No Budget? Don’t Flex! Cost Consideration when Planning to Adopt NLP for Your Business

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Abstract

Recent advances in Natural Language Processing (NLP) have largely pushed deep transformer-based models as the go-to state-of-the-art technique without much regard to the production and utilization cost. Companies planning to adopt these methods into their business face difficulties because of the lack of machine and human resources to build them. In this work, we compare both the performance and the cost of classical learning algorithms to the latest ones in common sequence and text labeling tasks. We find that classical models often perform on par with deep neural ones despite the lower cost. We argue that under many circumstances the smaller and lighter models fit better for AI-pivoting businesses and that we call for more research into low-cost models, especially for under-resourced languages.

1 Introduction

Research on benchmarking learning algorithms for NLP tasks (Kowsari et al., 2019; Minaee et al., 2020; Yadav and Bethard, 2018; Guntara et al., 2020) have largely focused on the quality of the models by some accuracy metrics such as the F1 score. The costs which include processing time, memory resources, computing power, and human expertise that is needed to train the models and be utilized for prediction are often ignored.

As NLP is getting popular to be implemented across industries, one of the biggest hurdles in this early adoption is determining which methods to use. Companies want to provide the best model but often had struggled with resources to build it (Magoula and Swoyer, 2020). This is especially true for companies operating within a large emerging market with under-resourced languages, which often means the lack of human expertise, data limitation, short experiment time, and budget limitation. For companies already serving a large number of users, they also need to consider how the model scales and keeps prediction time fast even without expensive GPU servers.

In this paper, we run experiments on text classification and sequence labeling tasks over a number of datasets in Indonesian language using a number of different learning algorithms. These two tasks are popular in Indonesia (Ruliputra et al., 2019), which is a large emerging market with under-resourced labeled text data. We report training time, resulting model’s size, F1-scores, and average prediction time with several inputs. We discuss how our experiment results have influenced our business decision as one of the industry players in Indonesia and how it can help other companies in adapting NLP technologies fast and more effectively.

Figure 1: Several NLP applications in production in Indonesia: machine translation in chat (top-left), chatbot (right), product search engine (bottom-left)

2 Indonesian AI/NLP Landscape

Over the last few years, NLP has gained popularity across industries in Indonesia. From creating chatbots, analyzing customer’s reviews, machine translation for chat, and improving product search engine, many companies progressively adopt NLP into their business. Amongst all, text analytics and chatbots are the most popular NLP product (Bahja, 2020), which utilize text classification and sequence labeling as their base tasks.
Indonesia market shows great potential for AI and NLP adoption (Chitturu et al., 2017). Unfortunately, Indonesian language is still under-researched on many NLP tasks. It poses multiple challenges, ranging from its ever-changing, ubiquitous, vastly-varying colloquialisms (Wibowo et al., 2020) to its lack of labeled data in many tasks and domains. Common academic literature suggests the use of multilingual models or transfer learning (Howard and Ruder, 2018; Ruder et al., 2019) to combat low-resourceness, but the use of large model size making them expensive to train.

Another challenge for Indonesian companies is the use of GPUs for training and inference, which is arguably a basic requirement for the latest NLP methods, yet it has not widely used in the Indonesian cloud market because of the expensive cost. Even if we use knowledge distillation (Hinton et al., 2015) to make a smaller and faster model for prediction, it requires a teacher system which is usually an ensemble of multiple larger neural models (Kim et al., 2019). Thus, creating a lightweight model often increases the training cost. In addition to that, deep learning has just gained its popularity in recent years, coupled with a slow adoption of deep learning into the standard study curriculum by Indonesian government, making the experts in this field is still scarce on the industry level.

Knowing the constraints, we explore learning algorithms from the classical ones to the latest ones in the hope of providing more insight and perspective for early-adopting NLP in business.

3 Learning Algorithms

Here we describe several algorithms that we use in this paper from the classic methods to the latest deep neural models.

3.1 Classical ML

Logistic regression (LR) and support vector machine (SVM) are often used to train models for text classification. Before the advent of deep learning, SVM models often top the chart in text classification tasks (Manevitz and Yousef, 2001). These two methods are also popular and within the repertoire of a typical Indonesian data scientists and engineers.

For sequence labeling, Conditional Random Field (CRF) is a common technique for NER task. Even in deep neural methods, CRF is often used as the last layer to improve the performance (Ma and Hovy, 2016; Chen et al., 2017). In this work, we only use basic features, such as orthography, prefix, suffix, bigram, and trigram, without external knowledge.

3.2 Bi-LSTM

Bidirectional-LSTMs (Bi-LSTM) are able to capture information from long sequences in forward and backward direction. It shows good results (Huang et al., 2015; Chen et al., 2017) and until recently was the go-to state-of-the-art technique for sequential data like text. We stack two Bi-LSTM layers to capture the information from both character and word level as shown in Figure 2. The result from the character level is concatenated with the word embedding before getting passed into another Bi-LSTM layer. For text classification, we concatenate the output from the forward and the backward word level layer, before passing it to a dense layer to get the result.

3.3 Convolutional Neural Network

Although it has roots in computer vision, Convolutional Neural Network (CNN) has been shown to perform well for text classification (Kim, 2014; Johnson and Zhang, 2015) via 1-dimensional convolution to capture sequence of words. We use Kim (2014) architecture for text classification with some adjustment. Instead of word2vec (Mikolov et al., 2013), we use FastText (Joulin et al., 2016) to handle out-of-vocabulary (OOV) words. For sequence labeling, we modify the previous character level representation (Subsection 3.2, Figure 2) to CNN before concatenating it to the word-level embedding and feeding it into the Bi-LSTM layer.

3.4 Transformers

The Transformer has become the latest state-of-the-art method in many NLP tasks as it has shown
to outperform other neural models like RNN or LSTM (Minaee et al., 2020). With sufficient computing power, it can run faster (relative to the RNNs) because of its ability to run in parallel (Vaswani et al., 2017). The Transformer also gave rise to pre-trained language models such as BERT (Devlin et al., 2019) and ALBERT (Lan et al., 2020), which is a lighter version of BERT with lower memory consumption.

Here, we use inductive transfer learning to extract knowledge from existing language models and fine-tune it to the downstream tasks. This method has shown the biggest improvement and widely used in many NLP applications (Ruder et al., 2019).

4 Algorithm benchmark

In this section, we describe how we benchmark the algorithms described in Section 3.

4.1 Tasks and Datasets

Some of the data used in our experiments are private, thus cannot be made public. However, we provide data description and statistic to give a general view of what the data is about.

4.1.1 Text Classification Task

Smltk. Bot intent classification for small talk (e.g. greetings, joking, etc.). The language is informal and the labels are imbalanced.

Health. Text classification for conversation between doctors and patients. The data is semi-formal and grouped into five labels: patient’s complaint, patient’s action, doctor’s diagnosis, doctor’s recommendation, and other.

Telco. Intent classification for a telecommunication’s bot. This dataset contains semi-formal question and instruction with a balanced data across labels.

Sent.1 Sentiment analysis data about product reviews from an e-commerce platform. The data was annotated based on user’s rating.

Table 1: Data statistics. Train: total training data. Dev: total validation data. Test: total testing data. N: total data. c: total label. d: average data per class for classification. l: average sentence length. V: vocab size. ts: average sentence length for 100 sample prediction data.

|        | Smltk | Health | Telco | Sent | EntK | POS | TermA | Prod |
|--------|-------|--------|-------|------|------|-----|-------|------|
| Train  | 11134 | 37938  | 11520 | 28717| 10955| 3000| 7222  | 1365 |
| Dev    | 1280  | 6894   | 1440  | 3191 | 1250 | 1000| 802   | 854  |
| Test   | 1272  | 6897   | 1440  | 4748 | 1372 | 1000| 2006  | 853  |
| N      | 13686 | 71729  | 14400 | 36656| 13577| 5000| 10030 | 3072 |
| c      | 96    | 5      | 144   | 2    | 14   | 3   | 23    | 69   |
| d      | 142.51| 14345.8| 100   | 18328| -    | -   | -     | -    |
| l      | 5.08  | 8.56   | 5.27  | 15.6 | 12.36| 15.72| 26.11 | 9.61 |
| V      | 2878  | 16892  | 3357  | 22896| 18004| 5211| 15624 | 5655 |
| ts     | 4.88  | 9.06   | 5.16  | 19.14| 12.13| 15.81| 26.47 | 9.93 |

4.1.2 Sequence Labeling Task

EntK. Extended NER with 14 different labels including person, location, email, phone, datetime, number, currency and 5 different units. This is our internal dataset that was manually gathered and annotated.

POS.2 POS Tagging dataset from the PAN Localization Project (Dinakaramani et al., 2014). We use one of the data splits that was done by Kurniawan and Aji (2018).

TermA.3 A semi-formal review data from Airy-Room, a hotel aggregator platform. The data is annotated into aspects and their sentiment (Fernando et al., 2019).

Prod.4 This dataset contains product title with its annotated attributes from several e-commerce websites in Indonesia (Rif’at et al., 2018).

4.2 Experiment Setup

For training we use a single GPU of Tesla T4 15GB. Whereas for prediction, we compare the same GPU machine with a CPU Intel(R) Xeon(R) CPU @ 2.20GHz (4 cores) with memory of 26.75 GB.

We use TF-IDF weighted n-grams ($n = 1, 2$) as the word vector in our classic methods. For the FastText, we use the pretrained Indonesian word vector5 with 300-dimension then fine-tune it on our training dataset. For pre-trained language models, we compare two base models. The first one is a multilingual BERT base model6 (Devlin et al., 2019) which contains 104 different languages, including Indonesian language. Secondly, we use

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1https://github.com/jordhy97/final_project
2https://github.com/kmkurn/id-pos-tagging
3https://github.com/jordhy97/final_project
4https://github.com/derhif/enamex-center
5https://fasttext.cc/docs/en/crawl-vectors.html
6https://huggingface.co/bert-base-multilingual-cased
IndoNLU’s (Wilie et al., 2020) lite model which is an ALBERT base model (Lan et al., 2020), which is much smaller than the multilingual BERT model.

We use AdamW Optimizer (Loshchilov and Hutter, 2017) with the learning rate of 1e-3, 1e-4, 1e-5. The batch size is set to 16, following IndoNLU’s standard hyperparameter settings, for all datasets and methods to ensure fairness in the experiment. We use early stopping, i.e. we train the neural models until we see no improvements for 3 consecutive validations.

4.3 Evaluation Metrics

Other than the model quality, we also observe training time, size of the model, and its prediction time.

4.3.1 F1 Score

F1-macro is used as our evaluation metric to average over classes. This metric is used for both binary and multi-label classification, also for the sequence labeling.

4.3.2 Training Resources

When training the neural models, we use one GPU and track the total training time. We only run them once as some algorithms took a long time to train and we do not have the privilege to rerun it multiple times or try to run it on a CPU. We report training time both in total and per epoch.

We also track every saved file that represents the model to calculate total model size. In the case of a company where the business provides a Platform-as-a-Service (PaaS), this size corresponds to the amount of storage and memory needed to load the model, and it scales according to the number of the users/clients.

4.3.3 Prediction Time

Loading the model into memory is a prerequisite before it can be used. In the case where we have hundreds of models with a limited machine resource, it is impossible to always host all models, especially if the models are not used often. Periodically, the model would be removed from memory and be rebuilt when it is needed. Knowing that, loading time becomes an information that needs to be taken into account.

We compare the prediction time between using one CPU and one GPU. For each dataset, we take 100 stratified random samples based on token’s length. We run prediction one-by-one for 100 samples then sum its prediction time. To heighten the accuracy of our experiment, we rerun the prediction using pytest-benchmark, which automatically minimizes outliers, for 100 rounds. For the classic algorithms, we only run on CPU.

5 Experiment Results

The ALBERT-based language model of IndoNLU achieves the best results for almost all experiments (see Table 2). Interestingly, the best classic approaches yield competitive results that are in average only around 0.03 lower than IndoNLU in terms of F1 accuracy, despite being much more resource-efficient. They train in seconds (on CPU) and hundreds of times faster than the Transformer which require GPU. Similarly, the prediction can be done on CPU and is about 10x faster than the prediction time of the Transformer-based models using the GPU (see Table 4).

A unique case occurs with Prod dataset where the CRF slightly outperforms Transformer. The Prod dataset has a large number of labels (69).

| Method  | F1   | T/E (E) | F1   | T/E (E) | F1   | T/E (E) | F1   | T/E (E) |
|---------|------|---------|------|---------|------|---------|------|---------|
|          | Smilk| Health  | Telco| Sent    |      |         |      |         |
| LR*     | 0.763| 23.23   | –    | –       | 0.697| 21.15   | –    | 0.857   | 28.21  | –       | 0.793 | 9.10   |
| SVM*    | 0.902| 2.16    | –    | –       | 0.730| 8.96    | –    | 0.904   | 2.65   | –       | 0.850 | 6.76   |
| Bi-LSTM | 0.787| 4.77    | (39) | 0.700   | 55.92| (16)    | 0.826| 9.14(41)| 0.806  | 24.79(9)|      |       |
| CNN     | 0.899| 4.32    | (31) | 0.724   | 37.11| (6)     | 0.902| 6.28(32)| 0.851  | 20.37(7)|      |       |
| BERT    | 0.925| 104.26  | (14) | 0.780   | 869.20| (5)    | 0.919| 111.77(15)|      | NA    |
| IndoNLU | 0.940| 39.90   | (13) | 0.807   | 499.80| (3)   | 0.941| 43.02(22)| 0.868  | 461.78(3)|      |       |
|          | EntK | POS     | TermA| Prod    |      |         |      |         |
| CRF†    | 0.857| 35.88   | –    | 0.958   | 67.84| –       | 0.884| 3.45    | 0.778  | 85.44   |
| Bi-LSTM | 0.850| 96.91(11)| 0.945| 72.51(13)| 0.817| 30.77(11)| 0.705| 15.57(38)|      |       |
| CNN     | 0.848| 29.49(10)| 0.942| 23.39(11)| 0.817| 11.58(9) | 0.682| 3.51(30)|      |       |
| BERT    | 0.891| 192.37(6)| 0.965| 154.99(9)| 0.871| 74.31(4) | 0.666| 24.60(16)|      |       |
| IndoNLU | 0.899| 110.37(6)| 0.957| 89.47(8) | 0.890| 38.65(5) | 0.711| 11.12(23)|      |       |

Table 2: F1: macro F1-score from test set. E: total epochs. T/E: average training time (seconds) per epoch. *for LR, SVM, and CRF it is total training time. †BERT for Sent dataset encounter CUDA out-of-memory.
compared to its small amount of training instances (3072) which might not be sufficient for Transformers. Also, despite using GPU, when the base model and the dataset are large, we can still encounter memory limitation issue like we did when using BERT with Sent data, our largest dataset. Training failure means that it has to be repeated in some other way, which translates to an additional cost. The memory error might be addressed by procuring bigger, better GPUs, but this is another cost.

In terms of model size, the classical methods are heavily affected by the amount of vocab and the labels whereas neural model’s size depends on the complexity of the model’s architecture (see Table 3). For early adaptation, it is expensive to have multiple customized BERT model as 1 model reach up to 2GB storage. The lighter version that we use with IndoNLU shows better feasibility to be deployed into production.

On almost all neural model cases, prediction using GPU is faster than CPU. With Transformer, performance on prediction with GPU is significantly better with around 2-6 seconds faster (Table 4 with the detail on Table 6). It shows the needs to use GPU on production when we want to use those model which becomes a new cost that have to be considered. An anomaly happened for BERT in Sequence Labeling where using GPU show a slower performance.

The Bi-LSTM and CNN could yield better results with hyper-parameter tuning. As it would be count as additional cost on training, in this exploration we did not do that.

### 6 Discussion

In the context of platform-as-a-service, we as a company learnt that users like to train many times everyday as they add a handful of new data and see whether there is an immediate improvement on the newly trained model. This is infeasible with such long training duration of the Transformer when the platform needs to serve a big number of users without inferring additional, often unwanted cost to them. Indeed, managing users expectation is also another way to address this, but it is not necessarily easy. Anecdotally, we also see that the vast majority of our users prefer the fast training and prediction, rather than the fraction of higher accuracy from the transformer models.

The large size of transformer models also make it costly to store them, especially when model versioning is wanted by the users. Moreover, it also causes model loading and reloading into the memory to take longer. Distilling the models would also require more resource (Kim et al., 2019). As long as these problems are still there, we see little incentive for us and other companies within the emerging market to move on from the classical approaches and fully embrace the benefits of the deep transformer models.

We observe that there are two potential ways by which this issue can be addressed.

1. Exploration into more efficient ways to distill large models such that it does not require large GPUs and the resulted model is very small and prediction is fast.

2. More efficient ways of transfer learning. We observe that lots of our clients actually share similar sets of labels (and similar training data that comes with them) both for text classification and NER, but we still need to store their own model separately, while intuitively they should be able to either “share a single model” to some extent or that the knowledge stored in each of their models can be “transferred”
more effectively into the others. This, as far as we know, is not possible with the current advances of transfer learning.

We also set them as our own future work.

7 Related Work

Surveys to compare and analyze various algorithms have been done, both for text classification (Kowsari et al., 2019; Minaee et al., 2020) and sequence labeling (Yadav and Bethard, 2018) which shows each advantages and limitations. All benchmarks gave good overview on what methods we could use, but the cost and resources were just briefly mention. Furthermore, the resource to host the model and its prediction time are not explored.

Knowing the long time and heavy resources it required, there are some studies for optimizing neural models. In terms of training duration, distributed training can be carried out to speed up the training process (Dean et al., 2012). Further improvement can be achieved by compressing communications between GPUs or between servers through gradient quantization (Seide et al., 2014) or sparsification (Han et al., 2015; Dryden et al., 2016; Aji and Heafield, 2017). However, these approaches can only be applied if the company or research institution has a lot of GPU resources to begin with.

Orthogonal to the training speed, some research attempted to make the model more efficient in terms of size or prediction time. One common way to make model size smaller and faster without sacrificing quality is to use knowledge distillation (Hinton et al., 2015). To implement knowledge distillation, initially a teacher system must be prepared, which is usually an ensemble of multiple larger neural models (Kim et al., 2019). Preparing such teacher system requires additional resources. Therefore, the training cost for creating a lightweight model is usually higher.

8 Conclusion

Our benchmark showed that the classic algorithms perform on par with deep neural methods, while being easier to implement and requiring significantly lower resources. The Transformer can easily outperform other methods but it requires extra cost in terms of training time, memory to store the model, and its prediction time. It also rely heavily on GPU which is still relatively uncommon and is expensive. Knowing that, it is recommended for early adaptation to use simple methods for their production environment. After having enough resources to host large models, using pre-trained Transformers with the right (ideally distilled) base model should give the best result. We call for more research into efficient models to give more incentives to industry players in emerging market to use the Transformer.

Acknowledgements

We would like to thank our linguistic data annotators - Suci Fitriany, Salma Qonitah, Tomi Santoso, Nadhifa Zulfa, and Yudha Pamungkas - who provided some of the training data used in the experiments of this paper.

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A Loading and Prediction Time

A detail comparison for model loading time and prediction time for each method and dataset in CPU and GPU.

| Method      | Smalltalk | Healthcare | Telco | Sentiment |
|-------------|-----------|------------|-------|-----------|
| LR          | 0.015     | –          | 0.009 | 0.044     |
| SVM         | 0.017     | –          | 0.011 | 0.044     |
| Bi-LSTM     | 1.022     | 1.169      | 7.363 | 7.338     |
| CNN         | 1.510     | 1.368      | 8.029 | 8.020     |
| BERT        | 9.195     | 9.121      | 21.371| 21.031    |
| IndoNLU     | 7.607     | 7.643      | 21.34 | 21.23     |

| Method      | Smalltalk | Healthcare | Telco | Sentiment |
|-------------|-----------|------------|-------|-----------|
| CRF         | 0.014     | –          | 0.007 | 0.030     |
| Bi-LSTM     | 0.409     | 0.416      | 0.407 | 0.411     |
| CNN         | 1.531     | 1.433      | 1.931 | 1.868     |
| BERT        | 9.175     | 8.253      | 9.117 | 8.213     |
| IndoNLU     | 6.420     | 6.265      | 6.311 | 6.197     |

Table 5: Load time in seconds for CPU and GPU

| Method      | Smalltalk | Healthcare | Telco | Sentiment |
|-------------|-----------|------------|-------|-----------|
| LR          | 0.369     | –          | 1.344 | 0.214     |
| SVM         | 0.101     | –          | 0.121 | 0.212     |
| Bi-LSTM     | 0.099     | 0.101      | 0.122 | 0.112     |
| CNN         | 0.120     | 0.107      | 0.128 | 0.148     |
| BERT        | 4.470     | 0.901      | 6.442 | 5.400     |
| IndoNLU     | 3.425     | 0.963      | 5.680 | 4.417     |

| Method      | Smalltalk | Healthcare | Telco | Sentiment |
|-------------|-----------|------------|-------|-----------|
| CRF         | 0.063     | –          | 0.039 | 0.195     |
| Bi-LSTM     | 0.604     | 0.444      | 0.494 | 0.671     |
| CNN         | 0.539     | 0.373      | 0.958 | 0.612     |
| BERT        | 109.581   | 134.869    | 112.975| 111.513   |
| IndoNLU     | 14.532    | 12.146     | 18.508| 15.843    |

Table 6: Prediction time in seconds for CPU and GPU