

# Sentiment Classification using encoders: Amazon Fine Food Reviews

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## Abstract

We perform the sentiment analysis using the classic approaches of Bidirectional Encoder and Fully Connected layers, and compare it to the SOTA results received with the Universal Sentence Encoder (USE) from TensorFlow by Google. Another bit of attention is put onto the complicated task of hyperparameters search; the Optuna and BOHB AutoML engines are applied and compared.

## 1. Introduction

Amazon Fine Food Reviews competition presented an important challenge to the community in application of state of the art approaches to the automatic extraction of useful information from the texts expressing public opinions about the quality of fine foods from Amazon, which can help them to improve the quality of their services. With the appearance of different attention-based transformer architectures and pre-trained models in the last two years the capacity of learning from real text data greatly increased, which is now a subject of extensive research, however it is interesting to see if the classic approaches, even being harder to construct, are capable to deal with the task.

## 2. Related work

Over the time the sentiment classification approaches evolved from TF-IDF and Logistic Regression methods, described in many articles for example [Underhill et al., 2007] and [Das et al., 2018] to the deep learning empowered approached. The important step in the NLP evolution was the famous Word2Vec [Mikolov et al., 2013], not performing the sentiment analysis by itself but introducing the powerful mechanism of the word embeddings.

The Recurrent Neural Networks, ones capable to handle the sequence of inputs, empowered with the Long Short Term Memory [Hochreiter et al., 1997] [Mikolov et al., 2015], provided powers for machine understanding of the textual sequence by utilizing the hidden state of the Encoder. Many of following works, for example [Zhou et al., 2016] and [Gopalakrishnan et al., 2020], demonstrated the capability to perform the Sentiment Analysis using the LSTM Encoder.

One of the complex problems in the Deep Learning is the hyperparameters search, with two worth noting approaches [Akiba et al., 2019] and [Falkner et al., 2018].

Another worth noting works are the overviews of the NLP landscape and existing methods, the good example is [Zhang et al., 2018] .

The further sparkling NLP development provided the community with massive, powerful pre-trained model of BERT, which could be used for variety of NLP tasks out of the box or with minimal fine tuning – few works to mention are [Devlin et al., 2018] and [Sun et al., 2019] . Another interesting approach is the Universal Sentence Encoder [Cer et al., 2018] providing the meaning of the sentence in so called meaning vector. Those are considered as the current SOTA.

### 3. Dataset

Amazon Fine Foods Dataset consists of reviews of fine foods from amazon. The data span a period of more than 10 years, including all ~500,000 reviews up to October 2012. Reviews include product and user information, ratings, and a plain text review. It also includes reviews from all other Amazon categories.

The original dataset contains 568454 records with long text comment, short summary, and score as integer from 1 to 5, 5 indicating the happiest customer. The dataset is dis-balanced as it shown on Fig 1: Amazon Fine Foods: Score

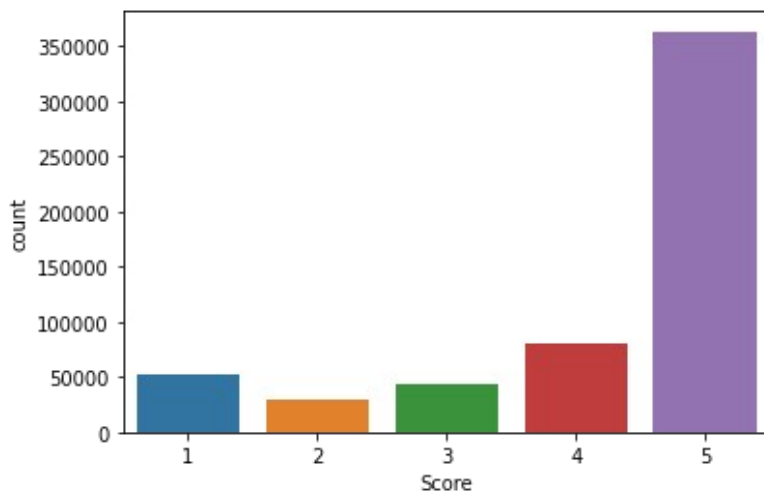


Fig 1: Amazon Fine Foods: Score

The reference SOTA solution, Amazon Fine Foods USE Sentiment Analysis is transforming the Score into binary positive-negative classification task such that positives are those with Score  $\geq 4$ . The dis-balance problem is solved with under- sampling approach - all negatives and equal amount of positives are taken. Result dataset has 249354 records.

### 4. Metric

The reference SOTA solution, Amazon Fine Foods USE Sentiment Analysis proposes simple accuracy metric:

$$\text{accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{FP} + \text{TN} + \text{FN})$$

Which makes sense as far as the dataset is down-sampled to become balanced. The dataset is split as

80% - for training

10% - for validation, i.e. training loss and hyperparameters selection

10% - for final test

## 5. Model

The model architecture is displayed on the Fig 2: Bidirectional Encoder and Fully Connected layers.

The raw inputs are lowercased, punctuation and stop words are removed, and contractions are replaced with their longer forms. The resulting words are replaced with Gensim pretrained embeddings. From the 30000 vocabulary size, around 5000 words were not found in Gensim, which are mostly popular typos, NERs or slang - the random embedding values were generated for those.

Embeddings are passed to Bidirectional Encoder, assembled of standard GRU units. The last hidden state (combined from both forward and backward passes) is flattened and passed as input layer into fully - connected network.

Single hidden layer is dedicated for features generation and followed by two output neurons responsible for positive and negative classes accordingly. The raw logits produced at output layer, are passed into CrossEntropyLoss:

$$\text{loss}(\mathbf{x}, \text{class}) = -\log \left( \frac{\exp(\mathbf{x}[\text{class}])}{\sum_j \exp(\mathbf{x}[j])} \right) = -\mathbf{x}[\text{class}] + \log \left( \sum_j \exp(\mathbf{x}[j]) \right)$$

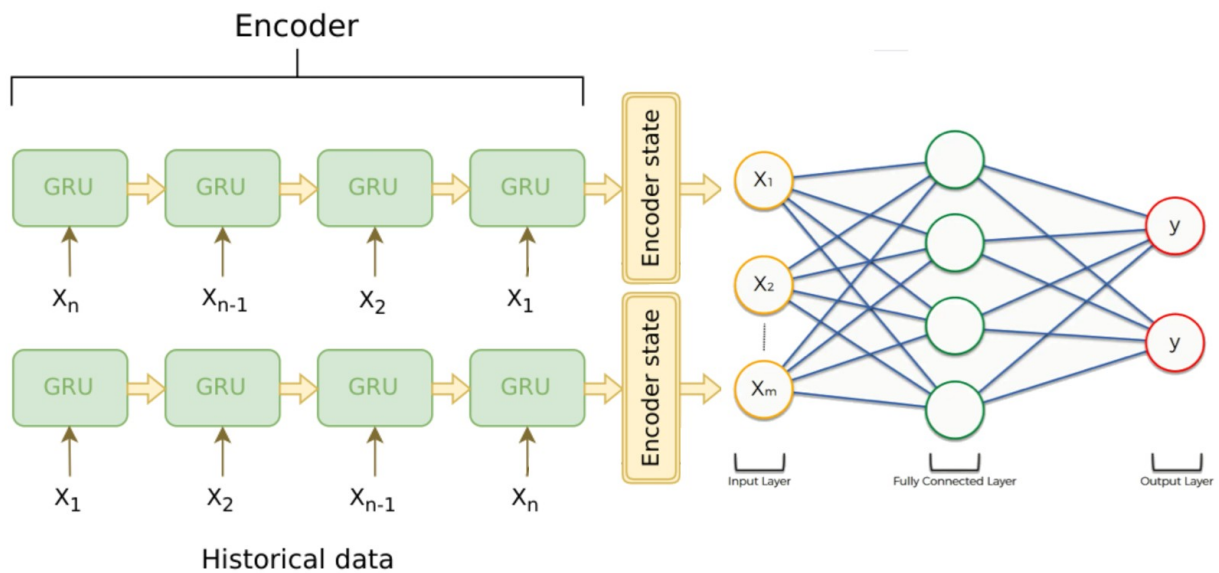


Fig 2: Bidirectional Encoder and Fully Connected layers

## 6. Experiments

The model weights are optimized using Adam optimizer.

The following model hyperparameters: `gru_hidden_size`, `gru_num_layers`, `gru_dropout`, `gru_bidirectional`, `fully_connected_size`; and the following learner hyperparameters: `learning_rate`, `weight_decay` are selected using one of two engines: Optuna or BOHB.

BOHB applies intellectual schema of trying many hypotheses on small budgets (either number of training epochs or dataset size) to probe the goal function space and spend less resources on full budgets. The budgets trials forms the pyramid of 1%-3%-11%-33%-100%, with approximately 100 trials of budget=1% and 1 trial of budget=100%. As number of epochs is relatively small it was decided to use dataset size as budget measure. Please refer to original paper [Falkner et al, 2018]

The number of trials for Optuna was limited to 20. BOHB has trickier parameter called `n_iterations` which is effectively number of budget pyramids. The iterations was set to 7 which led to approx 30 of full budget evaluations.

The `number_of_epochs` parameter is fixed to either 7, 12, or 20 epochs.

## 7. Results

The model presented in this work, Bidirectional Encoder with Fully Connected Layers (BEFC) is compared to SOTA Amazon Fine Foods USE Sentiment Analysis. The results are as follows:

Model	automl engine	n_epochs	training time	accuracy	size
SOTA	-	-	-	0.9050	916mb
BEFC	BOHB	7	5h	0.8419	36mb
BEFC	BOHB	12	8h	0.8605	25mb
BEFC	BOHB	20	10h	0.8435	28mb
BEFC	Optuna	7	4.5h	0.8877	26mb
BEFC	Optuna	12	8.5h	0.8950	35mb
BEFC	Optuna	20	14h	0.8908	30mb

## 8. Conclusions

The previous SOTA approaches, like Bidirectional Encoder with Fully Connected Layers presented in this work, are capable to solve the Sentiment Analysis task with similar quality as current USE SOTA.

It is important to note that Universal Sentence Encoder, utilized by SOTA solution, is 916Mb in size, whilst BEFC is 25-36Mb max. The size and performance of the model is crucial in deployment and especially in embedded solutions. The current research is demonstrating the possibility of achieving the SOTA quality using the 30x times smaller model.

In regards to hyper parameters search, BOHB is faster as it handles 1.5 more of full dataset budgets in comparison to Optuna in the same time. Optuna, however, managed to find the hyperparameters solution and train the model with SOTA-comparable quality.

## 9. References

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Amazon Fine Foods Dataset

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Amazon Fine Foods USE Sentiment Analysis

<https://www.kaggle.com/kshitijmohan/sentiment-analysis-universal-sentence-encoder-91>