ANALYSIS OF SYSTEM ON CHIP DESIGN USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

*Automation is a powerful word that lies everywhere. It shows that without automation, application will not get developed. In a semiconductor industry, artificial intelligence played a vital role for implementing the chip based design through automation .The main advantage of applying the machine learning & deep learning technique is to improve the i*mplementation *rate based upon the capability of the society. The main objective of the proposed system is to apply the deep learning using data driven approach for controlling the system. Thus leads to a improvement in design, delay ,speed of operation & costs. Through this system, huge volume of data's that are generated by the system will also get control.*

KEYWORDS

Deep learning, artificial intelligence, machine learning, semiconductor technology.

1. INTRODUCTION

The International Technology Roadmap for Semiconductors (ITRS) estimates that by 2020, IC designs will pack 1 trillion transistors per chip. The number of Design Rule Checks (DRC) have increased by a factor of 10X roughly every 10 years, and so have number of scenarios operating modes and corners – that must be evaluated by EDA tools to verify and implement designs. Product development schedules are getting shorter, which means productivity per engineer must increase by 15X from 1 million to 15 million gates per year to keep up with the complexity increase.

Semiconductor design activity produces vast amounts of data, but this data is not utilized in any systematic manner by chip design teams. Data driven approaches have demonstrated significant benefits in many industries and similar approaches can provide actionable insights and enable predictive technologies in semiconductor workflows. Two prominent data driven techniques are Machine Learning (ML) and big data.

1.1 Machine Learning

ML is a branch of Artificial Intelligence and is defined as the ability to learn without explicit programming. ML programs learn from data, and in many cases provide improved results given more data. There are three types of ML: Supervised, Unsupervised and Reinforcement.

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In supervised learning, labelled data is provided as input to the system. Labelled data is comprised of a set of samples that have been tagged with labels that are meaningful. For example, identifying a set of log files from tool runs with tags that denote whether they are good runs or attention-needing runs can be construed as providing labelled data. In supervised learning, a model is first trained based on given samples.

Training a model entails extracting features from the given samples, and providing the set of (input) features along with the label to an algorithm which learns the mapping of inputs to output. The output from the training phase is a model, which can be persisted if needed. This model is then deployed and used to infer the label for new and previously unseen data. A typical supervised learning system is shown in Figure 1.

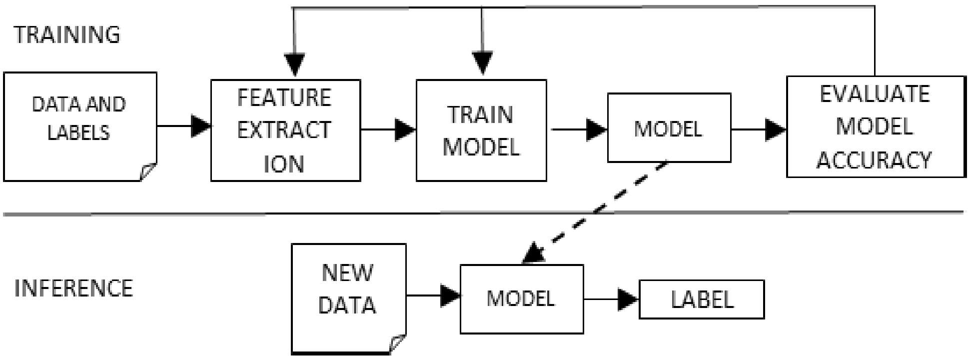

Figure. 1 Supervised learning workflow

Unsupervised learning systems do not require labelled data. Unsupervised learning algorithms are used to infer a function or underlying structure from unlabeled data. They are widely used in data analysis and data mining. While supervised learning is clearly more common today, unsupervised learning is likely to be more prevalent in the future, given the abundant internet data that is generated every day, and the expected interest from corporations to monetize this data.

The fundamental concept in reinforcement learning is that learning can be achieved by interacting with the environment. Just like a child learns without an explicit teacher that smiling or crying have different effects, reinforcement learning algorithms are based on cause and effect. The learner is not told what actions to take, but it must discover what actions (immediate or future) are most rewarding. In recent times, a branch of machine learning called deep learning has become popular. Deep learning systems [2] can be characterized as universal approximators capable of modeling non-linearity with a high level of accuracy. Growth in deep learning was primarily driven by the widespread availability of high-performance special-purpose computation platforms and the abundance of data. An anatomy of a deep learning system is shown in Figure 2.

Deep learning systems address a basic problem in ML.All ML systems learn the mapping of inputs to output by extracting features from input, and for most tasks, it is hard to know what features to extract. An approach popularly known as Representation Learning can be employed to learn features, and this is fundamental to all deep learning algorithms.

Learned representations are generally better than manually manually extracted features, with the added benefit of reduced human intervention. While representation learning was a known field, the advent of deep learning made it viable. Representation learning can be difficult to put in practice if it is as hard to get representations as it is to solve the original problem, which was the case until deep learning came along. The representation learning performed by deep learning systems is highly effective, since they build complex features (or concepts) from simple concepts.

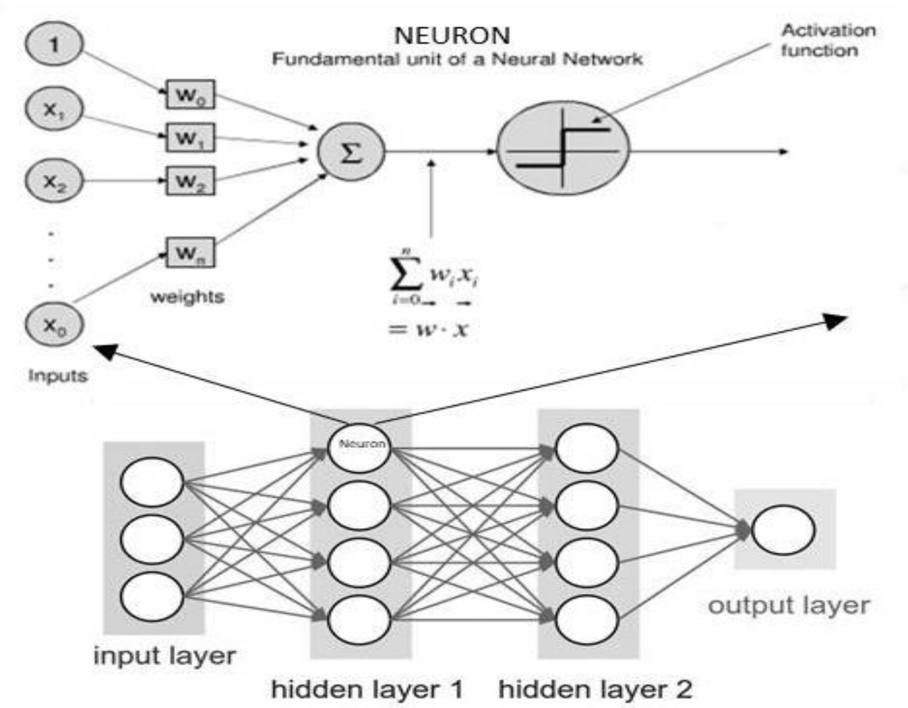

Figure 2. Components of a deep learning system

1.2`Big Data

Big data can be defined as a capability of providing actionable real-time insights from large amounts of data. For data to be classified as big data, in addition to its abundance and vastness, it is also expected that it is being generated at a very fast pace from various varied sources. In fact, big data systems are characterized by 3 Vs – Volume, Velocity and Variety. Such systems generate large amounts of data that is both structured (data that is highly organized, and can be stored in a relational database) and unstructured (data that does not have a predefined data model). The data is generated at a fast pace in big data systems. Furthermore, big data systems also encompass a large variety of data sources. Examples of systems demonstrating big data behaviour are IoT (Internet of Things) devices. The value of a big data system is in providing real time insights into chip design flows that would be otherwise unavailable, and in providing recommendations for actions that can be taken to improve production flows. A simplified flow of the phases in a big data system is provided below in Figure 3:

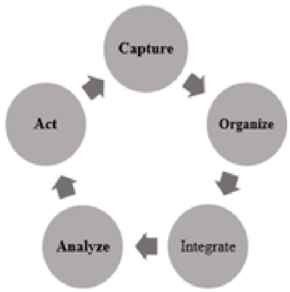

Figure3. Phases in Big Data

There is significant literature available on building a software stack for big data systems, and there is no one right stack.

However, it is typical to have either some or most of the components shown in Figure 4. The system can be further generalized into a pipeline of three key processes:

- Data Capture: During this process, all relevant data is captured systematically. For example, for an IoT based real-time analytics solution, device metric samples may be captured at regular intervals. Furthermore, all data that the device depends on should also be captured or acquired (and then captured).

- Data Processing: During this process, data captured is processed and stored. Depending on the type of data, an appropriate database or data store is used to store the data.

Data Extraction: During this process, user requests, such as web requests or API calls are received and processed

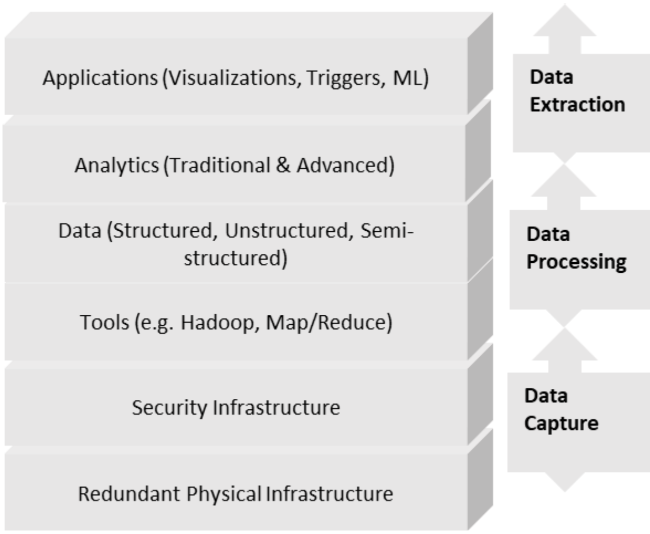

Figure 4. Big data software stack

Custom visualizations and triggers are typical interfaces to big data systems. Visualizations enable users of big data systems to understand if systems are operating as expected, and take necessary actions in real time.

2. RELATED WORK

Several efforts have shown the significance of MLbased efforts to solve optimization problems that are NPcomplete. In [6], the authors discuss a framework that optimizes FPGA flows. They present an ML-framework consisting of a set of classification and regression techniques to address the disconnect between different stages of FPGA design. The framework consists of five algorithms (Artificial Neural Network, Decision Tree, Support Vector Machine, K Nearest Neighbour, and Random Forest) that can be used to solve two problems: choosing between different placement flows and predicting various quality metrics related to FPGA placement.

The framework employs supervised training methods. Training data is generated from 372 benchmarks by running the benchmarks through seven academic configurations that vary in certain parameters. Experimental results from 372 benchmark designs show that 4 out of the 7 configurations show accuracy of 88 to 99% in choosing a configuration that best minimizes total wire length.

In [7], the authors describe how ML was used to predict DRC violations during the global routing stage. DRC violations during detailed routing prevent or delay tape outs. To prevent tape out delays, automatic place and route tools create a global routing map. The placer uses the routine map to optimize placement of blocks in a way so as to reduce or eliminate DRCs. However, at advanced nodes, the correlation between global and detailed routing weakens, leading to either aggressive optimization by the placer at the expense of area or power or too many DRCs in the final routing stage.

In [8], the authors motivate a need for advanced analytics for semiconductor design to streamline R&D processes, optimizing product portfolios and helping businesses reduce costs. The fundamental difference between traditional and advanced analytics is as follows: in traditional analytics, the data is in existence, and analytics enable better understanding of data whereas advanced analytics is a process where the data to be collected is first defined by the analytics that would be needed to drive decisions. In research conducted across 200 projects, it is found that advanced analytics enabled project teams to reduce their project times by approximately 10%.

In [9], the author describes use of big data techniques to improve verification efficiency. Verification is the most time consuming step in the chip design process, and a typical verification environment consists of geographically dispersed collaborative teams, and a flow that involves multiple systems. The author motivates the need for a central repository that can store metrics and data in a common format and shows the value of insights gathered by visualizing metrics.

3. METHODOLOGY RECOMMENDATIONS

A strategy that enables corporate goals be it improving turnaround time for designs or reducing resource costs should be the centre point of any methodology.

The research to date shows that chip design companies can incorporate data-driven methods in their workflows to improve quality of results, time to results or cost of results. These techniques require access to data from tool runs, flows and environment. Furthermore, chip design is a continuous process and a framework that continuously polls for new runs, captures meta data, and enables access to information through consistent interfaces is integral to reaping long-term benefits. Potential enterprise architecture for data driven applications is shown in Figure 5.

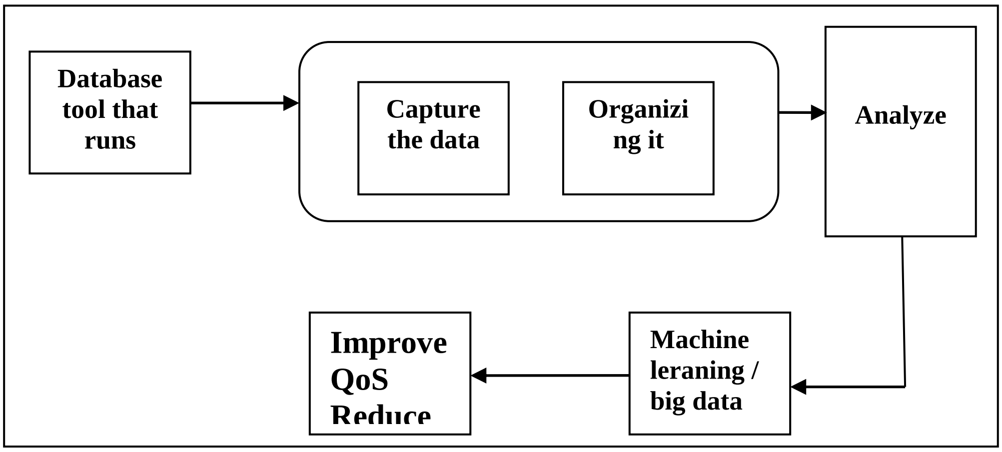

Figure 5. Enterprise Architecture for applications

robust capture mechanism should be in place to enable downstream processes. This framework should operate at the enterprise level, across geographically dispersed sites, be flexible enough to handle different types of tools and flows and scale to supporting hundreds of tool run every minute.

An easy-to-use access/analysis mechanism is the key to building a lasting solution. In ML and big data systems, APIs are the most extensible way to provide analysis capabilities. APIs can be used to build custom visualizations or standalone applications.

Formulating the ML problem requires the right expertise. It requires data scientists, domain experts and software engineers working together. It also requires the right kind of data, feature engineering and compute infrastructure. For many real-life problems, training times can be considerably long, and this may require special-purpose hardware.

Furthermore, model retraining is necessary in production instances, so that model accuracy meets requirements. Other important considerations when deploying ML models for production are inference time, and a framework to monitor model accuracy.

Some problems can be solved by using advanced analytics. Advanced analytics can enable users to understand what is happening, plan resource allocation, explore reasons for unexpected behaviour, identify anomalies, and get real-time information about project status. A common infrastructure consisting of capture-process organize phases can serve as the backbone for both ML and big data systems.

4. CONCLUSION

Data driven techniques have shown promising results in optimizing chip design workflows. To enable enterprise-wide digital intelligence via ML and big data backed strategies, a robust framework for enabling both ML and big data should be put in place. Distributed big data systems are the cornerstone for enabling such techniques. It is important to use discretion in identifying areas to pursue using data-driven technologies since ML and big data do not apply to all problems. Coordinated execution from all the relevant domains is required to produce complex data driven solutions and a soiled approach will not provide lasting benefits. Companies that adopt data driven optimizations will have highly efficient design teams. In other words, to remain competitive, companies should accelerate their plans for bringing digital intelligence into their flows.

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