Hi everyone! Thank you so much for taking the time to consider me for your open faculty position. I’m really excited about the potential opportunity to join you all. My name is Frankie and I’m currently an assistant professor in space systems at the University of Hawaii since January 2020. Before that, I got all my degrees at Cornell university. My bachelor’s is in mechanical engineering and my PhD is in aerospace engineering with a minor in computer science. My concentration was in dynamics, controls, and systems engineering. I really love to think about how robots move in space environments and how they think about movement, which translates into autonomous operations. If I were to breakdown the autonomy stack into perception, path planning, dynamics, and controls, my specific passions live in system identification of the dynamics model and active learning for path planning. I’m going to use this time to talk about the evolution of my research, which you’ll see a pattern in the types of physics and environments that govern the robot’s dynamics. OK, now I’m going to share my prepared slides as a visual aid.

As you can see by my slide, there’s a lot of hardware. I’m of the personal philosophy of doing research throughout the entire idea lifecycle, from cradle to grave. Of course I do fundamental research, like deriving mathematical proofs or applying first principles in a novel way, but I also write my own algorithms, build my own robots, and deploy them in relevant environments.
During my undergraduate and graduate degrees, I’ve worked on many different space things that aimed to operate in an orbital environment.
On the top left is a timelapse of Cornell’s Violet satellite being integrated and this is a picture of her final form. I was working on Violet, the most agile declassified satellite at the time, during my undergrad which was 2014-2018. Agile meaning it could slew about an axis really really quickly. There was really cool math behind the dynamics of this satellite because this 50 kg nanosatellite had 8 control moment gyroscopes onboard.
During my Master’s, I worked as a side project with Dr. Zac Manchester who launched a small satellite filled with even tinier small satellites, the size of a cracker. You can see us integrating KickSat-2 on the top right. His idea is demonstrated in this Youtube video on the top middle. The idea was to distribute sensing to a multitude of simpler spacecraft that could simultaneously be in different places at once at a very cheap mission price tag. What I loved about this project was the paradigm shift in how we think about space systems away from a centralized sensing platform but instead into a distributed sensing network.
On the bottom, for my PhD, I developed a docking technology using magnets and superconductors that had super interesting dynamics, super nonlinear, coupled, due to a massive combinatorial sum of pairwise electromagnetic interactions. I was responsible for raising the maturity of this technology from TRL 3 to 5 or 6, depending on how relevant you think a microgravity environment is for an orbital environment. I received a NASA Space Technology Research Fellowship which allowed me to spend a year on and off at NASA JPL to build the experiment tested that would demonstrate this technology, which you can see me doing here in this video. The culmination of my work was when we flew in microgravity and demonstrated successful docking in zero gravity! These flights are loving referred to as the vomit comet I can tell you I got the authentic vomit comet experience the first time I flew. Here’s a picture of me and Ty in the hangar doing some final checkouts. Here’s my and Bhavi observing the experiment during our microgravity flight. This video is a money shot of our docking technology actually working where the magnetic sphere

falls into and stays in the magnetic potential well of the superconductors.

After my education, I went to University of Hawaii because UH had a blossoming space flight laboratory that I wanted to steer the direction of, I wanted to collaborate with amazing planetary scientists, and I want to leverage Hawaii's planetary surface analogues. During this time, I pivoted my research to ground vehicles as the robot and planetary surfaces as the environment, all still with the goal of improving our capabilities to explore and learn about our universe.
During this period, I integrated planetary science instrumentation into my research, such spectrometers for the purpose of detecting water ice and bevameters for the purpose measuring geotechnical properties. These kinds of measurements are really important for the upcoming Artemis missions where we need to find water ice and identify locations to establish lunar habitats. This video here is a timelapse shows my team on the Big Island of Hawaii taking manual measurements of the surface at many different locations. Here's a video of Krystal, a graduate student I worked with, talking about how we select a site, calibrate the spectrometer, and then take spectra. Here's a video of Paolo and Christian, a couple of undergrads I worked with, talking about the same process but for sampling the load resistance of the ground. The reason why we manually measured spectra and the structural bearing capacity of the ground is because we want to eventually demonstrate this exploration algorithm called active learning, which is an autonomous alternative to scientists proposing waypoints for a robot to go sample. Imagine that you're a rover on the surface of the moon with no prior information and you only have a finite amount of power and time before you get too cold. You'd want fulfill your mission of collecting as much information dense measurements of your environment as possible. This video on the bottom left shows an active learning algorithm in action. On the top left subplot is a colored topography of the environment you're exploring, in this case we have a 3 km edge length swath of the lunar south pole in shoemaker crater. The black star is the rover and the black tail is its trajectory. The top right is the distribution of the variable of interest across the environment, in this case the amount of hydroxol a cousin of water. The colored surface is a ground truth as measured by LAMP, an instrument on the lunar reconnaissance orbiter, and the grey surface is the rover's internal learned model of the distribution of water ice where the surrogate model is a gaussian process with the radial basis kernel. The bottom left subplot is the average variance of the gaussian process model as we gather more samples, and the bottom right subplot is the rms error of the learned model with respect to number of samples. The active learning algorithm is using historical measurements to suggest locations where the measurement would be very surprising, or mathematically hold high information entropy. The rover iteratively measures and suggests places to measure to learn the real distribution of the variable of interest. We see this result in that the learned model grey surface collapses onto the colored real surface and the rms error nearly monotonically decreases as we accumulate samples. In real applications, we can't characterize rms error to the ground truth which is why we keep track of model variance, which correlates well with the RMS error if your kernel is well chosen to represent the underlying variable distribution.
This video right here is demonstrating a path planning algorithm on a digital twin rover and lunar surface environment, coded in ROS and Gazebo. My lab leverages and develops on these open source environments and I've made it a point to publish my code and data as openly as possible.

This video on the upper right is a different simulation leveraging the same ROS and Gazebo framework but instead emulating terramechanics, the physics behind terrain interactions. A big focus of my research group is understanding terramechanics, finding the right target model to represent and predict a rover's dynamics subject to terramechanical interactions, and finding the right pairing system identification method to converge on the target model. The regression problem we're trying to solve is finding a mapping from mobility sensor data, like visual odometry, IMU roll pitch yaw, angular velocity, and acceleration, then motor torques and encoder steps, to a terramechanical model structure, model parameters, and a vehicle state prediction. This plot on the bottom right is laying out the space of target model solutions along the dimensions of computation intensity and prediction error. There are tradeoffs to each of these models, thus the emergence of this Pareto front. Of the models my lab is working on, we cover physics-based differential equations, machine learning models like SINDy, and soil contact models. We want to improve these models to get to this desirable zone of high accuracy and low computation. The video you see up on the right is a simulation driven by a soil contact model, which is like a surface mesh network where deformation of nodes are dictated by penetrating volumes and node stiffnesses at the mm level. You can see that these node interactions are qualitatively representative of some of our experiments of traverses on soft soil with these tread imprints. We're working on quantitatively tuning the simulation to real data. The physics-based models operate at the length scale of the wheels and rover state, tens of centimeters. Some of the input model parameters are physically measurable, like the outputs from the geotechnical bevameter tests.

OK, I know I spent a lot of time talking about my current research but here's my justification, a lot of that research is going to be short term future research. If I were to join your ranks at UW, I would like to continue and carry my current research deeper and convince future spaceflight missions to adopt more autonomy. A big dream of mine is to have one of my robots or algorithms in a spaceflight mission. A way to do that is to get my foot in the door by offering active learning algorithms as a suggestion system for mission operators so that a human still gets to intervene in the decision making process. More broadly, I'd like to conduct shadow experiments to ideally show that these autonomous operations help us achieve mission objectives with a higher likelihood of success and more quickly so we have more time for extended operations. Ways that I'd like to extend my current research is to incorporate multiple objectives into my active learning algorithms, like balancing information gain and action cost, and to incorporate multiple agents into my active learning algorithms. A huge gap I see in current active learning research is that not many folks are looking into agents that are exploring spaces under a constrained trajectory, most of the focus is in remote sensing in which sequential sampling locations are relatively far away from each other so I want to form some algorithmic guarantees about constrained trajectroy exploration. I'd like to keep applying active learning to planetary surface applications, like installing a ground penetrating radar underneath a rover to map out the stratigraphy of the lunar subsurface, which will tell us how far down the bedrock is, which then tells us where we should build our persistent structures. Looking further into the future, we'll eventually be able to explore ocean worlds with mobile robots. This is a visual of a concept of operations for a bobbing lander and lake glider for a titan mission, in which the active learning strategy is trying to map a molecular tree that will give us clues about the composition of life and map currents to tell us

about fluid dynamics in a lake environment. This picture on the bottom right is preliminary work with a PhD student where we're trying to reconstruct the flow field of a double gyre ocean system just from measurements we collect along this blue trajectory in which we start from this black square, need to sample along these red dots, end at this black triangle, and are subject to the dynamics of this flow field along the way.
This final research thrust is the intersection of active learning for system identification or sensing for the sake of dynamics. Instead of learning the distribution of an physical environment, let's go a bit more abstract and learn the flow field of a phase portrait. How do we craft experiments in state and action space to learn the dynamics of an unknown system driven by differential equations? Here's a video of sequential proposed experiments where the red x's are sample locations in theta and omega space of an actuated dampled pendulum. These blue arrows at each grid point is the predicted state derivative at that state and we see that classic pendulum attractor shine through after a dozen or so measurements.

Since joining UH, I've taught 6 credit hours every year, which is three times what my contract dictated. I currently advise 14 students in my lab, graduated 3 Master's students and dozens of undergraduates. The two courses I have led the development and delivery of is spacecraft mission design and a graduate level machine learning seminar in dynamics systems. I've team taught space science and capstone courses. I've also helped administer an educator's course through the outreach college to teach high school and middle school educators how to integrate aerospace engineering into their classrooms. I advise and give grades to an undergraduate project team of about 30 – 40 students every year. These plots on the bottom left show some statistics about my quality of teaching, where I've received really high scores to the point where I've been nominated for excellence in teaching awards two years in a row now but am not yet eligible to receive the award because I haven't been teaching for three years yet. I may be eligible this year. This bottom plot shows the number of undergraduates, graduate students, and teachers I've reached through my courses. This picture is the cover page of a publicly accessible digital textbook that I wrote that guides people with little to no prior aerospace engineering education on how to build a satellite. These pictures are some sample pictures from the textbook software and hardware labs which leverage hands-on learning. This bottom right picture is a picture of my rover kids from the spring semester this year.
I'm super excited to contribute to your curriculum, in either collaborating with Justin on some aerospace engineering pedagogy from my experiences with my course, or developing a new course that I didn't find in your course catalog, a machine learning in dynamic systems graduate level course. These other courses I would feel comfortable teaching as I've taken them before, but may need to rethink for the quarter system. My general teaching philosophy is to flip the classroom and maximize engagement within the classroom as much as possible, which means recording lectures and requiring textbook reading prior to in-class interactions, then crafting activities that maximize peer to peer learning and instructor to peer learning. I also want activities to be as applicable to real-world skills as possible so class deliverables emulate realworld deliverables.

I care a lot of diversity equity and inclusion, to the point where I've likely contributed more time to DEI than most of my peers and have gotten recognition in this space, in the form of DEI leadership positions and DEI grants. Some of the ways

I’ve contributed to diversity equity and inclusion is through this NSF equity grant through the ADVANCE program where we collected institutional data, which is what I’m showing here in these plots, that demonstrated the under-representation of ethnic minorities across all academic career stages at University of Hawaii. The plot on the bottom right is from a talk I gave to the AI Institute in Dynamic Systems about how data access is a DEI issue, where wealthy institutions can build these awesome testbeds and generate quality data but less-well endowed universities do not have that privilege and access. That’s a reason why I’m so pro-open-source. In the interest of time, my future work at UW will carry some of my previous initiatives over, such as participating with UW’s ADVANCE program. I’m actually speaking to your space grant in January about my work with equity that may inspire actions in institutional data assessment. Through my previous observations, I’ve noticed that socioeconomic status may be a common link to inequitable distribution of resources but it’s so hard to measure then incorporate into analyses to promote equity, so I’d like to gather that data. At my core, I want to advocate mobility and opportunities regardless of identity, which I think I can promote through data accessibility and mentorship at an individual and institutional level. Every institution is different so I don’t want to come into your institution telling you what you should do. I come from a very data-driven perspective with respect to DEI so there’s going to be a learning period to see what actual obstacles are unique to UW but I think my track record does show I do act once I’m more embedded in the community. This is not a cop-out answer but I’m hoping to be as respectful as possible.