Comparative Study of Machine Learning Models and BERT on SQuAD

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Abstract—This study aims to provide a comparative analysis of
performance of certain models popular in machine learning and
the BERT model on the Stanford Question Answering Dataset
(SQuAD). The analysis shows that the BERT model, which
was once state-of-the-art on SQuAD, gives higher accuracy in
comparison to other models. However, BERT requires a greater
execution time even when only 100 samples are used. This shows
that with increasing accuracy more amount of time is invested
in training the data. Whereas in case of preliminary machine
learning models, execution time for full data is lower but accuracy
is compromised.

Index Terms—natural language processing, question answering,
SQuAD, BERT

I. INTRODUCTION

As information in everyday life is increasing, it becomes
difficult to retrieve a relevant piece of information efficiently.
Thus, a Question-Answering (QA) system can be used to
efficiently present the requested information. QA is an im-
portant application of NLP in real life which is a specific
type of information retrieval method. The QA system makes
an attempt to automatically find out the contextually and
semantically correct answer for the provided question in
text. Generally, the three components associated with the QA
system are question classification, information retrieval, and
answer extraction/generation.

Though QA does not come without its challenges, one
approach to get a machine to answer questions is Reading
Comprehension (RC). Reading a text and answering from it is
a challenging task for machines, requiring both understanding
of natural language and knowledge about the world. The first
step in the process to create such a system is a Question
Answering dataset. A popular benchmark QA dataset created
by Stanford University is known as the Stanford Question
Answering Dataset or SQuAD.

II. LITERATURE REVIEW

One of the first papers on applying machine learning ap-
proach for question answering tasks is Ng, et al., 2000. A
semi-supervised learning approach for word representations
was given by Turian et al., 2010. A fast hierarchical language
model was proposed by Mnih et al., 2009 which outperforms
non-hierarchical neural model and best N-gram models. The
task of QA is always challenging since it requires a compre-
hensive understanding of natural languages and the ability to
do further inference and reasoning. In the original June, 2016
paper introducing SQuAD, Rajpurkar, et al [1], developed a
logistic regression model based on detailed linguistic features
that achieved an F1 score of 51%. Then, Xiong, et al.
introduced a dynamic coattention network for encoding and
attention modeling, Seo, et al. utilize bidirectional attention
flow (BiDAF) encoding and attention schemes, combining
question and context influence via a bidirectional LSTM.
Later, using the self-attention based Transformer by Vaswani
et. al.[2][4], Devlin, Jacob et. al. [3] from Google AI release
the Bidirectional Encoder Representations and Transformer
(BERT) model which surpassed the performance of all pre-
vious SOTA models on SQuAD 1.1.

BERT has demonstrated to have a good performance in
question answering, sentence completion, and similar tasks
when trained on a large corpus. Lan et al. [2020] proposes
a lighter version of BERT called ALBERT [14] to address the
issue of the model size growing too large on pretraining tasks
and hurting overall performance. As of the time of writing
of this paper, ensemble models with a variation of ALBERT
paired with deep net architectures perform best on SQuAD 1.1
and SQuAD 2.0. To limit the scope of this paper, we perform
a comparative study on SQuAD 1.1 and the original BERT
model.

III. COMPARATIVE STUDY

A. Data Pre-processing

Stanford Question Answering Dataset (SQuAD) is a reading
comprehension dataset which comprises of nearly 1,00,000
questions posed on several Wikipedia articles. This is a
closed form dataset meaning that the answer to a question
is always a part of the context and also a continuous span
of context. For each observation in the training set, there is
a context(paragraph), question and the answer text. Currently
there are two versions of SQuAD available, but for simplicity
of comparison we employ SQuAD v1.1 and SQuAD 2.0. To limit the scope of this paper, we perform
a comparative study on SQuAD 1.1 and the original BERT
model.

We generate the sentence embeddings by using Facebook
researchs InferSent[5] which is a method that provides se-
mantic representations for English sentences. Being pretrained
on a larger corpus and after building a preliminary vocab-
ulary on SQuAD, we can get contextual embeddings with

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Fig. 1. Diagram

stronger weights to the more important/significant words of
the sentence. By calculating the Euclidean distance and cosine
similarity between sentences and questions, visualised in the
multidimensional vector space, we can get an idea about the
sentence that most closely gives the answer. See a diagram-
matic explanation in the Appendix. Further, we attempted
to use ML algorithms to determine the best fitting sentence
embedding. The flowchart below shows the data preprocessing
process.

B. Machine Learning Models

The following are all the machine learning models applied
on the SQuAD to show a detailed comparative study.

1) Logistic Regression: Logistic Regression is a supervised
classification algorithm which is used to classify the predic-
tions on the data into classes. Rajpurkar et al.[2016] showed
that the performance of their logistic regression model was
considerably low when compared with human performance.
Their F1 score turned out to be 51% for logistic regression
while human performance F1 score was around 87%. The f1
score calculated using our model turned out to be 52.5% which
is an improvement to the base model. Since, the dataset was
huge, we implemented the logistic regression model along with
principal component analysis.Z-score normalisation was per-
formed before computing the covariance matrix of the dataset.
After that, a projection matrix is formed using principal
components corresponding to larger eigenvalues. For checking
the effect of PCA on the data matrix, we again reconstructed it
in order to calculate the reconstruction loss. We observed that
on increasing number of principal components, reconstruction
error reduces as now more number of components are used to
span the dataset.

2) Gaussian Mixture Model: Gaussian Mixture Models
are probabilistic models which can cluster the data points
according to their probability distributions. Data points having
a single distribution are grouped together. The clustering
approach utilises both mean and variance and hence the
results are more accurate. In order to minimize the cost
function, Expectation-Maximisation(EM) Algorithm is used
to compute the responsibility from the current parameters
which is then used to update the parameters accordingly until
the convergence. The data matrix formed after pre-processing
was of $8519 \times 20$ dimension. The 20 features include 10
columns of euclidean distance and 10 columns of cosine
similarity which are normalised using Min-Max scalar. Since,
the Gaussian distribution is plotted against 2 features, we select
column 1 from the Euclidean distance and the corresponding
column from the cosine similarities. We choose the number of
components/clusters as 10.

3) Support Vector Machine: SVM separates out different
classes with margins for all the categories of classes. We
have applied SVM on SQuAD with different kernels (linear,
polynomial and radial basis function) and tuning the hyper-
parameter values. The results were generated using optimal
value of $\gamma=0.1$ (chosen from an array of different values
like [0.0001, 0.001, 0.005, 0.1, 1, 3, 5]) and error limit of 1000.
From all the kernels used above the RBF kernel
performs well on SQuAD with a training accuracy of 67% and test accuracy
of 66%. SVM is known to be one of the best classification
algorithm but does not create good enough representations of
the sentences.

4) Random Forest: The decision tree in random forest
forms nodes to obtain a large number of data points from
a class by finding values in the features which will divide
the data samples in classes. The training and testing accu-
raty depends on the number of samples at leaf nodes and
the number of trees. When the values of hyperparameters -
min_samples_leaf=8 and n_estimators=60,training accuracy is
77.8 percent and testing accuracy is 63.7 percent. However,
when min_samples_leaf=3 and n_estimators=5, training ac-
curacy is 85.5 percent and testing accuracy is 58.7 percent.
In general, as the value of both the parameters is decreased,
training accuracy increases while testing accuracy decreases
which denotes that model is overfitting the data.

5) XGBoost: The extreme gradient boosting mechanism
helps improve performance as opposed to random forest
because it works on trees with fewer splits. The training
accuracy is 67% and testing accuracy is 65% which is lower
than random forest. The testing accuracy will be more as we
increase the value of max_depth parameter since it represents
the depth of decision trees. But increasing it too much would
result in over-fitting just as in Random Forest. For now, we
keep max_depth=4. The default ‘deviance’ loss function works
well for such textual and probabilistic outputs.
C. BERT

In Devlin et al.[2019], the authors presented a language representation model called Bidirectional Encoder Representations from Transformers or BERT. During generation of sentence embedding vectors, BERT trains bidirectionally and looks at the whole sentence simultaneously in the way that humans look at the entire context of a sentence. A simple representation for understanding BERT is shown in Diagram 1 Using, BERT BASE (L=12, H=768, A=12, Total Parameters=110M) pretrained and finetuned on SQuAD v1.1 on cloud TPU we get a test accuracy of 77%.

IV. RESULTS

After applying various ML models and BERT to our dataset, we were able to derive the following inferences (as shown in the diagram below). Some models being too computational intensive for our PCs, we had to truncate our dataset to get a representative result.

- **Logistic Regression**
  Fig 3 and 4 shows the result obtained for logistic regression without regularisation. It can be observed that testing data accuracy starts little bit below than the training data whereas the loss for training and data curves are almost similar.

- **Principal Component Analysis**
  Fig 5 represents trend between eigen values and its indices. The eigen values are sorted in descending order. In our case, the eigen values are nearly of similar values except the first eigen value. On arranging the eigen values in an unsorted manner, mean square error changes slightly.
  Fig 6 shows the trend between the principal components and the variance. The components represent the reduced version of euclidean distance and the cosine similarity between questions and the sentences of the passage which are similar in some cases. Thus, on increasing the number of components, our variance didn’t change significantly because of similar components.

- **Gaussian Mixture Models**
  Fig 7 represents several clusters for different classified classes(10). The x-axis represents the euclidean distance and the y-axis represents the cosine similarity. Since, our total features were 20, we chose 2 from them—one column from euclidean and another from cosine similarity. The clusters obtained are closer too each other due to similarity between euclidean distances and cosine similarities between sentences of the passages.

V. CONCLUSION

We can conclude that despite using InferSent for generating contextual sentence representations, simple ML models could not perform well (in most cases we observed overfitting or poor performance despite increasing data samples or epochs). Comparing the results with a model like BERT, we can conclude that for comprehensive sentence representations larger and more complex models that employ DL techniques work better. Different versions of BERT such as BERT-Large, Multilingual-BERT, ALBERT (currently SOTA), RoBERTa, etc. can be studied to derive better inferences and results on SQuAD.
Fig. 3. Accuracy

Fig. 4. Loss

Fig. 5. Eigen Values VS Indices

Fig. 6. Principal Components VS Variance

Fig. 7. Gaussian Mixture Model Representation
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VI. APPENDIX

A. Preprocessing the data

Fig. 8. Preprocessing