

## IT@INTEL

# Artificial Intelligence Reduces Costs and Accelerates Time to Market

Our use of artificial intelligence to optimize the product-validation process helps to decrease costs and accelerate time to market.

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### Executive Overview

Intel IT is in a unique position to lead Intel's digital transformation. We have the experience needed to solve complex business challenges and deliver new value to the company. We are using our highly connected datasets and artificial intelligence (AI) expertise to improve our business processes. We are also working closely with Intel's business units to deploy new AI technologies that can improve how we plan, design, and test Intel's products.

For example, we are collaborating with Intel's product development teams to optimize the time-consuming validation stage by automating and augmenting human validation capabilities. Our work has resulted in the following competitive advantages for Intel:

- Improved product-validation processes
- Lower costs
- Faster time to market (TTM)

In this paper we present two of our AI-based solutions for augmenting the validation process performed as part of chip design:

- **CLIFF (Coverage LIFt Framework).** To speed validation in our chip-design process, we collaborated with the chip-design team to develop an advanced big data and AI platform. CLIFF creates new tests for hard-to-validate functionalities to discover hidden bugs as early as possible. CLIFF improves the targeted functionalities coverage by 230x on average, compared to standard regression tests.
- **ITEM (Intelligent Test Execution Management).** Based on CLIFF's success, we created an additional capability called ITEM, which creates the best testing suite each week. ITEM ensures that, from a bug-finding and functionality-coverage perspective, the teams run the most cost-effective tests. ITEM has reduced the number of required tests by 70 percent.

Following CLIFF and ITEM's success, we will continue to incorporate AI into other aspects of the chip-design process to optimize product validation.

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## Acronyms

<b>AI</b>	artificial intelligence
<b>CLIFF</b>	Coverage LIFt Framework
<b>ITEM</b>	Intelligent Test Execution Management
<b>TTM</b>	time to market

# Business Challenge

Product validation—regardless of industry—is a labor-intensive process and is more complex than ever before due to advances in technology. For example, Intel is developing approximately twice as many products as it did just a few years ago, and product complexity is growing exponentially as Intel packs more capabilities into increasingly smaller semiconductor products.

Ideally, design-phase product validation, called pre-silicon validation at Intel, discovers possible bugs prior to silicon prototype production. Historically, pre-silicon validation is one of the most expensive and time-consuming product-development processes, consuming up to 50 percent of the development cycle. This is because each of the dozens of Intel's pre-silicon validation teams runs many thousands of regression tests every week. These tests generate multiple terabytes of stored data—too much data for validation engineers to process in a timely manner, or deal with the underlying complexity to make appropriate decisions, such as creating new tests for precise test cases. In some cases, legacy tests are still being run but are no longer relevant because of lack of enough visibility into their diminishing quality. In other cases, some tests take so long to perform that they cannot be run as frequently as necessary—meaning bugs may be discovered later in the development process.

Intel IT, in partnership with our product design organization, has started using artificial intelligence (AI) to speed time to market (TTM), reduce costs, and improve the product-validation process.

# Overview of the Pre-Silicon Validation Process

Intel's silicon chip development process starts with defining the product and finalizing the architecture. Then an iterative process begins:

1. Create new product features.
2. Validate the new product features and pre-existing features.

First, design teams use software to simulate the product, then they build hardware prototypes. Validation applies to both of the pre-silicon validation and post-silicon validation phases. This paper describes work done for pre-silicon validation but can also be applied to post-silicon. Validation can be a lengthy process because its role is to discover as many bugs in the product as possible, early and cost-effectively. As Intel's products become more complex, so does the validation process. Our validation strategy involves running many randomized tests (thousands per team per week) under the assumption that the relevant functionalities will be triggered in many ways to identify bugs.

Figure 1 illustrates the four main steps involved in the pre-silicon validation process. It starts with determining whether the correct aspects (such as new features) are being tested. Then, the team creates the testing environment and new tests based on what needs to be tested. Next, these tests must be managed so that the right tests are run at the right time. At each testing stage, the team must debug any tests that failed to identify the causes of the bugs. The testing teams perform these steps iteratively throughout the validation lifecycle.

Vast amounts of data are created during the pre-silicon validation process. We collect between 200 and 250 GB of new test execution and management data from each validation team per week. We retain this data for the entire project duration; currently, we store more than 30 TB of validation data, and that amount grows each week.

The validation process relies heavily on the expertise and hard work of validation engineers, as they comb through this immense amount of data for important insights. AI poses a unique opportunity to relieve these engineers from some of the more tedious and time-consuming tasks, as well as augment their abilities by making intricate, data-centric decisions and processes.

For example, some tests may require defining values for 1,000 parameters or more. It is hard to find optimal values for such a large number of parameters manually. AI algorithms can efficiently scan the values of these 1,000 parameters in many thousands to millions of historical tests and deduce the best possible value for the desired result. In this case, AI can perform tasks at a complexity level that is impractical for humans to achieve. The sections below describe two solutions we developed to integrate AI into parts of the test creation and test execution tasks.

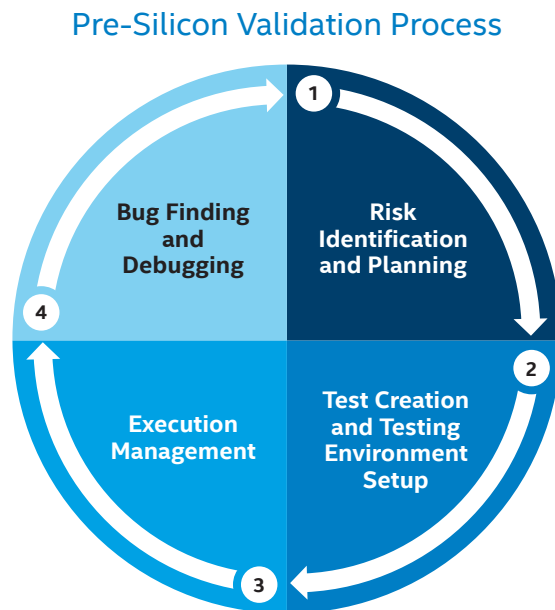


Figure 1. The pre-silicon validation process consists of four iterative and highly interdependent steps.

## Solution

To increase the efficiency and accuracy of pre-silicon validation, we have developed two AI-based solutions: CLIFF (Coverage LIFt Framework) and ITEM (Intelligent Test Execution Management). Both solutions are substantially improving the relevant validation tasks.

### Using AI for Test Creation

In 2016, we developed CLIFF, an AI platform that is designed to increase the validation quality by authenticating difficult-to-validate functionalities, and as a result, finds bugs that would otherwise have gone undiscovered during the product development design phase. CLIFF uses AI algorithms to quickly browse through many thousands of historical test records to identify hidden patterns—like needles in haystacks of irrelevant data. CLIFF accomplishes this task in just a few hours—whereas it would take human reviewers thousands of hours if they could even do it at all.

CLIFF uses this information to automatically generate new tests targeted at confirming difficult-to-validate functionalities, with the aim of discovering hidden bugs and improving product quality.

### Using AI for Test Execution Management

Each design-phase validation team runs thousands of tests each week ranging from short sanity checks to lengthy regression tests. Historically, these test suites are defined once per project at most. As testing continues, the test suite often includes many legacy, duplicate, or irrelevant tests.

In 2017, we expanded our use of AI in validation by developing ITEM capabilities. ITEM uses AI to process data from multiple sources and dynamically modify the test suites, based on predicted risk and test performance. This helps ensure that each test suite has the highest likelihood of cost-effectively discovering relevant bugs. ITEM eliminates tests that have no added value, thus reducing waste, shortening TTM, and identifying bugs as early as possible.

### AI Performance Wins Trust at Intel

In 2016, when Intel IT started developing our first artificial intelligence (AI) product-validation tool, called CLIFF (Coverage LIFt Framework), the product-validation management team was skeptical that AI could provide any substantial value. When they saw how CLIFF increased their test coverage, found hidden bugs, and improved validation quality, they became more enthusiastic.

“Initially, I was somewhat skeptical that AI could really provide any substantial value,” said Alon Flaisher, Intel Cores Validation Manager. “But once I witnessed CLIFF results, I became a believer.”

Subsequently, we have extended our work with that team to formulate a roadmap for transforming their validation process using AI. They are eager to learn more about the possibilities AI presents and are committed to making this roadmap materialize. Together, we are working to change the infrastructure and re-architect their validation methodology to better accommodate AI.

## Solution Architecture

When developing CLIFF and ITEM, we faced two primary challenges: choosing the most appropriate AI algorithms and building a big data architecture that can support current needs and scale as necessary to support additional validation teams as well as additional AI capabilities.

We use Agile and DevOps methodologies to develop and maintain both CLIFF and ITEM, including embedded continuous integration and behavioral-driven development tests. This approach accelerates development and deployment of code enhancements, enabling us to constantly improve the capabilities and increase their business value.

### Identifying the Right AI Algorithms

Choosing the most appropriate AI algorithms for a specific AI application is not always straightforward. The volume and type of data, as well as the expected output, can inform the decision about which algorithm, or set of algorithms, to use.

#### CLIFF Algorithms

Solving the issues addressed with CLIFF was challenging due to several factors:

- **Magnitude.** As mentioned earlier, input from hundreds of thousands of tests creates terabytes of data. Processing that data requires a big-data distributed infrastructure, including the use of industry-leading Apache Spark\*- and Scala\*-based algorithms to generate results in a timely manner.
- **Imbalanced data.** CLIFF data is highly imbalanced—we have a handful of desired historical examples (tests that were able to validate the functionality) but many thousands of tests that did not produce the desired result. Therefore, we need to identify the very precise and latent pattern that differentiates the two groups.
- **Evaluation.** Selecting the best results from the model output is not straightforward, because the validation process is based on random sampling of the various tests parameters. This means that the historical data generally contains only a partial sample of the full combination of test parameters. Therefore, we cannot perform a traditional offline evaluation process with the historical data at hand. Instead, we must follow a three-step process:
  1. Create the algorithm results based on an approximation of the expected results
  2. Run actual new tests accordingly
  3. Evaluate the real results and adjust the model and the offline evaluation approximation

This generates a lengthy feedback cycle and forces us to be creative with how we approximate the expected results during our algorithm development phase.



**30 TB**  
VALIDATION DATA

Currently, we store about 30 TB of validation data, and that number grows each week.

To deal with imbalanced data, we performed massive downsampling and chose an ensemble of AI algorithms. These algorithms include classifier inference (Random Forest and feature importance), filters (such as ignoring negative correlations), and Frequent Item set mining algorithms (Apriori and Frequent Pattern Growth).

We improved evaluation by using cross-validation loops and a tailored approximation method to assess the strength of our algorithms to fine-tune the recommendations provided by the algorithms. As a result, the new tests that CLIFF creates are more likely to be valuable. CLIFF's algorithms have already proven to be highly robust, and they generate impressive results across different validation teams with only minimal tuning of the parameters.

### ITEM Algorithms

Our experience with CLIFF—data, big-data framework, and algorithmic learnings—gave us a head start as we developed ITEM. However, ITEM posed its own unique challenges. ITEM's test-suite decisions are based on multiple considerations, including how efficiently a test finds bugs, functionality coverage, test metadata, and test inputs. Therefore, ITEM needs to ingest and integrate many more data sources compared to CLIFF. As a result, it is a complicated process to prepare the data for ITEM modeling from both a data management efficiency and algorithmic perspective. We use the following techniques to address these challenges:

- We created many built-in data integrity and cleanup processes.
- We parse each test's data and cluster similar test records to simplify the problem space.
- We use statistical methods to automatically detect the relevant history of data that can be used (data that still represents the current product design) and then densely organize the data to allow for efficient algorithm execution.

Once the data is prepared and cleaned we run a three-step process:

1. We identify the most cost-effective tests for identifying bugs.
2. We use boosting techniques to create new tests that will validate the harder-to-trigger bugs.
3. We use optimization algorithms, namely an adjusted version of the “weighted set coverage” algorithm, to identify the minimal set of tests that cover the maximum number of functionalities at minimal cost. (We consider both the number of tests and test runtime when figuring cost.)

## Building a Scalable, Resilient Architecture

Big data requires scalable, reliable, high-performance compute capabilities. Our validation AI solutions illustrate how a rich big-data environment can benefit from Intel® technology running on Cloudera Distribution for Hadoop\* (CDH\*). CDH is our distribution of choice, as it is an enterprise-grade distribution with built-in security and high-availability. CDH includes Apache Hadoop\* and several other components of the Apache Hadoop ecosystem. Cloudera has tested the components to ensure that they work well together, making it a very stable distribution.

We initially created the architecture for CLIFF (shown in Figure 2). Then, we expanded and improved the architecture to accommodate ITEM as well. We use micro-services to allow components to be added and modified efficiently. Micro-services also help us integrate additional AI solutions on the same framework, as demonstrated by adding in ITEM, as well as other capabilities we are currently researching and developing.

We deployed CLIFF and ITEM on a CDH cluster in our enterprise private cloud (see Figure 2). The CDH cluster runs on high-performance servers based on Intel® Xeon® Scalable processors. Multiple input datasets are converted into many thousands of structured log files each week. A persistent API transfers these logs to a tailor-made file-ingestion mechanism based on an Apache Kafka\* broker and Apache Spark Streaming\*, which then streams the data into a Hadoop Distributed File System\* (HDFS\*). Spark then processes the files that have been ingested during the last month (and sometimes older files). AI algorithms process the data (as discussed above), generating new tests. Finally, algorithm results and indicators are saved into Apache Hive\* tables.

The framework for future algorithms' evaluation, tuning, and success indicators collects the results of these new tests. The system processes many dozens of GBs generated by each team per week, and can store many TBs across multiple teams. The system features a high level of security with excellent persistence and performance.

The CDH platform consists of 56 Intel® Xeon® processor-based data nodes with 28 TB of memory and 2.6 PB of storage. We expect to scale both compute and storage as more teams adopt CLIFF and ITEM, and other AI use cases.

## CLIFF (Coverage LIft Framework) and ITEM (Intelligent Test Execution Management) Architecture

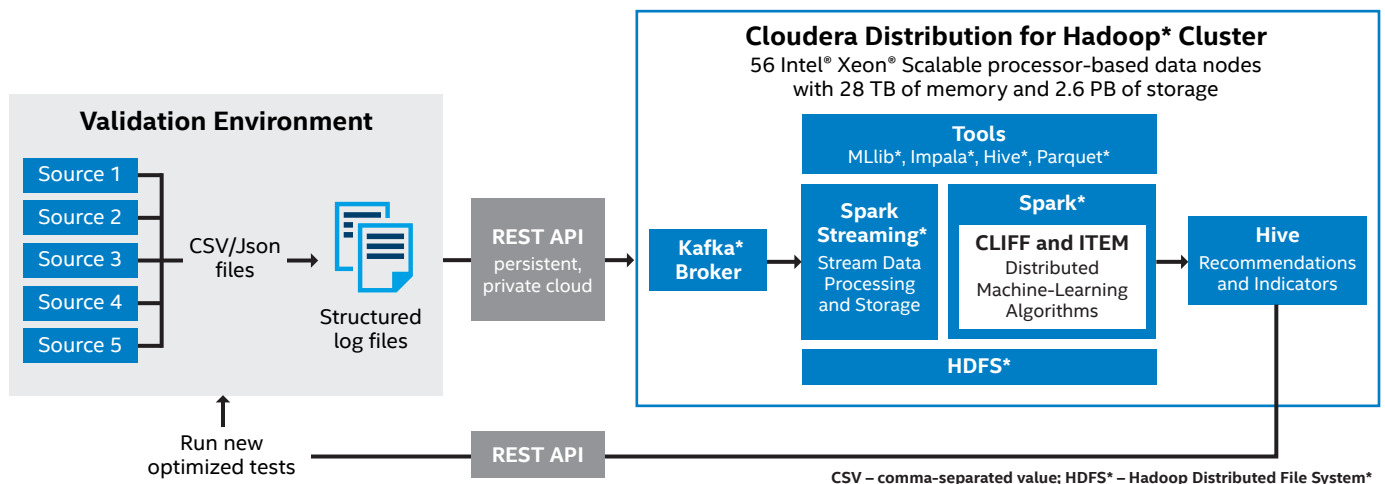


Figure 2. CLIFF and ITEM solutions run in our Cloudera Distribution for Hadoop\* (CDH\*) cluster running on high-performance servers based on Intel® Xeon® Scalable processors.

## Results

CLIFF is consistently increasing functionality validation that other validation tools are struggling with, as well as finding bugs not found by any other method. Identifying issues early creates a strategic advantage. The issues that CLIFF uncovers might not have been found until late in the product cycle, resulting in increased cost or a delay in product release.

As illustrated in Figure 3, our internal tests indicate that CLIFF increases validation of targeted functionalities by 230x on average, compared to standard regression testing, and can process vast amounts of data in just a few hours. Manual processing of that much data is not humanly possible. ITEM has reduced the number of required tests by 70 percent, again reducing costs and TTM.



We expect to improve efficiency by at least 20 percent across the validation cycle by embedding AI into critical validation processes.

## Next Steps

In 2018, we plan to proliferate CLIFF and ITEM to other relevant validation teams. We also plan to go beyond CLIFF and ITEM by using advanced AI algorithms to automate additional critical validation tasks, such as debugging. We expect to improve efficiency by at least 20 percent across the validation cycle by embedding AI into the critical validation processes at Intel, and training validation teams to extract optimal value from AI.

### CLIFF (Coverage LIFt Framework) and ITEM (Intelligent Test Execution Management) Dramatically Improve Our Validation Processes

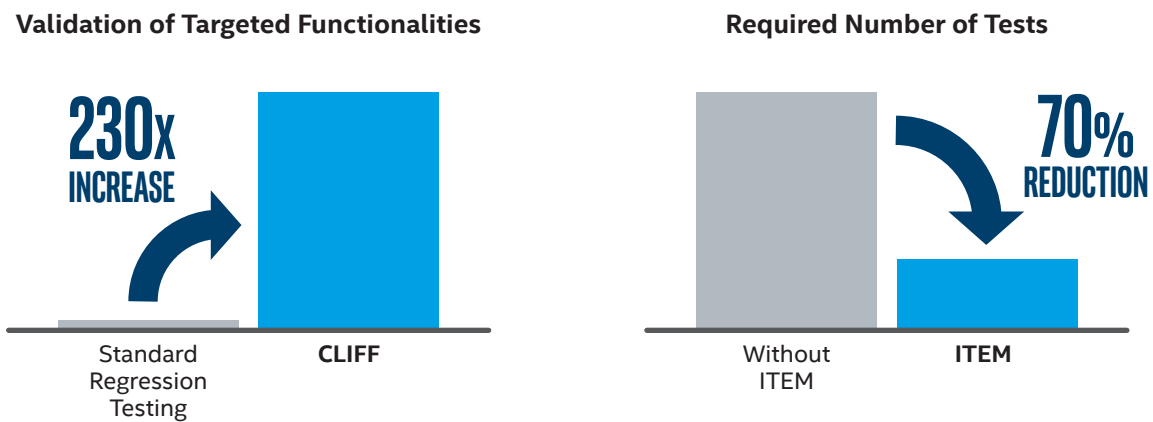


Figure 3. Integrating artificial intelligence (AI) into our pre-silicon validation process is increasing efficiency and shortening time to market (TTM).



## Conclusion

CLIFF and ITEM serve as compelling proof of the power unleashed by big data and AI to solve previously unsolvable critical business problems. Moreover, these tools support multiple teams simultaneously, which would be impossible without harnessing the power of big data to handle data processing and running the AI algorithms in a distributed fashion.

Beyond efficiency and shortened TTM, AI provides a unique ability to steer the validation process to focus on specific risk areas—reducing the number of bugs that evade discovery until more expensive stages, such as silicon testing. We will continue to integrate AI into Intel's business processes to transform how business units plan, design, and test Intel's products.

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