MACHINE LEARNING IN ENGINEERING

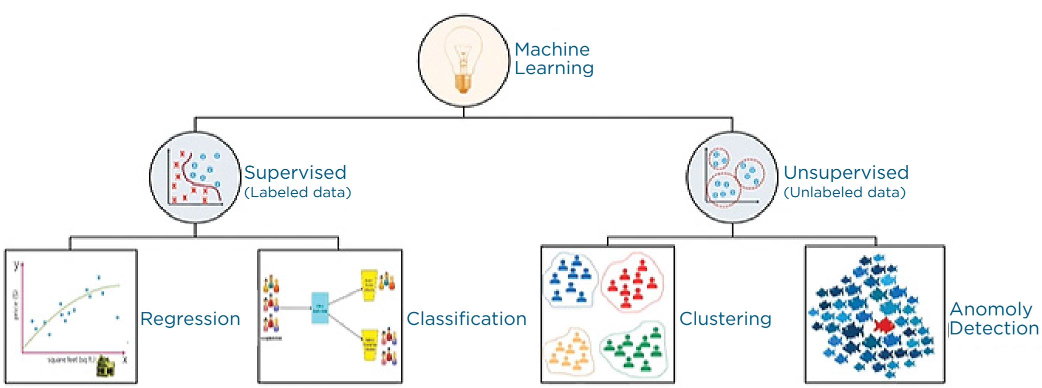
Machine learning (ML) has allowed companies to automatically detect damage to powerlines, predict the best time to buy a product online, and even build effective fraud detection systems, all adding to the convenience and safety of our lives.

When applied to engineering, ML can be a powerful tool to aid in a range of applications, from faster finite-element (FE) model building to optimizing manufacturing processes and obtaining more accurate results from physics-based simulations. Although incorporating this collection of technology is relatively new in the field of engineering, Altair has made leaps forward in this space to provide users with the tools they need to make a difference.

Machine Learning Techniques

When considering how ML can be used in an engineering application, it is important to understand the different approaches and methods. In its simplest organization, the two main categories are supervised and unsupervised ML, each with its own objectives and uses. Under the umbrella of these methods, a range of applications can be explored and optimized to provide faster workflow, optimized design, and more accurate predictions.

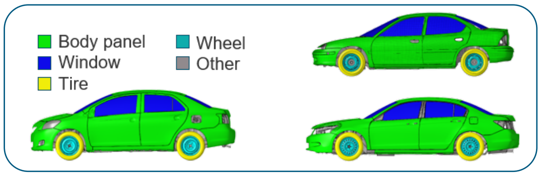
Overview of Machine Learning Techniques



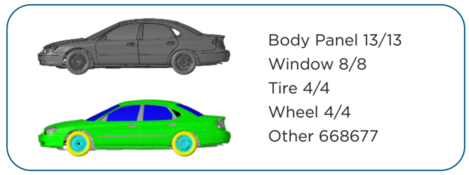
Learn More at:
altair.com/machine-learning

ALTAIR

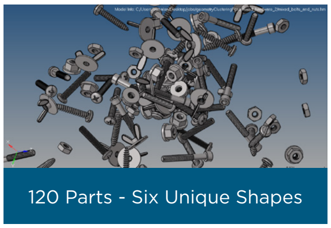
Database: Three Assemblies (2,121 parts)

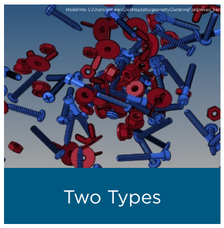


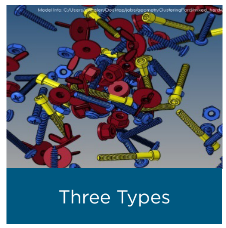
Classification Machine Learning Algorithm

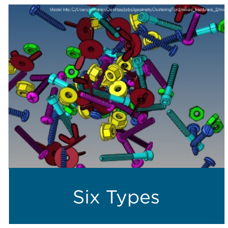


A classification model uses labeled data to predict outcomes for new data.
For example, identifying parts of a new assembly.









An unsupervised algorithm, such as clustering, works on its own with unlabeled data to discover patterns and information that was previously undetected. For example, identifying parts based on similar properties.

Machine Learning Revolves Around Data

Due to fast advancements in sensor and bandwidth technology, increased storage capacity, and computation power, the use of ML for engineering has become more feasible. Continuous method development and access to open-source codes have opened the doors for companies to experiment with ML and its capabilities. There are, however, still challenges pertaining to data:

1. Data on demand. When engineers do not have enough data to run an ML model, often the approach is to produce the data by using physics-based simulations. This method can be time consuming and could present issues with a lack of data. For this reason, extensible or adaptive sampling is critical to create the optimal set of data that maximizes the learning and minimizes simulation costs.

2. Data in hand. This refers to use of the historical data. Often data has been collected over a long period of time, perhaps 30 years or more, and stored in different places and formats created by different software versions. As a result, reliability can be an issue. Additionally, this data needs to be converted to metadata for it to be used by an ML model.

3. Data in flight. Internet of Things (IoT) sensors are typically responsible for collecting and producing large amounts of fast data from operations such as live telemetry data from F1 cars during a race. Volume and quality of data can be an issue in implementing an effective ML model.

Machine Learning Challenges within Engineering

Specific to CAE and CAD processes, ML can provide smarter, faster ways to process data and build optimized designs. However, these applications have challenges unique to engineering:

Volume. Incorporating ML methods into various CAE/CAD tasks can require access to large sets of data. Simulations must be run for useful data to be extracted, making this process computationally expensive and time consuming.

Format. Due to the non-tabular nature of CAD, the format of this data poses a problem when being used to teach an ML model. 3D shapes do not translate well to columns and rows, so establishing how to best achieve this is imperative.

Predictions. ML applications within engineering need to predict more than a simple yes or no answer when dealing with simulation. For example, when running a transient simulation, it is possible that millions of elements multiplied by thousands of time-steps need to be considered and calculated.

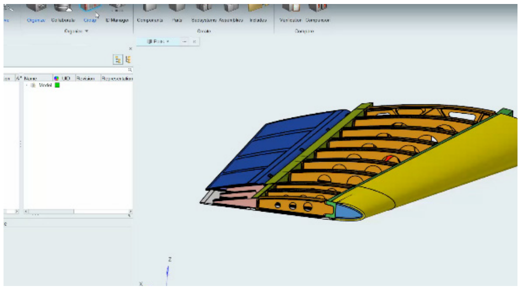
TOP: Airflow simulation using Atair AcuSolve™.

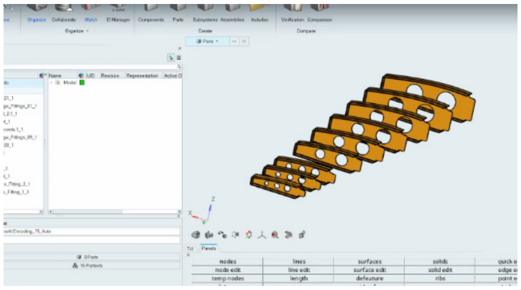
Variety. One aspect of ML within engineering that is advantageous however is the possibility to create intentional design failures through simulation. Unique to this discipline, leveraging this data leads to a more accurate ML model that can be used to further the development of software features and processes.

Given the advancements within ML and the relevant technologies associated with it, Altair has established several features within its solutions to help users achieve their goals:

Transforming Products with AI

Machine Learning with Altair HyperWorks™ for CAD/CAE





Search by Shape, Left Image

When building a CAE/CAD model, being able to search for similar shapes building the model is very useful. By selecting a part, it is now possible to search for similar shapes in Altair HyperWorks™, saving the user time and effort.

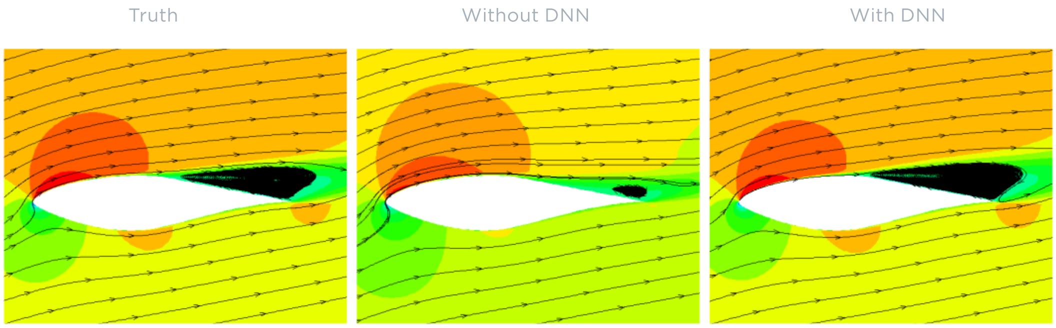
Part Clustering, Right Image

Going one step further, part clustering will take all parts included and cluster them with respect to their shape similarity, allowing the user to view all clusters within a build.

[To learn more watch this Presentation for ML for 3D Design](#)

Physics-Informed Neural Net in CFD

Incorporating ML into Altair AcuSolve™ has led to improved aerodynamics predictions by implementing a physics-informed data-driven ML model. This produces a more accurate prediction of flow separation when studying aerodynamic fluid flow in conjunction with a deep neural network (DNN).



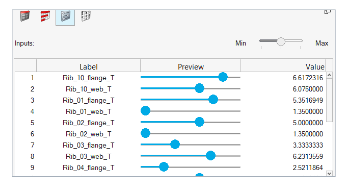
Improved prediction of flow separation with AcuSolve + DNN of a simplified wing/blade.

This process is achieved by appending a correction term to the equations governing the fluid flow and running several simulations with adjoint optimization to obtain training data. The key learning features are then identified in the generated training data and used to train and test the DNN models for the correction term.

Enhancing Product Design

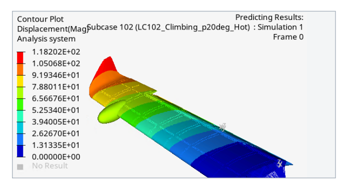
Field Predictions

Incorporating a design of experiments (DOE) methodology allows engineers to create variables, responses, and goals to obtain the best design results possible, which, when used in conjunction with a conventional ML prediction model, lead to predicted KPIs. More recently, advances in ML methods and engineering software have made it possible to make physics predictions leading to accurate contour plots, represented visually in real time.



Sliders Used to Edit Variables

By leveraging field predictive ML models engineers can explore more options without the use of a solver when designing different components and parts, saving time and resources. This ultimately produces higher quality results that can then be used to make more informed decisions throughout the design process.



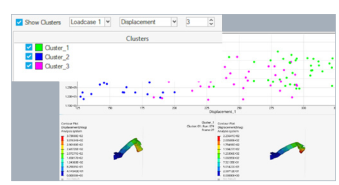
Predicted Contour Plot

[Learn more about unlocking data to speed up product design.]

[Read the Wall Street Journal article about the use of Machine Learning at Rolls Royce.]

Scaling Expertise in Design

In optimization, it is sometimes desirable but not possible to define constraints that fully reflect an expert's requirements. This may lead to a design that does not function as intended. ML enables the user to set up subjective constraints to ensure a design that has been trained to replicate the expert's opinion. In the automotive industry for example, this can be a huge advantage.



Deformed Shape Clustering in HyperWorks

In a project with one of Altair's major customers, ML methods were successfully employed to create a concept design for a reinforced bracket subjected to crash loads. The design space was sampled to avoid any folding modes after the crash event, with the modes then clustered to label them more easily.

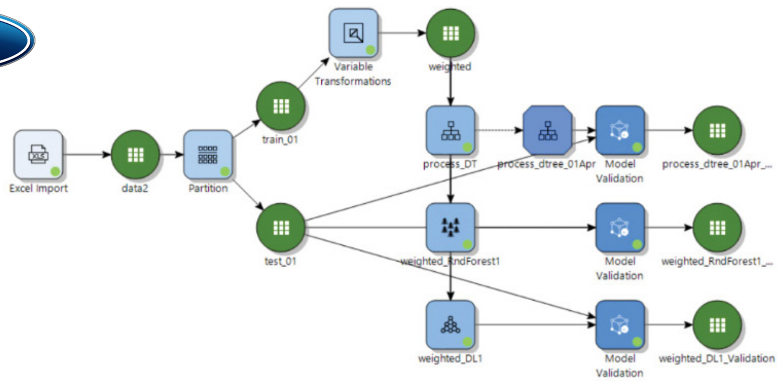
These designs could then be classified based on the desired shape and used to teach a machine learning model. By doing this, it is possible to incorporate expert preferences in an optimization, leading to faster design cycles and improved design.

To learn more, watch this presentation for crash optimization.

Leveraging Field Data

Scaling Expertise in Manufacturing

Sheet-metal stamping is one of the most common manufacturing processes in the automotive industry, yet it requires experience to sort-out the most adequate and cost-efficient sub-process for every part. To help with this, Ford used Altair to train a classification algorithm to predict the correct stamping process accurately and consistently for each new part.



Automated decision workflow to predict correct stamping process.

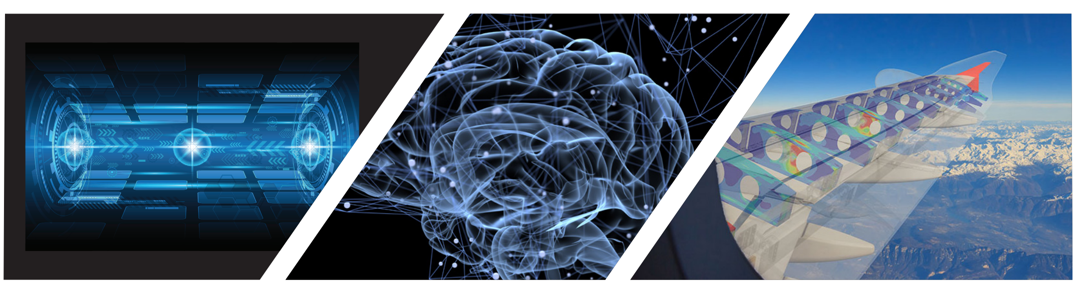
[To learn more, watch this presentation for Ford stamping.]

Working with Altair

Designed for people with different skill sets, our desktop-based predictive analytics and ML solutions helps users to quickly generate actionable insights from data.

Quickly build out predictive and prescriptive models that easily explain and quantify insight found in your data. Apply and share that insight by deploying models natively or exporting them to common business intelligence (BI) tools. Data scientists rely on Altair to efficiently build powerful and insightful predictive models to make better business decisions. Altair's code-optional development environment enables data science teams to build models using combinations of SAS language, Python, R, and SQL code.

Data Preparation		Modeling	Visualization	
STEP 1 Gather Data From Various Sources	STEP 2 Clean Data	STEP 3 Model Building — Selecting the Right ML Algorithm	STEP 4 Gather Insights From Results of Model	STEP 5 Data Visualization — Transform Results Into Visual Graphs



IoT
Altair SmartWorks™

Data Analytics Platform
Altair® RapidMiner®

Multiphysics Simulation
Altair HyperWorks™

Altair's simulation workflows are continuously evolving to create more conducive and intuitive environments for ML applications.

Learn more at **altair.com**