

1. Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data sample. Read the training data from csv file.

import random

import csv

```
attributes = [['sunny', 'rainy'], ['warm', 'cold'], ['windy', 'light'], ['strong', 'weak'], ['warm', 'cool'], ['same', 'change']]
```

print(attributes)

sun\_attributes = len(attributes)

print(sun\_attributes)

print("b the most general hypothesis: [ '?', '?', '?', '?', '?', '?']")

print("b the most specific hypothesis: [ 'o', 'o', 'o', 'o', 'o', 'o']")

q = []

print("b the gives training dataset")

with open('c:\Users\Adm\desktop\Ablo\data.csv', 'r') as csvfile:

reader = csv.reader(csvfile)

for row in reader:

q.append(row)

print(q)

print("the initial value of hypothesis: ")

h = ['o'] \* sun\_attributes

print(h)

for j in range(0, num\_attributes):

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$$\neg c_{ij} = \neg c_j[ij]$$

for  $i$  is range(1, len(a));

if ( $a[i][\text{sum-attributes}] == \text{'Yes'}$ ):

for  $j$  is range( $\text{sum-attributes}$ ):

if ( $c_{ijj} == '0'$  or  $b_{ij} == a[i][j]$ ):

$$b_{ijj} = \neg c_{ij}[ij]$$

else:

$$b_{ijj} = '?'$$

Prior ("1s for training examples : 20% the hypothesis") formed ( $i+1$ ), b)

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Dataset:

Sl. No	Sky	Airtemp	Humidity	Wind	water	Forecast	Enjoy Sport
1	Sunny	cooms	normal	strong	warm	same	Yes
2	Sunny	cooms	high	strong	warm	same	Yes
3	Rainy	cold	high	strong	warm	change	No
4.	Sunny	cooms	high	strong	cool	change	Yes

output:-

[['sunny', 'rainy'], ['cooms', 'cold'], ['normal', 'high'], ['strong', 'weak'], ['cooms', 'cool'], ['same', 'change']]

b.

the most general hypothesis. [?, ?, ?, ?, ?, ?, ?]

the most specific hypothesis: [0, 0, 0, 0, 0, 0, 0]

The given training dataset

['Sky', 'Airtemp', 'Humidity', 'Wind', 'water', 'Forecast', 'Enjoy Sport']

['sunny', 'cooms', 'normal', 'strong', 'warm', 'same', 'Yes']

['sunny', 'cooms', 'high', 'strong', 'warm', 'same', 'Yes']

['Rainy', 'cold', 'high', 'strong', 'warm', 'change', 'Yes']

The initial hypothesis is :

[0, 0, 0, 0, 0, 0]

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for training example : {0} the hypothesis is  
['sunni', 'wants', '?', 'strange', '?', '?']

2. for a given set of set of training data example stored in a .csv file, implement and demonstrate the candidate-elimination algorithm to output a description of the set of all hypothesis consistent with the training example.

```
import csv
```

```
with open('c://users//Admisi//Desktop//Hadoop//alltrn.csv')  
as f:
```

```
csv_file = csv.reader(f)
```

```
data = list(csv_file)
```

```
print(data)
```

```
s = data[1][:-1]
```

```
g = [[?] for i in range(len(s))] for j in range(  
len(s))]
```

```
for i in data:
```

```
if [-1] == "yes":
```

```
    for j in range(len(s)):
```

```
        if i[j] == s[j]:
```

```
            g[i][j] = '?'
```

```
        g[i][j] = '?'
```

```
elif [-1] == "No":
```

```
    for j in range(len(s)):
```

```
        if i[j] == s[j]:
```

```
            g[i][j] = s[j].
```

```
else:
```

```
    g[i][j] = "?"
```

```
print("10 steps of candidate elimination algorithm")  
data.index(i+1)
```

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printf(s)

printf(g)

gh = {}

for i is g:

for j is i:

if 'j' == '?' :

gb.append(i)

break

printf(") to find specific hypothesis: (", s)

printf(") to find general hypothesis: (", "igh")

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Dataset:

Sunny.	warm.	normal	strong	warm	same	Yes
Sunny	warm.	high.	strong	warm	same	No
Rainy.	cold.	high.	strong	warm	change	No
Sunny	warm	high.	strong	warm.	change	Yes

Output:

steps of candidate elimination algorithm 1

[['sunny', 'warm', '?', 'strong', '?', '?'],  
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'],  
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],  
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

steps of candidate elimination algorithm 2.

[['sunny', 'warm', '?', 'strong', '?', '?'],  
[['sunny', '?', '?', '?', '?', '?'], ['?', 'wind', '?', '?', '?', '?'],  
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],  
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

steps of candidate elimination algorithm 3.

[['sunny', 'warm', '?', 'strong', '?', '?'],  
[['sunny', '?', '?', '?', '?', '?'], ['?', 'wind', '?', '?', '?', '?'],  
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

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steps of candidate elimination algorithm &

[ 'sunray', 'wants', '?', 'strong', '?', '?' ]

[ 'sunray', '?', '?', '?', '?', '?' ], [ '?', 'wants', '?', '?', '?', '?' ],

[ '?', '?', '?', '?', '?', '?' ], [ '?', '?', '?', '?', '?', '?' ], [ '?', '?', '?', '?', '?', '?' ]

[ '?', '?', '?', '?', '?' ],

find specific by postnysis

[ 'sunray', 'wants', '?', 'strong', '?', '?' ]

find general hypothesis

[ [ 'sunray', '?', '?', '?', '?', '?' ], [ '?', 'wants', '?', '?', '?', '?' ] ]

3. 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.

```
import pandas as pd.
```

```
from pandas import DataFrame.
```

```
df_tennis = pd.read_csv('c://Users//Admin//Desktop//  
Aibin//playtennis.csv')
```

```
attribute_names = list(df_tennis.columns)
```

```
attribute_names.remove('playTennis').
```

```
print(attribute_names).
```

```
def entropy_of_list(lst):
```

```
from collections import Counter.
```

```
count = Counter(x for x in lst)
```

```
num_instances = len(lst)**1.
```

```
probs = [x/num_instances for x in count.values]
```

```
return entropy(probs).
```

```
def entropy(probs):
```

```
import math
```

```
return sum([-prob * math.log(prob) for  
prob in probs]).
```

```
Total_entropy = entropy_of_list(df_tennis['  
playTennis'])
```

```
def information_gains(df, split_attribute_name,  
target_attribute_name, tree_id=0):
```

```
df_split = df.groupby(split_attribute_name)
```

```
nobs = len(df.index)**1.
```

$\text{df\_agg\_ent} = \text{df split\_agg} (\{\text{target\_attribute\_name:}$   
 $\text{[entropy\_of\_list, lambda x: len(x)/len(df)}\}$   
 $\text{df\_agg\_ent.columns} = [\text{'entropy'}, \text{'prop observations'}]$   
 $\text{new\_entropy} = \text{sum}(\text{df\_agg\_ent}[\text{'entropy'}] * \text{df\_}$   
 $\text{agg\_ent}[\text{'prop observations'}])$   
 $\text{old\_entropy} = \text{entropy\_of\_list} (\text{df}[\text{target\_attribute\_name}])$   
 $\text{print(split\_attribute\_name, 'Ig:', old\_entropy\_new\_}$   
 $\text{entropy})$   
 returns  $\text{old\_entropy new\_entropy}$

$\text{def id3} (\text{df, target\_attribute\_name, attribute\_names, default\_class} = \text{None}):$

$\text{from collections import Counter}$

$\text{count} = \text{Counter} (\text{x for x in df[target\_attribute\_name]})$

$\text{if len(count)} = 1:$

$\text{return resetCtor(count)}$

$\text{elif df.empty or (not attribute\_names):}$

$\text{return default\_class}$

$\text{else:}$

$\text{default\_class} = \max(\text{count}.keys())$

$\text{gains} = [\text{Information\_gain} (\text{df}, \text{attr}, \text{target\_attribute\_name}) \text{ for attr in attribute\_names}]$

$\text{print('')}$

$\text{index\_of\_max} = \text{gains.index} (\max(\text{gains}))$

$\text{best\_attr} = \text{attribute\_names}[index\_of\_max]$

$\text{tree} = \{ \text{best\_attr: } \{ \dots \} \}$

$\text{remaining\_attribute\_names} = [i \text{ for } i \text{ in attribute\_names if } i \neq \text{best\_attr}]$

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name of  $\{ \} = \text{best-attr} \}$

for attr-val, data-subset is df. group by.  
(best attr):

subtree = DB (data-subset, target-attribute-  
name, remaining attribute-names-default-  
class).

tree [best attr] [attr-val] = subtree

returns:

from print to print print.

tree = DB (df, team's, 'playtennis', attribute-  
names).

print("b") The resultant decision tree is:  
b") print(tree)

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Output

['outlook', 'temperature', 'humidity', 'wind'].

outlook 16 = 0.2467498197744391

temperature 14 = 0.029222565658554647

humidity 19 : 0.15183550136234136

wind 19 : 0.04818703040826927

temperature 19 : 0.01924309402199489

humidity 19 : 0.0199730400197489

wind 19 : 0.9209505944546686

temperature 24 : 0.570909505944546686

humidity 14 : 0.9709505944546686

wind 14 : 0.01997309402197489

The result of decision tree is

{'outlook': {'overcast': 'Yes',

'Rain': {'wind': {'strong': 'No', 'weak': 'Yes'}},

'Sun': {'Humidity': {'High': 'No', 'Normal': 'Yes'}}}

{}

4 Build an artificial neural network by implementing the back propagation algorithm & test the same using appropriate data sets.

from import math as

from random import seed.

from random import random.

def initialize\_network (n\_inputs, n\_hidden,  
n\_outputs):

network = list()

hidden\_layer = [{}'weights': [random() for i in  
range (n\_inputs+1)]} for i in range (n\_hidden)]

network.append (hidden\_layer)

output\_layer = [{}'weights': [random() for i in  
range (n\_hidden+1)]} for i in range (n\_outputs)].

network.append (output\_layer)

return network

def activate (weights, inputs):

activation = weights [-1].

for i in range (len(weights)-1):

activation += weights [i] \* inputs [i].

return activation

def transfer (activation)

return log(1.0 + exp(-activation))

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def forward\_propagate (network, row):

    Input = row

    For layer i in network:

        new\_inputs = []

        For neuron i in layer:

            activations = activate (neuron['weights'])

            inputs = neuron['outputs'] = transfer  
            (activations)

            new\_inputs.append (neuron['outputs'])

        Inputs = new\_inputs.

    return inputs.

def transfer\_derivative (output):

    return output \* (1.0 - output).

def backward\_propagate\_error (network,  
    expected):

    for i in reversed (range (len (network))):

        layer = network [i].

        errors = [ ]

        if i != len (network) - 1:

            for j in range (len (layer)):

                error = 0.0.

            For neuron i in network [i+1]:

                error += (neuron['weights'][i])

                neuron['delta']).

            errors.append (error).

        else:

            for j in range (len (layer)):

                neuron = layer [j]

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errors.append(excepted[j].neuron['output'])  
 for j in range(len(layer)):  
 zeros = layer[i].  
 zeros['delta'] = error[j] \* transfer-  
 derivative(zeros['output'])

def update\_weights(network, row, l-rate):

for i in range(len(network)):

inputs = row[i-1]

if i == 0:

inputs = [zeros['output']] for zeros  
 in network[i-1].

for neuron in network[i]:

for j in range(len(inputs)):

zeros['weights'][i][j] += l-rate \* neuron.  
 ['delta'] \* inputs[i].

zeros['weights'][i][j] += l-rate \* neuron['  
 delta'].

def train\_network(network, train, l-rate, n-  
 epoch, n\_outputs):

for epoch in range(n-epoch):

sum\_error = 0.

for row in train:

outputs = forward\_propagate(network,  
 row).

expected = [0 for i in range(n-  
 outputs)]

expected[-1] = 1

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sum\_error += sum([expected[i] - outputs[i]]\*\*2)

for i in range(len(expected))])

broadcast\_propagate\_error(network, expected)

update\_weights(network, vars\_l\_rate)

print('epoch = ', d, 'l\_rate = ', l\_rate, 'error = ', error)

'\nL epoch, l-rate, sum error)'

seed(d)

dataset = [[2.4810850, 0.550537003, 0],  
[1.465489372, 0.862125076, 0],  
[3.326561688, 4.400293529, 0],  
[1.38807019, 1.8500000317, 0],  
[3.06407232, 3.00530599310],  
[7.627531014, 0.759262235, 1],  
[5.0330441048, 2.088626795, 1],  
[6.922596716, 1.77106367, 1],  
[8.675418631, -0.242068655, 1],  
[7.673756466, 3.505563011, 1]].

→ inputs = len(dataset) - 1

→ outputs = len(dataset) - 1 for var in dataset]) .

network = initialize\_network(inputs, 2, outputs)

train\_network(network, dataset, 0.8, 20, outputs)

For layer is network:

print(layer)

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epoch = 0	lrade = 0.500	error = 6.350
epoch = 1	lrade = 0.500	error = 5.531
epoch = 2	lrade = 0.500	error = 5.001
epoch = 3	lrade = 0.500	error = 4.998
epoch = 4	lrade = 0.500	error = 4.899
epoch = 5	lrade = 0.500	error = 4.173
epoch = 6	lrade = 0.500	error = 3.835
epoch = 7	lrade = 0.500	error = 3.806
epoch = 8	lrade = 0.500	error = 3.198
epoch = 9	lrade = 0.500	error = 0.898
epoch = 10	lrade = 0.500	error = 0.626
epoch = 11	lrade = 0.500	error = 0.347
epoch = 12	lrade = 0.500	error = 0.183
epoch = 13	lrade = 0.500	error = 1.953
epoch = 14	lrade = 0.500	error = 1.776
epoch = 15	lrade = 0.500	error = 1.614
epoch = 16	lrade = 0.500	error = 1.478
epoch = 17	lrade = 0.500	error = 1.366
epoch = 18	lrade = 0.500	error = 1.283
epoch = 19	lrade = 0.500	error = 1.152

{'weights': [-1.468875095432307, 1.950887325439314, 1.0858178629550299], 'output': 0.009980305604426185, 'delta': -0.059566604162323605},

{'weights': [0.37711098140462157, -0.0625909814552989, 0.027651237026427716], 'output': 0.94568890021123, 'delta': 0.00262796528508638379},

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[ $\{w\}$  weights]:  $[2.518394649397849, -0.339182750264,$   
 $5.988, -0.9671565426390275],$  'output': -  
 $6.2564879202357587,$  'delta': -  
 $-0.092700592783645873,$   
 $1.00364221062$

[ $\{w\}$  weights]:  $[-2.65891498484263, 0.423830864675827157]$   
 $0.9202, 0.423830864675827157],$  'output':  $0.7790535202438367,$   
'delta':  $0.83803132564373543].$

Copy & type your handwritten notes  
in the following boxes

s. create a program to implement the naive bayes classifier for a sample training data stored as .csv file. compute the accuracy of the classifier. Considering few test dataset.

```
import csv, random, math
import statistics as st
```

```
def loadCSV(filename):
    lines = csv.reader(open(filename, "r"))
    dataset = list(lines)
    for i in range(len(dataset)):
        dataset[i] = [float(x) for x in dataset[i]]
    return dataset
```

```
def splitDataset(dataset, splitRatio):
    testSize = int(len(dataset)*splitRatio)
    trainSet = list(dataset)
    testSet = []
    while len(testSet) < testSize:
        index = random.randrange(len(trainSet))
        testSet.append(trainSet.pop(index))
    return [trainSet, testSet]
```

```
def separateByClass(dataset):
    separated = {}
    for i in range(len(dataset)):
        x = dataset[i]
        if (x[-1] not in separated):
            separated[x[-1]] = []
            separated[x[-1]].append(x)
        else:
            separated[x[-1]].append(x)
```

separated[x[-1]] = [ ]

separated[x[-1]].append(x)

return separated.

def compute\_mean\_std (dataset):

mean\_std = [(ct - mean(attrs[attribute]) - st - stdv -  
(attribute))]

for attribute in zip(\*dataset) :

def mean\_std(f):

return mean\_std.

def summarize\_byclass (dataset):

separated = separate\_byclass (dataset):

summary = {}

for classvalue in instance in separated : items()

summary[classvalue] = compute\_mean\_std

(instances)

return summary.

def estimated\_probability (x, mean, stdv):

exponent = math.exp(-(math.pow(x

mean, 2) / (2 \* math.pow(stdv, 2)))

return (1 / math.sqrt(2 \* math.pi) \* stdv) \*  
exponent.

def calculate\_class\_probabilities (summary, testvector):

p = {}

for classvalue, classsummarized in summary:  
items():

$P[\text{classvalues}] = 1$

for  $i$  in range(len(classsumaries)):

mean, std = classsumaries[i].

x = testvector[i].

$P[\text{classvalue} \neq \text{estimated probability}(x, \text{mean}, \text{std})]$ :

return p.

def predict(classsumaries, testvector):

all\_p = calculateclassprobabilities(classsumaries, testvector).

bestlabel, bestprob = None, -1.

for lbl, p in all\_p.items():

bestprob = p

bestlabel = lbl.

return bestlabel.

def performclassification(classsumaries, testset):

predictions = []

for i in range(len(testset)):

results = predict(classsumaries, testset[i])

predictions.append(results)

return predictions.

def setAccuracy(testset, predictions):

correct = 0.

for i in range(len(testset)):

If testset[i][-1] == predictions[i]:

correct += 1.

return (correct / float(len(testset))) \* 100.0.

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```
dataset = loadcsv('C:/Users/Admin/Desktop/16N1  
diabetes.csv')  
print('Pima Indian Diabetes dataset loaded..!')  
print('Total instances available :', len(dataset))  
print('Total attributes present :', len(dataset[0]))  
print('First five instances of dataset :')  
for i in range(5):  
    print(i+1, ':', dataset[i])  
splitRatio = 0.2  
trainset, testset = splitDataset(dataset,  
splitRatio)  
print('Dataset is split into training and  
test set.')  
print('Training example =', len(trainset), 'testing examples  
= ', len(testset))  
summarize = summarizeByClass(trainset)  
prediction = performClassification(summarize,  
testset)  
accuracy = getAccuracy(testset, prediction)  
print('Accuracy of the Naive Bayesian  
classifier is :', accuracy)
```

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Output

pine indians diabetes dataset loaded.

Total instances available 768

Total attributes present - 8

first five rows ~~of dataset~~

1: [6.0, 148.0, 72.0, 35.0, 0.0, 33.6, 0.627, 80.0, 70]

2: [1.0, 85.0, 66.0, 0.0, 0.0, 26.6, 0.351, 31.0, 0]

3: [8.0, 183.0, 64.0, 0.0, 0.0, 23.3, 0.672, 32.0, 7.0]

4: [1.0, 89.0, 66.0, 23.0, 0.0, 28.1, 0.167, 21.0, 0.0]

5: [0.0, 133.0, 40.0, 35.0, 168.0, 43.1, 0.288, 33.0, 110]

~~dataset~~ is split into training and testing set

Training example - 615

Testing example = 103

Accuracy of the Naive Bayes classifier  
is 75. ~~76.222869281046~~.

Assuming a set of documents that need to be classified, use the naive bayesian classifier model to perform this task. Built-in Java classes / API can be used to write the program, calculate the accuracy, precision and recalls for your dataset.

Import pandas as pd.

```
msg = pd.read_csv('data.csv', names=['message', 'label'])
```

```
print('Total instances in the dataset: ', msg.shape[0])
```

```
msg['labelnum'] = msg.label.map({'pos': 1, 'neg': 0})
```

x = msg.message

y = msg.labelnum

```
print('The message and its label of first 5 instances are listed below')
```

```
x5, y5 = x[0:5], msg.label[0:5]
```

for x, y in zip(x5, y5):

```
    print(x, ' ', y)
```

```
from sklearn.model_selection import train_test_split
```

```
print('Dataset is split into training and testing sample')
```

```
print('Total training instances: ', xtrain.shape[0])
```

```
print('Total testing instances: ', xtest.shape[0])
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

Import CountVectorizer.

```
count_vect = CountVectorizer()
```

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```
xtrain-dtm = count-vec fit-transform (xtrain),  
xtest-dtm = count-vec + transform (xtest)  
print('Total features extracted using  
countvectorizer:', xtrain-dtm.shape[1])  
print('5 features for first 5 training instances  
listed below')  
df = pd.DataFrame(xtrain-dtm.toarray()), columns=  
count vec.get_feature_names()  
print(df[0:5])  
from sklearn.naive-bayes import MultinomialNB  
clf = MultinomialNB().fit(xtrain-dtm, ytrain)  
predicted = clf.predict(xtest-dtm)  
print('Classification results of testing samples  
are given below').  
for doc, pth in zip(xtest, predicted):  
    pred = 'pos' if q == 1 else 'neg'  
    print('{}s -> {}s'.format(doc, pred))  
from  
from sklearn import metrics  
print('Accuracy metrics')  
print('Accuracy of the classifier is', metrics.  
accuracy_score(ytest, predicted))  
print('Recall:', metrics.recall_score(ytest, predicted),  
'Precision:', metrics.precision_score(ytest,  
predicted))  
print('confusion matrix')  
print(metrics.confusion_matrix(ytest, predicted)).
```

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output

output : total instance in the dataset : 18

The message and its label of first 5 bytes  
are listed below:

I love sandwich, too

This is an amazing place, too.

I feel very good about these beers, ps.

This is my best work, pos

What an awesome view, pos

Dataset is split into training & testing + sensor

Total training instances: 13

Total testing instance is

Total feature extracted using count vectorizer  
feature for first 5 instances tracking are  
listed below.

about. ans ans ~~sweat~~

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	tomorrow	very	view	we	want	what	will	with	work
0	0	0	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0

[5 rows x 46 columns]

classification result of testing sample are given below:

I love to dance  $\rightarrow$  pos

I am sick and tired of this place  $\rightarrow$  neg

This is an amazing place  $\rightarrow$  pos

What a great holiday  $\rightarrow$  pos

This is a bad locality to stay  $\rightarrow$  neg

accuracy metrics:

accuracy of the classifier is 1.0.

Recall : 1.0

precision : 1.0

confusion matrix.

$[[0, 0], [0, 3]]$