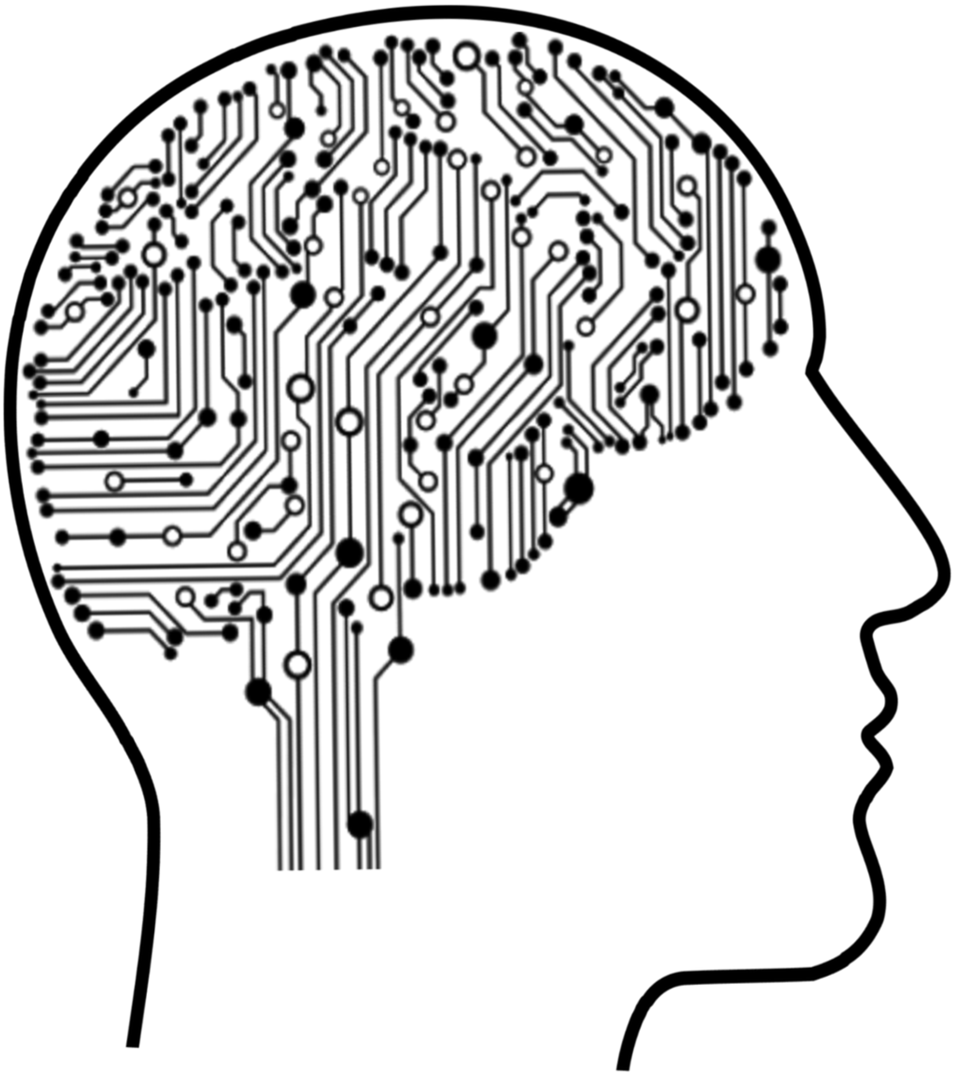

HBP Innovation Market Analysis Series

Recent Advancements on Deep Spiking Neural Networks algorithms and their implementation on neuromorphic chips: an emerging new market

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Abstract:	Advanced Spiking Neural Network (SNN) training algorithms are essential for the commercial exploitation of neuromorphic technologies. In fact, recent advancements in the area are already inspiring and paving the way of adaptive artificial intelligence. The purpose of this report is to serve as a bridge between scientists and non-expert readers in the field, demonstrate the potential of this research stream, and give a series of insights about the present state and future evolution of SNN and neuromorphic technologies. Towards this end, training methodologies of SNNs and related terminologies have been extensively reviewed. Advancements within and outside of the Human Brain Project are presented in the report, which also extracts and reflects on the required components for efficient, effective, and scalable SNN training. These components have been studied through patent analysis, which has helped to reveal trends and key actors within sectors. The potential of SNNs and neuromorphic technologies have been discussed from the perspective of what is, in fact, a new and incipient market. The results demonstrate that research and investment on SNN and related technologies are growing in parallel to the emergence and development of new and exciting industrial applications.
Keywords:	Spiking neural networks, Neuromorphic technologies, Learning algorithms, On-device edge training, Native spiking datasets
Target Users/Readers:	Non-experts interested in spiking neural networks; Investors interested in neuromorphic technologies; Experts looking for research and/or industrial actors in the field.

SUMMARY

1. Introduction

The investigation of the structure and functioning of neurons and synapses, together with the challenge to simulate the human brain electronically have given rise to an exciting and dynamic area of research and innovation: Spiking Neural Networks (SNNs)[1].

Bio-inspired SNNs came to the fore with their effective and efficient processing capabilities of spatiotemporal data. Although these special neural networks can be simulated in contemporary processors, their asynchronous nature has led to the development of special neuromorphic computer systems with non-von-Neumann architecture[2], which are able to process them much more efficiently (Durmaz, et al., 2020).

With the explosion of the artificial intelligence (AI) industry with AlexNet in 2010, artificial neural networks (ANN) entered again into the research and technology agendas worldwide (Krizhevsky, et al., 2017). The results of multiple studies and research have contributed to make AI a part of our daily life; however, and regardless how successful AI applications have become, it is still difficult to find solutions with effective self-learning capacities in the AI landscape. In addition, the ever-increasing volume of data, data-processing needs, and the large energy requested have motivated innovations in the area. The possibility that SNNs and neuromorphic chips could be the solution to effective self-learning capabilities and energy-efficiency, has provided an opportunity for mathematicians and computing scientists to try to bridge a gap between biological research and deep neural networks (DNN)[3] (Durmaz, et al., 2020).

SpiNNaker hardware architecture from the University of Manchester (Furber, et al., 2013), BrainScaleS from Heidelberg University (Schemmel, et al., 2017), and Neurogrid from Stanford (Benjamin, et al., 2014) proved the energy saving potential of spiking neuromorphic chips in DNNs and have led technology giants, like IBM and Intel, to focus on this area of research (Durmaz, et al., 2020). However, although neuromorphic chips have demonstrated their adaptation to DNN, they lack efficient inference and suitable training algorithms compliant with the spatiotemporal structure of the brain since the application of gradient backpropagation algorithms[4] are challenging to implement on neural structures (Neftci, et al., 2017). This lack restricts the application of neuromorphic hardware, preventing it from being scaled, and eliminates the competitive advantage they have over the currently utilised chips (Neftci, et al., 2017).

Within HBP, theorists Wolfgang Maass´ and Mihai Petrovici' studies (Bellec, et al., 2020) (Maas, 2020) (Scherr, et al., 2020) (Baumbach, et al., 2020) on SNN algorithms shed light on the mentioned problems and enabled practical connections between Biology and deep learning. The algorithms enable native gradient calculations with SNNs which improve efficiency of deep learning applications on neuromorphic chips and provide an

[1] Investigation on Spiking neurons as a computational unit started in 90s with biological experiment results which indicate most of the bio-neural systems use spike impulses. (Maass, 1997)

[2] Traditional von Neumann systems are multi-model systems consisting of three different units: processing unit, I/O unit, and storage unit. These modules communicate with each other through various logical units in a sequential way.

[3] DNNs are second generation artificial neural networks. The decision functions work among each visible and hidden layers of perceptron and create the structure called "deep neural networks" (Durmaz, et al., 2020)

[4] Gradient Backpropagation algorithms are the workhorse of Deep neural networks which optimize parameters of the model. (Machine Learning Glossary, 2017)

effective solution for on-device training with them. Moreover, they will certainly be useful to solve the problem of continual learning artificial intelligence.

The present report is inspired by the recent developments on deep SNNs and their potential impact on the AI domain. The objective is to serve as a bridge between scientists and non-expert readers in the area, demonstrate the potential of this research stream, and define the position of SNNs within the AI market. Hopefully, the report may help HBP researchers in the exploitation of their results by defining their roadmap to the markets, or to assess the possibilities of using current and near-future products on their own research.

In the next section, common methodologies of training SNNs are explained, and the advantages of the new algorithms are pointed out. In section 3, advancements within and outside of the Human Brain Project are presented and the required components for efficient, effective, and scalable SNN training are identified. Section 4 presents a trend analysis of these components. Finally, in the section 5 edge, online-training application areas are revisited and current actors in the field are analysed.

Software Tools such as Pytorch and Tensorflow play an important role on attracting developers.

2. SNN Learning Algorithms

The relevance and interest of DNNs rely on their deep layer structures and their backpropagation, which is the calculation method to assess the gradient of the loss function[5]. Although gradient calculations on these deep networks are time consuming and prone to error, automatic differentiation[6] (AD) tools such as Pytorch, Tensorflow, which have been developed in the last five years, made this work very simple (Wu, et al., 2019). SNNs were not able, however, to make use of these tools, because they are not differentiable, and consequently SNNs scientists had to search for other different learning algorithms.

SNN learning algorithms can be generally examined under three categories. The first one is those based on the Spike Time Dependent Plasticity[7] (STDP) Hebbian learning mechanisms (Figure 1), separated into two branches; "STDP Learning" & "Stochastic STDP[8]", the second one is the conversion of existing deep learning networks to spiking networks (Figure 1, "ANN-SNN Conversion"), and the third one is to backpropagation of spiking networks with approximate gradients[9] (Figure 1, "Backpropagation").

Direct SNN backpropagation algorithms promise solution for scalability of deep SNN.

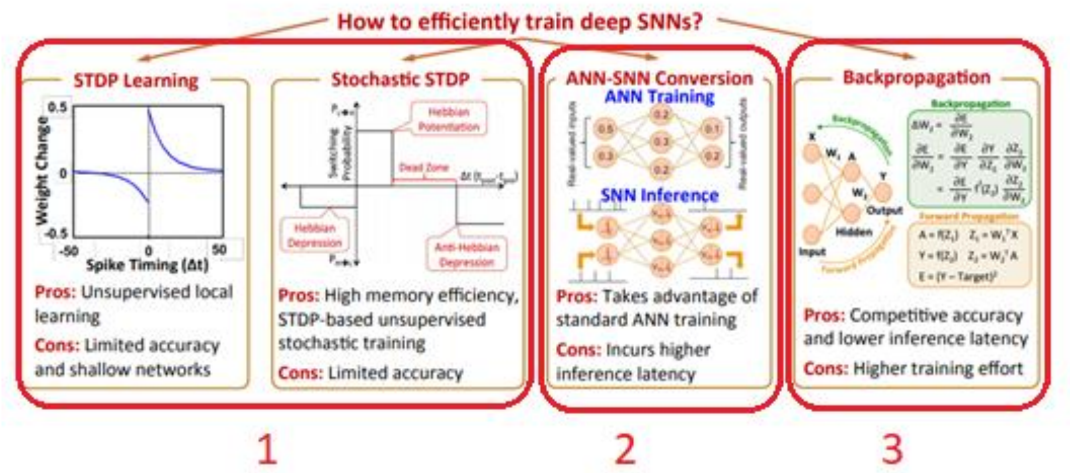

Figure 1 Comparison among SNN training methods (Srinivasan, et al., 2020)

[5] Calculating Gradient descent is the primary method for optimizing the performance of a neural network, i.e. reducing the network's loss/error rate. (Nelson, 2020)

[6] Automatic differentiation is a standard algorithm used to efficiently compute gradients of loss functions in generic neural networks (Guo & Poletti, 2021)

[7] STDP rule: If postsynaptic neuron fires after presynaptic activity the weight connecting them is strengthened (long term potentiation). On the other hand, If the presynaptic neuron fires after the postsynaptic activity, then the weight is weakened (long term depression). (Tavanaei, et al., 2019) It is based on the Canadian Neuropsychologist Donald Hebb's rule of learning. "*In a sense, then, cells that fire together wire together*" (Zheng & Mazumder, 2020)

[8] Stochastic STDP contributes by encoding the probability of switching from one state to another for the binary synaptic weights. Using this low-level precision instead of bit-precision (classical STPD) increases the efficiency of memory. (Srinivasan, et al., 2020)

[9] Gradient approximation algorithms can obtain differentiable spike activities, thus, enables backpropagation on spiking neural networks. (Hao, et al., 2020)

Algorithms based on STDP are the most biologically plausible methods among these categories[10]. However, discovery of the learning mechanism of the brain is a complex and long-term research endeavour. In addition, these algorithms, although efficient, are not scalable[11], and they are restricted with shallow networks which limits their accuracy. Consequently, STPD is not a preferred method for real-world applications.

Conversion-based methods are based on the transformation of the real-valued computing into spike-based computing. The ANNs are first trained and then mapped into SNNs. These methodologies are not native SNN learning and do not inherit from the STDP rule (Hao, et al., 2020). The purpose of these methods is to enable the use of deep learning mechanisms on neuromorphic chips thus benefiting from energy efficiency. However, they cannot achieve the required levels of performance as it is a process based on the time interval (Kugele, et al., 2020) (Figure 2). The time interval needs to be shortened to decrease latency, but this makes the incoming spikes difficult to be counted and thereby the accuracy of the method decreases compared to deep learning. If the time interval is extended to increase the accuracy, the energy-saving potential will be wasted as there will be latency. These methods work efficiently in small scale systems, but as far as the network scales up to the industrial-scale applications, they lose their advantages over deep learning methodologies since the required latency to reach accuracy level of DNNs cannot compensate the energy cost[12]. (Panda, et al., 2020).

The third algorithm method is based on the direct backpropagation of SNNs. The existence of backpropagation-like learning structure of the brain has been discussed for a long time (Lillicrap & Santoro, 2019). Sander Bohte developed the SpikeProp algorithm in 2000, which is one of the first steps in this strand of research (Zhou, et al., 2019). However, these networks could not scale and are restricted by shallow layers and their learning performance does not meet the requirements of real-world applications since it is far from the efficiency of the biological counterparts and computationally expensive (Xie, et al., 2016). This obstacle explains why attempts to merge deep learning and bio-inspired studies have been stuck until recently.

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[10] STDP learning rule experimentally observed in the rat's hippocampal glutamatergic synapses (Chakraborty, et al., 2019)

[11] At the time, The STDP algorithms is limited with <=4 layers, resulting in significantly lower state-of-art accuracy. Adding more layers deteriorates the accuracy. (Srinivasan, et al., 2020)

[12] It is worth to note that, the research on conversion methods is still on demand as these methods can benefit from state of art DNN algorithms. Another research of Wolfgang Maass (Stockl & Maass, 2020) is promising to find solution for the accuracy & energy-efficiency dilemma of conversion methods.

The development of deep learning methods, especially the recurrent network structures that can process spatiotemporal data and their ability to be backpropagated over time, attracted the attention of theorists to research on gradient based SNN backpropagation algorithms, again in 2016 (Lee, et al., 2018). At the same time, developments in biology and the discovery of different neuron structures that play a role in learning mechanism were an opportunity to reunite these two fields.

One of the most promising developments is the e-prop algorithm created by Wolfgang Maass and his team.

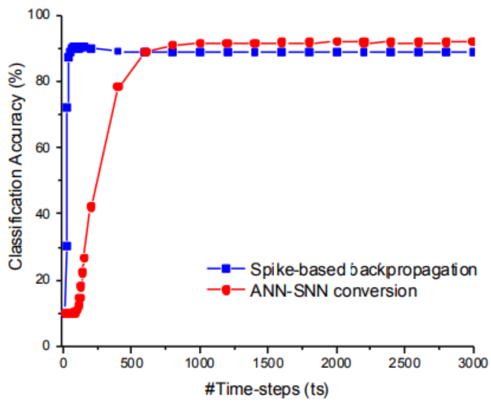

Figure 2 Spike based backpropagation requires lesser time-steps to reach top accuracy on CIFAR10 (Srinivasan, et al., 2020)

Gradient approximation algorithms contribute to SNNs with deeper layers, enable the implementation of deep learning methods on them, and have even the potential to be a solution to concepts that deep-learning cannot yet achieve (Bellec, et al., 2020) (Neftci, et al., 2019) (Wu, et al., 2018). One of the most promising developments is the e-prop algorithm (Bellec, et al., 2020) created by Wolfgang Maass and his team. In the last year, they enabled SNNs to learn directly supervised[13] and with reinforcement[14], combining biological STDP rule with gradient based methods, and most importantly, they offered a feasible online-learning[15] solution (Bohnstingl, et al., 2020). This not only facilitates its implementation on neuromorphic chips but also contributes to enhance the development of deep learning.

[13] *Supervised learning* means having a full set of labelled data while training an algorithm. (Salian, 2018)

[14] *Reinforcement Learning*, AI agents are attempting to find the optimal way to accomplish a particular goal or improve performance on a specific task through rewards and punishment. (Salian, 2018)

[15] *Offline learning* (Batch) is an approach that ingests all the data at one time to build a model, whereas *Online learning (Batchsize=1)* is an approach that ingests data one single observation at a time. (Ziganto, 2017)

3. Advancements within & outside HBP

Training of DNN models is mostly handled in the cloud data-centers

In this section, the advancements within and outside of the HBP are investigated to determine the short-term potential of the deep SNNs in the industry and to extract the required components to support the training of the deep SNNs. Training hardware and the dataset types directly influence the performance and the scalability of the SNNs. Therefore, developments and expectations among these two components are focused.

3.1 Training of SNNs

Every artificial intelligence model needs training to be used. During the training phase the model learns from the raw data and updates its parameters by comparing with the expected outcomes. The trained model is ready-for use to make prediction according to its use-case, and this phase is called inference (Figure 3).

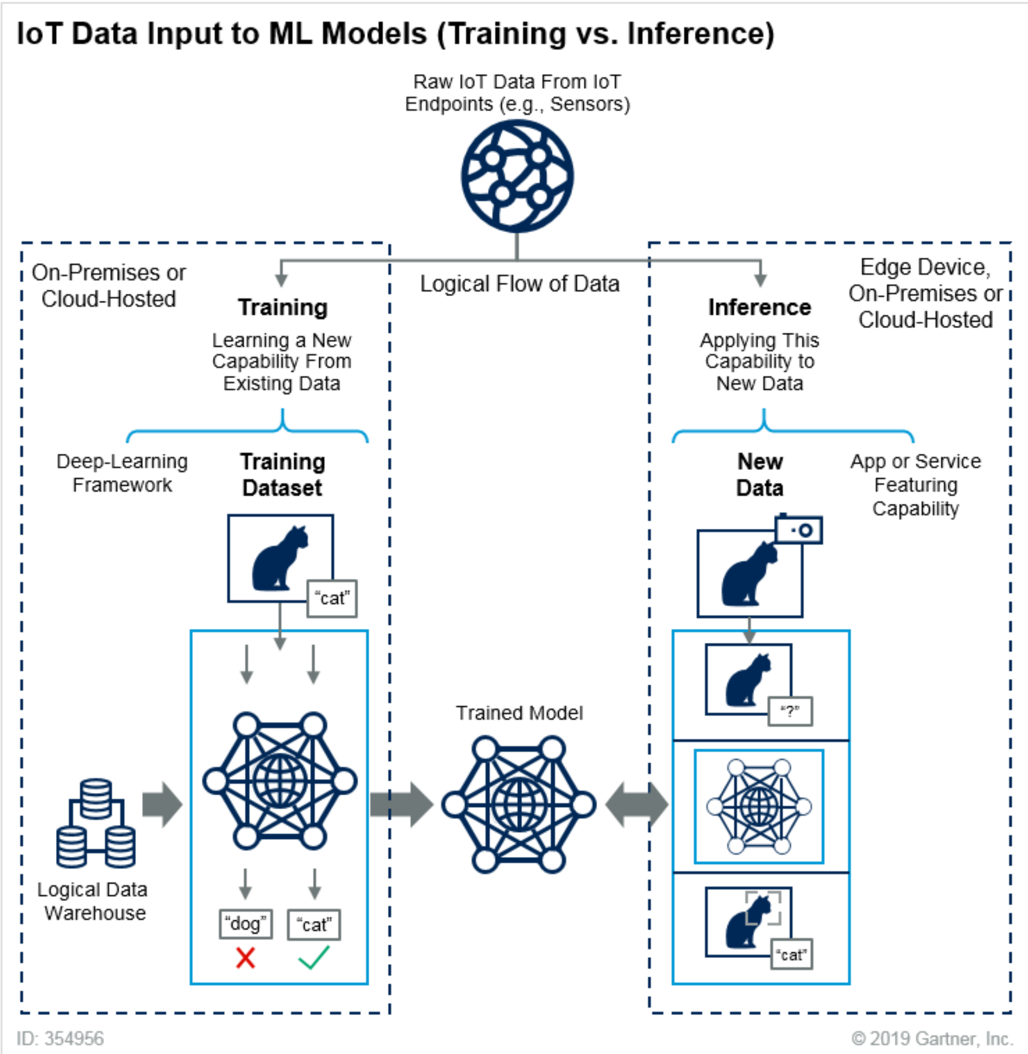

Figure 3 Training Phase (on the left) and Inference (on the right) (DeBeasi, 2019)

Training algorithms and hardware of the neural networks, determines the overall energy efficiency, scalability, and inference accuracy of the systems; therefore, the hardware to be used for SNN training, and the relevant developments are discussed.

3.1.1 Offline (Batch) Training

In situations where entire dataset is available, training is generally applied, in batches (offline), to the independent and identically distributed (i.i.d.)[16] datasets. The whole training dataset is presented, and their parameters are then processed (Figure 4).

Figure 4 Entire dataset is required to train the model (Förster, 2014)

The parallel structure of the Graphic Processing Unit (GPU) or customised AI accelerators are suitable for this process, and batch-training is carried out quickly through data-centers (Figure 5). As, new data becomes available, the model is re-trained from scratch by including new dataset to the previously trained ones.

Figure 5 Traditional training and inference model (NVIDIA, 2020)

Training industry-scale networks on Neuromorphic chips takes a lot of time due to their online characteristics (Stewart, et al., 2020). Therefore, Offline training maintains its importance to demonstrate the SNN inference capacity on neuromorphic chips. To speed up the process, the models are trained with simulators running on GPUs which accelerate operations with high batches and AD tools. Then, these ready-to-use models are mapped on the neuromorphic chips for inference. This

[16] A sequence of random variables is independent and identically distributed (i.i.d.) when each element of the sequence has the same probability distribution as the other values, and all values are mutually independent. (NIST, 2018)

Schemmel and his team trained spike-based backpropagation with hardware in a loop way in BrainScaleS.

mapping - from the simulator to hardware - can yet cause a reduction in accuracy because of the structural difference. To solve this issue, Schemmel and his team collaborated with Friedemann Zenke (as voucher) trained spike-based backpropagation with hardware in a loop way in HBP supported BrainScales and managed to minimize the differences in accuracy level (Figure 6) (Cramer, et al., 2020). Sequentially, they have developed a framework for in the loop training which maintains sparse spiking activity to exploit a superior power efficiency. (Cramer, et al., 2021). Heidelberg University is also cooperating with Dr. Mihai Petrovici from HBP (work package 3) and Intel Neuromorphic Research for spiking gradient-based algorithm solutions (Baumbach, et al., 2020). Complementarily, the Heidelberg group has developed an extension for the PyTorch called "hxtorch" (Spilger, et al., 2020). This extension enables BrainScaleS to benefit from the automatic calculation feature of the AD tools in both spiking and non-spiking operations. The combination of learning methodologies, AD tools and hardware in loop training accelerates the transition period of on chip training on neuromorphic devices. Likewise, the AI accelerators have been incorporated in the SpiNNaker 2 architecture (Furber & Bogdan, 2020), which represents a significant contribution to training.

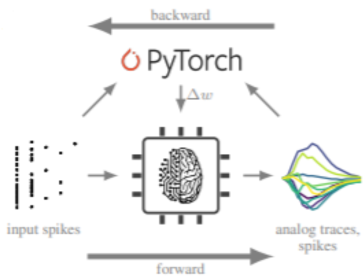

Figure 6 BrainScaleS 2- Hardware in the loop training enables to use AD Tools (Cramer, et al., 2020)

Zheng' study reached the layer size of 34 with the accuracy level of 67.05% on ImageNet dataset which is competitive in the edge computer vision field.

Another issue with the backpropagation of deep SNNs is that they inherit vanishing and exploding gradient problems, thus limiting the scalability of networks with 10 layers (Zheng, et al., 2020). More layers are required to compete with DNNs in terms of accuracy (Zheng, et al., 2020). Recently, a couple of studies have managed to increase the layer size through optimization algorithms (Zheng, et al., 2020) (Zhou, et al., 2019). Zheng' study reached the layer size of 34 with the accuracy level of 67.05% on ImageNet dataset which is competitive in the edge computer vision field. Besides the algorithms, the AI accelerator Cerebras-CS1, influenced by the wafer-scale BrainScaleS architecture, promises to have a capacity of industry-scale SNN training (Vassilieva, 2020). This will allow the rapidly trained models to be transferred to neuromorphic chips.

3.1.2 Online Training

In situations where data are not i.i.d. and flow continuously in time, online learning is needed. The model updates itself as new data arrives (Figure

7). These situations include environments with quickly and unexpected changes, areas requiring personalization, or environments where data security is important (Žliobaitė, et al., 2015). The system should adapt itself to environment changes. However, non-i.i.d. data can eventually be the cause of a catastrophic forgetting[17] (Stewart, et al., 2020).

Online learning

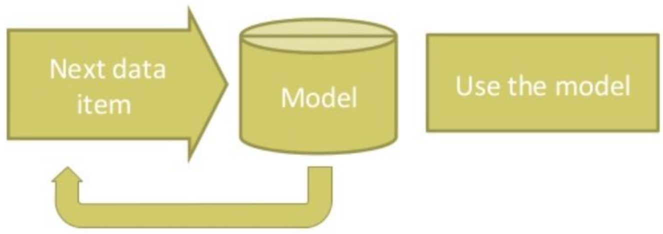

Figure 7 The model updates as new data arrives (Förster, 2014)

e-prop provides feasible on-chip online training solution for neuromorphic chips, as it calculates the loss function in forward in time.

Recent algorithms e-prop (Bellec, et al., 2020) and DECOLLE (Kaiser, et al., 2020) enable online training, as they calculate the loss function in forward mode and mitigate catastrophic forgetting risks (Zenke & Neftci, 2020). Recent studies present a memory-efficient solution for multi-layer recurrent networks, which cannot be achieved even in DNNs yet (Bohnstingl, et al., 2020) (Kaiser, et al., 2020).

Forward mode online training is a promising advance for the future of deep SNNs. However, high-scale datasets can take days for training with state-of-art neuromorphic chips. It seems that emerging memory technologies could theoretically solve this problem (Chen, et al., 2020) (Payvand, et al., 2020). Promisingly, research findings on simulations demonstrate the continuous online training capability and energy-efficiency of neuromorphic chips with memristors since the required vector-matrix calculations are handled on these memory architectures. (Payvand, et al., 2020).

Although there are remarkable improvements in this area, it is unlikely that such a chip will be available within five years because emerging memory technologies are still in early research phase and are expected to be in markets only after 2025 (Offrein, 2020). For this reason, online transfer-learning techniques such as meta-learning or federated-learning, that allow online training (Stewart & Gu, 2020) of pre-trained models for certain application purposes, are more appropriate approaches nowadays.

With the new algorithms, SNNs can manage the online meta-learning.

[17] Catastrophic forgetting: the model loses already learned tasks as new data arrives (Stewart, et al., 2020).

3.1.3 Online Meta-Learning

Meta-learning (learning-to-learn) is another approach to mitigate catastrophic forgetting problems and manages training from a few training samples (Beaulieu, et al., 2020). Meta-learning is a technique where the agents are learning to learn from past experiences. Instead of training from the scratch, the new task is learned with few samples from the previously available tasks (Finn, 2017). One of the most famous meta-learning models is the Model-Agnostic Meta-Learning (MAML) which allows a rapid adaptation of a new task (Figure 8) (Finn, et al., 2017) (Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks).

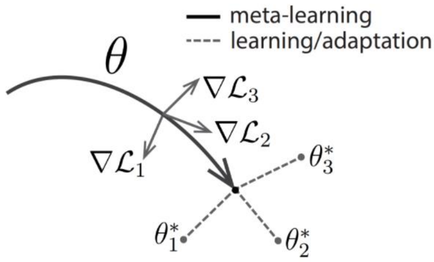

Figure 8 Meta-Learning Adaptation (Finn, et al., 2017)

In situations where rapidly changing factors exist and unexpected data streams are the norm, learning a new model on a short-time scale is impractical. Meta-learning is then a good alternative for adapting new required tasks. Especially, online meta-learning can be a good solution on intelligent systems that are functioning in real-time (Nagabandi, et al., 2018).

With the new algorithms, SNNs can manage the online meta-learning, and some applications have been presented during 2020. One of these applications is learning new gestures with few samples (Stewart, et al., 2020). Another one is an adaptation of the robotic arm to manage desired behaviour with learning from one trial. Other application is learning a new class of characters from a single example (Maas, 2020).

These applications are very relevant as they demonstrate the competitiveness of the SNNs compared to their counterparts. Moreover, online meta-learning has already been implemented on neuromorphic chips which contribute to the applicability of on-chip learning.

. Recent work has combined federated learning with online-meta learning and managed to show the distributed gesture learning capabilities of SNNs implemented on the Loihi neuromorphic chip.

3.1.4 Federated Learning

Federated Learning is an alternative method to centralized training, as it distributes learning among clients (Figure 9). A main concern of federated learning is to keep the privacy of the local data. Instead of sharing the dataset with the data-center, each client runs the learning algorithm in a distributed way and upload the models to the data-center; these collected models are then synchronized to generate a common model (Stewart & Gu, 2020).

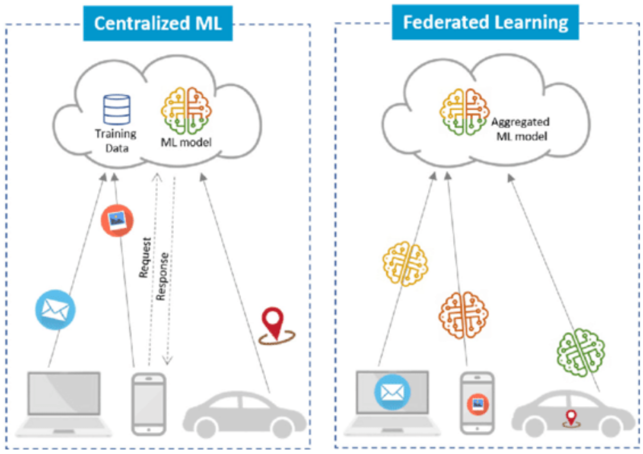

Figure 9 Centralised ML vs Federated Learning (Rahman, et al., 2020)

As this approach distributes the learning share among the edge devices, and on-chip training with neuromorphic hardware takes a lot of time, it can be a short-term solution to speed-up the on-chip training of neuromorphic hardware. The small models can be trained by using each client's neuromorphic chip with the data gathered through a relevant edge device, and a generic complex model can be created by merging these models.

Recent work has combined federated learning with online-meta learning and managed to show the distributed gesture learning capabilities of SNNs implemented on Intel's Loihi neuromorphic chip (Stewart & Gu, 2020).

3.2 Training Datasets

Direct SNN backpropagation algorithms enhance the capacity of SNNs to process temporal data. Temporal data are continuous dynamics signals like sound, radar, electrocardiograms, etc., or native spike data from event sensors. However, although SNNs are best known for processing dynamic data due to their recurrent structure, processing static data is also important, e.g. most of today's inferences are based on spatial data. Most of the SNN studies are therefore also considering static data in their experiments (Lecun, 2019).

3.2.1 Static datasets

Applications in this field provide output from static inputs such as images. They need high volumes of data, software tools, and large-scale data centers for their effective training (Lecun, 2019). Datasets and tools are optimized for ANNs and do not work with temporal factors, hence they are not suitable for native SNNs. SNNs have therefore lower accuracy than ANNs in the static dataset domain. However, the low-energy and fast processing capacity of SNNs, combined with neuromorphic hardware, are promising trade-off factors.

SNNs demonstrate better performance on temporal datasets like signals compared to static ones like images.

SNNs do not have yet sufficient native datasets, neither mature tools nor systems that can operate with static datasets on a large scale (Kugele, et al., 2020) since the native datasets requires neuromorphic sensors such as event-based cameras which are just emerging, and the common visual sensors are based on the static image data. Distribution and widespread of usage of event-based sensors is necessary for developing advanced native datasets. In this respect, we will describe a couple of solutions that have recently emerged.

One solution converts static data into spikes (Figure 10) (Deng, et al., 2020). Although practices in this area are very recent, a lot of work has been done during the last year. Energy efficiency in edge devices has been achieved by compromising accuracy at an acceptable rate (Sorbaro, et al., 2020). Recent papers demonstrate the possibility of processing ImageNet with a 50-layer deep SNN model, which is the deep required for higher accuracy. The MobileNet benchmark, which Intel's Mike Davies deems necessary for edge applications, has also achieved energy-efficient with this solution, as Brainchip Akida claims (Carlson, 2020) (Posey, 2020).

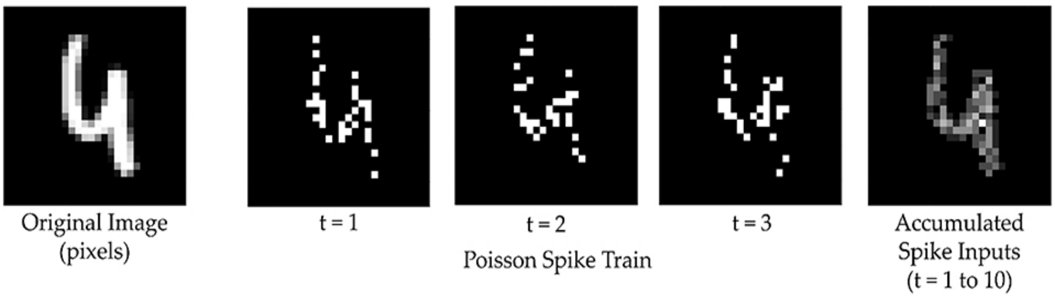

Figure 10 Conversion of Static Image to Event by incorporating time domain.

Another approach is the separation of the spatial and temporal processes within the hardware. Chinese researchers applied this solution to the Tianjic hybrid chip. Luping Shi and his collegues at Tsinghua University processed the object recognition & detection applications with GPUs, and the voice recognition and detection process with the neuromorphic chip on the smart bike they controlled with the Tianjic chip (Figure 11). This successful combination allows the system to benefit from the powerful features of both SNN and neuromorphic chips. It provides a framework for SNNs development, while addressing the successful applications of Convolutional Neural Networks (CNNs) (Zou, et al., 2020).

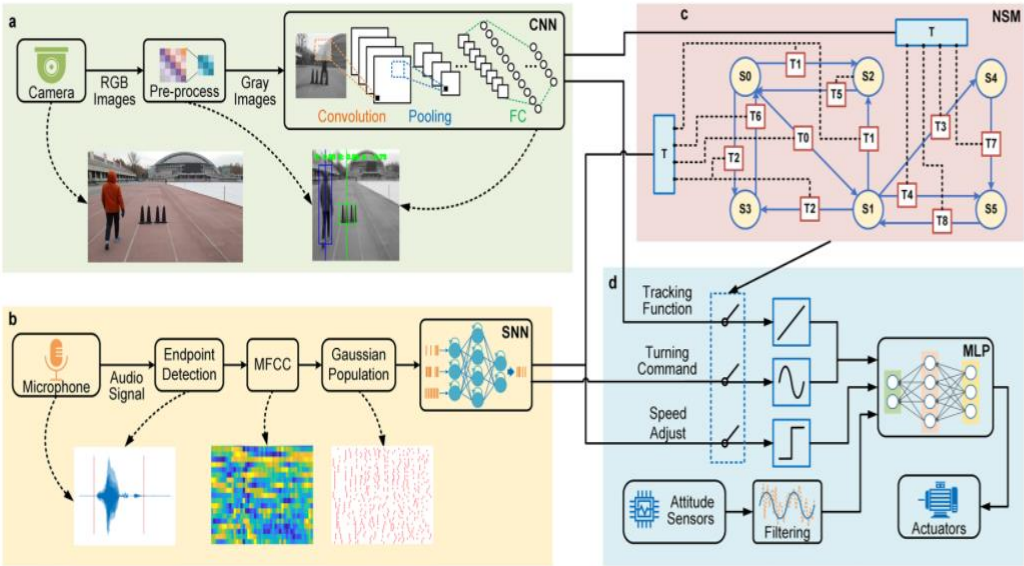

Figure 11 Autonomous Bicycle Controlled with Tianjic Chip. a) Visual sensors are controlled with CNN b) auditory sensors with SNN (Zou, et al., 2020)

Within HBP, the credit-card-size, edge-scale chip of Heidelberg University (Stradmann, et al., 2021) supports both spiking and conventional deep neural networks, thus gaining benefits from both domains. The architecture of the chip is based on the BrainScaleS-2 analog neuromorphic chip. Its analog structure enables the acceleration of the processes and reduces energy consumption since it reduces required calculations. As a result, BrainScaleS-2 helps to efficiently process the static visual data and support the current processing needs of the sensor data. Most importantly, portable BrainScaleS-2 supports the evolving event-based sensors by emulating spiking neural networks.

3.2.2 Native Spiking Datasets (Event-Based Cameras)

Native datasets are event based and contain time domain. One common approach is to create native neuromorphic datasets based on static data (Figure 12). The static datasets are scanned with event-based sensors which incorporate temporal information to process them natively on SNNs. This conversion dataset is a new area of research. In fact, not only visual ones are under development but also audio datasets.

Event-based cameras and sensors are one of the most promising areas for deep SNNs.

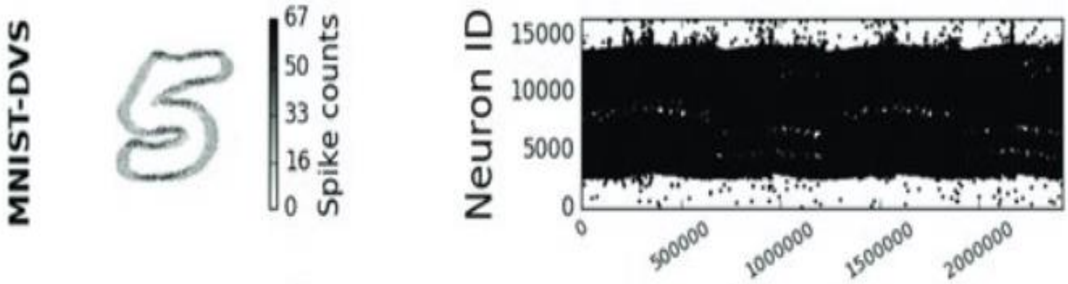

Figure 12 MNIST-DVS neuromorphic dataset, MNIST data-set is recorded with event-camera (on the left) from different angles and its representation on spike train by neuron id through time(on the right) (Stromatias, et al., 2017)

Event-based cameras and sensors are one of the most promising areas for deep SNNs. Event-cameras transmit the data continuously over time, and SNNs are fully compatible to process those temporal data. These cameras perceive changes in the environment, capture a lot of detail, and consume a very low amount of energy because of the lower volume of data input. Since most of the simultaneous localization and mapping (SLAM) applications are performed quickly, they have a usage area in every environment where sudden changes happen, e.g. Robotics, drones, autonomous vehicles, and sky observation, etc. Fast object-tracking has recently attracted attention in augmented reality, and eye-tracking. Controller tracking applications have also been developed in this area.

Until now, due to algorithm deficiencies, the processing of event data is preferably controlled with conventional processors. However, it implies to convert inputs from event-cameras into digital. Neuromorphic chips are already fed by events, so such a conversion is not necessary and both processing speed and energy efficiency are therefore available.

Last year, studies in this area have begun to implement SNN backpropagation algorithms. They aim to perform better than ANNs so that they could eventually become the best option as a control mechanism. Promisingly, state-of-the-art levels of accuracy has been also achieved this year on event-based datasets with direct backpropagation of SNNs (Zheng, et al., 2020).

Within HBP, University of Heidelberg has developed two native spiking datasets for speech classification and keyword spotting (Cramer, et al., 2020). These datasets are based on the *Heidelberg Digits* which is consist of 10K high-quality audio recordings from zero to nine, and *Speech Commands* which consist of 24 single word command from 1864 speakers. Combined with the native visual ones, Heidelberg's two audio datasets provide a generic benchmarking tool for neuromorphic community.

In the short term, application of deep SNNs will be mainly in the edge area.

3.3 Remarks

In the short term, application of deep SNNs will be mainly in the edge area, providing that required accuracy levels and energy requirements are achieved. Combination of neuromorphic chips and SNNs is especially promising for the processing of event-based data. The expansion of event-based sensors will be surely a relevant factor for this success. Also, with the development of algorithms, signal data and even static data (with conversion) can reach the desired level of accuracy for industry-scale applications at the edge area of application. Finally, advances on memory technologies (memristors, Re-Rams, C-Ram, Fe-Ram, etc.) are needed to fulfil successful on-chip training. The trend analysis developed below will examine the status of SNN algorithms, event-cameras, and emerging memory solutions.

4. Trend Analysis

The trend analyses described in this section are based on patents and academic journals insights. The factors analysed, namely SNN algorithms, event-cameras & sensors, and emerging memory technologies, will certainly contribute to foster the utilisation of SNNs and neuromorphic hardware in the edge market.

4.1 SNN Algorithms

If present interest and attention from enterprises and key actors continue, its popularity in industry will gradually increase and only then we will be able to affirm that SNN algorithms can reach a good position in the markets.

Backpropagation-based algorithms is a key factor of deep SNNs. Our trend analysis began by observing the progress of research papers publications in the area during the last decade.

As it can be extrapolated from the correlated results of published articles (figure 13) and patent applications (figure 14) through time, together with the success of the Deep learning methods, SNN with backpropagation studies started in 2012. Unfortunately, no promising results were obtained and the interest on it decreased. The second rise started with the launch of the IBM TrueNorth in 2014. The main reason for that rise could be the IBM interest to promote that its neuromorphic chip. However, research on SNN algorithms stepped back again in 2015. With the release of the Loihi, the wave caused by Intel can be seen in 2017. The studies during this period were non-novel conversion methods. With the emergence of direct backpropagation SNN algorithms, the rise can be seen again in 2019. A second peak is achieved then on backpropagation based SNN studies, and they have managed to still maintain the interest of researchers during the last year. The reflect of this interest has a similar pattern in the markets as can be seen in the patent search in the Figure 14, and the recent increase of the patent application is also observed. As it is too soon to comment on the rise, the evolution should have been observed in upcoming years to have a more concrete idea of this new wave.

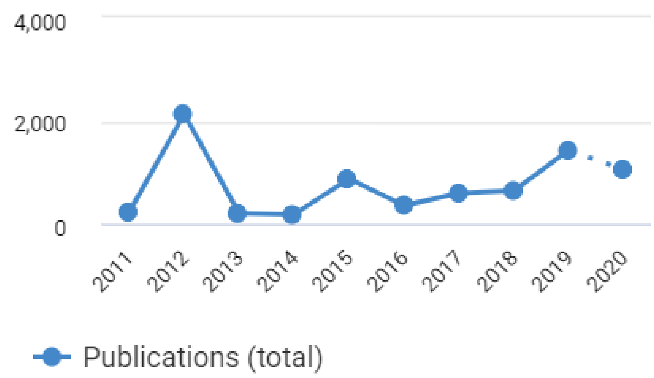

Figure 13. Academic publications over time, SNN backpropagation (source: app.dimensions.ai, Query 1, Appendix A)

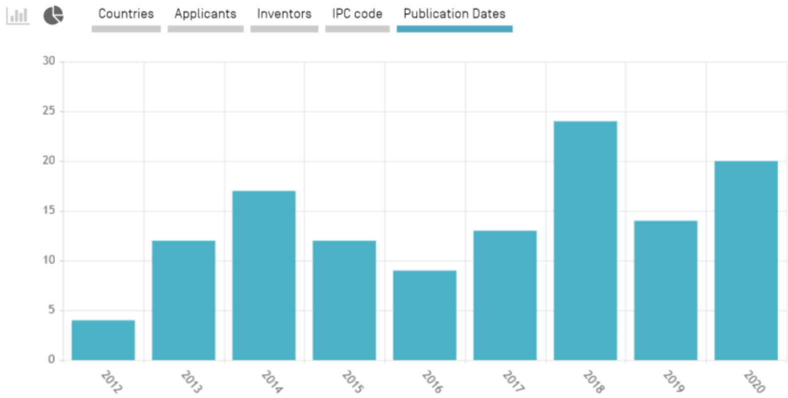

Figure 14. Patent applications by time, SNN training (source: https://patentscope.wipo.int, Query 2, Appendix A)

To examine the actors in the market better, it is necessary to shorten and analyse patent holders and their origin countries from 2019. This is because earlier waves, between 2016 and 2017, are less related with algorithms mentioned in this report.

IBM and Intel stand out among the companies with the highest volume of applications for SNN training patents, but according to patent offices by countries, China's patent application is higher than USA.

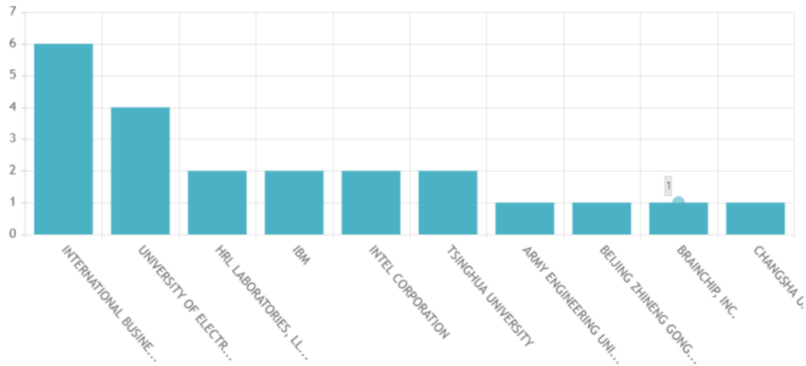

Figure 15. Patent applications by applicants between 2019-2021, SNN training (source: https://patentscope.wipo.int, Query 3, Appendix A)

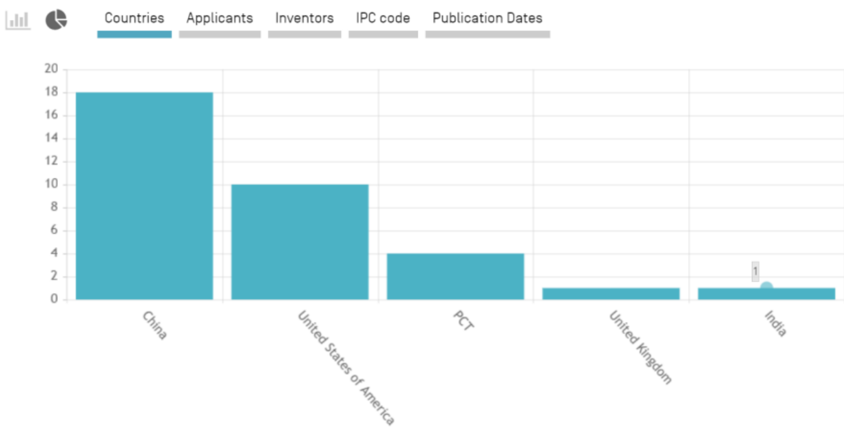

Figure 16. Patent applications by offices 2019-2021, SNN training (source: https://patentscope.wipo.int, Query 3, Appendix A)

IBM and Intel stand out among the companies with the highest volume of applications for SNN training patents, but according to patent offices by countries, China's patent application is higher than USA (Figure 15)

(Figure 16). Patent applications of China have been concentrated in research facilities which demonstrates the enthusiasm for SNN research.

Last May 2020, the Chinese company SynSense acquired the Zurich-based company aiCTX. As mentioned by the company's CEO, Ning Qiao, a new neuromorphic center will be established in China and this center will become the seed of an ecosystem where researchers will meet investors. It is therefore reasonable to anticipate that we will see some patents from Chinese companies soon.

BrainChip is one of the few neuromorphic chip companies that is expected to release their product into the market in 2021.

HRL Labs, which stands in the third place in the list, has developed meta-learning and vision-based patent applications for drones to be produced for the USA industry of defence. Likewise, Intel made a deal with Sandia, a USA governmental company, to research on how to scale up their Loihi neuromorphic chip.

On the list we also see that the Australian based BrainChip has patent applications. The company showed online-learning capability of their neuromorphic chip on its technology presentations last November. BrainChip is actually one of the few neuromorphic chip companies that is also expected to release their product into the market in 2021.

Among the inventors, Narayan Srivinasa, Angeliki Pantazi, and Stanislaw Wozniak worth to be mentioned. Narayan Srivinasa is the director of Intel labs and the CTO of Eta Compute. Eta Compute is a company that started with the idea of the producing neuromorphic chips that process SNN, in 2016. In 2018, they focused on deep AI accelerators, following investors' pressures, and they will launch their low energy consuming chips produced for the sensors during the next year. However, they left the door open for SNN operation on their chips. New patent applications from Narayan Srivinasa are signals of this intention. The other two names, Angeliki Pantazi and Stanislaw Wozniak, are IBM Europe researchers. The work of Wozniak and Wolfgang Maass on bridging SNN and DNN was published last September which shows IBM' interest to collaborate with European researchers.

4.2 Event Camera & Sensors

Increased investment and interest will play an active role in the development of event-cameras and, of course, in the increasing of neuromorphic datasets.

Tobi Delbruck - one of the first architects of event-based cameras – stated a "slow but steady rise of the event camera" (Delbruck, 2020), which is corroborated with the correlation observed on patent applications (Figure 17).

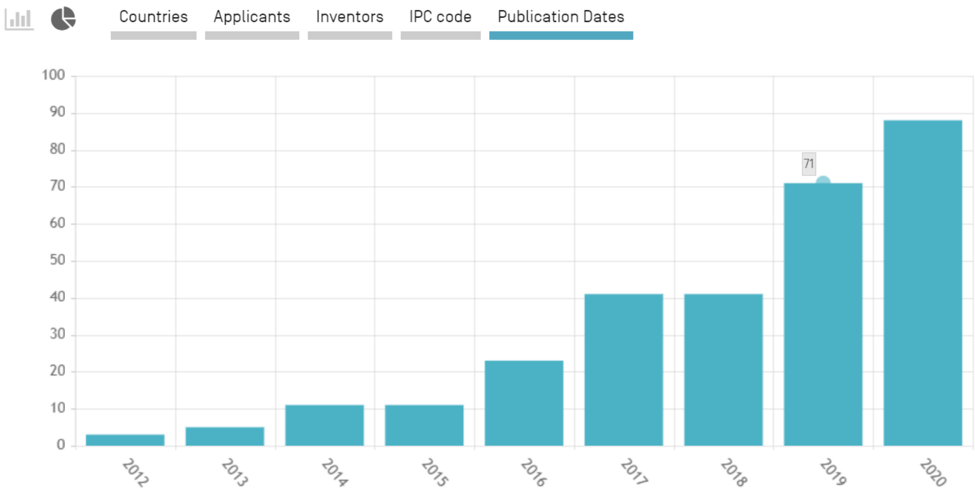

Figure 17. Patent applications over time, event-based sensors (source: https://patentscope.wipo.int, Query 4, Appendix A)

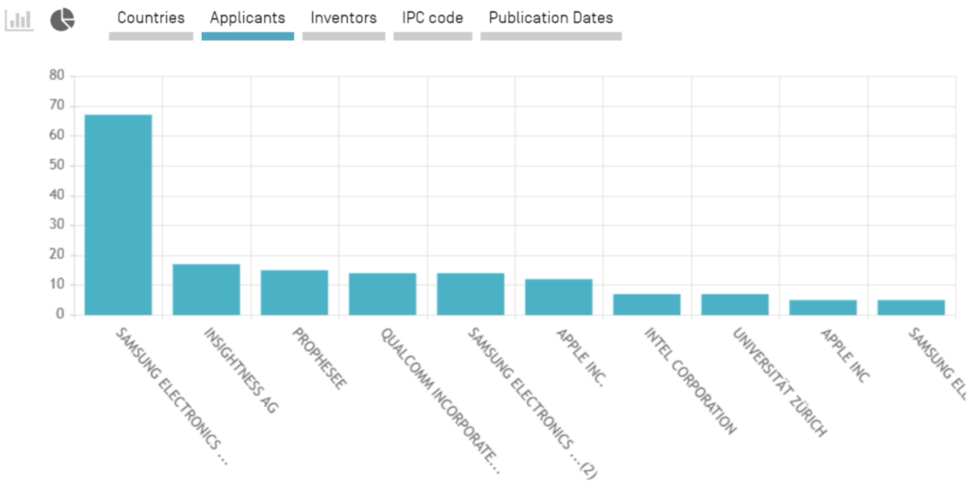

Figure 18. Patent applications by applicants, event-based sensors (source: https://patentscope.wipo.int, Query 4, Appendix A)

Event-based camera manufacturers are mostly European start-ups except the Samsung from Korea (Figure 18), e.g. Prophesee from France, Insightness and Inivation from Switzerland. In addition to these start-ups, there is also a Chinese company Celepixeli. Among the technology giants, Samsung holds the leadership.

Event-based camera manufacturers are mostly European start-ups and spin-offs and have attention investors from USA and China

In the past two years, the interest in event-based cameras has grown enormously. The acquisition of Insightness by Sony, the agreements between Sony, Bosch, and Intel with Prophesee, the patent applications of Toyota, Huawei, Bosh, and especially Apple, are clear indications of this interest. The interest is mainly based on the real-world impactful applications that even-cameras have. These areas include autonomous-vehicle sensors, IoT surveillance systems, and eye-tracking and control systems for augmented reality.

Samsung launched the first artificial intelligence security camera which can make on-device inference without sending data to servers, thus consuming lesser energy and maintains privacy (Figure 19) (Samsung, 2020).

Figure 19. Samsung SmartThings Vision is available in Australia (Samsung, 2020)

As expected, Toyota is working on autonomous vehicles. Interestingly, Apple and Sony are filing patent applications on Augmented Reality (AR), taking advantage of the precise tracking features of event-cameras. Another company that applied for a patent on AR is a Google-funded start-up "Magic-Leap". Magic-Leap, a company that has lagged behind its competitors in the AR race because of their high price, have just got a new funding increase of about 350 million dollars.

In the field of biology, the French company Gensight Biologics has filed a patent application combining its technology for the treatment of blindness with event-cameras. Another interesting company in the area is Medtronic. Medtronic seem to have applied for a patent on gesture recognition for adjusting the dosage of a patient´s medication, although no specific details have been publicly revealed yet.

When searches are restricted to "neuromorphic" and "spiking", we get two results. One of them is Tianjin University from China, which is known for its research on SNN learning. The other is the British company MindTrace, which counts with the participation of Steve Furber as non-exec director. MindTrace deals with the processing of event-data on neuromorphic chips, being the only patent-owner company in this area. MindTrace also focusses on the mainstream AI.

4.3 Emerging Memory Technologies

Emerging memories are another technology area that shows synergies with SNNs. The emerging memories can emulate the synaptic elements in a very compact fashion thus, enables massive parallel computations rapidly and efficiently (Chakraborty, et al., 2019). Advances in that area would not only increase the inference capabilities of SNNs but most importantly, can contribute to improve on-chip training. They allow

Emerging memories are another technology area that shows synergies with SNNs.

training on more complex applications, on an edge-scale, and manage efficient training on a large-scale. Interest in the use of non-volatile memories on neuromorphic chips has increased in the last few years (Figure 20).

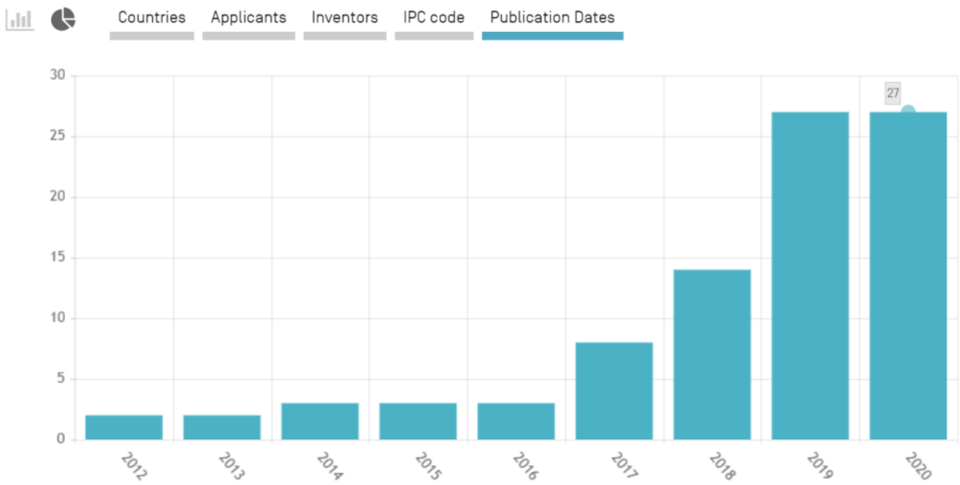

Figure 20. Patent applications over time, emerging memories with neuromorphic hardware (source: https://patentscope.wipo.int, Query 5, Appendix A)

The biggest interest is from the USA. IBM, Qualcomm, and HRL are continuing their research efforts in this area. Korea-based Samsung and Sk Hynix also appear to have leaped onto neuromorphic memory development. Sk Hynix has acquired Intel NAND Memory Business for US $ 9 billion last year. In China, patent applications are again owned by universities and research centers. In addition, the application of the CeRAM patent for spiking neurons by the ARM company, which Nvidia has acquired recently, deserves attention. However, there is not an obvious market yet in the area. All developments are still at design and prototype stages of maturity. One promising example is produced from MIT University with the support of IBM and Samsung (Chu, 2020).

Rain-neuromorphic have started to gather investors with the commitment to produce a memristor-based neuromorphic chip

Another promising start-up in the area is Rain-neuromorphic (Rain Neuromorphics, 2020). Even though they have not released much information, they have started to gather investors with the commitment to produce a memristor-based[18] neuromorphic chip (Figure 21).

[18] A memristor is a non-volatile electronic memory device. Unlike other memories, memristors can remain their state even the electric input is removed, and their resistance can be adjustable. These features show similarities with neurons where the synaptic weight is adjusted according to action potential. (Choi, et al., 2019)

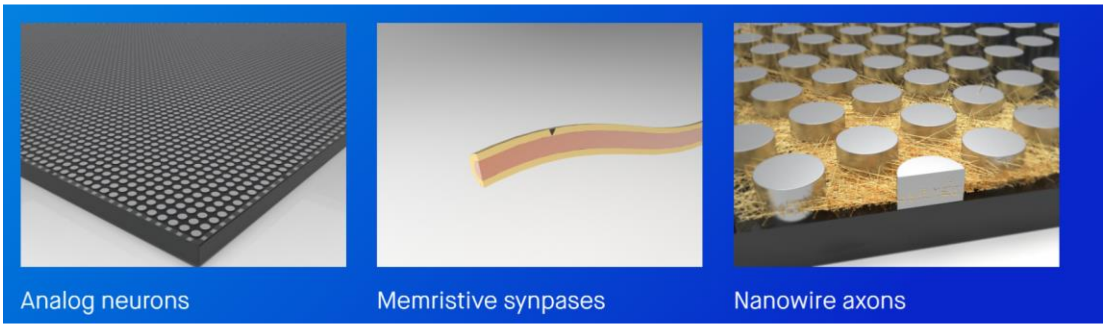

Figure 21. The Rain neuromorphic promises end-to-end training and inference with their Analog, Memristive and Nanowired axon chip (Rain Neuromorphics, 2020)

4.4 Remarks

Although the development of SNN algorithms, which gain momentum in 2018, is a promising area of technology development, we also need to observe that it has also experienced decreasing trend periods in the past. For this reason, its evolution should be only assessed in the upcoming years. If present interest and attention from enterprises and key actors continue, its popularity in industry will gradually increase and only then we will be able to affirm that SNN algorithms can reach a good position in the markets.

Event-cameras and sensors have found a place in markets before neuromorphic chips and deep SNNs. Increased investment and interest will play an active role in the development of event-cameras and, of course, in the increasing of neuromorphic datasets. Emergence of the neuromorphic datasets will result in optimized SNN algorithms. These developments would eventually facilitate a broader utilisation of neuromorphic chips as they are naturally efficient on processing events.

Finally, it seems highly relevant the interest of industry on emerging memories. They could become the key component of bio-inspired in-memory technologies. Although IBM's expectations go beyond 2025, the investments that Rain Neuromorphic has already made show that there is market potential for start-ups working in the area.

5. Application Areas of Edge Online, On-Device Learning & Market

Online-on-chip learning can be an important incentive for investment in neuromorphic chips and SNNs

Although online-on-chip learning has specific and impactful application areas, the practices in the area have not been effective until recently because of technical limitations. The market is not yet mature (Figure 22).

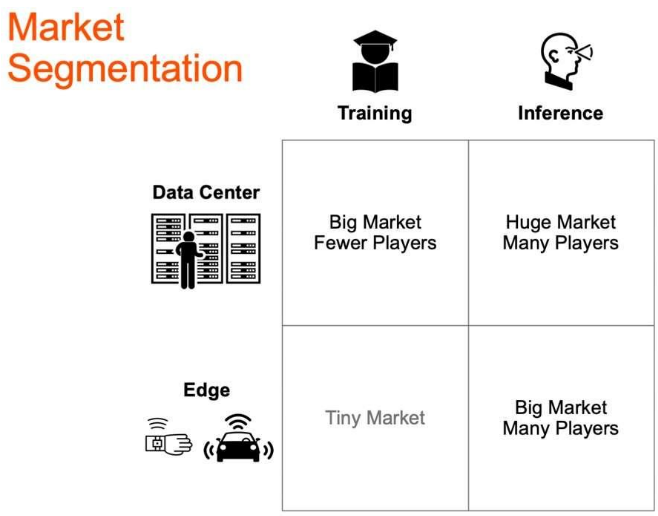

Figure 22 Edge-Training Market is limited compared to others (Shuler, 2019)

Rather than competing with already developed and mature technologies, online-on-chip learning can be an important incentive for investment in neuromorphic chips and SNNs. According to McKinsey the market of the edge-training will rise to the 1-1,5 billion Dollars in 2025 (Figure 23).

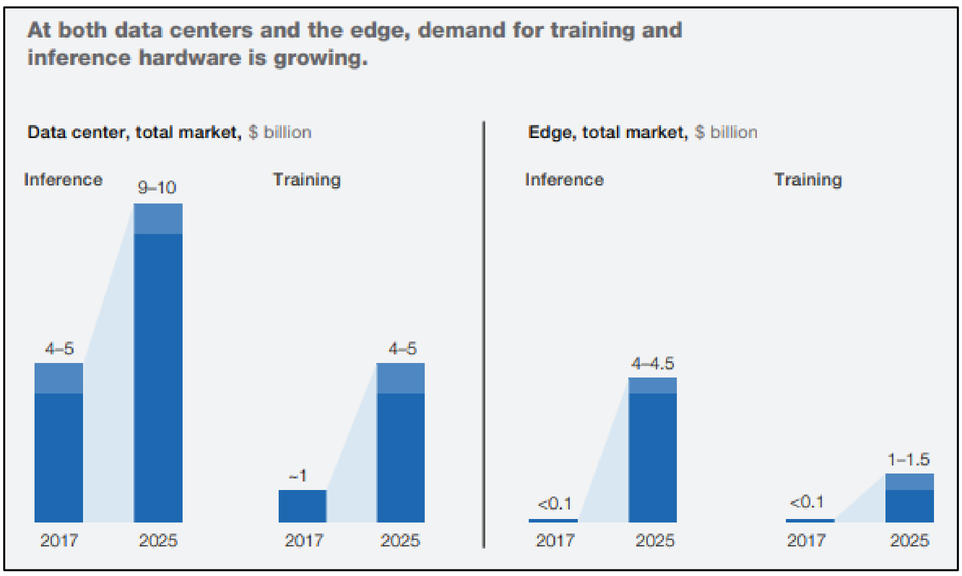

Figure 11 Expectation on Edge training market can be also seen on the right (Batra, et al., 2018)

It is important to note that, the edge on-chip training is the continuity of the edge inference on the technology transformation (Figure 24). If the accuracy of the edge inference is not satisfying, the edge training by itself is not worthy. Therefore, in this analysis, it is assumed that required levels of accuracy are achieved for edge inference in deep SNNs.

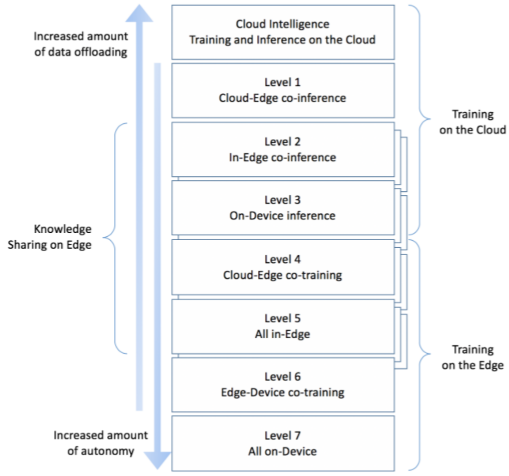

Figure 12. Transition of AI from Cloud to Edge. The current Level is 3-4 (6G Channel 2020).

5.1 Application Areas of Online-Learning

As stated before, online learning is necessary for applications that operate in changing environments with non-i.i.d. data. Application areas can be categorized into three fields: Monitoring and Control, Information Management and Analytics, and Diagnostics. Their functions in the industry are summarised in table 1.

Appl. / **Indust.**	**Monitoring and control**	**Information management**	**Analytics and diagnostics**
Security, Police	fraud detection, insider trading detection, adversary actions detection	next crime place prediction	crime volume prediction
Finance, Banking, Telecom, Insurance, Marketing, Retail, Advertising	monitoring & management of customer segments, bankruptcy prediction	product or service recommendation, including complimentary, user intent or information need prediction	demand prediction, response rate prediction, budget planning
Production industry	controlling output quality	–	predict bottlenecks
Education (e-Learning, e-Health), Media, Entertainment	gaming the system, drop out prediction	music, VOD, movie, news, learning object personalized search & recommendations	player-centered game design, learner-centered education

Table 1. Industry areas of three online-learning required categories (Žliobaitė, et al., 2015) (Babic, et al., 2021).

Online learning will be required in adaptive systems.

SNNs are suitable for input data incoming as a stream instead of batches. "Monitoring and Control" and "Analytics and Diagnostics" tasks are more relevant with streamed input data and Information Management tasks are in batches (e.g. the monitoring sensor system that detect anomaly where the abnormal behaviour is changing, needs to stream the incoming data continuously. On the on the hand, Amazon product recommendation system which is under category of "Information Management" can get the user's data in batches even though user's interest changes over time) Therefore, the focus should be on the application areas of "Monitoring and Control" and "Analytics and Diagnostics" (Žliobaitė, et al., 2015).

5.1.1 Monitoring and Control

The object of the Monitoring and Control is to detect and predict in contexts with uncertainty. These systems are classified as: (Table 2)

- "Monitoring for Management" tasks in the production and transportation industry. The complexity of the process both from human and environmental factors affect the data differences.
- "Automated Control" tasks in the mobile systems, robotics, augmented reality, and smart home industry. Changes happens frequently in these environments, and the agent needs to adapt itself when interacting with them.
- "Anomaly Detection" tasks in the computer security, telecommunication, medical and finance industry. The system's expected behaviour is well-defined; that system can be interrupted, however, by both human and environmental factors (Žliobaitė, et al., 2015). Medical signal monitoring devices such as electroencephalography (EEG) or Electrocardiography (ECG) do also require online learning. For example, brain computer interface devices that monitor EEG signals do need to adapt themselves for changes might come from mental state of the agent or from the environmental variations (Ma, et al., 2020).

Goal	Domain	Application task
Monitoring for management	transportation	traffic management
	remote sensing	place, activity recognition
	production industry	production quality control
	telecom. network	telecommunication monitoring
Automated control	mobile systems	controlling robots, vehicles
	smart home	intelligent appliances
	virtual reality	computer games, flight simulators
Anomaly detection	computer security	intrusion detection
	telecommunications	intrusion detection, fraud
	finance	fraud, insider trading

Table 2. Industry Domain and Application Tasks of "Monitoring and Control" (Žliobaitė, et al., 2015)

Due to the difficulties to deal with changing environments, online-learning is critical for the future of artificial intelligence.

5.1.2 Analytics and Diagnostics

Analytics and Diagnostics involve the prediction and classification tasks where characterization is relevant. Data changes usually occur slowly and depended on the population drift (e.g. face-detection systems needs to recognize relevant person (characterization) and it is expected to recognize that person even though his beard grows through time). These systems are separated by (Table 3);

- "Forecasting" tasks can be used in the banking and economy industry. Changes happen with the population drift over time based on events. Covid-19 epidemic outbreak and its predictions of spread can be a recent example for these.
- "Security" tasks are applied in the biometrics industry where authentication is relevant. Changing data may involve physiological factors. Face-detection with masks on smartphones is an example.
- "Medicine" tasks in the drug research and clinical research industry. Changes happen due to the adaptive nature of microorganisms and systems need to adapt themselves to these changes (Žliobaitė, et al., 2015) (Babic, et al., 2021).

Goal	Domain	Application task
Forecasting	banking	bankruptcy prediction
	economics	forecasting
	drug research	antibyiotic resistance
Medicine		drug discovery
	clinical research	disease monitoring
Security	biometrics	authentication

Table 3. Industry Domain and Application Tasks of "Analytics and Diagnostics" (Žliobaitė, et al., 2015) (Babic, et al., 2021)

5.2 On-device edge training Market Analysis

Artificial intelligence technologies have begun to show up in the Edge area in the last few years These developments primarily cover the inference area. Edge inference has barely started to have a place in the market. Therefore, in comments on the market competitiveness of edge-training cannot be properly discussed yet (Figure 25). In figure 25, Everest Group has differentiated the edge devices and the edge servers. In this report, both devices and edge gateways are counted into the edge basket as their computing capabilities are limited relative to cloud datacenters.

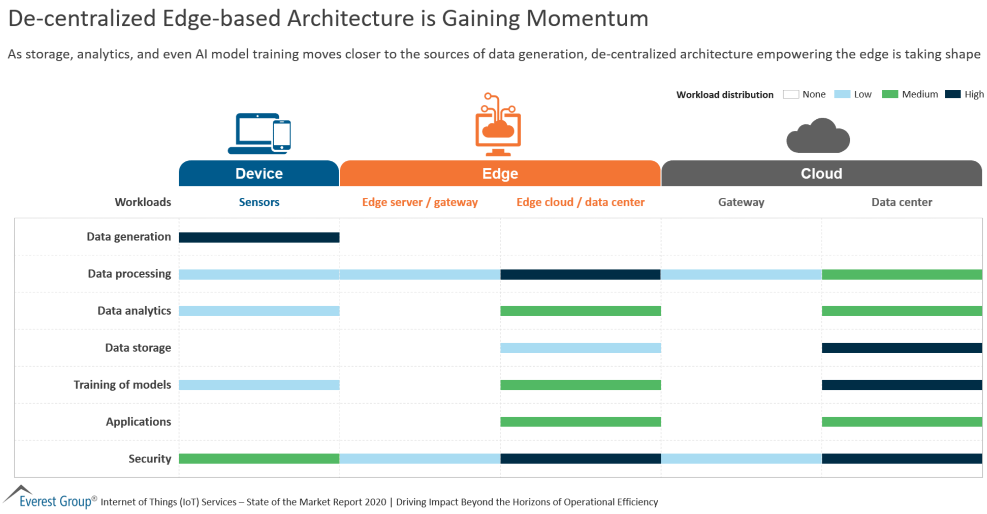

Figure 25 Edge(Edge Gateway & Device) Data Processing (Inference) has just started to find a place itself in the workload. (Everest Group, 2020)

The market competitiveness of edge-training cannot be properly discussed yet

The interest of investors will surely arrive to this promising sector. In the patent analysis, federated learning is included since its applicability with neuromorphic chips has been presented in an online manner.

The interest on the are has a history of 10 years, but the technical capabilities are only possible during last couple of years. Therefore, more than two-thirds of the patent applications were made after 2019 (Figures 26 and 27).

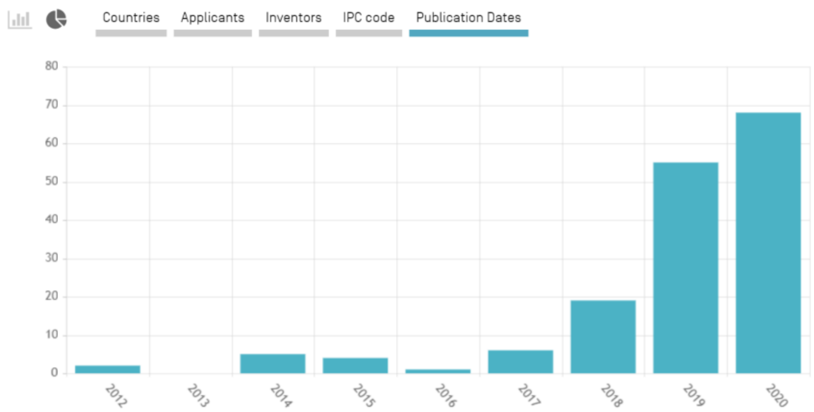

Figure 26. Patent applications overtime on online, on-chip training (source: https://patentscope.wipo.int, Query 6, Appendix A)

In this growing sector, China holds the leadership with the most relevant applications. China is also the country with the highest number of patents in the edge sector. This shows how much importance and value China gives to the edge area. USA and Europe follow China, and Korea also has found a place in the list.

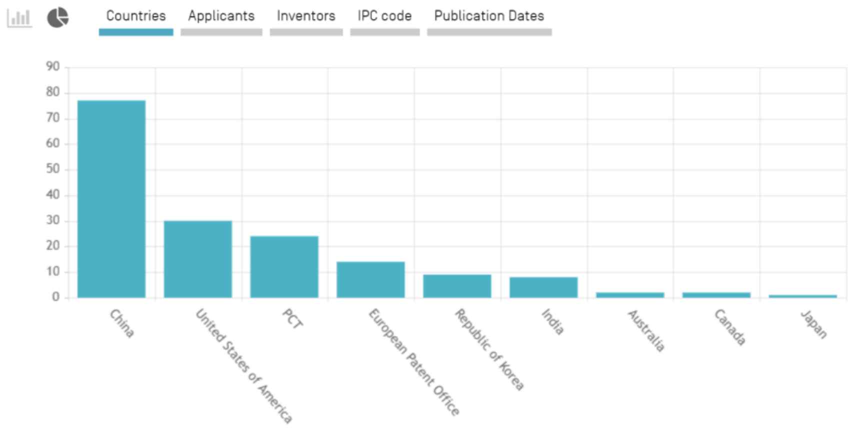

Figure 27. Patent applications by office online, on-chip training (source: https://patentscope.wipo.int, Query 6, Appendix A)

China' interest on edge development is reflected in its increasing patent protection.

As revealed in trend analysis, there are many Chinese applicants from research centres and universities (Figure 28). From the industry perspective, Google has the leading role, mostly dominated by its federated learning technologies. The huge potential of users enables the distributed learning among different devices. According to recent patents, Google even expand it by creating an API platform for developers to even build their federated learning apps.

Surprisingly, other tech giants like Qualcomm and Apple have their patent applications in China. Their applications include federated learning where privacy is the main concern, which might be related to restrictions of the Chinese government for collecting the data. This is a positive indicator of the future of federated learning; in fact, if tensions on data privacy become significant, federated learning can be a dominant option for training models.

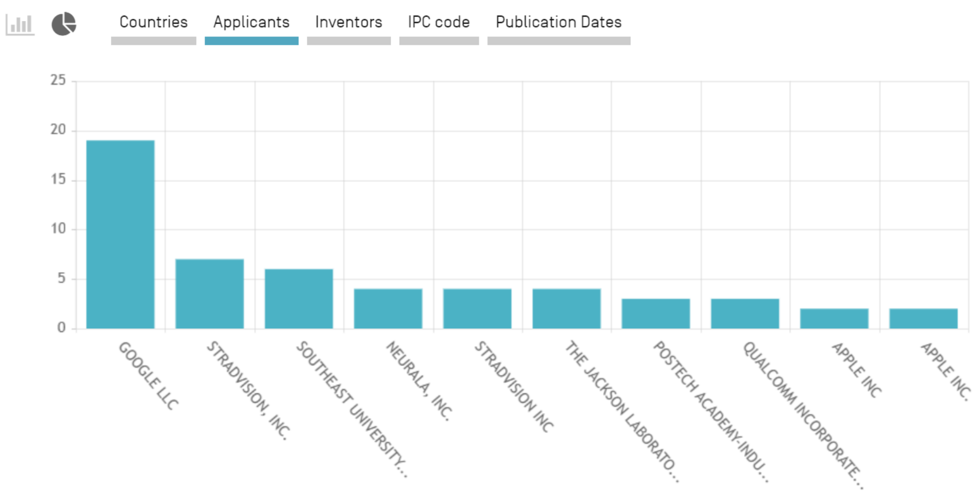

Figure 28 Patent applications by applicants, online on-chip training (source: https://patentscope.wipo.int, Query 6, Appendix A)

Bosch is another tech-giant that invests high amounts of capital on on-device learning chips. Their self-learning AI chip BHI260AP will be incorporated in wearables. Pre-trained exercise models can learn new exercises without connecting cloud or smartphones (Figure 29). The chip has been published the first quarter of 2021 and currently available for order (out of stock) according to Bosh-Sensortec's webpage (Bosch-Sensortec, 2020).

Self-Learning chip of Bosch will be available in the first quarter of 2021.

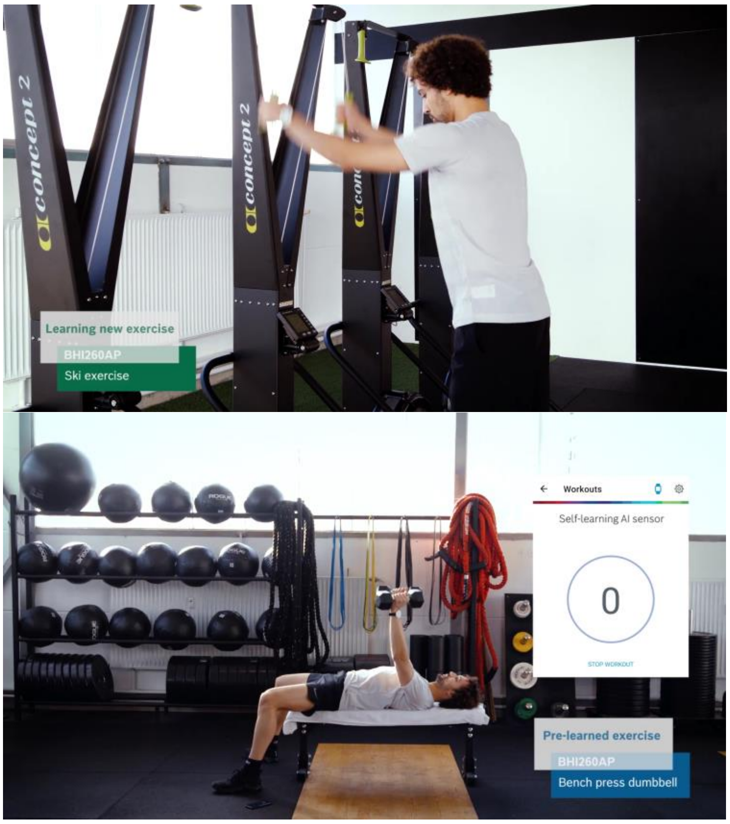

Figure 29 Self-Learning AI sensor of Bosch, the pre-trained smartwatch learns new exercises (Bosch Sensortec, 2020).

In 2021, applications of Samsung and LG have been approved. Samsung is working on on-device training for user recognition and language understanding and LG is bringing transfer learning to the edge systems.

Besides the tech giants, a Korean AI-assisted driving company StradVision holds the second position. Their on-device continual learning applications are varied from smartphones, drones, vessels, and military purposes where adaptation for changing environments is required. Multinational Tata Consultancy has recently applied a transfer learning patent for industrial anomaly detection systems. Another promising start-up Third Wave which provides cloud AI systems for automotive systems is researching continual-learning adaptive robotics. From the medical sector perspective, Doc AI, a medium-sized company, has a patent application for federated learning to train healthcare systems. The rest of the patents are mostly based on detection and classification tasks which include applications of autonomous vehicles, traffic regulation, and anomaly detection.

Other companies in the area, which are not yet involved in patent applications, are listed below (Table 4 & more can be found at Appendix B). These companies are focused either on ANN or SNN, and their size is small to medium. As this technology is recent, the assessment of their potential will be based on the level of the investment.

Company Name	Country	Main Product	Product Type	Size	Funding
AnotherBrain	France	Another brain	semiconductor	51-100	$20.8M
BrainChip	Australia	Brainchip	semiconductor	11-50	$27.8M
Doc AI	USA	Omix	Digital health trials	51-100	$41M
Edgecortix	Japan	DNA chip	semiconductor	11-50	$5M
Ekkono	Sweden	Ekkono SDK	Software library	11-50	$2.9M
ETA Compute	USA	TensAI (not spiking yet)	semiconductor/ sensor	11-50	$31.9M
mindtrace.ai	United Kingdom	Brain-Sense	AI Solutions	11-50	$3M
Neurala	USA	Lifelong-DNN	AI algorithm	11-50	$20.1M
Rain Neuromorphic	USA	APU	semiconductor	1-10	$5M
StradVision	Korea	SVNet	Software library	51-100	$42.2M
ThirdWave Automation	USA	shared autonomy	hardware+ software suit	11-50	$15M
Xayn	Germany	Xayn	Search Engine	11-50	€9.5M

Table 4. Total funding of the small-medium size actors in the edge online/on-device training sector (4 of them from Europe)

5.3 Remarks

Due to the difficulties to deal with changing environments, online-learning is critical for the future of artificial intelligence. Online-learning applications will emerge to prove its usefulness in the edge area rather than in the established cloud-based systems. Deep SNNs and neuromorphic chips can make a difference in this area due to their adaptive nature. Since they are not direct competitors to ANNs, they can provide integrity to edge systems and help them enter into the markets. In 2021, Brainchip is going to release the second version Akida

Neuromorphic system on chips. In order to increase the volume of potential customers they do also sell the intellectual property licenses of their designs (Mankar, 2020). Their stock value at Australian Securities Exchange (ASX) jumped up %973 during last year with the total Market Cap of $749.7M AUD (yahoo! finance, 2021) (stocklight, 2021). Impact of the Brainchip Akida should be monitored. It is observed that investors´ interest in this field has started.

6. Drivers of deep SNN algorithms development

Drivers are influential elements, those factors with sufficient capacity to exert force towards the success of the deep SNNs. They have been reviewed under four categories, namely: Technological, Economical, Educational and Governmental.

6.1. Technological Drivers

Research groups constitute the first pillar in the technology development processes. Advances in SNN algorithms and neuromorphic design will continue to be the main driver in the future. Research institutions and laboratories, public and/or private, laboratories are main actors of this driving.

Some leading institutions in Europe in this area are the University of Manchester, Heidelberg University, Graz University of Technology, and the Zurich Technical University. The first three leading institutions are also the members of the HBP organization. Apart from these, Stanford and California Universities from USA, Tsinghua and Zhejiang Universities from China are also prominent players (Appendix C). Leading public labs, working on Neuromorphic and SNN research, are Sandia Labs and the HRL Labs supported by the USA federation. Private actors include the labs of Intel & IBM, which show the ambition of driving the future of these technologies.

Getting benefit from both biology and DNN research results in advanced algorithms such as e-prop which pave the way of adaptive artificial intelligence.

Research on neuroscience and deep neural networks are another influential factor of the development for the future deep SNN learning algorithms. Discovery on the key elements of learning mechanism, defining their mathematical and physical models will lead to more efficient bio-SNN algorithms. Likewise, research on deep neural networks will contribute to this development. Contemporary DNN solutions already have outstanding perception (not cognition) capabilities and getting benefit from these research results in advanced algorithms such as e-prop which pave the way of adaptive artificial intelligence.

More technological drivers are based on the evolution of emerging memories, event-based sensors, and neuromorphic chips. Emerging memories will play an important role in SNN training and inference and will pave the way for new neuromorphic architectures. Even-based sensors are critical components to allow the entrance of SNNs to the market. Their unique technology separates their market from other sensors. Since event-based sensors are naturally compatible with neuromorphic chips, their market impact will directly correlate with the interest shown in SNNs.

Of course, new algorithms will require new neuromorphic chip designs. In this sense, technological developments on neuromorphic architecture are also important for the implementation of these algorithms.

Emerging in-memory AI accelerators can be both opportunity and threat for the deep SNN' market.

In-memory AI accelerators are also influencing drivers for an efficient and effective SNN training. They can lead to scalable neuromorphic computing in terms of inference. However, it is a double edge sword since they are also aiming for efficient edge systems. Moreover, they can also benefit from the emerging memory technologies and potentially become a competitor in the field.

6.2. Economic Drivers

Some economic drivers of deep SNN algorithms to consider are the work of public and private funding institutions. Public drivers include governmental funding and organizations indirectly supported by national or transnational governments. HBP is one of the samples of such a support. Private driving actors include technology giants like IBM & Intel and investment-oriented organisations that create and support market-ready companies.

Finance in the of battery-powered edge computing is between 30-80 billion US dollars and currently, neuromorphic devices represent almost 0 percent of it (Bains, 2020)

In sectors which require adaptive robotics and wearables, efficient sensors are required; however, the available technology is not mature enough to fill this gap. Deep spiking neural networks can push the market with demonstration of real-world applications. To be precise on these sectors, an analysis of energy-accuracy trade-off is required.

Therefore, the potential competitors or collaborators can be defined. Market of the battery-powered edge computing is between 30-80 billion US dollars and currently, neuromorphic devices represent almost 0 percent of it (Bains, 2020). From this giant cake, neuromorphic chips need to get its share. Technology giants, Intel and IBM will not enter to the market in the short term. They are still investing on collaborations and research with the expectation of competitive real-world applications. Therefore, start-ups and the spin-offs should take responsibility, and benefit from this market with tiny number of competitors (Appendix B).

6.3. Educational Drivers

Communities (Appendix B) and education are other important drivers, especially during technology exploitation stages. Communities facilitate collaboration environments among research groups. This serves to accelerate technology development processes. Besides, communities increase the visibility of the technology and have an impact on attracting industrial actors. Intel Neuromorphic Community, with increasing worldwide partners from industry to research, has gained the leading

The HBP Education also plays an important role with variety of conferences, workshops, summer schools, code jam sessions and post graduate positions. YouTube channel of HBP Education provides an opportunity for the people with interest in the area.

role. In Europe, NeuroTech European Network which has been founded by pioneer researchers with the support of H2020 grant, unites the community with the object of increasing impact and visibility, reach out industry stakeholders, promote public interest and shaping the neuromorphic education. E ducation is another factor that enhance the opportunities of exploitation. Attracting ANN developers is a crucial aspect for the sustainability of the limited community of SNNs. Telluride workshop in USA and CapoCaccia in Europe, brings the enthusiastic developers around the world and enables a foundation of supportive community among the actors of neuromorphic technology. The HBP Education also plays an important role with variety of conferences, workshops, summer schools, code jam sessions and post graduate positions. YouTube channel of HBP Education provides an opportunity for the people with interest in the area to exchange information and ideas. (Online library of HBP can be found in here)

6.4. Governmental Drivers

More data is required from the AI industry to improve their models. However, collection of private data legally or illegally causes a security concern and are prevented by policy makers. Especially, in the medical and communication sector. SNNs and Neuromorphic chips can be beneficial for preserving the privacy of the sensible data with their on-device processing capabilities at the edge.

7. Reflections on SNNs and HBP

The main objective of Brain-inspired computing, a key area of research in the Human Brain Project since its foundation, is to reveal the learning mechanism of the brain and emulating it on neuromorphic processors. Cumulative knowledge and experience in this domain, together with the impact machine learning applications are yet having on society, have driven HBP researchers´ efforts towards the integration of the most powerful features of spiking neural networks on artificial intelligence. In this sense, industrial relations have been explored with leading companies like Intel & IBM, and HBP is gradually achieving a leading role within the neuromorphic global communities through participative neuromorphic events as NICE, Telluride & Capo Coccia.

HBP work is distributed across different work packages, which are naturally dependent on each other. Neuroscience research generates knowledge on spiking neural networks which contribute to the creation of the new brain models as well as learning algorithms. The HBP Neurorobotics platform also requires these models and algorithms to validate neuroscience experiments and prototype adaptive robotics. In parallel, the HBP computing platform provides all the processing capabilities in this loop. Fundamentals of HBP efforts in the area can be seen in the scheme of figure 30.

Research on spiking neural network and neuromorphic technologies are essential for neuroscience research (by supplying processing capabilities) as well as for validation. In this report, we have principally focused on the utility of SNNs in artificial intelligence. Recent spiking neural network algorithms developed within work package 3 and collaboration with work package 6 are considered impactful advances that can bring high value to the development of neuromorphic devices. These algorithms improve the efficiency and accuracy of deep learning applications on neuromorphic chips and provide an efficient solution for on-device training. Integration of emerging memories, event-based sensors, and maturity of these algorithms could open new opportunities in the edge intelligence market.

According to our analysis, Europe presently plays a leading and centric role with respect to academic knowledge of spiking neural networks and their dissemination. However, Europe is still far below USA and China in terms of patent applications, probably due to a lack of investment initiatives. In fact, although Neuromorphic communities need each other's support and cooperation to advance, these conditions might change very soon due to the dynamism and growing rivalry with the AI markets. In addition, the lack of investments could give rise to a talent drain process, as European researchers could prefer to make agreements with non-EU companies. Investing in the integration of emerging technologies and advances in SNN would contribute to create a more solid and united European voice in the area.

The necessary investments could come from large private corporations (USA strategy) or be supported financially by the governments, e.g. by funding research centres (China strategy). Although start-ups and spin-offs activity is also increasing, we have observed that most of them struggle to survive and require big and decided investors to believe in technologies whose maturity is still low for the markets.

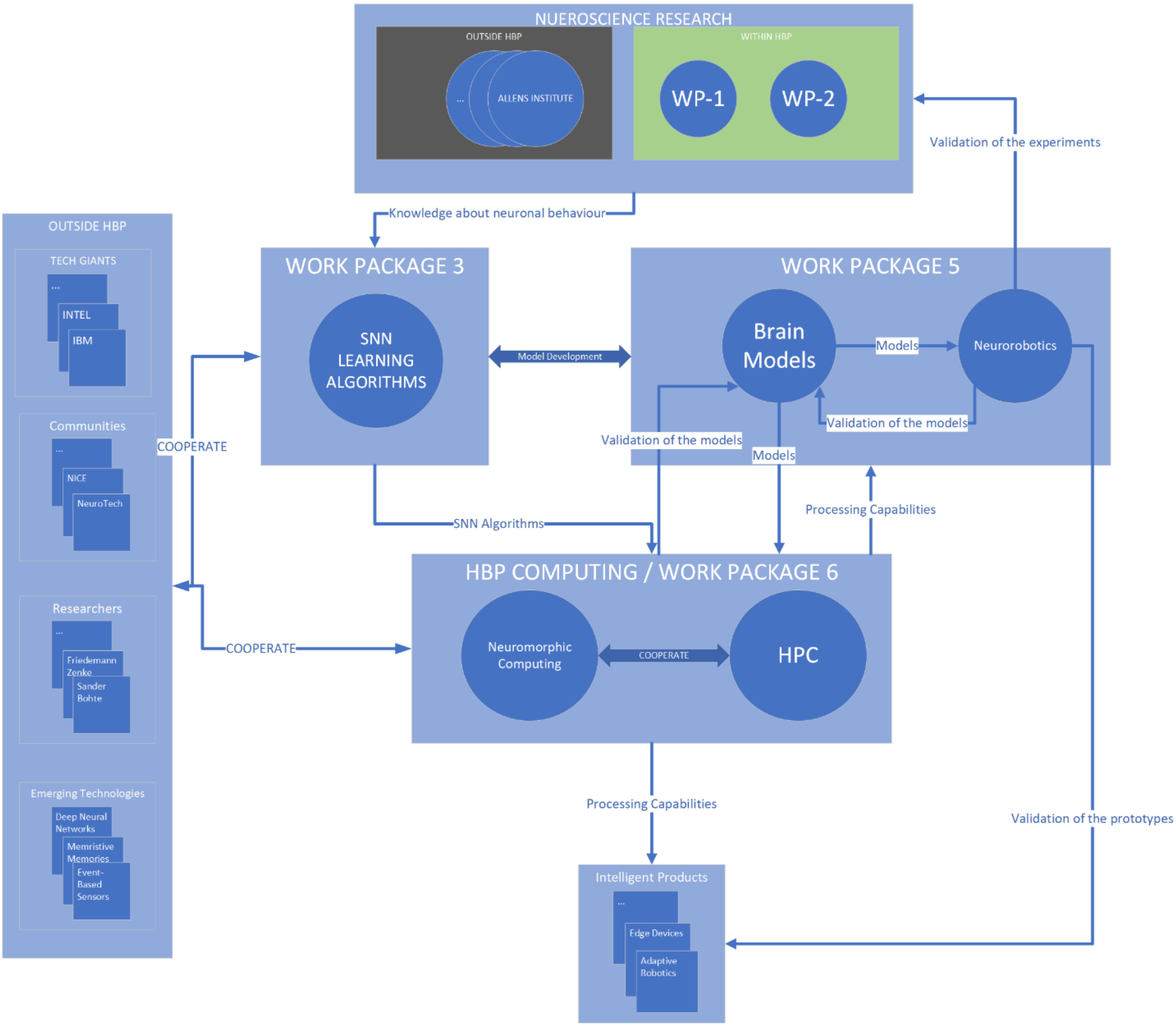

Figure 30 Basic Structure of SNN research among HBP

Last year, the European Commission ceased to finance large-scale neuromorphic hardware implementations as SpiNNaker-2 and BrainScaleS-2, which somehow paralysed some researchers´ works in the area. TU Dresden has managed to get an agreement for the development of SpiNNaker-2 with Dresden regional government afterwards. In this regard, a real threat exists that European knowledge and advances may be early captured and exploited by non-European companies as IBM and Intel. Promoting funding from European big players such as Mercedes, BOSCH, etc. could reverse the situation. Especially, neuromorphic devices combined with event-based sensors and emerging memories would surely bring very important added value to autonomous vehicles and intelligent edge devices markets.

8. Conclusion

Deep SNNs and neuromorphic chips have the potential to make an impact in the edge-scale applications markets soon. Although most of AI present applications are sufficiently well addressed by existing solutions, edge scale inference and training are features of increasing interest for industry, which is gradually transitioning from cloud technologies to on-chip solutions.

There are also mainstream companies, emerging start-ups, and research institutions that are, however, still trying to find solutions through DNNs instead of SNNs. Developing AI accelerators and DNN algorithms could be in this respect an alternative and threat for the progress of deep SNNs.

Deep SNNs are already demonstrating better accuracy of inference and energy efficiency when dealing with native datasets obtained from event-based sensors, or with signal datasets that contain time variability. Moreover, they can also show energy efficiency when working with static datasets in circumstances that compensate lower accuracy.

Given the large spectrum of edge Scale applications (sensors, mobile, autonomous vehicle control, etc.), an analysis[19] is required to identify the areas where deep SNNs are more advantageous than DNNs. In fact, it seems that SNNs will not replace DNNs but become a complement and supporting technology on different areas.

As for training, it is expected that emerging memories will boost the application of deep SNNs. However, memory technology impactful advances are not likely to be in the market before 2025 and new neuromorphic architectures will be needed for their application. During this transition period - which is too long for a highly dynamic sector as AI - neuromorphic hardware still have to demonstrate its attractiveness and the impact may have in future investments. Technology organizations, research centres, tech-giants, and especially market-ready start-ups are yet contributing to these expectations.

Although European knowledge in the SNN and Neuromorphic fields is higher than in other regions (see Appendix C), China and the USA are the countries that are showing highest financial efforts and policy interest. Intel's and IBM's collaborations with European scientists, and the acquisitions of European start-ups by Chinese and Japanese companies are clear indicators of such efforts. The Human Brain Project has some of the most important scientific leaders and teams in the area. Steve Furber, Wolfgang Maas, and Johannes Schemmel´s research work is placed at the frontiers of SNN and neuromorphic development. Supporting these endeavours and conducting international collaborations - not only with the USA but also with Chinese research faculties - can help to reverse this situation.

The emergence of new algorithms and the acceleration of SNN research in the upcoming few years seem to be essential for an impactful neuromorphic technology development. These algorithms will contribute to the effectiveness and efficiency of

[19] The analysis should assess what applications require high levels of energy efficiency and which ones demand high accuracy. For example, accuracy is critical in sensors used to detect objects in autonomous cars, which have sufficient battery capacity to feed the chip and guarantee the functioning. On the contrary, wearable devices used in your daily activity require energy efficiency and can sacrifice to some extent their level of accuracy and precision.

neuromorphic chips as well as the development of AI. New hardware designs will emerge in the short term, which should contribute to the transition to and the evolution of edge AI. Meanwhile, deep SNNs need to demonstrate their competitive advantages on real-world applications and thus attract further research and capital investments.

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Appendix A

Queries

[Q1] Query 1: "spiking" "network" ("training" OR "learning") ("back-propagation" OR "backpropagation") "deep"
From app.dimensions.ai
[Q2] Query 2 FP:(("training" OR "learning") "spiking" "NETWORK")
From https://patentscope.wipo.int/

[Q3] Query 3 FP:(("training" OR "learning") "spiking" "NETWORK") IC:(G*) DP:[01.01.2019 TO 01.01.2021]
From https://patentscope.wipo.int/

[Q4] Query 4 AB:((("event camera") OR ("DVS sensor") OR ("DVS camera") OR ("Dynamic vision") OR ("event-based" ("Camera" OR "vision" OR "sensor")) OR ("event-data" ("processing")))) OR TI:((("event camera") OR ("DVS sensor") OR ("DVS camera") OR ("Dynamic vision") OR ("event-based" ("Camera" OR "vision" OR "sensor")) OR ("event-data" ("processing")))) AND DP:([01.01.2012 TO 01.01.2021])
From https://patentscope.wipo.int/

[Q5] Query 5 FP:(("spiking" OR "neuromorphic") AND ("pcm" OR "feram" OR "non-volatile" OR "memristor" OR "reram" OR "ceram"))
From https://patentscope.wipo.int/

[Q6] Query 6 FP:((("online-learning"~1 OR "online-training"~1 OR "continual-training"~1 OR "continual-learning"~1 OR "meta-learning"~1 OR "one-shot learning" OR "few-shot learning" OR "incremental learning" OR "transfer learning" OR "federated learning") AND ("on-chip"~1 OR "on-device"~1 OR "edge" OR "sensor")) OR ("on-device training"~1 OR "on-chip training"~1 OR "on-device learning"~1 OR "on-chip learning"~1)) ANDNOT IC:("G06F?1*") ANDNOT IC:("G06Q?10*") ANDNOT IC:("G09B*") ANDNOT IC:("G06T*") ANDNOT IC:("G06Q*")
From https://patentscope.wipo.int/

[Q7] Query 7 FP:((("online-learning"~1 OR "online-training"~1 OR "continual-training"~1 OR "continual-learning"~1 OR "meta-learning"~1 OR "one-shot learning" OR "few-shot learning" OR "incremental learning" OR "transfer learning") AND ("on-chip"~1 OR "on-device"~1 OR "edge" OR "sensor")) OR ("on-device training"~1 OR "on-chip training"~1 OR "on-device learning"~1 OR "on-chip learning"~1)) ANDNOT IC:("G06F?1*") ANDNOT IC:("G06Q?10*") ANDNOT IC:("G09B*") ANDNOT IC:("G06T*") ANDNOT FP:("federated")
From https://patentscope.wipo.int/

Appendix B

Neuromorphic Communities.

Name	Type of Community	Location	Organized by	Since	Link
NICE	Workshop	Yearly Changes	NICE Workshop Foundation,USA	2013	https://niceworkshop.org/
CapoCaccia	Workshop	Italy	University of Zurich, Switzerland	2007	https://capocaccia.cc/
Telluride	Workshop	USA	National Science Foundation, USA	1993	https://sites.google.com/view/telluride2020/home
NEUROTECH	Project	Switzerland	H2020, Europe	2018	https://neurotechai.eu/
Intel Neuromorphic Research Community	Global Network	USA	Intel, USA	2019	https://www.intel.com/content/www/us/en/research/neuromorphic-community.html
International Conference on Neuromorphic Systems	Conference	USA	US Department of Energy, USA		https://icons.ornl.gov/

Event-Based Sensor and Related Companies

Company Name	Location	Related Product	Product-Type	Size (employees)	Funding	Link
CelePixel	Shanghai	CELEX SENSOR	visual event-sensor	1-10	$6M	http://www.celepixel.com/
GenSight Biologics	France	GS030 optogenetics	solution for sight-threatening diseases	11-50	$153M	https://www.gensight-biologics.com/
Inivation	Switzerland	Dynamic Vision Sensor	visual event-sensor	11-50	-	https://inivation.com/
Magic Leap	USA	image sensor (patent phase)	augmented reality sensor	11-50	$3B	https://www.magicleap.com/en-us
Pixium Vision	France	PRIMA SYSTEM	retinal-imlant system	1-10	€33.3M	https://www.pixium-vision.com/
Prophesee	France	METAVISION SENSOR	visual event-sensor	51-100	$65.3 M	https://www.prophesee.ai/
Samsung	Korea	Dynamic Vision Sensor	visual event-sensor	not-available	not applicable	https://www.samsung.com/us/ssic/session/event-based-vision-algorithms/
SonyAI (acq. Insightness)	Japan	Intelligent Vision Sensor	visual event-sensor	51-100	not applicable	https://www.sony.com/en/SonyInfo/sony_ai/technology/evs.html

Spiking Neuromorphic SMEs

Company Name	Location	Main Product	Product Type	On-device training	Application Area	Size	Funding	Link
AnaFlash	USA	neuromorphic edge chip	semicondutor	unknown	energy efficient edge IoT solutions	1-10	Granted by the National Science Foundation	http://anaflash.com/
BrainChip	Australia	Brainchip	semicondutor	yes	ultra-low latency and low power processing at the edge	11-50	$27.8M	https://brainchipinc.com/
ETA Compute	USA	TensAI (not spiking yet)	semicondutor /sensor	patent application	ultra-low latency and low power processing at the edge	11-50	$31.9M	https://etacompute.com/
Femtosense	USA	based on Stanford Braindrop	semicondutor	not mentioned	large-scale neural network processing to the edge	1-10	€1.1M	https://www.femtosense.ai/
GrAI Matter Labs	France	NeuronFlow	semicondutor	not mentioned	ultra-low latency and low power processing at the edge	51-100	$29M	https://www.graimatterlabs.ai/
Innatera Nanosystems	Netherlands	Innatera	semicondutor	not mentioned	sensor-driven applications at the extreme-edge	11-50	€5M	https://www.innatera.com/
Rain Neuromorphic	USA	APU	semicondutor	yes	ultra-low latency and low power processing at the edge	1-10	$5M	http://rain-neuromorphics.com/
SynSense (ex. aiCTX)	Switzerland	DYNAP	semicondutor	yes(DYNAP-SEL)	ultra-low latency and low power processing at the edge	11-50	$2.7M	https://www.synsense-neuromorphic.com/

On-device Learning SMEs

Company Name	Location	Main Product	Product Type	Application Area	Size	Funding	Link
AnotherBrain	France	another brain	semicondutor	ultra-low latency and low power processing at the edge	51-100	$20.8M	https://anotherbrain.ai/#home
BrainChip	Australia	Brainchip	semicondutor	ultra-low latency and low power processing at the edge	11-50	$27.8M	https://brainchipinc.com/

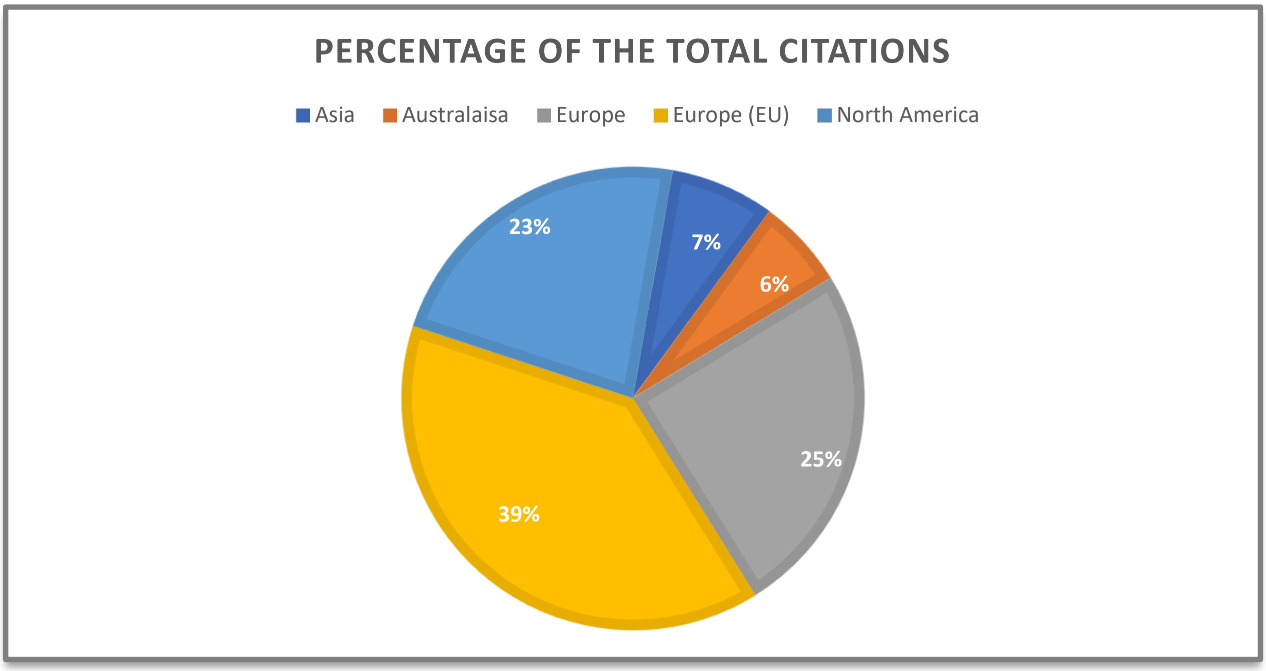
Doc AI	USA	Omix	Digital health trials	edge A.I. models in which the computation takes place where the data is captured, as well as federated learning,	51-100	$41M	https://doc.ai/
Edgecortix	Japan	DNA chip	semiconductor	Reconfigurable Artificial Intelligence Processor technology to the embedded edge	11-50	$5M	https://www.edgecortix.com/
Ekkono	Sweden	Ekkono SDK	Software library	edge incremental learning on streaming sensor data – onboard the device	11-50	$2.9M	https://www.ekkono.ai/
ETA Compute	USA	TensAI (not spiking yet)	semicondutor /sensor	ultra-low latency and low power processing at the edge	11-50	$31.9M	https://etacompute.com/
mindtrace.ai	United Kingdom	Brain-Sense	Ai Solutions	continuous AI learning	11-50	$3M	https://www.mindtrace.ai/
Neurala	USA	Lifelong-DNN	AI algorithm	on-device inference and allows it to learn on the device itself	11-50	$20.1M	https://www.neurala.com/
Rain Neuromorphic	USA	APU	semicondutor	ultra-low latency and low power processing at the edge	1-10	$5M	http://rain-neuromorphics.com/
StradVision	Korea	SVNet	Software library	AI Assisted Driving	51-100	$42.2M	https://stradvision.com/
Third Wave Automation	USA	shared autonomy	hardware+software suit	machine learning technology to material handling automation	11-50	$15M	https://www.thirdwave.ai/
Xayn	Germany	Xayn	Search Engine	Federated Learning-data private search engine for mobile	11-50	€9.5M	https://www.xayn.com/

Appendix C

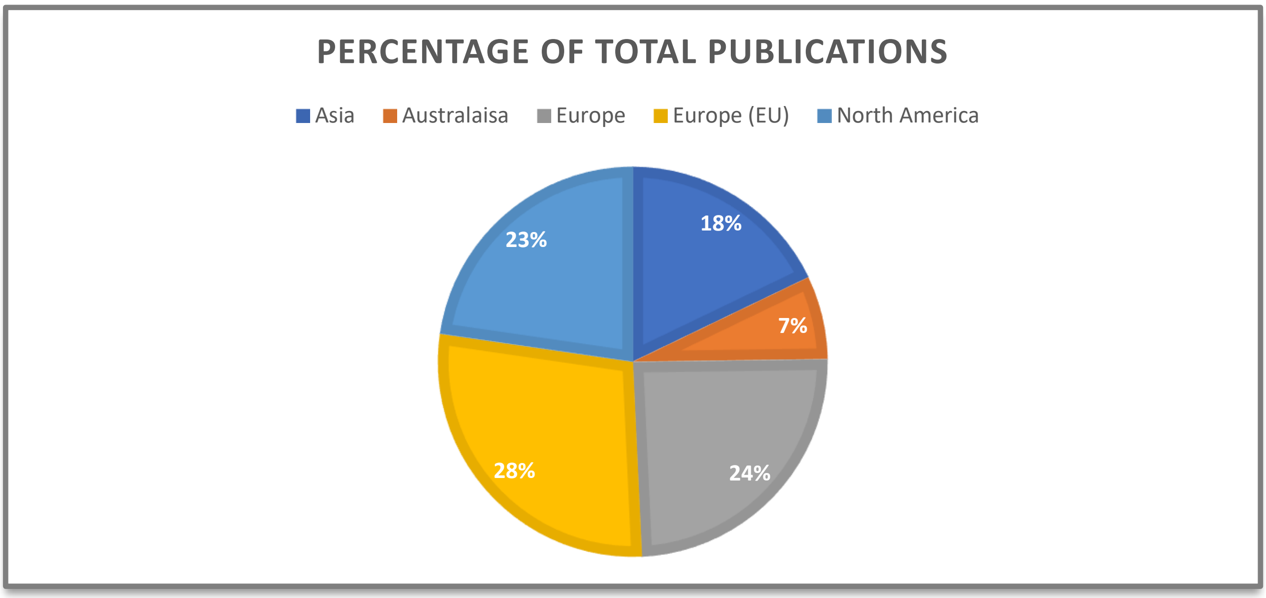
100 Scientist with top publications listed by Citations/Publication rate. query: "Spiking Neural Networks"

No	Name	Publications	Citations	Citations/Publications	Organization	Country	Zone
1	Hojjat Adeli	37	4354	117,68	The Ohio State University	United States	North America
2	Xiao-Jing Wang	33	3428	103,88	New York University	United States	North America
3	Christian Gamrat	29	1933	66,66	CEA LIST	France	Europe (EU)
4	Tobi Delbruck	27	1736	64,3	ETH Zurich	Switzerland	Europe
5	Romain Brette	34	2044	60,12	Institut de la Vision	France	Europe (EU)
6	Shih-Chii Liu	43	2572	59,81	University of Zurich	Switzerland	Europe
7	Benjamin Schrauwen	27	1589	58,85	Ghent University	Belgium	Europe (EU)
8	Teresa Serrano-Gotarredona	54	2489	46,09	Seville Institute of Microelectronics	Spain	Europe (EU)
9	Olivier Bichler	43	1937	45,05	CEA	France	Europe (EU)
10	Bernabe' Linares-Barranco	67	2987	44,58	Seville Institute of Microelectronics	Spain	Europe (EU)
11	Gert Cauwenberghs	36	1599	44,42	University of California	United States	North America
12	Markus Diesmann	55	2388	43,42	RWTH Aachen University	Germany	Europe (EU)
13	Alain Destexhe	26	1087	41,81	Délégation Ile-de-France Sud	France	Europe (EU)
14	Wulfram Gerstner	43	1786	41,53	Swiss Federal Institute of Technology in Lausanne	Switzerland	Europe
15	Timothée Masquelier	43	1654	38,47	Brain and Cognition Research Center	France	Europe (EU)
16	Damien Querlioz	52	1977	38,02	Centre for Nanoscience and Nanotechnology	France	Europe (EU)
17	Dan F M Goodman	32	1190	37,19	Imperial College London	United Kingdom	Europe
18	Wolfgang Maass	44	1622	36,86	Graz University of Technology	Austria	Europe (EU)
19	Luis A Plana	48	1730	36,04	University of Manchester	United Kingdom	Europe
20	Abigail Morrison	47	1683	35,81	Jülich Research Centre	Germany	Europe (EU)
21	Robert A Legenstein	31	1104	35,61	Graz University of Technology	Austria	Europe (EU)
22	Elisabetta Chicca	41	1445	35,24	Bielefeld University	Germany	Europe (EU)
23	Francesco Galluppi	38	1336	35,16	GenSight Biologics (France)	France	Europe (EU)
24	Johannes Schemmel	62	2055	33,15	Heidelberg University	Germany	Europe (EU)
25	Giacomo Indiveri	138	4459	32,31	ETH Zurich	Switzerland	Europe
26	Alexander N Tait	27	860	31,85	Princeton University	United States	North America
27	Andre X Van Schaik	50	1578	31,56	Western Sydney University	Australia	Australasia
28	Anders Lansner	28	871	31,11	Stockholm University	Sweden	Europe (EU)
29	Zhi-Gang Zeng	35	999	28,54	Huazhong University of Science and Technology	China	Asia
30	Abu Sebastian	33	917	27,79	IBM Research - Zurich	Switzerland	Europe
31	Tara Julia Hamilton	43	1170	27,21	Macquarie University	Australia	Australasia
32	Daniele Ielmini	27	722	26,74	Polytechnic University of Milan	Italy	Europe (EU)
33	Karlheinz Meier	47	1254	26,68	Heidelberg University	Germany	Europe (EU)
34	Gustavo Deco	29	749	25,83	Pompeu Fabra University	Spain	Europe (EU)
35	Steve B Furber	125	2846	22,77	University of Manchester	United Kingdom	Europe
36	Paul R Prucnal	41	870	21,22	Princeton University	United States	North America
37	Bhavin J Shastri	43	912	21,21	Queen's University	Canada	North America
38	Hai Helen Li	32	636	19,88	Duke University	United States	North America
39	Nikil D Dutt	32	630	19,69	University of California	United States	North America
40	Abhronil Sengupta	45	852	18,93	Pennsylvania State University	United States	North America
41	Yiran Chen	26	490	18,85	Duke University	United States	North America
42	Alejandro Linares-Barranco	38	709	18,66	University of Seville	Spain	Europe (EU)
43	Alexander D Rast	27	495	18,33	University of Manchester	United Kingdom	Europe
44	Eduardo Ros	49	889	18,14	University of Granada	Spain	Europe (EU)
45	Garrick Michael Orchard	32	580	18,13	National University of Singapore	Singapore	Asia
46	Ryad Benjamin Benosman	28	499	17,82	University of Pittsburgh	United States	North America
47	Ammar Belatreche	35	623	17,8	Northumbria University	United Kingdom	Europe
48	Yaochu Jin	27	480	17,78	University of Surrey	United Kingdom	Europe
49	Tarek M Taha	40	707	17,68	University of Dayton	United States	North America
50	Liam Philip Maguire	64	1126	17,59	University of Ulster	United Kingdom	Europe

51	Jeffrey L Krichmar	47	822	17,49	University of California	United States	North America
52	Nikola Kirilov Kasabov	174	2987	17,17	Auckland University of Technology	New Zealand	Australasia
53	Jesús Alberto Garrido	27	462	17,11	University of Granada	Spain	Europe (EU)
54	Christian Georg Mayr	26	431	16,58	TU Dresden	Germany	Europe (EU)
55	Lubica Luba Benuskova	28	464	16,57	Comenius University	Slovakia	Europe (EU)
56	Evangelos S Eleftheriou	33	545	16,52	IBM Research - Zurich	Switzerland	Europe
57	Haizhou Li	28	459	16,39	National University of Singapore	Singapore	Asia
58	Emre Ozgur Neftci	54	879	16,28	University of California	United States	North America
59	Fearghal Morgan	26	418	16,08	National University of Ireland	Galway, Ireland	Europe (EU)
60	Chris Eliasmith	46	728	15,83	University of Waterloo	Canada	North America
61	Johannes Partzsch	26	407	15,65	TU Dresden	Germany	Europe (EU)
62	Elisa Vianello	37	577	15,59	CEA LETI	France	Europe (EU)
63	Alois Christian Knoll	32	477	14,91	Technical University of Munich	Germany	Europe (EU)
64	Egidio Ugo D'Angelo	28	416	14,86	University of Pavia	Italy	Europe (EU)
65	Jonathan C Tapson	36	524	14,56	Western Sydney University	Australia	Australasia
66	Bipin Rajendran	51	732	14,35	King's College London	United Kingdom	Europe
67	Qiang Yu	26	362	13,92	Rochester Institute of Technology	United States	North America
68	Garrett S Rose	38	519	13,66	University of Tennessee at Knoxville	United States	North America
69	Kaushik Roy	115	1555	13,52	Purdue University West Lafayette	United States	North America
70	Priyadarshini Panda	36	485	13,47	Purdue University West Lafayette	United States	North America
71	Jim Harkin	73	979	13,41	University of Ulster	United Kingdom	Europe
72	Peng Li	31	390	12,58	University of California	United States	North America
73	Arindam Basu	47	585	12,45	Nanyang Technological University	Singapore	Asia
74	Gopalakrishnan Srinivasan	26	318	12,23	Purdue University West Lafayette	United States	North America
75	Thomas Martin Mcginnity	59	675	11,44	Nottingham Trent University	United Kingdom	Europe
76	Hua Jin Tang	64	724	11,31	Zhejiang University	China	Asia
77	Liam Joseph Mcdaid	83	907	10,93	University of Ulster	United Kingdom	Europe
78	Angel F Jimenez-Fernandez	29	311	10,72	University of Seville	Spain	Europe (EU)
79	Jörg Conradt	27	281	10,41	Royal Institute of Technology	Sweden	Europe (EU)
80	Kay Chen Tan	40	414	10,35	City University of Hong Kong	China	Asia
81	Alessandro E P Villa	43	436	10,14	University of Lausanne	Switzerland	Europe
82	Thomas Nowotny	29	287	9,9	University of Sussex	United Kingdom	Europe
83	Timothée Levi	31	278	8,97	University of Tokyo	Japan	Asia
84	Bin Deng	34	300	8,82	Tianjin University	China	Asia
85	Qing Xiang Wu	52	441	8,48	Fujian Normal University	China	Asia
86	Arash Ahmadi	45	368	8,18	University of Windsor	Canada	North America
87	Hiroyuki Torikai	33	265	8,03	Hosei University	Japan	Asia
88	Jiang Wang	37	294	7,95	Tianjin University	China	Asia
89	Kazuyuki Aihara	31	241	7,77	University of Tokyo	Japan	Asia
90	Junxiu Liu	50	334	6,68	Guangxi Normal University	China	Asia
91	Osvaldo Simeone	29	158	5,45	King's College London	United Kingdom	Europe
92	Yulia Sandamirskaya	30	161	5,37	ETH Zurich	Switzerland	Europe
93	Malu Zhang	33	177	5,36	National University of Singapore	Singapore	Asia
94	Naoyuki Kubota	150	798	5,32	Tokyo Metropolitan University	Japan	Asia
95	Arne Roennau	31	160	5,16	Research Center for Information Technology	Germany	Europe (EU)
96	Udayan Ganguly	34	160	4,71	Indian Institute of Technology Bombay	India	Asia
97	Catherine D Schuman	52	240	4,62	Oak Ridge National Laboratory	United States	North America
98	Byung-Gook Park	51	212	4,16	Seoul National University	South Korea	Asia
99	Dhireesha Kudithipudi	28	107	3,82	The University of Texas at San Antonio	United States	North America
100	Anup Kumar Das	30	98	3,27	Drexel University	United States	North America



Publications of European research centers have received 64% of the total citations.



European research centers have produced 52% of total publications

Organization	Country	Zone	Total Publications
University of Ulster	United Kingdom	Europe	220
University of Manchester	United Kingdom	Europe	200
University of California	United States	North America	200
ETH Zurich	Switzerland	Europe	195
Purdue University West Lafayette	United States	North America	177
Auckland University of Technology	New Zealand	Australasia	174
Tokyo Metropolitan University	Japan	Asia	150
Seville Institute of Microelectronics	Spain	Europe (EU)	121
CEA	France	Europe (EU)	109
Heidelberg University	Germany	Europe (EU)	109
National University of Singapore	Singapore	Asia	93
Western Sydney University	Australia	Australasia	86
King's College London	United Kingdom	Europe	80
University of Granada	Spain	Europe (EU)	76
Graz University of Technology	Austria	Europe (EU)	75
Tianjin University	China	Asia	71
Princeton University	United States	North America	68
University of Seville	Spain	Europe (EU)	67
IBM Research - Zurich	Switzerland	Europe	66
Zhejiang University	China	Asia	64
University of Tokyo	Japan	Asia	62
Nottingham Trent University	United Kingdom	Europe	59
Duke University	United States	North America	58
RWTH Aachen University	Germany	Europe (EU)	55
Centre for Nanoscience and Nanotechnology	France	Europe (EU)	52
TU Dresden	Germany	Europe (EU)	52
Fujian Normal University	China	Asia	52
Oak Ridge National Laboratory	United States	North America	52
Seoul National University	South Korea	Asia	51
Guangxi Normal University	China	Asia	50
Jülich Research Centre	Germany	Europe (EU)	47
Nanyang Technological University	Singapore	Asia	47
University of Waterloo	Canada	North America	46
Pennsylvania State University	United States	North America	45
University of Windsor	Canada	North America	45
University of Zurich	Switzerland	Europe	43
Swiss Federal Institute of Technology in Lausann	Switzerland	Europe	43
Brain and Cognition Research Center	France	Europe (EU)	43
Macquarie University	Australia	Australasia	43
Queen's University	Canada	North America	43
University of Lausanne	Switzerland	Europe	43
Bielefeld University	Germany	Europe (EU)	41
University of Dayton	United States	North America	40
City University of Hong Kong	China	Asia	40
GenSight Biologics (France)	France	Europe (EU)	38
University of Tennessee at Knoxville	United States	North America	38
The Ohio State University	United States	North America	37
Huazhong University of Science and Technology	China	Asia	35
Northumbria University	United Kingdom	Europe	35
Institut de la Vision	France	Europe (EU)	34
Indian Institute of Technology Bombay	India	Asia	34
New York University	United States	North America	33
Hosei University	Japan	Asia	33
Imperial College London	United Kingdom	Europe	32
Technical University of Munich	Germany	Europe (EU)	32
Research Center for Information Technology	Germany	Europe (EU)	31
Drexel University	United States	North America	30
Pompeu Fabra University	Spain	Europe (EU)	29
University of Sussex	United Kingdom	Europe	29
Stockholm University	Sweden	Europe (EU)	28
University of Pittsburgh	United States	North America	28
Comenius University	Slovakia	Europe (EU)	28
University of Pavia	Italy	Europe (EU)	28
The University of Texas at San Antonio	United States	North America	28
Ghent University	Belgium	Europe (EU)	27
Polytechnic University of Milan	Italy	Europe (EU)	27
University of Surrey	United Kingdom	Europe	27
Royal Institute of Technology	Sweden	Europe (EU)	27
Délégation Ile-de-France Sud	France	Europe (EU)	26
National University of Ireland	Galway, Ireland	Europe (EU)	26
Rochester Institute of Technology	United States	North America	26

Research Centers with top publications (based on the data of top researchers)

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