CS5242 Deep Learning and Neural Networks

Dynamic Malware Analysis – Group 12

Group 12

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Final Model

The final model is an ensemble of 3 RNN models by applying 0.5, 0.25 and 0.25 weightage respectively, which reduces the chance of overfitting.

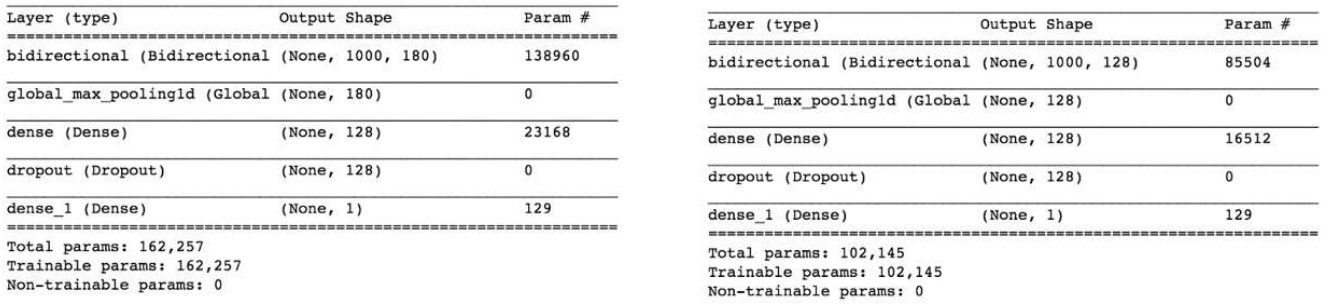
Model 1: 10-fold Cross Validation Model

As the training set is relatively small with only 18662 samples, this model applies the K-fold cross validation [1]. After splitting the training data into 10 sets (folds), 10 models are trained independently, where each model is trained on 9 out of the 10 sets and validated on the other 1 set. The final prediction is an average of the prediction results of the 10 models.

The architecture of Model 1 is shown in *Figure 1*. The input data is first passed to an RNN layer with LSTM units with output dimension size 128. After the LSTM layer, global max pooling would be applied before sending the data to a ReLU activation layer. Finally, a dropout layer with 0.2 dropout rate is applied before passing the result for binary classification.

Model 2: 8-fold Cross Validation Model

This model has identical layer architecture as Model 1, with differences in LSTM output size (180), global max pooling output size (180) and dropout rate (0.1). Also, 8-fold cross validation was applied to this model.



Layer (type)	Output Shape	Param #
bidirectional (Bidirectional	(None, 1000, 180)	138960
global_max_pooling1d (Global	(None, 180)	0
dense (Dense)	(None, 128)	23168
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 162,257
Trainable params: 162,257
Non-trainable params: 0

Model 1

Layer (type)	Output Shape	Param #
bidirectional (Bidirectional	(None, 1000, 128)	85504
global_max_pooling1d (Global	(None, 128)	0
dense (Dense)	(None, 128)	16512
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 102,145
Trainable params: 102,145
Non-trainable params: 0

Model 2

Figure 1

Model 3: Boosting Model

Model 3 has the same architecture and hyperparameters as Model 1. Similarly, it trains 10 different models and averages the result. In contrast, bagging and boosting techniques [2] are used in order to reduce the variance and validation loss. Every time before training a new model, the bagging algorithm samples the original training data into a bag, whose size is 60% of the original training data. Meanwhile, the boosting algorithm will also apply a higher probability to select samples that were poorly predicted by the models it trained in the earlier rounds. With the help of bagging and boosting, this model reduces the chance of overfitting.

Experimental Study

Hyper-Parameter Setting

Optimizer related parameters were set for the 3 final models as *Table 1* by choosing parameters that yielded the best validation accuracy:

Model	Optimizer	Learning Rate	Beta1	Beta2	LSTM Output Dim	Dense Layer Output Dim	Dropout Rate	Loss Function
Model 1	Adam	1×10^{-4}	0.9	0.999	128	128	0.2	Cross Entropy
Model 2	Adam	1×10^{-5}	0.9	0.999	180	128	0.1	Cross Entropy
Model 3	Adam	1×10^{-4}	0.9	0.999	128	128	0.2	Cross Entropy

Table 1

Data Pre-Processing

We observed that the given input dataset has been pre-processed by doing hashing trick, which means no embedding is needed. However, each sample input data has varied length with a max of 1000. Thus, padding was done to make the input dimension (1000, 102) for all input data by adding zero vectors at the end of each sample.

We have also explored data normalization. Two approaches have been explored: **1)** normalize by dividing input data with global maximum value and **2)** normalize each feature by dividing maximum feature value respectively. However, it turns out model without data normalization had better validation accuracy, so data normalization was not used in our final model.

Result Comparison and Analysis

We explored a few different model architectures: **1)** Bidirectional LSTM; **2)** Stacked LSTM; **3)** CNN + LSTM; **4)** Bidirectional LSTM + Global Max Pooling, whose validation accuracy and loss are shown in *Table 2*:

Model	Validation Loss	Validation Accuracy
1) Bidirectional LSTM	0.2084	0.933
2) Stacked LSTM	0.2045	0.9324
3) CNN + LSTM	0.32	0.87
4) LSTM + Global Max Pooling	0.1763	0.9498

Table 2

It was observed that complex models such as **2)** and **3)** had obvious convergence issues (spikes and high variance) and overfitting, which led us to use a relatively simple model architecture **4)** as base model. It was also observed that adding global max pooling layer has massively improved model stability.

However, even with our best model **4)**, the validation loss could not be reduced to below 0.15 despite various hyper-parameter tuning. We then set our eyes on ensemble methods (bagging and boosting) that are believed to reduce the variance and bias of the prediction [1]. With ensemble methods, we managed to improve Kaggle public score from 0.97993 to 0.98963. Finally, we explored K-fold cross validation [2] to make full use of the training data to further decrease the variance. With a weighted average of our best few submissions, we obtained our final predicted result that scored 0.99035 on public dataset and 0.99130 on private dataset.

We observed that we are one of the very few teams whose Kaggle private score is higher than the public score. This observation may be a result of our extensive use of ensemble methods, which led to lower variance in the prediction.

Workload distribution

- Model Training:
    - Initial model: all team members
    - Research: all team members
    - Data normalization: Gejing Wang, Ningshuang Chen
    - Ensemble Methods: Hao Zhang
    - Model training: Hao Zhang, Huiqi Mao
- Presentation: Hao Zhang, Huiqi Mao
- Report Writing: Gejing Wang, Ningshuang Chen
- Code Submission Script: Hao Zhang

Reference

[1] Ng, A. (2019, August). Regularization and model selection. CS229. Retrieved from http://cs229.stanford.edu/notes/cs229-notes5.pdf

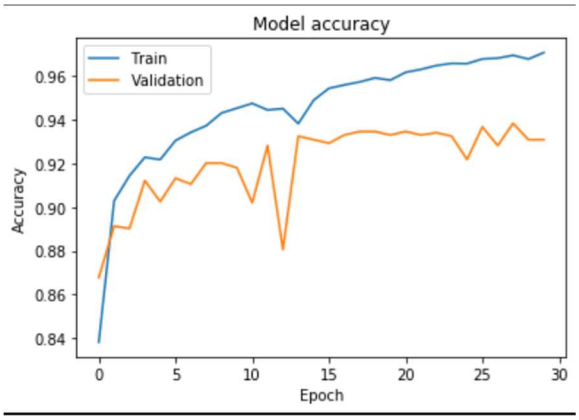
[2] Townshend, R. J. L. (2019, November). Ensembling Methods. CS299. Retrieved from http://cs229.stanford.edu/notes/cs229-notes-ensemble.pdf

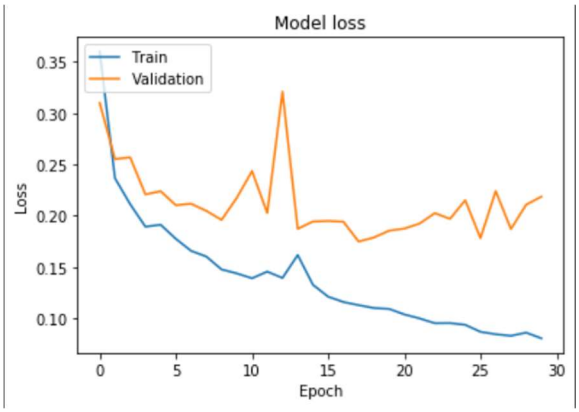
Appendix

Bidirectional LSTM

```
import tensorflow as tf

model = tf.keras.Sequential([
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(128)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

model.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.Adam(1e-4),
              metrics=['accuracy'])
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional (Bidirectional multiple                  236544
_________________________________________________________________
dense (Dense)                multiple                  16448
_________________________________________________________________
dense_1 (Dense)              multiple                  65
=================================================================
Total params: 253,057
Trainable params: 253,057
Non-trainable params: 0
_________________________________________________________________
```

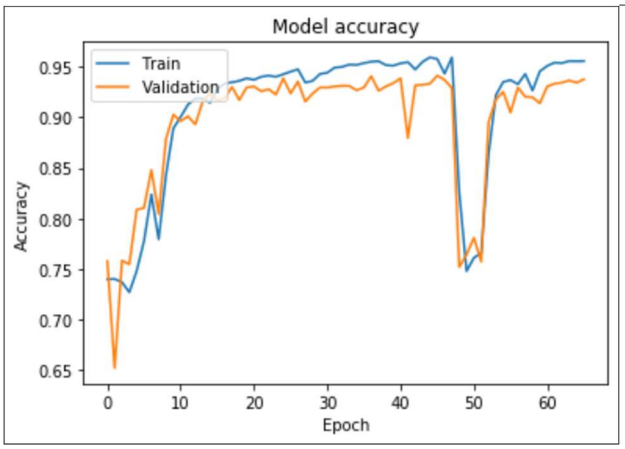


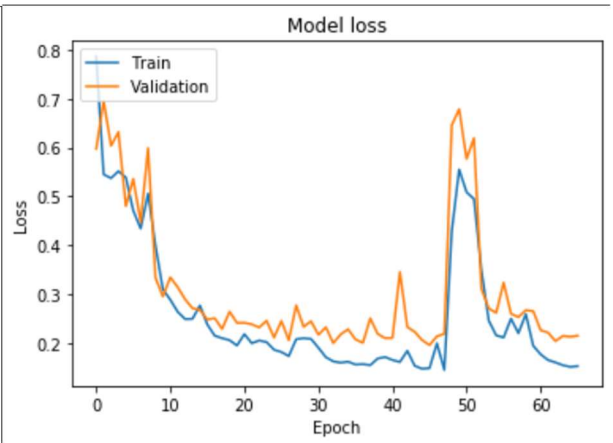


Stacked LSTM

```
import tensorflow as tf

model = tf.keras.Sequential([
    tf.keras.layers.LSTM(50, return_sequences=True),
    tf.keras.layers.LSTM(10),
    tf.keras.layers.Dense(8, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

model.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.Adam(1e-3),
              metrics=['accuracy'])
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_5 (LSTM)                multiple                  118272
_________________________________________________________________
lstm_6 (LSTM)                multiple                  49408
_________________________________________________________________
dense_6 (Dense)              multiple                  2080
_________________________________________________________________
dense_7 (Dense)              multiple                  33
=================================================================
Total params: 169,793
Trainable params: 169,793
Non-trainable params: 0
_________________________________________________________________
```

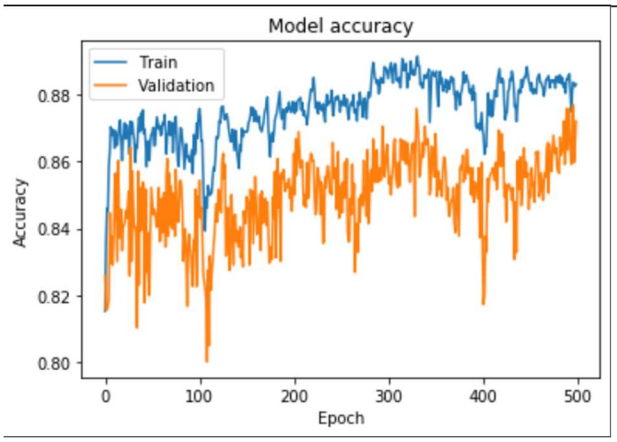


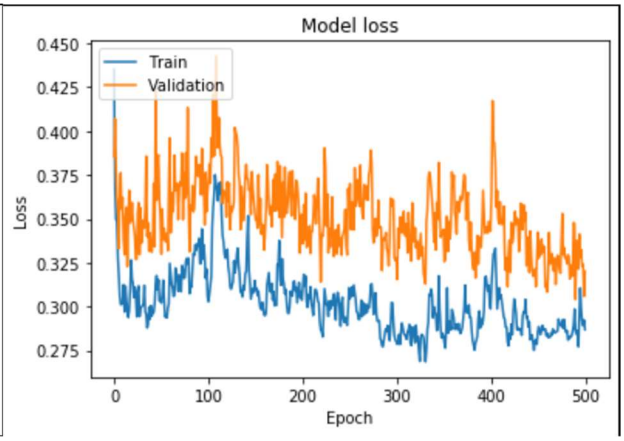


CNN + LSTM

```
import tensorflow as tf

physical_devices = tf.config.experimental.list_physical_devices('GPU')
tf.config.experimental.set_memory_growth(physical_devices[0], True)

model_name = 'conv2d'

model = tf.keras.Sequential([
    tf.keras.layers.Reshape(target_shape=(1000,102,1),input_shape=(1000,102)),
    tf.keras.layers.Conv2D(filters=64, kernel_size=(20, 2),strides=(10,2),input_shape=(1000, 102,1),padding='valid'),
    tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=2, padding='valid'),
    tf.keras.layers.Conv2D(filters=64, kernel_size=(10, 2),strides=2,padding='valid'),
    tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=1, padding='valid'),
    tf.keras.layers.Reshape(target_shape=(19,11*64)),
    tf.keras.layers.Dropout(rate=0.3),
    tf.keras.layers.LSTM(32),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

model.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.Adam(1e-3),
              metrics=['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
reshape (Reshape)            (None, 1000, 102, 1)      0
_________________________________________________________________
conv2d (Conv2D)              (None, 99, 51, 64)        2624
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 49, 25, 64)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 20, 12, 64)        81984
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 19, 11, 64)        0
_________________________________________________________________
reshape_1 (Reshape)          (None, 19, 704)           0
_________________________________________________________________
dropout (Dropout)            (None, 19, 704)           0
_________________________________________________________________
lstm (LSTM)                  (None, 32)                94336
_________________________________________________________________
dense (Dense)                (None, 32)                1056
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 33
=================================================================
Total params: 180,033
Trainable params: 180,033
Non-trainable params: 0
```





Bidirectional LSTM + Global Max Pooling (Final Base Model)

```
def create_model(show_summary = False):
    model = tf.keras.Sequential([
        tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64,return_sequences=True),input_shape=(1000,102)),
        tf.keras.layers.GlobalMaxPooling1D(),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dropout(rate=0.2),
        tf.keras.layers.Dense(1, activation='sigmoid')
])

    model.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.Adam(1e-4,0.9,0.999),
              metrics=['accuracy',tf.keras.metrics.AUC()])
```

```
Training bag 0
[1. 1. 1. ... 1. 1. 1.]
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional_1 (Bidirection (None, 1000, 128)         85504
_________________________________________________________________
global_max_pooling1d_1 (Glob (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               16512
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 102,145
Trainable params: 102,145
Non-trainable params: 0
```