



The moonshot: use AI/ML to help keep astronauts healthy

Research and terrestrial support



Biomarker discovery, validation

Radiation, cardiovascular, CNS dysfunction biomarkers Successful countermeasure biomarkers Pairing with phenotypes



Health assessment

Pre-, mid-, post-flight Longitudinal observation -omic baselines Enable AI anomaly detection



Experimental models

Human analogues Model organisms Biological mechanisms Modelling



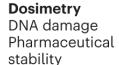
Mission control center

Medical consults (life support) Prioritized upload/ download data/models Crew health management Environmental control management

Real-time support and operations

Spaceflight hazards and stressors

Hostile confinement. distance, radiation, microgravity, regolith, temperature, atmosphere



Wristband

Vital signs Movement Glucose



Environmental Monitoring

retina, OCT

analysis

factor

Voice, behaviour

Stress, mood,

psychological

Ultrasound

diagnostics

Internal organ

AI-guided

Blood flow

imaging

Vibration, radiation, carbon dioxide, oxygen, relative humidity. acoustics, temperature, partial pressures



Countermeasures



AI/ML risk prediction Pattern recognition Predictive modelling Actionable response



Digital twin

Simulated human Model organism replicate Augmented deployment



Personalized medicine

Procedural-specific AI Human-machine pairing AI-assisted learning Augmented reality



Intervention determined



through AI/ML, crew, and CMO

Behaviour change Specific testing Early intervention



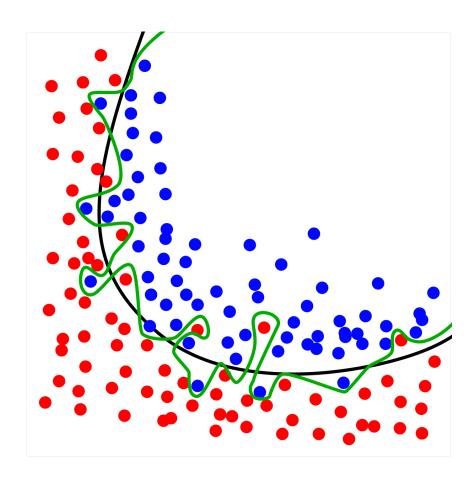


Stool analysis Microbiome



Space biology is under-understood in part for lack of data

Molecular biology is difficult to study for sparse data



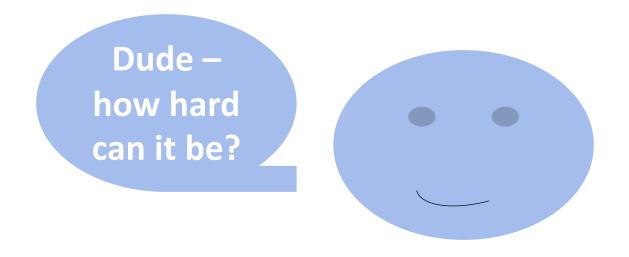
AI/ML is a promising approach to study sparse data

ML Model	Description
Support vector machine	SVM uses support vectors to arbitrarily partition the feature space.
Logistic regression	LR uses regularization to prevent overfitting.
K-nearest neighbors	KNN computes distances between data points.
Multi-layer perceptron	MLP uses gradient descent for optimization.
Decision tree & random forest	DT and RF can work well when coupled with gradient boosting.

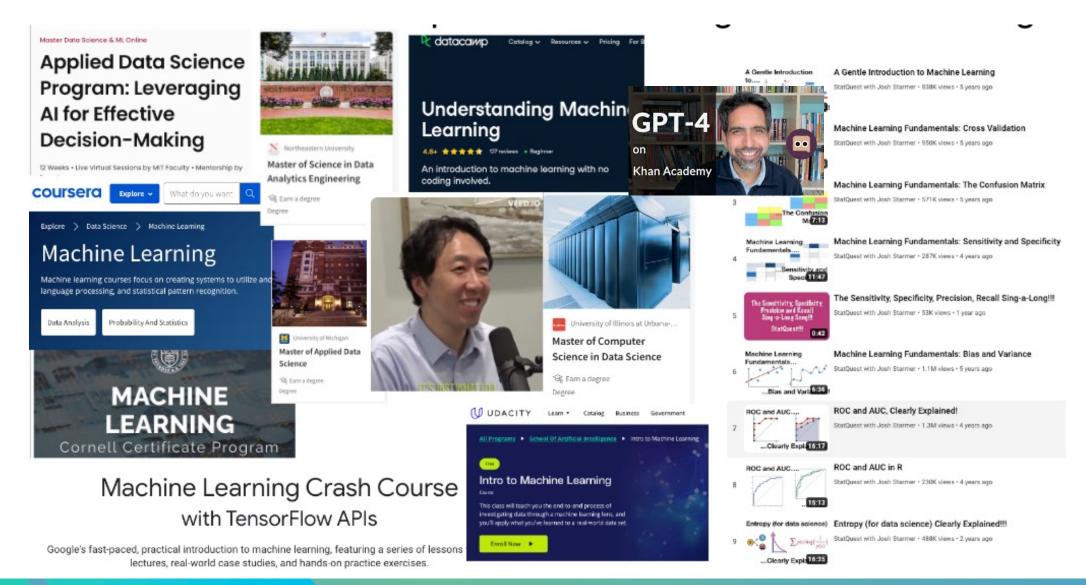
Calling all citizen scientists!



AI/ML, while ubiquitous, is poorly understood by many



There are LOTS of options to learn machine learning



There are NO options to learn AI/ML for space biology

https://github.com/nasa/Transform-to-Open-Science/





Choice 1: How to design the curriculum?

Options	Pros	cons
Design in a vacuum	simplecontrol deliverables	biasedlacks user perspective
Design by committee	fairly simpleless biased	lack of expertiseconflict resolution

Choice 2: How to develop the curriculum?

Options	Pros	cons
Build from scratch	control over productconsistent look/feel	time and effortwheel re-invention
Curate collection	less time/effortleverage what's good	inconsistent look/feelno ML-for-space-bio

Choice 3: How to deploy the curriculum?

Options	Pros	cons
Instructor- led	high touch/interactiondynamic	doesn't scalesmall reach
Self-paced	scalesglobal reach	limited interactiondistractions/motivation

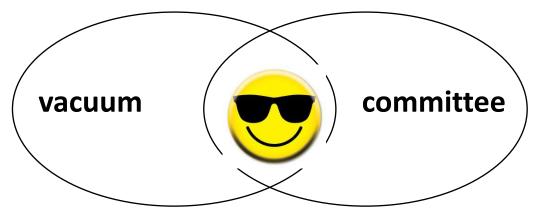
Choice 4: How to deploy the labs?

Options	Pros	cons
Student computer	zero costreproducible results	may exclude studentsinconsistent experience
Cloud IaaS	scales wellconsistent experience	costinternet requirement

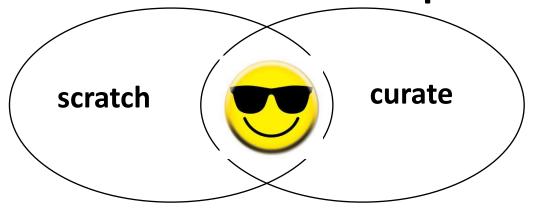


Our decision: meet in the middle

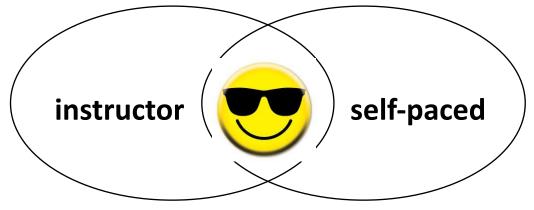
curriculum design



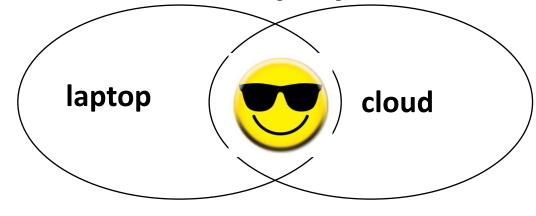
curriculum development



curriculum deployment



lab deployment



Design: start in vacuum, pivot with users

- I. intro to course
- A. intro to space biology
- B. intro to data engineering
- C. intro to AI/ML
- D. intro to lab environment
- II. building basic models
- A. using scikit-learn
- B. clustering
- C. classification
- D. regression
- III. working with data
- A. OSDR & FAIR
- B. processing tabular data
- C. processing image data
- D. visualizing data

- IV. interpreting results
- A. bioinformatic tools
- B. literature search
- C. ethical considerations
- D. reproducibility
- V. advanced topics
- A. transfer learning
- B. causal inference
- C. explainable AI
- D. biological interpretations
- VI. capstone projects
- A. use deep learning to find DNA damage in irradiated immune cells (microscopy)
- B. use causal inference machine learning ensemble to find genes correlated to lipid dysfunction (RNA-seq)

Development: build space bio, borrow AI/ML (CC)

coursera





Open Learning





StatQuest!!!

towards data science

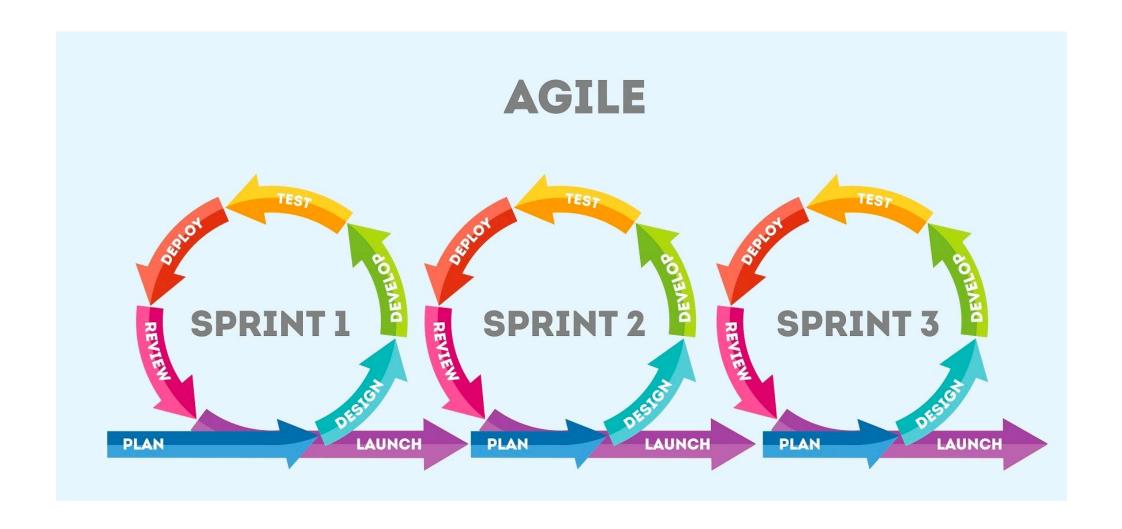
Curriculum and lab deployment: Python notebooks







We are borrowing from Agile to manage the project



Which data will we use?

RNA-seq benchmarking data



https://registry.opendata.aws/bps_rnaseq

Microscopy benchmarking data



https://registry.opendata.aws/bps_microscopy



Extra credit: use AI/ML to design, develop, deliver

- 1. Syllabus design and course structure
- 2. Course overview, module introductions, and summaries
- 3. Discussion forums with chatbots
- 4. Code walkthroughs and commenting
- 5. Integrate context in case studies
- 6. Resource recommendations
- 7. Quiz/assessment generation
- 8. Design and generate feedback surveys

Join our user community!

https://bit.ly/tops-aiml-users



Acknowledgements

Al for Life in Space

- Lauren Sanders
- Sylvain Costes



Compute

Science Managed Compute Environment

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- Andre Avelino Paniagua
- Ellen Salmon
- Daniel Duffy



Open Science for Life in Space Teams







NASA Center for Climate Simulation



Support

- NASA Space Biology Program
- NASA Science Mission Directorate
- NASA Human Research Program
- NASA Biological and Physical Sciences