Application of Machine Learning to Motion Signatures to Detect Cognitive Conditions such as Intoxication, Concussions, and Traumatic Brain Injury

David DiPaola, CSCS, NBC-HWC & Lanny Johnson, MD
508-982-4752 (mobile)

Overview

- No uniform testing program exists for TBI / cognitive conditions that includes both a means of immediate assessment on the field and comprehensive clinical management using a validated instrument
- This protocol proposes testing modalities based upon tactile edge orientation processing (TEOP), motion signatures, and machine learning as a rapid test and classification of a cognitive condition
- First assessment of this was performed using cognitive impairment with blood alcohol content (BAC) of 0.00 to 0.09%

Purpose

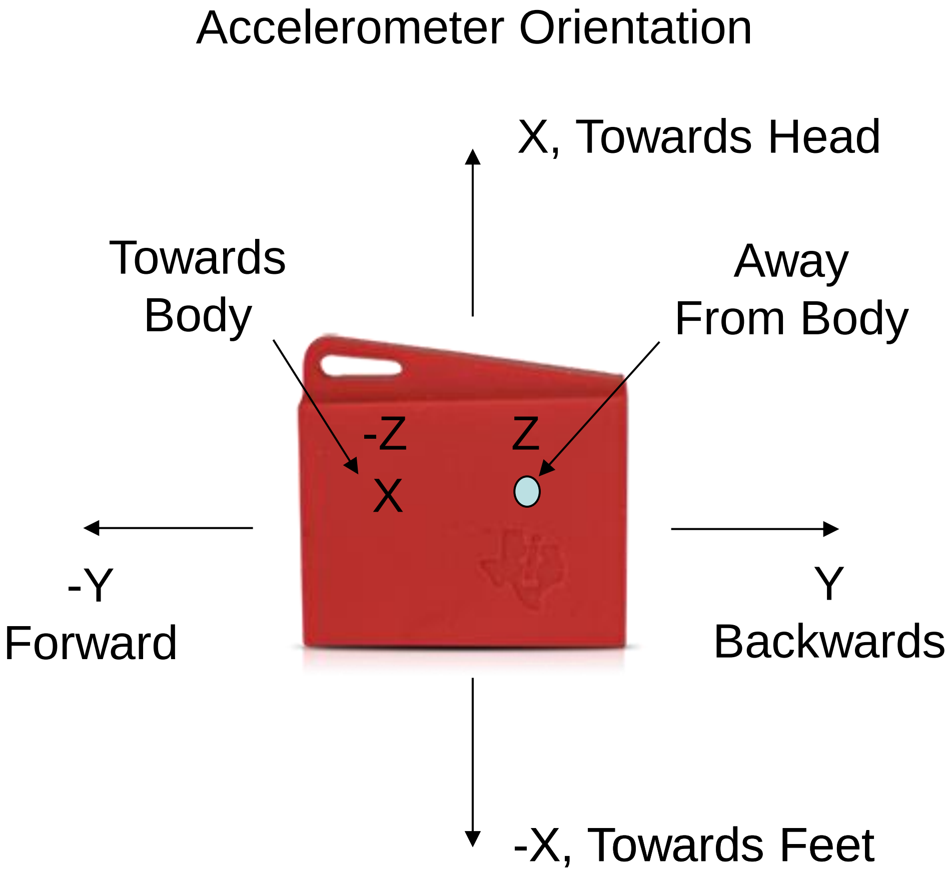
- Identify a rapid cognitive test to properly classify the presence and severity of a TBI / cognitive condition using tactile edge orientation processing, motion signatures, and machine learning

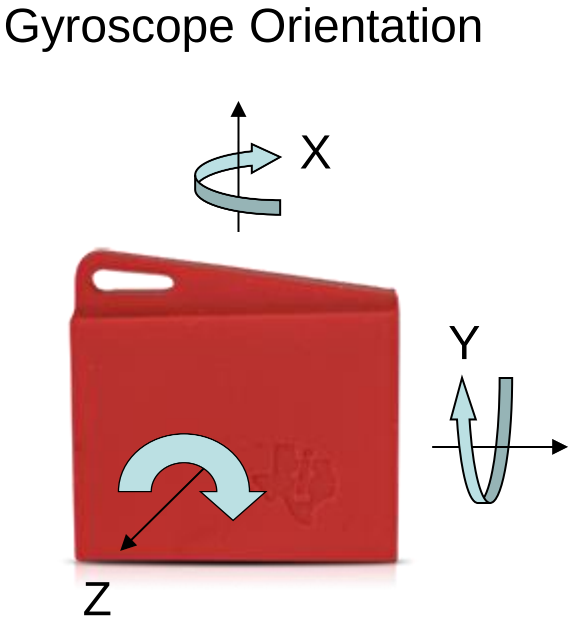
Methods

- Random subjects (60% men; 40% women) with varied ages participated
- This resulted in a sample size of 20 divided between train and test groups for the machine learning algorithm
- Participants were asked to perform two movements, TEOP, sober and under the influence of alcohol
  - Movement of heel sliding along the tibia of the opposite leg from bottom of shin to knee and back (seated position)
  - Movement of arm at side and then reading time of wristwatch
- Cognitive conditions were simulated with BAC (blood alcohol content) levels:
  - The first round of testing was conducted sober and repeated three times
  - Subsequent rounds of testing were conducted at BAC of 0.02, 0.04, 0.06, 0.08, and 0.09%
  - BAC was measured using a breathalyzer

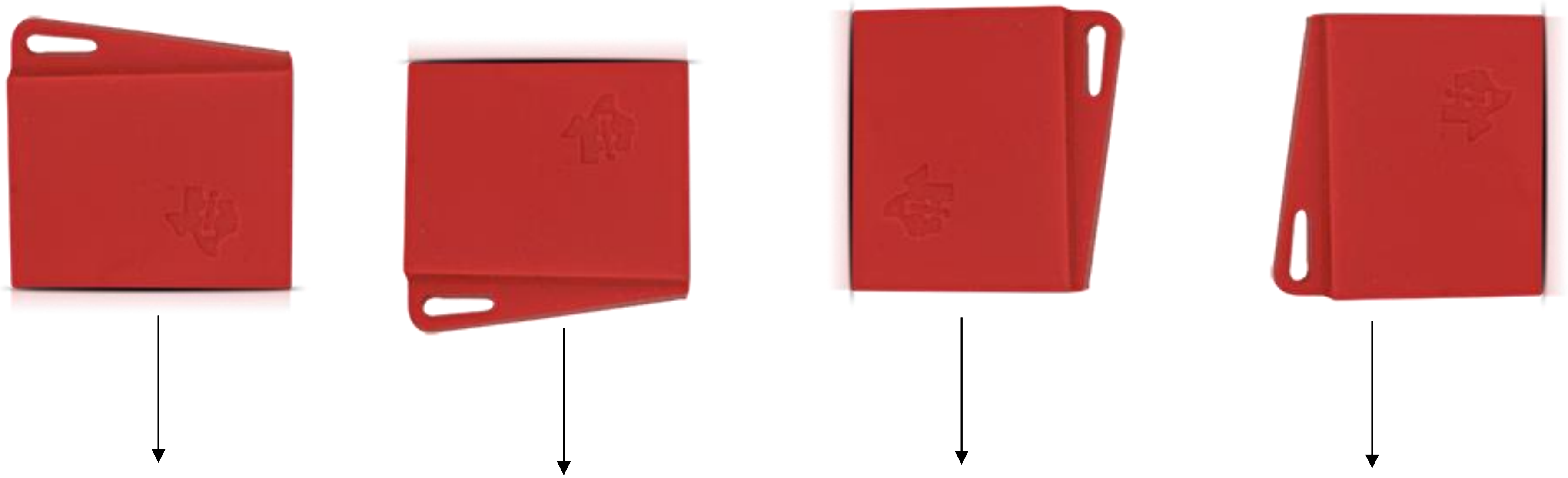
Methods

- Motion signature data for defined movement captured via accelerometer and gyroscope



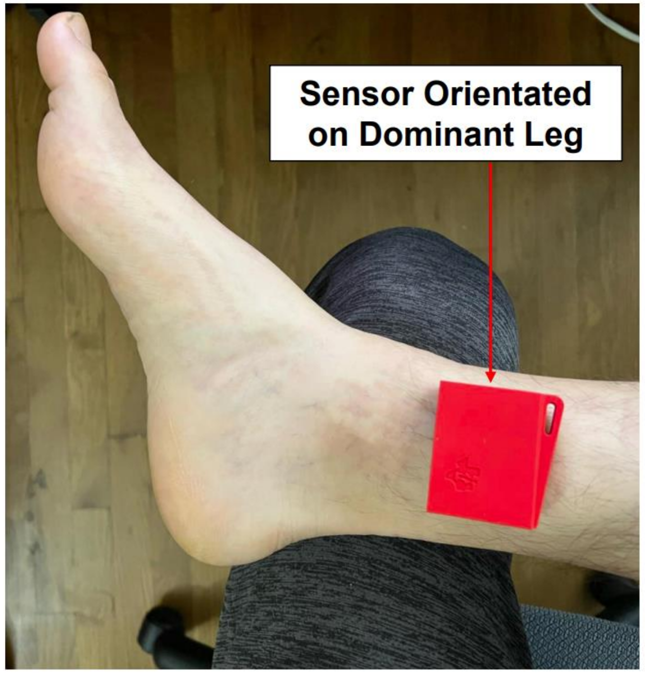


Effect of Gravitation Field on Sensor



-1g, Due to Gravity | 1g, Due to Gravity | 1g, Due to Gravity | -1g, Due to Gravity

Sensor Locations



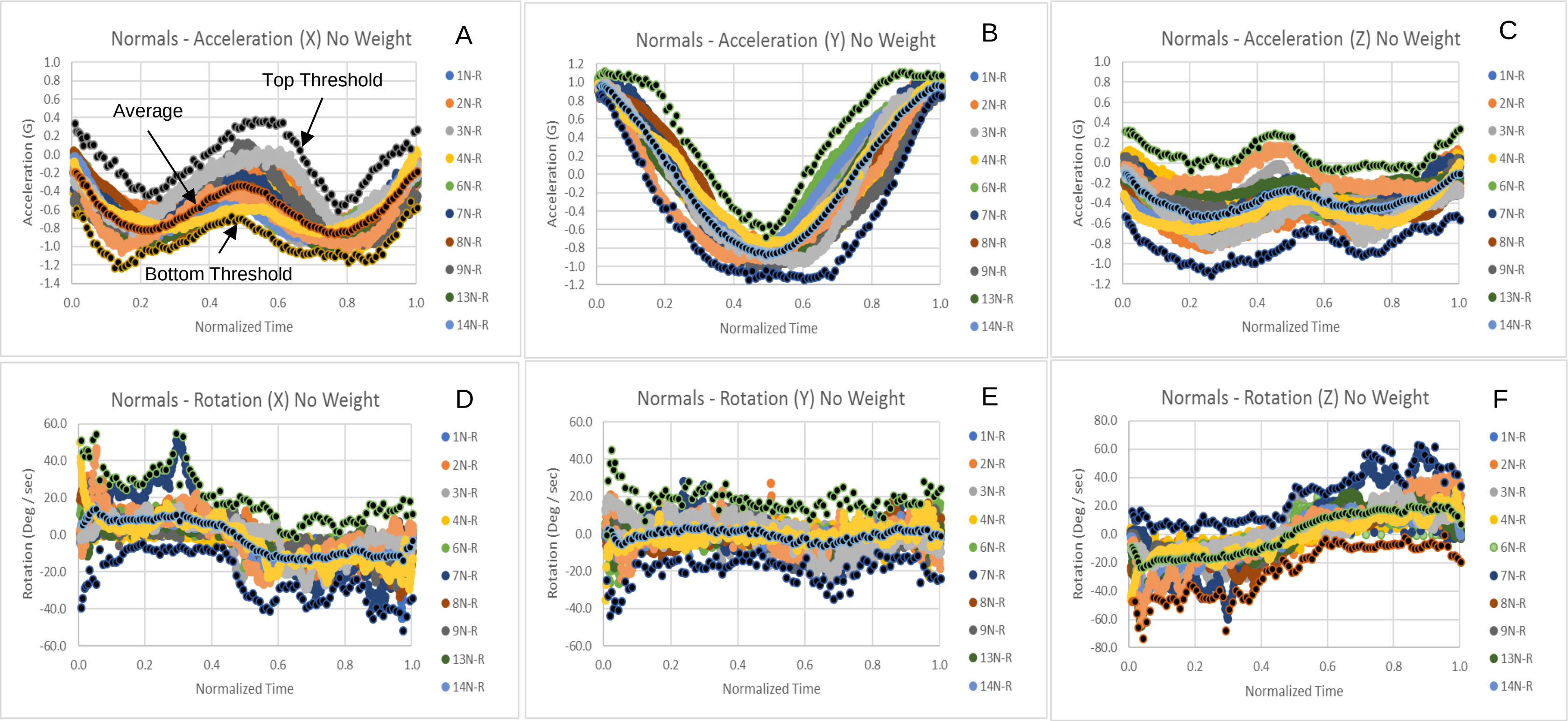
Basis of Innovation

- Machine learning can properly classify a torn rotator cuff that may need surgery versus referral to physical therapy for no tear using sensor motion data from two simple motion tests 1) forward extension (in scapular plane) and 2) external rotation
  - Supervised, RandomShapeletTransform machine learning algorithm achieved 96 – 100% accuracy
- Motion sensor was placed in the sulcus of the inside upper arm
- Normals (14) and an abnormal (1 / 10 example) are shown in subsequent slides with and without weight added to the patient's hand to get a sense for the data
- This is significant because a highly trained and experienced orthopedic surgeon cannot make this diagnosis without the use of an MRI hence this invention may replace the need for an MRI for ~98% of cases significantly reducing cost and increasing speed of separating those who need physical therapy and those who need further evaluation for surgery (< 5 min test)

Sensibly　　DynaMotion Medical　　dc DiPaola Consulting

Machine Learning Time Series Classification

Training and Test Sets → Transformed → Array of Values Over Periods For Each Subject



Shoulder: 24 – Subjects, 12 – Tests, 500 – Data Points - Total (test / train): 288,000 data points
Cognitive: 10 – Subjects, 12 – Tests, 291 – Data Points - Total (test / train): 69840 data points

Sensibly

DynaMotion Medical

dc DiPaola Consulting

- Forward Extension
- Right Shoulder
- No Weights
- MRI: Full thickness tear of supraspinatus, large subacromial spur

Top Threshold

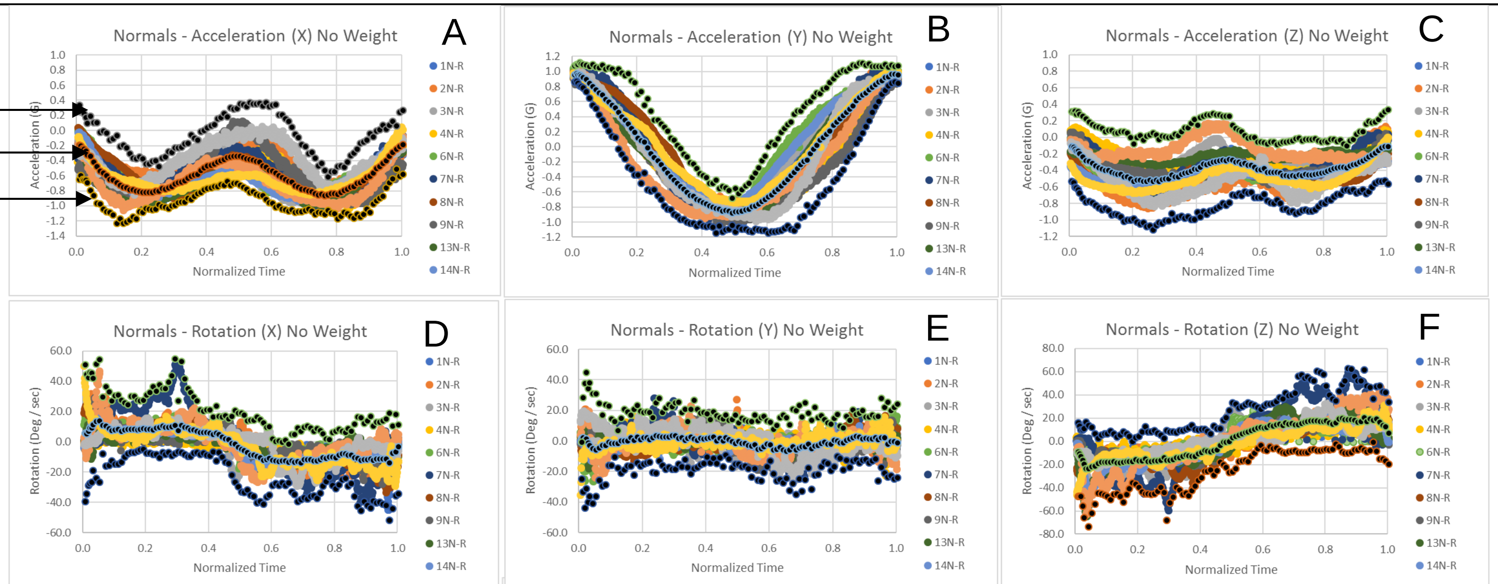
+ 3 Stdev

Average

- 3 Stdev

Bottom Threshold

Normals

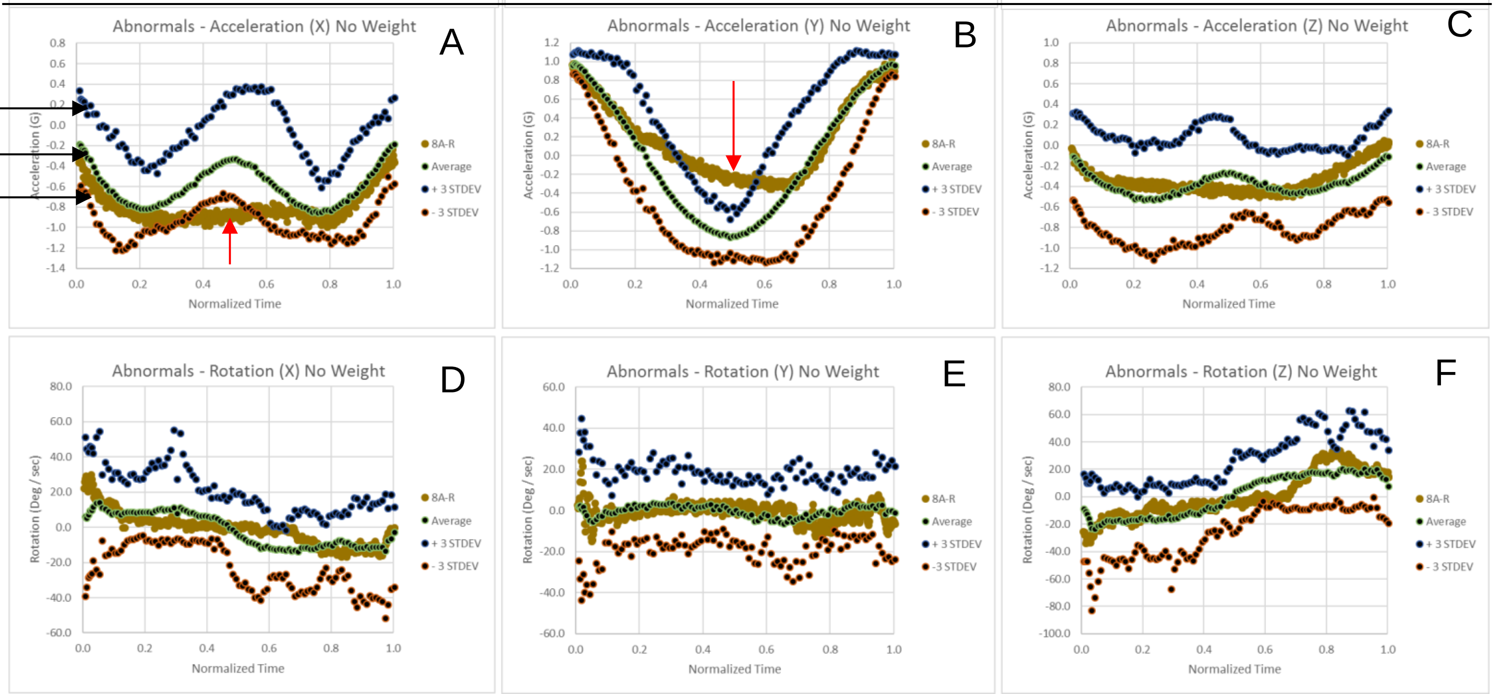


+ 3 Stdev

Average

- 3 Stdev

8A-R
Abnormal



Sensibly

DynaMotion Medical

DiPaola Consulting

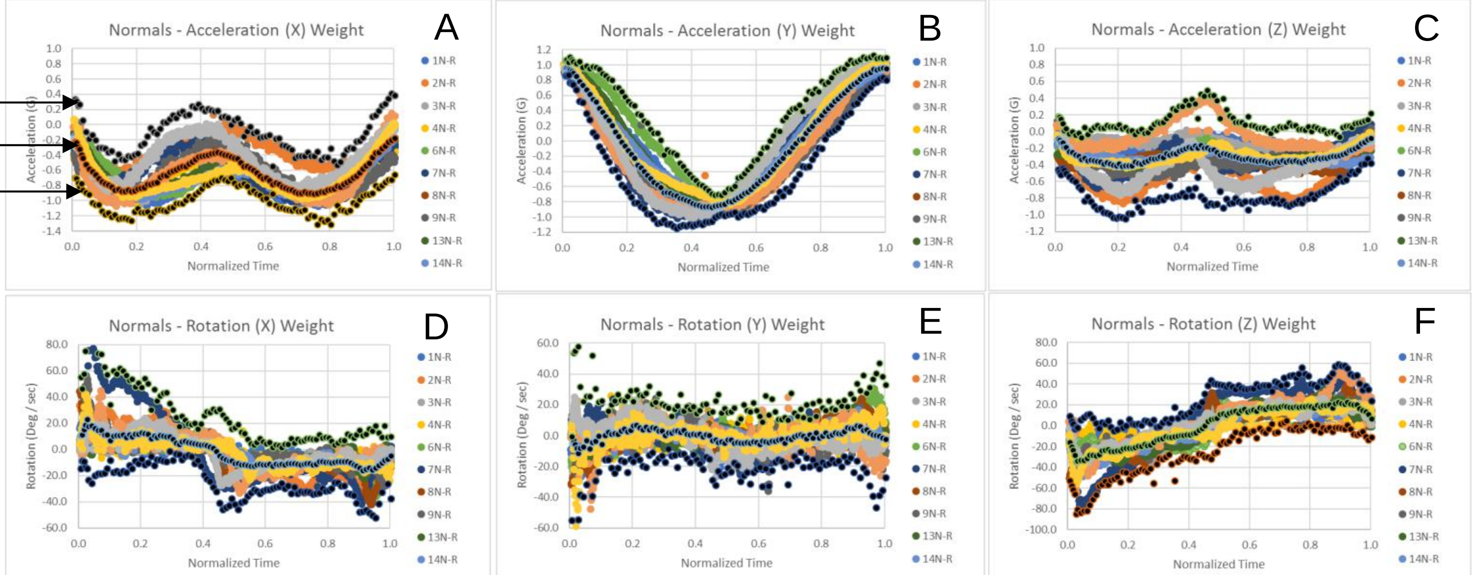
- Forward Extension
- Right Shoulder
- Weights
- MRI: Full thickness tear of supraspinatus, large subacromial spur

+ 3 Stdev

Average

- 3 Stdev

Normals

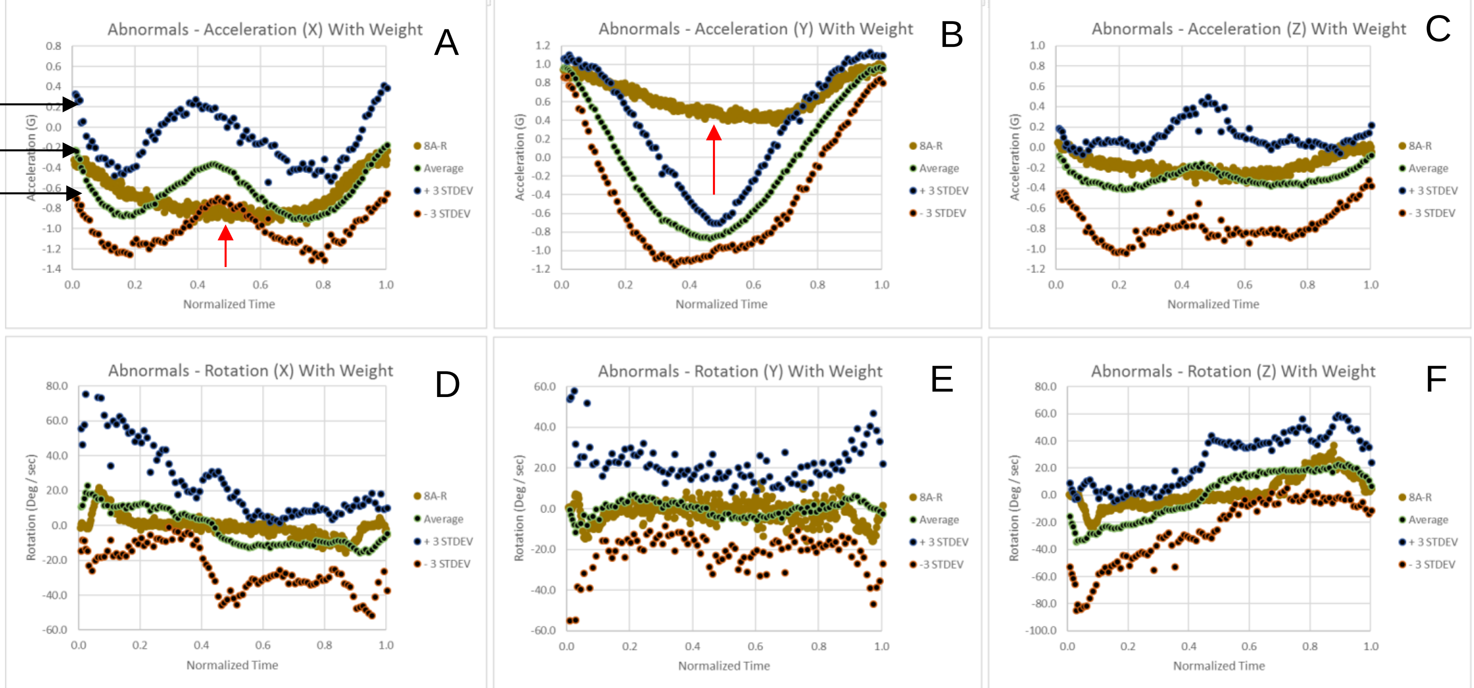


+ 3 Stdev

Average

- 3 Stdev

8A-R Abnormal



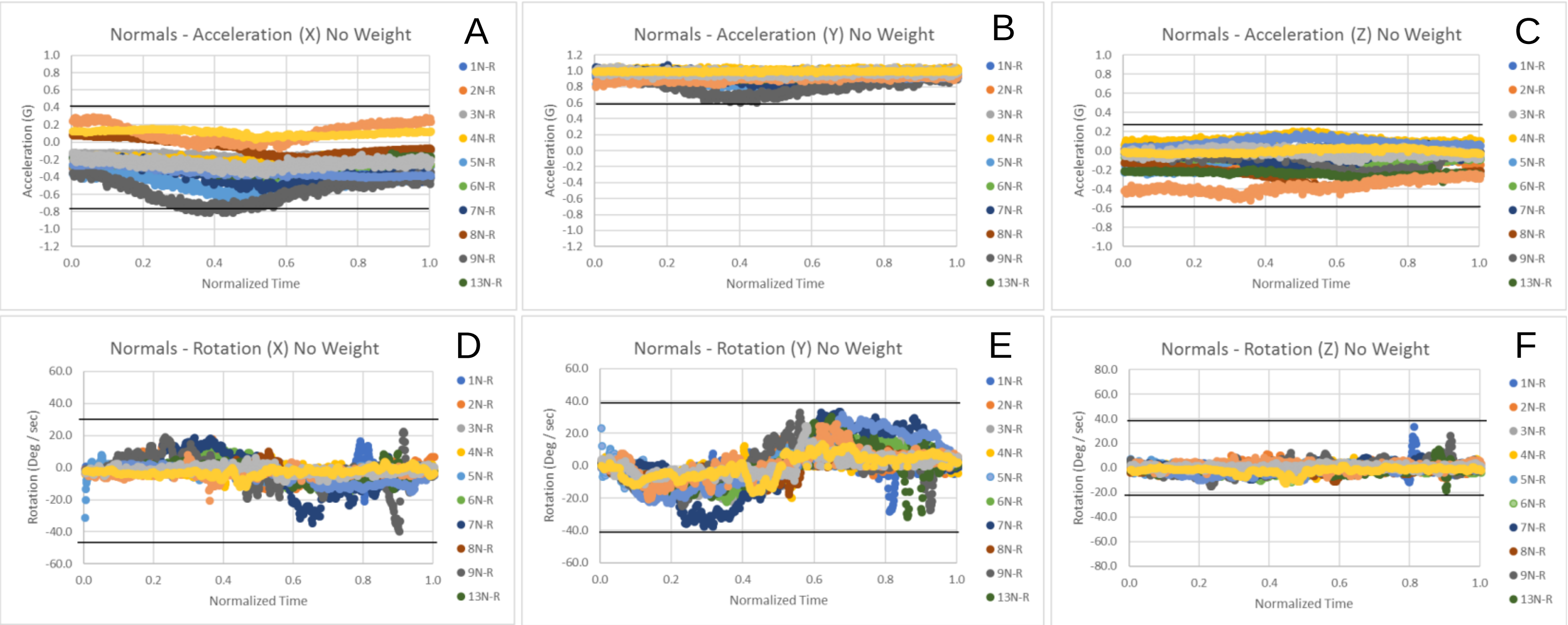
Sensibly

DynaMotion Medical

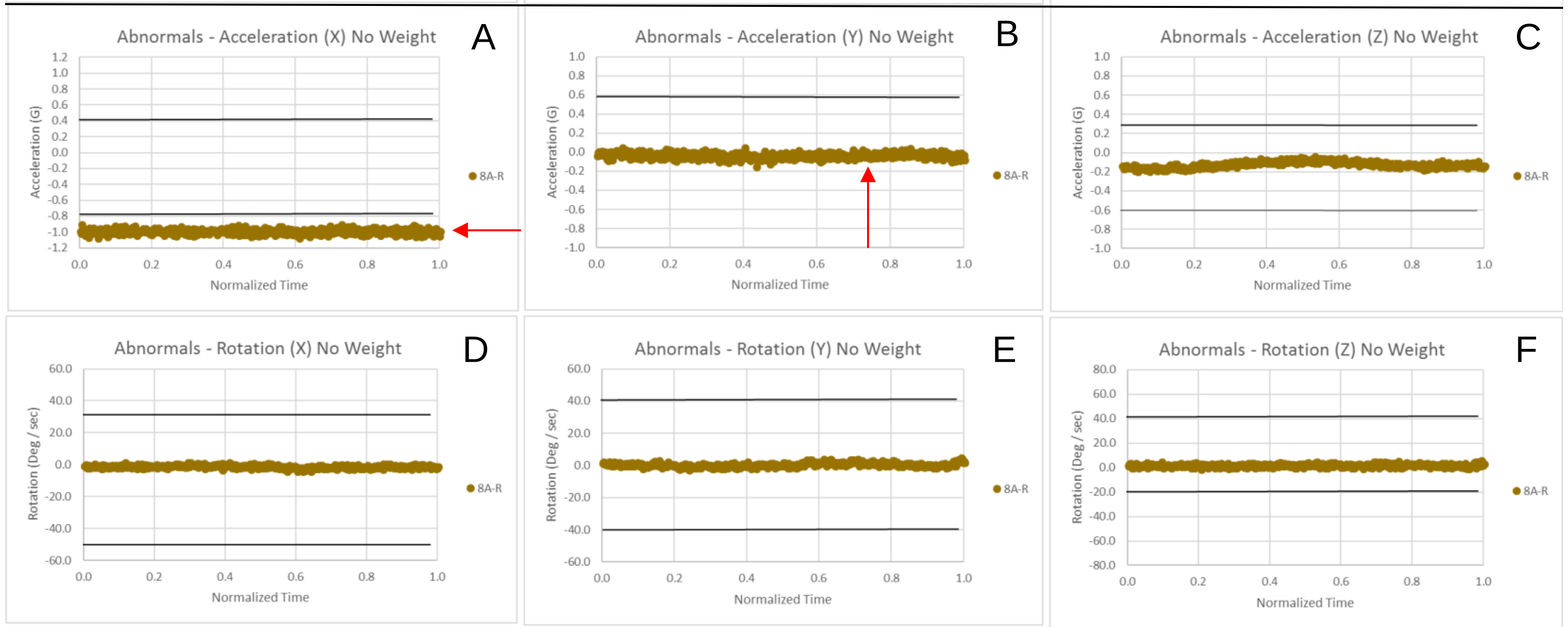
DiPaola Consulting

- External Rotation
- Right Shoulder
- No Weights
- MRI: Full thickness tear of supraspinatus, large subacromial spur

Normals



8A-R Abnormal



Sensibly

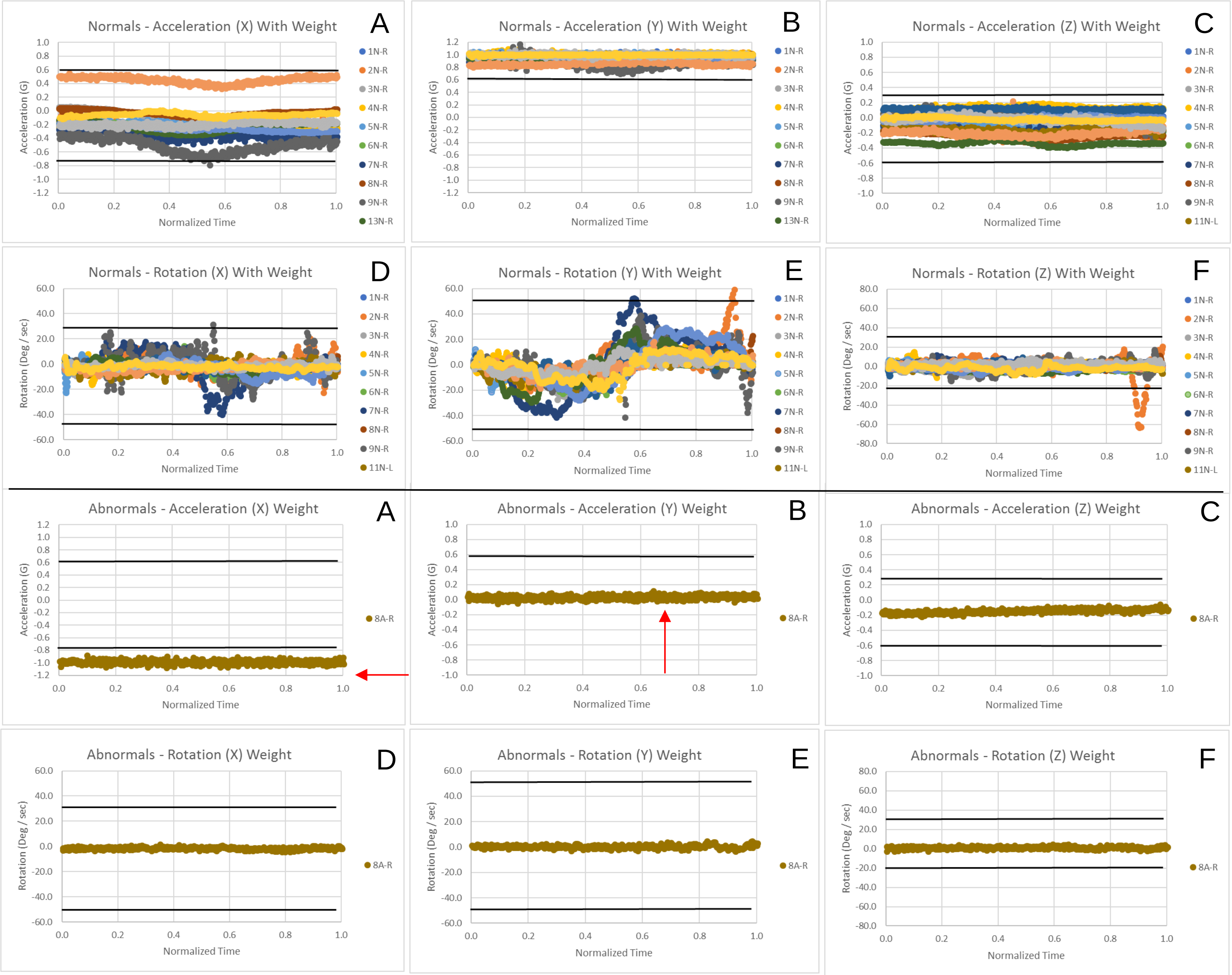
DynaMotion Medical

DiPaola Consulting

- External Rotation
- Right Shoulder
- Weights
- MRI: Full thickness tear of supraspinatus, large subacromial spur

Normals

8A-R Abnormal



Machine Learning (ML) is the programming of machines to think and act like humans with predictions or decisions based on data without being specifically programmed to

- Supervised – More human oversight over the training of the data with labels
- Unsupervised – Find things not explicitly stated (no labels)
- Deep Learning Neural Networks with multiple layers

Artificial Intelligence (AI)

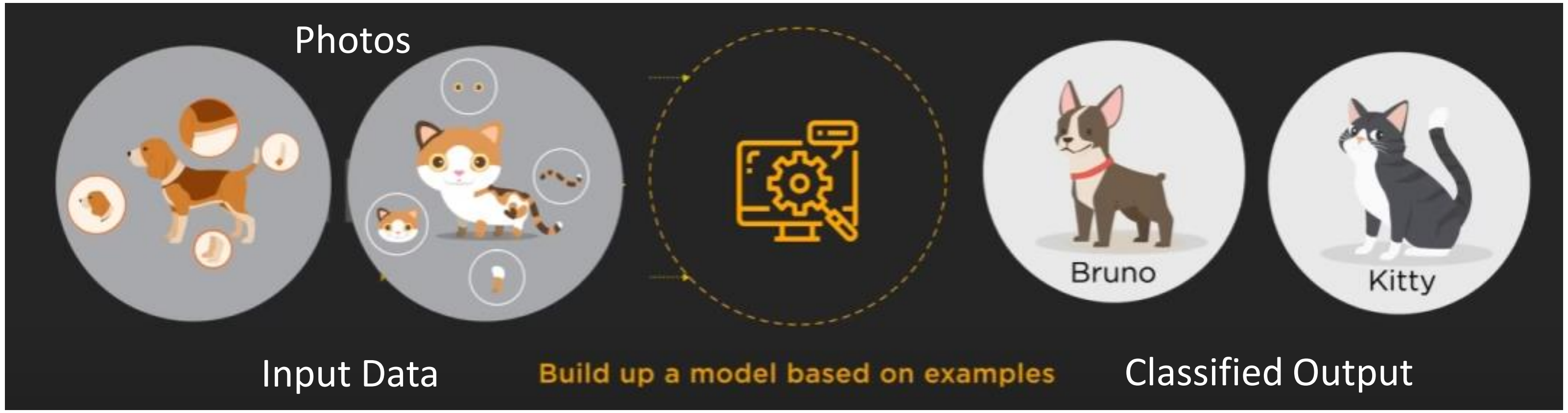
- Natural Language Processing
- Vision
- Hearing
- Text to speech
- Motion
- ML → ML – AI Subset: Supervised, Unsupervised, Deep Learning
- Search

AI ≥ discover, infer, reason

Machine Learning Supervised Learning (focus of this presentation)

- Regression – Output Continuous
  - Examples: Blood alcohol content level 0.02% - 0.10% (0.065%)
  - Linear regression, decision trees, random forests, neural networks
- Classification – Output Discrete
  - Examples: Normal / abnormal, Dog / Cat, or Sun / Fog / Rain / Sleet / Snow
  - Logistic regression, support vector machine (separating groups), Naïve Bayes, decision trees, random forests, neural networks

Increase Accuracy to 96 - 100%



How is Machine Learning Implemented?

Data Set

50 – 75% Training Set

25 – 50% Test Set

Training Set

ML
Algorithm
Python

Test

96% Accuracy

Machine Learning Time Series Classification Array (Matrix) for Cognitive

Cognitive Test:
10 – Subjects
12 – Tests
291 – Data Points

Total (test / train):
69840 data points

Subject 1

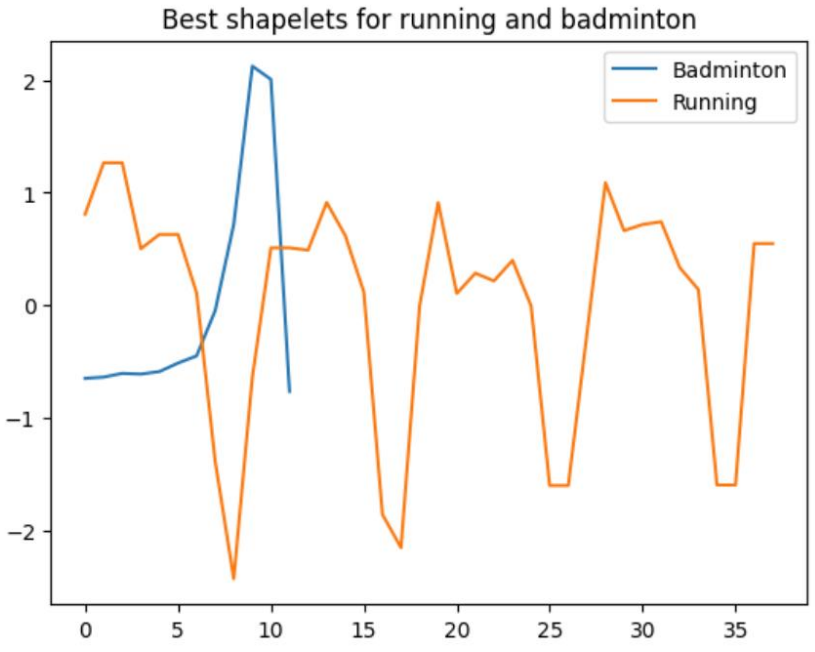
	1	2	3	4	5	6	7	8	9	10	11	...	291
1	-4.81	-4.70	-2.91	-2.75	-2.42	-2.88	-3.03	-4.17	-4.02	-3.62	-4.81	...	-2.42
2	-95.02	-84.01	-68.92	-42.21	-4.63	8.45	7.37	0.94	-3.14	8.53	24.04	...	-4.63
3	-4.46	-4.47	-4.70	-4.48	-4.82	-4.61	-4.43	-3.72	-3.68	-4.64	-5.45	...	-4.82
4	-7.24	-8.43	-9.65	-10.05	-9.27	-9.55	-9.04	-6.58	-4.01	-1.79	-0.33	...	-9.27
5	-3.46	-3.52	-3.78	-3.36	-3.26	-3.17	-2.82	-2.24	-3.82	-3.46	-3.52	...	-3.26
6	-7.57	-6.88	-4.60	-2.98	31.14	-2.10	-2.16	-2.87	-3.21	-3.47	31.07	...	31.14
7	-6.66	-6.45	-6.47	-7.04	-7.01	-5.94	-5.43	-5.04	-3.91	-2.30	-0.77	...	-7.01
8	-6.94	-6.56	-5.14	-3.03	-2.11	-3.99	-5.00	-4.34	-2.98	-2.21	-2.94	...	-2.11
9	-1.74	-1.82	31.20	-1.66	-1.44	-1.70	-1.56	-1.55	-1.51	-1.79	-2.25	...	-1.44
10	-4.17	-4.05	-4.20	-3.46	-2.85	-2.53	-2.48	-3.49	-4.15	-3.29	-1.80	...	-2.85
11	-7.24	-8.43	-9.65	-10.05	-9.27	-9.55	-9.04	-6.58	-4.01	-1.79	-0.33	...	-9.27
12	-95.02	-84.01	-68.92	-42.21	-4.63	8.45	7.37	0.94	-3.14	8.53	24.04	...	-2.11

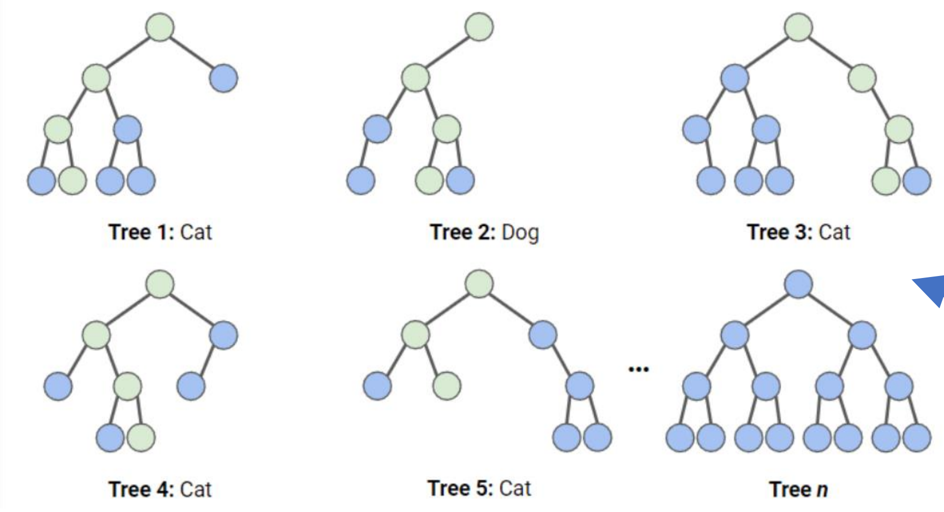
Machine Learning Algorithms – Implemented Using Aeon Tool Kit

- Rocket
- Catch22 Classifier (will not be discussed)
- RandomShapeletTransform
- Convolutional Neural Network (CNN)
- HIVE-COTE V2

Machine Learning Algorithms – RandomShapeletTransform

- Randomly samples n_shapelet_samples keeping the best max_shapelets
- Resulting shapelets are used in the transform function to create a new tabular dataset, where each row represents a time series instance, and each column stores the distance from a time series to a shapelet
- Random Forest Classifier used to classify resulting tabular data





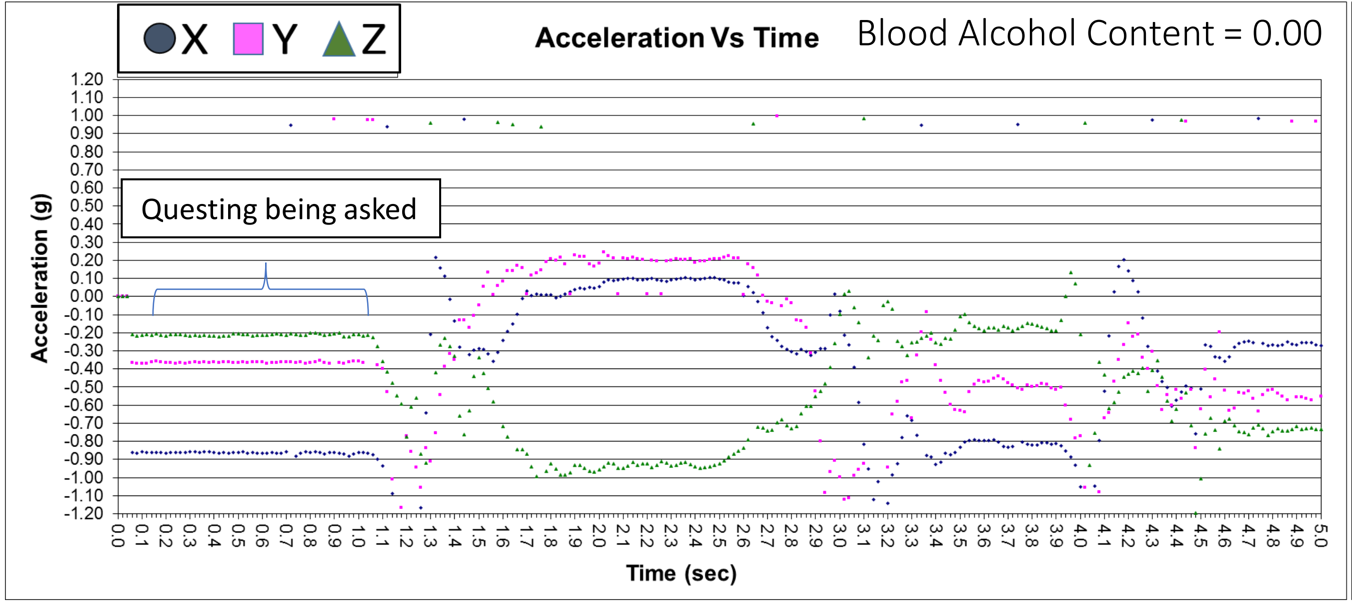
Each Random Forest Tree is different:
Exposed to a different number of features and a different sample of the original dataset.
Most popular prediction chosen.

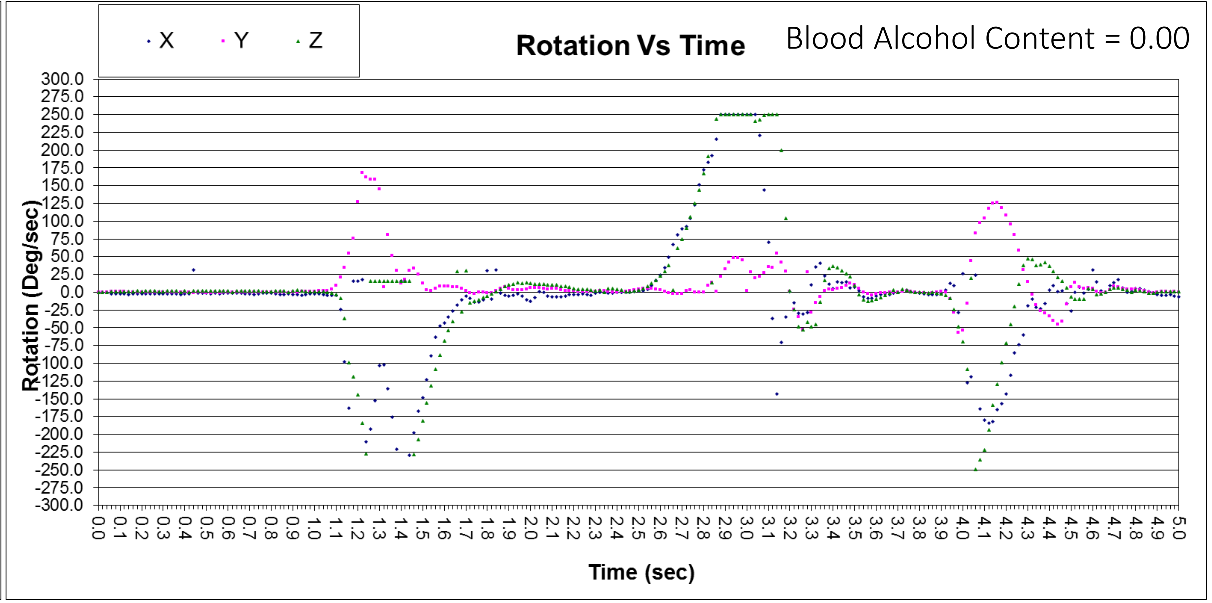
Example Trace - What time is it?

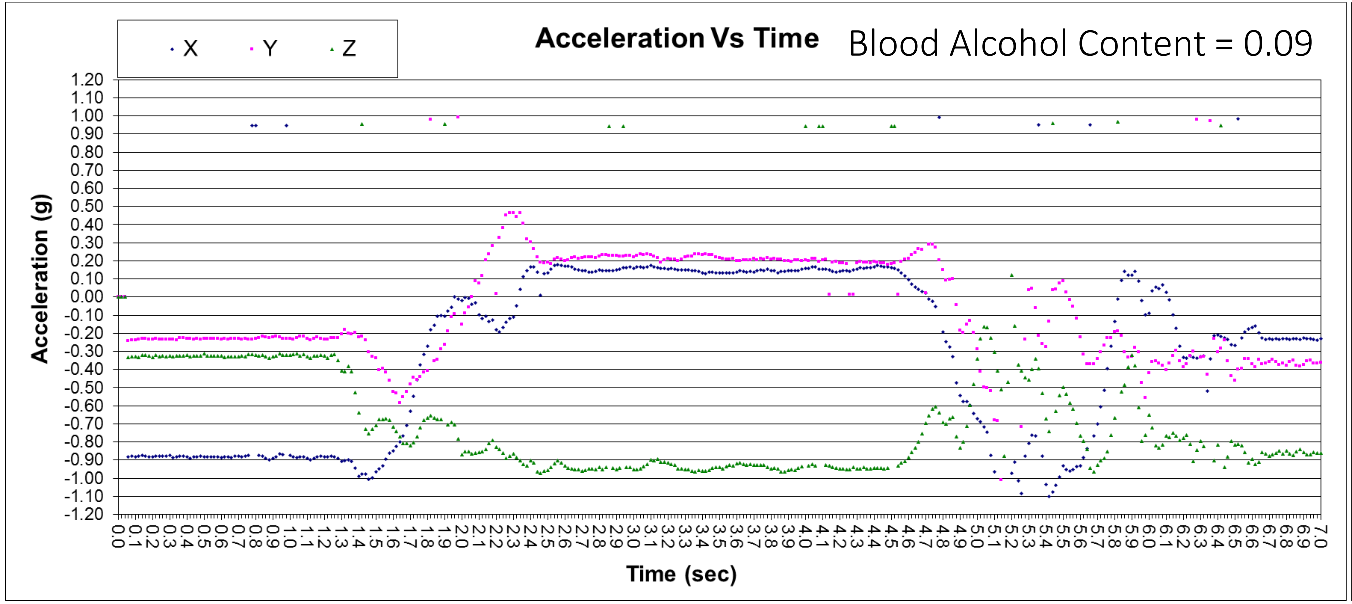
Sensibly

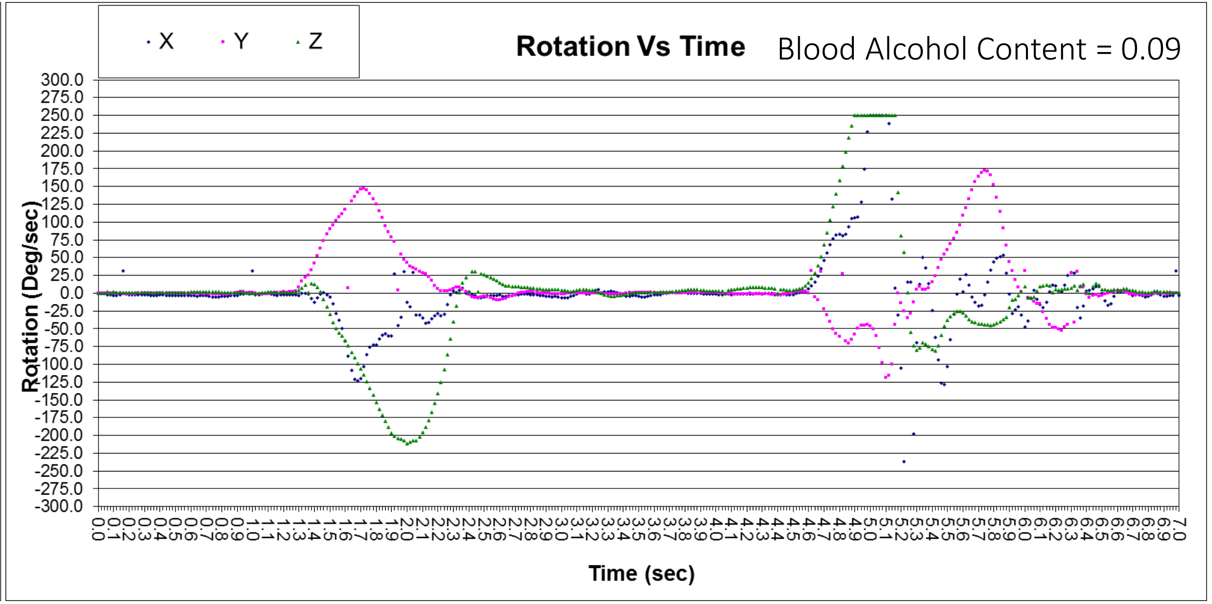
DynaMotion Medical

DiPaola Consulting



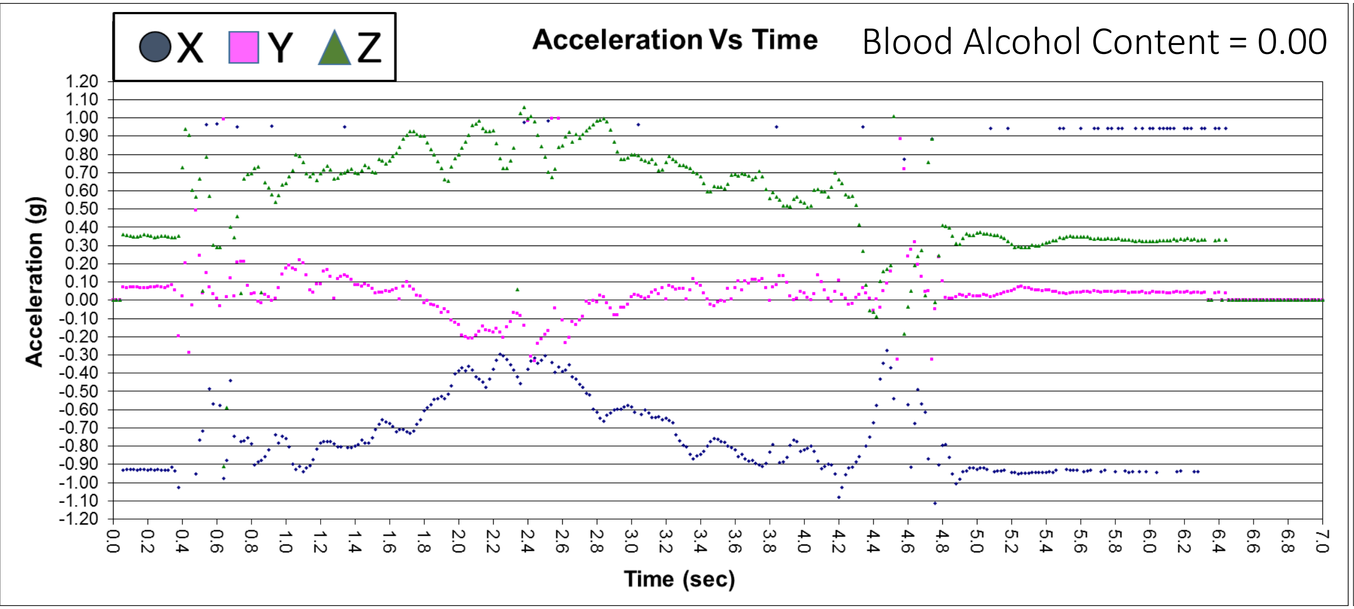


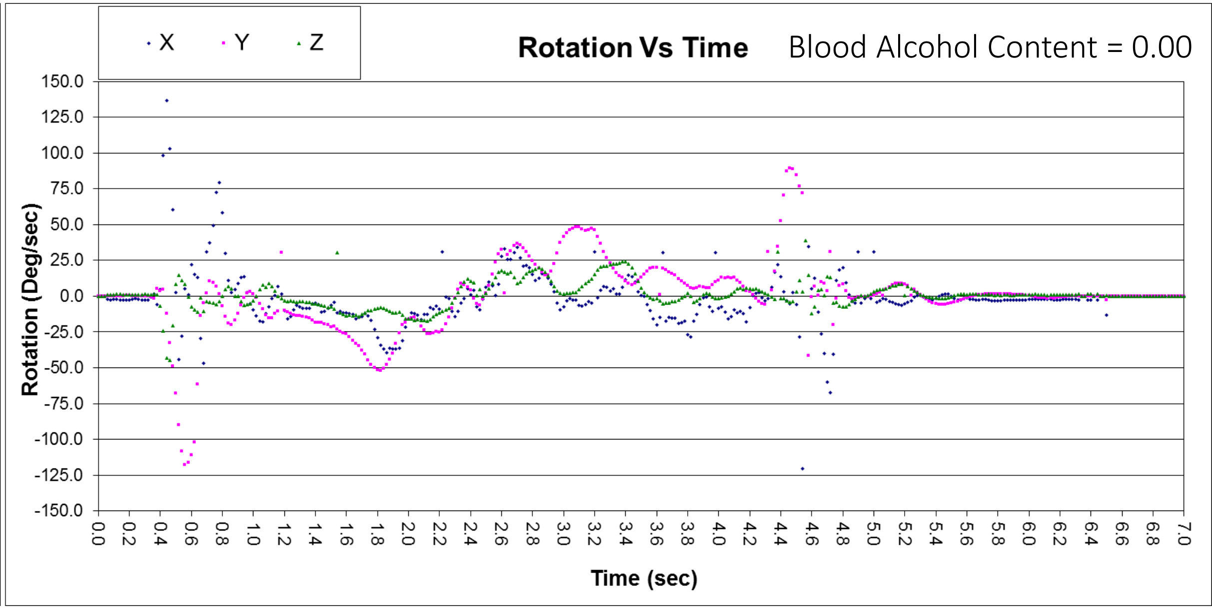


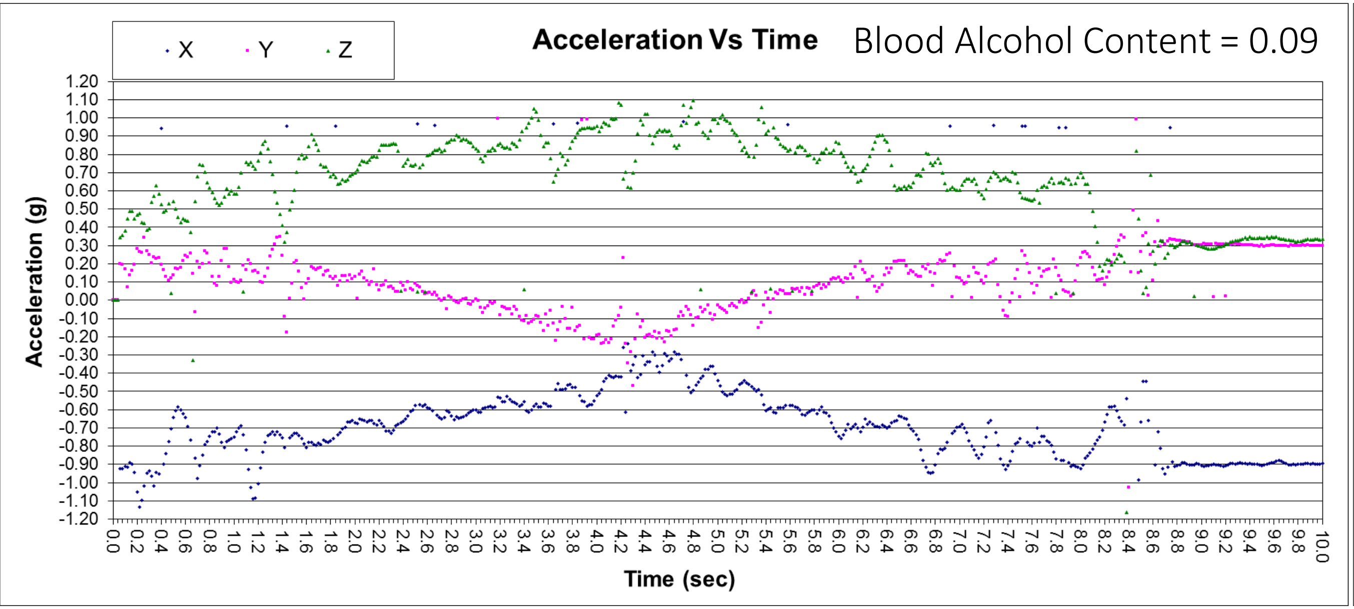


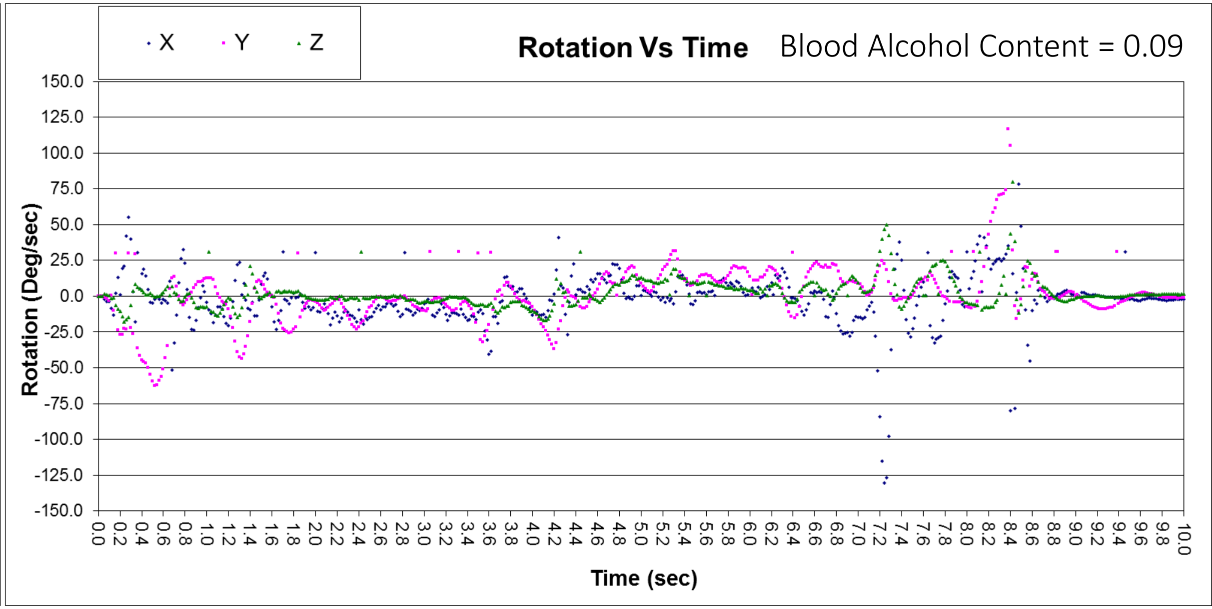
Example Trace - Heel on Shin Ankle to Knee

DynaMotion Medical









Results

- Cognitive impairment (blood alcohol content of 0.00 (sober) vs. 0.09 (legally drunk)) increased time to perform test with the motion signature being similar with noticeable differences.
  - Trying to perform the test faster while cognitively impaired may result in a more jagged movement signature (seen in initial testing and needs to be validated on a larger sample size).
  - A learned tolerance can occur at impaired levels. Hence some subjects did better in the last round than the previous round (for example BAC = 0.06 resulted in longer reaction time than at BAC = 0.08). Hence conducting the same test multiple times may result in better performance.

- Machine learning using RandomShapeletTransform was used to properly classify 80% of the cases.
  - Careful review of the data showed men lost more motor control than women with intoxication. Hence the machine learning properly classified all sober subjects and men intoxicated, but not women intoxicated.

- Right hand motion signatures are slightly different than left hand due to the movement differences between right and left arms when the sensor is positioned in the same orientation hence the test can automatically detect which hand was used (also with leg movements)

Conclusions

- Not yet the holy grail … more testing is needed as data trains the model
- The utilization of machine learning and TEOP has the potential to properly classify a cognitive condition such as sober versus intoxicated for men with additional testing needed to validate this approach with women (possibly different TEOP tests) who demonstrate superior motor control while cognitively impaired
- Goal is to refine approach for TBI and cognitive conditions to the level of torn rotator cuff in shoulder with greater than 96% accuracy

PRACTICAL APPLICATION: Concussions and TBI often occur in athletes playing popular sports, police, and soldiers in the field. This approach may be a fast, standardized method of diagnosis and monitoring of these cognitive conditions to allow patients to safely return to play and work