ADAPTIVE INITIALIZATION FOR RECURRENT PHOTONIC NETWORKS USING SIGMOIDAL ACTIVATIONS

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STRUCTURE

- Introduction to Photonic Deep Learning
- Proposed Method
- Experimental Evaluation
- Conclusions

- **Deep Learning (DL)** provided state-of-the-art solutions to many challenging problems
    - … but **DL models are especially complex**
    - … **powerful hardware is needed both for training and deploying DL models**
- Several **hardware accelerators** have been developed
    - Graphics Processing Units (GPUs)
    - Tensor Processing Units (TPUs)
    - …
- Neuromorphic solutions are especially promising providing **fast and energy efficient DL** accelerators by directly providing the functionality of neurons

- Photonic DL accelerators use **light to represent signals**
- These signals can be then **appropriately manipulated,** using either purely **optical** components, or a combination of **electro-optical** components, to perform computations
- Several advantages
  - Information is **propagated near to the speed of light**
  - **Enormous bandwidth** that provides a **massive parallelism potential**
  - Photonic neurons can operate at **extremely high frequencies**

LIMITATIONS

- Photonic neuromorphic platforms currently face **several important limitations**
- Among them is that many DL-oriented **activation functions cannot be precisely implemented using photonic hardware**
- **DL models must be retrained** using photonic-compliant activation functions before deployment
- Using such functions is not straightforward, e.g., saturable functions can lead to vanishing gradients phenomena, slowing down or even **stopping the learning process**

LIMITATIONS

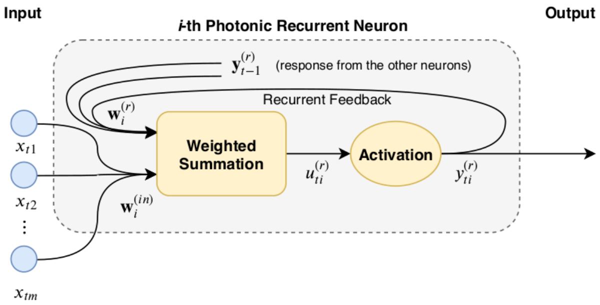
- In “traditional” DL this problem was solved by developing **appropriate activation functions,** e.g., ReLU, along with appropriate **initialization** schemes
- This is not always possible for photonic DL
- Developing the appropriate initialization scheme to ensure that the models will be initialized into a region that **allows for information to be propagated**
- This is even more **critical for recurrent architectures**, where **both vanishing and exploding gradient phenomena** can be occur

CONTRIBUTION

- We propose an **adaptive data-driven initialization method** that can overcome these limitations
  - The proposed method is **activation-agnostic** (i.e., can be used with any activation function)
  - **Does not require manually and analytically calculating the initialization variance** for different activation functions[1]
  - Takes into account both the **actual distribution** of the data used to train the network and the **task at hand**
  - **Simple and easy to implement!**
- **Solid step toward the effective training of photonic DL models**, overcoming many limitations of existing variance-preserving initialization methods

[1] Passalis, Nikolaos, et al. "Training deep photonic convolutional neural networks with sinusoidal activations." IEEE Transactions on Emerging Topics in Computational Intelligence (2019).

- This work focuses on **training deep recurrent neural networks using a sigmoid-based activation** function that can be implemented using a recently proposed all-optical activation mechanism[2]



[2]G. Mourgias-Alexandris, A. Tsakyridis, N. Passalis, A. Tefas, K. Vyrsokinos, and N. Pleros, "An all-optical neuron with sigmoid activation function," Optics express, vol. 27, no. 7, pp. 9620–9630, 2019

- The proposed method exploits the **effectiveness in training shallow (up to two layers) neural networks** to estimate the optimal initialization variance of a layer
- The proposed method estimates the initialization variance **layer-by-layer** (starting with the input layers)
- Each layer is equipped with a trainable scaling factor α_i that is used to estimate the optimal initialization variance:

$$\mathbf{y}_t^{(i)} = f(|\alpha_i|\mathbf{W}_i\mathbf{y}_{t-1}^{(i-1)} + \mathbf{b}_i), \tag{1}$$

where $f(\cdot)$ is the employed activation function, and $\mathbf{W}_i$ and $\mathbf{b}_i$ the weights and biases of the layer.

- Then, **an auxiliary classification layer** is used on top of each layer of the network and trained using regular gradient descent
- Only the **auxiliary classification layer** and **the scaling factor** are trained (the layer's weights are kept fixed)
- The value of the **scaling factor implicitly provides an estimation for the optimal initialization variance**
- After estimating the variance for a layer, this process is repeated with the next one
- The **scaling factors are discarded** after this process is completed and the **network is re-initialized and can be directly trained**

Algorithm 1 Adaptive Data-driven Initialization

Input: Initial weights $\mathbf{W}_i$, learning rate η, number of iterations N_{est}

Output: Initialization variance for each layer σ_i^2

Initialize the layers $\mathbf{W}_i$ using any initialization scheme
for i=1 **to** n **do**
  Initialize α_i to 1
  for j=1 **to** N_{est} **do**
    Update parameters using gradient descent($\frac{\partial \mathcal{L}}{\partial \alpha_i}, \frac{\partial \mathcal{L}}{\partial \mathbf{W}_i^{class}}$)
  end for
  Calculate the variance as $\sigma_i^2 = (\alpha_i \sigma_{init})^2$
end for
return Estimated values for σ_i

EXPERIMENTAL SETUP

- **Two different time-series datasets**, suitable for recurrent neural architectures, were used:
  - a **high-frequency limit order book dataset** (abbreviated as “FI-2010”), and
  - a **household power consumption forecasting dataset** (abbreviated as “HPCF”)
- A **recurrent neural networks with 32 recurrent units**, followed by **two fully connected layers** with 512 units and N_C output neurons (number of classes)
- The **RMSprop optimization algorithm** was used for all the conducted experiments.
- The optimization ran for **20 epochs for the FI-2010** dataset and for **10 epochs for the HPCF dataset**

Model	Initialization	Avg. F1	Cohen's κ
MLP	Xavier	35.27 ± 1.05	0.1058 ± 0.0108
LSTM	Xavier	43.61 ± 1.17	0.1796 ± 0.0142
RNN (sigmoid)	Xavier	40.44 ± 1.77	0.1648 ± 0.0184
Photonic RNN	Xavier	34.46 ± 1.78	0.0928 ± 0.0175
Photonic RNN	He	33.43 ± 0.87	0.0849 ± 0.0098
Photonic RNN	Proposed (Xav.)	41.21 ± 1.78	0.1635 ± 0.0216
Photonic RNN	Proposed (He)	**41.68 ± 2.73**	**0.1693 ± 0.0300**

EXPERIMENTAL RESULTS (HPCF DATASET)

Model	Initialization	Accuracy
MLP	Xavier	60.07%
LSTM	Xavier	75.46%
RNN (sigmoid)	Xavier	69.58%
Photonic RNN	Xavier	63.20%
Photonic RNN	He	57.29%
Photonic RNN	Proposed (Xavier)	73.03%
Photonic RNN	Proposed (He)	**73.63%**

CONCLUSIONS

- An **adaptive data-driven initialization approach** for recurrent **photonic neural networks** was proposed
- Can be directly used with any photonic activation function
- It takes into account the actual distribution of the data used to train the network
- Provides a solid approach for training DL models, that would be otherwise very difficult to train and would **require manually tuning the variance** for each layer or **analytically deriving the optimal layer-wise** initialization variance
- Sample implementation available at `https://github.com/passalis/adaptive_phos`

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