AI Predictive Scoring for Training Simulators

Proof of Concept

Project Report

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Project Summary

Zetane Systems built a preliminary proof-of-concept (POC) of a predictive AI model for CM Labs using data collected on a CM Labs deployed simulator. In this project a machine learning (ML) model was trained to predict the subsequent score of a trainee operating an excavator simulator. The model relies on the present behaviors and system variables during a training simulation to make accurate score predictions. This work has demonstrated the capacity to realize deep learning predictions for trainees' performance during a simulator training session.

Objectives

The objectives of the POC project were to:

1. Facilitate AI and machine learning initiative at CM Labs;
2. Evaluate the quantity, quality and accessibility of the data;
3. Create and train a preliminary model to test the predictive potential of the data; and
4. Establish if this project can continue to a second phase.

Process

After establishing the objectives and discussing with CM Labs domain experts, it was decided to predict the future score of an operator trainee during training on an excavator simulator or other heavy machinery. The created ML model ingest data (engine torque, fuel consumption, etc.) and predicts the likely test score the trainee will get based on the present maneuvers or behaviors. If such a solution would be deployed, a trainee (or teacher) could quantitively assess their performance in real-time. This could lead to advice from the teacher on how to improve or inform the trainee that his present actions should be adjusted and lead to a better-trained trainee. This approach of providing feedback is used in the aviation pilot training industry where "train to competency" frameworks ensure a better outcome. The purpose of AI would be to augment the instructor's feedback process and/or automate this process altogether.

The team at Zetane when through the following steps:

a) Data definition done jointly with CM Labs domain experts
b) Data evaluation
c) Data preparation for training a machine learning models (data validation, completeness and engineering)
d) Training and improving the model (done multiple times)
e) Improving the model with Zetane xAI technology (done multiple times)
f) Evaluating the potential to go to a second phase

Zetane Tasks	CM Labs Tasks
Jointly define with CM Labs the data needs following a kickoff and planning meeting.	Jointly define with Zetane the data needs following a kickoff and planning meeting
Help validate the objectives and data inputs/outputs to the AI models	
Support as necessary to answer questions and facilitate data preparation	Gather agreed data files and deliver all data in the agreed format to Zetane as per the schedule
Review data and validate data, including data quality and completeness	Augment data collection and provide new data following Zetane evaluation
Extensive data preparation (multiple iterations)	
Create AI models (multiple iterations)	
Models training and validation (multiple iterations)	
Model testing and evaluation using Zetane xAI tools (multiple iterations)	

Results

Following this process, it was concluded that all objectives (1 to 4) above were completed with success. Here is an overview of the conclusions.

1. *Facilitate AI initiative at CM Labs*
   Discussion with CM Labs leadership contributed to refine their AI strategies and lead to define a solid data acquisition pipeline and develop internal expertise. These discussions also contributed to articulating business objectives that are achievable with modern AI techniques.
2. *Data evaluation*
   The data was found to be of good quality and quantity. By nature, a simulation can produce a vast amount of raw data from a large number of variables, but extracting and storing it correctly can be challenging. CM Labs now has the proper pipeline and rights

of use to extract raw data from the simulators and supply them in a proper format to data scientists.

3. *Predictive potential of the data*
   We found that the data has good predictive potential due to its quality, quantity and the variety of variable types that can be extracted from the simulators. A model was successfully trained to accurately predict the trainee exercise scores. This demonstrates the predictive potential of CM Labs' data.
4. *Second phase*
   The success of point 1, 2 and 3 indicates that a next second phase is possible. Moreover, since CM Labs now has the expertise retrieve more data and better evaluate the type of data which can be efficiently leveraged. This helps make their wealth of data useful and highly valuable.

Data Evaluation

We will now give a summary analysis of the data provided by CM Labs by commenting on important aspects to consider when using data for building AI solutions. Based on the following evaluation, we believe that CM Labs is well on its way to achieve their long-term data objectives:
'Our strategic long-term goal is to gather information about simulator and editor usage by aggregating, anonymizing, and then analyzing data to provide value to our customers.'

Type

The data used in this project was tabular and we used CSV files because of their ease of use for POC projects.

Accessibility

CM Labs obtained the rights to use the data in this project from one of their clients. This demonstrates good relationship with their client, but importantly it shows that clients are ready to participate in AI projects. This indicates that there is a demand and needs for AI solutions in their domain of application.

Anonymity

Anonymization of the data was done by CM Labs and Zetane had no contact with the original data. In particular, all information about the trainees and also the name of client providing data was removed.

Quantity

Simulators can produce large amount of raw data. CM Labs succeeded in retrieving the proper data, handle conversion and delivery to Zetane. The quantity and infrastructure were appropriate for the POC, but the data pipeline will need to be scaled appropriately for a large-scale ML project.

Number of features

With 45 features (variables), there was enough to have a model that can achieve good predictions. We were told that there are many other features that could be accessed and extracted for a future project.

Targets

The students' scores were readily available to be integrated in the final training dataset. These scores were essential for training this model (supervised learning). Depending on the business objectives, we also believe that unsupervised leaning methods could be fruitful.

Quality

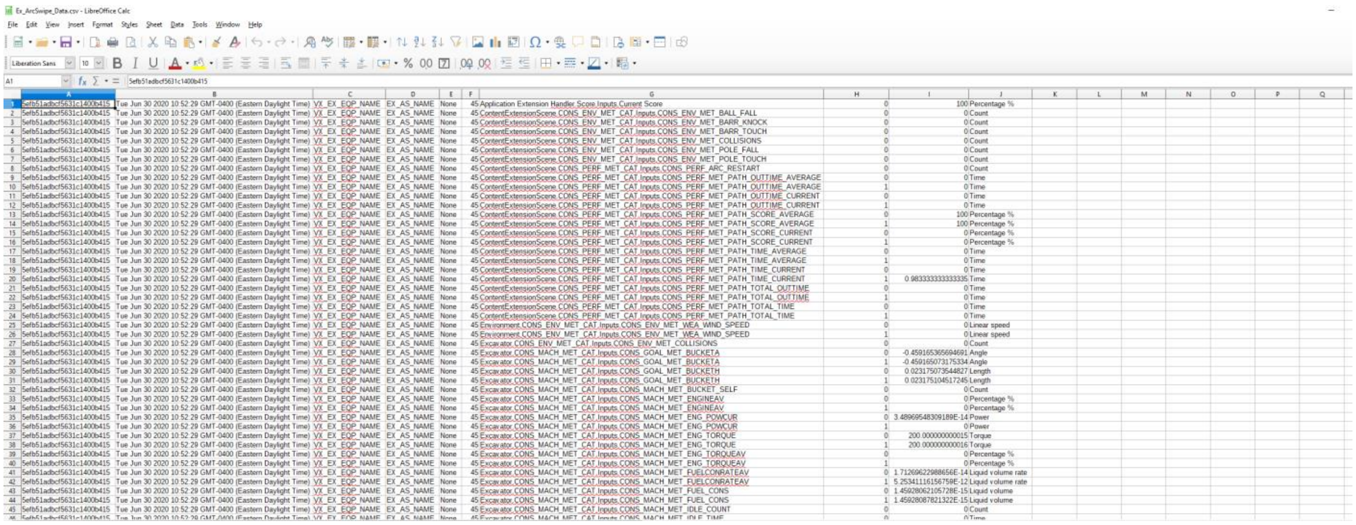
There were not many missing values or gaps in the datasets. In the future, there could be a way for CM Labs to automatically consolidate the data into a dataset that is readily usable by a data scientist.

Data Preparation Process

Before training ML models, it is necessary to prepare the data. This usually needs extensive discussions with the domain experts to understand the meaning of each feature and understand the business objectives. When the data is well understood, the data needs to be transformed appropriately (merges, cleaned, normalized, etc.).

Raw Dataset

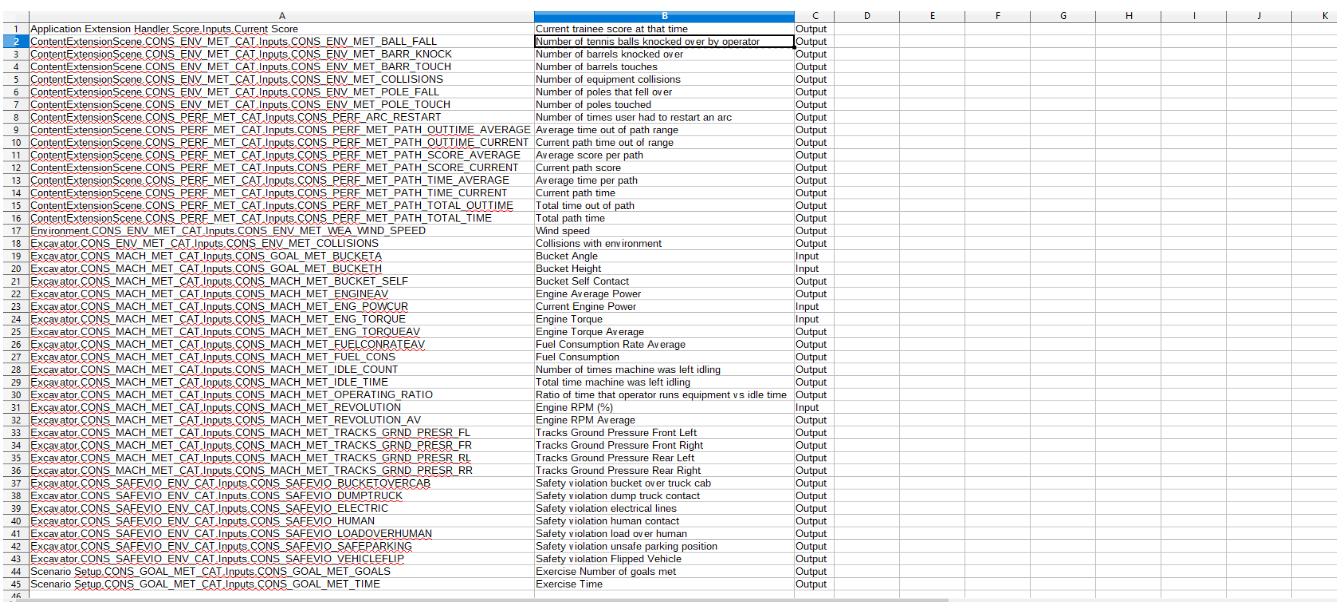
The original raw dataset given by CM Labs contains about 600 thousand rows which were composed of 45 variables and their corresponding values. The dataset contains multiple trainees' sessions on an excavator simulator.



	A	B	C	D	E	F	G	H	I	J
1	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Application Extension Handler Score Inputs Current Score	0	100	Percentage %
2	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_BALL_FALL	0	0	Count
3	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_BARR_KNOCK	0	0	Count
4	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_BARR_TOUCH	0	0	Count
5	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_COLLISIONS	0	0	Count
6	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_POLE_FALL	0	0	Count
7	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_POLE_TOUCH	0	0	Count
8	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_ARC_RESTART	0	0	Count
9	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_OUTTIME_AVERAGE	0	0	Time
10	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_OUTTIME_AVERAGE	1	0	Time
11	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_OUTTIME_CURRENT	0	0	Time
12	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_OUTTIME_CURRENT	1	0	Time
13	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_SCORE_AVERAGE	0	100	Percentage %
14	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_SCORE_AVERAGE	1	100	Percentage %
15	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_SCORE_CURRENT	0	0	Percentage %
16	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_SCORE_CURRENT	1	0	Percentage %
17	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TIME_AVERAGE	0	0	Time
18	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TIME_AVERAGE	1	0	Time
19	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TIME_CURRENT	0	0	Time
20	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TIME_CURRENT	1	0.983333333333335	Time
21	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TOTAL_OUTTIME	0	0	Time
22	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TOTAL_OUTTIME	1	0	Time
23	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TOTAL_TIME	0	0	Time
24	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TOTAL_TIME	1	0	Time
25	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Environment.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_WEA_WIND_SPEED	0	0	Linear speed
26	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Environment.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_WEA_WIND_SPEED	1	0	Linear speed
27	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_COLLISIONS	0	0	Count
28	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETA	0	-0.459165365694691	Angle
29	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETA	1	-0.459165073175334	Angle
30	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETH	0	0.023175073544827	Length
31	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETH	1	0.023175104517245	Length
32	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_BUCKET_SELF	0	0	Count
33	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENGINEAV	0	0	Percentage %
34	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENGINEAV	1	0	Percentage %
35	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_POWCUR	0	3.48969548309189E-14	Power
36	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_POWCUR	1	0	Power
37	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUE	0	200.000000000015	Torque
38	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUE	1	200.000000000016	Torque
39	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUEAV	0	0	Percentage %
40	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUEAV	1	0	Percentage %
41	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_FUELCONRATEAV	0	1.71269622988656E-14	Liquid volume rate
42	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_FUELCONRATEAV	1	5.25341116156759E-12	Liquid volume rate
43	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_FUEL_CONS	0	1.45928062105728E-15	Liquid volume
44	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_FUEL_CONS	1	1.45928087821322E-15	Liquid volume
45	5efb51adbcf5631c1400b415	Tue Jun 30 2020 10:52:29 GMT-0400 (Eastern Daylight Time)	VX_EX_EQP_NAME	EX_AS_NAME	None	45	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_IDLE_COUNT	0	0	Count

Variables' dataset

In the variables' dataset, there are variables such as are engine torque, fuel consumption, idle time and number of collisions and tracks ground pressure.



	A	B	C
1	Application Extension Handler Score Inputs Current Score	Current trainee score at that time	Output
2	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_BALL_FALL	Number of tennis balls knocked over by operator	Output
3	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_BARR_KNOCK	Number of barrels knocked over	Output
4	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_BARR_TOUCH	Number of barrels touches	Output
5	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_COLLISIONS	Number of equipment collisions	Output
6	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_POLE_FALL	Number of poles that fell over	Output
7	ContentExtensionScene.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_POLE_TOUCH	Number of poles touched	Output
8	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_ARC_RESTART	Number of times user had to restart an arc	Output
9	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_OUTTIME_AVERAGE	Average time out of path range	Output
10	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_OUTTIME_CURRENT	Current path time out of range	Output
11	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_SCORE_AVERAGE	Average score per path	Output
12	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_SCORE_CURRENT	Current path score	Output
13	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TIME_AVERAGE	Average time per path	Output
14	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TIME_CURRENT	Current path time	Output
15	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TOTAL_OUTTIME	Total time out of path	Output
16	ContentExtensionScene.CONS_PERF_MET_CAT.Inputs.CONS_PERF_MET_PATH_TOTAL_TIME	Total path time	Output
17	Environment.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_WEA_WIND_SPEED	Wind speed	Output
18	Excavator.CONS_ENV_MET_CAT.Inputs.CONS_ENV_MET_COLLISIONS	Collisions with environment	Output
19	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETA	Bucket Angle	Input
20	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETH	Bucket Height	Input
21	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_BUCKET_SELF	Bucket Self Contact	Output
22	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENGINEAV	Engine Average Power	Output
23	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_POWCUR	Current Engine Power	Input
24	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUE	Engine Torque	Input
25	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUEAV	Engine Torque Average	Output
26	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_FUELCONRATEAV	Fuel Consumption Rate Average	Output
27	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_FUEL_CONS	Fuel Consumption	Output
28	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_IDLE_COUNT	Number of times machine was left idling	Output
29	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_IDLE_TIME	Total time machine was left idling	Output
30	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_OPERATING_RATIO	Ratio of time that operator runs equipment vs idle time	Output
31	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_REVOLUTION	Engine RPM (%)	Input
32	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_REVOLUTION_AV	Engine RPM Average	Output
33	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_TRACKS_GRND_PRESR_FL	Tracks Ground Pressure Front Left	Output
34	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_TRACKS_GRND_PRESR_FR	Tracks Ground Pressure Front Right	Output
35	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_TRACKS_GRND_PRESR_RL	Tracks Ground Pressure Rear Left	Output
36	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_TRACKS_GRND_PRESR_RR	Tracks Ground Pressure Rear Right	Output
37	Excavator.CONS_SAFEVIO_ENV_CAT.Inputs.CONS_SAFEVIO_BUCKETOVERCAB	Safety violation bucket over truck cab	Output
38	Excavator.CONS_SAFEVIO_ENV_CAT.Inputs.CONS_SAFEVIO_DUMPTRUCK	Safety violation dump truck contact	Output
39	Excavator.CONS_SAFEVIO_ENV_CAT.Inputs.CONS_SAFEVIO_ELECTRIC	Safety violation electrical lines	Output
40	Excavator.CONS_SAFEVIO_ENV_CAT.Inputs.CONS_SAFEVIO_HUMAN	Safety violation human contact	Output
41	Excavator.CONS_SAFEVIO_ENV_CAT.Inputs.CONS_SAFEVIO_LOADOVERHUMAN	Safety violation load over human	Output
42	Excavator.CONS_SAFEVIO_ENV_CAT.Inputs.CONS_SAFEVIO_SAFEPARKING	Safety violation unsafe parking position	Output
43	Excavator.CONS_SAFEVIO_ENV_CAT.Inputs.CONS_SAFEVIO_VEHICLEFLIP	Safety violation Flipped Vehicle	Output
44	Scenario Setup.CONS_GOAL_MET_CAT.Inputs.CONS_GOAL_MET_GOALS	Exercise Number of goals met	Output
45	Scenario Setup.CONS_GOAL_MET_CAT.Inputs.CONS_GOAL_MET_TIME	Exercise Time	Output

Training Dataset

These two previous datasets along with a scores' dataset were combined to create a larger dataset which contains all the information about the exercise performed multiple times by different trainees on an excavator simulator.

Data comes from different disjoint files needed to be understood thoroughly so that they can be merged correctly to build a proper dataset that will be used to train a machine learning model. The dataset went through a series of transformations meant to prepare the dataset to be used to train the model. In particular, it was engineered in order to remove noises, skewness and unwanted behavior. The Yeo-Johnson transformation and standardized scaling was used to remove some of these effects.

The final dataset contains the input features (45 features or columns) and the target (training targets needed for the model to learn).

1	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETA_Value	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_GOAL_MET_BUCKETH_Value	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_POWCUR_Value	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUE_Value	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENG_TORQUEAV_Value	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_ENGINEAV_Value	Excavator.CONS_MACH_MET_CAT.Inputs.CONS_MACH_MET_FUEL_CONS_Value
2	0.433650632	-1.767281161	-1.629015315	-0.694015456	3.038470752	-1.504081011	-1.720997285
3	0.433651013	-1.767281087	-1.599992835	-0.552873632	1.854733136	-1.595645469	-1.716673784
4	0.433651394	-1.767281006	-1.602062335	-0.556781776	1.236018866	-1.641025444	-1.712273737
5	0.433651774	-1.767280942	-1.601763545	-0.555870023	0.848490262	-1.669306963	-1.707877715
6	0.433652155	-1.767280879	-1.60182906	-0.556074372	0.582794786	-1.688674185	-1.703489013
7	0.433652535	-1.767280816	-1.601811115	-0.556018546	0.389333607	-1.702769832	-1.699107728
8	0.433652914	-1.767280753	-1.601815065	-0.556031104	0.242205014	-1.713486461	-1.694733814
9	0.433653294	-1.767280691	-1.601814002	-0.556027732	0.126556898	-1.721908885	-1.690367263
10	0.433653673	-1.767280628	-1.601814236	-0.556028492	0.03326929	-1.7287023	-1.686008053
11	0.433654053	-1.767280566	-1.601814174	-0.556028291	-0.043567376	-1.734297536	-1.681656168
12	0.433654431	-1.767280504	-1.601814188	-0.556028337	-0.107949778	-1.73898582	-1.67731159
13	0.43365481	-1.767280441	-1.601814184	-0.556028325	-0.162677518	-1.742971096	-1.672974299
14	0.433655189	-1.767280379	-1.601814185	-0.556028328	-0.209769908	-1.746400432	-1.668644279
15	0.433655567	-1.767280317	-1.601814185	-0.556028327	-0.250720028	-1.749382555	-1.664321511
16	0.433655945	-1.767280255	-1.601814185	-0.556028327	-0.286655609	-1.751999578	-1.660005977
17	0.433656323	-1.767280193	-1.601814185	-0.556028327	-0.318444311	-1.754314675	-1.65569766
18	0.433656701	-1.767280131	-1.601814185	-0.556028327	-0.346764587	-1.75637724	-1.651396542
19	0.433657078	-1.767280069	-1.601814185	-0.556028327	-0.372154582	-1.758226451	-1.647102604
20	0.433657456	-1.767280008	-1.601814185	-0.556028327	-0.395046611	-1.759893782	-1.64281583
21	0.433657833	-1.767279946	-1.601814185	-0.556028327	-0.415791951	-1.761404806	-1.638536202
22	0.43365821	-1.767279884	-1.601814185	-0.556028327	-0.434678977	-1.762780517	-1.634263703
23	0.433658587	-1.767279822	-1.601814185	-0.556028327	-0.451946633	-1.764038312	-1.629998314
24	0.433658963	-1.76727976	-1.601814185	-0.556028327	-0.46779459	-1.765192726	-1.625740018
25	0.43365934	-1.767279699	-1.601814185	-0.556028327	-0.482390992	-1.766256001	-1.621488798
26	0.433659716	-1.767279637	-1.601814185	-0.556028327	-0.495878444	-1.76723852	-1.617244637
27	0.433660092	-1.767279575	-1.601814185	-0.556028327	-0.508378682	-1.768149146	-1.613007518
28	0.433660467	-1.767279514	-1.601814185	-0.556028327	-0.519996252	-1.76899549	-1.608777423
29	0.433660843	-1.767279452	-1.601814185	-0.556028327	-0.530821447	-1.769784128	-1.604554335
30	0.433661218	-1.767279391	-1.601814185	-0.556028327	-0.54093265	-1.770520765	-1.600338237
31	0.434564453	-1.766506381	-1.68607996	-1.52938557	-0.502993395	-1.756394669	-1.595114172
32	0.454173717	-1.760018255	-1.442448628	-0.670324226	-0.519793646	-1.754202316	-1.591219797
33	0.470765148	-1.753405569	-1.808076461	-1.58330468	-0.538254196	-1.753184616	-1.587408404
34	0.470761197	-1.753404841	-1.647894391	-0.789392232	-0.563397888	-1.756670793	-1.583678112
35	0.470767479	-1.753402953	-1.635442242	-0.670324226	-0.575596496	-1.758333953	-1.579622392
36	0.470775539	-1.753400749	-1.601983627	-0.556780526	-0.583566029	-1.759420322	-1.575467354
37	0.470783433	-1.753397337	3.989527971	4.545681937	-0.420428744	-1.701537117	-1.56555775
38	0.470790944	-1.753395463	2.613554439	2.51836158	-0.332530292	-1.62830481	-1.554624258
39	0.470797641	-1.753394955	-0.005182235	-0.670324226	-0.343572902	-1.593688286	-1.547221795
40	0.470803891	-1.753393369	-0.005593781	-0.670324226	-0.355959922	-1.561544945	-1.539868534
41	0.470809642	-1.753391911	-0.004845217	-0.670324226	-0.36755538	-1.530416322	-1.532525697
42	0.470814939	-1.753390565	-0.005561734	-0.670324226	-0.378832528	-1.500486223	-1.525217443
43	0.470819828	-1.753389344	-0.005479753	-0.670324226	-0.389462726	-1.471512005	-1.517923155
44	0.470824348	-1.753388215	-0.005414299	-0.670324226	-0.39961345	-1.443522596	-1.510650586
45	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Model Architecture and Training

We used an artificial neural network model composed of many fully connected layers (Multilayer Perceptron) in order to achieve the resultant output. We could have used other model structures such as transformers and LSTM to increase the accuracy of the predictions, but we chose a multilayer perceptron as starting point to better evaluate the potential of the data. The model was trained with the dataset described above with a 80-20 split (80% of the data is used for training the model and 20% of the data is used to validate that the model has learned).

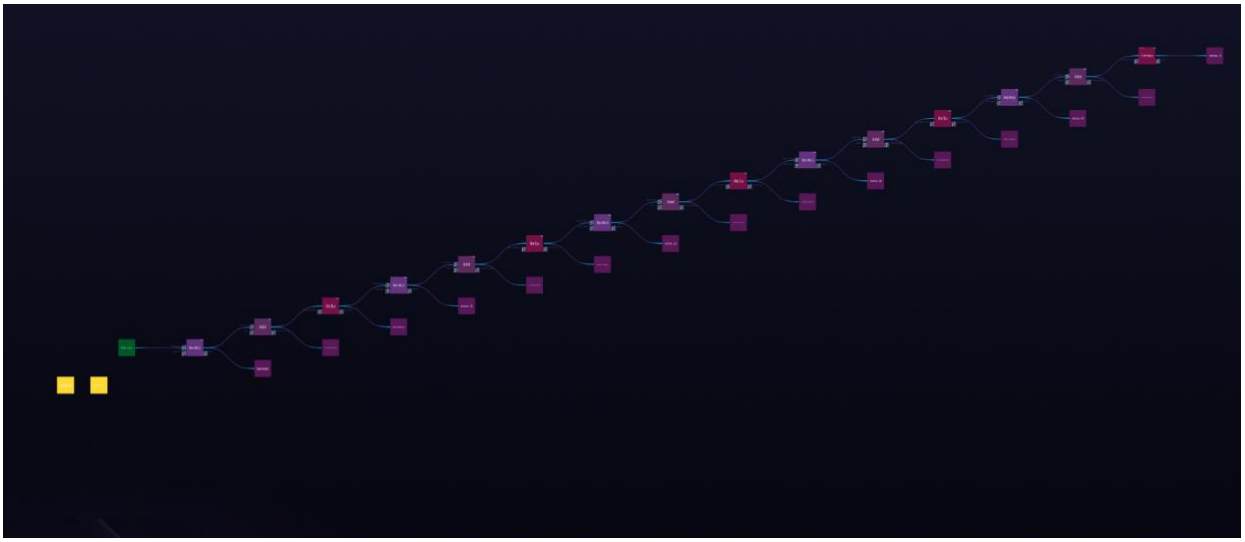


Figure 1. The model architecture as seen in the Zetane AI Viewer

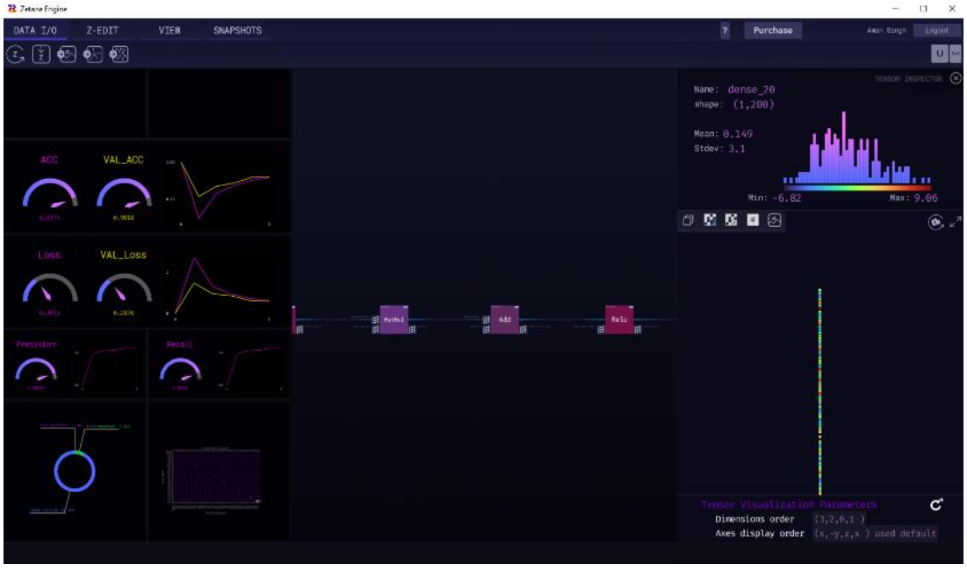


Figure 2. Zetane xAI dashboard

The model input was taking 10 steps (i.e. rows) with all the features such as engine torque, fuel consumption, idle time and number of collisions and tracks ground pressure to predict the next score. One of our trained models achieved the following evaluation metrics scores on the validation dataset:

Accuracy was 93.0%,
F1 score of 92.2%
Precision 92.6%
Recall 92.3 %.

This tells us that the data given by CM Labs has the proper quality and quantity to be used to predict students' scores. In a few words, the data has predictive potential.

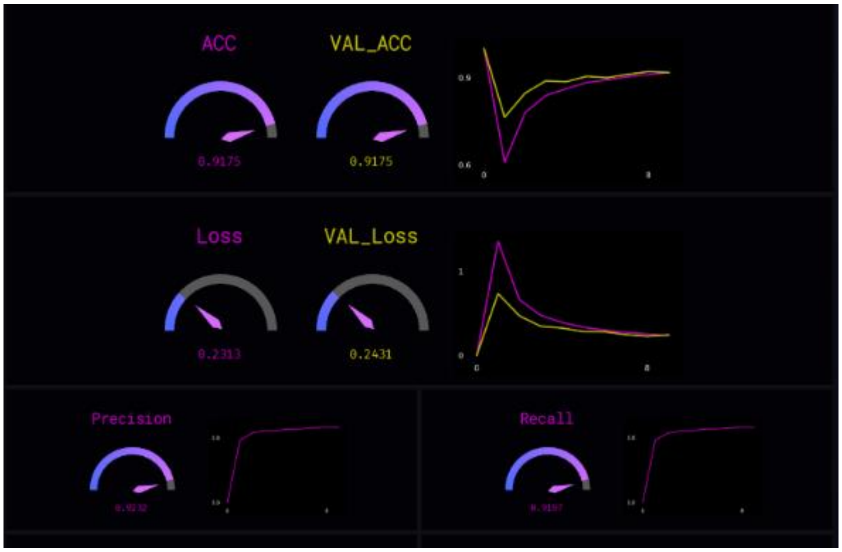


Figure 3. Zetane evaluation metric dashboard during training

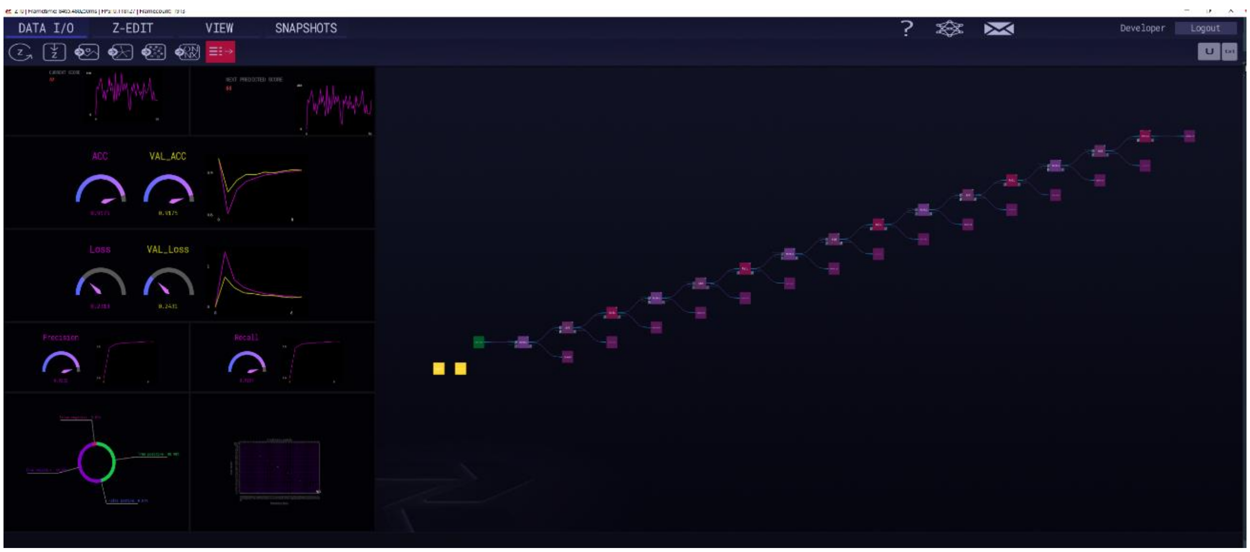


Figure 4. Full Zetane AI dashboard

Zetane xAI Analysis

The Zetane AI Viewer (www.zetane.com/download) allows users to look at the internal data of neural networks. It played a significant role in the data engineering phase. It enabled the data scientist to identify areas where the data was skewed to the right or the left and had a negative impact on the accuracy of the model. Visualizing this in Zetane Viewer reduced trial and error and gave insights into where the model could benefit from more feature engineering. In particular, looking at the input data behavior in the model it was possible to conclude that we should use Yeo-Johnson transformation in order to represent the data more symmetrically which contributed greatly to increase the accuracy and performance of the model.

Figure 5. Node output tensor values distribution before applying the Yeo-Johnson transformation. Notice the skewed distribution (top left corner).

Figure 6. After applying the Yeo-Johnson transformation.

Figure 7. Node output tensor values have centered distribution after applying the transformations.

Using the Zetane Viewer, we were able to assess which optimizer and parameters should be used to train the model most efficiently.

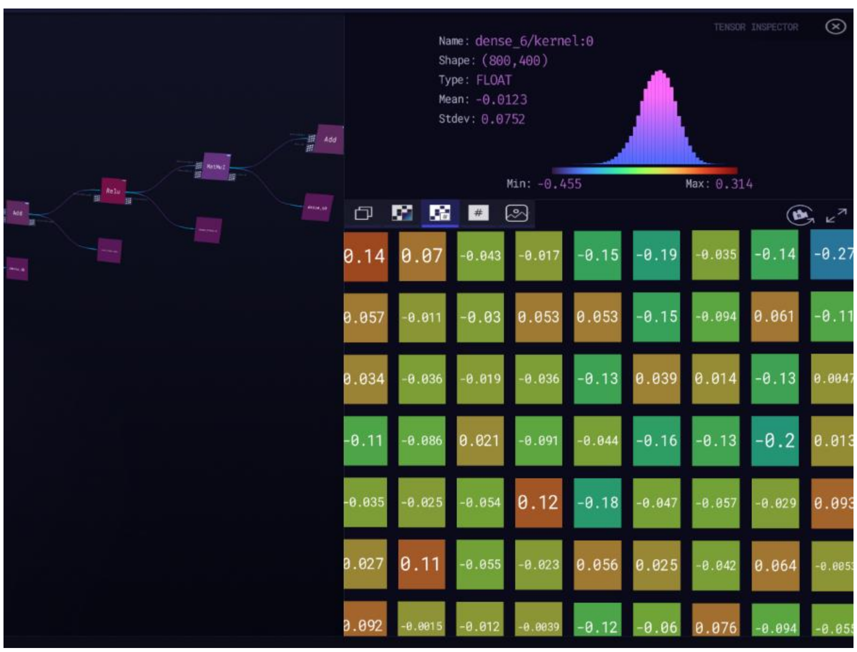


Figure 8. The distributions shape of the weights helps assess the best training parameters and optimizer to select.

Next Phase: Development of AI-assisted training and improved operational efficiency and safety

Zetane Systems has taken a preliminary look at the data and built a proof-of-concept predictive models providing an estimated score based on the current simulator states. This work has demonstrated the capacity to build and train a deep learning algorithm to evaluate the performances of trainees or operators on a training simulator.

This opens the possibility of building an integrated platform dedicated to support the instructor management of trainees. Such a platform would provide multiple type of instructor or trainee support.

1. Assessment of the inherent capability of a trainee
2. Assessment of the current level of proficiency of a trainee regarding a standard level of performance (certification)
3. Detection of specific performance deficiencies regarding a standard level of performance
4. Training exercise recommendation based on performance

In such platform, using the exercise's predictive scoring, a ML model would identify what behavior should be adjusted and offer specific scenarios to train on. It would also provide real-time feedback on the performance of the operator, giving an indication if the operator is evolving in the right direction. This could be used in processes that are repetitive but technical like digging a trench with an excavator. The goal would be for the tips to improve efficiency without compromising safety.

The AI assistance would free up instructors to work with more students at any given time. The instructor would get insights such as how rough a student is with the machine (as determined by the various metrics such as machine wear metric or fuel consumption). The AI assistant would suggest the next scenario to train on in order to focus on specific goals. This allows the group of simulators at the school to be treated as a lab where the instructor is freed up to address problem areas, allowing the training of more operators through automation of some of the instructor’s tasks.

The quantity and quality of the data that appears to be available from CM Labs deployed simulators leads us to believe that one can envision that student performance data could be collected and aggregated over time by type of simulator, type of operator, type of operational scenario and client. AI solutions could be developed and used to determine the best training performances. A virtual instructor could be trained to provide students with feedback during phases of training.

Furthermore, the data collected this way could be linked to client equipment specifications and operational guidelines and provide each client organization with an indication of operator tendencies that can be costly due to the inefficient operation of the equipment leading to more equipment wear and tear. Clients would value this type of information as it would permit them to develop corrective measures in operations to improve efficiency and safety.