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ENHANCE BERT WITH RADIAL BASIS FUNCTION AND MULTI–HEAD ATTENTION FOR MULTI–LABEL MOVIE GENRE CLASSIFICATION: A TRANSFER LEARNING APPROACH

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Abstract: Labelling large movie scripts on respective genre is an exigent problem, thus, may belong to multiple genres. This is based on the language features and formatting, many of such scripts lead to multi–label classification problem. In this study, the dataset consists of 1263 movie scripts, extracted from IMSDb with five different labels. Due to the size of the scripts, double–weighted transformation through data augmentation is adopted to produce associated weight to each instance. This increases the training instances of the movie scripts to 6749 with over 300000 sentences. This study adapted pretrained BERT as transfer learning to pad and masked feature representations as downstream model with Radial Basis Function (B–RBF) and Multi–head attention (B–MHA) as upstream models, enhance with ADAM optimizer for better classification. Evaluations are done for each model using hamming loss and weighted average to calculate the accuracy of each model. The weighted accuracy values are 0.8177 and 0.9262 for RBF and Multi–head attention and hamming loss are 0.0099 and 0.1305 respectively. The models measure the closeness of the test labels against the predicted labels such that values for MHA and RBF accuracy are 0.8222 and 0.1200 respectively. From the results, it shows that RBF minimises error while MHA produces better performance in parallel.
Keywords: Multi–label, BERT, Radial basis function, Movie Script, Multi–head attention, Transfer learning

1. INTRODUCTION

In traditional classification, a single–label only associated with a single class label but, not effective for multi–label classification. Many real–world problems are categorised into multi–label classes to deals with complexity of text data where label is represented by a single instance. Multi–label context is applicable to different domains such as images, audio, video, text, and bioinformatics etc. which may belong to more than one class label (Tsoumakas et al. 2007; Tsoumakas et al. 2010; Hiteshri and Mahesh, 2012). Classifying movie scripts into multi–label deals with the problem in which samples contain many labels such as entertainment, drama, comedy, horror, relationship, etc. Most existing work on movies are based on multimedia content classification such as image, audio–visual, extraction from trailers, motion features, posters etc. Ivasic–Kos et al. (2015) presented a multi–label classification with visual features extraction from movie posters to classify genres. While textual topics are basically based on plot summary (Ertugrul and Karagoz, 2018) or using synopsis for movies' genres classification (Ihteshamur and Sajidul, 2017). Although, movie plot summaries reflect the movie genres such that textual information about the movie can easily be captured but restrictions are on all the creativity in the movie. Movie scripts provide textual data with rich information that give full content descriptions but varied in format or writing style but represent narrative structure of the storylines (Eliashberg et al. 2006). Intuitively, this can be ambiguous due to synonymy and polysemy involve in textual analysis, analysing the content of movies generated by a user can be complicated to manage and time–consuming. Deep learning pretrained language models have proven to be a successful method on unlabeled dataset for transfer learning. Basically, it was shown that Word2vec (Mikolov et al. 2013a, Mikolov et al. 2013b) performed better on articles such as news, movies for effective and higher accuracy.

The improvement over classic embedding to captured long dependency input sequence such as vanishing problems, time step dependence as well as parallel training ability can be replaced with Transformer (Vaswani et al. 2017). The Bidirectional Embedding Representation Transformer (BERT) used pretrained via self–supervised learning on large amount of raw textual data, thus, produce sentence–level encodings with low speed, good performance and minimum supervision. Labutov and Lipson (2013) presented a model to fine–tune pretrained word embedding for supervised tasks and assigned a sentiment label of zero and one to each sentence of the movie review. Although, the method shared undesirable pattern, continual outlier across hidden layer that give small or large values of feature vector. Deep learning models have solutions due to high–dimensional and unstructured datasets in multi–label. Razavian et al. (2014) focused on the comparison of pretrained CNN as feature extractor with hand–crafted feature algorithms with consistent and better results for CNN. To address

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the issues of BERT language models due to long sequence length and complexity of the text scripts, there is needs to enhance the embedding to generate better movie genre multi–label classification. Faruqui et al. (2015) showed the use of semantic lexicons to constitute word vectors by connecting words with similar vectors representation. Abdalla et al. (2019) enriched unlabeled word embedding trained with lexicon with pseudo–labels predicted by a regressor to add some degree of separation between words. Tang et al. (2016), Lan et al. (2016), Ren et al. (2016) presented method that enriched embedding with loss function to improve the context loss in analyzing the classification to balance the learning tasks.

Subsequently, only BERT cannot solve the problem of multi–label movie genre classification to some extent, this study adapted pretrained BERT as transfer learning on each token in a sequence when there is no enough labelled dataset. Hence, the language understanding can be enriched using BERT as downstream model while Radial Basis Function (RBF) and/or Multi–Head Attention classifiers as upstream task. Many multi–label learning models adopted traditional supervised learning approaches to learn from training instances like Bayesian (Ueda and Saito, 2003), multi–label decision tree (De Comite et al. 2003), K–nearest neighbor (KNN) algorithm (Zhang and Zhou, 2006), multi–label kernel methods (Elissee and Weston, 2002). Although, Support Vector Machine (SVM) handled non–linear classification tasks and mapped pattern into high–dimension space using kernel functions, thus, perform well with Radial Basis Function (RBF) (Abdullah et al. 2019; Suykens and Vandewalle, 1999). Lu et al. (2019) added co–attention to BERT in enhancing visual and textual information, but a multimodal model used Multi–Head Attention (MHA) to enriched encoded image and text information between transformer blocks (Lin et al. (2020). The Attention mechanism is a weighting probability to obtain superior results (Wang et al. 2016; Rush et al. 2015). Basically, solving multi–label classification problem requires categories of problem transformation and algorithm adaptation methods. This study involved small data scripts due to this a double–weighted transformation is adopted to movie script such that it produces associate weight to each instance. This method increases the instances, but no information loss such that a single label classifier is trained, based on the combination of genres that covered all labels. This leads to the motivation of this work such that two (2) different classifier models are proposed to enhance multi–label movie genres classification using pretrained BERT transfer learning model as embedding layer. This gives more weight to important parts in the embedding to enhance the training process. The concept of pretrained BERT enhanced with RBF compute the inner product in high dimensional space to minimises error of the adjustable weight using linear optimisation. This lessens the tolerance of input noise in the embedding for multi–label classification. While pretrained BERT combined with multi–head attention mechanism extract the semantic information in the movie scripts many times in parallel with different representation. The Adaptive Moment Estimation (ADAM) is added to optimize the network. then, comparison evaluation of each model is considered using weighted accuracy and hamming loss. The rest of the paper is structured as follows; description of the approach methodologies; BERT–RBF and BERT–Multi–head self–attention models are described. In Section 3, the performance of the proposed models is analysed and compared. Finally, Section 4 provides a summary and recommendations.

2. MATERIALS AND METHODS

- *Data Source:* The dataset contains 1,264 movie scripts were collected from the website of the Internet Movie Script Database (IMSDb) (data) with each in a separate text file. The file contains (script.txt) titles of all movies with its corresponding file name in numerical ascending order. The *BeautifulSoup* library—a Python HTML parsing tool is used for the extraction. To augment the size of the datasets, movie scripts which contains approximately 300,000 sentences were divided into 500 sentences in batches given a total of 6,749 which indicate whopping 60% increment. The scripts is divided into 80:20 as training sets and test set respectively.
- *Method Stage 1:* After preprocessing, the preprocessed movie scripts are fed into the pretrained BERT model as input and produces an output of a fixed dimensional embedding vector. The representation of the pretrained BERT Embedding is adapted for the movie scripts sentence–level and the initial values are randomly generated such that the input i^{th} is represented as a feature vector

$X_i = \{x_{i1}, x_{i2} \cdots x_{id}\}$, each element x_{in} is a feature, where $1 \le n \le d$ and d as dimension of the input feature space. X_i is associated with a label set vector $Y_i = \{y_{i1}, y_{12}, \cdots y_{1M}\}$ where M as dimension of the output feature space. A set of training labeled sentences is represented as $T = \{(X_i, Y_i)\}_{i=1}^{n}$ from the target domain and pretrained sentence embedding model S_1 such that the embedding X from S_1 is denoted as $X_{1_s} = S_1(x) \in \Re^{d_1}$. The S_1 is transferred to the target domain using T for the movie scripts sentence embedding S_2. Thus, pretrained BERT used MLM such that the tokens are padded and masked which randomly hides the input words to predicts the original vocabulary size of the hidden part based on the context.

- *Method Stage 2*: Radial Basis Function and Multi–Head Attention Models: The output of the pre–trained BERT $X \in \Re^n$ are fed into the classifier models with weighted matrices $W \in \Re^{d_a \times n}$ as input into the classifiers. The pretrained embedding $\hat{X}_{c=1}^{C} n_c$ are partition to find a cluster centre (ω) so that dissimilarity measure between each group is minimized such that $2 \le C \le N$ belong to two or more clusters. In this study, multi–label learns classifier $\lambda : X \to 2^C$ from M to classify a set of labels in movie scripts such that $2 \le C \le N$. For each class label $c \in K$, there are two (2) parameters; μ_{ik} is considered membership value and ω_k is k data point belong to cluster ω, which is performed on the matrices with the constraint $0 \le \mu_{ik} \le 1,\ i = 1,2,\cdots,N,\ k = 1,2,\cdots C$ with hyper–parameter λ. Thus, $\sum_{k=1}^{C} \mu_{ik} = 1,\ i = 1,2,\cdots n$ and $0 < \sum_{i=1}^{n} \mu_{ik} < N,\ k = 1,2,\cdots C$ holds.

The objective function of the cluster partition ℓ_λ is depicted in equation 1 such that:

$$\ell_\lambda(X;\mu,\omega) = \sum_{i=1}^{N}\sum_{k=1}^{C} \mu_{ik}^{\lambda} \left\| \theta(x_{ij}) - \theta(\omega_{kj}) \right\|^2 \tag{1}$$

if $\lambda = 2,\ \omega = \omega_{kj} \middle| k = 1,2,\cdots C, j = 1,,\cdots,\lambda$

Therefore, similarity measure between each feature vector can be defined in equation 2:

$$\text{Euclidean distance} \quad \delta = \left\| (x_{ij}) - (\omega_{kj}) \right\|^2 \tag{2}$$

In this study, Gaussian (RBF) is considered in equation (3) as:

$$\Omega(x,\omega) = \frac{\exp(-\left\|(x_{ij}) - (\omega_{kj})\right\|^2}{2\partial^2} \tag{3}$$

where $\partial \in \Re$ is a parameter of Ω. Minimizing loss function, all the parameters are optimized with ADAM (μ,ω).

- *Method Stage 3:* Multi–head Attention

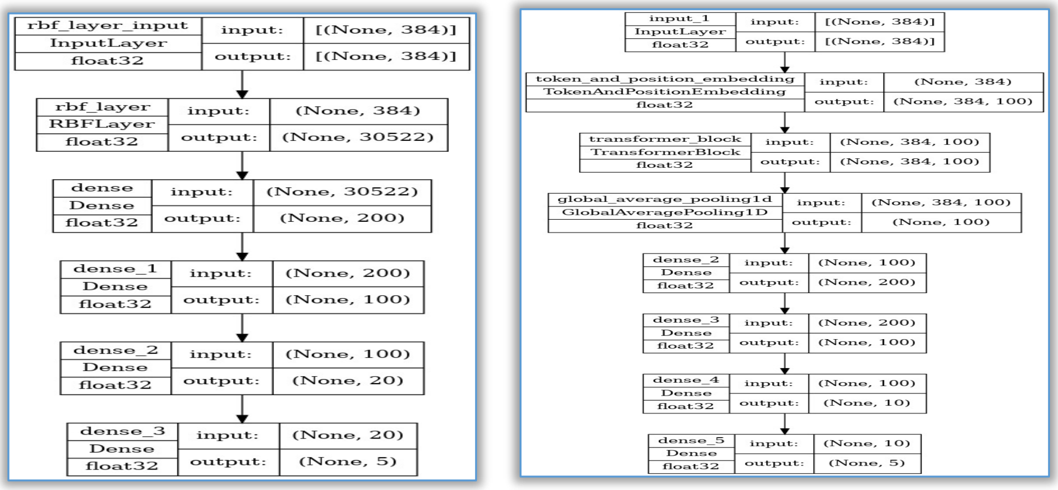
For Multi–head attention focused on the multiple target part of the BERT embedding sequence such that heads resulting in multiple attention so as to presents different representation subspaces as query–key–value (Q, K, V) respectively on a single feature. For short or long range of movie scripts sequence are considered in parallel which are fully learned from datasets through the dense layer. The feature matrix $X \in \Re^{d \times n}$ for the same linear transformation W is used to generate a new matrix input. Hence, the attention function for a set of queries is found in parallel and concatenated into a matrix Q. Then, keys and values are concatenated as well into matrices K and V.

$\text{Multihead}(Q,K,V) = [\text{head}_1, \cdots \text{head}_n]W'$ where $\text{head}_i = \text{attention}(QW_i', KW_i', VW_i')$ would be encoded such that the attention function (Q, K, V) is computed for the output as in equation (4)

$$\text{soft}\max(X') = \left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

where $X' \in \Re^{d \times n}$

Figure (1a) describes the architecture of RBF layer where the model has 6–layer network with the 1st layer being the RBF layer follow by fully connected layer of 200,100, and 20 neurons respectively. The output layer is a dense layer with total number of the output label. While Figure (1b) represent the multi head attention models which have an input layer of 384 neurons with a token and position layer to represent words and its order in a sentence then, sums the output followed by transformer layer and dense layer.



(a) (b)

Figure 1(a and b): RBF and MHA Model Architecture

The evaluation is done using hamming loss (H) and weighted accuracy (W_t) as represented in equation (5a and b) for the multi–label classification.

$$H=\frac{1}{NL}\sum_{i=1}^{N}\sum_{i=1}^{L}\iota[\hat{y}_j^{(i)} \neq y_j^{(i)}], \tag{5a}$$

$$W_t=\sum_{i=1ton} W_i \times \frac{TP_i+TN_i}{TP_i+TN+FP_i+FN_i} \tag{5b}$$

3. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental environment is GPU GeForce, the CPU is AMD Rhyen i7, the memory is 64GB, the GPU is Nvida Titan, and the software platform is Google Tensor flow. The experiment compares the RBF and multi–head attention for multi–label classification models. The first layer is an embedding layer that takes in BERT embedding containing low dimensional vectors into the network. The neurons in each layer is set to 128, 64, and the activation function used Rectified Linear Unit (*Relu*) while the fully connected layer contains dense layer.

The output layer is sigmoid function which contain number of classes. Setting the training and test into 80:20 respectively, hence, 10% of the training set was used as validation. The genre and content (class) are categorise describing the genre of the movies scripts where each belong to any number of the categories as presented in table 1. The table 1 shows the distribution of each label of the dataset of the movie scripts with its respective classes for the proposed models; RBF and Multi–Head attention models.

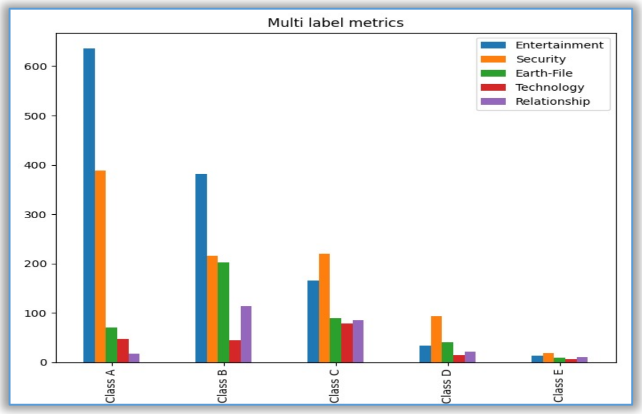


Figure 2: The Genre Distribution and Class of the Multi–Label Movie Scripts

Table 1: The Genre Distribution and Class of the Multi–Label Movie Scripts

Class	Entertainment	Security	Technology	Relationship	Earth–file
Class A	636	388	48	18	70
Class B	382	216	45	114	202
Class C	165	220	78	86	90
Class D	34	94	15	21	40
Class E	14	19	7	10	9

From the table 1 and table 2 results, it was shown that the categorical cross entropy loss (training loss) and the hamming loss decreases at each epoch for both RBF training and Multi–Head attention. While the accuracy of RBF increases as epoch increases but at epoch 9 accuracy decreases.

Table 1: Training Metric for RBF in Multi–Label Classification

Epoch	Training Loss	Training Accuracy	Hamming Loss	Validation Loss	Validation Accuracy	Validation Hamming Loss
0	0.3277	0.0424	0.2069	0.2299	0.0601	0.1283
1	0.1372	0.0583	0.0867	0.2359	0.0602	0.1414
2	0.0881	0.0595	0.0612	0.2487	0.0602	0.1133
3	0.0671	0.0567	0.0463	0.2849	0.0602	0.1111
4	0.0545	0.0611	0.0375	0.3310	01111	0.1337
5	0.0445	0.0933	0.0287	0.3118	0.0611	0.1160
6	0.0336	0.1229	0.0214	0.2851	0.0611	0.1017
7	0.0264	0.1551	0.0169	0.2986	0.0611	0.1189
8	0.0212	0.2792	0.0137	0.2938	0.0722	0.1358
9	0.0144	0.1912	0.0099	0.3883	0.0611	0.17465

Table 2: Training Metric for MHA in Multi–Label Classification

Epoch	Training Loss	Training Accuracy	Hamming Loss	Validation Loss	Validation Accuracy	Validation Hamming Loss
0	0.3810	0.9009	0.2315	0.2935	0.9167	0.1706
1	0.2752	0.9204	0.1522	0.2425	0.9167	0.1230
2	0.2513	0.6733	0.1342	0.2347	0.0602	0.1377
3	0.2475	0.0583	0.1319	0.2315	0.0602	0.1286
4	0.2471	0.0583	0.1307	0.2316	0.0602	0.1111
5	0.2468	0.0583	0.1305	0.2310	0.0602	0.1258
6	0.2468	0.0583	0.1309	0.2309	0.0602	0.1254
7	0.2463	0.0583	0.1302	0.2332	0.0602	0.1362
8	0.2473	0.0583	0.1313	0.2320	0.0602	0.1320
9	0.2464	0.0583	0.1305	0.2314	0.0602	0.1118

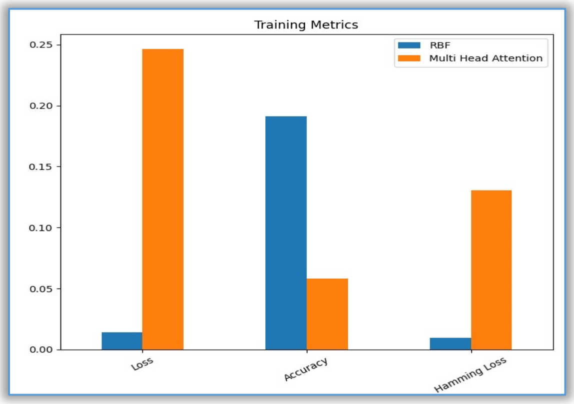


Figure 2a: RBF and Multi–Head Attention Training Metric at 10 Epoch

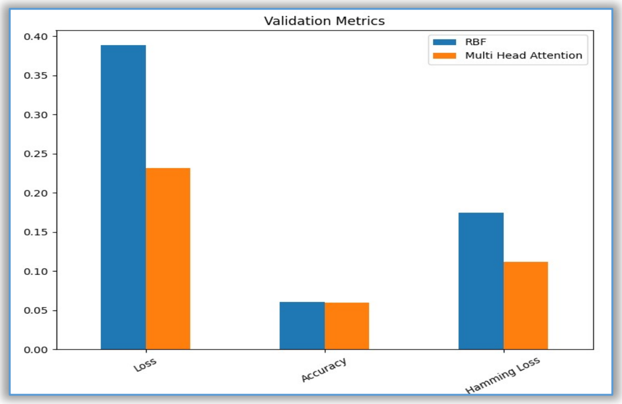


Figure 2b: RBF and Multi–head Attention Validation Metric at 10 Epoch

From the figure 2(a and b), it shows the bar chart of the table 1 and 2, the loss for MHA is high compared to the RBF and the accuracy of RBF is high in comparison with MHA for table 1 while hamming loss is low compared to categorical loss. Validation metric shows the quantitative between model prediction and real–world accuracy.

The predicted weighted accuracy values are 0.8177 and 0.9262 for RBF and Multi–head attention and hamming loss are 0.0099 and 0.1305 respectively. The models measure the closeness of the test labels against the predicted labels such that values for MHA and RBF accuracy are 0.8222 and 0.1200 respectively.

4. CONCLUSION AND RECOMMENDATION

Multi–label movie scripts genre classification is challenging but with the help of BERT pretrained model integrated with RBF and MHA, the problem is minimised. From the results, it shows that RBF minimises error while MHA compute the attention function in parallel with better performance.

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