TensAIR: Online Learning from Data Streams via Asynchronous Iterative Routing

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Abstract—Online learning (OL) from data streams is an emerging area of research which encompasses numerous challenges from stream processing, machine learning, and networking. Recent extensions of stream-processing platforms, such as Apache Kafka and Flink, already provide basic extensions for the training of neural networks in a stream-processing pipeline. However, these extensions are not scalable and flexible enough for many real-world use-cases, since they do not integrate the neuralnetwork libraries as a first-class citizen into their architectures.

In this paper, we present TensAIR, which provides an endto-end dataflow engine for OL from data streams via a protocol to which we refer as asynchronous iterative routing. TensAIR supports the common dataflow operators, such as Map, Reduce, Join, and has been augmented by the data-parallel OL functions train and predict. These belong to the new Model operator, in which an initial TensorFlow model (either freshly initialized or pre-trained) is replicated among multiple decentralized worker nodes. Our decentralized architecture allows TensAIR to efficiently shard incoming data batches across the distributed model replicas, which in turn trigger the model updates via a form of asynchronous stochastic gradient descent. We empirically demonstrate that TensAIR achieves a nearly linear scale-out in terms of (1) the number of worker nodes deployed in the network, and (2) the throughput at which the data batches arrive at the dataflow operators. We exemplify the versatility of TensAIR by investigating both sparse (Word2Vec) and dense (CIFAR-10) use-cases, for which we are able to demonstrate very significant performance improvements in comparison to Kafka, Flink, and the Horovod distributed learning framework recently developed by Uber. We also demonstrate the magnitude of these improvements by depicting the possibility of real-time concept drift adaptation of a sentiment analysis model trained over a Twitter stream.

Index Terms—Online Learning, Neural Networks, Asynchronous Stream Processing, Asynchronous Stochastic Gradient Descent

I. INTRODUCTION

Machine learning (ML) has become ubiquitous in modern data-analytics and decision-making tasks. Current ML solutions demand a considerable amount of training time, which usually renders it infeasible to retrain the entire ML machinery "from scratch" whenever new data arrives. Online learning (OL) is a branch of ML that studies solutions to timesensitive problems which demand real-time answers based on fractions of data received in the form of *data streams* [1]. Moreover, a common characteristic of data streams is the presence of *concept drifts* [2], i.e., changes in the statistical properties among the incoming data objects over time. To adapt to concept drifts, one may rely on either passive or active adaptation strategies [3]. The passive strategy updates the trained model indefinitely, with no regard to the actual presence of concept drifts. Active drift adaptation strategies, on the other hand, only adapt the model when a concept drift has been explicitly identified. In OL, a passive strategy (which is the default strategy we consider in this work) can be seen as the computationally more demanding approach, since the buffering capabilities of a stream-processing engine are limited, such that the model needs to be constantly kept up-to-date with the incoming data batches.

Due to the intrinsic characteristics of OL, especially with respect to real-world applications, it is not feasible to depend on solutions that spend an undue amount of time on retraining, nor on those that cannot adapt to concept drifts. Therefore, until recently, complex OL problems could not rely on robust solutions common to other ML problems, like those involving Artificial Neural Networks (ANNs). Training in OL and ANNs is remarkably similar and yet is not exactly the same. Both are trained on incremental steps but differ with respect to the source and distribution of the training samples. ANNs sample their training data repeatedly (using so-called "epochs") from a pre-defined dataset with a fixed data distribution [4]. OL approaches, on the other hand, inherently need to sample data from an unbounded data stream with changing data distribution [5]. However, by analyzing subsets of a data stream between two significant concept drifts, in which the data is fixed and its distribution does not change significantly, both OL and ANN training become analogous again. Therefore, by overcoming limitations related to the convergence-time it takes to train ANNs, their usage to solve complex OL problems could substantially improve current solutions. Despite their apparent similarities, the usage of ANNs on OL scenarios is not straightforward. Therefore, we highlight the following challenges:

 Multiple *epochs* are usually necessary to train ANNs, in particular when modelling complex problems [4]. Meanwhile, OL only allows for processing incoming data batches once (or at most a limited amount of times), depending on the general buffering capabilities of the underlying streaming engine.

- (2) The convergence-time for training ANNs still is too high for many OL use-cases. Current systems still rely on libraries tailored to perform offline learning. Thus, their scale-out performance is limited when training from a data stream (see, e.g., Flink's *dl-on-flink* [6] extension, and Horovod [7] developed by Uber).
- (3) Finally, ANNs are highly sensitive to the *availability and quality of labeled input data*, which is easier to be provided and assessed on a fixed dataset than on a data stream.

Current stream-processing platforms, such as Apache Flink [8] and Kafka [9] already provide basic extensions [6], [10] for training ANNs under a streaming setting. However, these extensions are not prepared to sustain real-time training on a high-throughput scenario due to the following limitations: (1) Kafka does not currently support any form of distributed training in TensorFlow [9]; (2) Flink indeed exploits the distributed TensorFlow APIs (tf.distribute) which, to this end, is however limited to buffering the entire training data and thereby suffers performance issues under an OL setting (see Section IV); (3) overall, both of the Kafka and Flink extensions are still largely tailored to a few pre-defined use-cases and do not generalize well to the requirements of OL under different data formats, neural-network configurations, and streaming setups.

Solutions to increase the training efficiency of ANN algorithms, such as Apache SystemML [11], Horovod [7] and the distributed Tensorflow [12] APIs, on the other hand, do not natively target OL problems and their characteristics. Therefore, it is still an open research problem to develop a system that can, in real-time, train an ANN from a highthroughput data stream. Moreover, current research on OL is mostly focused on how to improve the quality of the input data and how to adapt to concept drifts [13]-[17]. Typical scale-up approaches for training ANNs are limited by the computational power of a single GPU and the server's memory/CPU capacity. Thus, scale-out approaches, like, e.g., Horovod [7] used by Uber for several years, come with their own distributed libraries for training ANNs but are still limited by their synchronous networking protocols, SGD updates, and further buffering requirements for the training data.

Finally, under an asynchronous SGD (ASGD) setting [18], workers are allowed to compute their gradient computations also on stale model parameters. This behaviour helps to minimize idle times but makes it harder to mathematically prove SGD convergence. Recent developments on ASGD [19]–[27], however, have tackled exactly this issue under different assumptions. In particular, Koloskova et al. [19] recently proved ASGD convergence with varying computation and communication frequencies among the worker nodes within very good error bounds. Moreover, they also proved that ASGD is always faster than mini-batch SGD—independently of the delay of the model updates.

Contributions. In this paper, we present the architecture of TensAIR, an end-to-end dataflow engine combining our AIR stream-processing engine [28] with TensorFlow [12], thus yielding a fully distributed OL framework implemented in C++. Different from current approaches, TensAIR focuses on scaling-out in particular the training of ANNs via an asynchronous and decentralized architecture. This architecture relies on asynchronous message passing in combination with asynchronous SGD updates, thereby eliminating the bottleneck of a centralized parameter server for training. Its current programming interface is flexible enough to let users specify their desired TensorFlow model structure and optimizer (via the Keras Python APIs), as well as the concept-drift identification algorithm. Although the asynchronous and decentralized training of ANNs is not a completely new direction [26], we believe that TensAIR is the first architecture to truly enable the asynchronous and decentralized training of ANNs under an OL scenario by incorporating the neural-network components as first-class dataflow operators-both for training and prediction.

II. BACKGROUND & RELATED WORK

A. Online Learning

Online learning (OL) recently gained visibility due to the increase in the velocity and volume of available data sources compared to the past decade [29]. OL algorithms are trained using data streams as input, which differs from traditional ML algorithms that have a pre-defined training dataset.

Streams & Batches. Formally, a data stream S consists of ordered *events e* with *timestamps s*, i.e., $(e_1, s_1), \ldots, (e_{\infty}, s_{\infty})$, where the s_i denote the processing time at which the corresponding events e_i are ingested into the system. These events are usually analysed in *batches B_j* of fixed size *b*, as follows:

$$B_1 = (e_1, s_1), \dots, (e_b, s_b)$$

$$B_2 = (e_{b+1}, s_{b+1}), \dots, (e_{2b}, s_{2b})$$

Batches B_j are analyzed individually. Thus, if processed in an asynchronous stream-processing scenario, the batches (and in particular the included events e_i) can become out-oforder as they are handled within the system, even if the initial s_i were ordered. In common stream-processing architectures, such as Apache Flink [8], Spark [30] and Samza [31], batches are distinguished into *sliding windows*, *tumbling windows* and (per-user) *sessions* [32].

Latency vs. Throughput. When analyzing systems that process data streams, one typically benchmarks them by their latency and throughput [33]. Formally, *latency* is the time it takes for a system to process an event, from the moment it is ingested to the moment it is used to produce a desired output. *Throughput*, on the other hand, is the number of events that a system can receive and process per time unit. The *sustainable throughput* is the maximum throughput at which a system can handle a stream over a sustained period of time

(i.e., without exhibiting a sudden surge in latency, then called "backpressure" [34], or even a crash).

B. Artificial Neural Networks

ANNs denote a family of supervised ML algorithms which are designed to be trained on a pre-defined dataset [35]. A training dataset is composed of multiple (x, y) pairs, in which x is a training example and y is its corresponding label. ANNs are usually trained using *mini-batches* X, which are sets of (x, y) pairs of fixed size N that are iteratively (randomly) sampled from the training dataset, thus $X = (x_i, y_i), \ldots, (x_{i+N}, y_{i+N})$.

BGD vs. SGD. An ANN model is represented by the weights and biases of the network, described together by θ . We train the network using Batch Gradient Descent (BGD) [36] which is based on Stochastic Gradient Descent (SGD) [37]. BGD updates θ by considering $\nabla L(X, \theta)$, which is the gradient of a pre-defined *loss function* L with respect to θ when taking X as input. Thus, we can represent the update rule of θ as in Equation 1, in which t is the iteration in BGD, and α is a pre-defined learning rate.

$$\theta_{t+1} = \theta_t - \alpha \nabla L(X, \theta_t) \tag{1}$$

Based on Equation 1, θ_{t+1} is defined based on two terms. The second term is the more computationally expensive one to calculate, which we refer to as *gradient calculation* (GC). The remainder of the equation we call *gradient application* (GA), which consists of the subtraction between the two terms and the assignment of the result to θ_{t+1} .

Convergence. Despite the differences between OL and ANNs, they have a similar training pipeline. Both approaches are trained based on analogous sets of data points, which are the batches for OL and the mini-batches for ANNs. A seminal result for training ANNs [35] is that SGD converges to a (local) minimum of the loss function as the number of batches approaches *infinity*—even when not all of the actually available training examples fall into these batches. So-called epochs were introduced to ANN training in order to compensate for the lack of labeled training examples by performing repeated iterations over the available examples. A main conjecture we follow with TensAIR thus is that, instead of using epochs, we may train the underlying ANN by using new batches from a data stream as input and hence converge as long as the principal distribution of the (x, y) pairs in the data stream remains unchanged (e.g., between two major concept drifts).

C. Distributed Artificial Neural Networks

Over the last years, ANN models have grown in size and complexity. Consequently, the usage of traditional centralized architectures has become unfeasible when training complex models due to the high amount of time they spend until convergence [7]. Researchers have been studying how to distribute ANN training to mitigate this. Distributed ANNs reduce the time it takes to train a complex ANN model by distributing its computation across multiple compute nodes. This distribution can follow different parallelization methods, system architectures, and synchronization settings [38].

1) Parallelization methods: There are many possible parallelization strategies for ANNs [38]. We describe below the two most common ones: model and data parallelism.

Model Parallelism. In model parallelism [18], the ANN model is split into different parts which are distributed among the worker nodes. The major challenge when using model parallelism is to determine how to partition the model and keep the computation balanced among the workers [38]. Considering the inherent difficulty of developing a splitting method that is generic enough to be used on different ANN models and scalable enough to be distributed across multiple nodes, we omit the consideration of model parallelism in this work.

Data Parallelism. In data parallelism [18], the N training pairs within a mini-batch are assumed to be independent of each other [39]. Thus, workers are initialized as replicas and trained with different splits of those N pairs. The replicas perform the GC steps over the data received and then synchronize their parameters among themselves. This method of parallelism is the most common one and has existed since the first implementations of ANNs [38]. Frameworks like TensorFlow [12] or PyTorch [40] use data parallelism by default when deployed on multi-core compute nodes or GPUs.

2) System Architectures: The synchronization among the workers' parameters in a data-parallel ANN setting is either *centralized* or *decentralized* [38], as described below.

Centralized. In a centralized architecture [18], workers systematically send their parameter updates to one or multiple parameter servers. Those servers aggregate the updates of all workers and apply them to a centralized model [38]. Then, the workers use the centralized model on the next iterations of BGD. Despite being easier to manage compared to decentralized architectures, the scalability when using parameter servers is limited. Thus, by relying on parameter servers to aggregate updates and broadcast them to all workers, the parameter servers may become the actual bottleneck of such an architecture [41].

Decentralized. In a decentralized architecture [18], the workers synchronize themselves using a broadcasting-like form of communication [42] which eliminates the bottleneck of the parameter servers. An *AllReduce* operation may be performed on a fully connected network, generating a communication cost of $O(n^2)$ over *n* workers; or, on ring-like topologies, an *Ring-AllReduce* operation may reduce the communication to O(n) [38] but typically increases the time it takes to propagate the parameters through the network.

3) Synchronization Settings: The aggregation and application of the model updates in a data-parallel ANN system can be synchronous or asynchronous. Those settings are described below.

Synchronous. In a synchronous setting [18], workers have to synchronize themselves after each iteration. Therefore, they can only initialize the next GC step if their models are

synchronized. This synchronization barrier directly facilitates the proof of convergence of SGD (as in a centralized setting) but wastes computational resources at idle times (i.e., when workers have to wait for others to resume their computation) [38].

Asynchronous. In an asynchronous SGD (ASGD) setting [18], workers are allowed to compute GC steps also on stale model parameters. This behaviour obviously minimizes idle times but makes it harder to mathematically prove SGD convergence. Recent developments on ASGD [19]–[25], [27], [43], however, have tackled exactly this issue under different assumptions. Koloskova et al. [19] recently proved that ASGD is always faster than BGD. Furthermore, they also show that ASGD converges under a parameter-server setting within $\mathcal{O}(\frac{\sigma^2}{\epsilon^2} + \sqrt{\frac{\tau max \tau avg}{\epsilon}})$ iterations to an ϵ -small error, with τ being the gradient delay and a bounded variance for the gradients $\sigma^2 \geq 0$.

D. TensorFlow

TensorFlow (TF) provides a collection of APIs to implement and execute ML algorithms [12]. It is one of the most popular ANN frameworks and is used by companies such as Google, Intel, Twitter, and Coca-Cola. TensorFlow is open-source, and it is available in multiple languages such as Python, Java, C, C++, and Go. Noteworthy TF features are its performance, transparent acceleration via GPUs, and its integration with Keras [44]. Keras is a high-level framework, written in Python, that simplifies ANN implementations. TF supports distributed training via the tf.distribute.Strategy API. This API allows the user to choose among multiple distributed strategies, such as the MirrorredStrategy (referred to as "TF_Mirror" in our experiments), which is decentralized and synchronous, and the ParameterServerStrategy, which is centralized and can be either synchronous or asynchronous.

E. AIR Distributed Dataflow Engine

Asynchronous Iterative Routing (AIR) is a distributed dataflow engine which implements a light-weight iterative sharding protocol [45] on top of the Message Passing Interface (MPI). It is a native stream-processing engine that processes complex dataflows, consisting of direct acyclic graphs (DAGs) of logical dataflow operators. AIR's main features are that it uses an asynchronous MPI protocol and does not rely on a master-client architecture (but follows a pure client-client pattern) for communication. Both of these characteristics differ AIR both from existing bulk-synchronous processing (BSP) systems, such as Apache Spark [30], and asynchronous streamprocessing (ASP) engines, such as Apache Flink [8] and Samza [31]. AIR is implemented in C++ using POSIX threads (pthreads) for multi-threading and MPI for communication among nodes. Due to its light-weight and robust architecture, AIR's scale-out performance has been shown to be up to 15 times better than Spark and up to 9 times better than Flink [28], on a variety of HPC settings.

III. TENSAIR ARCHITECTURE

We now introduce the architecture of *TensAIR*, a distributed stream-processing engine (supporting the common dataflow operators like Map, Reduce, Join, etc.), which has been augmented with the *data-parallel*, *decentralized*, *asynchronous* ANN operator Model, with train and predict as two new OL functions. TensAIR is a TensorFlow framework developed on top of AIR [28], [45], which enables a remarkable scale-out performance for training ANNs in an online learning scenario.

A. TensAIR

Just like AIR, TensAIR is a native stream-processing engine that processes complex dataflows consisting of logical dataflow operators. This means that TensAIR can scale out both the training and prediction tasks of an ANN model to multiple compute nodes, either with or without GPUs associated with them. TensAIR has its dataflow defined based on AIR operators and can be visualized using a graph (see Figure 1). However, different from AIR, a TensAIR dataflow is not a DAG because it allows cycles among the model operators. Other than some adaptations to the source code to allow cycles in an AIR dataflow, our TensAIR extension did however not affect the general AIR framework (nor TensorFlow itself).



Fig. 1: TensAIR dataflow with n distributed Model^{W2V} instances and a single instance of Map, Split, UDF and Model^{SA}.

Figure 1 depicts the dataflow for a *Sentiment Analysis* (SA) use-case on a Twitter data stream. This dataflow predicts the sentiments of live tweets using a pre-trained ANN model ($Model^{SA}$). However, it does not rely on pre-defined word embeddings. The dataflow constantly improves its embeddings on a second *Word2Vec* (W2V) ANN model ($Model^{W2V}$), which it trains using the same input stream as used for the predictions. By following a passive concept-drift adaptation strategy, it can adapt its sentiment predictions in real-time based on changing word distributions among the input tweets. Moreover, it does not require any sentiment labels for newly streamed tweets at $Model^{SA}$, since only $Model^{W2V}$ is re-

trained in a self-supervised manner by generating mini-batches of word pairs (x, y) directly from the input tweets.

TensAIR Dataflows. Generally, a *TensAIR dataflow* is composed of logical dataflow operators which all extend a basic Vertex superclass in AIR [45]. Vertex implements AIR's asynchronous MPI protocol via multi-threaded queues of incoming and outgoing messages, which are exchanged among all nodes (aka. "ranks") in the network asynchronously. The number of instances of each Vertex subclass can be configured beforehand. In Figure 1, we represent $Model^{W2V}$ with *n* instances, while Map, Split, UDF and $Model^{SA}$ have 1 instance here for simplicity.

Our SA dataflow starts with Map which receives tweets from a Twitter input stream (implemented via cURL or a file interface) and tokenizes the tweets based on the same word dictionary also used by $Model^{W2V}$ and $Model^{SA}$. Split then identifies whether the tokenized tweets shall be used for re-training the word embeddings, for sentiment prediction, or for both. If the tokenized tweets are selected for training, they are turned into mini-batches via the UDF operator. The (x, y) word pairs in each mini-batch X are sharded across $Model_1^{W2V}, \ldots, Model_n^{W2V}$ with a standard hash-partitioner using words x as keys. $Model^{W2V}$ implements a default skip-gram model. If the tokenized tweets are selected for prediction, a tweet is vectorized by using the word embeddings obtained from any of the $Model^{W2V}$ instances (as discussed in Section III-C, they will all eventually converge to the same common model) and sent to the pre-trained $Model^{SA}$ which then predicts the tweets' sentiments as either positive or negative. All $Model^{W2V}$ instances are initialized with a copy of the same TensorFlow model, which can be pre-configured in Keras and be loaded from a file into TensAIR.

Stream Processing. As shown in Algorithm 1, a TensAIR Model operator has two new OL functions train and predict, which can asynchronously send and receive messages to and from other operators. For $Model^{SA}$, predict receives *embedded tweets* as input, which are obtained from the current parameters of any of the $Model^{W2V}$ instances. For a $Model^{W2V}$, train receives either *encoded mini-batches* X or *gradients* ∇x as messages. Each message encoding a gradient that was computed by another model instance is immediately used to update the local model accordingly. Each mini-batch first invokes a local gradient computation and is then used to update the local model. Each such resulting gradient is also locally buffered until a desired buffer size (maxGradBuffer) for the outgoing gradients is reached, upon which the buffer then is broadcast to all other model instances.

B. Model Consistency

Despite TensAIR's asynchronous nature, it is necessary to maintain the models consistent among themselves during training in order to guarantee that they are aligned and, therefore, they eventually convergence to a same common model. In TensAIR, this is given by the exchange of gradients between the various Model instances.

Algorithm 1: TensAIR Model class with additional OL functions train and predict (pseudocode)

1	1 Constructor Model (tfModel, maxBuffer) extends Vertex:							
2	model = tfModel;							
3	maxGradBuffer = maxBuffer;							
4	gradients = \emptyset ;							
5	ALIVE = true;							
6	6 Function streamProcess(msq):							
7	while ALIVE do							
8	if $msq.mode == TRAIN$ then							
9	train(msg);							
	else							
10	predict(<i>msg</i>);							
	end							
	end							
11	1 Function train (msg):							
12	if msg.isGradient then							
13	$model = apply_gradient(model, msg);$							
	else							
14	$gradient = calculate_gradient(model, msq);$							
15	model = apply_gradient(model, gradient);							
16	gradients = gradients \cup {gradient};							
17	if $ gradients \geq maxGradBuffer$ then							
18	send_gradients(gradients);							
	end							
	end							
19 Function predict (msg):								
20	predictions = model.make_predictions(msg)							
21	send_results(predictions)							

Due to our asynchronous computation and application of the gradients on the distributed model instances, $Model_i^{W2V}$ receives gradients calculated by $Model_j^{W2V}$ (with $j \neq i$) which are similar but not necessarily equal to itself. This occurs whenever $Model_i^{W2V}$, which has already applied to itself a set of $G_i = \{\nabla x, \nabla y, ..., \nabla z\}$ gradients, calculates a new gradient ∇a , and sends it to $Model_j^{W2V}$, such that $G_i \neq G_j$ at the time when $Model_j^{W2V}$ applies ∇a . The difference $|G_i \cup G_j| - |G_i \cap G_j|$ between these two models is defined as *staleness* [46]. This *staleness*_{i,j}(∇_a) metric is the symmetric distance between G_i and G_j with respect to the times at which a new gradient ∇_a was computed by a model *i* and is applied to model *j*, respectively. This phenomenon and the staleness metric are illustrated in Figure 2.



Fig. 2: ASGD staleness on a distributed framework.

Figure 2 illustrates the timeline of messages (containing both mini-batches and gradients) exchanged among TensAIR models considering max GradBuffer = 1. Assume the UDF distributes 5 mini-batches to 3 models. After receiving their first mini-batch, each $Model_i^{W2V}$ calculates a corresponding gradient. Note that, when applied locally, the staleness of any gradient is 0 because it is computed and immediately

applied by the same model. While computing or applying a local gradient, each $Model_i^{W2V}$ may receive more gradients to calculate and/or apply from either the UDF or other models *asynchronously*. In our protocol, the models first finish their current gradient computation, immediately apply it locally, then buffer and send maxGradBuffer many locally computed gradients to the other models, and wait for their next update.

As illustration, take a look at Model₁ in Figure 2. While computing ∇_{blue} , it receives the yellow mini-batch from the UDF, which it starts computing immediately after it finishes processing the blue one—which it had already started when it received the yellow mini-batch. During the computation of ∇_{yellow} , Model₁ receives ∇_{green} to apply, which it does promptly after finishing ∇_{yellow} . Note that when Model₂ computed ∇_{green} and Model₃ computed ∇_{red} , they have not applied a single gradient to their local models at that time. Thus, $|G_2| = |G_3| = 0$. However, before applying ∇_{green} , $G_1 = {\nabla_{blue}, \nabla_{yellow}}$ with $|G_1| = 2$ and staleness_{1,2}(∇_{green}) = 2. Along the same lines, before applying ∇_{red} , $|G_1| = 3$ and staleness_{1,3}(∇_{red}) = 3.

C. Model Convergence

Since TensAIR operates on data streams and is both asynchronous and fully decentralized (i.e., it has no centralized parameter server), it exhibits characteristics which current SGD proofs of convergence [20], [21], [23] do not cover. Therefore, we next discuss under which circumstances TensAIR is guaranteed to converge.

First, we consider that training is performed between significant concept drifts. Therefore, we assume that the minibatches between two subsequent concept drifts do not change. Thus, if a concept drift occurs during the training, the model will not converge until the concept drift ends. By considering this, the data stream between two concept drifts will behave like a fixed data set. In this case, if given enough training examples, as seen in [35], each of the local model instances will eventually converge.

Second, considering TensAIR's asynchronous and distributed nature, our SGD updates can be staled. We are not aware of any ASGD proofs of convergence that contemplate staleness in a decentralized setting. However, Koloskova et al. [19] recently proved a tighter convergence rate for ASGD in a parameter-server setting with varying computation and communication frequency among the worker nodes. Specifically, they show ASGD convergence within $\mathcal{O}(\frac{\sigma^2}{\epsilon^2} + \frac{\sqrt{\tau_{max}\tau_{avg}}}{\epsilon})$ iterations to an ϵ -small error, with τ being the gradient delay and a bounded variance for the gradients $\sigma^2 \ge 0$. Although TensAIR does not rely on a centralized parameter server, its convergence rate can be the same as the one from a parameter-server setting under specific conditions. One may achieve this by introducing global synchronization steps to ensure that all local models become synchronized periodically, a strategy called Stale-Synchronous Parallelism (SSP) [39]. Under the SSP strategy, the local gradients can still be computed asynchronously but the models updates are limited to a synchronous communication. We note that staleness under SSP is analogous to the gradient delay τ in [19]. Both τ and *staleness* measure the difference between the state of the model in which a gradient was calculated versus in which it is applied. Considering this, we can reduce the SSP convergence proof to a special case of the parameter-server based proof from [19], in which all worker nodes from the parameter server are updated simultaneously.

In practice, we however did not observe any degradation in the convergence rate of TensAIR when compared to synchronous SGD (see Section IV). Therefore, we did not further explore the SSP strategy due to its performance limitations when compared to a fully asynchronous system.

D. Implementation

TensAIR is completely implemented in C++. It includes the TensorFlow 2.8 native C API to load, save, train, and predict ANN models. Therefore, it is possible to develop a TensorFlow/Keras model in Python, save the model to a file, and load it directly into TensAIR. TensAIR is completely open-source and available from our Gitlab repository¹.

IV. EXPERIMENTS & DISCUSSION

To assess TensAIR, we performed experiments to measure its performance on solving prototypical ML problems such as Word2Vec (word embeddings) and CIFAR-10 (image classification). We empirically validate TensAIR's model convergence by comparing its training loss curve at increasing levels of distribution across both CPUs and GPUs. Our results confirm that TensAIR's ASGD updates achieve similar convergence on Word2Vec and CIFAR-10 as a synchronous SGD propagation. At the same time, we achieve a nearly linear reduction in training time on both problems. Due to this reduction, TensAIR significantly outperforms not just the Apache Kafka and Flink extensions (based on both the standard and distributed TensorFlow APIs), but also Horovod which is a long-standing effort to scale-out ANN training. Finally, by providing an in-depth analysis of a sentiment analysis (SA) use-case on Twitter, we demonstrate the importance of OL in the presence of concept drifts (i.e., COVID-19 related tweets with changing sentiments). In particular the SA usecase is an example of task that would be deemed too complex to be adapted in real-time (at a throughput rate of ca. 6,000 tweets per second) when using other OL frameworks.

HPC Setup. We carried out the experiments described in this section using the HPC facilities of the University of Luxembourg [47]. We distributed the ANNs training using up to 4 Nvidia Tesla V100 GPUs per node with 768 GB RAM each. We also deployed up to 16 regular nodes, with 28 CPU cores and 128 GB RAM each, for the CPU-based (i.e., without using GPU acceleration) settings.

Event Generation. We trained both sparse (word embeddings²) and dense (image classification³) models based on

¹https://gitlab.uni.lu/mdalle/TensAIR

²https://www.tensorflow.org/tutorials/text/word2vec

³https://www.tensorflow.org/tutorials/images/cnn

English Wikipedia articles and images from CIFAR-10 [48], respectively. Instead of connecting to actual streams, we chose those static datasets to facilitate a consistent analysis of the results and ensure reproducibility. Moreover, to simulate a streaming scenario, we implemented an additional MiniBatchGenerator as an entry-point Vertex operator (compare to Figure 1) which generates events e_i with timestamps s_i , groups them into mini-batches X_j by using a tumbling-window semantics, and sends these mini-batches to the subsequent operators in the dataflow. Furthermore, this allows us to simulate streams of unbounded size by iterating over the datasets multiple times (in analogy to training with multiple epochs over a fixed dataset).

Sparse vs. Dense Models. We chose Word2Vec and CIFAR-10 because they represent prototypical ML problems with *sparse* and *dense* model updates, respectively. Sparse updates mean that only a small portion of the neural network variables actually become updated per mini-batch [49]. Hence, sparseness should assist the model convergence when using ASGD, as observed also in Hogwild! [49]. We trained by sampling 1% from English Wikipedia which corresponds to 11.7M training examples (i.e., word pairs). On the other hand, we chose CIFAR-10 for being dense. Thus, we could analyze how this characteristic possibly hinders convergence when models are distributed and updated asynchronously. We train on all of the 50,000 labeled images of the CIFAR-10 dataset.

A. Convergence Analysis

We first explored TensAIR's ability to converge by determining if and how ASGD might degrade the quality of the trained model (Figure 3). We compared the training loss curve of Word2Vec and CIFAR-10 by distributing TensAIR models from 1 to 4 GPUs using 1 TensAIR rank per GPU (Figures 3b & 3d). We additionally explored the models convergence when trained with distributed CPU nodes (Figures 3a & 3c). In this second scenario, we trained up to 64 ranks on 16 nodes simultaneously without GPUs. Note that, when using a single TensAIR rank, TensAIR's gradient updates behave as in a synchronous SGD implementation.

The *extremely low variance* among all loss curves shown in Figures 3a and 3b demonstrates that our asynchronous and distributed SGD updates do not at all negatively affect the convergence of the Word2Vec models. We assume that this is due to (1) the sparseness of Word2Vec, and (2) a low staleness of the gradients (which are relatively inexpensive to compute and apply for Word2Vec). The low staleness indicates a fast exchange of gradients among models.

In Figure 3c, we however observe a remarkable degradation of the loss when distributing CIFAR-10 across multiple nodes. This is due to the fixed learning rate used on all settings being the same. When distributing dense models on multiple ranks without adapting the mini-batch size, it is well known to result in a degradation of the loss curve (even on synchronous settings). This degradation occurs because the behaviour of training N models with mini-batches of size x is similar to training 1 model with mini-batches of size $N \cdot x$. To mitigate this issue, Horovod recommends to increase the learning rate α by the number of ranks used to distribute the model [50], i.e., $\alpha_{new} = \alpha \cdot N$. Accordingly, in Figure 3d, we again do not see any degradation of the loss when distributing CIFAR-10 across multiple GPUs because we use a maximum of 4 GPUs.

B. Speed-up Analysis

Next, we explore the performance of TensAIR under increasing levels of distribution and with respect to varying mini-batch sizes over both Word2Vec and CIFAR-10. This experiment is also deployed on up to 64 ranks (16 nodes) and up to 4 GPUs (1 node). We observe in Figure 4 that TensAIR achieves a *nearly-linear scale-out* under most of our settings. In most cases, TensAIR achieves a better speedup when training with smaller mini-batches. This difference is because the mini-batch size is inversely proportional to the training time. Hence, the smaller the training time, the bigger is the fraction of the computation that is not distributed. Thus, models with expensive gradient computations will have a better scale-out performance.

C. Baseline Comparison

Apart from TensAIR, it is also possible to train ANNs by using Apache Kafka and Flink as message brokers to generate data streams of varying throughputs. Kafka is already included in the standard TensorFlow I/O library (tensorflow_io), which however allows no actual distribution in the training phase [10]. Flink, on the other hand, employs the distributed TensorFlow API (tensorflow.distribute). However, we were not able to run the provided *dl-on-flink* use-case [6] even after various attempts on our HPC setup. We therefore report the direct deployment of our Word2Vec and CIFAR-10 use-cases (Figures 5 & 6) on both the standard and distributed TensorFlow APIs (the latter using the MirroredStrategy option of tensorflow.distribute). We thereby, simulate a streaming scenario by feeding one mini-batch per training iteration into TensorFlow, which yields a very optimistic upper-bound for the maximum throughput that Kafka and Flink could achieve. In a similar manner, we also determined the maximum throughput of Horovod [7], which is however not a streaming engine by default.

In Figures 5 and 6, we see that TensAIR clearly surpasses both the standard and distributed TensorFlow setups as well as Horovod. This occurs because, as opposed to TensAIR, their architectures were not developed to train on batches arriving from data streams. Thus, in a streaming scenario, the overhead of transferring the training data to the worker nodes increases by the number of training steps. On the other hand, TensAIR is an end-to-end dataflow engine prepared to train ANNs from streaming data. Thus, the transfer of training data overhead is mitigated by the asynchronous iterative routing protocol. This allows TensAIR to (1) reduce both computational resources and idle times while the data is being transferred, and (2) have an optimized buffer management for incoming mini-batches and outgoing gradients, respectively.



Fig. 3: Convergence analysis of TensAIR on the Word2Vec and CIFAR-10 use-cases.



Fig. 4: Speedup analysis of TensAIR on the Word2Vec and CIFAR-10 use-cases.





■ TF (Kafka) ■ TF_Mirror (Flink) ■ Horovod ■ TensAIR

Fig. 5: Throughput comparison between TensAIR, Tensor-Flow (standard and distributed), and Horovod in the W2V use-case.

Fig. 6: Throughput comparison between TensAIR, TensorFlow (standard and distributed), and Horovod in the CIFAR-10 use-case.

In our experiments, we could sustain a maximum training rate of 285,560 training examples per second on Word2Vec and 200,000 images per second on CIFAR-10, which corresponds to sustainable throughputs of 14.16 MB/s and 585 MB/s respectively. We reached these values by training with 3 GPUs on Word2Vec and 4 GPUs on CIFAR-10.

D. Sentiment Analysis of COVID19

Here, we exemplify the benefits of training an ANN in realtime from streaming data. To this end, we analyze the impact of concept drifts on a sentiment analysis setting, specifically drifts that occurred during and due to the COVID19 pandemic. First, we trained a large Word2Vec model using 20% of English Wikipedia plus the Sentiment140 dataset [51] from Stanford. Then, we trained an LSTM model [52] using the Sentiment140 dataset together with the word embeddings we trained previously. After three epochs, we reached 78% accuracy on the training and the test set. However, language is always evolving. Thus, this model may not sustain its accuracy for long if deployed to analyze streaming data in real-time. We exemplify this by fine-tuning the word embeddings with 2M additional tweets published from November 1st, 2019 to October 10th, 2021 containing the following keywords: covid19, corona, coronavirus, pandemic, quarantine, lockdown, sarscov2. Then, we compared the previously trained word embeddings and the fine-tuned ones and found an average cosine difference of only 2%. However, despite being small, this difference is concentrated onto specific keywords.

Term	rt	corona	pandemic	booster	2021
Difference	0.728	0.658	0.646	0.625	0.620

TABLE I: Cosine differences after updating word embeddings.

As shown in Table I, keywords related to the COVID-19 pandemic are the ones that most suffered from a concept drift. Take as example pandemic, booster and corona, which had over 62% of cosine difference before and after the Word2Vec models have been updated. Due to the concept drift, the sentiment over specific terms and, consequently, entire tweets also changed. One observes this change by comparing the output of our LSTM model when: (1) inputting tweets embedded with the pre-trained word embeddings; (2) inputting tweets embedded with the fine-tuned word embeddings. Take as an example the sentence "I got corona.", which had a sentiment of +2.0463 when predicted with the pre-trained embeddings; and -2.4873 when predicted with the fine-tuned embeddings. Considering that the higher the sentiment value the more positive the tweet is, we can observe that *corona* (also representing a brand of a beer) was seen as positive and now is related to a very negative sentiment.

To tackle concept drifts in this use-case, we argue that TensAIR with its OL components (as depicted in Figure 1) could be readily deployed. A real-time pipeline with Twitter would allow us to constantly update the word embeddings (our sustainable throughput would be more than sufficient compared to the estimated throughput of Twitter). Consequently, the sentiment analysis algorithm would always be up-to-date with respect to such concept drifts.

V. CONCLUSIONS

OL is an emerging area of research which still has not extensively explored the real-time training of ANNs. In this paper, we introduced TensAIR, a novel end-to-end dataflow engine for OL from data streams. It uses an asynchronous iterative routing (AIR) protocol to train and predict ANNs in a distributed manner. One major feature of TensAIR is its high performance due to its direct inclusion of TensorFlow as a first-class dataflow operator. TensAIR achieves a nearly linear scale-out performance in terms of sustainable throughput and with respect to its number of worker nodes. It uses TensorFlow models and supports the common dataflow operators, such as Map, Reduce, and Join, which facilitates the implementation of diverse use-cases. Therefore, we highlight the following capabilities of TensAIR: (1) process multiple data streams simultaneously; (2) train models using either CPUs, GPUs, or both; (3) train ANNs in an asynchronous and distributed manner; and (4) incorporate user-defined data pre- and post-processing pipelines. We empirically demonstrate that, on a real-time streaming scenario, TensAIR surpasses both the standard and distributed TensorFlow APIs (representing upper bounds for the throughput of Apache Kafka and Flink, respectively) when training ANNs from streaming data. We also show that, in our experiments, the model degradation due to ASGD is insignificant in practice.

As future work, we believe that TensAIR may also lead to novel online learning use-cases which were previously considered too complex but now become feasible due to very good scale-out performance of TensAIR. Specifically, we intend to study similar learning tasks over audio/video streams which we see as the main target domain for stream processing. To reduce the computational cost of training an ANN indefinitely, we shall also investigate how different active concept-drift detection algorithms behave under an OL setting with ANNs.

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