

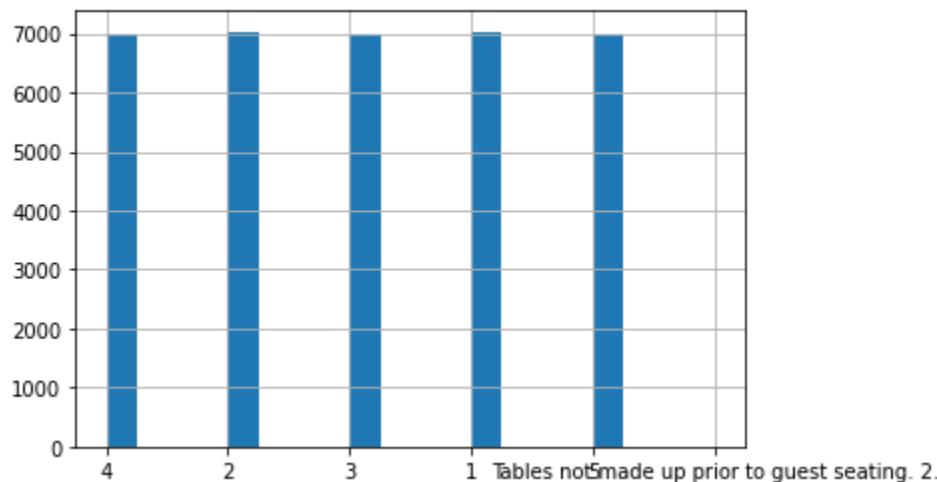
Analysis:

Given dataset has reviews and ratings for a hotel range from 1 to 5. After observing the dataset, one row in rating column has a text along with the rating. So, the data needs to be cleaned, tokenized and should be converted to tensors. The converted tokens along with labels are fed into the model for training. The trained model needs to be evaluated based on given dev dataset and predictions should be made to a given test dataset.

Data exploration:

Since all the labels are balanced and no missing text or labels, we don't have to use imputing or upsampling at least for the base model.

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2641e735f8>
```



I have cleaned the rating column with regex method to select only numeric elements between 1-5.

Model Selection:

Base Model – Naïve Bayes:

Naïve Bayes is based on Bayes' theorem which assumes that each of the features it uses is conditionally independent of one another given some class.

Bayes' theorem:

$$P(y | x_1, \dots, x_n) = \frac{P(y)P(x_1, \dots, x_n | y)}{P(x_1, \dots, x_n)}$$

Using naive conditional independence, for each x_i is independent of for all i , the formula is simplified to

$$P(x_i | y, x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) = P(x_i | y)$$

And since $P(x_1, \dots, x_n)$ is constant, the prediction is

$$\hat{y} = \arg \max_y P(y) \prod_{i=1}^n P(x_i | y)$$

The different naïve Bayes classifier is based on assumptions they are regarding define the distribution of $p(y/x_i)$

I have used Multinomial Naïve Bayes which is a specific instance of a Naive Bayes classifier which uses a multinomial distribution for each of the features.

SOTA Model – LSTM (Long Short Term Memory):

Recurrent neural networks are a type of artificial neural network which is designed to recognize the pattern from the sequence of the data. It takes a fixed-size vector as input which is limited to usage of series type inputs. RNNs remembers past and its decisions are influenced by what it has learnt in the past. Basic neural networks remember things too, but they remember things they learnt during training. While RNNs learn similarly during training also besides, they remember things learnt from prior inputs while generating outputs. The hidden state captures the relationship that neighbours might have with each other in serial input and it keeps changing every time.

LSTMs are similar to vanilla RNNs, but it introduces some changes to how we compute outputs and hidden states using inputs. LSTM introduces additional gates and cell state, which addresses the problem of keeping or resetting context across sentences regardless of the distance between such context resets. So, LSTM is a special kind of recurrent neural network that is capable of learning long-term dependencies, remembering information for long periods. A)The network decides what to learn and what to forget. B)It selectively updates cell state values. C) The network decides what part of current states makes it to output.

Evaluation measures:

Basemodel Performance:

The training accuracy of Naïve Bayes model is 52% and evaluation accuracy is 50%.

SOTA Model Performance:

The training accuracy of LSTM Model is 90% and evaluation accuracy is 73%. This accuracy is obtained for just 7 epochs. We can increase the model performance even more, but I have run only 7 epochs due to time constraint.

Parameters considered:

<i>Metrics</i>	:	accuracy
<i>Loss function</i>	:	categorical_crossentropy
<i>Optimizer</i>	:	adam
<i>Learning rate</i>	:	0.001 (default)
<i>Epochs</i>	:	7

Model comparison:

The Naïve Bayes model performance is less than LSTM model. This makes sense because LSTM model looks for a relationship with its neighbours within a sentence whereas Naïve Bayes calculates each word independently. Since the reviews are sometimes sarcastic, meaning though the words are positive the overall sentence is negative. Naive bayes could not understand the sarcastic comments since it does not capture underlying relationship which could lead to low performance.

Reference:

1. Sequence models course by Andrew NG