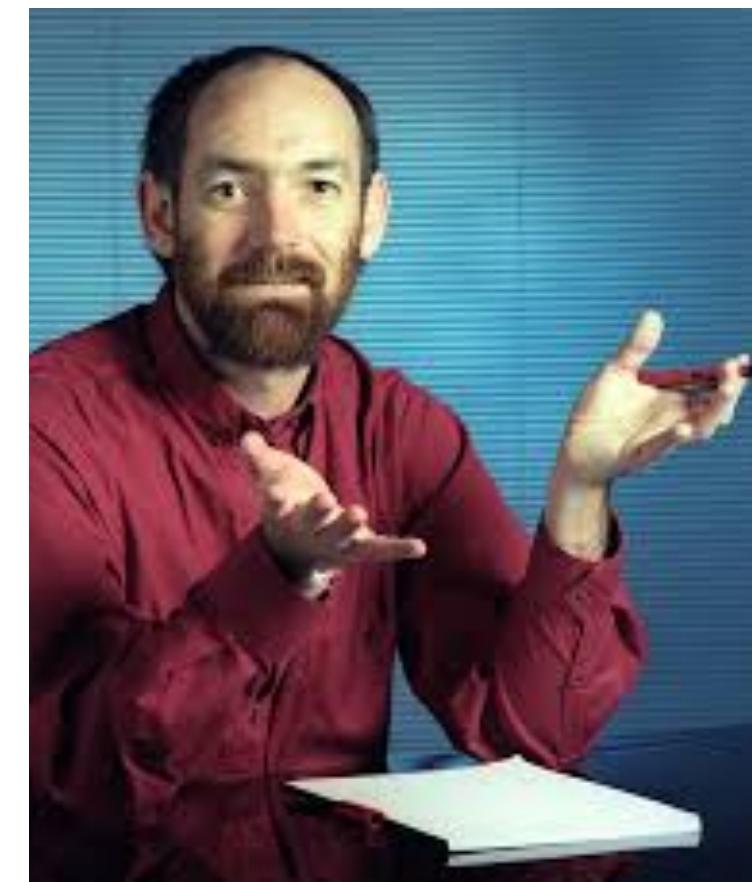


How to train your Assistant Professor

Sylvia Herbert, Assistant Professor



Number of weeks I've been at UCSD: 176

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Number of separate email threads I've had with Bob:

The screenshot shows a Gmail search interface. The search bar contains the query "in:sent rbitmead@ucsd.edu OR rbitmead@eng.ucsd.". Below the search bar are several filter buttons: "Mail" (selected), "Conversations", "Spaces", "From", "Any time", "Has attachment", "To", and "Advanced search". On the left, there are filters for "All" (unchecked), "C", and "More". On the right, it shows "151–176 of 176" with a red box around the number 176. The main area displays one email thread from Robert Bitmead, with his name and email address (rbitmead@ucsd.edu) visible.

Number of weeks I've been at UCSD: 176

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"I did not know that never responding and being useless was an option. My own mentor, whoever that was, never told me."



Robert Bitmead <rbitmead@eng.ucsd.edu>
to Sylvia ▾

Wed, Oct 7, 2020, 11:57 AM ⭐ ← ⋮

Hi Sylvia,

Nice to hear from you and glad that you are about to start in earnest. Hey, you already have a UCSD email address. There is no more.

I would be happy to chat but have a plenary talk in Sapporo tomorrow night followed by an IEEE Control Systems Society Executive Committee meeting all weekend ... nominally in Mysore India. But I have time on Friday (ExCom Happy Hour is at noon!) either in the morning or afternoon. I have one meeting being scheduled with the Med School people for the afternoon. How about some time in the morning.

I shall gather all the juiciest departmental gossip in preparation.

As for attending the seminars, please email Lusia Veksler (lveksler@eng.ucsd.edu) who is our very efficient admin person looking (inter alia) after the Controls Group characters. And thank you for pointing me to the seminar page. I learnt something.

Sherbet is just one of the many Australian slang words for beer. It was also a boppy 1970s aussie band who are perhaps best forgotten but were at least fizzy like sherbet.

Please let me know a suitable time to talk on Friday. I can set up the Zoom.

Benvenuto e ciao,
Bob.

P.S. No, I do not speak Italian. Although I did purchase a cheese grater in Milan once using my Frenchy mock Italian and gesticulating wildly.

Robert Bitmead
IEEE Control Systems Society Immediate Past President 2020
Editor-in-Chief IFAC Journal of Systems & Control
University of California, San Diego
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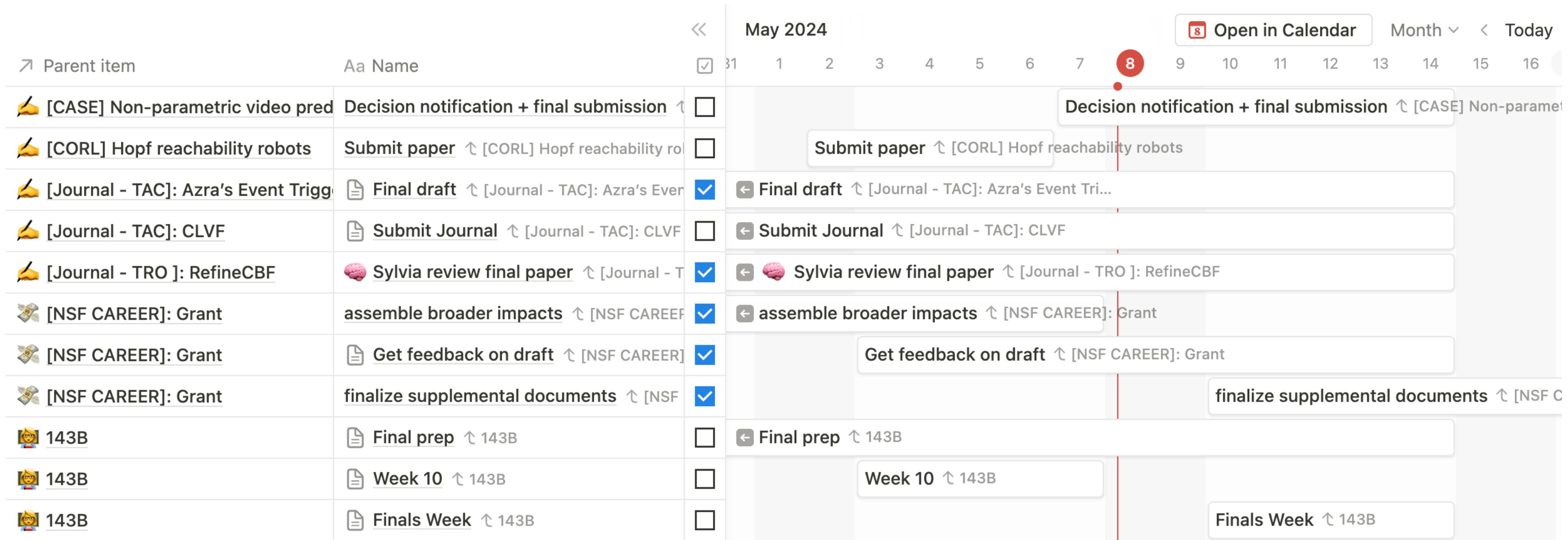
Strategic Plan

Bob's goal suggestions:

1. Build up research slowly and well (don't rush to have a ton of students and a ton of papers)
 2. Understand the grant process
 3. Explore San Diego
 4. Build up my network of external important people who can write tenure letters for me
 5. Practice saying no to most service/student requests

Default view All Category Timeline Focus Tasks This week

Strategic Plan - Goals/Areas



Strategic Plan

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Strategic Plan - Goals/Areas

Aa Name		May 2024	Open in Calendar	Month	Today
↗ Parent item		31 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16			
👉 [CASE] Non-parametric video pred	Decision notification + final submission	<input type="checkbox"/>	Decision notification + final submission	↑ [CASE] Non-paramet	
👉 [CORL] Hopf reachability robots	Submit paper	<input type="checkbox"/>	Submit paper	↑ [CORL] Hopf reachability robots	
👉 [Journal - TAC]: Azra's Event Trigg	📄 Final draft	<input checked="" type="checkbox"/>	◀ Final draft	↑ [Journal - TAC]: Azra's Event Tri...	
👉 [Journal - TAC]: CLVF	📄 Submit Journal	<input type="checkbox"/>	◀ Submit Journal	↑ [Journal - TAC]: CLVF	
👉 [Journal - TRO]: RefineCBF	🧠 Sylvia review final paper	<input checked="" type="checkbox"/>	◀ 🧠 Sylvia review final paper	↑ [Journal - TRO]: RefineCBF	
💰 [NSF CAREER]: Grant	assemble broader impacts	<input checked="" type="checkbox"/>	◀ assemble broader impacts	↑ [NSF CAREER]: Grant	
💰 [NSF CAREER]: Grant	📄 Get feedback on draft	<input checked="" type="checkbox"/>	Get feedback on draft	↑ [NSF CAREER]: Grant	
💰 [NSF CAREER]: Grant	finalize supplemental documents	<input checked="" type="checkbox"/>		finalize supplemental documents	↑ [NSF C
👩 143B	📄 Final prep	<input type="checkbox"/>	◀ Final prep	↑ 143B	
👩 143B	📄 Week 10	<input type="checkbox"/>	Week 10	↑ 143B	
👩 143B	📄 Finals Week	<input type="checkbox"/>		Finals Week	↑ 143B

Here is my off-the-cuff discussion of your pitch.

My suggestion, for what it is worth (since I gave up on applying to NSF years ago), is that you might want to make this less technical. The reasons for this are that (a) you need to be an expert to understand what it is about, notably scalability and verification; and (b) program managers are always looking for material they can take up the chain to their bosses to show what they are funding. So (IMHO) having the content more fit-for-educated-public consumption would help. You are using subtle technical terms like "known information" and "learned information" which makes the reader's job hard to work out what is meant and then what the word "guarantee" might possibly mean. Is a "theoretical safety guarantee" any guarantee at all, for example?

Maybe if you were to write the problem up in terms of evolving safety certification for dynamic systems. Explain the safety problem in terms of ensuring the state of the system never reaches an unsafe operating point and that this needs to be done using available information. This available information starts with computer based models of the (controlled) central dynamic process and of its (uncontrolled) environment - maybe together with some idea of their accuracy limitations - but, with operation, needs to be augmented by observed data, which might or might not conflict with the original models. Be careful of the word "general" as in "general dynamic systems" and "general nonlinear systems." It could mean different things to different people.

You could start by saying that there are \textit{reachability} methods which evaluate the set of all possible future states which might be accessed from a given current state. \textit{State} here connotes the position, velocity, configuration, etc of the system which constrains future evolution with time. If the reachability set avoids an unsafe region, then safety is achieved. These methods are based on Hamilton-Jacobi methods on which the PI has published recently. If safety cannot be achieved inherently, then it is possible to control the system using CBFs to prevent entering unsafe areas. Finding CBFs currently is limited to systems of certain structured but the research plan includes using the more generally applicable HJ methods to generate CBFs. [The aim should be to get the problem concept across. My version might be gobbledegook but the idea is to describe the problem importance rather than technique.]

[Different topic now] Systems operating in the real world present significant additional challenges for safety. Not only should the modeled system avoid unsafe states in the modeled environment, but the real system should do this in the real environment, each of which might be at variance from the models. Data taken in real time is the only way to amend the safety certification to accommodate new information. We envisage [I am making this up] two central ways that this might be done. Firstly, if the initial theoretical models are equipped with conservative bounds on their deviation from reality, then the models might be refined to tighten these bounds and thereby admit greater authority while preserving safety. Alternatively, the models themselves, rather than their bounds, might be adapted based on measured data so that the safety sets become closer to reality.

There is a host of underlying research problems associated with achieving this ...

You can guess how much time I have put into cogitating about this. But my main point is to think about how to equip the program manager with material to sell to their boss, who probably thinks Hamilton Jacobi is Derek Jacobi's younger brother and that Lyapunov was a famous dessert chef.

Anyway, those are my ideas. I hope they help.

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2.1 System Verification

Consider a state trajectory of the continuous-time time-invariant controlled system with disturbance, satisfying

$$\dot{x}(s) = f(x(s), u(s), d(s)), s \in [t, t'], \text{ and } x(t) = x,$$

where t and x are the initial time and state, respectively. $u \in U \subset \mathbb{R}^m$ is the control input, where U is considered bounded (in the HJ reachability case) or potentially unbounded (in the CBF case). Bounded uncertainties or disturbances can be represented by $d \in D \subset \mathbb{R}^w$, where D is a compact and convex set. The function and $f : \mathbb{R}^n \times U \times D \rightarrow \mathbb{R}^n$ is assumed to be Lipschitz continuous in the state.

Based on current information about the system, environment, and uncertainties in the dynamics or disturbances, safety verification seeks to keep the system outside of states that may lead to failure.

To define the notion of failure for a given environment, a reward function (also called a target function) $l : \mathbb{R}^n \rightarrow \mathbb{R}$ is constructed over the state space, with negative reward inside of obstacles (and/or other failure sets) and positive reward outside. Therefore, the zero-superlevel set of the function defines the set \mathcal{L} that the system must remain in, i.e. $\mathcal{L} = \{x : l(x) \geq 0\}$. An example of this set \mathcal{L} and the corresponding reward function $l(x)$ can be seen in Fig. 3a and Fig. 3b. The objective of the safety control is to guarantee that the trajectory will remain in \mathcal{L} for $s \in [t, 0]$ under the worst case disturbance. This involves computing the safe set, or viability kernel $\mathcal{S}(t)$, which is the set of all the initial states at time t from which there exists an admissible control signal that keeps the system safe under the worst-case disturbance. The corresponding robust safety controller is also computed to ensure this guarantee within the safe set. More formally we want to compute:

- The viability kernel $\mathcal{S}(t)$ [1] for \mathcal{L} : Verify $\mathcal{S}(t) := \{x \in \mathcal{L} : \forall \xi_d \in \Xi_{[t,0]}, \exists u(\cdot) \in U_{[t,0]} \text{ s.t. } \forall s \in [t, 0], x(s) \in \mathcal{L} \text{ where } x(s) \text{ solves (1) for } (x, t, u, \xi_d)\}$ for $t < 0$.
- A robust safe control $u(\cdot)$ for \mathcal{L} : For each $x \in \mathcal{S}(t)$, verify a control signal $u(\cdot) \in U_{[t,0]}$ that renders the trajectory safe for $s \in [t, 0]$, under the worst-case disturbance.

Two popular techniques for safety verification are Hamilton-Jacobi (HJ) reachability, and control barrier functions (CBFs). While there are many similarities between the two approaches, the fields have been largely disjoint. In the following sections we will briefly introduce the theory and tools for both approaches.

2.2 Hamilton-Jacobi Reachability Analysis

Given a model of an autonomous system (e.g. a UAV, a glucose monitor, an HVAC system) and initial knowledge of what would be unsafe for that system (e.g. hitting obstacles, allowing glucose to drop to dangerous levels, letting a house get too warm or too cold). HJ reachability analysis computes the set of initial conditions from which your system will inevitably enter those unsafe conditions [1-3] (e.g. when a car is driving at high speeds and headed straight for an obstacle, and no matter how hard it brakes or turns it is going too fast to prevent a crash). The complement of this set is therefore the safe set.

First, we define a cost function as

$$J(x, t, u(\cdot), d(\cdot)) := \min_{s \in [t, 0]} l(x(s)), \quad (2)$$

You are using the word "safe" colloquially + as a specialist word - reads too woolly.

Why?

Draft: October 12, 2021

Using l is like reward & we maximize

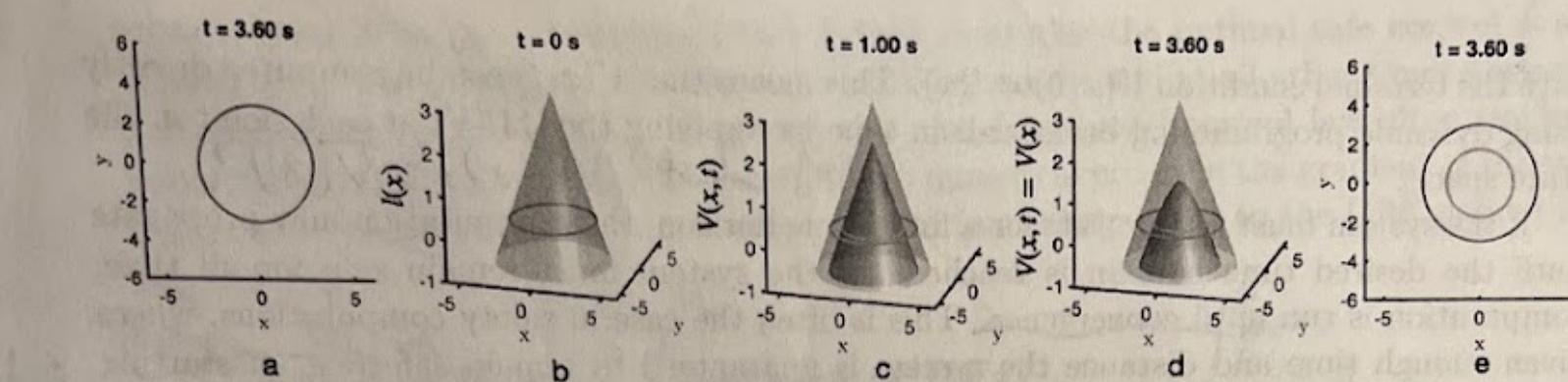


Figure 3: Process of constructing the safe set for HJ reachability. (a) Define the region \mathcal{L} that the system should remain within (in this case, inside the black circle). (b) Define $l(x)$ with negative reward outside the desire region and positive inside. (c) Use (4) to propagate the value function backwards in time using dynamic programming. (d) If the analysis converges (which happens in this case at a time horizon of 3.6s), then the value function holds for an infinite time horizon, thus $V(x, 3.6) = V(x)$. Positive regions of $V(x)$ correspond to positive regions of $l(x)$. (e) The super-zero-level set of $V(x)$ gives the guaranteed safe set (inside the green set). This is a viability kernel that guarantees the system will remain inside the safe set for all time despite worst-case disturbances.

which captures the minimal value of the reward $l(\cdot)$ along the trajectory $x(\cdot)$ that solves (1) for (x, t, u, d) . Intuitively, if this cost function J is negative, it means that the trajectory violated the safety constraint at some point in the time horizon (obtaining a negative value of l), and is therefore unsafe. If J is positive, then over the entire time horizon the trajectory maintained a positive reward and therefore remained safe.

The objective of the safety control is to make J as big as possible, increasing the region within which the system can remain safe. Under the worst case, the disturbance would act in a direction of decreasing J as much as it can. Based on this, we can define the value function $V : \mathbb{R}^n \times (-\infty, 0] \rightarrow \mathbb{R}$ as

$$V(x, t) := \min_{\xi_d \in \Xi_{[t,0]}} \max_{u \in U_{[t,0]}} J(x, t, u(\cdot), \xi_d[u](\cdot)), \quad (3)$$

An example of the value function is shown for different time stamps in Fig. 3c and Fig. 3d. The sign of this value function for every (x, t) captures whether the system starting from those initial conditions will be able to remain safe under optimal control and worst-case disturbances. This dissects the space into the safe regions with positive value (where there exists a controller to keep the system safe despite worst-case disturbances and uncertainties), and unsafe regions with negative value (where, for example, even if a car brakes and swerves, it is too close to avoid hitting an obstacle). More formally, the viability kernel (safe set) for \mathcal{L} is $\mathcal{S}(t) = \{x \in \mathbb{R}^n : V(x, t) \geq 0\}$. In Fig. 3e, \mathcal{L} is the region inside the black circle, and the computed safe set \mathcal{S} is shown in green.

To solve for this value function $V(x, t)$, it has been shown that the function is the viscosity solution to the following Hamilton-Jacobi-Isaacs Variational Inequality (HJI-VI) [3]:

$$0 = \min \left\{ l(x) - V(x, t), D_t V(x, t) + \max_{u \in U} \min_{d \in D} D_x V(x, t) \cdot f(x, u, d) \right\}$$

use $\frac{\partial}{\partial t}$

$\frac{\partial}{\partial x}$

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keep it formal

Figure

Why do you need this?

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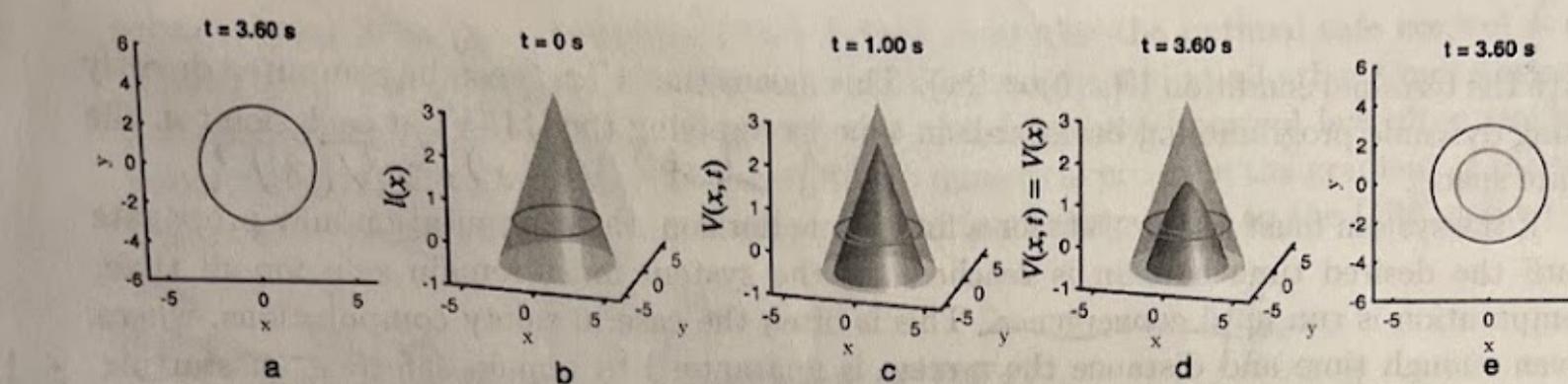


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The sign of this value function for every (x, t) captures whether the system starting from those initial conditions will be able to remain safe under optimal control and worst-case disturbances. This dissects the space into the safe regions with positive value (where there exists a controller to keep the system safe despite worst-case disturbances and uncertainties), and unsafe regions with negative value (where, for example, even if a car brakes and swerves, it is too close to avoid hitting an obstacle). More formally, the viability kernel (safe set) for \mathcal{L} is $\mathcal{S}(t) = \{x \in \mathbb{R}^n : V(x, t) \geq 0\}$. In Fig. 3e, \mathcal{L} is the region inside the black circle, and the computed safe set \mathcal{S} is shown in green.

To solve for this value function $V(x, t)$, it has been shown that the function is the viscosity solution to the following Hamilton-Jacobi-Isaacs Variational Inequality (HJI-VI) [3]:

$$0 = \min \left\{ l(x) - V(x, t), D_t V(x, t) + \max_{u \in U} \min_{d \in D} D_x V(x, t) \cdot f(x, u, d) \right\}$$

use $\frac{\partial}{\partial t}$

$\frac{\partial}{\partial x}$

Draft: October 12, 2021

keep it formal

Figure

Why do you need this?

2.1 System Verification

Consider a state trajectory of the continuous-time time-invariant controlled system with disturbance, satisfying

$$\dot{x}(s) = f(x(s), u(s), d(s)), s \in [t, t'], \text{ and } x(t) = x,$$

where t and x are the initial time and state, respectively. $u \in U \subset \mathbb{R}^m$ is the control input, where U is considered bounded (in the HJ reachability case) or potentially unbounded (in the CBF case). Bounded uncertainties or disturbances can be represented by $d \in D \subset \mathbb{R}^w$, where D is a compact and convex set. The function and $f : \mathbb{R}^n \times U \times D \rightarrow \mathbb{R}^n$ is assumed to be Lipschitz continuous in the state.

Based on current information about the system, environment, and uncertainties in the dynamics or disturbances, safety verification seeks to keep the system outside of states that may lead to failure.

To define the notion of failure for a given environment, a reward function (also called a target function) $l : \mathbb{R}^n \rightarrow \mathbb{R}$ is constructed over the state space, with negative reward inside of obstacles (and/or other failure sets) and positive reward outside. Therefore, the zero-superlevel set of the function defines the set \mathcal{L} that the system must remain in, i.e. $\mathcal{L} = \{x : l(x) \geq 0\}$. An example of this set \mathcal{L} and the corresponding reward function $l(x)$ can be seen in Fig. 3a and Fig. 3b. The objective of the safety control is to guarantee that the trajectory will remain in \mathcal{L} for $s \in [t, 0]$ under the worst case disturbance. This involves computing the safe set, or viability kernel $\mathcal{S}(t)$, which is the set of all the initial states at time t from which there exists an admissible control signal that keeps the system safe under the worst-case disturbance. The corresponding robust safety controller is also computed to ensure this guarantee within the safe set. More formally we want to compute:

- The viability kernel $\mathcal{S}(t)$ [1] for \mathcal{L} : Verify $\mathcal{S}(t) := \{x \in \mathcal{L} : \forall \xi_d \in \Xi_{[t, 0]}, \exists u(\cdot) \in U_{[t, 0]} \text{ s.t. } \forall s \in [t, 0], x(s) \in \mathcal{L} \text{ where } x(s) \text{ solves (1) for } (x, t, u, \xi_d)\}$ for $t < 0$.
- A robust safe control $u(\cdot)$ for \mathcal{L} : For each $x \in \mathcal{S}(t)$, verify a control signal $u(\cdot) \in U_{[t, 0]}$ that renders the trajectory safe for $s \in [t, 0]$, under the worst-case disturbance.

Two popular techniques for safety verification are Hamilton-Jacobi (HJ) reachability, and control barrier functions (CBFs). While there are many similarities between the two approaches, the fields have been largely disjoint. In the following sections we will briefly introduce the theory and tools for both approaches.

2.2 Hamilton-Jacobi Reachability Analysis

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First, we define a cost function as

$$J(x, t, u(\cdot), d(\cdot)) := \min_{s \in [t, 0]} l(x(s)), \quad (2)$$

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Why?

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Using l is like reward & we maximize

?

4

5

see Fig 3

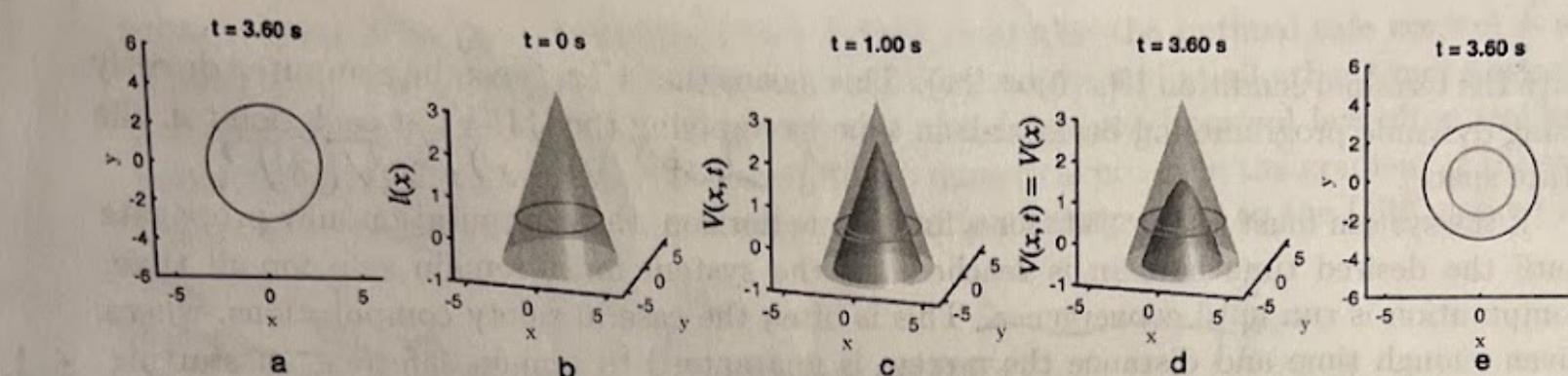


Figure 3: Process of constructing the safe set for HJ reachability. (a) Define the region \mathcal{L} that the system should remain within (in this case, inside the black circle). (b) Define $l(x)$ with negative reward outside the desire region and positive inside. (c) Use (4) to propagate the value function backwards in time using dynamic programming. (d) If the analysis converges (which happens in this case at a time horizon of 3.6s), then the value function holds for an infinite time horizon, thus $V(x, 3.6) = V(x)$. Positive regions of $V(x)$ correspond to positive regions of $l(x)$. (e) The super-zero-level set of $V(x)$ gives the guaranteed safe set (inside the green set). This is a viability kernel that guarantees the system will remain inside the safe set for all time despite worst-case disturbances.

which captures the minimal value of the reward $l(\cdot)$ along the trajectory $x(\cdot)$ that solves (1) for (x, t, u, d) . Intuitively, if this cost function J is negative, it means that the trajectory violated the safety constraint at some point in the time horizon (obtaining a negative value of l), and is therefore unsafe. If J is positive, then over the entire time horizon the trajectory maintained a positive reward and therefore remained safe.

The objective of the safety control is to make J as big as possible, increasing the region within which the system can remain safe. Under the worst case, the disturbance would act in a direction of decreasing J as much as it can. Based on this, we can define the value function $V : \mathbb{R}^n \times (-\infty, 0] \rightarrow \mathbb{R}$ as

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use $\frac{\partial}{\partial t}$

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keep it formal

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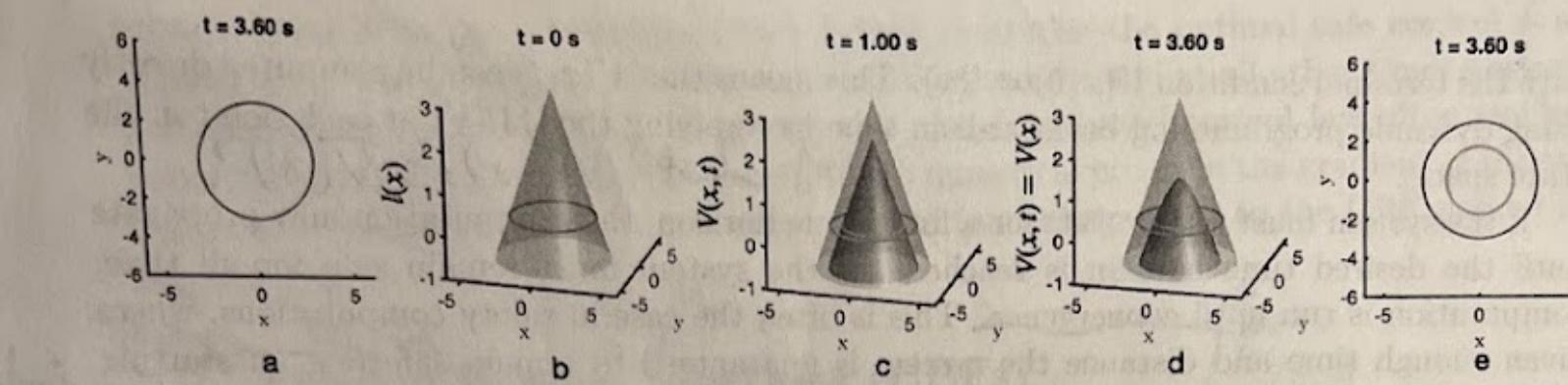


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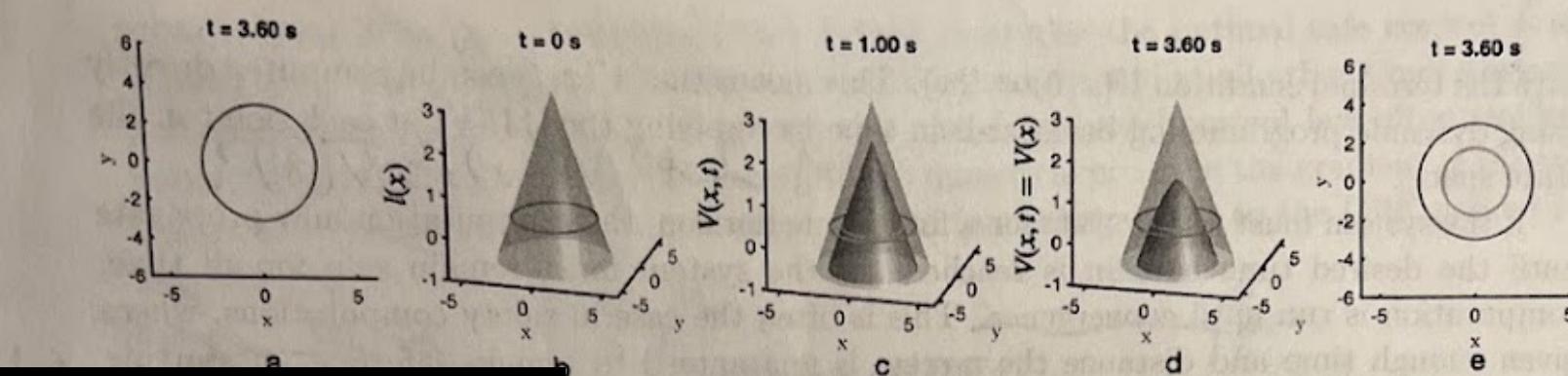
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$$u_n \frac{\partial}{\partial t} \quad \overbrace{\frac{\partial}{\partial x}}$$

Draft: October 12, 2021

Advice throughout the years

Research & Funding

- Whether to collaborate with other faculty in research
- Feedback on grant proposals, white papers
- How to talk to program managers
- Starting and joining technical program committees
- Which editorial jobs have the best cost/benefit ratio
- Introduction to relevant professional society members

Teaching

- How to pick out a good TA
- Creating a special topics course
- Teaching during COVID
- Handling disgruntled students
- Teaching material
- Running a class while sick
- How to update undergrad controls courses

Service, Politics, Etc.

- Advice on whether to accept/reject a particular service request (and whether it involved free food)
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- Handling confidential government emails
- When and how to tell the department I'm pregnant
- Whether to delay promotion due to childbirth or submit my file, feedback on my file
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Service requests

This looks “mostly harmless,” which is how the Earth is described in *The Hitchhiker’s Guide to the Galaxy*. This could give you some service without impacting much on your available time. The good part about any service is not so what you can do for the university but the contacts that you make from serving on committees. That can prove valuable and, at the very least, a good learning experience. The risk of it being a time sink appears to be negligible.

- [1] Dobbin, Frank, and Alexandra Kalev. "Why diversity programs fail." *Harvard Business Review* 94.7 (2016): 14.
- [2] Dobbin, Frank, and Alexandra Kalev. "Why doesn't diversity training work? The challenge for industry and academia." *Anthropology Now* 10.2 (2018): 48-55.
- [3] Hightower J.L., "10 Things Colleges & Universities Can Do to Increase Racial & Ethnic Diversity of Faculty" Medium, 2016.
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Evidence-based Methods to Promote Recruitment and Retention of Under-Represented Minorities in STEM

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- Promoting effective mentorship

[1] Dobbin, Frank, and Alexandra Kalev. "Why diversity programs fail." *Harvard Business Review* 94.7 (2016): 14.

[2] Dobbin, Frank, and Alexandra Kalev. "Why doesn't diversity training work? The challenge for industry and academia." *Anthropology Now* 10.2 (2018): 48-55.

[3] Hightower J.L., "10 Things Colleges & Universities Can Do to Increase Racial & Ethnic Diversity of Faculty" Medium, 2016.

[4] Kaiser C.R., Major B., Jurcevic I., Dover T., Brady L.M., and Shapiro J.R., "Presumed Fair: Ironic Effects of Organizational Diversity Structures," *Journal of Personality and Social Psychology* 2012.

Evidence-based Methods to Promote Recruitment and Retention of Under-Represented Minorities in STEM

- Active recruitment programs
- Increasing role models
- Promoting effective mentorship
- The mentorship aspect was especially effective: “...on average [mentorship programs] boost the representation of black, Hispanic, and Asian-American women, and Hispanic and Asian-American men, by 9% to 24%” [1].

[1] Dobbin, Frank, and Alexandra Kalev. "Why diversity programs fail." *Harvard Business Review* 94.7 (2016): 14.

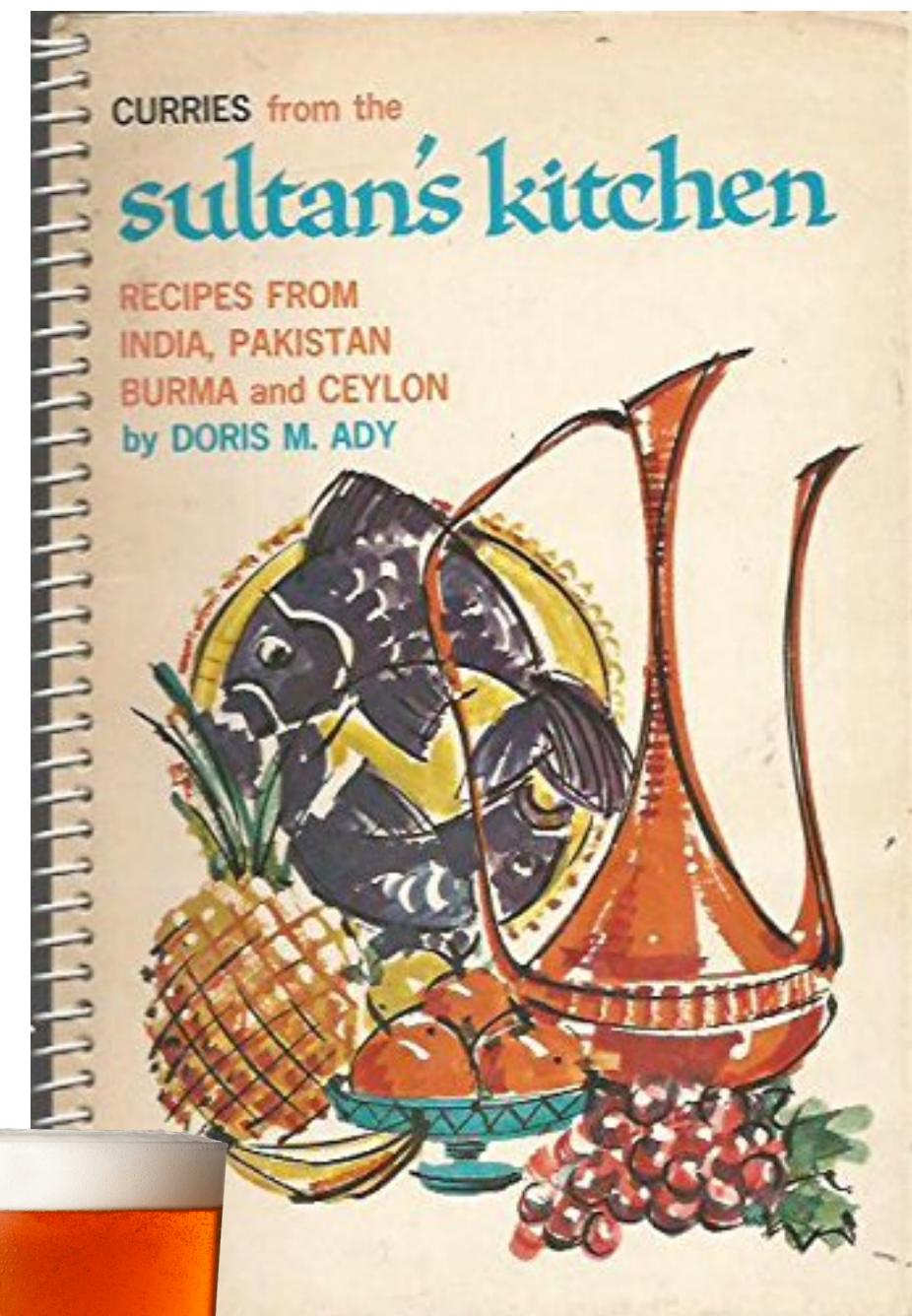
[2] Dobbin, Frank, and Alexandra Kalev. "Why doesn't diversity training work? The challenge for industry and academia." *Anthropology Now* 10.2 (2018): 48-55.

[3] Hightower J.L., "10 Things Colleges & Universities Can Do to Increase Racial & Ethnic Diversity of Faculty" Medium, 2016.

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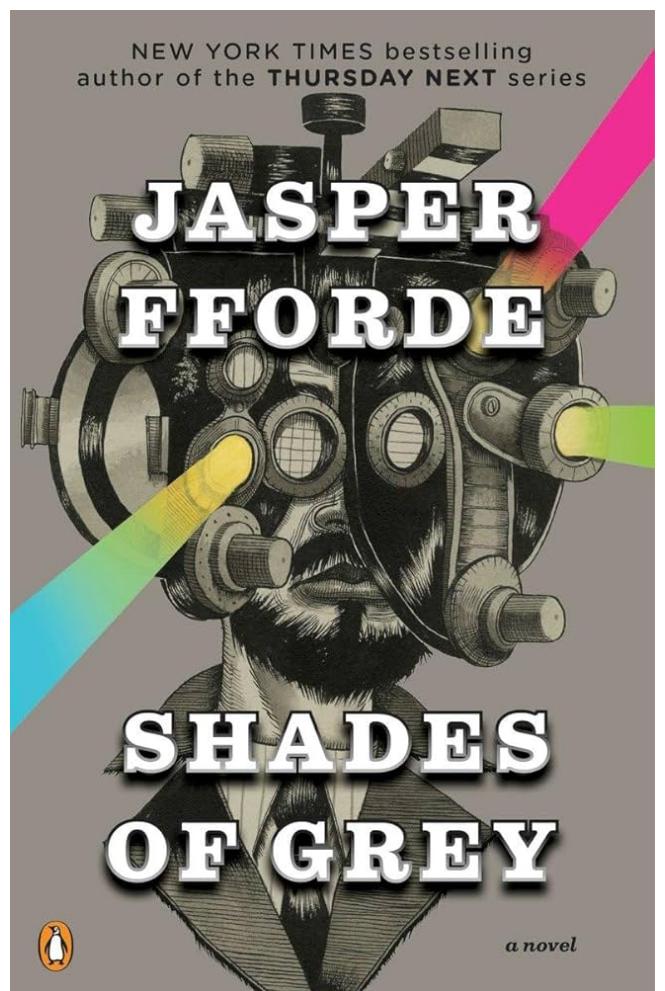
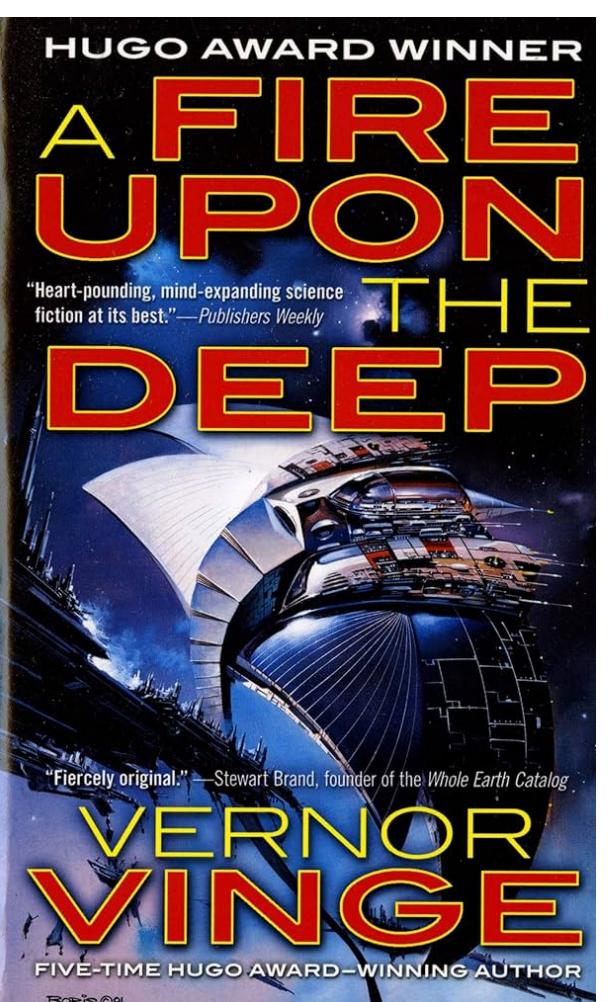
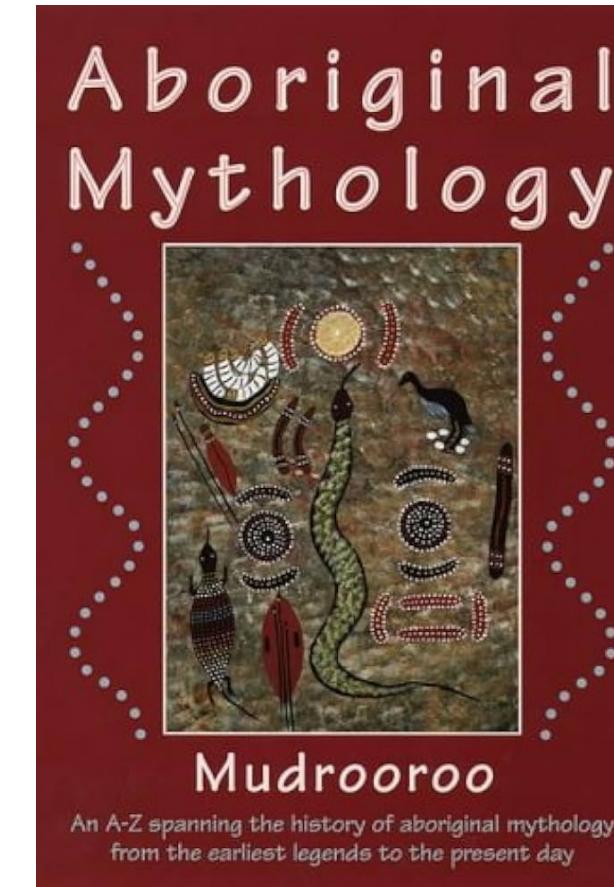
Advice for young faculty

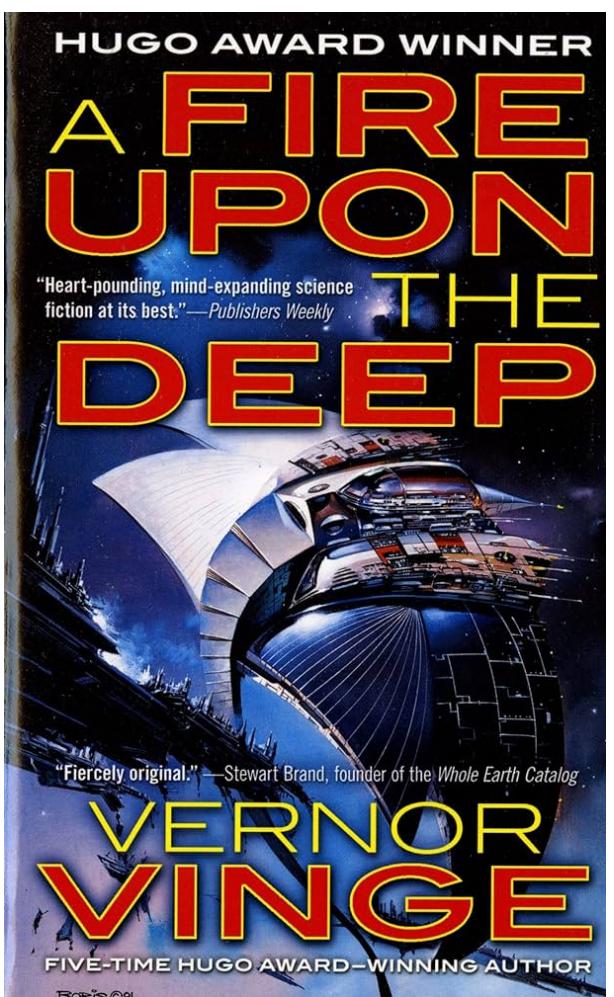
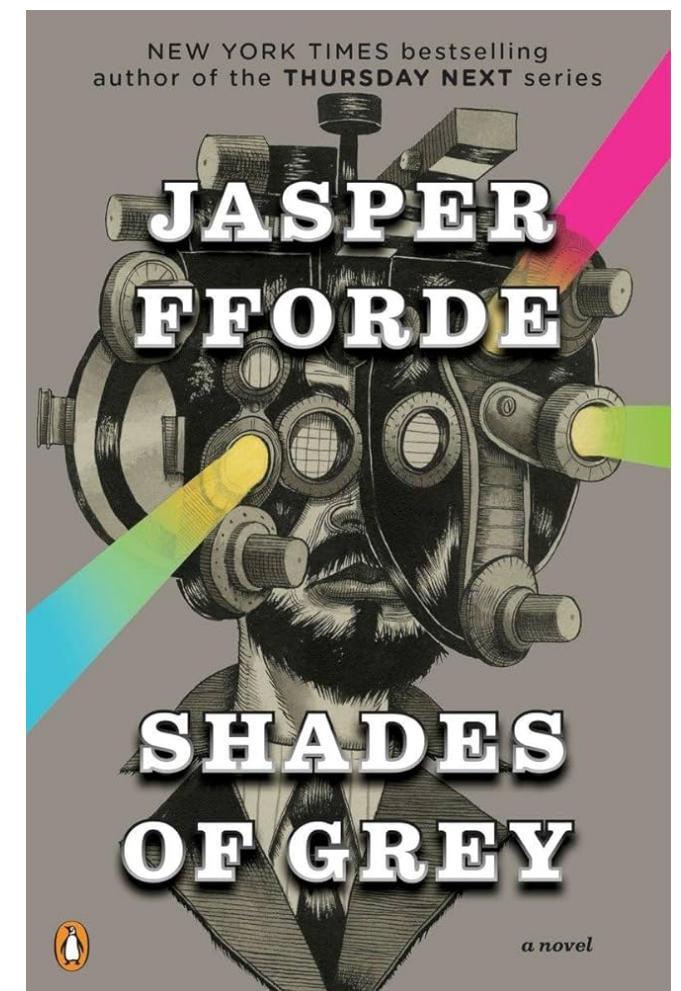
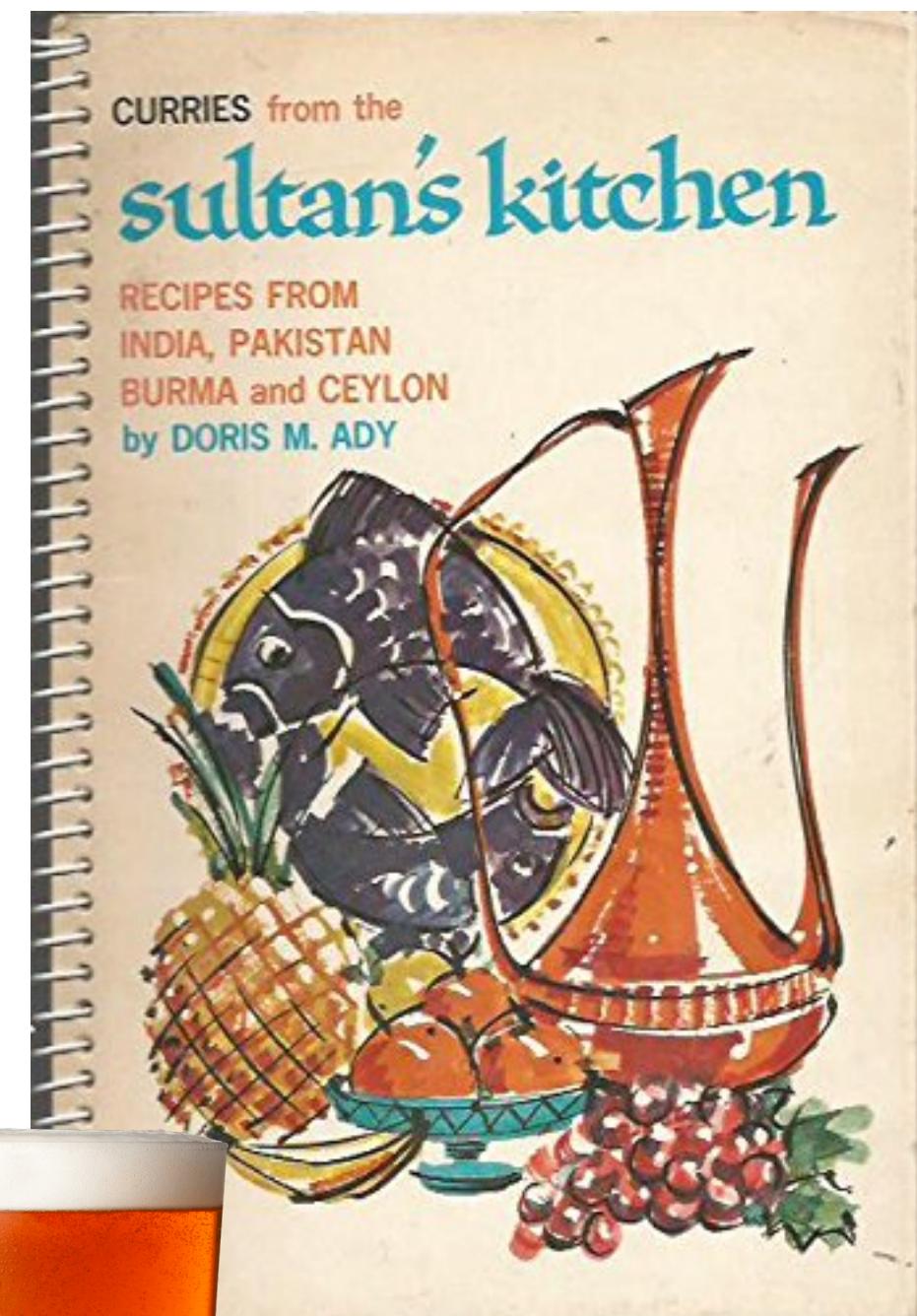
Be sure to have fun.



Thank you

DON'T PANIC





DON'T PANIC

