Private Machine Learning in TensorFlow using Secure Computation

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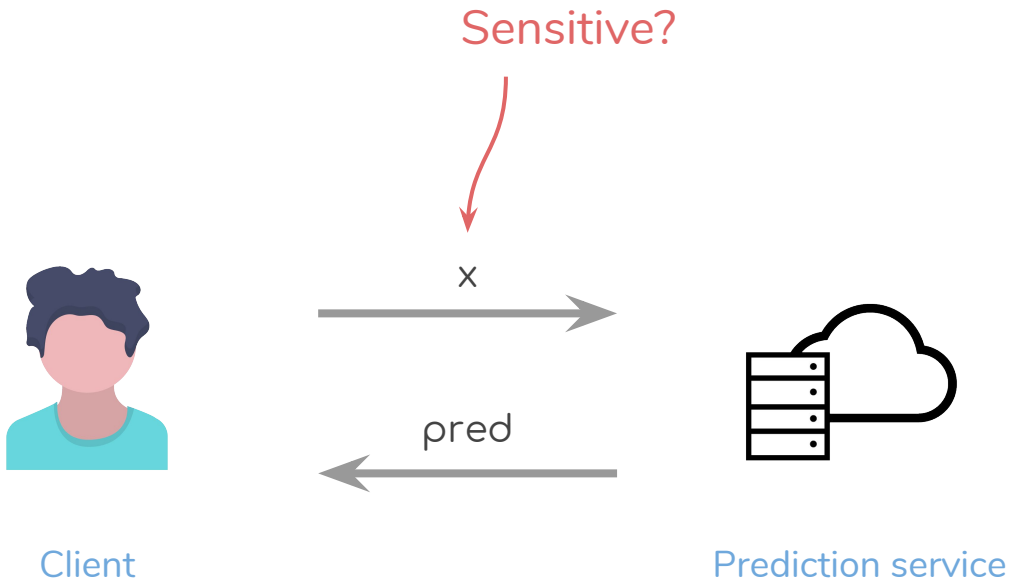
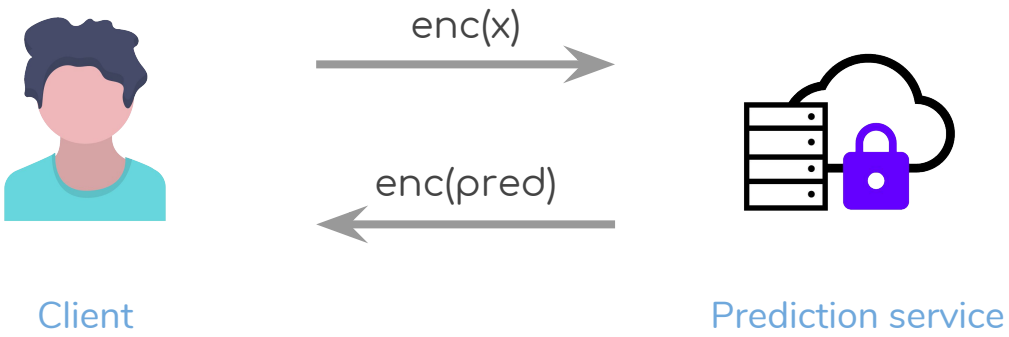
DropoutLabs

Privacy Preserving Machine Learning workshop, NeurIPS 2018

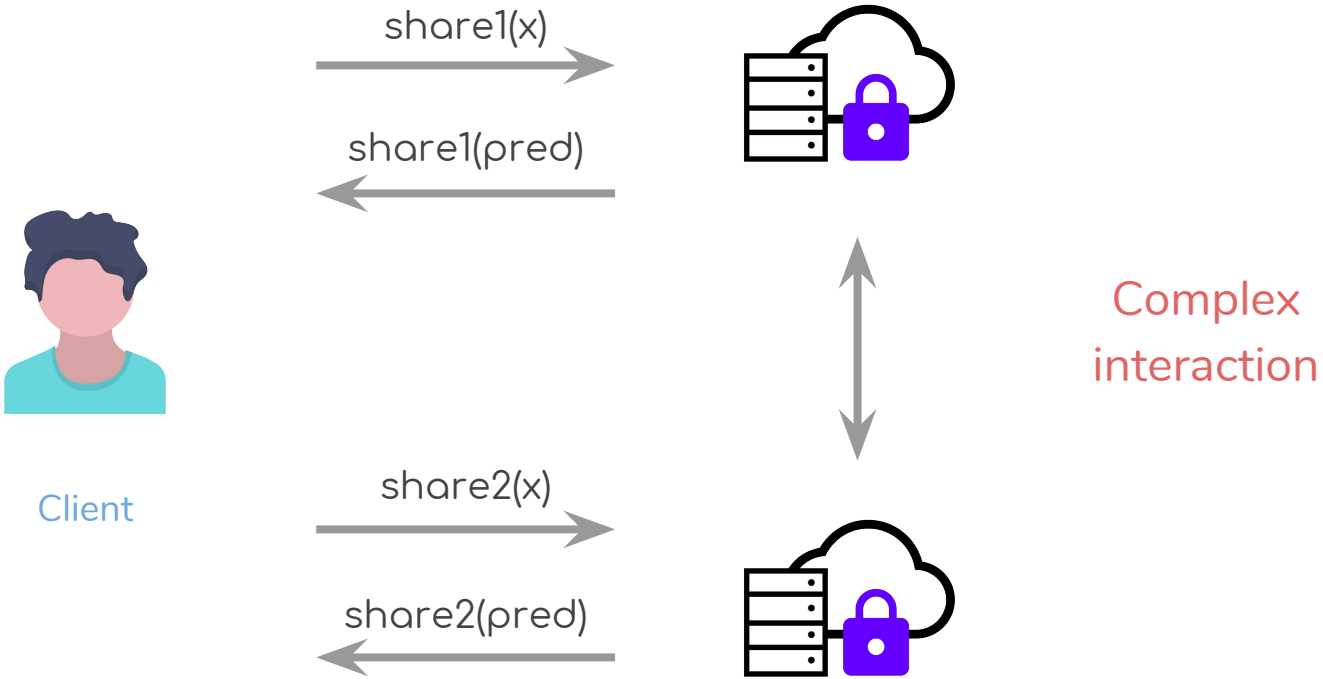
Prediction



Encrypted Prediction



Encrypted Prediction using Secure Computation



Multidisciplinary Challenges

Engineering
(distributed, multi-core, readability)

Cryptography
(protocols, techniques, guarantees)

Machine learning
(models, activations, approx)

Data science
(use-cases, workflow, deployment)

Nice To Have

Easy to experiment

- Flexibility
- Separation of concerns
- Benchmarking

Easy to explore

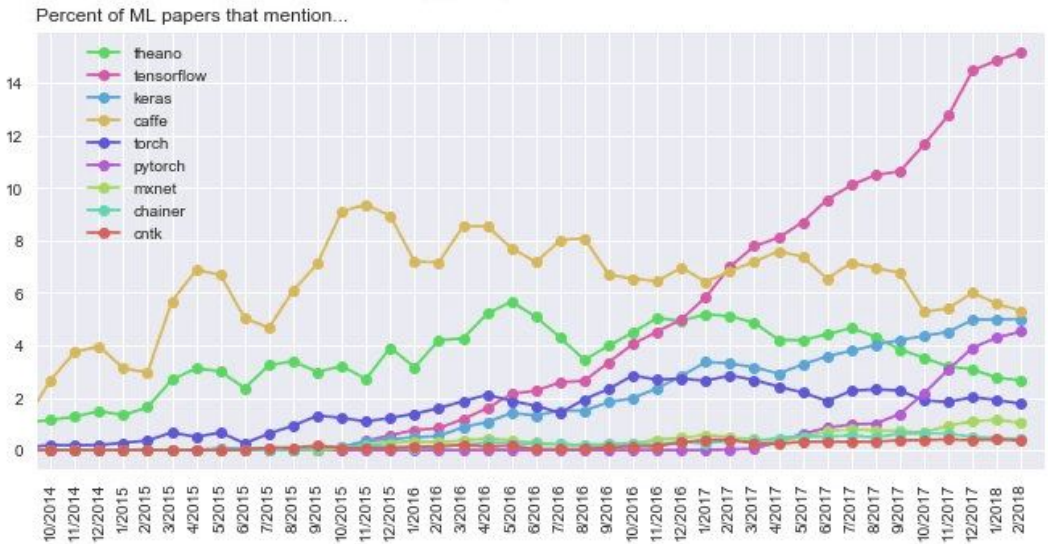
- High-level interface
- Familiar framework
- Gradual adaptation

Leverage existing efforts and minimize boilerplate

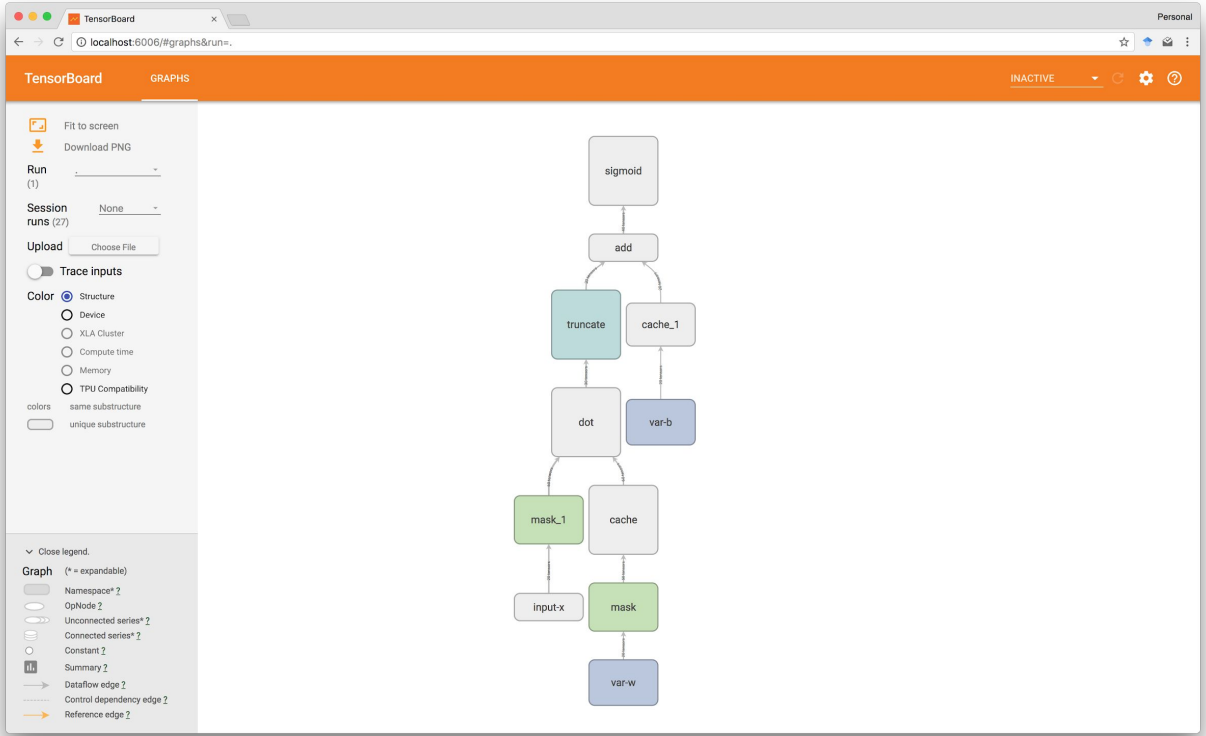
TensorFlow

Backed by Google

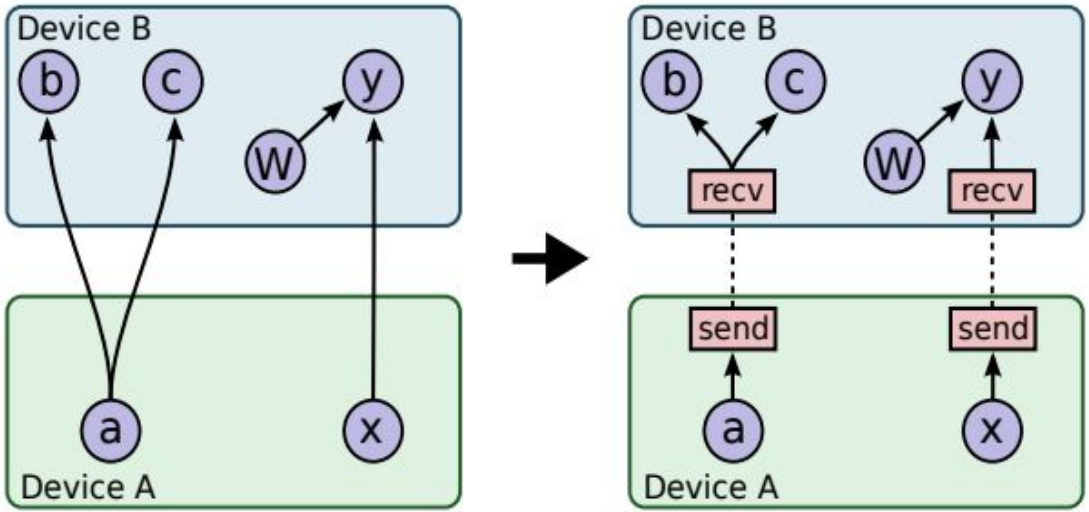
Used for production-level model training and deployment



Dataflow Graphs



Distributed TensorFlow

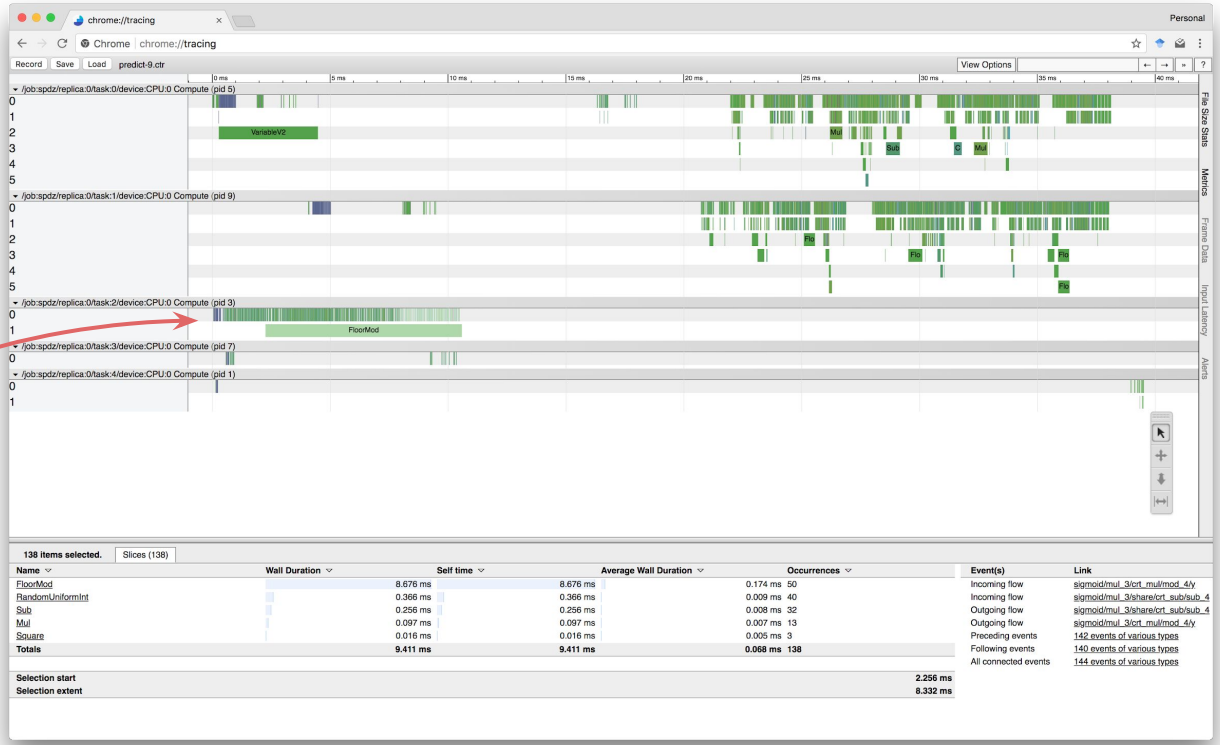


[Abadi et al '16.] TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems

Optimized Execution

Concurrent

Batching



tf-encrypted

Open source community project for exploring and experimenting with privacy-preserving machine learning in TensorFlow

Public vs Private Prediction

```python
import tensorflow as tf

def provide_weights():""" Load from disk """
def provide_input(): """ Pre-process """
def receive_output(logits): return tf.Print([], [tf.argmax(logits)])

# get model weights
w0, b0, w1, b1, w2, b2 = provide_weights()

# get prediction input
x = provide_input()

# compute prediction
layer0 = tf.nn.relu((tf.matmul(x, w0) + b0))
layer1 = tf.nn.relu((tf.matmul(layer0, w1) + b1))
logits = tf.matmul(layer2, w2) + b2

# process result of prediction
prediction_op = receive_output(logits)

# run graph execution in a tf.Session
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    sess.run(prediction_op)
```

```python
import tensorflow as tf
import tf_encrypted as tfe

def provide_weights():""" Load from disk """
def provide_input(): """ Pre-process """
def receive_output(logits): return tf.Print([], [tf.argmax(logits)])

# get model weights as private tensors from owner
w0, b0, w1, b1, w2, b2 = tfe.define_private_input("model-owner", provide_weights)

# get prediction input as private tensors from client
x = tfe.define_private_input("prediction-client", provide_input)

# compute private prediction on servers
layer0 = tfe.relu((tfe.matmul(x, w0) + b0))
layer1 = tfe.relu((tfe.matmul(layer0, w1) + b1))
logits = tfe.matmul(layer1, w2) + b2

# process result of prediction on client
prediction_op = tfe.define_output("prediction-client", logits, receive_output)

# run secure graph execution in a tf.Session
with tfe.Session() as sess:
    sess.run(tf.global_variables_initializer())
    sess.run(prediction_op)
```

Protocols in TensorFlow

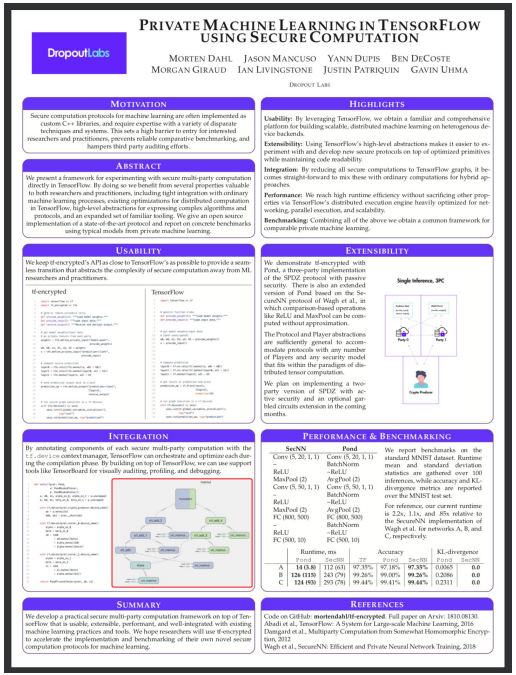
```
1  def _matmul_masked_masked(prot, x, y):
2      a, a0, a1, alpha_on_0, alpha_on_1 = x.unwrapped
3      b, b0, b1, beta_on_0, beta_on_1 = y.unwrapped
4
5      with tf.name_scope('matmul'):
6
7          with tf.device(prot.crypto_producer.device_name):
8              ab = a.matmul(b)
9              ab0, ab1 = prot._share(ab)
10
11         with tf.device(prot.server_0.device_name):
12             z0 = ab0 + a0.matmul(beta) + alpha.matmul(b0) + alpha.matmul(beta)
13
14         with tf.device(prot.server_1.device_name):
15             z1 = ab1 + a1.matmul(beta) + alpha.matmul(b1)
16
17         return PondPrivateTensor(prot, z0, z1)
```

Benchmarks

	Runtime, ms		Accuracy			KL-divergence	
	Pond	SecNN	TF	Pond	SecNN	Pond	SecNN
A	**14 (3.8)**	112 (63)	97.35%	97.18%	**97.35%**	0.0065	**0.0**
B	**126 (115)**	243 (79)	99.26%	99.00%	**99.26%**	0.2086	**0.0**
C	**124 (93)**	293 (78)	99.44%	99.41%	**99.44%**	0.2311	**0.0**

2.2x, 1.1x, 0.85x relative to reference custom C++ implementation

Common high-level framework for machine learners and cryptographers with promising performance



PRIVATE MACHINE LEARNING IN TENSORFLOW USING SECURE COMPUTATION

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MOTIVATION

Secure computation protocols for machine learning are often implemented as custom C++ libraries, and require expertise with a variety of disparate techniques and systems. This sets a high barrier to entry for interested researchers and practitioners, prevents reliable comparative benchmarking, and hampers third party auditing efforts.

HIGHLIGHTS

Usability: By leveraging TensorFlow, we obtain a familiar and comprehensive platform for building scalable, distributed machine learning on heterogenous device backends.

Extensibility: Using TensorFlow's high-level abstractions makes it easier to experiment with and develop new secure protocols on top of optimized primitives while maintaining code readability.

Integration: By reducing all secure computations to TensorFlow graphs, it becomes straight-forward to mix these with ordinary computations for hybrid approaches.

Performance: We reach high runtime efficiency without sacrificing other properties via TensorFlow's distributed execution engine heavily optimized for networking, parallel execution, and scalability.

Benchmarking: Combining all of the above we obtain a common framework for comparable private machine learning.

ABSTRACT

We present a framework for experimenting with secure multi-party computation directly in TensorFlow. By doing so we benefit from several properties valuable to both researchers and practitioners, including tight integration with ordinary machine learning processes, existing optimizations for distributed computation in TensorFlow, high-level abstractions for expressing complex algorithms and protocols, and an expanded set of familiar tooling. We give an open source implementation of a state-of-the-art protocol and report on concrete benchmarks using typical models from private machine learning.

USABILITY

We keep tf-encrypted's API as close to TensorFlow's as possible to provide a seamless transition that abstracts the complexity of secure computation away from ML researchers and practitioners.

tf-encrypted

```
import tensorflow as tf
import tf_encrypted as tfe

# private input producing parties
w0 = tfe.PrivateTensor('weight_owner', weights)
x0 = tfe.PrivateTensor('input_owner', None)
# private computation happening remotely
# on the machine_learning_cluster
w = tfe.define_private_input('model-owner',
                             provide_weights)
x = tfe.define_private_input('input-owner',
                             provide_input)
# private prediction
layer0 = tfe.conv2d(x, w, padding='SAME')
layer1 = tfe.reshape(layer0, [-1, 28 * 28])
layer2 = tfe.matmul(layer1, w0 + w1)
# send prediction output back to client
prediction_op = tfe.define_output('input-owner',
                                  layer2,
                                  receive_output)
# run session which executes the computation
with tfe.Session(target=master) as sess:
  sess.run(tf.global_variables_initializer(),
           tag='init')
  sess.run(prediction_op, tag='prediction')
```

TensorFlow

```
import tensorflow as tf

# private inputs node
w = tf.placeholder(tf.float64, shape=[weights, ...])
x = tf.placeholder(tf.float64, shape=[None, ...])
# private computation happening remotely
# on the machine_learning_cluster
w0, w1, w2, w3, w4 = private_split(w)
layer0 = tf.nn.conv2d(x, w0 + w1 + w2 + w3 + w4,
                      padding='SAME')
layer1 = tf.reshape(layer0, [-1, 28 * 28])
layer2 = tf.matmul(layer1, w0 + w1)
# send prediction output back to client
prediction_op = tf.print(layer2,
                         [layer2],
                         message="Output:")
# run session which executes the computation
with tf.Session(target=master) as sess:
  sess.run(tf.global_variables_initializer())
  sess.run(prediction_op)
```

EXTENSIBILITY

We demonstrate tf-encrypted with Pond, a three-party implementation of the SPDZ protocol with passive security. There is also an extended version of Pond based on the SecureNN protocol of Wagh et al., in which comparison-based operations like ReLU and MaxPool can be computed without approximation.

The Protocol and Player abstractions are sufficiently general to accommodate protocols with any number of Players and any security model that fits within the paradigm of distributed tensor computation.

We plan on implementing a two-party version of SPDZ with active security and an optional garbled circuits extension in the coming months.

INTEGRATION

By annotating components of each secure multi-party computation with the `tf.device` context manager, TensorFlow can orchestrate and optimize each during the compilation phase. By building on top of TensorFlow, we can use support tools like TensorBoard for visually auditing, profiling, and debugging.

PERFORMANCE & BENCHMARKING

SecNN	Pond
Conv (5, 20, 1, 1)	Conv (5, 20, 1, 1)
BatchNorm	BatchNorm
ReLU	ReLU
MaxPool (2)	AvgPool (2)
Conv (5, 50, 1, 1)	Conv (5, 50, 1, 1)
BatchNorm	BatchNorm
ReLU	ReLU
MaxPool (2)	AvgPool (2)
FC (800, 500)	FC (800, 500)
BatchNorm	BatchNorm
ReLU	ReLU
FC (500, 10)	FC (500, 10)

We report benchmarks on the standard MNIST dataset. Runtime mean and standard deviation statistics are gathered over 100 inferences, while accuracy and KL-divergence metrics are reported over the MNIST test set.

For reference, our current runtime is 2.2x, 1.1x, and .85x relative to the SecureNN implementation of Wagh et al. for networks A, B, and C, respectively.

	Runtime, ms		Accuracy			KL-divergence	
	Pond	SecNN	TF	Pond	SecNN	Pond	SecNN
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SUMMARY

We develop a practical secure multi-party computation framework on top of TensorFlow that is usable, extensible, performant, and well-integrated with existing machine learning practices and tools. We hope researchers will use tf-encrypted to accelerate the implementation and benchmarking of their own novel secure computation protocols for machine learning.

REFERENCES

Code on GitHub: **mortendahl/tf-encrypted**. Full paper on Arxiv: 1810.08130.
Abadi et al., TensorFlow: A System for Large-scale Machine Learning, 2016
Damgard et al., Multiparty Computation from Somewhat Homomorphic Encryption, 2012
Wagh et al., SecureNN: Efficient and Private Neural Network Training, 2018

Thank you!