SplitEasy: A Practical Approach for Training ML models on Mobile Devices in a split second

Kamalesh Palanisamy
kamalesh800@gmail.com
NIT Trichy

Vivek Khimani
vck29@drexel.edu
Drexel University

Moin Hussain Moti
mhmoti@cse.ust.hk
HKUST

Dimitris Chatzopoulos
dcab@cse.ust.hk
HKUST

ABSTRACT
Modern mobile devices, although resourceful, cannot train state-of-the-art machine learning models without the assistance of servers, which require access to privacy-sensitive user data. Split learning has recently emerged as a promising technique for training complex deep learning (DL) models on low-powered mobile devices. The core idea behind this technique is to train the sensitive layers of a DL model on the mobile devices while offloading the computationally intensive layers to a server. Although a lot of works have already explored the effectiveness of split learning in simulated settings, a usable toolkit for this purpose does not exist. In this work, we propose SplitEasy, a framework for training ML models on mobile devices using split learning. Using the abstraction provided by SplitEasy, developers can run various DL models under split learning setting by making minimal modifications. We provide a detailed explanation of SplitEasy and perform experiments under varying networks to demonstrate its versatility. We demonstrate how SplitEasy can be used to train state-of-the-art models while incurring nearly constant computational cost on mobile devices.

KEYWORDS
Deep learning, neural networks, split learning, on-device training

For the code of SplitEasy please visit the following link and contact the authors for any concern: https://github.com/kamalesh0406/SplitEasy

ACM Reference Format:
Kamalesh Palanisamy, Vivek Khimani, Moin Hussain Moti, and Dimitris Chatzopoulos. 2018. SplitEasy: A Practical Approach for Training ML models on Mobile Devices in a split second. In Proceedings of ACM Woodstock conference (WOODSTOCK’21). ACM, New York, NY, USA, Article 4, 6 pages. https://doi.org/10.475/123_4

1 INTRODUCTION
Deep learning (DL) is a widely adopted technique in mobile applications. The basic idea behind applications that use DL is to train and embed neural network (NN) models on users’ data to learn their usage patterns. Thus, enabling the models to predict user actions and assist in various tasks such as text auto-completion, email tagging, and content recommendation. However, these applications do not train models on the device because of the limited hardware capabilities. Instead, they upload user data to the cloud and train the models on powerful servers. Notably, this exposure to the outside environment compromises users’ privacy.

One solution is to employ transfer learning (TL) techniques [11], which involve using pre-trained models on public data as the starting point of on-device training. Using TL, one can also use lite machine learning frameworks like Squeezenet [6] for reduced model size. Pre-trained models require less effort than training models from scratch, but the process is still inefficient compared to cloud training, mainly due to hardware limitations. Federated learning (FL) [9] is another machine learning paradigm that proposes training several instances of a model on separate devices and then aggregating all these instances into a unifying model. However, this paradigm also suffers from similar issues because the user device still needs to perform training on some part of the data to capture its specific usage pattern. Hence, it is impossible to avoid inefficient on-device training while safeguarding users’ privacy using current learning frameworks.

We develop a novel framework, named SplitEasy, that solves this problem by splitting the training procedure into three parts, the first and the last parts are handled by the mobile device, and a server handles the middle part. More
specifically, as shown in Figure 1, for a multilayered network, we execute the first few layers on the device and then send the output for further training to a server; the server then propagates the received data through many in-between hidden layers before returning them to the device; finally, the device then executes the last few layers of the network and computes the training loss. The loss similarly propagates in the opposite direction (backpropagates). Thus, we only exchange the output of intermediate layers that conveys no meta information about the input data or labels. For example, in the case of image classification, the images are input only to the mobile-side and then transformed to floating points (irrelevant to an outside entity) after the first few layers. Next, the output returned from the server is propagated through the last few layers on the mobile side before comparing that to the labels stored only on the mobile side. Overall, outside entities know neither the input data nor what the model is trying to learn in our framework, thus preserving the user’s privacy. Moreover, since almost the whole network executes on the server-side, it is equivalent to training on the cloud.

SplitEasy is very flexible and can work with simple vanilla NN architectures to complex CNN-based architectures like Densenet and ResNet. Even the devices need not be mobile devices. In fact, any computer with minimal computational capabilities will work with our framework. Similarly, any computer with high enough computational power can act as a server. Users can set different split limits for their devices depending on the type of network connection in usage, neural network architecture employed, and the device and server specifications. To this extent, we perform a thorough empirical analysis of our framework in varying settings.

In summary, the major contributions of this work are: (i) an in-depth explanation of our privacy-preserving and robust split learning framework for mobile devices. (ii) an empirical analysis in varying network settings to show the versatility of SplitEasy. (iii) the open-source code of SplitEasy for the benefit of the research community.

2 RELATED WORK

Split learning [4, 19] was first introduced with a particular emphasis on the collaborative yet privacy-preserving training of health data. These papers demonstrate the effectiveness of split learning in comparison to FL [10] and shows the reduced number of floating-point operations per second (FLOPS) on the client devices.

Both split learning and FL have emerged as popular techniques for collaborative, privacy-preserving training of the DL models [8], so the authors of [15] compare the overall communication requirements of split learning and FL. Whereas, Thapa et al. [17] unite the two approaches, eliminate their inherent drawbacks, and analyze the change in communication efficiency. Moreover, Gao et al. [3] evaluate split learning for Internet-of-Things (IoT) applications and record the time and communication overhead for the split learning setting.

Lastly, Abuadbba et al. [2] evaluate the applicability of split learning for 1-dimensional CNN applications, especially with ECG signals as inputs to the model. Similarly, Poir et al. [13] explore split learning for health care applications while Kairouz et al. [8] suggest exploring the parallel server-client architectures by building upon the ideas presented in [7] and [5]. Lastly, a variation of split learning attempts to reduce the potential leakage via communicated activations by reducing their distance correlation with the raw data and maintaining the good model performance is discussed by the authors of [20]. While these works do not directly collude with our contributions, they can be potentially integrated into our framework, which would allow us to develop a better solution for the problem.

3 SPLIT LEARNING

Deep learning frameworks such as PyTorch [12] and TensorFlow [1] use automatic differentiation (AD) [18] to dynamically compute the gradients for performing optimization tasks such as backpropagation [14]. AD is a collection of techniques employed to calculate the derivatives of a function specified by the program. A typical DL framework represents the variables and operations as a directed graph, with the final node being a custom loss function. AD computes the gradients of intermediate layers (operations) by backtracing through the graph that begins at the node, which represents the loss function.

However, when a split learning architecture splits a network between multiple models, graphs get disconnected, and so AD techniques can no longer be used to directly compute the gradients for layers present on models apart from the last model where the loss is computed. In addition, the technical differences between frameworks used for mobile and server implementation result in additional costs associated with data manipulation, transformation, and parsing. Therefore, we propose a novel, platform-independent approach for updating the model purely based on the gradients acquired from the previous split, instead of relying on the overall loss,
SplitEasy: A Practical Approach for Training ML models on Mobile Devices in a split second

WOODSTOCK’21, July 2018, El Paso, Texas USA

which is computed on the last model. The rest of this section provides a theoretical background of our approach.

We will focus on a double split architecture where a model is split twice, that is, into three separate models. The first and the third model reside independently on the mobile device, while the second model is hosted on a server. \( f_A(x) \) denotes the function representing the layers of the first model, \( f_B(x) \) represents the layers of the second model, and \( f_C(x) \) the layers of the third model.

For the sake of simplicity we consider a model with four layers and assume that \( f_A \) contains the first layer, \( f_B \) contains the next two layers, and \( f_C \) contains the last layer, as shown in Figure 1. Hence the output \( \hat{y} \) of the network with input \( x \) can be represented as:

\[
\hat{y} = f_C(f_B(f_A(x)))
\]

Let \( y_t \) be the target for the network. The loss \( L \) calculated using the objective function \( J \) can be represented as:

\[
L = J(y_t, \hat{y})
\]

As per the standards, we will consider the mean squared error (MSE) as an objective function and cross-entropy loss (CE) as an objective function \( J \) in a classification problem. The forward pass equations for each of the layers can be represented as:

\[
a = g(U^T \cdot x + U_b) \quad b = h(V^T \cdot a + V_b) \\
c = i(W^T \cdot b + W_b) \quad \hat{y} = j(Z^T \cdot c + Z_b)
\]

where \( \{a, g(x), U, U_b\}, \{b, h(x), V, V_b\}, \{c, i(x), W, W_b\}, \{\hat{y}, j(x), Z, Z_b\} \) represent the outputs, activation functions, weights and biases of each of the layers respectively. The update equation for weight \( Z \) on the mobile device at time step \( t \) is:

\[
Z_t = Z_{t-1} - \eta \frac{\partial L}{\partial Z_{t-1}}
\]

where \( Z_{t-1} \) represents the weights at time step \( t - 1 \) and \( \eta \) is the learning rate. The learning rate remains the same for Model A, Model B and Model C. The update equation for \( W \) at time step \( t \) on the server is:

\[
W_t = W_{t-1} - \eta \frac{\partial L}{\partial W_{t-1}}
\]

where, \( \frac{\partial L}{\partial W_{t-1}} \) can be sent from the mobile device to the server, but the weights cannot be updated without AD. Therefore, we propose using auxiliary labels such that when models update their values using these labels, the result is equivalent to the scenario when there is no split.

We first send the gradients \( \frac{\partial L}{\partial W_{t-1}} \) from the mobile device to the server. For Model B, in the server, we now define the auxiliary loss \( L_B \) as follows:

\[
L_B = \frac{1}{2} \sum (\hat{c} - c)^2, \text{ where } \hat{c} = c + \frac{\partial L}{\partial c}
\]

We use residual sum squared error (RSSE) to update the weights in \( W \) instead of MSE as it leads to better gradients. Since there is no dependency on the number of values \( N \) in Equation 4, using MSE will reduce the gradient updates in \( W \) by a factor of \( N \). The updated equation for \( W \) under the new loss becomes:

\[
W_t = W_{t-1} - \eta \frac{\partial L_B}{\partial W_{t-1}}
\]

Substituting \( \hat{c} \) above we get,

\[
\frac{\partial L_B}{\partial W_{t-1}} = (c + \frac{\partial L}{\partial c} - \hat{c}) \frac{\partial c}{\partial W_{t-1}} = \frac{\partial L}{\partial c} \frac{\partial c}{\partial W_{t-1}}
\]

By substituting Equation 9 in Equation 7 we get the same equation as Equation 4. Thus, we are able to update the weights of the model in the server although there is no direct connection between the models on the mobile device and the server. The main advantage of this implementation is that it works on both the server and the mobile device since it just requires modifying the targets and the loss.

4 OVERVIEW OF SPLITEASY

SplitEasy can function between any number of devices, but for the purpose of this section, we will stick with a simple client-server architecture as shown in Figure 2. The client is a mobile device that acts as both the starting and the ending point. That is, at any point of time, there are two separate instances running in parallel on the mobile device. We denote the start point as model A and the endpoint as model C. We use a single stand-alone server as model B.

A reliable connection between the models is crucial to the working of SplitEasy. Therefore, the first step is to establish a persistent socket connection between the mobile device and the server. Next, the data is pre-processed on the mobile device. Data can be input in batches. Let \( B \) denote the batch size of the data. We input the data to model A. After propagating through the first few layers of the network, model A sends the generated output to Model B through a POST request. The size of data sent is equal to \( B \cdot R \cdot C \cdot F \), where \( R \times C \) are the dimensions of the output features and \( F \) denotes the number of filters. Model B propagates the received data through its layers (that is, most of the hidden layers) and broadcasts a message notifying the listeners of the task completion. Model C listening on its end, receives the message and sends a GET request to model B to get its output values. The size of the data received is equal to \( B \cdot E \), where \( E \)
denotes the embedding size. These values are subsequently propagated through the layers of Model C.

Since model C is the endpoint of the network, it holds all the labels for computing the loss of the network. For model C, we simply use these labels to compute the loss and gradients to backpropagate through its layers. Note that the output from model B acts as the input layer for model C; we compute the gradients of this layer as well and then issue a POST request from model C to model B to send these gradients. Model B uses these gradients to generate its labels. Once the labels are obtained, we follow the standard procedure to compute the loss and update the model’s weights. Next, similar to model C, model B computes the gradient of its input layer (that is, the output received from model A) and notifies model A to collect it. The size of these gradients is equal to $B \cdot R \cdot C \cdot F$. Model A then collects these gradients using a GET request and uses them to generate its labels. After that, we follow the standard procedure for backpropagation.

5 EXPERIMENTS

As, to the best of our knowledge, SplitEasy is the first of its kind split learning framework, we made implementation-related decisions based on the existing technical support. We list below the reasoning behind these decisions.

Mobile Framework. Android does not provide any official support for training deep learning models, but only inferencing with a pre-trained models. Therefore, we chose iOS as our mobile platform. On iOS, we had four deep learning libraries to choose from, namely, Tensorflow, CoreML, Metal Performance Shaders (MPS) and LibTorch. There is no official Tensorflow API for iOS yet, but it provides compatible API(s) in the form of Tensorflow.js. We chose TensorFlow.js (with TensorFlow React Native) for implementing our framework as we found the following limitations in the other libraries:

1. CoreML and MPS: It is critical for our framework to be able to access all the gradients and define custom models. Both CoreML and MPS are very difficult to customize and access all the variables.
2. LibTorch: This is Pytorch’s C++ library, which could be used for implementation on iOS with an Objective-C wrapper. But the library only supports CPU computations for mobile devices.

After taking all of the above factors into consideration, we concluded TensorFlow.js to be the best candidate since it allows access to weights and gradients and also used a WebGL backend for GPU computations.

Server Framework. We used Python Flask1 and Pytorch2 to implement the server. We use two different servers in our experiments, an Amazon Web Services (AWS) instance with an NVIDIA K80 GPU, and a university server with an NVIDIA RTX 2080 GPU.

The authors of [4, 19] compare split learning with other architectures based on the number of FLOPS executed. However, this is not a fair metric of comparison, as it does not take into account the time spent on communication with other models. It is not surprising that the number of FLOPS executed on the mobile device is far less in split learning as only a small part of the network is executed on it. We, therefore, use runtime as the comparison metric in our experiments. We use image datasets for all our experiments as it’s the most popular use case, but the framework can be easily extended to support more cases. Moreover, since mobile users have a highly variable number of images in their devices, we report all statistics with respect to a single image, that is, time taken to train the model on a single image.

First, to prove our modification to backpropagation works, we simulate the new training procedure using VGG and DenseNet on CIFAR 100 dataset. As shown in Figure 3, the test accuracy of our method follows an almost identical curve to the conventional backpropagation procedure. Now that our proof of concept is established, we will discuss two different split settings and then choosing split location and server in the rest of this section.

Single Split. In this setup, we split the network only once (dividing it into two models) such that the input data is accessible only to the first model, and the labels are accessible only to the second model. Table 1 shows the time taken to run different NN architectures using this setup.

\[1\] Flask: https://flask.palletsprojects.com/en/1.1.x/
\[2\] Pytorch: https://pytorch.org/
Double Split. In this setup, we do two splits in the network to divide it into three different models, such that the input data is accessible only to the first model, and the labels are only accessible to the third model. The runtimes for these experiments are shown in Table 1. When both the first and last model are on the mobile device, it becomes the most secure and private setting as both input data and labels are accessible only to the mobile device. We believe this to be the most ideal setting for private usage. Note that the increased privacy comes at the cost of increased runtime as the communication overhead increases with the number of splits. In Figure 4a, we show the changes in runtime as the number of parameters increases for three different NN architectures on two datasets. The difference between the least and the highest runtime is around 0.6s despite a three fold increase in the number of parameters.

Finding the Split Location. In both single and double split setup, choosing where to split is a crucial design decision. To understand this, we do a case study with the Inception-ResNetV2 architecture, which has 164 layers in total. The first seven layers of the network and the output shapes are given in Table 2.

In Figure 4b, we show how the communication time and overall time changes with respect to changes in the split location. It is clear that the overall time depends heavily on where we make the cut. This is because the size of the data sent depends on the layer where the split is made, and the communication costs increase as the size of the data increases. However, in the case of old and low-end mobile devices that have low memory, even executing as many as three layers can be difficult. Therefore, depending on the type of hardware available, one can optimize the splits to get the best possible runtime.

Choosing the appropriate server. The location of the server, and most importantly the connection to it, can also influence the overall runtime. Having the server in the same network as the mobile device will give faster runtimes, but this is not always the case. It’s common to use cloud platforms like Amazon Web Services (AWS) or Google Cloud Platform to host the servers. To see how the performance varies with change in server types, we conduct experiments on three different server configurations, (i) A desktop server on the same network as the mobile device, (ii) An AWS instance with a direct TCP connection to the mobile device (iii) A University server accessible through tunneling services like
We propose SplitEasy, a novel framework designed to offer a quiver to anyone who wants to employ split learning in the training of a model in a mobile device. As demonstrated in our experiments, split learning techniques are a solution for training complex DL models on low-end mobile devices. To the best of our knowledge, we are the first to implement split learning techniques and measure the associated computational and communication costs on mobile devices. Additionally, we have open-sourced our framework to help the research community expand our work.

As discussed in Section 5, we implemented SplitEasy using React Native and Tensorflow.js in iOS devices. As React Native can be used for cross-platform development, we plan to extend our work to Android devices in the future. Additionally, as gradient transfers account for a major part of communication cost in SplitEasy, we plan to explore the effectiveness of existing compression techniques (quantization, distillation, pruning, etc.) in split learning. Furthermore, as on-device training is one of the major components of a typical FL pipeline, we hope to add FL support in SplitEasy, which would allow the community to collaboratively train state of the art models on mobile devices. Lastly, we have only explored the supervised training of the models in the split learning settings. Hence, we plan to explore the possibilities of expanding SplitEasy to other domains like unsupervised and reinforcement learning.

6 CONCLUSION AND FUTURE WORK

We propose SplitEasy, a novel framework designed to offer a quiver to anyone who wants to employ split learning in the training of a model in a mobile device. As demonstrated in our experiments, split learning techniques are a solution for training complex DL models on low-end mobile devices. To the best of our knowledge, we are the first to implement split learning techniques and measure the associated computational and communication costs on mobile devices. Additionally, we have open-sourced our framework to help the research community expand our work.

As discussed in Section 5, we implemented SplitEasy using React Native and Tensorflow.js in iOS devices. As React Native can be used for cross-platform development, we plan to extend our work to Android devices in the future. Additionally, as gradient transfers account for a major part of communication cost in SplitEasy, we plan to explore the effectiveness of existing compression techniques (quantization, distillation, pruning, etc.) in split learning. Furthermore, as on-device training is one of the major components of a typical FL pipeline, we hope to add FL support in SplitEasy, which would allow the community to collaboratively train state of the art models on mobile devices. Lastly, we have only explored the supervised training of the models in the split learning settings. Hence, we plan to explore the possibilities of expanding SplitEasy to other domains like unsupervised and reinforcement learning.

REFERENCES

[1] Martin Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, and et al. 2016. TensorFlow: A System for Large-Scale Machine Learning. In Proceedings of the 12th USENIX Conference on Operating Systems Design and Implementation (OSDI’16). USENIX Association, USA, 265–283.

[2] Sharif Abuadbba, Kyuyeon Kim, Minki Kim, Chandra Thapa, Seyit A Camtepe, Yansong Gao, Hyoungshick Kim, and Surya Nepal. 2020. Can We Use Split Learning on 1D CNN Models for Privacy Preserving Training? arXiv preprint arXiv:2003.12365 (2020).

[3] Yansong Gao, Minki Kim, Sharif Abuadbba, Yeonjae Kim, Chandra Thapa, Kyuyeon Kim, Seyit A Camtepe, Hyoungshick Kim, and Surya Nepal. 2020. End-to-End Evaluation of Federated Learning and Split Learning for Internet of Things. arXiv preprint arXiv:2003.13376 (2020).

[4] Otkrist Gupta and Ramesh Raskar. 2018. Distributed learning of deep neural network over multiple agents. Journal of Network and Computer Applications 116 (2018), 1–8.

[5] Zhouyuvan Huo, Bin Gu, and Heng Huang. 2018. Training Neural Networks Using Features Replay. In Proc. of the 32nd International Conference on Neural Information Processing Systems (NIPS’18). 6660–6669.

[6] Forrest N. Iandola, Matthew W. Moskewicz, K. Ashraf, Song Han, W. Dally, and K. Keutzer. 2017. SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <1MB model size. ArXiv abs/1602.07360 (2017).

[7] Max Jaderberg, Wojciech Marian Czarnecki, Simon Osindero, Oriol Vinyals, Alex Graves, David Silver, and Koray Kavukcuoglu. 2017. Decoupled Neural Interfaces Using Synthetic Gradients. In Proceedings of the 34th International Conference on Machine Learning - Volume 70 (Sydney, NSW, Australia) (ICML’17). JMLR.org, 1627–1635.

[8] Peter Kairouz, H. Brendan McMahan, Brendan Avent, and et al. 2019. Advances and Open Problems in Federated Learning. arXiv:1912.04977 [cs.LG]

[9] Jakub Konečný, H. Brendan McMahan, Felix X. Yu, Peter Richtarik, Ananda Theertha Suresh, and Dave Bacon. 2016. Federated Learning: Strategies for Improving Communication Efficiency. In NIPS Workshop on Private Multi-Party Machine Learning.

[10] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguer y Arcas. 2017. Communication-Efficient Learning of Deep Networks from Decentralized Data (Proceedings of Machine Learning Research, Vol. 54). PMLR, 1273–1282.

[11] Sinno Jialin Pan and Qiang Yang. 2010. A Survey on Transfer Learning. IEEE Trans. on Knowledge and Data Engineering 22 (2010), 1345–1359.

[12] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, and et al. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In Advances in Neural Information Processing Systems 32. 8024–8035.

[13] Maarten G Poirot, Praneeth Vepakomma, Ken Chang, Jayashree Kalpathy-Cramer, Rajiv Gupta, and Ramesh Raskar. 2019. Split Learning for collaborative deep learning in healthcare. arXiv preprint arXiv:1912.12115 (2019).

[14] David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. 1988. Learning Representations by Back-Propagating Errors. MIT Press, Cambridge, MA, USA, 496–499.

[15] Abhishek Singh, Praneeth Vepakomma, Otkrist Gupta, and Ramesh Raskar. 2019. Detailed comparison of communication efficiency of split learning and federated learning. arXiv:1909.09145 [cs.LG]

[16] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alex Alemi. 2016. Inception-v4, inception-resnet and the impact of residual connections on learning. arXiv preprint arXiv:1602.07261 (2016).

[17] Chandra Thapa, M. A. P. Chamikara, and Seyit Camtepe. 2020. SplitFed: When Federated Learning Meets Split Learning. arXiv:2004.12088 [cs.LG]

[18] Bart van Merriënboer, Olivier Breuleux, Arnaud Bergeron, and Pascal Lamblin. 2018. Automatic differentiation in ML: Where we are and where we should be going. https://arxiv.org/pdf/1810.11530.pdf

[19] Praneeth Vepakomma, Otkrist Gupta, Tristan Swedish, and Ramesh Raskar. 2018. Split learning for health: Distributed deep learning without sharing raw patient data. arXiv preprint arXiv:1812.00564 (2018).

[20] Praneeth Vepakomma, Abhishek Singh, Otkrist Gupta, and Ramesh Raskar. 2020. NoPeek: Information leakage reduction to share activations in distributed deep learning. arXiv:2008.09161 [cs.LG].

ngrok.3 The results for this experiment are shown in Figure 4c. It is clear that the time spent in communication is the biggest factor for varying runtimes. When the server and the mobile device are located in the same network, the split network performs the best, whereas when the server and the mobile device are connected through multiple routing channels like in the case of ngrok, it performs the worst.