BONE MINERAL DENSITY MAINTENANCE DURING LONG-DURATION SPACEFLIGHT

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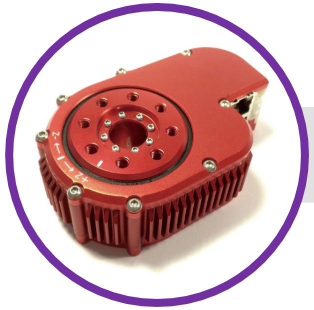
LM Machine Learning Forum, June 2021

Based on: Schepelmann, A. *et al*. (2018) Overview and evaluation of a computational bone physiology modeling toolchain and its application to testing of exercise countermeasures. *NASA Technical Memorandum*.

* Presented work performed while an employee of ZIN Technologies, Inc., Cleveland, Ohio, USA in conjunction with the Cross-Cutting Computational Modeling Project (CCMP) at NASA Glenn Research Center.

ABOUT ME

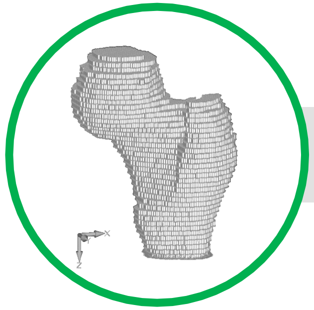
2009: CWRU Cutter



2016: Modular Actuators

2020: Planetary Robotics

2010: Robotic Neuromuscular Leg
2014: Compact Nonlinear Springs



2017: Computational Modeling

WHAT IS NASA CCMP?

- The Cross-Cutting Computational Modeling Project (CCMP) is located within NASA's Human Research Program (HRP).
- The programs seeks to fuse traditional research with computational modeling to characterize risks and improve decision making for human spaceflight.

NASA's Cross-Cutting Computational Modeling Project.

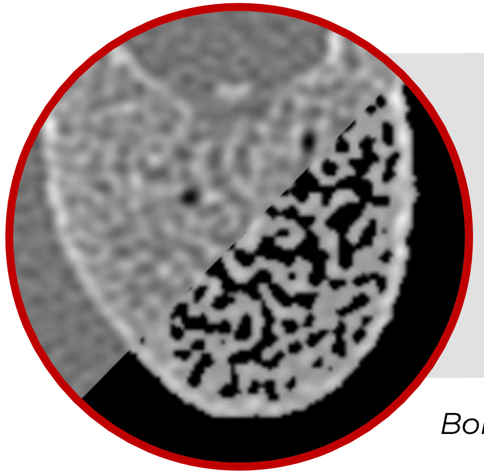
- Machine learning is currently used to support HRP efforts in areas related to in-flight, in-mission, and long-term medical risk assessment.
- Machine learning has further application to unique health and performance concerns and specific human physiology changes during spaceflight.

NASA's Human Research Program.

RESISTIVE EXERCISE PREVENTS BONE LOSS DURING SPACEFLIGHT

- Astronauts experience 0.4-2.7% monthly volumetric bone mineral density (vBMD) loss during long-duration missions.
- Resistive exercise counters the effects of microgravity, but the required exercise frequency and duration for individuals is unclear.

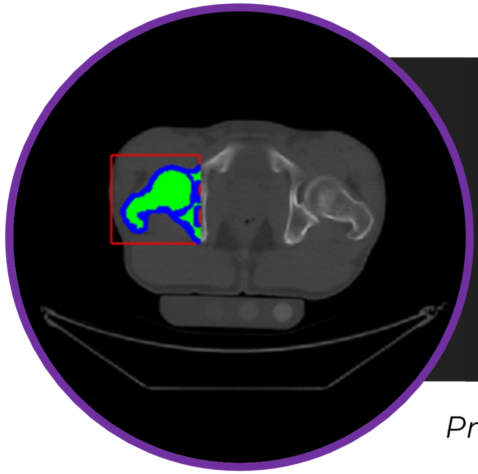
The Hybrid Ultimate Lifting Kit (HULK) exercise device during parabolic flight.



- Personalized computational models may provide insight into the required amount of exercise for vBMD maintenance.
- Subject-specific bone finite element (FE) models are required for these models but generating them can be slow and laborious.

Bone CT cross section. L: Raw, R: Pixel-based thresholding segmentation.

BAYESIAN CLASSIFIERS CAN AUTOMATE FE MODEL GENERATION

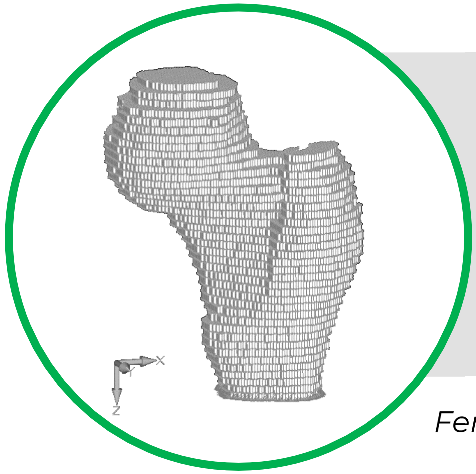


Given: $X^{new} =< X_1, ..., X_n >$

Classify: $\hat{y} = \underset{j \epsilon \{1,...,J\}}{\arg\max} \propto P(Y = y_j) \prod_{i=1}^{n} P(X_i^{new} | Y = y_j)$

Probabilistic segmentation result of a DICOM CT image slice.

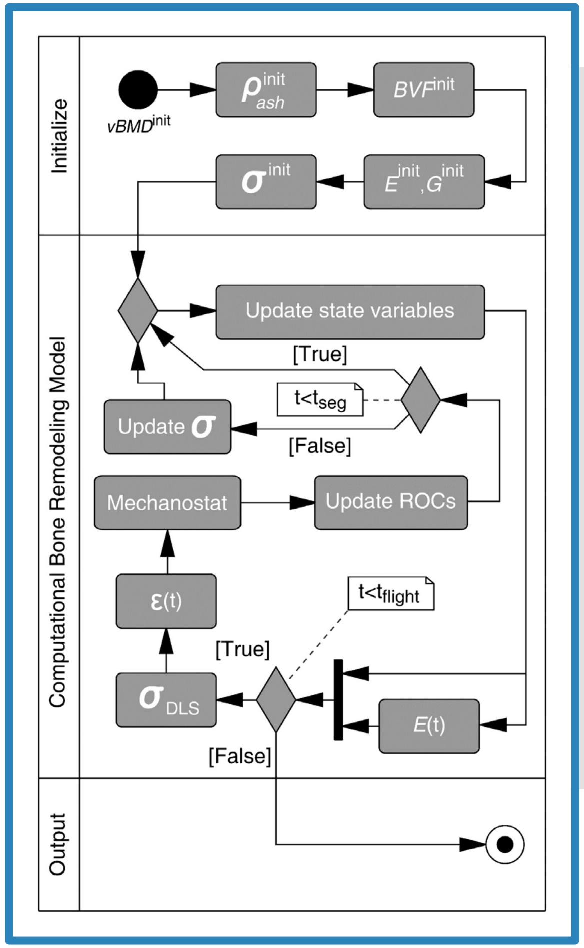
GNB Appendix



- The probabilistic classification scheme successfully segments bone containing images into 3 material types, requiring minimal post-processing.
- The Bayesian classification scheme decreases the required time to build a subject-specific FE model from 8 hours to 10 minutes.

Femur FE model generated from segmented CT image slices.

NASA'S BONE MODEL RELATES vBMD TO LOAD INDUCED STRESSES



- NASA has developed a bone remodeling dynamics model to estimate changes in vBMD in response to skeletal unloading and exercise.
- The model is initialized from CT image data and estimates mean cortical and trabecular bone mineral density as a function of time.
- Chemical remodeling rates are related to the aggregate daily bone strain resulting from exercise via Frost's mechanostat theory [1].
- Bone strain can be calculated for specific resistive exercises via the *daily load stimulus*, a relationship that relates induced single-cycle cortical and trabecular stresses to the frequency and number of exercise repetitions [2].

Overview of the computational bone remodeling model.

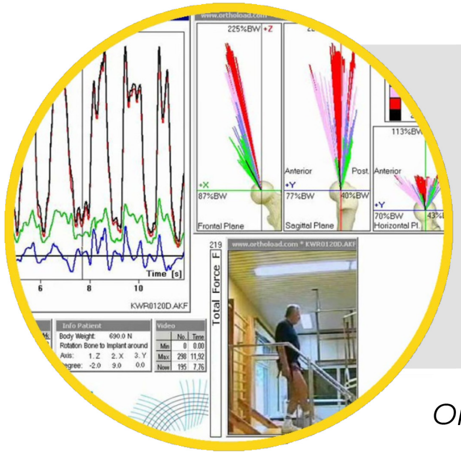
[1] Frost, H.M. (2003). Bone's mechanostat: A 2003 update. *Anatomical Record Part A: Discoveries in Molecular, Cellular, and Evolutionary Biology.*
[2] Turner, C.H. and Robling, A.G. (2003). Designing exercise regiments to increase bone strength. *Exercise and Sport Sciences Reviews.*

ANALOG BEDREST STUDY DATA IS USED TO VALIDATE THE MODEL

- The computational bone model is evaluated using data from subjects participating in a spaceflight analog 70-day bed rest study.
- A subset of participants performed exercises consistent with NASA's integrated resistance and aerobatic training regiment (iRAT) study [3].

Vertical treadmill in the NASA Flight Analog Research Unit.

[3] Ploutz-Snyder, L.L. et al. (2014). Integrated resistance and aerobic exercise protects fitness during bed rest. *Medicine and Science in Sports and Exercise.*



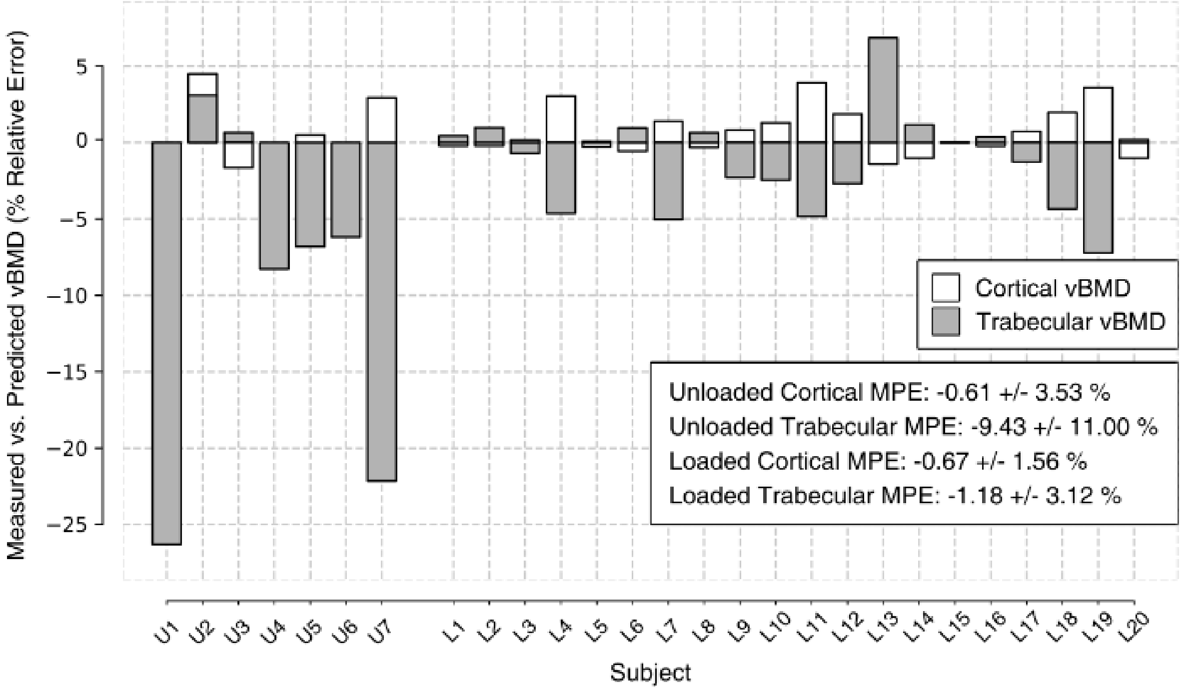
- The required vBMD maintenance force is assumed to be equivalent to femoral head contact forces resulting from walking 5,000 steps per day [4].
- Stochastic optimization of femoral head contact forces is used to simultaneously test model convergence and evaluate model behavior.

Orthoload public database.

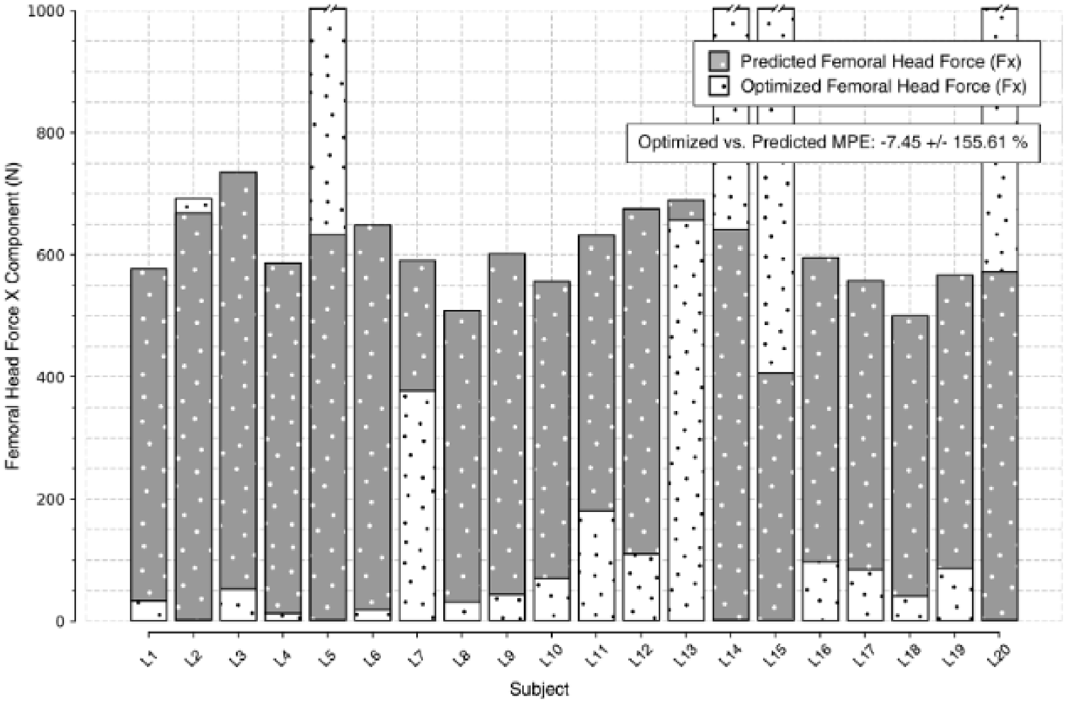
CMA-ES Appendix

[4] Bergman, G. (2008). Orthoload. Charite Universitatsmedizin Berlin. http://www.Orthoload.com.

MODEL PREDICTS POST-STUDY vBMD, BUT FORCES ARE LOW

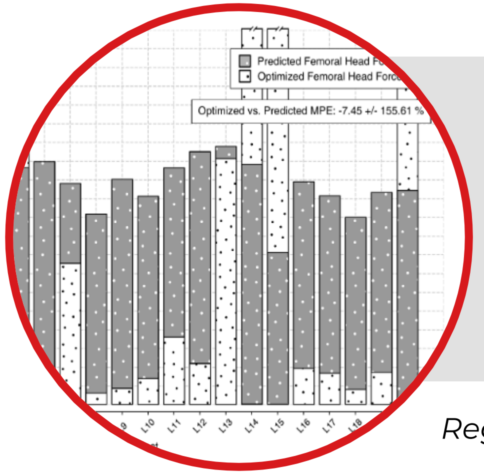


Measured vs. predicted post-study vBMD. U: Unloaded L: Loaded.



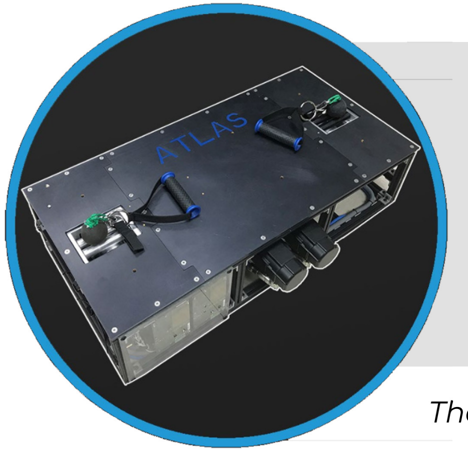
Regression vs. model predicted vBMD maintenance forces.

FUTURE WORK FOCUSES ON QUANTITATIVE FORCE PREDICTION



- The model predicts post-study vBMD of subjects with a low mean relative error, but predicted forces only qualitatively show the benefits of exercise.
- This behavior likely results from the use of a single remodeling model parameter set and the same FE bone model for all subjects.

Regression vs. model predicted vBMD maintenance forces.



- The probabilistic classification scheme successfully segments bone containing images into 3 material types, requiring minimal post-processing.
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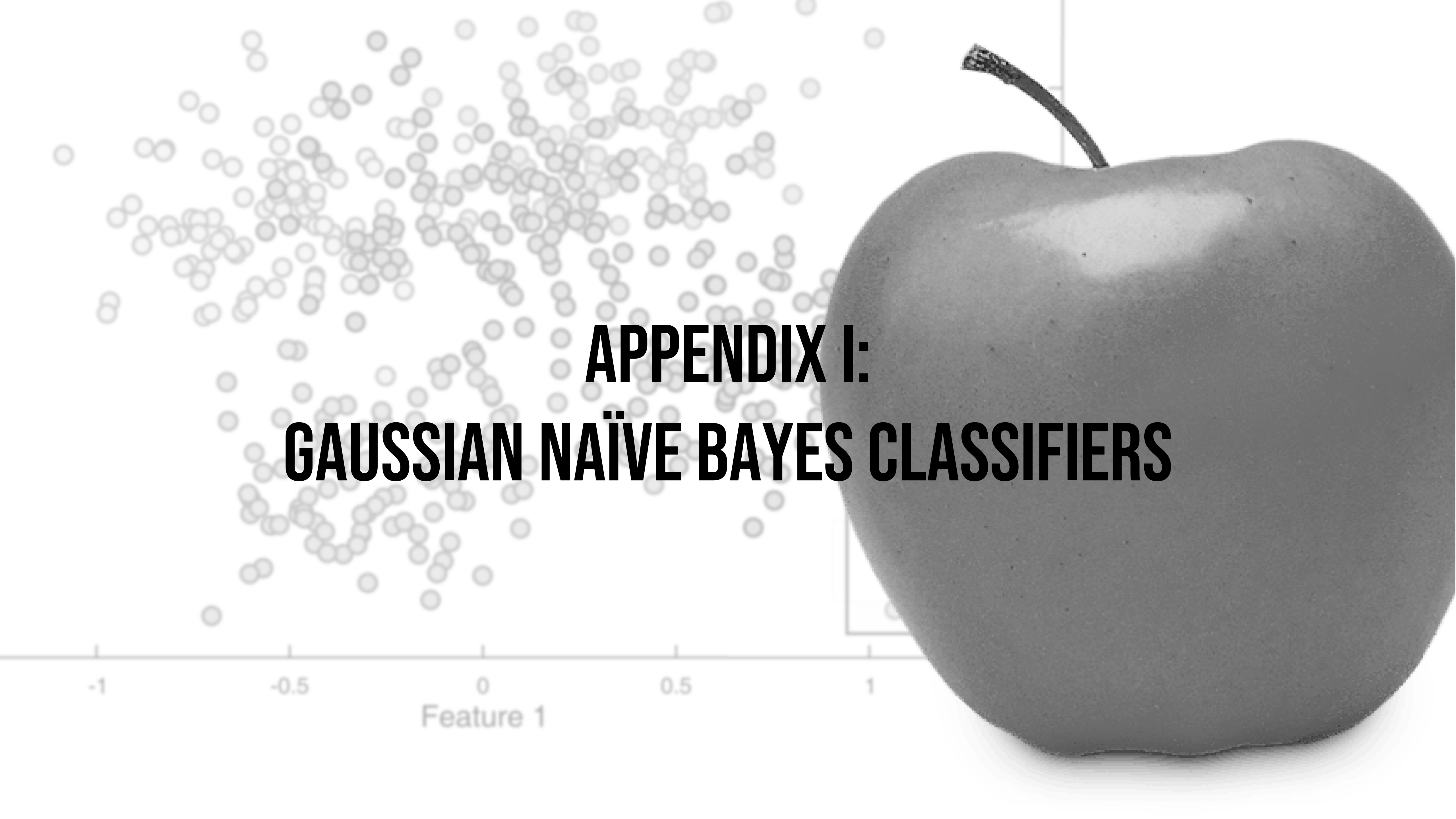
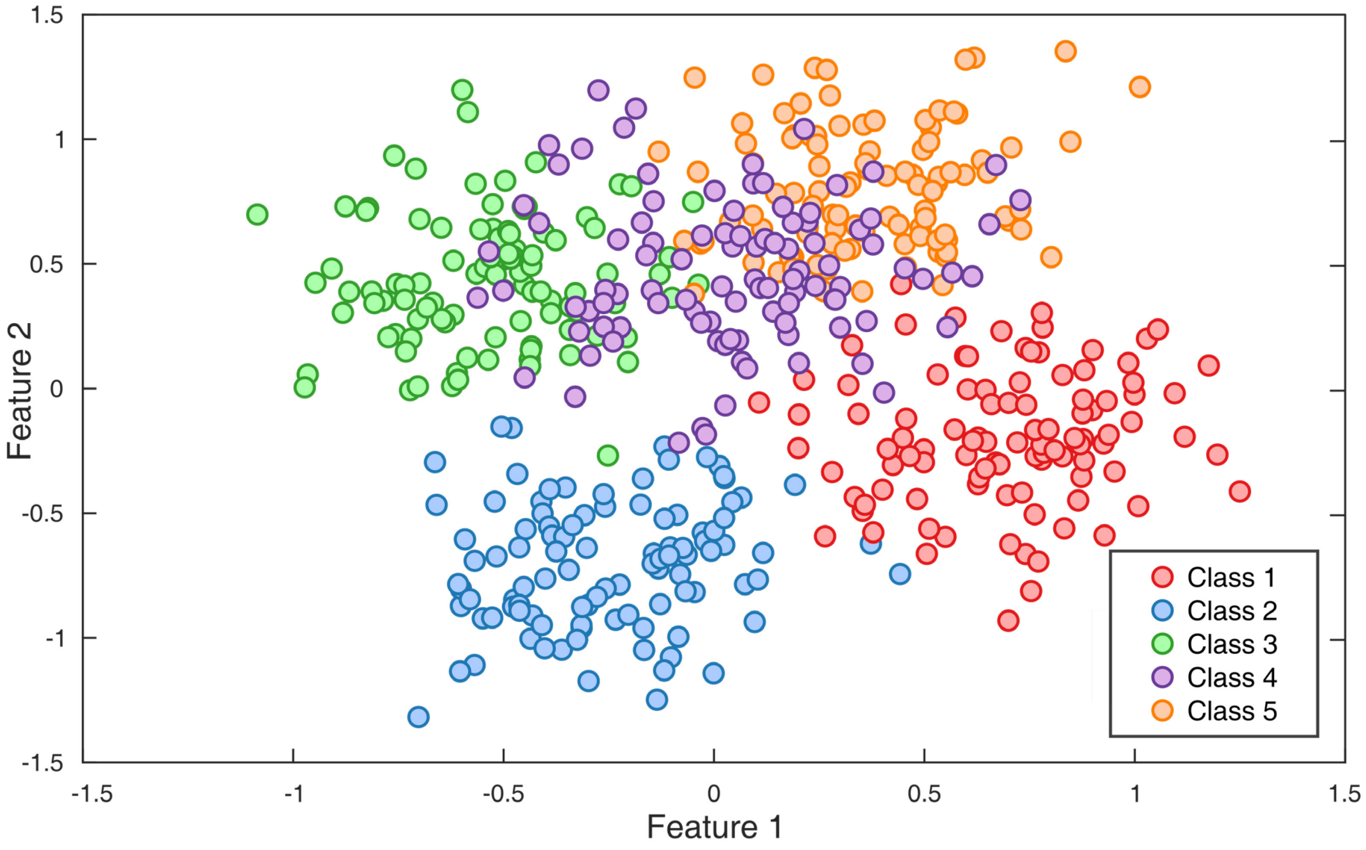
The Advanced Twin Lifting and Aerobic System (ATLAS).

APPENDIX I: GAUSSIAN NAÏVE BAYES CLASSIFIERS



CLUSTERING CAN BE USED TO SEGMENT DATASETS



Classifying data based on clustering from two features.

CLUSTERING CAN BE USED TO SEGMENT DATASETS

Given a set of features X^{new} *to describe a sample...*

$$X^{new} = < X_1, ..., X_n >$$

$$\hat{y} = \underset{j \in \{1,...,J\}}{\operatorname{argmax}} \propto P(Y = y_j) \prod_{i=1}^{n} P(X_i^{new} | Y = y_j)$$

... the sample described by those features most likely came from group y_j ...

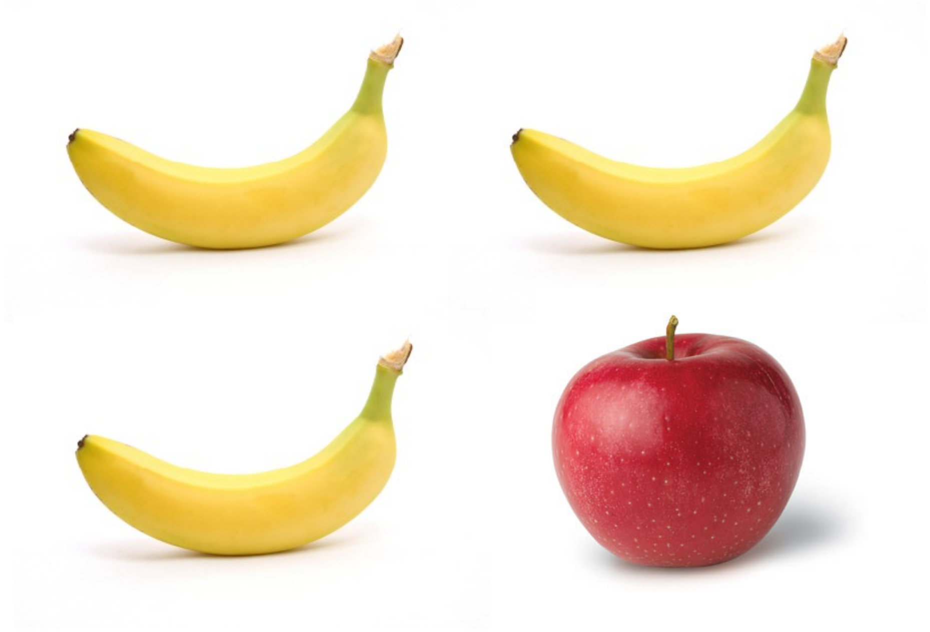
... based on other samples with the same features.

Naïve Bayes classifier using the maximum a posteriori decision rule.

EXAMPLE: CLASSIFYING FRUIT USING ONE FEATURE

$$P(Y = \ |X = \square) \propto P(X = \square|Y = \ )P(Y = \ )$$
$$\propto 0 * 0.25 = 0$$

$$P(Y = \ |X = \square) \propto P(X = \square|Y = \ )P(Y = \ )$$
$$\propto 1 * 0.75 = 0.75$$



The banana-apple universe, where 75% of all fruit are bananas.

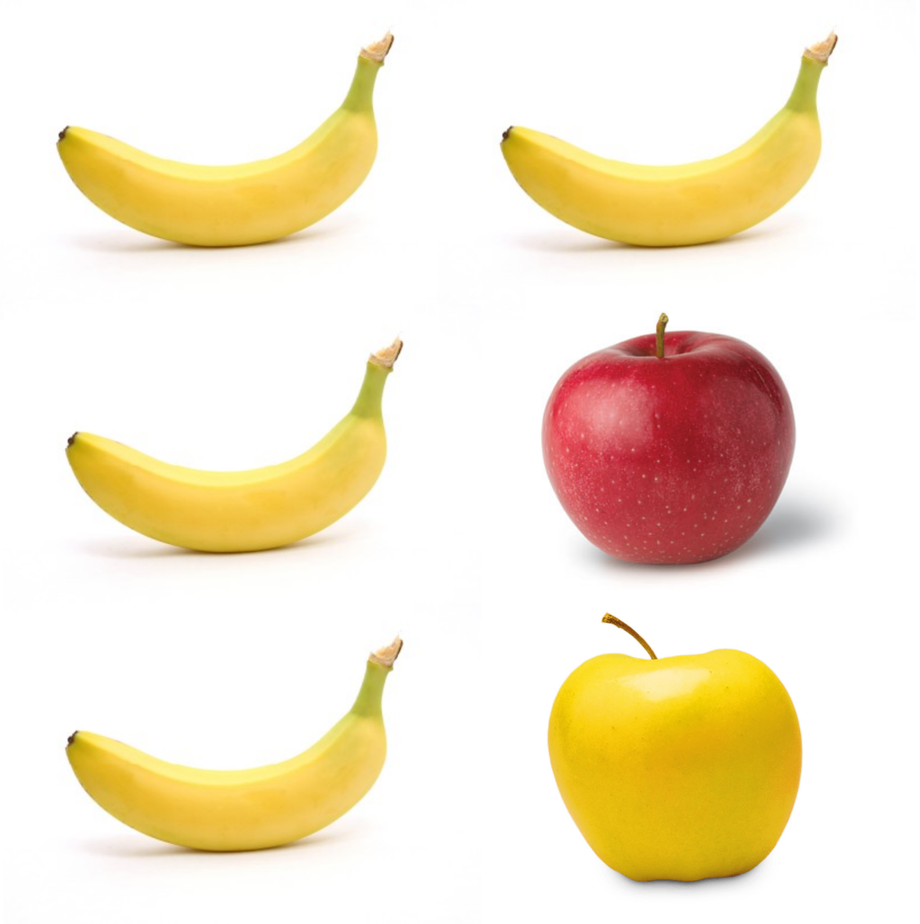
CLASSIFYING APPLES WITH INSUFFICIENT FEATURES

$$P(Y = \quad | X = \quad) \propto P(X = \quad | Y = \quad) P(Y = \quad)$$

$$\propto 0.2 * 0.33 = 0.07$$

$$P(Y = \quad | X = \quad) \propto P(X = \quad | Y = \quad) P(Y = \quad)$$

$$\propto 0.8 * 0.66 = 0.53$$



The banana-apple universe, where 66% of all fruit are bananas and yellow apples exist.

CLASSIFYING APPLES WITH MULTIPLE FEATURES

$$P(Y = \;|X = \square, round)$$

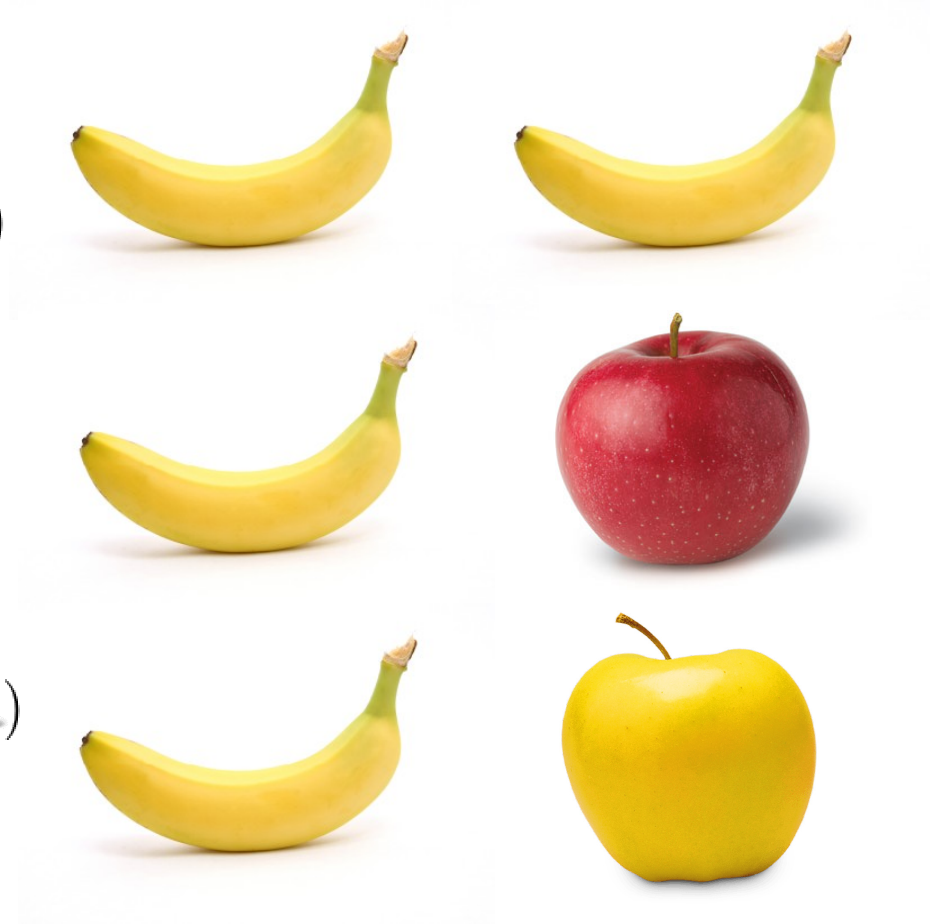
$$\propto P(Y = \;) * P(X = \square|Y = \;)P(X = round|Y = \;)$$

$$\propto 0.66 * 0.8 * 0 = 0$$

$$P(Y = \;|X = \square, round)$$

$$\propto P(Y = \;) * P(X = \square|Y = \;)P(X = round|Y = \;)$$

$$\propto 0.33 * 0.2 * 1 = 0.07$$



The banana-apple universe, where 66%
of all fruit are bananas and yellow apples exist.

ESTIMATING CONDITIONAL PROBABILITIES OF CONTINUOUS VALUES

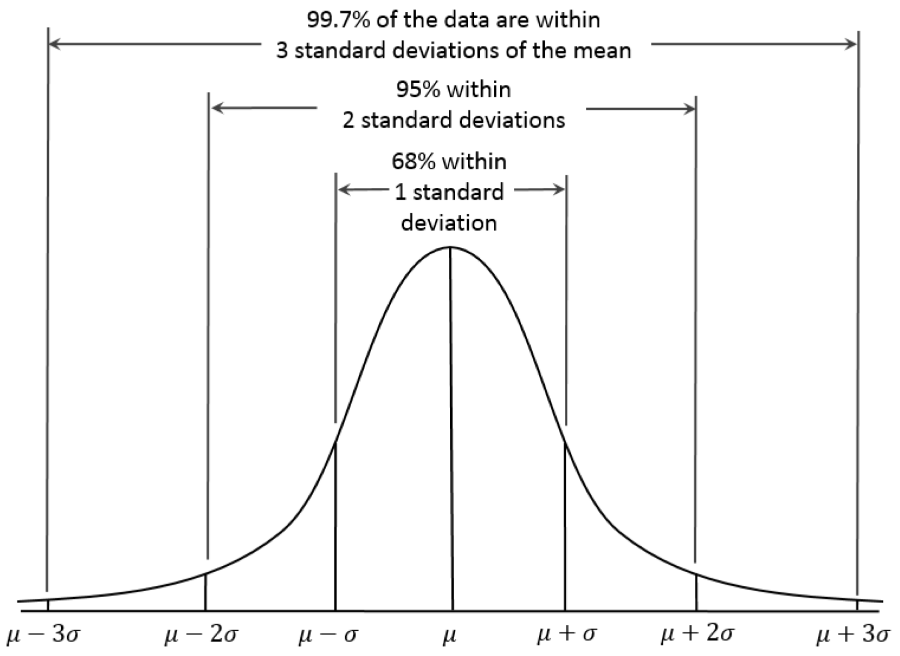
$$P(Y = y_j)\prod_{i=1}^{n} P(X_i|Y = y_j)$$

Calculated as (n_{class} / n_{tot})

Feature mean of class

$$P(X = x_i|Y = y_j) = \frac{1}{\sqrt{2\pi\sigma^2_{y_j}}}e^{-(x_i-\mu_{y_j})^2/(2\sigma^2_{y_j})}$$

Feature standard deviation of class



The probability density function of a Gaussian distribution [5].

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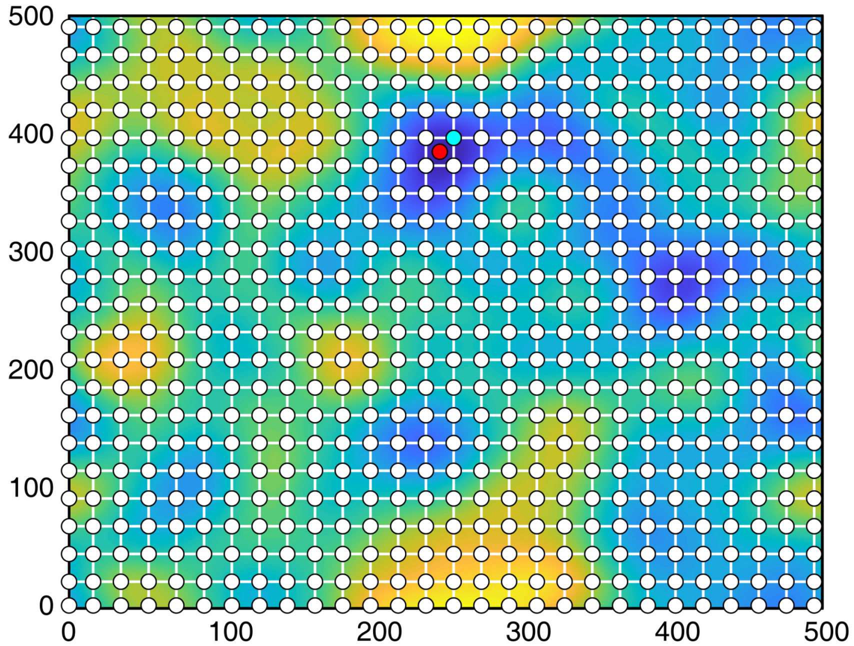
[5] Normal Distribution. Wikipedia, https://en.wikipedia.org/wiki/Normal_distribution. Accessed 2019.

APPENDIX II:
STOCHASTIC OPTIMIZATION VIA CMA-ES

GOAL: FIND OPTIMAL PARAMETERS WHILE MINIMIZING EVALUATIONS

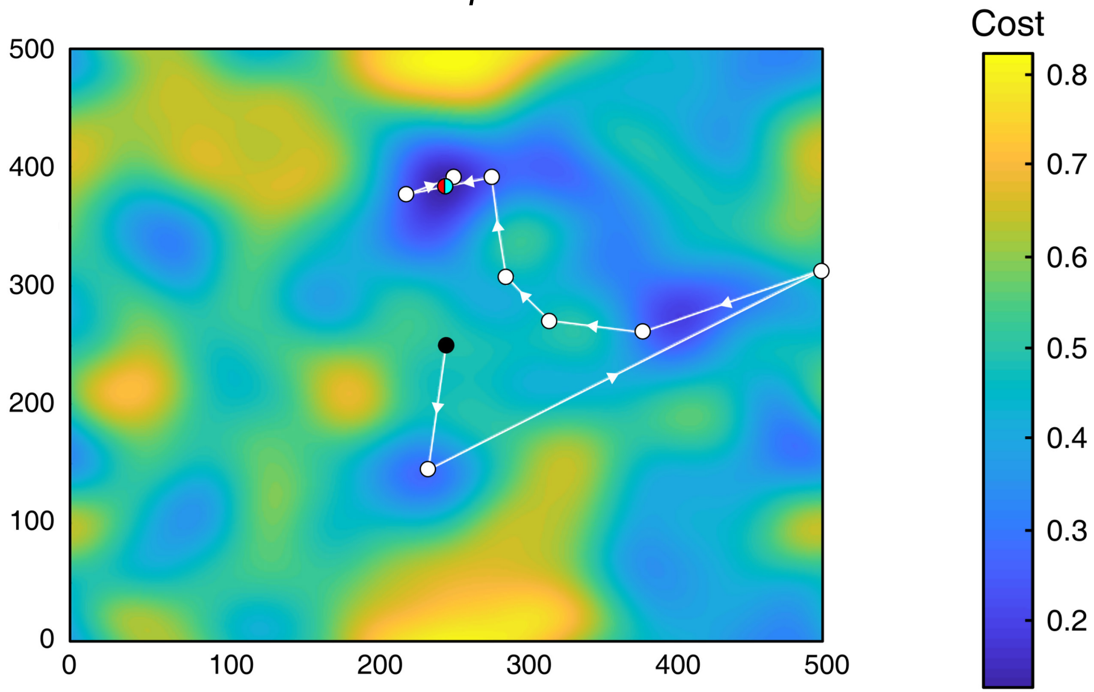
Parameter Sweep



$$\underset{n_1,n_2}{\operatorname{argmin}}\{C(n_1,n_2)\}$$

$$n_1 = [n_1^i : \Delta n_1 : n_1^f] \quad n_2 = [n_2^i : \Delta n_2 : n_2^f]$$

Stochastic Optimization



$$\underset{n_1,n_2}{\operatorname{argmin}}\{C(n_1,n_2)\}$$

$$n_1^i \leq n_1 \leq n_1^f \qquad n_2^i \leq n_2 \leq n_2^f$$

COVARIANCE MATRIX ADAPTATION-EVOLUTION STRATEGY (CMA-ES)

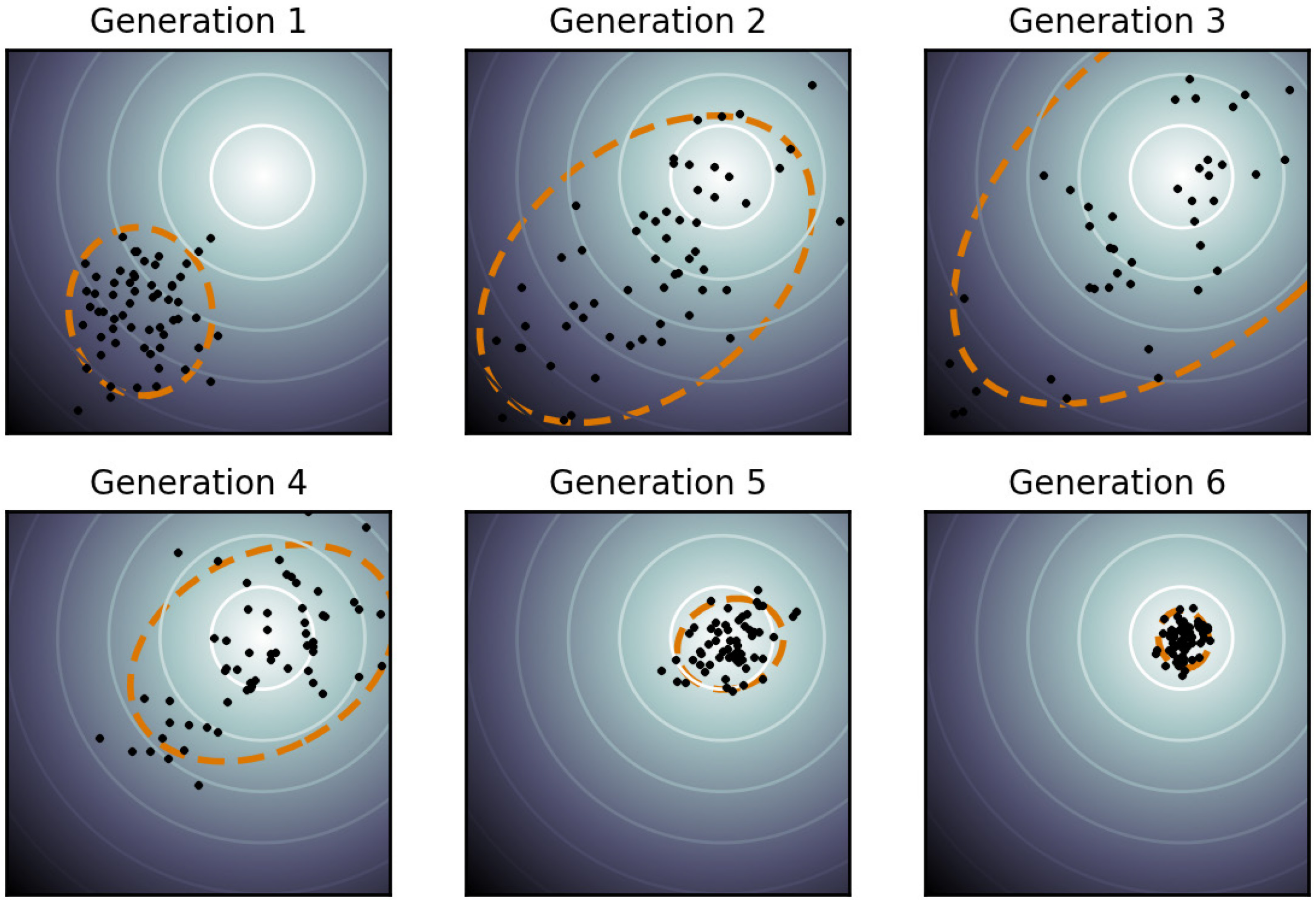


Illustration of the covariance matrix adaptation evolution strategy (CMA-ES) over 6 iterations [6].

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[6] Covariance Matrix Adaptation Evolution Strategy. Wikipedia, https://en.wikipedia.org/wiki/CMA-ES. Accessed 2021.