Automated Code Transformation for Distributed Training of TensorFlow Deep Learning Models

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Abstract

Distributed training of deep learning models reduces training time by parallelizing training workloads across multiple GPUs. Distributed training frameworks, such as Horovod and DeepSpeed, provide APIs, and model engineers rewrite deep learning models using the APIs to parallelize their training. However, the rewriting is time-consuming and labor-intensive because it requires engineers to read and understand documents and examples of the frameworks as well as manual efforts to rewrite code.

In this paper, we propose an automated code transformation approach that transforms TensorFlow deep learning models designed for non-distributed training to models training on multiple GPUs with the Horovod framework. We closely inspect the Horovod document and code examples and identify four common training patterns of TensorFlow deep learning models. Then, we formalize code transformation rules for each training pattern. Using the rules, we implement an automated code transformation tool that takes a TensorFlow deep learning model written in Python and rewrites it with the Horovod APIs for distributed training. Through source-code level transformation, our approach enables developers to efficiently scale existing DL models to multiple GPUs. Our evaluation shows that the tool correctly transforms 15 out of 16 open-source TensorFlow deep learning models. To the best of our knowledge, our work is the first automatic transformation technique for distributing existing TensorFlow deep learning models at the source code level. We believe that our approach significantly reduces manual efforts to parallelize training of existing TensorFlow deep learning models.

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1. Introduction

With recent advancements in artificial intelligence, deep learning (DL) has been widely utilized in various fields. Model engineers construct DL models as neural networks consisting of independent layers of several perceptrons, and each layer gets input signals from the previous layer and sends output signals to the next layer. Several DL frameworks, such as TensorFlow [1] and PyTorch [2], provide APIs to easily implement deep neural networks in general purpose high-level programming languages like Python. VGG [3] and ResNet [4] for image recognition and BERT [5] and GPT-3 [6] for natural language processing are popular deep learning applications.

The training phase is the most time-consuming stage in developing DL models. During this phase, the model's parameters are repeatedly optimized using the gradient descent algorithm over a training dataset. Model engineers train models on a huge training dataset for better accuracy, but a larger dataset also requires more training time. According to the report by You et al. [7], it takes 14 days on a single GPU to train the ResNet-50 model on the ImageNet benchmark dataset containing 1.28 million images [8]. Because models are frequently modified and retrained during development, the model development cost increases as the training time increases.

Taking advantages of parallelism, distributed training has emerged to reduce the training time. Since distributed training parallelizes training workload across multiple GPUs, model engineers can train models in significantly less time than non-distributed training. Research in various fields utilizes distributed training without losing the accuracy of trained models. Goyal et al. [9] trained the ResNet-50 model on the ImageNet benchmark in one hour with 256 GPUs, which is over 300 times faster than the non-distributed training result. Silver et al. [10] trained AlphaGo with 176 GPUs and 48 TPUs, Zhang et al. [11] used 16 GPUs to train a speech recognition model, and Tian et al. [12] used two GPUs to train a web attack detection model on edge devices.

Meanwhile, DL models designed for non-distributed training are not directly trainable on multiple GPUs. Model engineers need to rewrite the models for distributed training with additional configurations in their training code to identify GPUs in the system, spawn processes for each GPU, and assign the training dataset to each process. To simplify distributed training, developers have introduced frameworks such as Horovod [13] and DeepSpeed [14]. These frameworks provide simple APIs for defining distributed models and training them on multiple GPUs without writing complex low-level configurations.

However, manually rewriting the DL models is error-prone, time-consuming, and labor-intensive. Although distributed training frameworks can reduce the effort required to distribute DL models, developers still need to understand the frameworks' APIs and documentation thoroughly. The challenge intensifies when migrating multiple DL models simultaneously to a distributed system. To transform each model into a corresponding distributed model, developers must deeply understand not only the distributed training frameworks but also the target model's semantics and code structure. This process significantly burdens developers and increases the likelihood of errors. Consequently, manually distributing existing DL models requires significant time and resources and introduces a high risk of human errors into the codebase.

We propose to address this problem using an *automatic code transformation* technique. Our key observation is that developers follow similar steps when rewriting single-GPU-based deep learning (DL) models for distributed systems. We modeled this manual process as a source code-level transformation from single-GPU-based DL models to distributed ones. By formalizing the typical steps of this rewriting process as code transformation rules, we can programmatically apply these transformations to existing models, resulting in automatically distributed DL models. This approach effectively reduces the developer burden of manually rewriting models and lowers the cost of distributed training.

This paper presents an automated approach that transforms TensorFlow DL models to ones training on multiple GPUs with the Horovod framework. We closely inspected the Horovod library documentation and the code examples that describe the code transformation required to train DL models on multiple GPUs. From the description, we identified four common training patterns used in TensorFlow DL models and the code transformation required for each training pattern. Then, we formally defined transformation rules that rewrite models with Horovod APIs for distributed training. Based on the formal rules, we implemented an automated model transformation tool for distributed training. Our tool first analyzes an input DL model to identify its training pattern and code locations on which modifications for distributed training are required. It then rewrites the model by applying the transformation rules of the identified training pattern. Our evaluation shows that our tool successfully transforms 15 out of 16 open-source TensorFlow DL models, and the transformed models with newly tuned hyperparameters train about 2.28 times faster than the original models. We also discuss the effects of distributed training of the models in the evaluation.

The contributions of this paper are as follows:

- **We formalize the code transformation rules for distributed training of TensorFlow DL models.** The formal rules allow model engineers to understand the transformation in an explicit way rather than implicit code examples, as well as provide a basis for automation.
- **We design and implement an automated code transformation tool for distributed training.** Our tool can reduce manual efforts in rewriting models for distributed training via automation.
- **We reveal that distributed training often requires additional hyperparameter tuning.** Our empirical evaluation shows that distributed training without newly tuned hyperparameters may perform worse in training time and inference precision than non-distributed training.

2. Background

2.1. TensorFlow Deep Learning Models

This section describes two different forms of TensorFlow DL models written in Python. TensorFlow provides two major version libraries: TensorFlow 1.x published in 2016 and TensorFlow 2.x published in 2019. DL models significantly differ in their forms depending on which library they use. On TensorFlow 1.x, model engineers manually construct models as computational graphs using tensor variables and operations and execute them lazily for training and inference on an encapsulated environment called *session*. On the other hand, TensorFlow 2.x supports the eager execution that executes all tensor operations as they occur in code. With the eager execution feature, engineers no longer need to construct computational graphs and use encapsulated environments. In addition, TensorFlow 2.x integrates with the Keras library, a layer-based deep learning model library that provides a convenient interface to construct models.

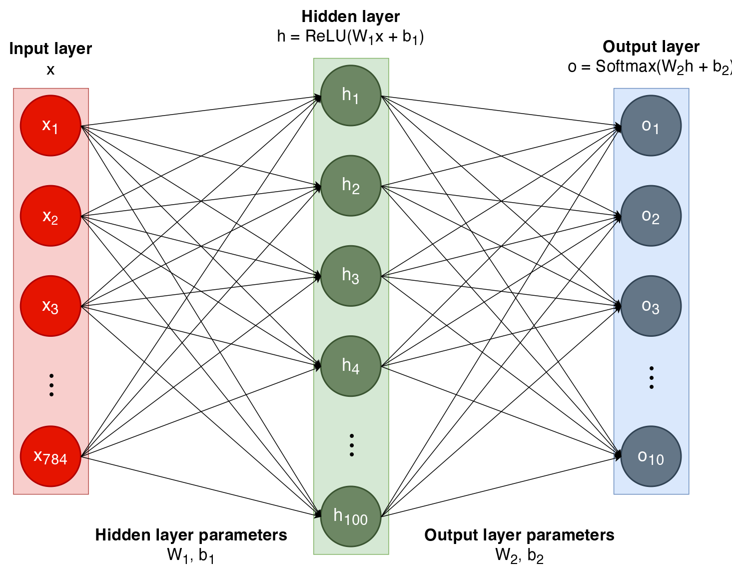


Figure 1: An example neural network

Figure 1 illustrates an example neural network that classifies input images into ten categories. The network consists of three layers: an input, an output, and a hidden layer between the two layers. The input layer has a vector of length 784, and the data in the vector is the pixels of an input image. The hidden layer is parametrized by the two-dimensional weight matrix W_1 of size 784×100 and the bias vector b_1 of length 100. The output layer is parametrized by the two-dimensional weight matrix W_2 of size 100×10 and the bias vector b_2 of length 10. The weight matrices and the bias vectors in the network are model parameters, and the training phase adjusts the model parameters repeatedly, to classify input images correctly.

Figure 2a shows the TensorFlow 1.x training code for the neural network. First, lines 5 to 14 define the network structure and the operations between the layers. After constructing the neural network, the code defines the training algorithm in lines 16 and 17. Line 16 defines the categorical cross-entropy loss function, and line 17 defines the Adam gradient descent algorithm [15]. Lines 19 to 22 start the main training loop by creating a `Session` object and repeatedly executing the training operation `train_op`.

Figure 2b shows an implementation on TensorFlow 2.x for the same model shown in Figure 1. Lines 5 to 8 construct the neural network as a sequential model from a hidden layer to an output layer using the `Sequential` API of the

```python
import tensorflow.compat.v1 as tf

dataset = ...

x = tf.placeholder(tf.float32, [BATCH_SIZE, 784])
y = tf.placeholder(tf.float32, [BATCH_SIZE, 10])

W_1 = tf.Variable(tf.random_uniform([784, 100]))
b_1 = tf.Variable(tf.zeros([100]))
layer_1 = tf.nn.relu(tf.matmul(x, W_1) + b_1)

W_2 = tf.Variable(tf.random_uniform([100, 10]))
b_2 = tf.Variable(tf.zeros([10]))
layer_2 = tf.nn.softmax(tf.matmul(layer_1, W_2) + b_2)

loss = -tf.reduce_sum(y * tf.log(layer_2), 1) # Categorical cross entropy
train_op = tf.train.AdamOptimizer(0.001).minimize(loss)

with tf.Session() as sess:
  sess.run(tf.global_variables_initializer())
  for images, labels in dataset.take(10000):
    sess.run(train_op, {x: images, y: labels})
```

(a) TensorFlow 1.x model example

```python
1 import tensorflow as tf
2
3 dataset = ...
4
5 model = tf.keras.Sequential([
6     tf.keras.layers.Dense(100, activation='relu'),
7     tf.keras.layers.Dense(10, activation='softmax')
8 ])
9
10 loss = tf.losses.CategoricalCrossentropy()
11 opt = tf.optimizers.Adam(0.001)
12
13 for images, labels in dataset.take(10000):
14     with tf.GradientTape() as tape:
15         probs = model(images)
16         loss_value = loss(labels, probs)
17
18     grads = tape.gradient(loss_value, model.trainable_variables)
19     opt.apply_gradients(zip(grads, model.trainable_variables))
```

(b) TensorFlow 2.x model example

Figure 2: TensorFlow model examples

library. Lines 10 and 11 define a loss function and an optimizer object. Lines 13 to 19 train the model by iterating a loop over ten thousand datasets. The code uses the `GradientTape` API to perform forward- and back-propagations. The model parameters are optimized based on the chosen gradient descent algorithm.

2.2. Horovod Distributed Training Library

Horovod [13] is a Python library for distributed training of TensorFlow models. The library adopts a model-parallel approach that copies the same instance of a DL model for each GPU and distributes multiple batches of training data across the GPUs. This allows engineers to harness parallelism to train DL models on multiple GPUs in a shorter time.

Horovod requires model engineers to rewrite TensorFlow DL models with the Horovod API for distributed training. Figure 3 represents a distributed model rewritten from the TensorFlow 1.x model example in Figure 2a. The distributed model has four big differences from the single-GPU model. 1) It configures GPUs and processes for distributed training. Lines 4 to 7 create a Horovod configuration and pin each GPU with a single dedicated model instance. 2) The distributed model uses the distributed version of the gradient descent algorithm. Line 23 multiplies the learning rate of the optimizer object by `hvd.size()`, and wraps it with the `DistributedOptimizer` API. 3) The distributed model synchronizes the model's and the optimizer's variables across the training processes via the `broadcast_global_variables` API in line 27. 4) The distributed model divides input data into multiple batches of the same number as the training processes, as shown in lines 28 and 29.

Figure 4 is a distributed model rewritten from the TensorFlow 2.x model example in Figure 2b. There are two main differences in distributing TensorFlow 2.x models compared to TensorFlow 1.x models. First, the main training loop is eagerly executed in the TensorFlow 2.x version; thus the Horovod API is changed accordingly. For instance, the `DistributedGradientTape` API in line 26 supports the automatic gradient computation in TensorFlow 2.x. Second, the variable broadcasting is explicitly executed at the first training epoch as shown in lines 31 to 34.

3. Overview

This paper proposes an automated code transformation method that rewrites TensorFlow DL models to the distributed versions with Horovod. As discussed in the previous section, distributed training with the Horovod library requires model engineers to understand the Horovod library and rewrite model code manually. To alleviate this burden, our proposed method utilizes

```python
import tensorflow.compat.v1 as tf
import horovod.tensorflow as hvd

hvd.init()
config = tf.ConfigProto()
config.gpu_options.allow_growth = True
config.gpu_options.visible_device_list = str(hvd.local_rank())

dataset = ...

x = tf.placeholder(tf.float32, [BATCH_SIZE, 784])
y = tf.placeholder(tf.float32, [BATCH_SIZE, 10])

W_1 = tf.Variable(tf.random_uniform([784, 100]))
b_1 = tf.Variable(tf.zeros([100]))
layer_1 = tf.nn.relu(tf.matmul(x, W_1) + b_1)

W_2 = tf.Variable(tf.random_uniform([100, 10]))
b_2 = tf.Variable(tf.zeros([10]))
layer_2 = tf.nn.softmax(tf.matmul(layer_1, W_2) + b_2)

loss = -tf.reduce_sum(y * tf.log(layer_2), 1) # Categorical cross entropy
train_op = hvd.DistributedOptimizer(tf.train.AdamOptimizer(0.001 * hvd.size())).minimize(loss)

with tf.Session() as sess:
  sess.run(tf.global_variables_initializer())
  sess.run(hvd.broadcast_global_variables(root_rank=0))
  for images, labels in dataset.take(10000 // hvd.size()):
    sess.run(train_op, {x: images, y: labels})
```

Figure 3: Horovod distributed model example for TensorFlow 1.x model

static analysis and code transformation techniques to rewrite TensorFlow DL model code automatically based on our formal transformation rules.

Figure 5 illustrates the overview of our automated code transformation approach for distributed training of DL models with Horovod. Our approach first parses a given model into Abstract Syntax Trees (ASTs) to analyze and modify the model code mechanically. In order to define the code transformation rules for the distributed training of TensorFlow DL models, we

```python
import tensorflow as tf
import horovod.tensorflow as hvd

hvd_broadcast_done = False
hvd.init()

gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
if gpus:
    tf.config.experimental.set_visible_devices(gpus[hvd.local_rank()], 'GPU')

model = tf.keras.Sequential([
    tf.keras.layers.Dense(100, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')
])

loss = tf.losses.CategoricalCrossentropy()
opt = tf.optimizers.Adam(0.001 * hvd.size())

for images, labels in dataset.take(10000 // hvd.size()):
    with tf.GradientTape() as tape:
        probs = model(images)
        loss_value = loss(labels, probs)

    tape = hvd.DistributedGradientTape(tape)

    grads = tape.gradient(loss_value, model.trainable_variables)
    opt.apply_gradients(zip(grads, model.trainable_variables))

    if not hvd_broadcast_done:
        hvd.broadcast_variables(model.variables, root_rank=0)
        hvd.broadcast_variables(opt.variables(), root_rank=0)
        hvd_broadcast_done = True
```

Figure 4: Horovod distributed model example for TensorFlow 2.x model

manually inspected the Horovod library documentation and code examples. Through this analysis, we found that different transformation rules are necessary for TensorFlow models depending on the specific TensorFlow APIs used

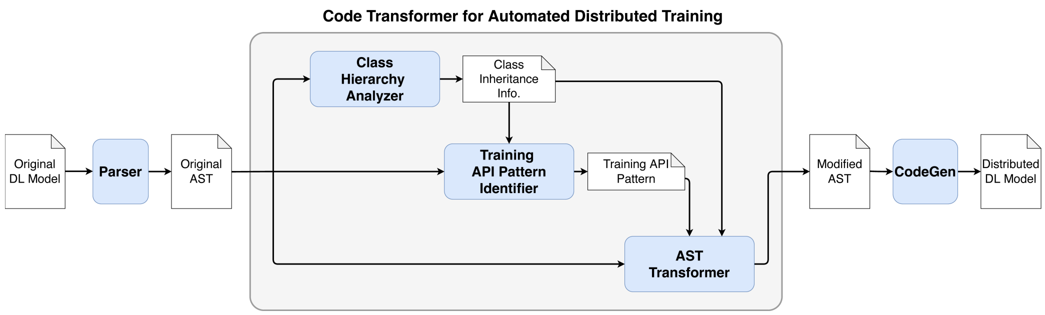


Figure 5: Overall structure of the automated transformation for distributed training

in the models. Thus, we defined four *training API patterns* that represent common code patterns of TensorFlow APIs that appear in TensorFlow DL models. The Class Hierarchy Analyzer analyzes the ASTs and extracts the class inheritance information relations between TensorFlow built-in and user-defined classes. Using the inheritance information, the Training API Pattern Analyzer identifies the training API pattern of the input model. Then, the AST Transformer selects the appropriate transformation rules based on the identified training API pattern and applies the rules to the model's ASTs. The modified ASTs are then finally converted back into a TensorFlow DL model, and the model can now train on multiple GPUs with the support of the Horovod library.

The subsequent sections provide detailed explanations of each component of our proposed approach. Section 4 describes the necessity of the class hierarchy analysis for our approach. Section 5 explains the concept of training API patterns and the implementation of the Training API Pattern Analyzer. Finally, Section 6 provides a detailed description of the code transformation process for each identified training API pattern, including the formalization of the corresponding transformation rules.

4. Class hierarchy analysis

Figure 6a demonstrates how ones use TensorFlow APIs to create and train models using user-defined classes. The key concept in the code is the inheritance of the TensorFlow library class `keras.Model` by the user-defined class `ResNet`, which allows the user to access the methods provided by `keras.Model` and use them to train the model. Line 4 of the code defines the user-defined class `ResNet` by inheriting from `keras.Model`. Based on the

```python
1 from tensorflow import keras
2
3 # `ResNet` inherits `keras.Model`
4 class ResNet(keras.Model):
5     def __init__(self, block_list):
6         ...
7
8 model = ResNet([2,2,2])
9 model.fit(x_train, y_train)
```

(a) Single-GPU DL model

```python
from tensorflow import keras
import horovod.tensorflow.keras as hvd

class ResNet(keras.Model):
    def __init__(self, block_list):
        ...

model = ResNet([2,2,2])

model.fit(
    x_train,
    y_train,
    callbacks=[hvd.callbacks.BroadcastGlobalVariablesCallback(0)])
```

(b) Distributed DL model

Figure 6: Code example of distributing a single-GPU DL model using a user-defined class

Python inheritance mechanism, the `ResNet` class inherits all the methods and attributes of the `keras.Model` class and can also define its methods and attributes. The code then creates and trains the model using the `ResNet` class instead of the `keras.Model` class. In line 8, a model is created with six blocks containing two layers each, using the `ResNet` class instead of the `keras.Model` class. Finally, in line 9, the `fit` method provided by the `keras.Model` class is called to train the network on the given data.

Distributing such models is simple, but we cannot transform them syntactically. Figure 6b demonstrates a modification of the model presented in Figure 6a to a distributed model. The example highlights the importance of recognizing the inheritance relationship between user-defined classes and the

TensorFlow library classes in identifying the training-related methods. The transformation involves adding a keyword argument, `callbacks`, to the `fit` method call, as shown in line 13. However, without recognizing the inheritance relationship between `ResNet` and `keras.Model`, we cannot identify the training method call in line 9 of Figure 6a, and we cannot make the necessary modification to add the `callbacks` keyword argument.

The class hierarchy analysis is an essential pre-analysis step to solve the problem of identifying the training-related methods in DL models. The class hierarchy analysis is a static analysis technique that identifies the inheritance relationship between the classes in the code. By applying the class hierarchy analysis on the input DL models, we can identify which user-defined classes inherit TensorFlow library classes and check whether call statements target training-related methods inherited from TensorFlow library classes. In the code example in Figure 6a, the class hierarchy analyzer reads the class definition in line 4 to conclude that the class `ResNet` inherits the class `keras.Model`. The Training API Pattern Analyzer takes this information to recognize the `fit` method call as the call to the training method provided by the `keras.Model` and selects appropriate transformation rules for the training pattern. The information is also sent to AST Transformer to identify the training method call statement and apply the transformation rules.

5. Training API Pattern Identification

5.1. Training API Patterns of TensorFlow DL Models

Our transformation approach needs to apply different transformation rules based on the API usage in the TensorFlow model. Figure 7 illustrates two TensorFlow model codes that use different APIs to define the training process. While both codes train the model similarly, they use different training APIs in different patterns. Inspecting the Horovod documentation and open-source TensorFlow models manually, we define **four categories of training API patterns** that require different transformation rules. The training API patterns are the code patterns of TensorFlow API calls that commonly appear in the models belonging to the same categories. For instance, models in the GradientTape category commonly use a `with` statement to create a `GradientTape` object, as illustrated in Figure 7a. We define patterns for such common API usages, and our tool identifies the training API

```python
for x, y in train_data.take(training_steps):
    with tf.GradientTape() as tape:
        pred = model(x, is_training=True)
        loss = loss_compute(y, pred)

    trainable_vars = model.trainable_variables
    gradients = tape.gradient(loss, trainable_vars)
    pairs = zip(gradients, trainable_vars)
    optimizer.apply_gradients(pairs)
```

(a) Using low-level training API

```python
model.compile(
    optimizer = optimizer,
    loss = loss_compute)
model.fit(train_data.take(training_steps))
```

(b) Using high-level training API

Figure 7: TensorFlow model code example using two different API patterns

patterns of given models automatically to choose appropriate transformation rules for the models.

Table 1 represents the four training API patterns. The first column shows TensorFlow versions on which models are built, and the second and third columns show training API pattern names and descriptions, respectively. We provide a detailed description of each pattern in the subsequent paragraphs and then present an algorithm that identifies the categories of models in Section 5.2.

Session Pattern. The Session pattern appears in TensorFlow 1.x models that invoke the training computation directly via the `Session` class instance. Figure 8 illustrates a code example of the Session pattern. The pattern creates the `Session` object, which provides the `run` method to execute the model computation.

```python
with tf.Session() as sess:
    for images, labels in dataset.take(10000):
        sess.run(train_op, {x: images, y: labels})
```

Figure 8: Session pattern code example

Table 1: Four types of training API patterns

TF version	API Pattern	Description
1.x	Session	Using the `Session` API to invoke training operations
1.x	MonitoredSession	Using the `MonitoresSession` API to invoke training operations.
2.x	GradientTape	Using the `GradientTape` API to explicitly repeat the training step.
2.x	Keras	Using the `keras.Model` class to define the model and the `fit` API to train the model.

MonitoredSession Pattern. Figure 9 demonstrates a code example of the MonitoredSession pattern. This TensorFlow 1.x pattern bears similarities to the Session pattern, wherein the training computation is invoked directly. Instead of using the `Session` object, the MonitoredSession pattern codes use the `MonitoredSession` object that provides hook methods. For instance, the code in Figure 9 uses the `SummarySaverHook` to automatically save the model summaries after each training step.

```
summary_hook = SummarySaverHook(...)

with MonitoredTrainingSession(hooks=[summary_hook]) as
    mon_sess:
     while not mon_sess.should_stop():
         mon_sess.run(train_op, feed_dict=feed_dict)
```

Figure 9: MonitoredSession pattern code example

GradientTape Pattern. The GradientTape pattern is a classification for TensorFlow 2.x models that utilize the `GradientTape` class instance to initiate training computations manually. Figure 10 demonstrates an example of the GradientTape pattern. It creates the `GradientTape` object through a `with` statement. The `with` statement body runs the model computation. Then, the `Optimizer` class instance calls the method `apply_gradients` to update the model parameters.

```python
optim = tf.optimizers.Adam(0.001)

for images, labels in dataset.take(10000):
    with tf.GradientTape() as tape:
        probs = model(images)
        loss_value = loss(labels, probs)
    grads = tape.gradient(loss_value, model.trainable_variables)
    optim.apply_gradients(zip(grads, model.trainable_variables))
```

Figure 10: GradientTape pattern code example

Keras Pattern. The Keras pattern is another classification for TensorFlow 2.x models that utilize the keras library in both model creations and training. Figure 11 represents an example of the Keras pattern. The pattern defines the `ResNet` class inherited from the `keras.Model` and uses it to construct the model object. The `fit` method is then invoked to automatically train the model with a given dataset.

```python
class ResNet(keras.Model):
    def __init__(self, params):
        ...

model = ResNet([2, 2, 2], num_classes)
model.fit(dataset, epochs=50)
```

Figure 11: Keras pattern code example

5.2. Training API Pattern Identifier

We implemented Training API Pattern Analyzer, which classifies a TensorFlow model into one of four training API patterns. Our approach traverses the input model AST to identify statements that match one of these patterns. Note that the input model may not contain any statements or may contain multiple statements that match the training API patterns. In such cases, the identifier must inform the user that the input model is unsuitable for the automatic transformation.

To handle these scenarios, Training API Pattern Analyzer performs a simple static analysis based on a flat lattice domain composed of

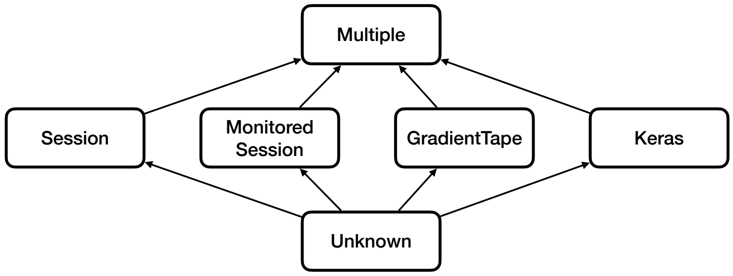


Figure 12: Flat lattice for the training API pattern identification

the four training API patterns with two additional elements, *Unknown* and *Multiple* elements. The Unknown element represents that an AST does not match any of the four training API patterns, and the Multiple element represents that an AST matches multiple training API patterns. Figure 12 depicts the lattice structure. The lattice represents a partially ordered set, where the boxes denote elements and the directed edges denote the given order between their *from* elements and their *to* elements. We also define a join operation ($\sqcup$) between any two elements on the lattice, which calculates the least element of their common successors. For example, the Session element results from joining Session and Unknown elements, and the Multiple element results from joining MonitoredSession and Keras elements. By utilizing the join operation, Training API Pattern Analyzer ensures that it always identifies a single API pattern even when the statements of a model match multiple training API patterns.

Algorithm 1 describes the pseudocode of the training API pattern identification. The function `IdentifyPattern` takes both an input AST and the class hierarchy analysis result, traverses the AST to identify its training API pattern, and returns it. The algorithm first tries to match the AST with four training API patterns. The case statement in lines 3 and 4 checks whether the AST is a `with` statement that creates a `Session` instance and calls the `run` method of the instance in the body statements. If the match succeeds, the algorithm returns the Session element as the AST's identified training API pattern. The case statement in lines 5 and 6 checks whether the AST is a `with` statement that creates a `MonitoredSession` instance and calls the `run` method of the instance in the body statements. If the match succeeds, the algorithm returns the MonitoredSession element. The case statement in line 7 checks whether the AST is a `with` statement that creates a `GradientTape` instance. Line 8 also checks whether the parent AST has

Algorithm 1 Training API pattern identification

Input: an abstract syntax tree (*ast*) and the class hierarhcy analysis result (*cha*)
Output: the identified training API pattern

```
1: function IdentifyPattern(ast, cha)
2:     match ast with
3:         case with Session() as name : body :
4:             if body includes name.run() then Session
5:         case with MonitoredTrainingSession() as name : body :
6:             if body includes name.run() then MonitoredSession
7:         case with GradientTape() as name : body :
8:             if ast.parent includes name.apply_gradients() then GradientTape
9:         case model.fit(...) :
10:            if cha.isSubclassOf(type(model), keras.Model)) then Keras
11:        otherwise :
12:            pattern ← Unknown
13:            for each child in ast.children
14:                pattern ← pattern ⊔ IdentifyPattern(child, cha)
15:            pattern
```

a child statement that calls the `apply_gradients` method of the instance. If both matches succeed, the algorithm returns the GradientTape element. The case statement in line 9 checks whether the AST is a `call` statement that invokes the `fit` method of the object assigned into an arbitrary variable *model*. The algorithm then analyzes the object's class type by tracking the variable's definition site and tests whether the class is a subclass of the `keras.Model` using the class hierarchy analysis result. If the match succeeds, the algorithm returns the Keras element. Lines 12 to 15 operate when the input AST does not match with any of the four training API patterns. The code invokes the `IdentifyPattern` function recursively for each child of the AST, joins all the results of the function calls, and returns the join operation result as the training API pattern. If the AST has no children, the algorithm identifies it as Unknown.

AST Transformer transforms an input model via appropriate transformation rules, depending on the model's training API pattern identified by Training API Pattern Analyzer. When the identified pattern is Multiple or Unknown, our tool fails to transform the model automatically and terminates. Note that the transformation failures are rare because our evaluation shows that Training API Pattern Analyzer identifies only one of the 16 target TensorFlow models as Multiple or Unknown.

6. Code Transformation

6.1. Formalization of Transformation Rules

```
1 trans_S(`import {aliases}`, ctx):
2   let ctx_1 = trans_A(`{aliases}`, ctx).context
3   if diff(ctx_1, ctx) == ["tensorflow" -> `{id}`]:
4     return (`import {aliases}; import horovod.tensorflow as hvd`, ctx_1)
5   else:
6     return (`import {aliases}`, ctx_1)
```

(a) Transform function of import statements

```
import tensorflow as tf
```

(b) Original DL python code

```
import tensorflow as tf
import horovod.tensorflow as hvd
```

(c) Transformed DL python code

Figure 13: Transform function example

We formalize the rules for transforming single-GPU models into multi-GPU models using pure functions called *transform functions*. Transform functions take a Python AST and a *context* object as inputs, and return a Python AST and a context object as output. A context object is a mapping from strings to Python identifier ASTs; context objects store and propagate necessary identifiers. This enables (pure) transform functions to pass relevant contextual information to subsequent transform function calls and utilize the information from outside their input AST.

Figure 13a illustrate the pseudocode of an example transform function that transforms an import statement. The transform function `trans_S` gets an input AST and a context object. In the pseudocode, we use back-quoted notation `` `import {aliases}` `` to represent a Python AST object; the brace-surrounded expression represents a child AST. Line 2 creates a new context object by calling the transformation function on the child AST, `` `{aliases}` ``. Then, line 3 computes the difference between the original context object `ctx` and the new context object `ctx_1`. If the new context additionally stores the `"tensorflow"` entry, it infers that the import statement imports the TensorFlow library. In this case, the transform function places a new import statement, `import horovod.tensorflow as hvd`, right after the TensorFlow import statement and returns the modified AST. Otherwise, the function leaves the input AST unchanged.

The following subsection briefly presents essential code transform rules for each training API pattern with formal descriptions. We also provide the full formal transform rules as a companion report [1].

6.2. Transformation Rules for API Patterns

6.2.1. Rules for the Session Pattern

```
trans_S(`{id_r} = {expr}({a_1}, ..., {a_n})`, ctx):
  if isSubclass(`{expr}`, `keras.optimizer.Optimizer):
    for i in 1...n:
      if `{a_i}` == `learning_rate = {lr}`:
        let new_stmt =
          `{id_r} = {expr}({a_1}, ..., {a_i}*hvd.size(), ..., {a_n})`
        let wrap_stmt =
          `{id_r} = hvd.DistributedOptimizer({id_r})`
        return (new_stmt; wrap_stmt), ctx["optimizer"->`{id_r}`]
```

(a) Transform function for Session pattern

```
optimizer = tf.train.MomentumOptimizer(learning_rate = 0.01)

with tf.Session() as sess:
  for step in range(num_epochs):
    sess.run(optimizer, feed_dict)
```

(b) Session pattern example

```
optimizer = tf.train.MomentumOptimizer(learning_rate = 0.01 *
    hvd.size())
optimizer = hvd.DistributedOptimizer(optimizer)

with tf.Session() as sess:
  for step in range(num_epochs):
    sess.run(optimizer, feed_dict)
```

(c) Distributed Session pattern example

Figure 14: Example transformation of the Session pattern

Figure 14 illustrates the transform function for the Session pattern with code examples. The transform function described in Figure 14a transforms the original code in Figure 14b to the distributed code in Figure 14c. In the

[1]https://github.com/kaist-plrg/python-analyzer/blob/main/trans/trans.pdf

`Optimizer` object's constructor, the `learning_rate` argument is multiplied by `hvd.size()`. Then, the constructed `Optimizer` object is wrapped with the Horovod API, `DistributedOptimizer`.

Given a call assignment statement, the transform function checks whether the callee function is the constructor of the `Optimizer`'s subclasses. If true, the `for` loop searches for the `learning_rate` argument from the function arguments to construct a new call assignment statement with the `learning_rate` argument multiplied by `hvd.size()`. The function finally returns the new statement concatenated by another assignment statement that wraps the `Optimizer` object with `DistributedOptimizer`.

6.2.2. Rules for the MonitoredSession Pattern

Figure 15 illustrates the transform function for the MonitoredSession pattern with code examples. In the example code, a `with` statement first constructs the `MonitoredTrainingSession` object and binds it to the name `mon_sess`. We refer to the pair of the object and its name appearing in the `with` statement as a *with item*. The `MonitoredTrainingSession` object constructor is transformed to append `hvd.BroadcastGlobalVariablesHook(0)` to the end of the `hooks` argument.

Figure 15a describes two transform functions. The first function, `trans_S`, takes a `with` statement AST as an input, then applies `trans_W` to its with items. The second function, `trans_W`, first checks if the given with item constructs the `tf.train.MonitoredSession` subclass object. If true, the function finds the `hooks` argument from the constructor call and appends the `hvd.BroadcastGlobalVariablesHook(0)`. The function returns the modified with item AST to the `trans_S` function. As a result, the `trans_S` function returns the newly modified `with` statement with its body statements recursively transformed by `trans_S`.

6.2.3. Rules for the GradientTape pattern

Figure 16 illustrates an example GradientTape pattern code and its distributed version. There are two main transformations applied in the codes. First, the `GradientTape` object defined by the `with` statement is wrapped with `hvd.DistributedGradientTape` API. The transformation also re-assigns the `grads` variable with the result of calling the `gradient` method before using it in the `apply_gradients` method. Second, the code for broadcasting variables is appended after the `with` statement, as shown in lines 13 to 17 in Figure 16b.

```
trans_S(`with {with_items} : {stmts}`, ctx):
  let `{with_items_1}`, ctx_1 = trans_W(`{with_items}`, ctx)
  let `{stmts_1}`, ctx_2 = trans_S(`{stmts}`, ctx_1)
  return (`with {with_items_1} : {stmts_1}`, ctx_2)

trans_W(`{e_1}({a_1, ..., a_n}) as {id}`, ctx):
  if isSubclass(e_1, tf.train.MonitoredSession):
    for i in 1...n:
    if `{a_i}` == `hooks = {e_i}`:
      let new_hooks =
        `{e_i}.append(hvd.BroadcastGlobalVariableHook(0))`
      let new_with =
        `{e_1}({a_1, ..., hooks={new_hooks}, ..., {a_n})`
      return (new_with, ctx["monsess"->`{id}`])
```

(a) Transform function for MonitoredSession pattern

```
with tf.train.MonitoredTrainingSession(hooks=hooks) as
   mon_sess:
  while not mon_sess.should_stop():
    mon_sess.run()
```

(b) MonitoredSession pattern example

```
with tf.train.MonitoredTrainingSession(hooks=hooks.append(hvd
   .BroadcastGlobalVariablesHook(0)) as mon_sess:
  while not mon_sess.should_stop():
    mon_sess.run()
```

(c) Distributed MonitoredSession pattern example

Figure 15: Example transformation of the MonitoredSession pattern

Figure 17 describes the transform function responsible for the first transformation. After transforming the with items and body statements, the function checks if the with items define a new `gradient_tape` item. If true, the function constructs a statement that wraps the `gradient_tape` item with the `hvd.DistributedGradientTape` API. Finally, the function returns the new `with` statement concatenated with the new wrapping statement.

Figure 18 describes the transform function responsible for the second transformation, which transforms a call assignment statement. The function first searches for an `optimizer` variable in the context object. Then, it checks

```python
import tensorflow as tf

with tf.GradientTape() as tape:
  probs = model(images)
  loss_value = loss(labels, probs)

grads = tape.gradient(loss_value, model.trainable_variables)
opt.apply_gradients(zip(grads, model.trainable_variables))
```

(a) GradientTape pattern example

```python
import tensorflow as tf
import horovod.tensorflow as hvd
hvd_broadcast_done = False

with tf.GradientTape() as tape:
  probs = model(images)
  loss_value = loss(labels, probs)
tape = hvd.DistributedGradientTape(tape)
grads = tape.gradient(loss_value, model.trainable_variables)
id_new = zip(grads, model.trainable_variables)
opt.apply_gradients(id_new)

global hvd_broadcast_done
if not hvd_broadcast_done:
  hvd.broadcast_variables([x[1] for x in id_new], root_rank
    =0,)
  hvd.broadcast_variables(opt.variables(), root_rank=0,)
  hvd_broadcast_done = True
```

(b) Distributed GradientTape pattern example

Figure 16: Example transformation of the GradientTape pattern

```
trans_S(`with {with_items} : {stmts}`, ctx):
  let `{with_items_1}`, ctx_1 = trans_W(`{with_items}`, ctx)
  let `{stmts_1}`, ctx_2 = trans_S(`{stmts}`, ctx_1)
  if diff(ctx_1, ctx) == ["gradient_tape" -> `{id}`]:
    let wrap_stmt =`{id} = hvd.DistributedGradientTape({id})`
    return (`with {with_items_1} : {stmts_1}; {wrap_stmt}`, ctx_2)
  else:
    return (`with {with_items_1} : {stmts_1}`, ctx2)
```

Figure 17: First transform function for GradientTape pattern

```
trans_S(`{id} = {expr}({a_1}, ..., {a_n})`, ctx):
if ctx["optimizer"] == `{id_t}` && `{expr}` == `{id_t}.apply_gradients`:
  let id_z = `id_new`
  let input_stmt = `{id} = {expr}({a_1}, ..., {a_n})`
  let broadcast_stmts =
    `{id} = {expr}({a_1}, ..., {a_n})`;
     global hvd_broadcast_done;
     if not hvd_broadcast_done:
       hvd.broadcast_variables([x[1] for x in {id_z}, root_rank=0)
       hvd.broadcast_variables({id_t}.variables(), root_rank=0)
       hvd_broadcast_done = True`
  return (input_stmt; broadcast_stmts, ctx)
```

Figure 18: Second transform function for GradientTape pattern

if the input statement calls the `apply_gradients` method of the `optimizer` variable. If true, the function places the code for broadcasting variables right after the input statement.

6.2.4. Rules for the Keras pattern

Figure 19 illustrates the transform function for the Keras pattern with code examples. The function transforms the original code in Figure 19b to the distributed code in Figure 19c. The transformation first constructs a new list that contains a callback object, `BroadcastGlobalVariablesCallback(0)`. Then, the callback list is propagated to the `fit` function as a new `callback` argument.

The transform function takes a function call statement as an input. The context object contains information about the variable that holds the `Model` subclass object. Using the information, the function first checks if the callee function is the `fit` method of a model object. If true, the function constructs a statement that creates a list of a `BroadcastGlobalVariablesCallback` object and assigns it to a new variable. Then, it modifies the input call statement to propagate the list as the keyword argument, `callbacks`. Finally, the function replaces the input call statement with the sequence of two statements.

7. Evaluation

We evaluate the proposed approach for the following research questions:

- RQ1. (Correctness) Does the transformation correctly distribute the training of non-distributed models?

```
trans_S(`{expr}({a_1}, ..., {a_n})`, ctx):
  let `{id_m}` = ctx["model"]
  if `{expr}` == `{id_m}.fit`:
    let cb_stmt =
      `cb = [hvd.callbacks.BroadcastGlobalVariablesCallback(root_rank=0)]`
    let new_stmt =
      `{expr}({a_1}, ..., {a_n}, callbacks=cb)`
    return (cb_stmt; new_stmt, ctx)
```

(a) Transform function for Keras pattern

```
class ResNet(keras.Model):
  def __init__(self, block_list):
    ...

model = ResNet([2, 2, 2])

model.fit(x_train, y_train)
```

(b) Keras pattern example

```
class ResNet(keras.Model):
  def __init__(self, block_list):
    ...

model = ResNet([2, 2, 2])

cb=[hvd.callbacks.BroadcastGlobalVariablesCallback(0)]
model.fit(x_train, y_train, callbacks=cb)
```

(c) Distributed Keras pattern example

Figure 19: Example transformation of the Keras Pattern

- RQ2. (Efficiency) How much more efficiently do automatically transformed distributed training codes perform compared to original single-GPU-based training codes?

To answer the questions, we implemented an automatic code transformation tool and applied the tool to 16 TensorFlow DL models. We collected the evaluation target models from five open repositories: Hovorod [16], TensorFlow Model Garden [17], TensorFlow Examples by Americ Damien [18], CIFAR-10 Example with TensorFlow 2.0 [19], and TensorFlow 2.x Tutorials [20]. We excluded two from 18 models in the repositories because one abnormally terminates with a runtime error in its execution, and the other duplicates. Our tool is written in Scala and is publicly available[2].

We do not include large-scale real-world models in our evaluation because they depend on external training libraries or non-Python scripts in the training process. Since our work focuses on the transformation of pure TensorFlow DL models, applying our tool to other types of models lies beyond this paper's scope. We discuss this limitation and a possible solution in Section 9.

Table 2: Experiment result for the automated code transformation

Source	Model Name	API Pattern	Transform Result
TensorFlow Examples by Americ Damien [18]	LSTM-MNIST	GradientTape	○
	SimpleCNN-GradientTape-1	GradientTape	×
Horovod GitHub [16]	SimpleCNN-GradientTape-2	GradientTape	○
	SimpleCNN-MonitoredSession	MonitoredSession	○
TensorFlow Model Garden [17]	SimpleCNN-Session	Session	○
CIFAR-10 Example with TensorFlow 2.0 [19]	VGG-CIFAR10	Keras	○
TensorFlow 2.x Tutorials [20]	Play-with-MNIST	GradientTape	○
	Linear-Regression	GradientTape	○
	Fashion-MNIST	Keras	○
	CIFAR10-VGG16	GradientTape	○
	Inception-Network	GradientTape	○
	RNN-Sentiment-Analysis	Keras	○
	Stacked-LSTM-ColorBot	GradientTape	○
	Auto-Encoder	GradientTape	○
	Variational-Auto-Encoder	GradientTape	○
	DCGAN	GradientTape	○

7.1. RQ1: Correctness of the transformation

To show the correctness of the transformation, we transformed each of the 16 non-distributed models using our tools and compared them to the distributed training versions of those models. For the models obtained from the Horovod repository, we used their distributed training versions available in the repository as the correct results. For the other models, the first author manually transforms the code into distributed training code by referring to the Horovod documentation [21]. Precisely, the first author followed step-by-step instructions in the Horovod documentation to convert each evaluation

[2]https://github.com/kaist-plrg/python-analyzer

target code into its distributed version. Subsequently, the second author independently compared them with the codes transformed by our tool. If the two codes are identical except for minor syntactic differences such as whitespaces or variable declaration order, we concluded that our tool had correctly transformed the original model code.

```python
# Model object is not used, instead a function used
def conv_net(x):
    x = tf.reshape(x, [-1, 28, 28, 1])
    conv1 = conv2d(x, weights['wc1'], biases['bc1'])
    conv1 = maxpool2d(conv1, k=2)
    conv2 = conv2d(conv1, weights['wc2'], biases['bc2'])
    conv2 = maxpool2d(conv2, k=2)
    fc1 = tf.reshape(conv2, [-1, weights['wd1'].get_shape().as_list()[0]])
    fc1 = tf.add(tf.matmul(fc1, weights['wd1']), biases['bd1'])
    fc1 = tf.nn.relu(fc1)
    out = tf.add(tf.matmul(fc1, weights['out']), biases['out'])
    return tf.nn.softmax(out)

optimizer = tf.optimizers.Adam(learning_rate)

def run_optimization(x, y):
    with tf.GradientTape() as g:
        pred = conv_net(x)
        loss = cross_entropy(pred, y)
    trainable_variables = list(weights.values()) + list(biases.values())
    gradients = g.gradient(loss, trainable_variables)
    optimizer.apply_gradients(zip(gradients, trainable_variables))
    # cannot perform variable broadcast with Model.variables

# training loop
for step, (batch_x, batch_y) in enumerate(train_data.take(training_steps), 1):
    run_optimization(batch_x, batch_y)
```

Figure 20: Training code of SimpleCNN-GradientTape-1 model

The results in Table 2 show that our tool correctly transformed **15 out**

of 16 target models. The tool failed to transform only the SimpleCNN-GradientTape-1 model. In the failed case, our tool raised a transformation failure error because some of the GradientTape transformation rules do not apply to the model.

We manually investigated the SimpleCNN-GradientTape-1 model code to identify the cause of the transformation failure. Figure 20 illustrates the training code snippet of the model. The code uses a GradientTape object in lines 17 to 22 to train a model constructed via a sequence of TensorFlow API calls in lines 3 to 12. As described in Section 6.2.3, our approach transforms the GradientTape pattern code by injecting statements that broadcast trainable variables of a `Model` instance. However, because the code does not construct the model as a `Model` instance, our tool cannot obtain the trainable variables from the model and fails to transform the code correctly. The case is rare since the other 11 GradientTape models use the `Model` API to construct models.

In conclusion, the results of the RQ1 experiment demonstrate that our code transformation approach successfully transforms most TensorFlow DL models. However, our tool fails in one case where the code utilizes the training APIs in an uncommon manner, which is a limitation of our approach.

7.2. RQ2: Efficiency of the automatically distributed training

For the second research question, we conducted a comparative analysis between the training time of the automatically transformed models and their respective original models. We calculate the training time as the time taken to reach minimum losses in training. To measure the losses, we manually injected the TensorBoard [22] API calls into the model codes, which log the loss value of each training epoch. Among the 16 models, we targeted 13 models in the experiment; we excluded two TensorFlow 1.x models with which the TensorBoard APIs are incompatible and one that our tool failed to transform. We experimented on a Linux machine with Intel Xeon CPU E5-2690 v4 @ 2.60GHz, 131GB memory, and four NVIDIA TITAN Xp GPUs.

The result of the RQ2 experiment shows that the distributed training of the transformed model is, on average, **2.28 times faster** than that of the original models. When the distributed training models outperform the original ones, the **performance enhancement ranges from x1.37 to x6.58**. We omit the distributed training time of the Stacked-LSTM-ColorBot case from the result because the loss of its first epoch already reached minimal

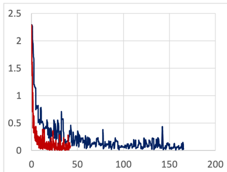
Table 3: Training time comparison results

Model Name	Non-distributed training time (s)	Distributed training time (s)	Speedup
LSTM-MNIST	78.675	11.951	×6.58
SimpleCNN-GradientTape-2	3.192	1.753	×1.82
VGG-CIFAR10	967.076	299.229	×3.23
Play-with-MNIST	148.101	80.040	×1.85
Linear-Regression	0.607	0.371	×1.63
Fashion-MNIST	110.274	29.294	×3.76
CIFAR10-VGG16	1060.296	1159.293	×0.91
Inception-network	956.261	995.597	×0.96
RNN-Sentiment-Analysis	338.984	451.985	×0.74
Stacked-LSTM-ColorBot	57.327	-	-
Auto-Encoder	567.230	412.214	×1.37
Variational-Auto-Encoder	1120.291	699.777	×1.60
DCGAN	2389.052	828.428	×2.88

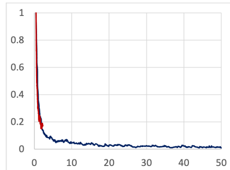
in the experiment. We conclude that while the distributed training of automatically transformed models does not ensure faster training time in every case, it enhances the training performance by x2.28 on average.

Our further investigation shows that the distributed training of transformed models does not present the same accuracy as the original ones. Figure 21 illustrates the change in the loss over time during training. The blue and red lines represent the losses of the original models and their transformed models, respectively. In six out of 13 models, distributed training reaches a higher loss compared to the original model. For instance, in the original VGG-CIFAR10 model, the loss gradually decreases during training. However, in its distributed training, the loss does not meaningfully decrease and remains unchanged, with only minor fluctuations. In conclusion, while our approach may improve the training performance by automatically distributing them, it does not always ensure that the resulting model has the same accuracy to its original one.

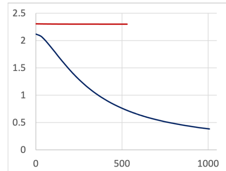
Tuning training hyperparameters can improve the training performance of automatically distributed models. We conducted an additional experiment on the VGG-CIFAR10 model by applying three different learning rate parameters and comparing their training performances. Figure 22 shows the experiment result. The gray line represents the result of non-distributed training, the red line represents the result of distributed training with the original learning rate of $1e-3$, and the blue and black lines represent the



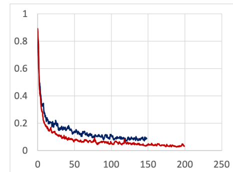
(a) LSTM-MNIST



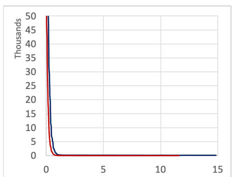
(b) SimpleCNN-GradientTape-2



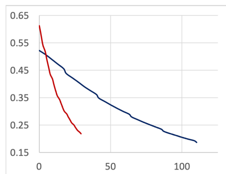
(c) VGG-CIFAR10



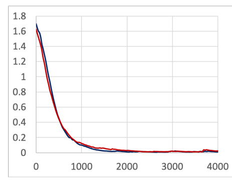
(d) Play-with-MNIST



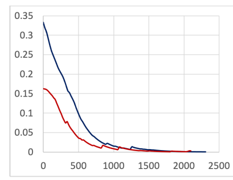
(e) Linear-Regression



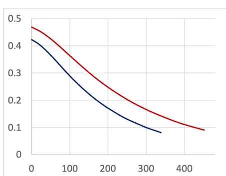
(f) Fashion-MNIST



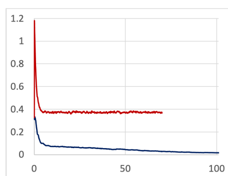
(g) CIFAR10-VGG16



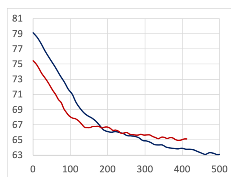
(h) Inception-network



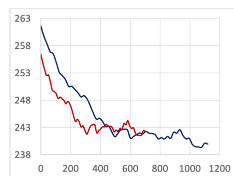
(i) RNN-Sentiment-Analysis



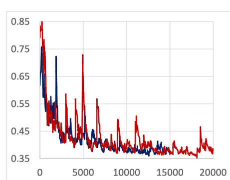
(j) Stacked-LSTM-ColorBot



(k) Auto-Encoder



(l) Variational-Auto-Encoder



(m) DCGAN

Figure 21: Comparison of training between the distributed models and the original models (X-axis: time in seconds, Y-axis: loss value, blue-line: original model, red-line: distributed model)

results of distributed training with adjusted learning rates of $1e-4$ and $1e-5$, respectively. The three distributed training cases reached the minimum loss nearly simultaneously but exhibited significant differences in the achieved minimum loss for each training. In the case of distributed training

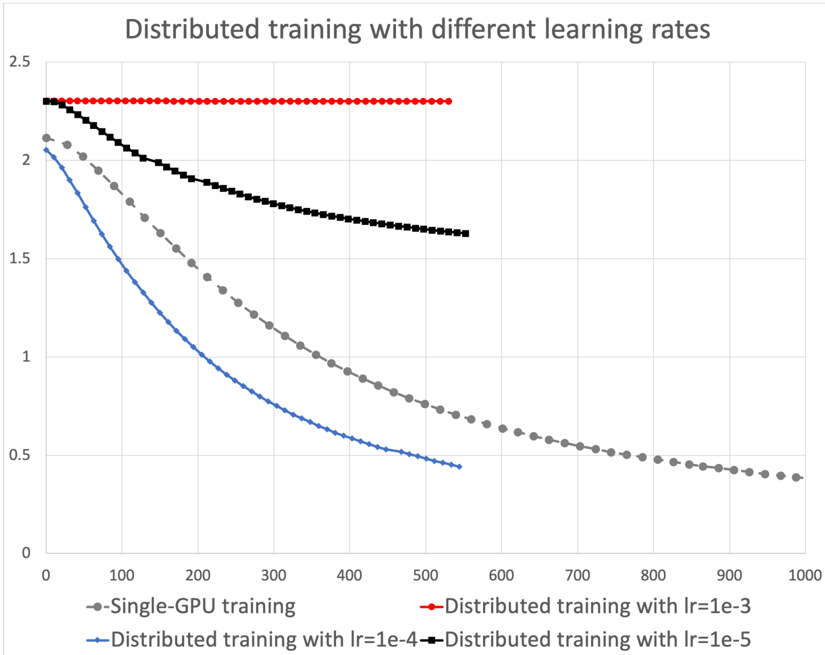


Figure 22: Distributed training on the VGG-CIFAR10 model with different learning rates

with the original learning rate, the training led to only slight changes in loss. However, when adjusting the learning rate to $1e-4$ in distributed training, we observed that the minimum loss significantly decreased to a similar level to that of non-distributed training. In the case of distributed training with the learning rate adjusted to $1e-5$, the result for the minimum loss was better than distributed training with the original learning rate but worse than non-distributed training.

This experiment shows that developers may need to configure hyperparameters differently from original single-GPU-based models to obtain the benefits of distributed training. There are several previous works [23][24][25] on automatically tuning the hyperparameters of specific settings. However, there is yet to be a known automated method that finds the optimal hyperparameters of distributed models. Engineers may still need to adjust hyperparameters by trial and error to optimize the training performance of distributed models generated by our approach. Future works can benefit engineers by enabling automatic hyperparameter tuning for distributed models.

8. Related Work

8.1. Distributed DL frameworks

Horovod [13] is a popular distributed training library that supports multiple DL frameworks such as TensorFlow and PyTorch. Besides Horovod, there are several frameworks and libraries for distributed training. TensorFlowOnSpark [26] is a Python library that combines TensorFlow with Apache Spark and Hadoop to distribute DL tasks on server clusters. DeepSpeed [14] is a distributed programming library developed by Microsoft, built on top of PyTorch [2]. DeepSpeed supports multiple distributed training methods and features, including model and pipeline parallelisms. TensorFlow officially provides a package of APIs, `tf.distribute`, for distributed training [27]. The package supports multiple implementations of `tf.distribute.Strategy`, enabling model engineers to perform distributed learning using various strategies. To train DL models in distributed environments, model engineers have to choose a library and manually rewrite the models following the library's documentation. Our approach automatically transforms existing DL models into distributed ones, reducing engineers' burdens of understanding the document and modifying models.

8.2. Automatically Distributing Deep Learning Models

Several works proposed techniques for automatically optimizing the distributed training of DL models. A line of work searches for optimal parallelization plans before the runtime of DL model training codes. Megatron-LM [28] is one of the earliest works on automatically finding efficient DNN model training parallelization plans. The Megatron-LM framework distributes operations inside the layers of transformer networks by adding synchronization primitives. Pipedream [29] is an asynchronous distributed training framework that improves parallel training throughput by adding pipelining and intra-batch parallelism. PipeDream also minimizes communication costs by partitioning the training computation based on a profiling run on a single GPU. Alpa [30] is an automatic model-parallel training framework that organizes different parallelization techniques into a hierarchy and maps them to the hierarchical structure of computing devices. This allows Alpa to optimize plans for both inter-operator parallelization and intra-operator parallelization. Lin et al. [31] introduce new primitive operators that allow domain experts to compose their own search space, and their proposed framework generates an efficient parallelization plan for the DNN model training.

AutoDDL [32] adds new tensor operators to expand the search space for parallelization strategies. The framework uses an analytical performance model with a Coordinate Descent-based search algorithm to optimize the communication cost.

Another line of work focuses on optimizing resource usage during the training runtime. DAPPLE [33] is a synchronous distributed training framework that combines data and pipeline parallelism for large DNN models, which finds the optimal parallelization plan with a novel parallelization strategy planner and a new runtime scheduling algorithm to reduce memory usage. Tiresias [34] is a GPU cluster manager that efficiently schedules DL training jobs to reduce their job completion times. Because predicting DL jobs' completion time is challenging, the authors propose two scheduling algorithms tailored to minimize the average job completion times.

Compared to these works, our work's primary technique is to boost the DL model training by automatically transforming single-GPU-based training codes into distributed ones. The aforementioned works require developers to write distributed training codes according to the proposed framework manually. Our work utilizes the Horovod library's data-parallel distributed training to distribute existing single-GPU-based DL training codes without rewriting them. While previous works' primary technique is to distribute low-level, primitive computing operations over multiple GPUs, our primary technique is to transform a single-GPU-based DL training code to a distributed version at the Python source code level. By reusing the Horovod library and converting the training code at the source code level, we allow non-expert developers to distribute the training code efficiently without manually rewriting the original training code.

8.3. Code Transformation

Code transformation is techniques that modify code into a different form. Visser devised a taxonomy [35] that classifies code transformation techniques into two types: *translation*, where input and output code are written in different languages, and *rephrasing*, where input and output code are written in the same language. Our approach belongs to *renovation*, one of the subtypes of *rephrasing*, which changes the behaviors of input code and generates output code in the same language.

Researchers have proposed several code transformation techniques in Python. Loulergue and Philippe [36] devised a framework that optimizes PySke programs by automatically rewriting terms in the programs based on transformation rules they define. Haryono et al. [37] developed MLCatchUp, a code transformation tool that enables Python machine learning programs to migrate from deprecated APIs to new and stable APIs automatically. In Zhang et al. [38], the authors develop AST-rewriting operations to detect non-idiomatic code for each Pythonic idiom and refactor non-idiomatic Python codes into idiomatic codes. Rózsa et al. [39] introduce a framework that transforms conditional branches into structural pattern-matching without changing the original behavior. This improves the readability and maintainability of codes written in legacy Python. Tangent [40] is a new library that transforms a subset of Python and NumPy code to perform automatic differentiation on a source code level. Compared to these works, our work targets TensorFlow DL models written in Python, and provides concrete and correct transformation rules for their distributed training. To our knowledge, our work is the first to utilize the Python code transformation technique to distribute single-GPU-based DL training codes automatically.

9. Conclusion

This paper proposes an automated approach to transform TensorFlow DL models written in Python to models training on multiple GPUs. We categorized TensorFlow DL models by four patterns of training API usage and devised a static analysis technique that identifies the training pattern of the given model code. Then, we defined code transformation rules for each training API pattern, which parallelize the training process via Horovod library APIs. To this end, we implemented a code transformation tool that takes a single-GPU-based DL model training code, identifies its training pattern, and applies the corresponding source code transformation to output a distributed training code for the model.

We conducted two experiments to evaluate our proposed approach. First, we show that our approach correctly transforms 15 out of 16 open-source TensorFlow LD models. Second, we show that our approach efficiently distributes the training process so that the transformed models train about 2.28 times faster than the original models. By an additional experiment, we claim that the hyperparameters of transformed models can be tuned to obtain better training speeds. As a result, we argue that our approach reduces developers' burden in rewriting models for distributed training.

We still leave limitations for further studies. Since many state-of-the-art models and real-world DL applications depend on external training libraries or non-Python scripts to train the model, we need to extend our tool to identify API patterns of various training libraries and transform them into distributed versions. We also expect that our code transformation approach can be extended to support other deep learning libraries, such as PyTorch [2], and to other distributed training frameworks, such as DeepSpeed [14]. Finally, to correctly transform DL training codes embedded in real-world applications, future work can develop a static analysis technique that identifies only related parts to DL model training from complex multi-lingual applications.

The training performance of automatically transformed models could be further improved by automatically finding optimal hyperparameters. Previous works [23][24][25] have proposed techniques automated to tune hyperparameters of specific models. Incorporating the techniques into the pipeline of our approach, we can further improve the distributed training performance in a fully automated way. By addressing these future directions, we believe that the DL developer community can benefit from a wide range of advantages our code transformation approach provides.

10. Data Availability

The datasets generated and/or analyzed during the current study are available in https://github.com/kaist-plrg/python-analyzer.

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