```
       26, 480, 5, 144, 30, 5535, 18, 51, 36, 28, 224, 92, 25, 104, 4, 226, 65, 16, 38,
       1334, 88, 12, 16, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32]),
              list([1, 194, 1153, 194, 8255, 78, 228, 5, 6, 1463, 4369, 5012, 134, 26,
       4, 715, 8, 118, 1634, 14, 394, 20, 13, 119, 954, 189, 102, 5, 207, 110, 3103,
       21, 14, 69, 188, 8, 30, 23, 7, 4, 249, 126, 93, 4, 114, 9, 2300, 1523, 5, 647,
       4, 116, 9, 35, 8163, 4, 229, 9, 340, 1322, 4, 118, 9, 4, 130, 4901, 19, 4, 1002,
       5, 89, 29, 952, 46, 37, 4, 455, 9, 45, 43, 38, 1543, 1905, 398, 4, 1649, 26,
       6853, 5, 163, 11, 3215, 2, 4, 1153, 9, 194, 775, 7, 8255, 2, 349, 2637, 148,
       605, 2, 8003, 15, 123, 125, 68, 2, 6853, 15, 349, 165, 4362, 98, 5, 4, 228, 9,
       43, 2, 1157, 15, 299, 120, 5, 120, 174, 11, 220, 175, 136, 50, 9, 4373, 228,
       8255, 5, 2, 656, 245, 2350, 5, 4, 9837, 131, 152, 491, 18, 2, 32, 7464, 1212,
       14, 9, 6, 371, 78, 22, 625, 64, 1382, 9, 8, 168, 145, 23, 4, 1690, 15, 16, 4,
       1355, 5, 28, 6, 52, 154, 462, 33, 89, 78, 285, 16, 145, 95]),
              list([1, 14, 47, 8, 30, 31, 7, 4, 249, 108, 7, 4, 5974, 54, 61, 369, 13,
       71, 149, 14, 22, 112, 4, 2401, 311, 12, 16, 3711, 33, 75, 43, 1829, 296, 4, 86,
       320, 35, 534, 19, 263, 4821, 1301, 4, 1873, 33, 89, 78, 12, 66, 16, 4, 360, 7,
       4, 58, 316, 334, 11, 4, 1716, 43, 645, 662, 8, 257, 85, 1200, 42, 1228, 2578,
       83, 68, 3912, 15, 36, 165, 1539, 278, 36, 69, 2, 780, 8, 106, 14, 6905, 1338,
       18, 6, 22, 12, 215, 28, 610, 40, 6, 87, 326, 23, 2300, 21, 23, 22, 12, 272, 40,
       57, 31, 11, 4, 22, 47, 6, 2307, 51, 9, 170, 23, 595, 116, 595, 1352, 13, 191,
       79, 638, 89, 2, 14, 9, 8, 106, 607, 624, 35, 534, 6, 227, 7, 129, 113]),
              ...,
              list([1, 13, 1408, 15, 8, 135, 14, 9, 35, 32, 46, 394, 20, 62, 30, 5093,
       21, 45, 184, 78, 4, 1492, 910, 769, 2290, 2515, 395, 4257, 5, 1454, 11, 119, 2,
       89, 1036, 4, 116, 218, 78, 21, 407, 100, 30, 128, 262, 15, 7, 185, 2280, 284,
       1842, 2, 37, 315, 4, 226, 20, 272, 2942, 40, 29, 152, 60, 181, 8, 30, 50, 553,
       362, 80, 119, 12, 21, 846, 5518]),
              list([1, 11, 119, 241, 9, 4, 840, 20, 12, 468, 15, 94, 3684, 562, 791,
       39, 4, 86, 107, 8, 97, 14, 31, 33, 4, 2960, 7, 743, 46, 1028, 9, 3531, 5, 4,
       768, 47, 8, 79, 90, 145, 164, 162, 50, 6, 501, 119, 7, 9, 4, 78, 232, 15, 16,
       224, 11, 4, 333, 20, 4, 985, 200, 5, 2, 5, 9, 1861, 8, 79, 357, 4, 20, 47, 220,
       57, 206, 139, 11, 12, 5, 55, 117, 212, 13, 1276, 92, 124, 51, 45, 1188, 71, 536,
       13, 520, 14, 20, 6, 2302, 7, 470]),
              list([1, 6, 52, 7465, 430, 22, 9, 220, 2594, 8, 28, 2, 519, 3227, 6, 769,
       15, 47, 6, 3482, 4067, 8, 114, 5, 33, 222, 31, 55, 184, 704, 5586, 2, 19, 346,
       3153, 5, 6, 364, 350, 4, 184, 5586, 9, 133, 1810, 11, 5417, 2, 21, 4, 7298, 2,
       570, 50, 2005, 2643, 9, 6, 1249, 17, 6, 2, 2, 21, 17, 6, 1211, 232, 1138, 2249,
       29, 266, 56, 96, 346, 194, 308, 9, 194, 21, 29, 218, 1078, 19, 4, 78, 173, 7,
       27, 2, 5698, 3406, 718, 2, 9, 6, 6907, 17, 210, 5, 3281, 5677, 47, 77, 395, 14,
       172, 173, 18, 2740, 2931, 4517, 82, 127, 27, 173, 11, 6, 392, 217, 21, 50, 9,
       57, 65, 12, 2, 53, 40, 35, 390, 7, 11, 4, 3567, 7, 4, 314, 74, 6, 792, 22, 2,
       19, 714, 727, 5205, 382, 4, 91, 6533, 439, 19, 14, 20, 9, 1441, 5805, 1118, 4,
       756, 25, 124, 4, 31, 12, 16, 93, 804, 34, 2005, 2643])],
             dtype=object)
```

```
label #label is a numpy array that contains all the sentiment labels from the IMDB dataset,
```

```
array([1, 0, 0, ..., 0, 0, 0])
```

```
X_train.shape
```

```
(25000,)
```

```
X_test.shape
```

```
(25000,)
```

```
y_train
```

```
array([1, 0, 0, ..., 0, 1, 0])
```

```
y_test # y_test is 25000, which indicates that it contains 25000 sentiment labels, one for
```

```
array([0, 1, 1, ..., 0, 0, 0])
```

```
# Function to perform relevant sequence adding on the data
# Now it is time to prepare our data. We will vectorize every review and fill it with zeros
# That means we fill every review that is shorter than 500 with zeros.
# We do this because the biggest review is nearly that long and every input for our neural
# We also transform the targets into floats.
# sequences is name of method the review less than 1000 we perform padding overthere

def vectorize(sequences, dimension = 10000):
  # Create an all-zero matrix of shape (len(sequences), dimension)
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1
    return results

# The script transforms your dataset into a binary vector space model.
# First, if we examine the x_train content we see that each review is represented as a sequ
# print(train_data[0])  # print the first review
# [1, 14, 22, 16, 43, 530, 973, ..., 5345, 19, 178, 32]
# the size of the entire dictionary, dictionary=10000 in your example.
# We will then associate each element/index of this vector with one word/word_id.
# So word represented by word id 14 will now be represented by 14-th element of this vector


# Each element will either be 0 (word is not present in the review) or 1 (word is present i
# And we can treat this as a probability, so we even have meaning for values in between 0 a
# Furthermore, every review will now be represented by this very long (sparse) vector which
# word      word_id
# I      -> 0
# you    -> 1
# he     -> 2
# be     -> 3
# eat    -> 4
# happy  -> 5
# sad    -> 6
# banana -> 7
# a      -> 8

# the sentences would then be processed in a following way.


# I be happy      -> [0,3,5]   -> [1,0,0,1,0,1,0,0,0]
# I eat a banana. -> [0,4,8,7] -> [1,0,0,0,1,0,0,1,1]

# Now I highlighted the word sparse.
```

```
# That means, there will have A LOT MORE zeros in comparison with ones.
# We can take advantage of that. Instead of checking every word, whether it is contained in
# we will check a substantially smaller list of only those words that DO appear in our revi

# Therefore, we can make things easy for us and create reviews × vocabulary matrix of zeros
# And then just go through words in each review and flip the indicator to 1.0 at position c

# result[review_id][word_id] = 1.0
# So instead of doing 25000 x 10000 = 250 000 000 operations,
# we only did number of words = 5 967 841. That's just ~2.5% of original amount of operatio


# The for loop here is not processing all the matrix. As you can see, it enumerates element
# t = np.array([1,2,3,4,5,6,7,8,9])
# r = np.zeros((len(t), 10))

#Output

# array([[0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
#   [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
#   [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
#   [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
#  [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
#  [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
#  [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
#  [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
# [0., 0., 0., 0., 0., 0., 0., 0., 0., 0.]]) #

# then we modify elements with the same way you have :

# for i, s in enumerate(t):
#  r[i,s] = 1.
# array([[0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
#   [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.],
#   [0., 0., 0., 1., 0., 0., 0., 0., 0., 0.],
#   [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
#   [0., 0., 0., 0., 0., 1., 0., 0., 0., 0.],
#   [0., 0., 0., 0., 0., 0., 1., 0., 0., 0.],
#   [0., 0., 0., 0., 0., 0., 0., 1., 0., 0.],
#   [0., 0., 0., 0., 0., 0., 0., 0., 1., 0.],
#   [0., 0., 0., 0., 0., 0., 0., 0., 0., 1.]])
  # you can see that the for loop modified only a set of elements (len(t))
  # which has index [i,s] (in this case ; (0, 1), (1, 2), (2, 3), an so on))


# Now we split our data into a training and a testing set.
# The training set will contain  reviews and the testing set

test_x = data[:10000]
test_y = label[:10000]
train_x = data[10000:]
train_y = label[10000:]


test_x
```

```
array([list([1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941,
4, 173, 36, 256, 5, 25, 100, 43, 838, 112, 50, 670, 2, 9, 35, 480, 284, 5, 150,
4, 172, 112, 167, 2, 336, 385, 39, 4, 172, 4536, 1111, 17, 546, 38, 13, 447, 4,
192, 50, 16, 6, 147, 2025, 19, 14, 22, 4, 1920, 4613, 469, 4, 22, 71, 87, 12,
```

```
16, 43, 530, 38, 76, 15, 13, 1247, 4, 22, 17, 515, 17, 12, 16, 626, 18, 2, 5,
62, 386, 12, 8, 316, 8, 106, 5, 4, 2223, 5244, 16, 480, 66, 3785, 33, 4, 130,
12, 16, 38, 619, 5, 25, 124, 51, 36, 135, 48, 25, 1415, 33, 6, 22, 12, 215, 28,
77, 52, 5, 14, 407, 16, 82, 2, 8, 4, 107, 117, 5952, 15, 256, 4, 2, 7, 3766, 5,
723, 36, 71, 43, 530, 476, 26, 400, 317, 46, 7, 4, 2, 1029, 13, 104, 88, 4, 381,
15, 297, 98, 32, 2071, 56, 26, 141, 6, 194, 7486, 18, 4, 226, 22, 21, 134, 476,
26, 480, 5, 144, 30, 5535, 18, 51, 36, 28, 224, 92, 25, 104, 4, 226, 65, 16, 38,
1334, 88, 12, 16, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32]),
       list([1, 194, 1153, 194, 8255, 78, 228, 5, 6, 1463, 4369, 5012, 134, 26,
4, 715, 8, 118, 1634, 14, 394, 20, 13, 119, 954, 189, 102, 5, 207, 110, 3103,
21, 14, 69, 188, 8, 30, 23, 7, 4, 249, 126, 93, 4, 114, 9, 2300, 1523, 5, 647,
4, 116, 9, 35, 8163, 4, 229, 9, 340, 1322, 4, 118, 9, 4, 130, 4901, 19, 4, 1002,
5, 89, 29, 952, 46, 37, 4, 455, 9, 45, 43, 38, 1543, 1905, 398, 4, 1649, 26,
6853, 5, 163, 11, 3215, 2, 4, 1153, 9, 194, 775, 7, 8255, 2, 349, 2637, 148,
605, 2, 8003, 15, 123, 125, 68, 2, 6853, 15, 349, 165, 4362, 98, 5, 4, 228, 9,
43, 2, 1157, 15, 299, 120, 5, 120, 174, 11, 220, 175, 136, 50, 9, 4373, 228,
8255, 5, 2, 656, 245, 2350, 5, 4, 9837, 131, 152, 491, 18, 2, 32, 7464, 1212,
14, 9, 6, 371, 78, 22, 625, 64, 1382, 9, 8, 168, 145, 23, 4, 1690, 15, 16, 4,
1355, 5, 28, 6, 52, 154, 462, 33, 89, 78, 285, 16, 145, 95]),
       list([1, 14, 47, 8, 30, 31, 7, 4, 249, 108, 7, 4, 5974, 54, 61, 369, 13,
71, 149, 14, 22, 112, 4, 2401, 311, 12, 16, 3711, 33, 75, 43, 1829, 296, 4, 86,
320, 35, 534, 19, 263, 4821, 1301, 4, 1873, 33, 89, 78, 12, 66, 16, 4, 360, 7,
4, 58, 316, 334, 11, 4, 1716, 43, 645, 662, 8, 257, 85, 1200, 42, 1228, 2578,
83, 68, 3912, 15, 36, 165, 1539, 278, 36, 69, 2, 780, 8, 106, 14, 6905, 1338,
18, 6, 22, 12, 215, 28, 610, 40, 6, 87, 326, 23, 2300, 21, 23, 22, 12, 272, 40,
57, 31, 11, 4, 22, 47, 6, 2307, 51, 9, 170, 23, 595, 116, 595, 1352, 13, 191,
79, 638, 89, 2, 14, 9, 8, 106, 607, 624, 35, 534, 6, 227, 7, 129, 113]),
       ...,
       list([1, 14, 9, 6, 66, 327, 5, 1047, 20, 15, 4, 436, 223, 70, 358, 45,
44, 107, 2515, 5, 6, 1132, 37, 26, 623, 245, 8, 412, 19, 294, 334, 18, 6, 117,
137, 21, 4, 1389, 92, 391, 5, 36, 1090, 5, 140, 8, 169, 4, 223, 23, 68, 205, 4,
1132, 9, 773, 5621, 5, 59, 456, 56, 8, 41, 403, 580, 9, 4, 1155, 912, 37, 694,
6, 176, 44, 113, 23, 4, 1004, 7, 4, 6567, 2694, 9, 4, 922, 5, 2, 912, 37, 5190,
183, 276, 148, 289, 295, 23, 35, 1154, 5, 12, 166, 18, 6, 654, 5, 253, 1061, 58,
50, 26, 57, 318, 302, 7, 4, 6849, 728, 38, 12, 218, 954, 33, 32, 45, 4, 118,
662, 1626, 20, 15, 207, 110, 38, 230, 45, 6, 66, 52, 20, 18, 2166]),
       list([1, 14, 20, 9, 43, 160, 856, 206, 509, 21, 12, 100, 28, 77, 38, 76,
128, 54, 4, 1865, 216, 46, 36, 66, 887, 49, 3822, 339, 294, 40, 1798, 2, 37, 93,
15, 530, 206, 720, 11, 3567, 17, 36, 847, 56, 4, 890, 39, 4, 4565, 62, 28, 679,
4, 753, 206, 844, 83, 142, 318, 88, 4, 360, 7, 4, 22, 16, 2659, 727, 21, 1753,
128, 74, 25, 62, 535, 39, 14, 552, 7, 20, 95, 385, 4, 477, 136, 4, 123, 180, 4,
31, 75, 69, 77, 1064, 18, 21, 16, 40, 149, 142, 39, 4, 6, 768, 11, 4, 2084, 36,
1258, 5261, 164, 1936, 5, 36, 521, 187, 6, 313, 269, 8, 516, 257, 85, 172, 154,
172, 154]),
       list([1, 51, 527, 487, 5, 116, 57, 1613, 51, 25, 191, 97, 6, 52, 20, 19,
6, 686, 109, 7660, 12, 16, 224, 11, 2, 19, 532, 807, 10, 10, 38, 14, 554, 271,
23, 6, 1189, 8, 67, 27, 336, 4, 554, 1655, 304, 6, 1707, 5, 4, 1811, 47, 6, 483,
1274, 5, 1442, 1696, 2817, 38, 4, 554, 6141, 11, 6, 2144, 5, 6095, 95, 29, 1129,
187, 4247, 11, 4, 5152, 366, 29, 214, 6590, 10, 10, 315, 15, 58, 29, 1860, 6,
2123, 1453, 4, 86, 58, 29, 1860, 12, 125, 11, 4, 2144, 4, 333, 58, 29, 166, 6,
2, 46, 7, 6, 9459, 5, 9866, 4, 2123, 107, 665, 7, 1214, 541, 2, 46, 7, 4, 2,
4539, 1578, 72, 7, 6498, 2, 4, 3942, 9997, 10, 10, 82, 4, 554, 1068, 8, 1968, 6,
2, 19, 727, 1901, 10, 10, 3288])],
      dtype=object)
```

```
test_y
```

```
array([1, 0, 0, ..., 1, 0, 0])
```

```
train_x
```

```
array([list([1, 13, 104, 14, 9, 31, 7, 4, 4343, 7, 4, 3776, 3394, 2, 495, 103,
141, 87, 2048, 17, 76, 2, 44, 164, 525, 13, 197, 14, 16, 338, 4, 177, 16, 6118,
5253, 2, 2, 2, 21, 61, 1126, 2, 16, 15, 36, 4621, 19, 4, 2, 157, 5, 605, 46, 49,
7, 4, 297, 8, 276, 11, 4, 621, 837, 844, 10, 10, 25, 43, 92, 81, 2282, 5, 95,
947, 19, 4, 297, 806, 21, 15, 9, 43, 355, 13, 119, 49, 3636, 6951, 43, 40, 4,
375, 415, 21, 2, 92, 947, 19, 4, 2282, 1771, 14, 5, 106, 2, 1151, 48, 25, 181,
8, 67, 6, 530, 9089, 1253, 7, 4, 2]),
       list([1, 14, 20, 16, 835, 835, 835, 51, 6, 1703, 56, 51, 6, 387, 180, 32,
812, 57, 2327, 6, 394, 437, 7, 676, 5, 58, 62, 24, 386, 12, 8, 61, 5301, 912,
37, 80, 106, 233]),
       list([1, 86, 125, 13, 62, 40, 8, 213, 46, 15, 137, 13, 244, 24, 35, 2809,
4, 96, 4, 3100, 16, 2400, 80, 2384, 129, 1663, 4633, 4, 2, 115, 2085, 15, 2, 2,
165, 495, 9123, 18, 199, 4, 2, 88, 36, 70, 79, 35, 1271, 5, 4, 4824, 18, 24,
116, 23, 14, 17, 160, 2, 301, 2, 2799, 16, 2085, 9508, 4129, 36, 343, 3973, 17,
4, 2, 37, 47, 965, 602, 5, 60, 80, 2, 11, 4, 3100, 63, 9, 43, 379, 48, 4, 2619,
69, 1668, 90, 8, 2, 15, 96, 36, 62, 28, 839, 11, 294, 9954, 900, 36, 62, 30, 43,
2254, 18, 35, 1271, 2, 14, 506, 16, 115, 1803, 3383, 1204, 44, 4, 2, 34, 4, 2,
2, 1373, 7, 4, 1494, 525, 5, 60, 54, 1803, 34, 4, 4824, 3383, 1204, 40, 54, 12,
645, 29, 100, 24, 1527, 48, 15, 218, 3793, 824, 13, 92, 124, 51, 9, 5, 6, 3275,
2408, 62, 28, 1840, 35, 2, 10, 10, 1324, 347, 12, 517, 125, 73, 19, 4, 2, 7,
112, 4, 4069, 7, 6, 506, 19, 2, 21, 4, 3100, 166, 14, 20, 5028, 1297]),
       ...,
       list([1, 13, 1408, 15, 8, 135, 14, 9, 35, 32, 46, 394, 20, 62, 30, 5093,
21, 45, 184, 78, 4, 1492, 910, 769, 2290, 2515, 395, 4257, 5, 1454, 11, 119, 2,
89, 1036, 4, 116, 218, 78, 21, 407, 100, 30, 128, 262, 15, 7, 185, 2280, 284,
1842, 2, 37, 315, 4, 226, 20, 272, 2942, 40, 29, 152, 60, 181, 8, 30, 50, 553,
362, 80, 119, 12, 21, 846, 5518]),
       list([1, 11, 119, 241, 9, 4, 840, 20, 12, 468, 15, 94, 3684, 562, 791,
39, 4, 86, 107, 8, 97, 14, 31, 33, 4, 2960, 7, 743, 46, 1028, 9, 3531, 5, 4,
768, 47, 8, 79, 90, 145, 164, 162, 50, 6, 501, 119, 7, 9, 4, 78, 232, 15, 16,
224, 11, 4, 333, 20, 4, 985, 200, 5, 2, 5, 9, 1861, 8, 79, 357, 4, 20, 47, 220,
57, 206, 139, 11, 12, 5, 55, 117, 212, 13, 1276, 92, 124, 51, 45, 1188, 71, 536,
13, 520, 14, 20, 6, 2302, 7, 470]),
       list([1, 6, 52, 7465, 430, 22, 9, 220, 2594, 8, 28, 2, 519, 3227, 6, 769,
15, 47, 6, 3482, 4067, 8, 114, 5, 33, 222, 31, 55, 184, 704, 5586, 2, 19, 346,
3153, 5, 6, 364, 350, 4, 184, 5586, 9, 133, 1810, 11, 5417, 2, 21, 4, 7298, 2,
570, 50, 2005, 2643, 9, 6, 1249, 17, 6, 2, 2, 21, 17, 6, 1211, 232, 1138, 2249,
29, 266, 56, 96, 346, 194, 308, 9, 194, 21, 29, 218, 1078, 19, 4, 78, 173, 7,
27, 2, 5698, 3406, 718, 2, 9, 6, 6907, 17, 210, 5, 3281, 5677, 47, 77, 395, 14,
172, 173, 18, 2740, 2931, 4517, 82, 127, 27, 173, 11, 6, 392, 217, 21, 50, 9,
57, 65, 12, 2, 53, 40, 35, 390, 7, 11, 4, 3567, 7, 4, 314, 74, 6, 792, 22, 2,
19, 714, 727, 5205, 382, 4, 91, 6533, 439, 19, 14, 20, 9, 1441, 5805, 1118, 4,
756, 25, 124, 4, 31, 12, 16, 93, 804, 34, 2005, 2643])],
      dtype=object)
```

```
train_y
```

```
array([0, 0, 0, ..., 0, 0, 0])
```

```
print("Categories:", np.unique(label))
print("Number of unique words:", len(np.unique(np.hstack(data))))
# The hstack() function is used to stack arrays in sequence horizontally (column wise).

#>>> import numpy as np
#>>> x = np.array((3,5,7))
#>>> y = np.array((5,7,9))
#>>> np.hstack((x,y))
# array([3, 5, 7, 5, 7, 9])


# You can see in the output above that the dataset is labeled into two categories, either 0
# which represents the sentiment of the review.

# The whole dataset contains 9998 unique words and the average review length is 234 words, \
```

```
Categories: [0 1]
Number of unique words: 9998
```

```
length = [len(i) for i in data]
print("Average Review length:", np.mean(length))
print("Standard Deviation:", round(np.std(length)))

# The whole dataset contains 9998 unique words and the average review length is 234 words, \
```

```
Average Review length: 234.75892
Standard Deviation: 173
```

```
# If you look at the data you will realize it has been already pre-processed.
# All words have been mapped to integers and the integers represent the words sorted by the
# This is very common in text analysis to represent a dataset like this.
# So 4 represents the 4th most used word,
# 5 the 5th most used word and so on...
# The integer 1 is reserved for the start marker,
# the integer 2 for an unknown word and 0 for padding.

# Let's look at a single training example:

print("Label:", label[0])
```

```
Label: 1
```

```
print(data[0])
```

```
[1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941, 4, 173, 36, 2
```

```
# Let's decode the first review
# Above you see the first review of the dataset which is labeled as positive (1).
# The code below retrieves the dictionary mapping word indices back into the original words
# It replaces every unknown word with a “#”. It does this by using the get_word_index() fun


# Retrieves a dict mapping words to their index in the IMDB dataset.
index = imdb.get_word_index()
```

```
# If there is a possibility of multiple keys with the same value, you will need to specify
# ivd = dict((v, k) for k, v in d.items())
# If you want to peek at the reviews yourself and see what people have actually written, yo
reverse_index = dict([(value, key) for (key, value) in index.items()])
decoded = " ".join( [reverse_index.get(i - 3, "#") for i in data[0]] ) #The purpose of subt
print(decoded)
```

```
# this film was just brilliant casting location scenery story direction everyone
```

```
index
```

```
{'fawn': 34701,
 'tsukino': 52006,
 'nunnery': 52007,
 'sonja': 16816,
 'vani': 63951,
 'woods': 1408,
 'spiders': 16115,
 'hanging': 2345,
 'woody': 2289,
 'trawling': 52008,
 "hold's": 52009,
 'comically': 11307,
 'localized': 40830,
 'disobeying': 30568,
 "'royale": 52010,
 "harpo's": 40831,
 'canet': 52011,
 'aileen': 19313,
 'acurately': 52012,
 "diplomat's": 52013,
 'rickman': 25242,
 'arranged': 6746,
 'rumbustious': 52014,
 'familiarness': 52015,
 "spider'": 52016,
 'hahahah': 68804,
 "wood'": 52017,
 'transvestism': 40833,
 "hangin'": 34702,
 'bringing': 2338,
 'seamier': 40834,
 'wooded': 34703,
 'bravora': 52018,
 'grueling': 16817,
 'wooden': 1636,
 'wednesday': 16818,
 "'prix": 52019,
 'altagracia': 34704,
 'circuitry': 52020,
 'crotch': 11585,
 'busybody': 57766,
 "tart'n'tangy": 52021,
 'burgade': 14129,
 'thrace': 52023,
 "tom's": 11038,
```

'snuggles': 52025,
'francesco': 29114,
'complainers': 52027,
'templarios': 52125,
'272': 40835,
'273': 52028,
'zaniacs': 52130,
'275': 34706,
'consenting': 27631,
'snuggled': 40836,
'inanimate': 15492,
'uality': 52030,
'bronte': 11926,

```
reverse_index
```

{34701: 'fawn',
52006: 'tsukino',
52007: 'nunnery',
16816: 'sonja',
63951: 'vani',
1408: 'woods',
16115: 'spiders',
2345: 'hanging',
2289: 'woody',
52008: 'trawling',
52009: "hold's",
11307: 'comically',
40830: 'localized',
30568: 'disobeying',
52010: "'royale",
40831: "harpo's",
52011: 'canet',
19313: 'aileen',
52012: 'acurately',
52013: "diplomat's",
25242: 'rickman',
6746: 'arranged',
52014: 'rumbustious',
52015: 'familiarness',
52016: "spider'",
68804: 'hahahah',
52017: "wood'",
40833: 'transvestism',
34702: "hangin'",
2338: 'bringing',
40834: 'seamier',
34703: 'wooded',
52018: 'bravora',
16817: 'grueling',
1636: 'wooden',
16818: 'wednesday',
52019: "'prix",
34704: 'altagracia',
52020: 'circuitry',
11585: 'crotch',

```
 57766: 'busybody',
 52021: "tart'n'tangy",
 14129: 'burgade',
 52023: 'thrace',
 11038: "tom's",
 52025: 'snuggles',
 29114: 'francesco',
 52027: 'complainers',
 52125: 'templarios',
 40835: '272',
 52028: '273',
 52130: 'zaniacs',
 34706: '275',
 27631: 'consenting',
 40836: 'snuggled',
 15492: 'inanimate',
 52030: 'uality',
 11926: 'bronte',
```

```
decoded
```

```
'# this film was just brilliant casting location scenery story direction everyon
e's really suited the part they played and you could just imagine being there ro
bert # is an amazing actor and now the same being director # father came from th
e same scottish island as myself so i loved the fact there was a real connection
with this film the witty remarks throughout the film were great it was just bril
liant so much that i bought the film as soon as it was released for # and would
recommend it to everyone to watch and the fly fishing was amazing really cried a
t the end it was so sad and you know what they say if you cry at a film it must
```

```
#Adding sequence to data
# Vectorization is the process of converting textual data into numerical vectors and is a p
data = vectorize(data)
label = np.array(label).astype("float32")

# Now it is time to prepare our data. We will vectorize every review and fill it with zeros
# That means we fill every review that is shorter than 1000 with zeros.
# We do this because the biggest review is nearly that long and every input for our neural n
# We also transform the targets into floats.
```

```
data
```

```
array([[0., 1., 1., ..., 0., 0., 0.],
       [0., 1., 1., ..., 0., 0., 0.],
       [0., 1., 1., ..., 0., 0., 0.],
       ...,
       [0., 1., 1., ..., 0., 0., 0.],
       [0., 1., 1., ..., 0., 0., 0.],
       [0., 1., 1., ..., 0., 0., 0.]])
```

```
label
```

```
array([1., 0., 0., ..., 0., 0., 0.], dtype=float32)
```

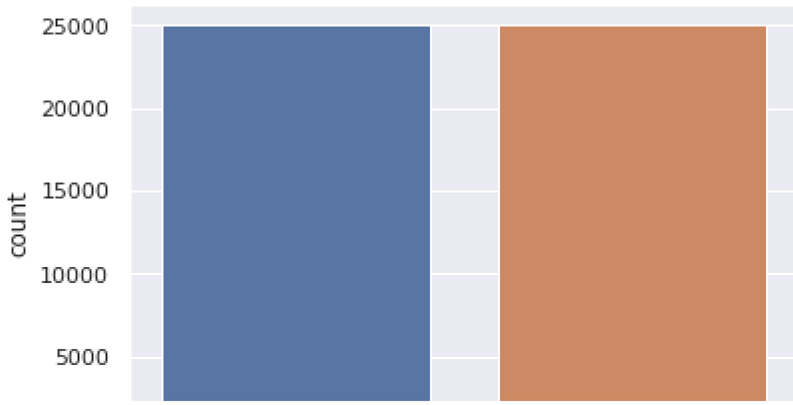
```
# Let's check distribution of data

# To create plots for EDA(exploratory data analysis)
import seaborn as sns #seaborn is a popular Python visualization library that is built on to
sns.set(color_codes=True)
import matplotlib.pyplot as plt # %matplotlib to display Matplotlib plots inline with the no
%matplotlib inline
```

```
labelDF=pd.DataFrame({'label':label})
sns.countplot(x='label', data=labelDF)

# For below analysis it is clear that data has equel distribution of sentiments.This will he
```

<Axes: xlabel='label', ylabel='count'>




```
# Creating train and test data set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data,label, test_size=0.20, random_stat
```

```
X_train.shape
```

(40000, 10000)

```
X_test.shape
```

(10000, 10000)

```
# Let's create sequential model,In deep learning, a Sequential model is a linear stack of la

from keras.utils import to_categorical
from keras import models
from keras import layers
```

```
model = models.Sequential()
# Input - Layer
# Note that we set the input-shape to 10,000 at the input-layer because our reviews are 10,0
# The input-layer takes 10,000 as input and outputs it with a shape of 50.
```

```
model.add(layers.Dense(50, activation = "relu", input_shape=(10000, )))
# Hidden - Layers
# Please note you should always use a dropout rate between 20% and 50%. # here in our case 
# By the way, if you want you can build a sentiment analysis without LSTMs(Long Short-Term 
model.add(layers.Dropout(0.3, noise_shape=None, seed=None))
model.add(layers.Dense(50, activation = "relu")) #ReLU" stands for Rectified Linear Unit, a
model.add(layers.Dropout(0.2, noise_shape=None, seed=None))
model.add(layers.Dense(50, activation = "relu"))
# Output- Layer
model.add(layers.Dense(1, activation = "sigmoid")) #adds another Dense layer to the model, 
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 50)                500050

 dropout (Dropout)           (None, 50)                0

 dense_1 (Dense)             (None, 50)                2550

 dropout_1 (Dropout)         (None, 50)                0

 dense_2 (Dense)             (None, 50)                2550

 dense_3 (Dense)             (None, 1)                 51

=================================================================
Total params: 505,201
Trainable params: 505,201
Non-trainable params: 0
_________________________________________________________________
```

```
#For early stopping
# Stop training when a monitored metric has stopped improving.
# monitor: Quantity to be monitored.
# patience: Number of epochs with no improvement after which training will be stopped.
import tensorflow as tf #TensorFlow provides a wide range of tools and features for data pr
callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=3)
```

```
# We use the “adam” optimizer, an algorithm that changes the weights and biases during trai
# During training, the weights and biases of a machine learning model are updated iterative
# We also choose binary-crossentropy as loss (because we deal with binary classification) a

model.compile(
 optimizer = "adam",
 loss = "binary_crossentropy",
 metrics = ["accuracy"]
)
```

```
# Now we're able to train our model. We'll do this with a batch_size of 500 and only for tw
# batch size defines the number of samples that will be propagated through the network.
# For instance, let's say you have 1050 training samples and you want to set up a batch_siz
# The algorithm takes the first 100 samples (from 1st to 100th) from the training dataset a
# Next, it takes the second 100 samples (from 101st to 200th) and trains the network again.
```

```
# We can keep doing this procedure until we have propagated all samples through of the netw
# Problem might happen with the last set of samples. In our example, we've used 1050 which
# The simplest solution is just to get the final 50 samples and train the network.
##The goal is to find the number of epochs that results in good performance on a validation
results = model.fit(
 X_train, y_train,
 epochs= 2,
 batch_size = 500,
 validation_data = (X_test, y_test),
 callbacks=[callback]
)
```

```
Epoch 1/2
80/80 [==============================] - 8s 80ms/step - loss: 0.4230 - accuracy:
Epoch 2/2
80/80 [==============================] - 4s 55ms/step - loss: 0.2198 - accuracy:
```

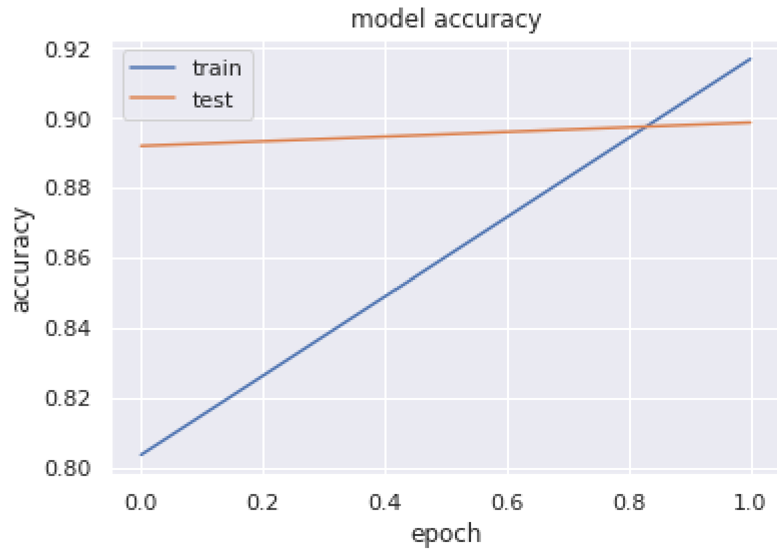
```
# Let's check mean accuracy of our model
print(np.mean(results.history["val_accuracy"])) # Good model should have a mean accuracy si
```

```
0.8953500092029572
```

```
#Let's plot training history of our model

# list all data in history
print(results.history.keys())
# summarize history for accuracy
plt.plot(results.history['accuracy']) #Plots the training accuracy of the model at each epo
plt.plot(results.history['val_accuracy']) #Plots the validation accuracy of the model at ea
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(results.history['loss'])
plt.plot(results.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```




```
model.predict(X_test)
```

```
313/313 [==============================] - 2s 6ms/step
array([[0.17430142],
       [0.9865479 ],
       [0.86662334],
       ...,
       [0.9772741 ],
       [0.9754161 ],
       [0.9927141 ]], dtype=float32)
```

```
#Out put analysis,
#[0.9865479] is a single prediction value for a particular input sample in the test data.
#It is the predicted probability of the positive sentiment class (class 1) for that input.
#Since the output activation function of the last layer of the model is sigmoid, which maps
#,the output values represent the probabilities of the positive class.
#In this case, the probability of the positive class for the given input sample is 0.986547
```