



BONE MINERAL DENSITY MAINTENANCE DURING LONG-DURATION SPACEFLIGHT



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ABOUT ME



2009: CWRU Cutter



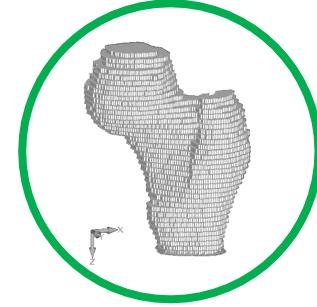
2016: Modular Actuators



2020: Planetary Robotics



2010: Robotic Neuromuscular Leg
2014: Compact Nonlinear Springs



2016: Computational Modeling



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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



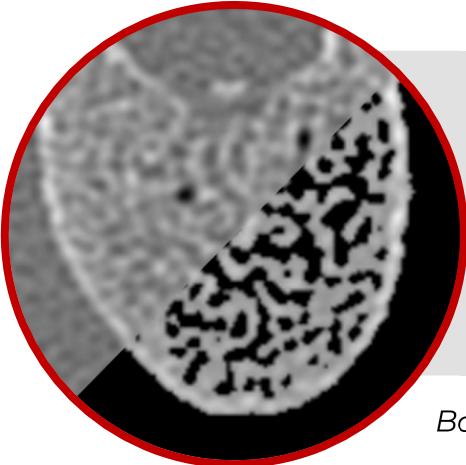
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RESISTIVE EXERCISE PREVENTS BONE LOSS DURING SPACEFLIGHT



- 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.

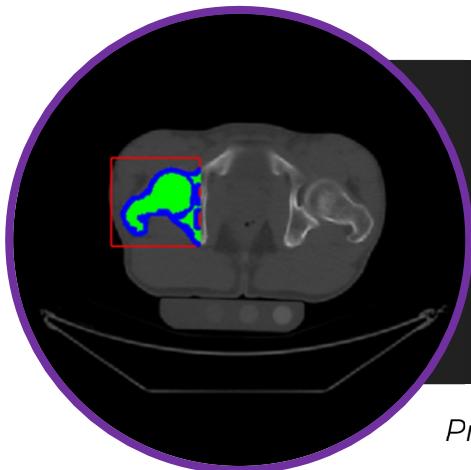


- Personalized computational models may provide insight into the required amount of exercise for vBMD maintenance.
- Subject-specific bone finite element (FE) models are required for these models but generating them can be slow and laborious.

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



BAYESIAN CLASSIFIERS CAN AUTOMATE FE MODEL GENERATION

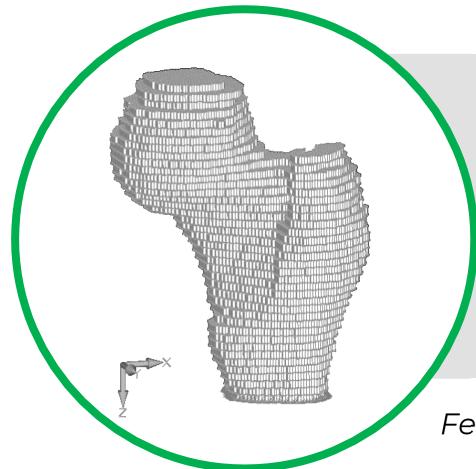


Given: $X^{new} = \langle X_1, \dots, X_n \rangle$

Classify: $\hat{y} = \arg \max_{j \in \{1, \dots, J\}} P(Y = y_j) \prod_{i=1}^n P(X_i^{new} | Y = y_j)$

Probabilistic segmentation result of a DICOM CT image slice.

[GNB Appendix](#)



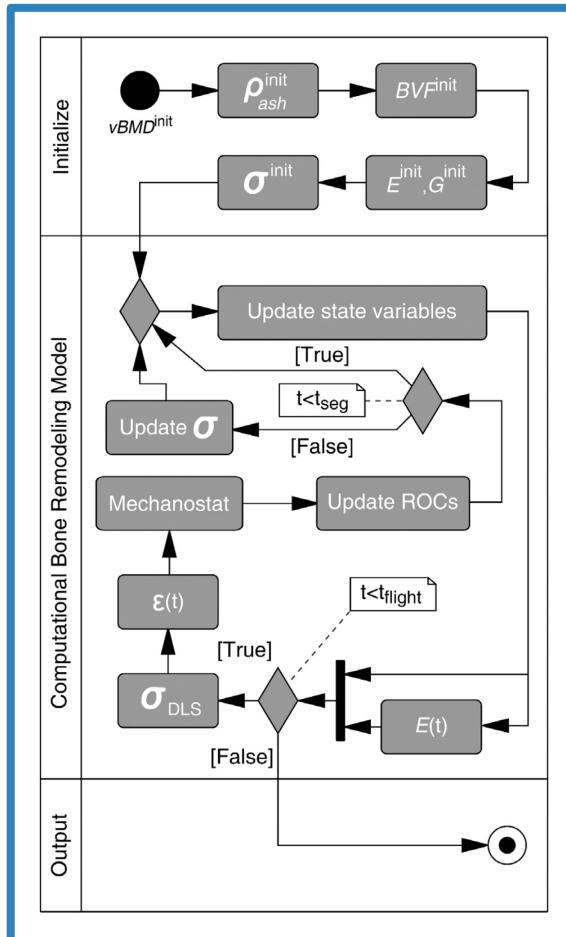
- The probabilistic classification scheme successfully segments bone containing images into 3 material types, requiring minimal post-processing.
- The Bayesian classification scheme decreases the required time to build a subject-specific FE model from 8 hours to 10 minutes.

Femur FE model generated from segmented CT image slices.



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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 regimens to increase bone strength. *Exercise and Sport Sciences Reviews*.



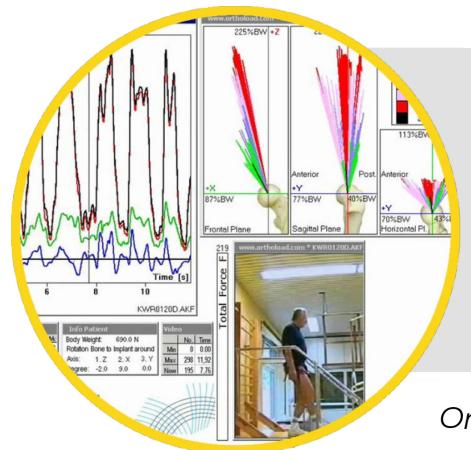
ANALOG BEDREST STUDY DATA IS USED TO VALIDATE THE MODEL



- 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 aerobic training regimen (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.

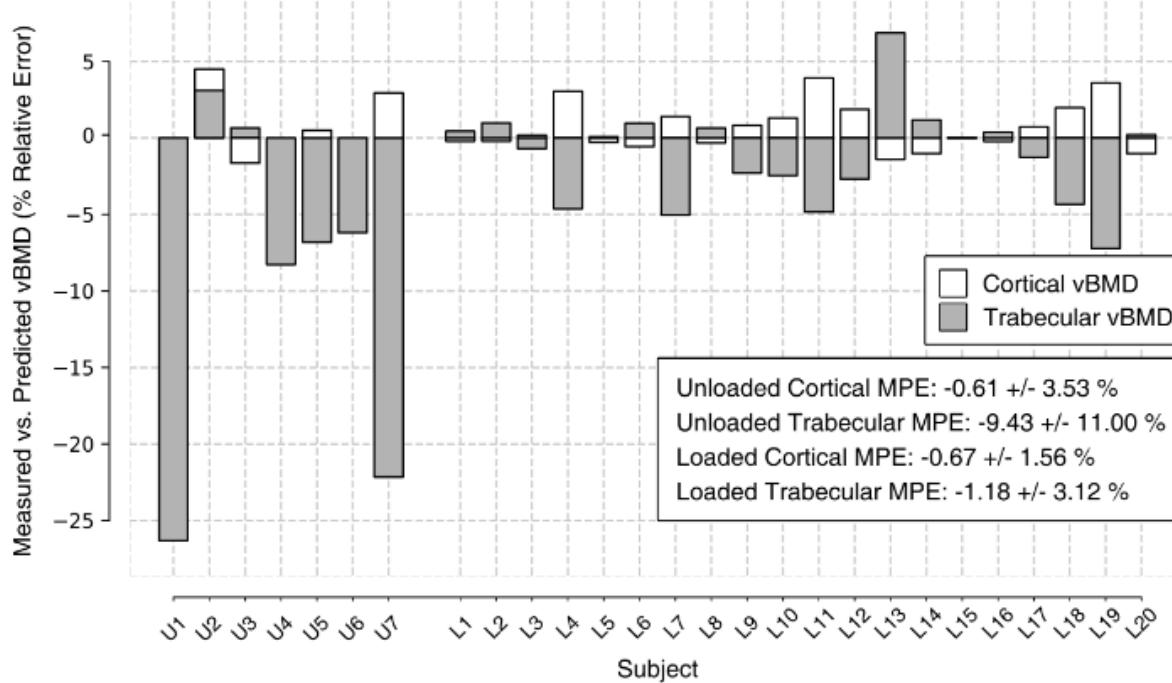
Orthoload public database.

[CMA-ES Appendix](#)

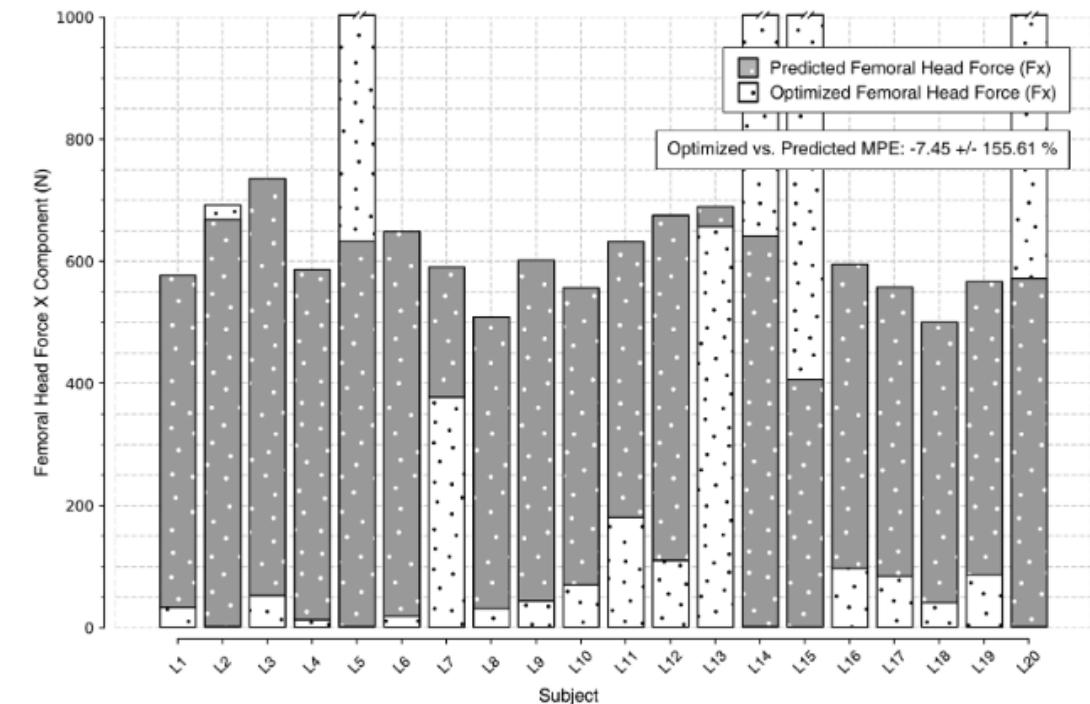
[4] Bergman, G. (2008). Orthoload. Charite Universitätsmedizin Berlin. <http://www.Orthoload.com>.



MODEL PREDICTS POST-STUDY vBMD, BUT FORCES ARE LOW



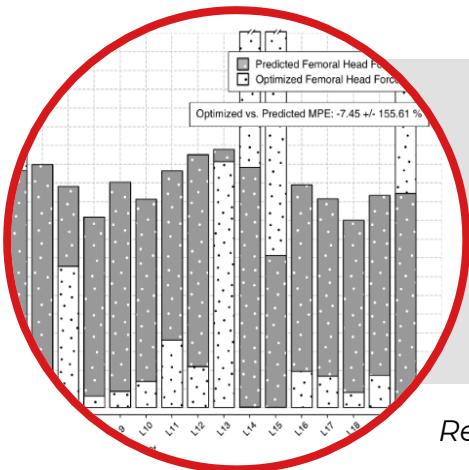
Measured vs. predicted post-study vBMD. U: Unloaded L: Loaded



Regression vs. model predicted vBMD maintenance forces.

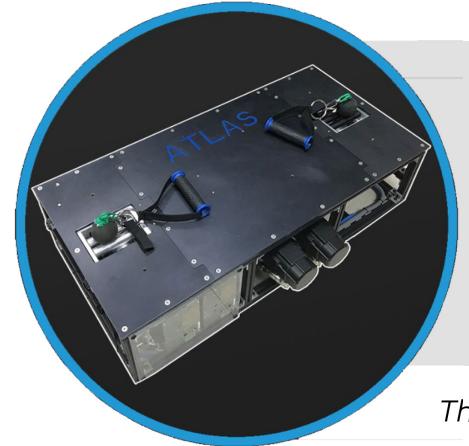


FUTURE WORK FOCUSES ON QUANTITATIVE FORCE PREDICTION



- 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.

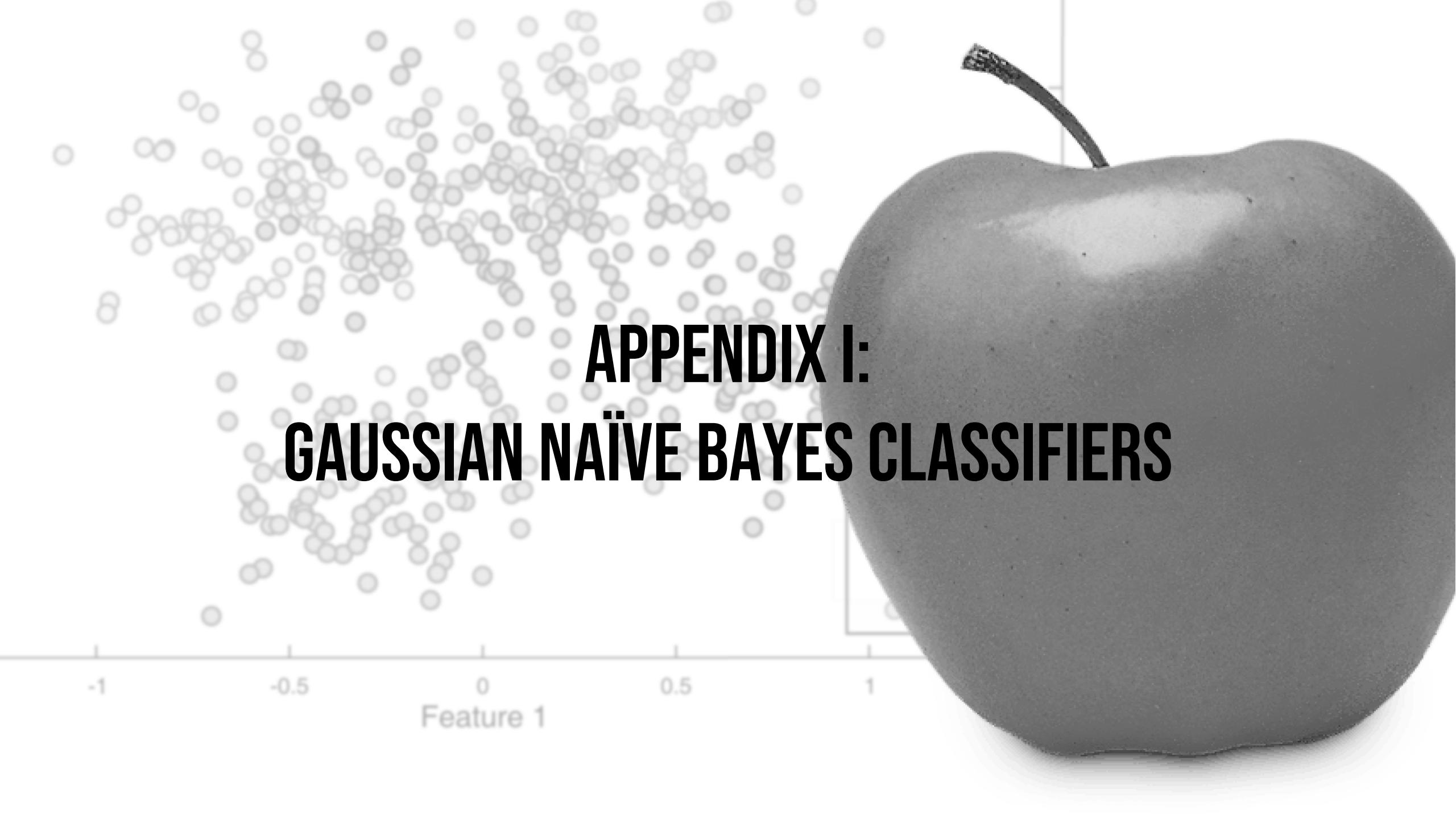
Regression vs. model predicted vBMD maintenance forces.



- 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).

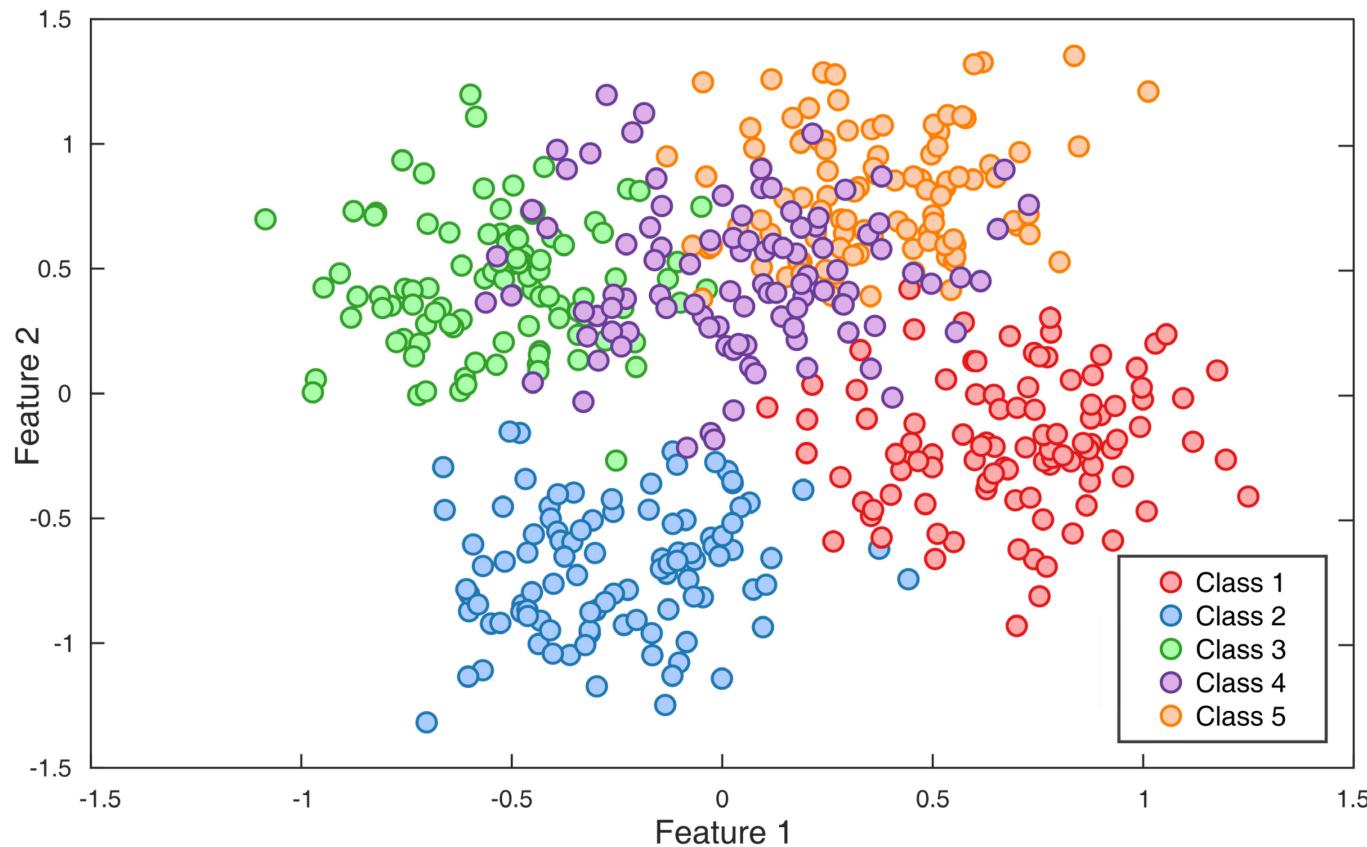




APPENDIX I:

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...

$$X^{new} = \langle X_1, \dots, X_n \rangle$$

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

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

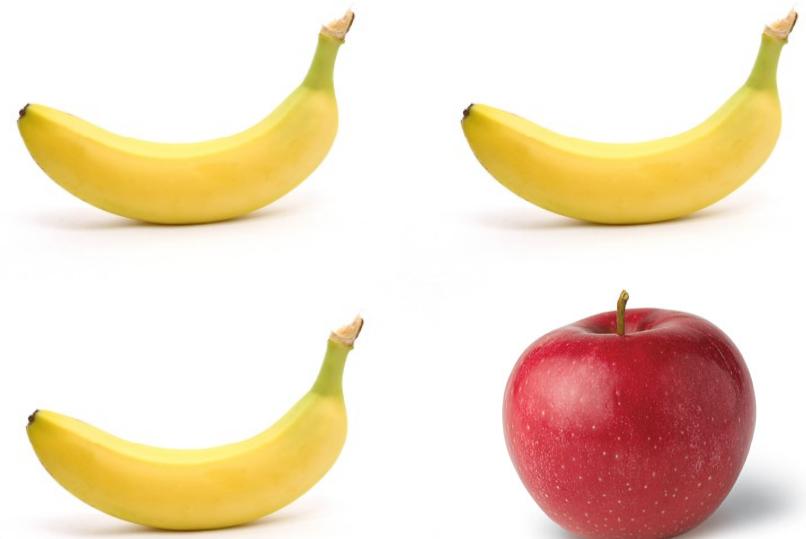
... based on other samples with the same features.

Naïve Bayes classifier using the maximum a posteriori decision rule.

EXAMPLE: CLASSIFYING FRUIT USING ONE FEATURE

$$P(Y = \text{apple} | X = \text{banana}) \propto P(X = \text{banana} | Y = \text{apple})P(Y = \text{apple}) \\ \propto 0 * 0.25 = 0$$

$$P(Y = \text{banana} | X = \text{banana}) \propto P(X = \text{banana} | Y = \text{banana})P(Y = \text{banana}) \\ \propto 1 * 0.75 = 0.75$$

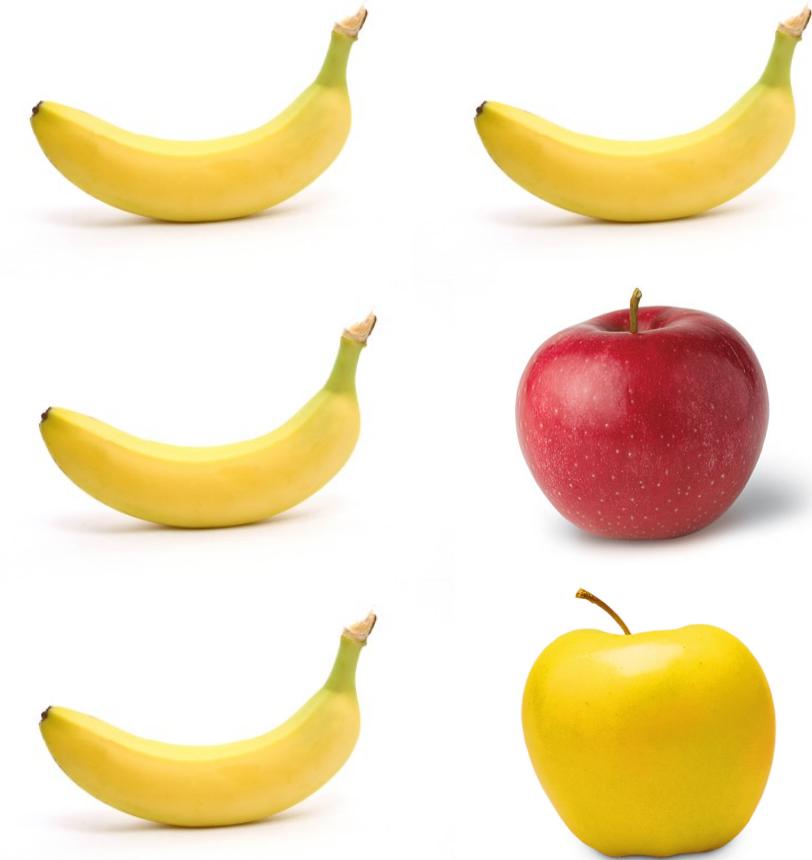


*The banana-apple universe, where
75% of all fruit are bananas.*

CLASSIFYING APPLES WITH INSUFFICIENT FEATURES

$$P(Y = \text{apple} | X = \text{banana}) \propto P(X = \text{banana} | Y = \text{apple})P(Y = \text{apple}) \\ \propto 0.2 * 0.33 = 0.07$$

$$P(Y = \text{banana} | X = \text{banana}) \propto P(X = \text{banana} | Y = \text{banana})P(Y = \text{banana}) \\ \propto 0.8 * 0.66 = 0.53$$



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

CLASSIFYING APPLES WITH MULTIPLE FEATURES

$P(Y = \text{apple} | X = \text{yellow}, \text{round})$

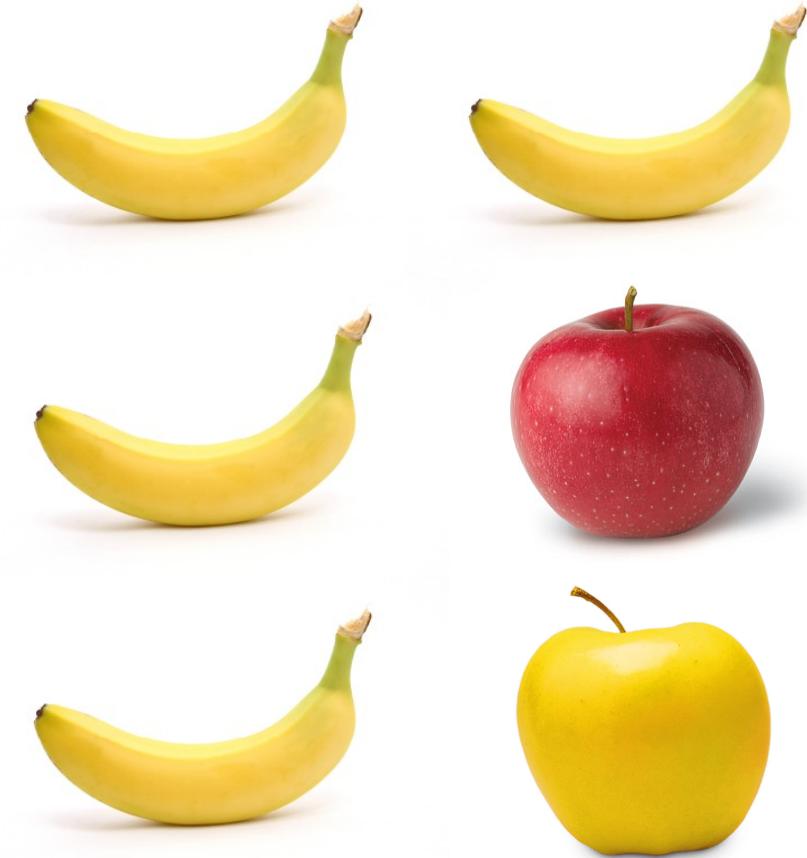
$$\propto P(Y = \text{apple}) * P(X = \text{yellow} | Y = \text{apple})P(X = \text{round} | Y = \text{apple})$$

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

$P(Y = \text{banana} | X = \text{yellow}, \text{round})$

$$\propto P(Y = \text{banana}) * P(X = \text{yellow} | Y = \text{banana})P(X = \text{round} | Y = \text{banana})$$

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



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

ESTIMATING CONDITIONAL PROBABILITIES OF CONTINUOUS VALUES

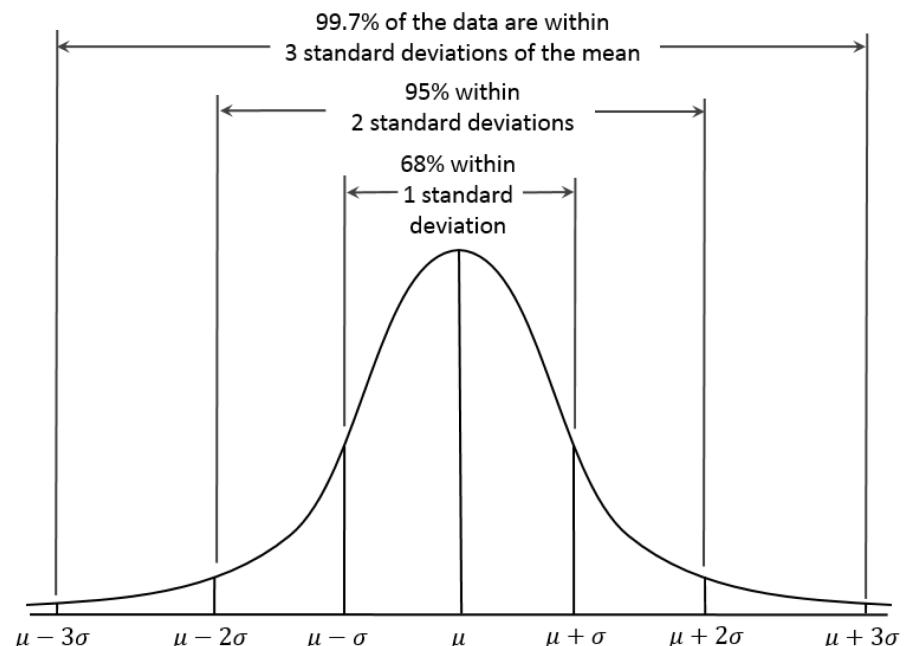
$$P(Y = y_j) \prod_{i=1}^n P(X_i|Y = y_j)$$

Calculated as $(n_{\text{class}} / n_{\text{tot}})$

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

Feature mean of class

Feature standard deviation of class

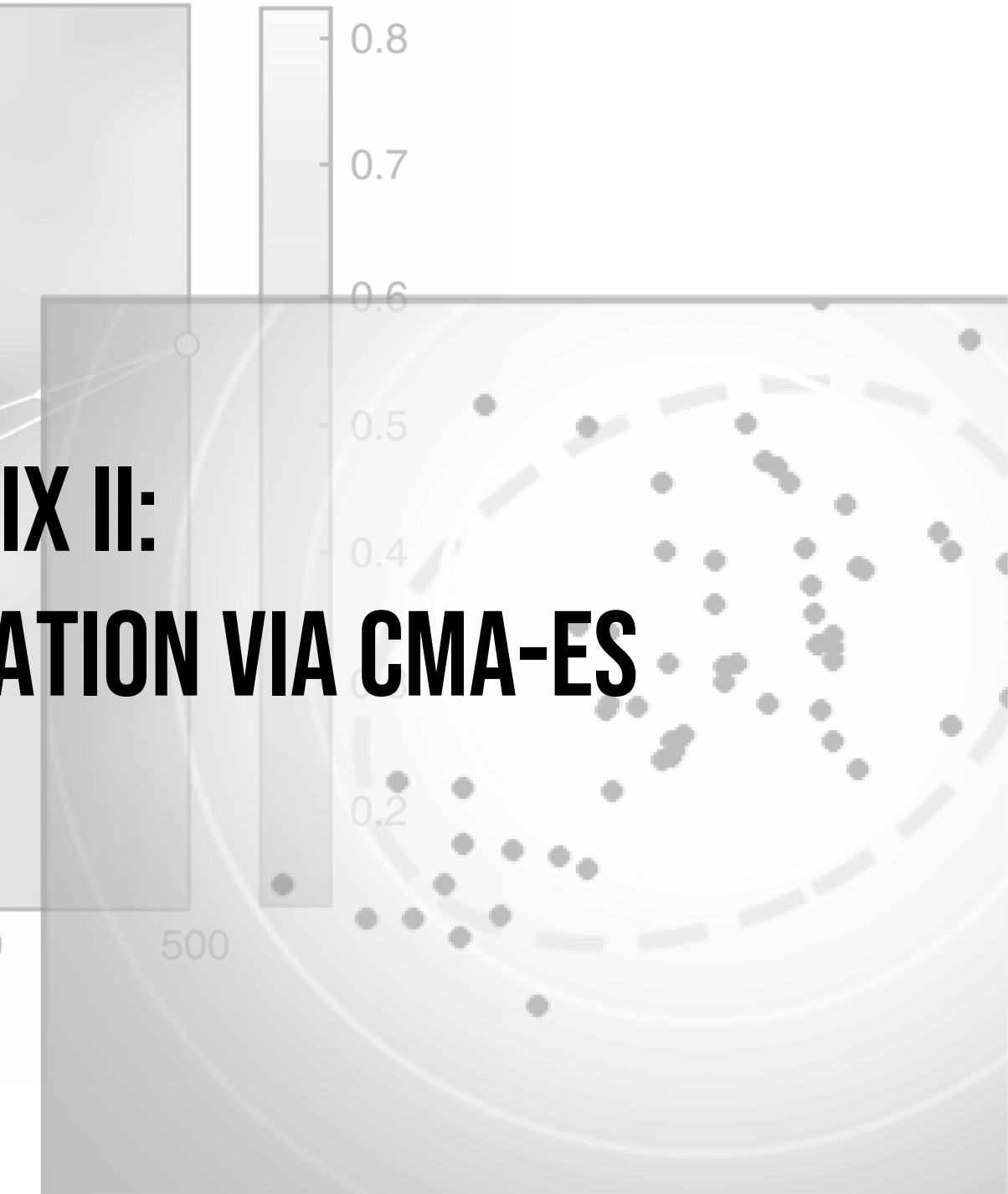


The probability density function of a Gaussian distribution [5].



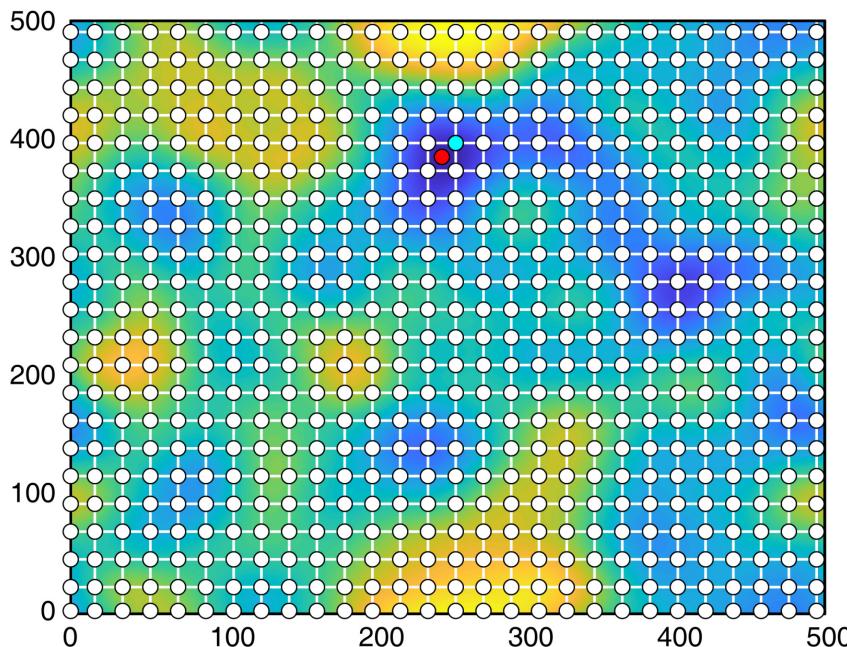
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APPENDIX II: STOCHASTIC OPTIMIZATION VIA CMA-ES



GOAL: FIND OPTIMAL PARAMETERS WHILE MINIMIZING EVALUATIONS

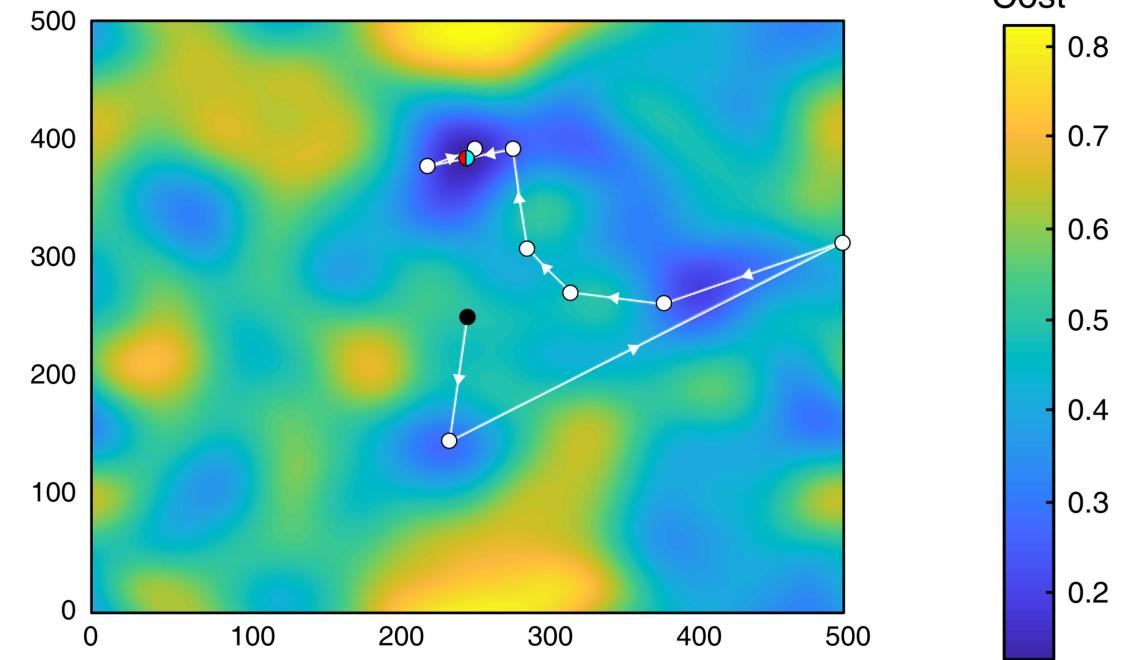
Parameter Sweep



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

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

Stochastic Optimization



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

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



COVARIANCE MATRIX ADAPTATION-EVOLUTION STRATEGY (CMA-ES)

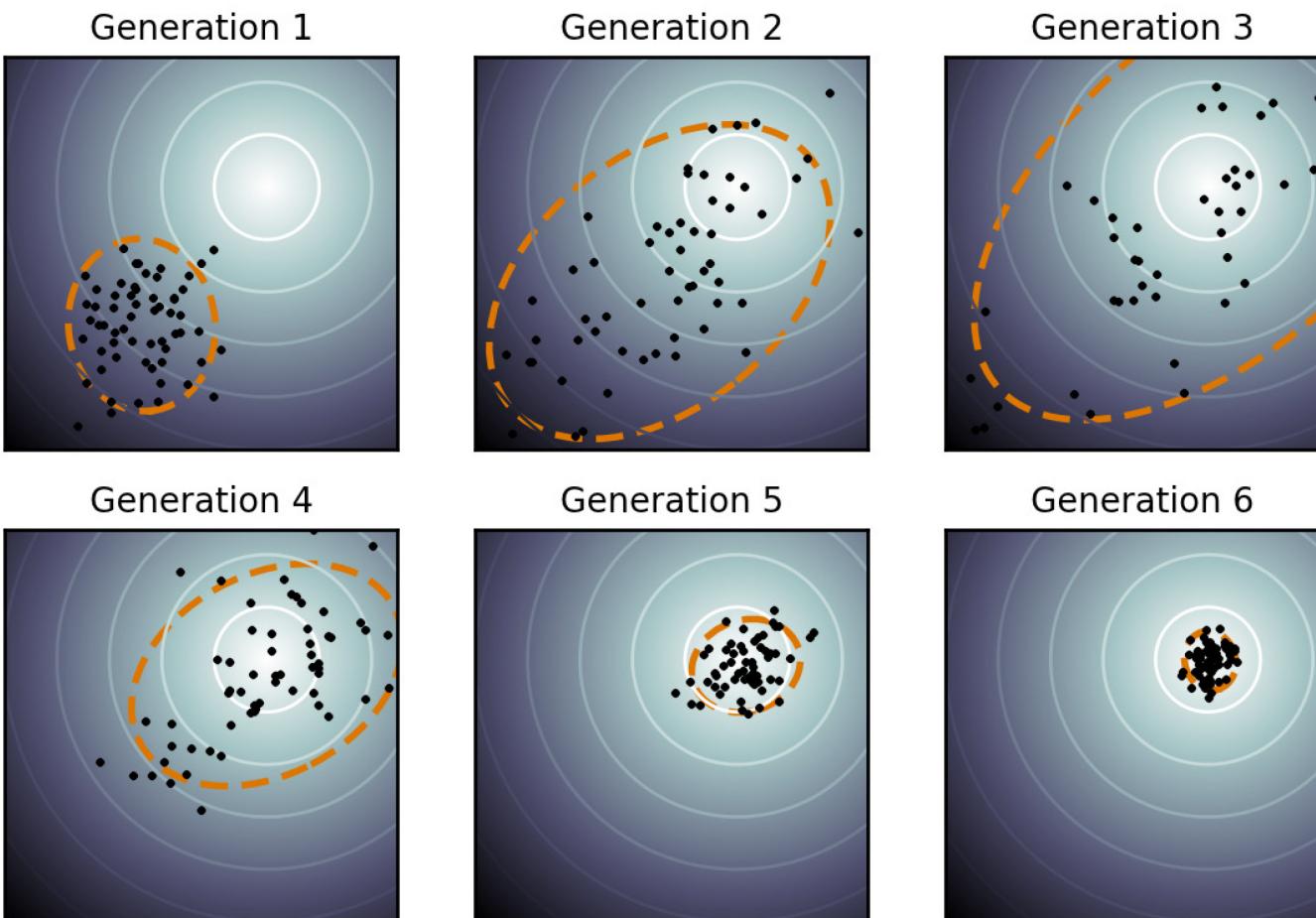


Illustration of the covariance matrix adaptation evolution strategy (CMA-ES) over 6 iterations. [6]

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