/50
140/140 - 1s - loss: 0.0436 - accuracy: 0.9854 - val_loss: 0.0432 - val_accuracy: 0.9883 - 690ms/epoch - 5ms/step
Epoch 30/50
140/140 - 1s - loss: 0.0421 - accuracy: 0.9852 - val_loss: 0.0429 - val_accuracy: 0.9892 - 853ms/epoch - 6ms/step
Epoch 31/50
140/140 - 1s - loss: 0.0405 - accuracy: 0.9863 - val_loss: 0.0430 - val_accuracy: 0.9892 - 777ms/epoch - 6ms/step
Epoch 32/50
140/140 - 1s - loss: 0.0398 - accuracy: 0.9865 - val_loss: 0.0450 - val_accuracy: 0.9839 - 705ms/epoch - 5ms/step
Epoch 33/50
140/140 - 1s - loss: 0.0390 - accuracy: 0.9870 - val_loss: 0.0437 - val_accuracy: 0.9857 - 827ms/epoch - 6ms/step
Epoch 34/50
140/140 - 1s - loss: 0.0404 - accuracy: 0.9870 - val_loss: 0.0510 - val_accuracy: 0.9865 - 640ms/epoch - 5ms/step
Epoch 35/50
140/140 - 1s - loss: 0.0380 - accuracy: 0.9863 - val_loss: 0.0416 - val_accuracy: 0.9901 - 624ms/epoch - 4ms/step
Epoch 36/50
140/140 - 1s - loss: 0.0374 - accuracy: 0.9872 - val_loss: 0.0417 - val_accuracy: 0.9892 - 773ms/epoch - 6ms/step
Epoch 37/50
140/140 - 1s - loss: 0.0364 - accuracy: 0.9872 - val_loss: 0.0415 - val_accuracy: 0.9892 - 739ms/epoch - 5ms/step
Epoch 38/50
140/140 - 1s - loss: 0.0353 - accuracy: 0.9883 - val_loss: 0.0424 - val_accuracy: 0.9892 - 588ms/epoch - 4ms/step
Epoch 39/50
140/140 - 0s - loss: 0.0357 - accuracy: 0.9890 - val_loss: 0.0470 - val_accuracy: 0.9848 - 350ms/epoch - 3ms/step
Epoch 40/50
140/140 - 0s - loss: 0.0350 - accuracy: 0.9872 - val_loss: 0.0417 - val_accuracy: 0.9901 - 426ms/epoch - 3ms/step
Epoch 41/50
140/140 - 0s - loss: 0.0344 - accuracy: 0.9890 - val_loss: 0.0411 - val_accuracy: 0.9901 - 377ms/epoch - 3ms/step
Epoch 42/50
140/140 - 0s - loss: 0.0331 - accuracy: 0.9888 - val_loss: 0.0411 - val_accuracy: 0.9901 - 357ms/epoch - 3ms/step
Epoch 43/50
140/140 - 0s - loss: 0.0318 - accuracy: 0.9899 - val_loss: 0.0413 - val_accuracy: 0.9883 - 358ms/epoch - 3ms/step
Epoch 44/50
140/140 - 0s - loss: 0.0321 - accuracy: 0.9890 - val_loss: 0.0413 - val_accuracy: 0.9892 - 375ms/epoch - 3ms/step
Epoch 45/50
140/140 - 0s - loss: 0.0309 - accuracy: 0.9892 - val_loss: 0.0415 - val_accuracy: 0.9910 - 371ms/epoch - 3ms/step
Epoch 46/50
140/140 - 0s - loss: 0.0314 - accuracy: 0.9890 - val_loss: 0.0436 - val_accuracy: 0.9874 - 382ms/epoch - 3ms/step
Epoch 47/50
140/140 - 0s - loss: 0.0309 - accuracy: 0.9899 - val_loss: 0.0415 - val_accuracy: 0.9883 - 355ms/epoch - 3ms/step
Epoch 48/50
140/140 - 0s - loss: 0.0297 - accuracy: 0.9908 - val_loss: 0.0419 - val_accuracy: 0.9910 - 345ms/epoch - 2ms/step
Epoch 49/50
140/140 - 0s - loss: 0.0297 - accuracy: 0.9912 - val_loss: 0.0414 - val_accuracy: 0.9892 - 356ms/epoch - 3ms/step
Epoch 50/50
140/140 - 0s - loss: 0.0285 - accuracy: 0.9910 - val_loss: 0.0453 - val_accuracy: 0.9901 - 363ms/epoch - 3ms/step
35/35 [=====] - 0s 2ms/step - loss: 0.0453 - accuracy: 0.9901
[+] Accuracy: 99.01%
SPAM MESSAGE
NOT SPAM

```

Practical 4

AIM :- Demonstrate Text Mining and Webpage Pre-processing using meta information from the web pages (Local/Online).

THEORY :-

Web mining is the application of data mining techniques to discover patterns from the World Wide Web. It uses automated methods to extract both structured and unstructured data from web pages, server logs and link structures. There are three main sub-categories of web mining.

Preprocessing stage helps to clean the records and determine the interesting user patterns and session creation. Data preprocessing is an important job of Web usage mining application. So, data must be processed before applying data mining methods to determine user access patterns from web log.

A meta description is an HTML element that provides a brief summary of a web page. A page's meta description tag is displayed as part of the search snippet in a search engine results page (SERP) and is meant to give the user an idea of the content that exists within the page and how it relates to their search query.

CODE / OUTPUT :-

```
"""Pract5.ipynb"""

# Commented out IPython magic to ensure Python compatibility.

# Imports

import requests
import numpy as np
import pandas as pd
from bs4 import BeautifulSoup
import matplotlib.pyplot as plt

# IMDB's homepage
imdb_url = 'https://www.imdb.com'
```

```

# Use requests to retrieve data from a given URL
imdb_response = requests.get(imdb_url)

# Parse the whole HTML page using BeautifulSoup
imdb_soup = BeautifulSoup(imdb_response.text, 'html.parser')

# Title of the parsed page
imdb_soup.title.text

```

```

Out[3]: 'IMDb: Ratings, Reviews, and Where to Watch the Best Movies & TV Shows'

```

```

# Find all links
links = [link.get('href') for link in imdb_soup.find_all('a')]

# Add homepage and keep the unique links
unique_links = []
for link in links:
    if not link in unique_links:
        unique_links.append(imdb_url + link)

# Box Office Mojo - UK Weekend box office
boxofficemojo_url =
'https://www.boxofficemojo.com/intl/uk/?yr=2019&wk=33&currency=local'

# Use requests to retrieve data from a given URL
bom_response = requests.get(boxofficemojo_url)

# Parse the whole HTML page using BeautifulSoup
bom_soup = BeautifulSoup(bom_response.text, 'html.parser')

print(f"NUMBER OF TABLES IN THE PAGE: {len(bom_soup.find_all('table'))}")

```



```
table = bom_soup.find_all('table')[0]
```

table

NUMBER OF TABLES IN THE PAGE: 1

```
<table class="a-bordered a-horizontal-stripes a-size-base a-span12 mojo-body-table mojo-table-annotated"><tr><th class="a-text-left mojo-field-type-date_interval mojo-sort-column mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=startDate&sortDir=asc&ref=bo_vey__resort#table" title="Dates"><span class="a-color-state">Dates</span><span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand" role="presentation"></i></span></a></th><th class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=top10Gross&ref=bo_vey__resort#table" title="Top 10 Gross">Top 10 Gross<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th><th class="a-text-right mojo-field-type-percent_delta mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=top10GrossDelta&ref=bo_vey__resort#table" title="Top 10 Gross Change/Week">%± LW<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th><th class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=grossLastWeekDelta&ref=bo_vey__resort#table" title="Overall Gross">Overall Gross<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th><th class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=grossLastWeekDelta&ref=bo_vey__resort#table" title="Overall Gross Change/Week">%± LW<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th><th class="a-text-right mojo-field-type-positive_integer mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=numReleases&ref=bo_vey__resort#table" title="Number of Releases">Releases<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th><th class="a-text-left mojo-field-type-release mojo-cell-wide mojo-sortable-column a-nowrap"><span title="#1 Release">#1 Release</span></th></tr><tr><td class="a-text-left mojo-field-type-genre hidden mojo-sortable-column hidden a-nowrap"><span title="Genre">Genre</span></td><td class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=top10Gross&ref=bo_vey__resort#table" title="Top 10 Gross">Top 10 Gross<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></td><td class="a-text-right mojo-field-type-percent_delta mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=top10GrossDelta&ref=bo_vey__resort#table" title="Top 10 Gross Change/Week">%± LW<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></td><td class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=grossLastWeekDelta&ref=bo_vey__resort#table" title="Overall Gross">Overall Gross<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></td><td class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=grossLastWeekDelta&ref=bo_vey__resort#table" title="Overall Gross Change/Week">%± LW<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></td><td class="a-text-right mojo-field-type-positive_integer mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=numReleases&ref=bo_vey__resort#table" title="Number of Releases">Releases<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></td><td class="a-text-left mojo-field-type-release mojo-cell-wide mojo-sortable-column a-nowrap"><span title="#1 Release">#1 Release</span></td></tr></table>
```

```
table.find_all('tr')[0].contents
```

```
[<th class="a-text-left mojo-field-type-date_interval mojo-sort-column mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=startDate&sortDir=asc&ref=bo_vey__resort#table" title="Dates"><span class="a-color-state">Dates</span><span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand" role="presentation"></i></span></a></th>,
<th class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=top10Gross&ref=bo_vey__resort#table" title="Top 10 Gross">Top 10 Gross<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th>,
<th class="a-text-right mojo-field-type-percent_delta mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=top10GrossDelta&ref=bo_vey__resort#table" title="Top 10 Gross Change/Week">%± LW<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th>,
<th class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=grossLastWeekDelta&ref=bo_vey__resort#table" title="Overall Gross">Overall Gross<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th>,
<th class="a-text-right mojo-field-type-money mojo-sortable-column a-nowrap"><a class="a-link-normal a-nowrap" href="?area=GB&sort=grossLastWeekDelta&ref=bo_vey__resort#table" title="Overall Gross Change/Week">%± LW<span class="a-letter-space"></span><span class="icon aok-relative"><i class="a-icon a-icon-expand table-sort-desc-placeholder" role="presentation"></i></span></a></th>,
<th class="a-text-left mojo-field-type-release mojo-cell-wide mojo-sortable-column a-nowrap"><span title="#1 Release">#1 Release</span></th>,
<th class="a-text-left mojo-field-type-genre hidden mojo-sortable-column hidden a-nowrap"><span title="Genre">Genre</span></th>]
```

```
table.find_all('tr')[0].text.split('\n')
```

```
['DatesTop 10 Gross%± LWOverall Gross%± LWReleases#1 Release',
'Genre',
'Budget',
'Running Time',
'WeekLong Weekend',
'']
```

```

lst = []
for row in table.find_all('tr')[1:-1]:
    s = pd.Series([data.text for data in row.find_all('td')])
    lst.append(s)

data = pd.concat(lst, axis=1).T

data.head(2)

print(f'(MOVIES, COLUMNS) -> {data.shape}')

print(f'% OF MISSING VALUES PER COLUMN\n{(data.isnull().sum() /
data.shape[0]) * 100}')
```

```

NUMBER OF TABLES IN THE PAGE: 1
DatesTop 10 Gross%± LWOverall Gross%± LWReleases#1 Release
Genre
Budget
Running Time
WeekLong Weekend

(MOVIES, COLUMNS) -> (51, 12)
% OF MISSING VALUES PER COLUMN
0      0.0
1      0.0
2      0.0
3      0.0
4      0.0
5      0.0
6      0.0
7      0.0
8      0.0
9      0.0
10     0.0
11     0.0
dtype: float64
```

Practical 5

AIM :- Apriori Algorithm implementation in case study.

THEORY :-

Apriori algorithm refers to an algorithm that is used in mining frequent products sets and relevant association rules. Generally, the apriori algorithm operates on a database containing a huge number of transactions. For example, the items customers buy at a Big Bazar.

CODE / OUTPUT :-

Minimum Support = 50 %

Minimum Confidence = 70 %

Itemset = { Bread, Chicken, Butter, Milk, Toast }

Transaction ID	Items
100	{Bread, Butter, Milk}
200	{Chicken, Butter, Toast}
300	{Bread, Chicken, Butter, Toast}
400	{Chicken, Toast}

Item	Support
Bread	$2 / 4 = 0.5 = 50\%$
Chicken	$3 / 4 = 0.75 = 75\%$
Butter	$3 / 4 = 0.75 = 75\%$
Milk	$1 / 4 = 0.25 = 25\%$
Toast	$3 / 4 = 0.75 = 75\%$

Itemset = { Bread, Chicken , Butter, Toast }

Item	Support
{Bread, Chicken}	$1 / 4 = 0.25 = 25\%$
{Bread, Butter}	$2 / 4 = 0.50 = 50\%$
{Bread, Toast}	$1 / 4 = 0.25 = 25\%$
{Chicken, Butter}	$2 / 4 = 0.50 = 50\%$
{Chicken, Toast}	$3 / 4 = 0.75 = 75\%$
{Butter, Toast}	$2 / 4 = 0.50 = 50\%$

Itemset = ({Bread, Butter}, {Chicken, Butter} , {Chicken, Toast}, {Butter, Toast})

Item	Support
{Bread, Butter, Toast}	$1 / 4 = 0.25 = 25\%$
{Chicken, Butter, Toast}	$2 / 4 = 0.50 = 50\%$
{Bread, Butter, Chicken}	$1 / 4 = 0.25 = 25\%$

Minimum Support = 50%

Minimum Confidence = 70%

Final Resultant Set based on Support = {Chicken, Butter, Toast}

Rules

1. (Chicken & Butter) -> Toast 2 (50%)
2. (Butter & Toast) -> Chicken 2 (50%)
3. (Chicken & Toast) -> Butter 2 (50%)
4. Chicken -> (Butter & Toast) 2 (50%)
5. Toast -> (Chicken & Butter) 2 (50%)
6. Butter -> (Chicken & Toast) 2 (50%)

Confidence = $S(A \cup B).count / S(A).count$

1. (Chicken & Butter) -> Toast 2 (50%)

$S((\text{Chicken \& Butter}) \cup (\text{Toast})) / S(\text{Chicken \& Butter})$

$= 2 / 2 = 1 = \underline{100\%}$

2. (Butter & Toast) -> Chicken

Confidence = $S(A \cup B).count / S(A).count$

$S((\text{Butter \& Toast}) \cup \text{Chicken})) / S(\text{Butter \& Toast})$

$= 2 / 2 = 1 = \underline{100\%}$

3. (Chicken & Toast) -> Butter 2 (50%)

Confidence = $S(A \cup B).count / S(A).count$

$S((\text{Chicken \& Toast}) \cup (\text{Butter})) / S(\text{Chicken \& Toast})$

$= 2/3 = 0.666 = \underline{67\%}$

4. Chicken -> (Butter & Toast) 2 (50%)

Confidence = $S(A \cup B).count / S(A).count$

$S((\text{Chicken}) \cup (\text{Butter \& Toast})) / S(\text{Chicken})$

$= 2/3 = 0.666 = \underline{67\%}$

Minimum Support = 50%

Minimum Confidence = 70%

5. Toast -> (Chicken & Butter) 2 (50%)

Confidence = $S(A \cup B).count / S(A).count$

$S((\text{Toast}) \cup (\text{Chicken \& Butter}))/S(\text{Toast})$

$= 2/3 = 0.666 = 67\%$

6. Butter -> (Chicken & Toast) 2 (50%)

Confidence = $S(A \cup B).count / S(A).count$

$S((\text{Butter}) \cup (\text{Chicken \& Toast}))/S(\text{Butter})$

$= 2/3 = 0.666 = 67\%$

Final Associated Items rules are

1. (Chicken & Butter) -> Toast 2 (50%)
2. (Butter & Toast) -> Chicken 2 (50%)

Practical 6

AIM :- Develop a basic crawler for the web search for user defined keywords.

THEORY :-

A Web crawler, sometimes called a spider or spiderbot and often shortened to crawler, is an Internet bot that systematically browses the World Wide Web and that is typically operated by search engines for the purpose of Web indexing (web spidering).

CODE / OUTPUT :-

```
import requests

url = 'https://en.wikipedia.org/wiki/Stock_market'

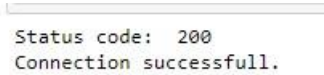
response = requests.get(url, timeout=3) #timeout set to stop the request
action in case of hanging
print('Status code: ',response.status_code)

if response.status_code==200:
    print('Connection successfull.\n\n')
else:
    print('Error. Check status code table.\n\n')

print(f"{'---'*20}\n\tContents of Response.items():\n{'---'*20}")

for k,v in response.headers.items():
    print(f"{k:{25}}: {v:{40}}") # Note: add :{number} inside of a

print(f"{'---'*20}\nStatus code: {response.status_code}\n{'---'*20}\n")
```



```

from bs4 import BeautifulSoup

# Feed the response's .content into BeautifulSoup
page_content = response.content

soup = BeautifulSoup(page_content, 'lxml') #'html.parser')

# Preview soup contents using .prettify()
print(soup.prettify()[:2000])

body = soup.body
for child in body.children:
    # print child if its not empty
    print(child if child is not None else ' ', '\n\n') # '\n\n' for visual
    separation

title = soup.head.title
print(title.parent.name)

results = soup.find_all()

```

results

```

Status code: 200
Connection successfull.

-----
Contents of Response.items():
-----
date           : Thu, 19 May 2022 09:30:47 GMT
vary           : Accept-Encoding, Cookie, Authorization
server        : ATS/8.0.8
x-content-type-options : nosniff
p3p           : CP="See https://en.wikipedia.org/wiki/Special:CentralAutoLogin/P3P for more info."
content-language : en
last-modified  : Tue, 17 May 2022 10:43:05 GMT
content-type   : text/html; charset=UTF-8
content-encoding : gzip
age           : 173
x-cache       : cp5016 hit, cp5012 hit/14
x-cache-status : hit-front

```

```

server-timing      : cache;desc="hit-front", host;desc="cp5012"
strict-transport-security: max-age=106384710; includeSubDomains; preload
report-to         : { "group": "wm_nel", "max_age": 86400, "endpoints": [{ "url": "https://intake-logging.wikimedia.org/v1/events?stream=w3c.reportingapi.network_error&schema_uri=w3c/reportingapi/network_error/1.0.0" }] }
nel               : { "report_to": "wm_nel", "max_age": 86400, "failure_fraction": 0.05, "success_fraction": 0.0 }
set-cookie        : WMF-Last-Access=19-May-2022;Path=/;HttpOnly;secure;Expires=Mon, 20 Jun 2022 00:00:00 GMT, WMF-Last-Access-Global=19-May-2022;Path=/;Domain=.wikipedia.org;HttpOnly;secure;Expires=Mon, 20 Jun 2022 00:00:00 GMT, GeoIP=IN:MH:Mumbai:19.07:72.89:v4; Path=/; secure; Domain=.wikipedia.org
accept-ch         : Sec-CH-UA-Arch,Sec-CH-UA-Bitness,Sec-CH-UA-Full-Version-List,Sec-CH-UA-Model,Sec-CH-UA-Platform-Version
permissions-policy : interest-cohort=(),ch-ua-arch=(self "intake-analytics.wikimedia.org"),ch-ua-bitness=(self "intake-analytics.wikimedia.org"),ch-ua-full-version-list=(self "intake-analytics.wikimedia.org"),ch-ua-model=(self "intake-analytics.wikimedia.org"),ch-ua-platform-version=(self "intake-analytics.wikimedia.org")
x-client-ip       : 203.192.230.166
cache-control     : private, s-maxage=0, max-age=0, must-revalidate
accept-ranges     : bytes
content-length    : 65676
date              : Thu, 19 May 2022 09:30:47 GMT
vary              : Accept-Encoding, Cookie, Authorization

```

```

x-content-type-options: nosniff
p3p: CP="See https://en.wikipedia.org/wiki/Special:CentralAutoLogin/P3P for more info."
content-language: en
last-modified: Tue, 17 May 2022 10:43:05 GMT
content-type: text/html; charset=UTF-8
content-encoding: gzip
age: 173
x-cache: cp5016 hit, cp5012 hit/14
x-cache-status: hit-front
server-timing: cache;desc="hit-front", host;desc="cp5012"
strict-transport-security: max-age=106384710; includeSubDomains; preload
report-to: { "group": "wm_nel", "max_age": 86400, "endpoints": [{ "url": "https://intake-logging.wikimedia.org/v1/events?stream=w3c.reportingapi.network_error&schema_uri=w3c/reportingapi/network_error/1.0.0" }] }
nel: { "report_to": "wm_nel", "max_age": 86400, "failure_fraction": 0.05, "success_fraction": 0.0 }
set-cookie: WMF-Last-Access=19-May-2022;Path=/;HttpOnly;secure;Expires=Mon, 20 Jun 2022 00:00:00 GMT, WMF-Last-Access-Global=19-May-2022;Path=/;Domain=.wikipedia.org;HttpOnly;secure;Expires=Mon, 20 Jun 2022 00:00:00 GMT, GeoIP=IN:MH:Mumbai:19.07:72.89:v4; Path=/; secure; Domain=.wikipedia.org
accept-ch: Sec-CH-UA-Arch,Sec-CH-UA-Bitness,Sec-CH-UA-Full-Version-List,Sec-CH-UA-Model,Sec-CH-UA-Platform-Version
permissions-policy: interest-cohort=(),ch-ua-arch=(self "intake-analytics.wikimedia.org"),ch-ua-bitness=(self "intake-analytics.wikimedia.org"),ch-ua-full-version-list=(self "intake-analytics.wikimedia.org"),ch-ua-model=(self "intake-analytics.wikimedia.org"),ch-ua-platform-version=(self "intake-analytics.wikimedia.org")

```

```

permissions-policy: interest-cohort=(),ch-ua-arch=(self "intake-analytics.wikimedia.org"),ch-ua-bitness=(self "intake-analytics.wikimedia.org"),ch-ua-full-version-list=(self "intake-analytics.wikimedia.org"),ch-ua-model=(self "intake-analytics.wikimedia.org"),ch-ua-platform-version=(self "intake-analytics.wikimedia.org")
x-client-ip: 203.192.230.166
cache-control: private, s-maxage=0, max-age=0, must-revalidate
accept-ranges: bytes
content-length: 65676
Status code: 200
Status code: 200
Status code: -----200
<!DOCTYPE html>
<html class="client-nojs" dir="ltr" lang="en">
<head>
<meta charset="utf-8"/>
<title>
Stock market - Wikipedia
</title>
<script>
document.documentElement.className="client-js";RLCONF={"wgBreakFrames":false,"wgSeparatorTransformTable":["",""],"wgDigitT
<a id="top"></a>
<div id="siteNotice"><!-- CentralNotice --></div>
<div class="mw-indicators">
</div>
<h1 class="firstHeading mw-first-heading" id="firstHeading">Stock market</h1>
<div class="vector-body" id="bodyContent">
<div class="noprint" id="siteSub">From Wikipedia, the free encyclopedia</div>
<div id="contentSub"></div>
<div id="contentSub2"></div>
<div id="jump-to-nav"></div>
<a class="mw-jump-link" href="#mw-head">Jump to navigation</a>
<a class="mw-jump-link" href="#searchInput">Jump to search</a>
<div class="mw-body-content mw-content-ltr" dir="ltr" id="mw-content-text" lang="en"><div class="mw-parser-output"><div class="shortdescription nomobile noexcerpt noprint searchaux" style="display:none">Place where stocks are traded</div>
<p class="mw-empty-elt">
</p>
<style data-mw-deduplicate="TemplateStyles:r1045330069">.mw-parser-output .sidebar{width:22em;float:right;clear:right;margin:0.5em 0 1em 1em;background:#f8f9fa;border:1px solid #aaa;padding:0.2em;text-align:center;line-height:1.4em;font-size:88%;border-collapse:collapse;display:table}body.skin-minerva .mw-parser-output .sidebar{display:table!important;float:right!important

```

```
<li><a href="/wiki/Murray_Rothbard" title="Murray Rothbard">Murray Rothbard</a></li>
<li><a href="/wiki/Joseph_Schumpeter" title="Joseph Schumpeter">Joseph Schumpeter</a></li>
<li><a href="/wiki/Thorstein_Veblen" title="Thorstein Veblen">Thorstein Veblen</a></li>
<li><a href="/wiki/Max_Weber" title="Max Weber">Max Weber</a></li>
<li><a href="/wiki/Ronald_Coase" title="Ronald Coase">Ronald Coase</a></li></ul>,
<li><a href="/wiki/Adam_Smith" title="Adam Smith">Adam Smith</a></li>,
<a href="/wiki/Adam_Smith" title="Adam Smith">Adam Smith</a>,
<li><a href="/wiki/John_Stuart_Mill" title="John Stuart Mill">John Stuart Mill</a></li>,
<a href="/wiki/John_Stuart_Mill" title="John Stuart Mill">John Stuart Mill</a>,
<li><a href="/wiki/David_Ricardo" title="David Ricardo">David Ricardo</a></li>,
<a href="/wiki/David_Ricardo" title="David Ricardo">David Ricardo</a>,
<li><a href="/wiki/Thomas_Robert_Malthus" title="Thomas Robert Malthus">Thomas Robert Malthus</a></li>,
<a href="/wiki/Thomas_Robert_Malthus" title="Thomas Robert Malthus">Thomas Robert Malthus</a>,
<li><a href="/wiki/Jean-Baptiste_Say" title="Jean-Baptiste Say">Jean-Baptiste Say</a></li>,
<a href="/wiki/Jean-Baptiste_Say" title="Jean-Baptiste Say">Jean-Baptiste Say</a>,
<li><a href="/wiki/Karl_Marx" title="Karl Marx">Karl Marx</a></li>,
<a href="/wiki/Karl_Marx" title="Karl Marx">Karl Marx</a>,
...]
```


Practical 7

AIM :- Develop a focused crawler for local search .

THEORY :-

A focused crawler is a web crawler that collects Web pages that satisfy some specific property, by carefully prioritizing the crawl frontier and managing the hyperlink exploration process. Some predicates may be based on simple, deterministic and surface properties. For example, a crawler's mission may be to crawl pages from only the .jp domain. Other predicates may be softer or comparative, e.g., "crawl pages about baseball", or "crawl pages with large PageRank". An important page property pertains to topics, leading to 'topical crawlers'. For example, a topical crawler may be deployed to collect pages about solar power, swine flu, or even more abstract concepts like controversy while minimizing resources spent fetching pages on other topics.

CODE / OUTPUT :-

```
import requests
import lxml
from bs4 import BeautifulSoup

url = "https://www.rottentomatoes.com/top/bestofrt/"
f = requests.get(url)

soup = BeautifulSoup(f.content, 'html')
#parse in normal html

movies = soup.find_all('div',{'class':'discovery-
tiles__wrap'})[1].find_all_next('a')

movies_list = []
num = 0
for movie in movies:
```

```

try:
    url = 'https://www.rottentomatoes.com' + movie["href"]
    movie_f = requests.get(url)
    movie_page = BeautifulSoup(movie_f.content, 'html')
    num += 1
    title = movie_page.find('h1', {'class': 'scoreboard__title'})
    movie_content = movie_page.find('div', {'class': 'movie_synopsis'})
    movies_list.append({
        "#": num,
        "url": url,
        "title": title.text,
        "content": movie_content.getText()
    })
except:
    continue

len(movies_list)

```

Out[5]: 30

```

for movie in movies_list[:10]:
    print(f"{movie['#']} \nurl: {movie['url']} \ntitle: {movie['title']} \ncontent: {movie['content']}")

```

1
url: https://www.rottentomatoes.com/m/emergency_2022
title: Emergency
content:
Kunle (Donald Elise Watkins) and his best friend, Sean (RJ Cyler), are both seniors in college about to embark on an epic night of Spring Break parties. Sean has the whole night planned out, including every party they will hit on their "legendary tour." Kunle is down, yet mostly concerned with finishing up his mold experiment in his lab, as his acceptance to Princeton is hinging on the results. They return to their apartment to pre-game, yet find that their roommate, Carlos (Sebastian Chacon), left the door open. As they enter with trepidation, Sean and Kunle discover a drunk, semi-conscious White female they don't know on the floor and an oblivious Carlos, who didn't hear her come in over the videogame blaring in his ears. Kunle wants to call the cops but Sean vehemently opposes the idea concerned how it will look when the cops show up (two Black men, one Latino man and a passed out White woman). Together, Carlos, Sean and Kunle load the girl -- who they nickname Goldilocks, but whose real name is Emma (Maddie Nichols) -- into Sean's van, with the intention of taking her somewhere safe rather than calling the police. Meanwhile, Emma's sister, Maddy (Sabrina Carpenter), has realized that Emma left the party they were at, and begins to search for her in a drunk panic using Emma's phone's location. What ensues is a chaotic, hilarious, and tension-filled chase all over town as our trio grapples with their differences while attempting to bring Emma to safety.

2
url: https://www.rottentomatoes.com/m/chip_n_dale_rescue_rangers
title: Chip 'n' Dale: Rescue Rangers
content:
In "Chip 'n Dale: Rescue Rangers," Chip and Dale are living amongst cartoons and humans in modern-day Los Angeles, but their lives are quite different now. It has been decades since their successful television series was canceled, and Chip (voice of John Mulaney) has succumbed to a life of suburban domesticity as an insurance salesman. Dale (voice of Andy Samberg), meanwhile, has had CGI surgery and works the nostalgia convention circuit, desperate to relive his glory days. When a former cast mate mysteriously disappears, Chip and Dale must repair their broken friendship and take on their Rescue Rangers detective personas once again to save their friend's life.

3
url: https://www.rottentomatoes.com/m/the_lost_city
title: The Lost City
content:
Reclusive author Loretta Sage writes about exotic places in her popular adventure novels that feature a handsome cover model named Alan. While on tour promoting her new book with Alan, Loretta gets kidnapped by an eccentric billionaire who hopes she can lead him to an ancient city's lost treasure from her latest story. Determined to prove he can be a hero in real life and not just on the pages of her books, Alan sets off to rescue her.

4
url: https://www.rottentomatoes.com/m/operation_mincemeat
title: Operation Mincemeat
content:
It's 1943. The Allies are determined to break Hitler's grip on occupied Europe, and plan an all-out assault on Sicily; but they face an impossible challenge -- how to protect a massive invasion force from potential massacre. It falls to two remarkable intelligence officers, Ewen Montagu (Colin Firth) and Charles Cholmondeley (Matthew Macfadyen) to dream the most inspired and improbable disinformation strategy of the war -- centered on the most unlikely of secret agents: a dead man. Operation Mincemeat is the extraordinary and true story of an idea that hoped to alter the course of the war -- defying logic, risking countless thousands of lives, and testing the nerves of its creators to breaking point.

5
url: https://www.rottentomatoes.com/m/x_2022
title: X
content:
A group of actors sets out to make an adult film in rural Texas under the noses of their reclusive hosts, but when the elderly couple catches their young guests in the act, the cast finds themselves in a desperate fight for their lives.

6
url: https://www.rottentomatoes.com/m/the_batman
title: The Batman
content:
Batman ventures into Gotham City's underworld when a sadistic killer leaves behind a trail of cryptic clues. As the evidence begins to lead closer to home and the scale of the perpetrator's plans become clear, he must forge new relationships, unmask the culprit and bring justice to the abuse of power and corruption that has long plagued the metropolis.

7
url: https://www.rottentomatoes.com/m/the_innocents_2022
title: The Innocents
content:
Terror strikes when a group of Nordic children reveals mysterious powers that take a dark and violent turn.

8
url: https://www.rottentomatoes.com/m/you_wont_be_alone
title: You Won't Be Alone
content:
Set in an isolated mountain village in 19th century Macedonia, YOU WON'T BE ALONE follows a young girl who is kidnapped and taken to a remote location where she must learn to survive on her own.

9
url: <https://www.rottentomatoes.com/m/hatching>
title: Hatching
content:
In HATCHING, 12-year-old gymnast, Tinja (Siiri Solalinna), is desperate to please her image-obsessed mother, who uses popular blog 'Lovely Everyday Life' presents their family's idyllic existence as manicured suburban perfection. One day, after finding a wounded bird in the woods, Tinja brings its strange egg home, nestles it in her bed, and nurtures it until it hatches. The creature that emerges becomes her closest friend and a living nightmare, plunging Tinja beneath the impeccable veneer into a twisted reality that her mother refuses to see.

10
url: https://www.rottentomatoes.com/m/on_the_count_of_three
title: On the Count of Three
content:
From Annapurna Pictures (Spring Breakers, Sorry to Bother You, Booksmart) and Orion Pictures, Jerrod Carmichael makes his directorial debut and stars in On the Count of Three, a darkly comic feature about two best friends, Val (Carmichael) and Kevin (Christopher Abbott), on the last day of their lives.

Practical 8

AIM :- Sentiment analysis for reviews by customers and visualize the same.

THEORY :-

Sentiment analysis (also known as opinion mining or emotion AI) is the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Sentiment analysis is widely applied to voice of the customer materials such as reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine. With the rise of deep language models, such as RoBERTa, also more difficult data domains can be analyzed, e.g., news texts where authors typically express their opinion/sentiment less explicitly.

CODE / OUTPUT :-

```
"""Pract10_WM.ipynb"""

!pip install matplotlib pandas nltk textblob

import nltk

nltk.download('vader_lexicon')
nltk.download('movie_reviews')
nltk.download('punkt')
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data] C:\Users\harsh\AppData\Roaming\nltk_data...
[nltk_data] Package vader_lexicon is already up-to-date!
[nltk_data] Downloading package movie_reviews to
[nltk_data] C:\Users\harsh\AppData\Roaming\nltk_data...
[nltk_data] Package movie_reviews is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data] C:\Users\harsh\AppData\Roaming\nltk_data...
[nltk_data] Package punkt is already up-to-date!
```

```
Out[1]: True
```

```
from nltk.sentiment.vader import SentimentIntensityAnalyzer as SIA
```

```
sia = SIA()

sia.polarity_scores("This restaurant was great, but I'm not sure if I'll
go there again.")
```

```
Out[2]: {'neg': 0.153, 'neu': 0.688, 'pos': 0.159, 'compound': 0.0276}
```

```
text = "I just got a call from my boss - does he realise it's Saturday?"
sia.polarity_scores(text)
```

```
Out[3]: {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
```

```
text = "I just got a call from my boss - does he realise it's Saturday?
:)"
```

```
sia.polarity_scores(text)
```

```
Out[4]: {'neg': 0.225, 'neu': 0.775, 'pos': 0.0, 'compound': -0.4926}
```

```
text = "I just got a call from my boss - does he realise it's Saturday?
😊"
```

```
sia.polarity_scores(text)
```

```
Out[5]: {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
```

```
from textblob import TextBlob
from textblob import Blobber
from textblob.sentiments import NaiveBayesAnalyzer
```

```
blob = TextBlob("This restaurant was great, but I'm not sure if I'll go
there again.")
```

```
blob.sentiment
```

```
Out[7]: Sentiment(polarity=0.275, subjectivity=0.8194444444444444)
```

```
blobber = Blobber(analyzer=NaiveBayesAnalyzer())
```

```
blob = blobber("This restaurant was great, but I'm not sure if I'll go
there again.")
```

```
blob.sentiment
```



```
Out[2]: Sentiment(classification='pos', p_pos=0.5879425317005774, p_neg=0.41205746829942275)
```

```
import pandas as pd

df = pd.DataFrame({'content': [
    "I love love love love this kitten",
    "I hate hate hate hate this keyboard",
    "I'm not sure how I feel about toast",
    "Did you see the baseball game yesterday?",
    "The package was delivered late and the contents were broken",
    "Trashy television shows are some of my favorites",
    "I'm seeing a Kubrick film tomorrow, I hear not so great things about it.",
    "I find chirping birds irritating, but I know I'm not the only one",
]})

df
```

```
Out[3]:
```

	content
0	I love love love love this kitten
1	I hate hate hate hate this keyboard
2	I'm not sure how I feel about toast
3	Did you see the baseball game yesterday?
4	The package was delivered late and the contents were broken
5	Trashy television shows are some of my favorites
6	I'm seeing a Kubrick film tomorrow, I hear not so great things about it.
7	I find chirping birds irritating, but I know I'm not the only one

```
def get_scores(content):
    blob = TextBlob(content)
    nb_blob = blobber(content)
    sia_scores = sia.polarity_scores(content)

    return pd.Series({
        'content': content,
        'textblob': blob.sentiment.polarity,
        'textblob_bayes': nb_blob.sentiment.p_pos -
nb_blob.sentiment.p_neg,
        'nltk': sia_scores['compound'],
    })

scores = df.content.apply(get_scores)
scores.style.background_gradient(cmap='RdYlGn', axis=None, low=0.4,
high=0.4)
```

Out[4]:

	content	textblob	textblob_bayes	nltk
0	I love love love love this kitten	0.500000	-0.087933	0.957100
1	I hate hate hate hate this keyboard	-0.800000	-0.214151	-0.941300
2	I'm not sure how I feel about toast	-0.250000	0.394659	-0.241100
3	Did you see the baseball game yesterday?	-0.400000	0.613050	0.000000
4	The package was delivered late and the contents were broken	-0.350000	-0.574270	-0.476700
5	Trashy television shows are some of my favorites	0.000000	0.040076	0.421500
6	I'm seeing a Kubrick film tomorrow, I hear not so great things about it.	0.800000	0.717875	-0.629600
7	I find chirping birds irritating, but I know I'm not the only one	-0.200000	0.257148	-0.250000