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Detection of elementary particles with the WiSARD n-tuple classifier

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Abstract. This work presents a weightless neural network model that learns multiple elementary particle collision phenomena. Having the ATLAS Higgs Boson Machine Learning Challenge as the target dataset, a couple of abstractions were developed in order to achieve a fast and simple algorithm that would otherwise require much more sophisticated tools. Experimental results over the Higgs Boson τ-τ decay and the B^+ meson decay shows that the WiSARD n-tuple classifier provide a generic and lightweight method for studying a broad range of particle decay modes.

1 Introduction

The distinction of high-energy particle collision events between signal and background is a real-time application in modern physics with an increasing agility demand. The most common computational models available for this class of problems may spend plenty of time on the training process [5], which makes it interesting to explore the speed of Weightless Neural Models[4] in this situation.

Particle physics arise as an important subject, mainly as a path to understand the very beginning of our universe. Also known as High-energy Physics, this research field is concerned about understanding the behaviour inherent to the elementary entities that constitute matter and radiation. In this context, scientists from all around the world meet at the *European Organisation for Nuclear Research* (*CERN*), where most of the experiments take place.

A single glimpse on the data retrieved by *CERN*'s detectors provides a handful of information to deal with. For instance, during the lapse of a second inside the particle accelerator, about 600 million events take place inside *ATLAS* experiment, generating approximately 600 TB of raw data, considering that each event accounts for 1 megabyte[10].

What happens, in fact, is that most of the events observed by the detectors are not interesting to the goals of a specific experiment, thus much of the information collected must be filtered as soon as possible in order to handle mostly relevant data for a more tactful analysis. As having huge amounts of information is, at the same time, the bless and the curse, this work introduces the application of a weightless neural network model as an agile approach to tell

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signal from background when learning from and classifying multiple inputs read from *CERN*'s experimental machinery.

1.1 WiSARD

WiSARD (**Wi**lkie, **S**toneham & **A**leksander **R**ecognition **D**evice) is a weightless neural network model based on Bledsoe and Browning's *n-tuple classifier* [1]. WiSARD is well-know for it's fast operation (training and inference) and straightforward hardware implementation. Weightless neural network models have been around for six decades now, and its early applications were usually found within the computer vision context[2]. Despite that, interesting and successful applications can now be found in many other areas, such as in finance[12] and linguistics[13].

The classification process basically consists on writing in *RAM* units during the training phase, and then reading their contents to know which group of memories (discriminator) is the most familiar with the pattern presented, thus telling which class the input belongs to. For greater detail, each *RAM* unit is addressed by a given number of bits, randomly mapped from the binary input pattern in sight. This mapping is defined before the training phase, and remains the same while the system is being used either for training or classifying data.

In order to recognise a pattern, the system counts how many RAMs are *activated*, i.e., contain at least a 'one' written in the accessed address, at each discriminator. The discriminator that holds the greater number of RAMs activated is considered as the associated class. Like most Machine Learning algorithms, this one is also prone to the effects of *over-training*, because after many patterns presented, it is probable that most of the RAM addresses are likely to have been written.

In this context, there is a technique called **bleaching**[4][15], that consists into raising the RAM activation threshold whenever two classes gather similar scores, which is basically a tiebreaker. The *confidence rate* γ should be defined in order to know when to use the *bleaching* process, which is disable by default. Basically, given that the winning class has r_1 RAMs activated and the second has r_2, another classification round takes place every time the inequality $1-\frac{r_2}{r_1} < \gamma$ is satisfied. What happens this time is that RAM addresses with too few accesses are not taken into account.

2 Detecting elementary particles

The raw data collected by the detectors is usually turned into a synthetic form before algorithms start distinguishing its samples. Its attributes may account for the mass of the particles and also measures on their trajectory. This kind of study often rely on datasets with a few hundred thousands of events which, in fact, doesn't even correspond to a whole second under the collision beam.

There are many datasets available with similar goals that keep being released by the *CERN* as more studies are developed. One of these releases contains

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observations from the B^+ meson decay at the *LHCb* experiment[3]. It displays a very similar set of attributes in comparison with the Higgs Boson contest from *ATLAS*.

In both cases, the main struggle with the weightless neural approach comes from the discrete nature of the algorithm in contrast with the continuous profile of the observations. At this point, there is a representation problem, which can be tackled by many different encoding strategies[9]. With this in mind, the **thermometer** concept will be briefly introduced: As the name speaks for itself, this method consists in filling with 1's a vector initialised with 0's, in a manner that is proportional to the input received. For simplicity, we shall consider that the input lies on the interval $[0, 1]$. To achieve this condition, one could choose to build the thermometer input by looking at the sample and normalise the data by its linear placement between the minimum and maximum records on X.

This, in fact, is not a good idea since the training sample might not be as wide as the validation one. Also, it is known that most attributes follow (usually non-symmetric) bell-shaped distributions. With this fact in mind, it would be the next step to encode the input after evaluating it through some sort of non-linear function $f(x; \lambda)$ whose parameters λ are defined based on the characteristics of the sample.

The most straightforward fashion to achieve this is by choosing f to be a *probability density function* (PDF) or a *cumulative distribution function* (CDF). It's important to notice that when looking at a CDF one can say that its non-decreasing feature is a clear advantage while encoding a given pattern.

In general, Φ_k is given directly by the choice of the function f_k, e.g. if we choose $f_k = e^{-\frac{(x-\mu)^2}{2\sigma^2}}$, the normal distribution PDF, we should have the sample mean and variance as usual and thus, $\lambda_k = (\mu, \sigma^2)$. If we had chosen the CDF of the normal distribution instead, we would still have the same Φ_k and the same λ_k.

As the presented procedure suggests, choosing f_k to correctly describe the behaviour of the event variables is not as important as finding well-suited approximations whose complexity is lower and computation is faster. To exemplify this statement, consider the *Crystal Ball Distribution*[8]. This function is very important since it is used very often to represent many different lossy processes within High-Energy Physics. It is, in fact, complicated to express and compute its values, and speed is one of our main concerns. Thankfully, Das (2016), built a simpler approximation: The *GaussExp*[11]. Approximations like these are of great help. We can go further and use a few other very simple distributions like Maxwell-Boltzmann.

3 Experimental results

3.1 AMS score

The main measurement of model efficiency used during the *ATLAS* contest was called **AMS**[7], given by:

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Setup:

For each attribute k, let $\lambda_k \in \Lambda$ be the associated statistical parameters. Choose $f_k(x;\lambda_k)$ such that $f_k : X \subseteq \mathbb{R} \times \Lambda \to [0,1]$ and $m_k \in \mathbb{N}$, the number of thermometer bits to represent the attribute k. Choose also the corresponding $\varPhi_k$, in order to initialize each $\lambda_k \leftarrow \varPhi_k(X)$.

Training:

$$\begin{tikzcd}
\boxed{\text{input } \vec{\mathbf{x}}, \omega} \arrow[r] & \boxed{\text{evaluate } \vec{\mathbf{z}} \leftarrow \vec{\mathbf{f}}(\vec{\mathbf{x}}; \vec{\lambda})} \arrow[r] & \boxed{\text{evaluate } \mathbf{T} \leftarrow T_{\vec{\mathbf{m}}}(\vec{\mathbf{z}})} \arrow[d] \\
 & & \boxed{\text{WiSARD}[\omega] \leftarrow \mathbf{T}}
\end{tikzcd}$$

Classifying & Validation:

$$\begin{tikzcd}
\boxed{\text{input } \vec{\mathbf{x}}, \omega} \arrow[r] & \boxed{\text{evaluate } \vec{\mathbf{z}} \leftarrow \vec{\mathbf{f}}(\vec{\mathbf{x}}; \vec{\lambda})} \arrow[r] & \boxed{\text{evaluate } \mathbf{T} \leftarrow T_{\vec{\mathbf{m}}}(\vec{\mathbf{z}})} \arrow[d] \\
 & & \boxed{\text{WiSARD}(\mathbf{T}) == \omega \text{ ?}}
\end{tikzcd}$$

Fig. 1: The Experiment Pipeline

$$\text{AMS}^2 = 2\left((s+b+b_r)\log\left(1+\frac{s}{b+b_r}\right) - s\right)$$

where s and b stand for true signal and false signal respectively. $b_r = 10$ is a regularisation constant. This was the most relevant score for validation and comparison purposes within the *Higgs Boson* Challenge context.

3.2 Results analysis and discussion

After defining the whole model operation and its metrics, the respective experiments were made and it's results are as shown on table 1. Accuracy and, of course, the AMS were taken into consideration, as long as the time elapsed in the process.

One will notice that its performance is not actually comparable to the winners of the Kaggle Challenge. Although, further development and tuning of the model may lead to a great advantage due to its much faster computer time. It is expected, from this approach, to play a significant role in sweeping through the multiple particle decay scenarios instead of diving deeper into a specific one or just a few.

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Table 1: Higgs Boson τ-τ decay

Model	WiSARD	WiSARD	WiSARD	NN Ensemble[6]
RAM address bits	[60 bits]	[42 bits]	[60 bits]	-
Function	Gaussian	Many†	Linear	-
Accuracy	0.82	0.81	0.67	-
AMS	2.75	2.77	1.21	3.78
Time Elapsed	97.46s	47.68s	63.62s	3h20m*
$\hookrightarrow$ Training	36.02s	22.83s	31.72s	3h
$\hookrightarrow$ Classifying	61.44s	24.85s	31.90s	20m

† - Every attribute had its own function, in contrast with the *Gaussian* and *Linear* approaches.
$\star$ - Time as measured by [6], in a machine with similar characteristics to the one used in this experiment.

Following this observation, the experiment was made in a similar fashion with the B^+ meson decay [3], for a self-comparison purpose. The emerging hypothesis was that the very same method could be useful for other related problems, since the "*blurred*", non-selective approach behaved much like its "*sharpened*" counterpart. Indeed, when the same technique was applied to another decay process, the behaviour seen before appeared once again, as presented on table 2.

Table 2: B^+ meson decay

Model	WiSARD	WiSARD	WiSARD
RAM address bits	[60 bits]	[42 bits]	[60 bits]
Function	Gaussian	Many	Linear
Accuracy	0.84	0.89	0.62
Time Elapsed	62.46s	31.79s	42.19s
$\hookrightarrow$ Training	22.14s	15.22s	21.03s
$\hookrightarrow$ Classifying	40.32s	16.57s	21.16s

This encourages us to think in a generalised approach, as refining the "*blurred*" forthcoming can lead to a solid sweeping method, to be designed for looking at the event's diversity resourcefully. Instead of being trained to recognise a single kind of phenomena, weightless systems are able to be trained multiple times effortlessly, temporarily specialising themselves as wanted, before looking at the next goal.

4 Conclusion

This paper presented WiSARD as a lightweight online learning system for big classification tasks. In the case under study, the Weightless approach did not

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perform as good as its weighted counterpart. However, as expected for Weightless Systems, WiSARD implementations got their job done much faster than the NN Ensemble. Since most of the data generated at particle detectors cannot be held long after gathering, it's fundamental to learn from it very quickly. An interesting follow up probably lies at a combined system with WiSARD and NN. The Weightless Neural Network could be used as a primary approach, even allowing a considerable rate of false positive events, and then the NN could work with greater precision at already filtered data. That said, further investigation is expected to better understand how to enhance WiSARD's performance with other techniques and also define its role in a major process, considering applications in other fields.

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