Picking Projects

CS 197 & 197C | Stanford University | **Sean Liu** & Lauren Gillespie
cs197.stanford.edu | cs197c.stanford.edu

Slides adapted from previous iterations of the course by Michael Bernstein


FORWARD
THINKERS
Can
artificial intelligence
have a bias?

Picking Projects

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Overview From Here: 197

Final Advising: Thurs 6/1—Wed 6/7

Final Project Report: Wed 6/7 EOD

Extra Credit (Peer review)**:** Wed 6/7 EOD

Due **Tues** 6/13, 3:30pm:

Final paper, final talk, project due.

Final Team Dynamics form due.

Final exam slot: (3:30-6:30pm): we will meet in 60-109 for presentations!

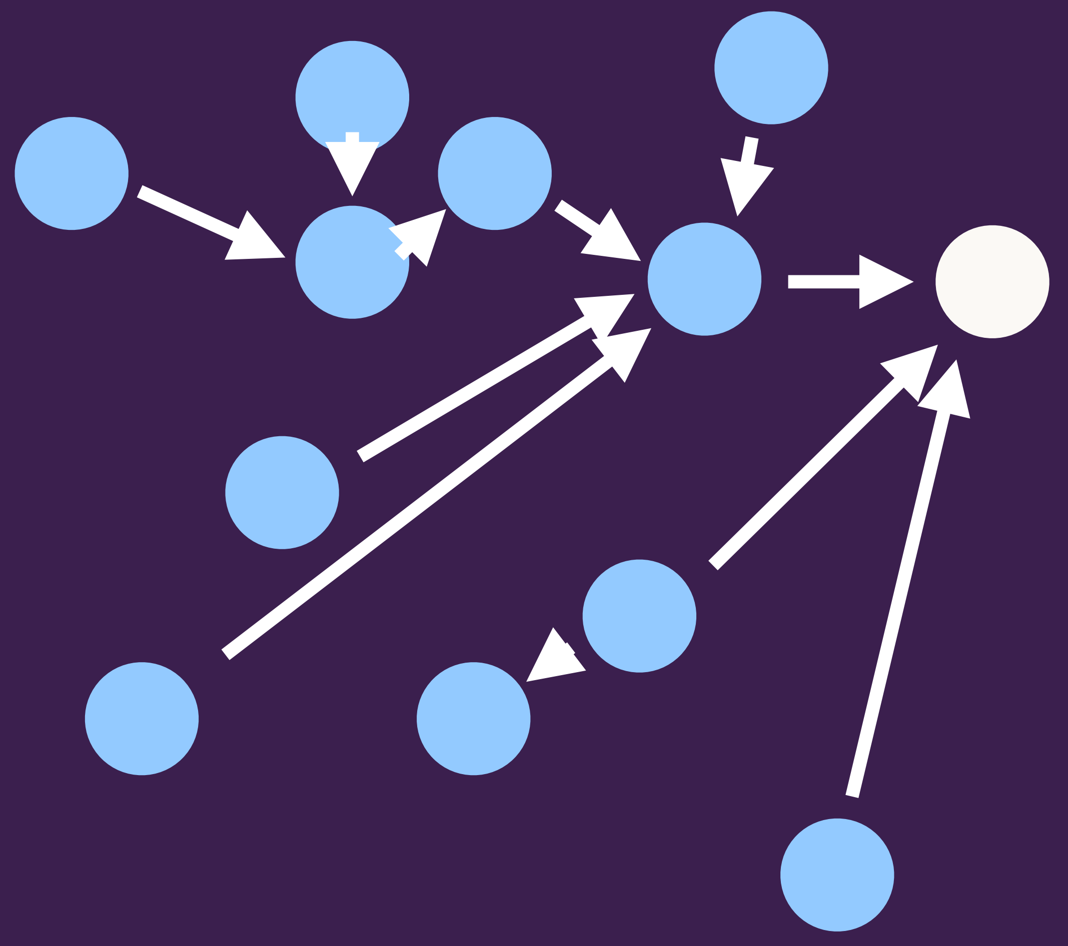
Overview From Here: 197C

- Due **Wed** 6/7 EOD: Revisions of Milestone Proposal
  - No action needed if you don't have any changes.
  - Update proposal, send to mentor for sign-off.
- **Extra Credit** (Peer review)**:** Wed 6/7 EOD
- Due **Tues** 6/13, 3:30pm:
  - Final paper, final talk, milestone due.
  - Final exam slot: (3:30-6:30pm): we will meet in 60-109 for presentations!

Final presentations are in 60-109

T4 Drinks will be provided!
(Courtesy of Michael Bernstein)

Look how far we've come!



Related work and Lit search

Problem motivation

Set up the bit

Flip the bit

Instantiate the bit

Evaluation

Broader Implications

Introduction

Vectoring & Velocity

Evaluation

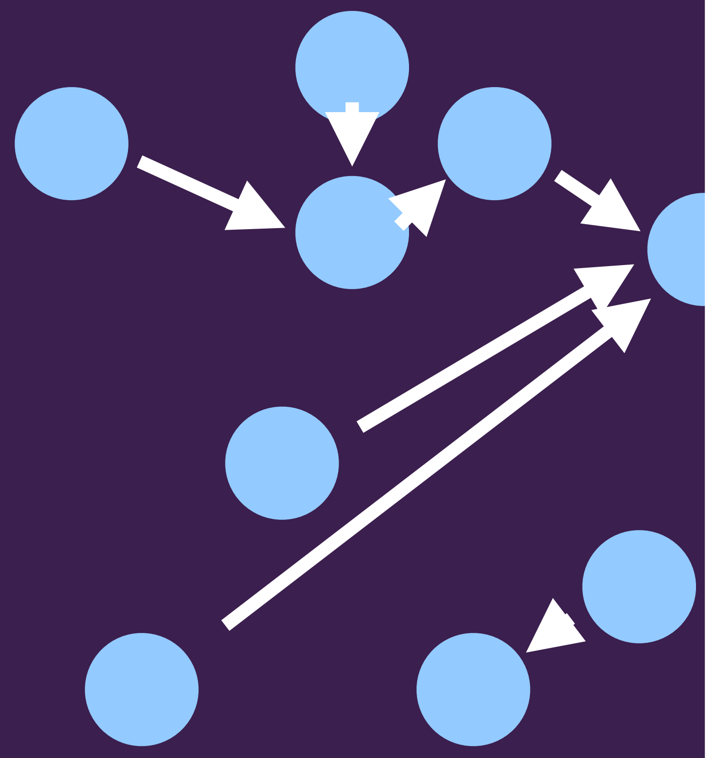
x > y

∃ x

bounding x / measuring x

Loo e come!

locity



NUM. LABELED ($\leq n$)	**200**	**175**	**150**	**125**	**100**	**75**	**50**	**25**	**10**	**5**
% RELATIONSHIPS	99.09	99.00	98.87	98.74	98.52	98.15	97.57	96.09	92.26	87.28

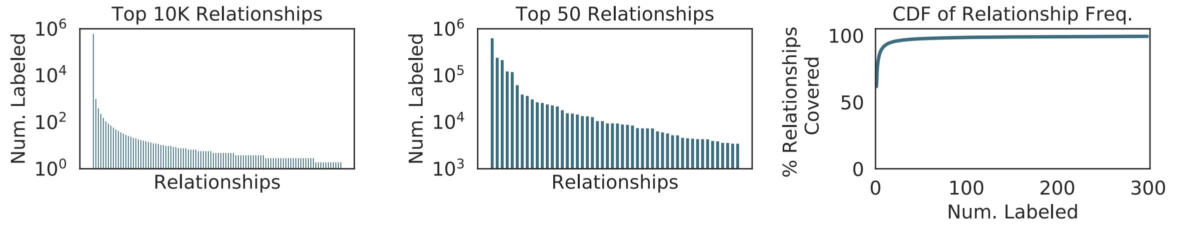


Figure 2. Visual relationships have a long tail (left) of infrequent relationships. Current models [49, 54] only focus on the top 50 relationships (middle) in the Visual Genome dataset, which all have thousands of labeled instances. This ignores more than 98% of the relationships with few labeled instances (right, top/table).

features can characterize *some* visual relationships very well, they might fail to capture *complex relationships* with high variance. To quantify the efficacy of our image-agnostic features, we define "subtypes" that measure spatial and categorical complexity (Section 3).

Based on our analysis, we propose a semi-supervised approach that leverages image-agnostic features to label missing relationships using as few as 10 labeled instances of each relationship. We learn simple heuristics over these features and assign probabilistic labels to the unlabeled images using a generative model [39, 46]. We evaluate our method's labeling efficacy using the completely-labeled VRD dataset [31] and find that it achieves an F1 score of 57.66, which is 11.84 points higher than other standard semi-supervised methods like label propagation [57]. To demonstrate the utility of our generated labels, we train a state-of-the-art scene graph model [54] (see Figure 6) and modify its loss function to support probabilistic labels. Our approach achieves 47.53 recall@100[1] for predicate classification on Visual Genome, improving over the same model trained using only labeled instances by 40.97 points. For scene graph detection, our approach achieves within 8.65 recall@100 of the same model trained on the original Visual Genome dataset with 108× more labeled data. We end by comparing our approach to transfer learning, the de-facto choice for learning from limited labels. We find that our approach improves by 5.16 recall@100 for predicate classification, especially for relationships with high complexity, as it generalizes well to unlabeled subtypes.

Our contributions are three-fold. (1) We introduce the first method to complete visual knowledge bases by finding missing visual relationships (Section 5.1). (2) We show the utility of our generated labels in training existing scene graph prediction models (Section 5.2). (3) We introduce a metric to characterize the complexity of visual relationships and show it is a strong indicator ($R^2 = 0.778$) for our semi-supervised method's improvements over transfer learning (Section 5.3).

[1] Recall@K is a standard measure for scene graph prediction [31].

2. Related work

Textual knowledge bases were originally hand-curated by experts to structure facts [4,5,44] (e.g. `<Tokyo - capital of - Japan>`). To scale dataset curation efforts, recent approaches mine knowledge from the web [9] or hire non-expert annotators to manually curate knowledge [5, 47]. In semi-supervised solutions, a small amount of labeled text is used to extract and exploit patterns in unlabeled sentences [2, 21, 33–35, 37]. Unfortunately, such approaches cannot be directly applied to visual relationships; textual relations can often be captured by external knowledge or patterns, while visual relationships are often local to an image.

Visual relationships have been studied as spatial priors [14, 16], co-occurrences [51], language statistics [28, 31, 53], and within entity contexts [29]. Scene graph prediction models have dealt with the difficulty of learning from incomplete knowledge, as recent methods utilize statistical motifs [54] or object-relationship dependencies [30, 49, 50, 55]. All these methods limit their inference to the top 50 most frequently occurring predicate categories and ignore those without enough labeled examples (Figure 2).

The de-facto solution for limited label problems is **transfer learning** [15, 52], which requires that the source domain used for pre-training follows a similar distribution as the target domain. In our setting, the source domain is a dataset of frequently-labeled relationships with thousands of examples [30, 49, 50, 55], and the target domain is a set of limited label relationships. Despite similar objects in source and target domains, we find that transfer learning has difficulty generalizing to new relationships. Our method does not rely on availability of a larger, labeled set of relationships; instead, we use a small labeled set to annotate the unlabeled set of images.

To address the issue of gathering enough training labels for machine learning models, **data programming** has emerged as a popular paradigm. This approach learns to model imperfect labeling sources in order to assign training labels to unlabeled data. Imperfect labeling sources can come from crowdsourcing [10], user-defined heuristics [8, 43], multi-instance learning [22, 40], and distant su-

Related w
and Lit se

on

Writing a paper

Giving a talk

∃ x

bounding x /
measuring x

Today's goals

How to pick projects?

How to stay up-to-date?

And….how to deal with rejection :(

Picking Projects

Where do research ideas come from?

A common mindset: riffing

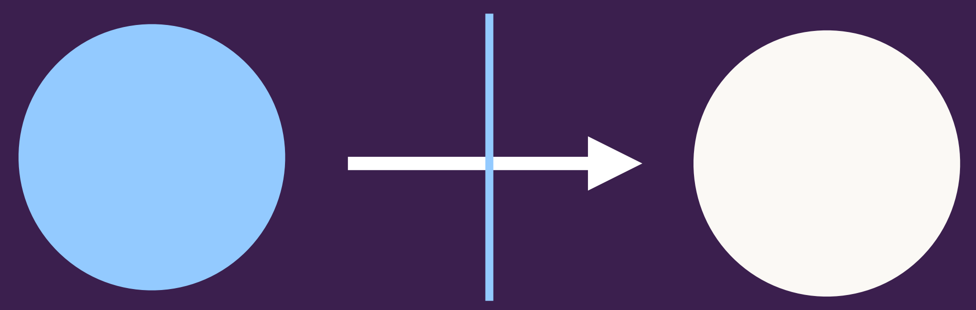
Ye Olde Riffing Recipe, from The Bernstein Cookbook for People Who Don't Cook Well But Can At Least Do Research:

Read a bunch of papers

Pick a paper you really like

Ask yourself: how could I extend this to another domain, or make progress on one of its challenging assumptions, or otherwise extend it?

This is a process for generating a one-paper bit flip



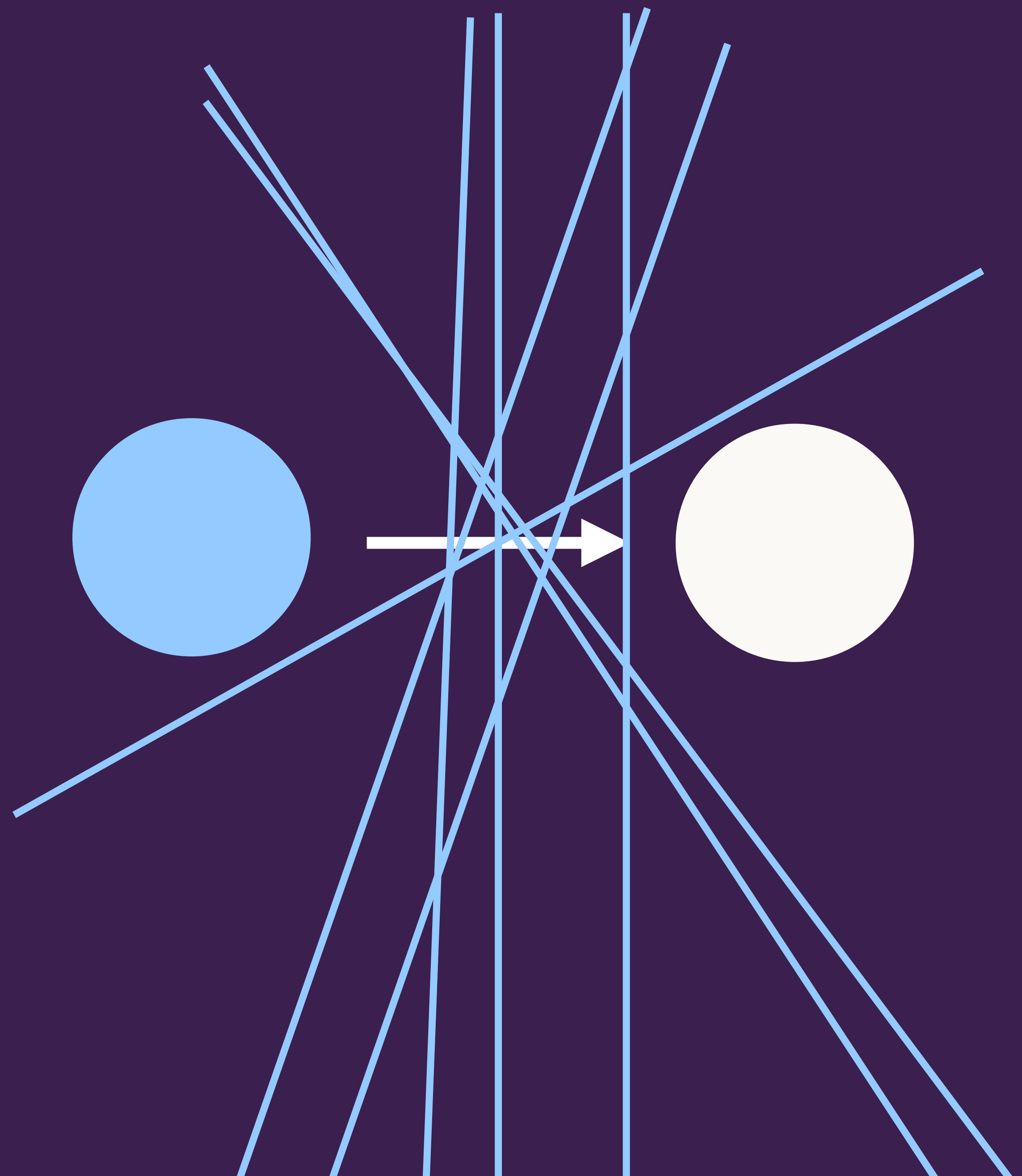
Riffing is often a good starting point for a first independent project

It places focus on execution, and gives you most of the inputs, outputs, and constraints—the assumptions—up front

What are the risks here?

It's not clear that all bit flips are worthwhile.

My misappropriated quote: "*Your scientists were so preoccupied with whether or not they could that they didn't stop to think if they should.*"



"Salami Science": possibility of incremental work when we don't view the field's assumptions broadly

What we mean when we say “incremental”

Research and science are not neutral: they embed values

Incrementally is a push back against minor adjustments to models that don’t build substantial theory

What we mean when we say science isn't neutral

Science and Technology Studies (STS) establishes that what counts as a contribution, or as major vs. incremental, or even what counts as Computer Science, is socially constructed by elites in the field.

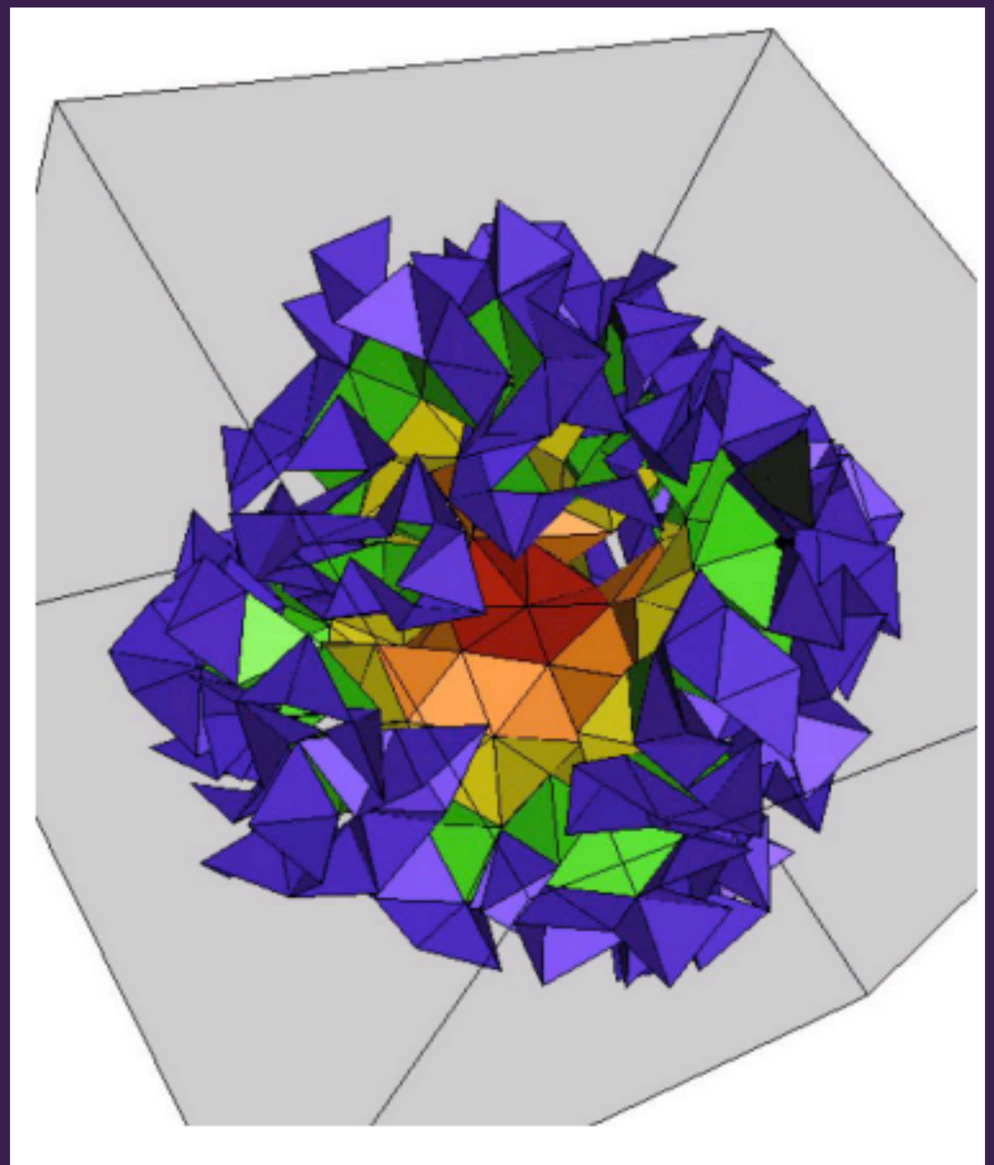
Not so long ago, HCI and Ethics were not seen as legitimate CS

Also not so long ago, CS itself was not seen as a legitimate field

Problem

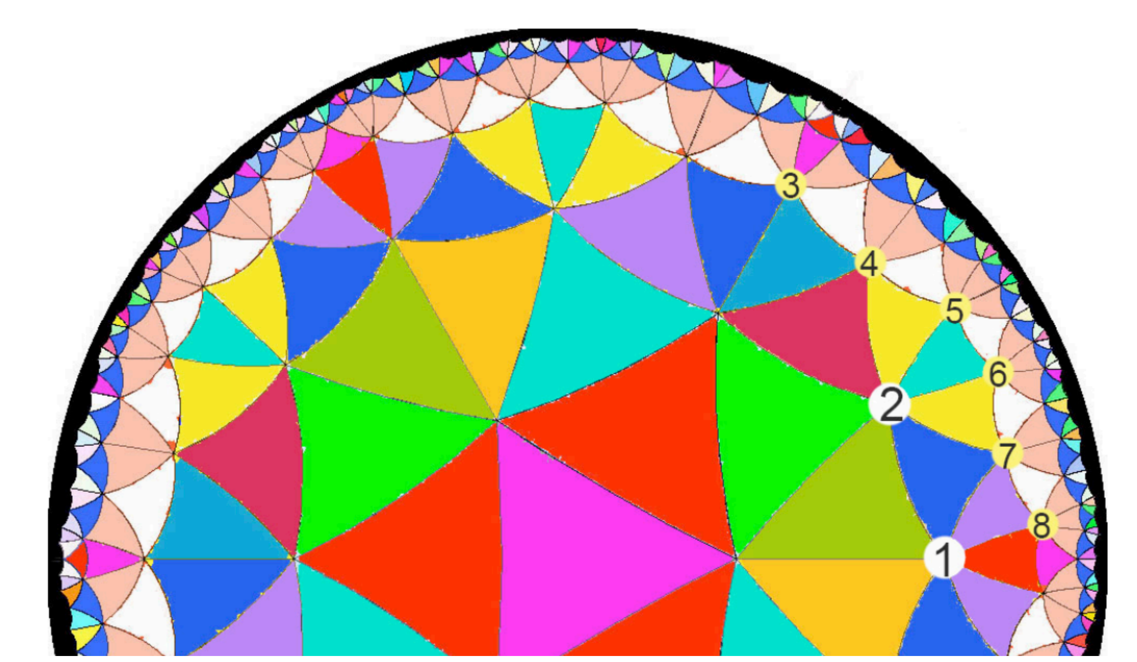
Previous grad student:

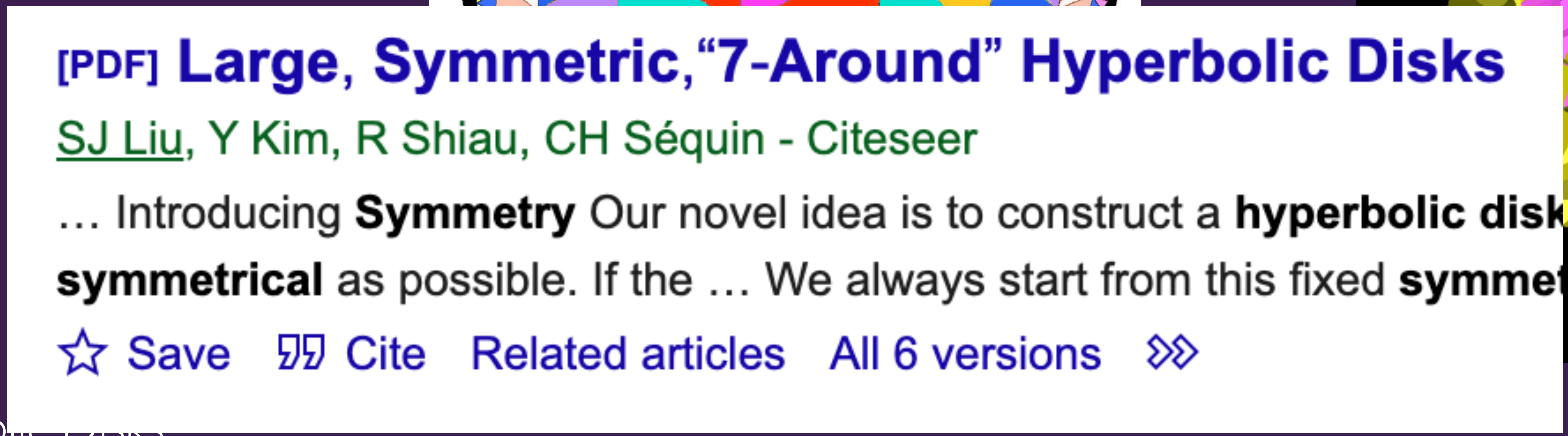
810 triangles



My professor:

Bit flip





[PDF] **Large, Symmetric, “7-Around” Hyperbolic Disks**

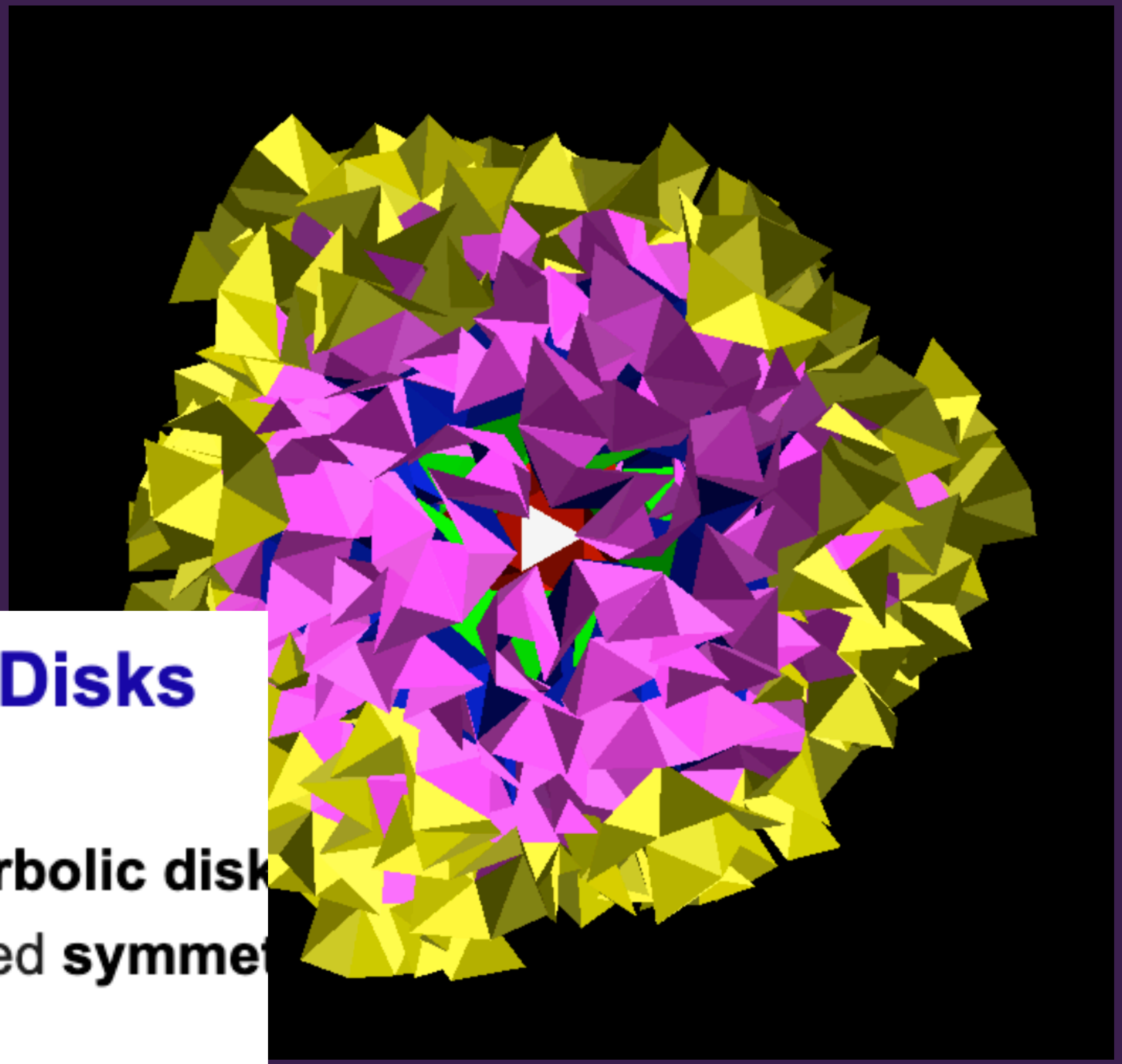
SJ Liu, Y Kim, R Shiau, CH Séquin - Citeseer

… Introducing **Symmetry** Our novel idea is to construct a **hyperbolic disk** **symmetrical** as possible. If the … We always start from this fixed **symme**

☆ Save 99 Cite Related articles All 6 versions

Undergrad me:

2197 triangles



Liu et al. 2015 “Large, “7-Around” Hyperbolic Disks

General Tips

1. Stay up-to-date with literature

    Problems: what does the field care about?

    Solutions: what ideas will change how the field thinks?

    In other words, what are the "frontiers" of your field?

Staying Up-To-Date

Attend top conferences

Twitter

Google Scholars / arXiv: subscribe to important researchers and labs

Build skills and habits

- Read papers efficiently — you got practice in this class!
- Make it a daily routine to read X number of papers per day (esp. for fast-paced fields like AI)

Read outside your field

General Tips

1. Stay up-to-date with literature

    Problems: what does the field care about?

    Solutions: what ideas will change how the field thinks?

    In other words, what are the "frontiers" of your field?

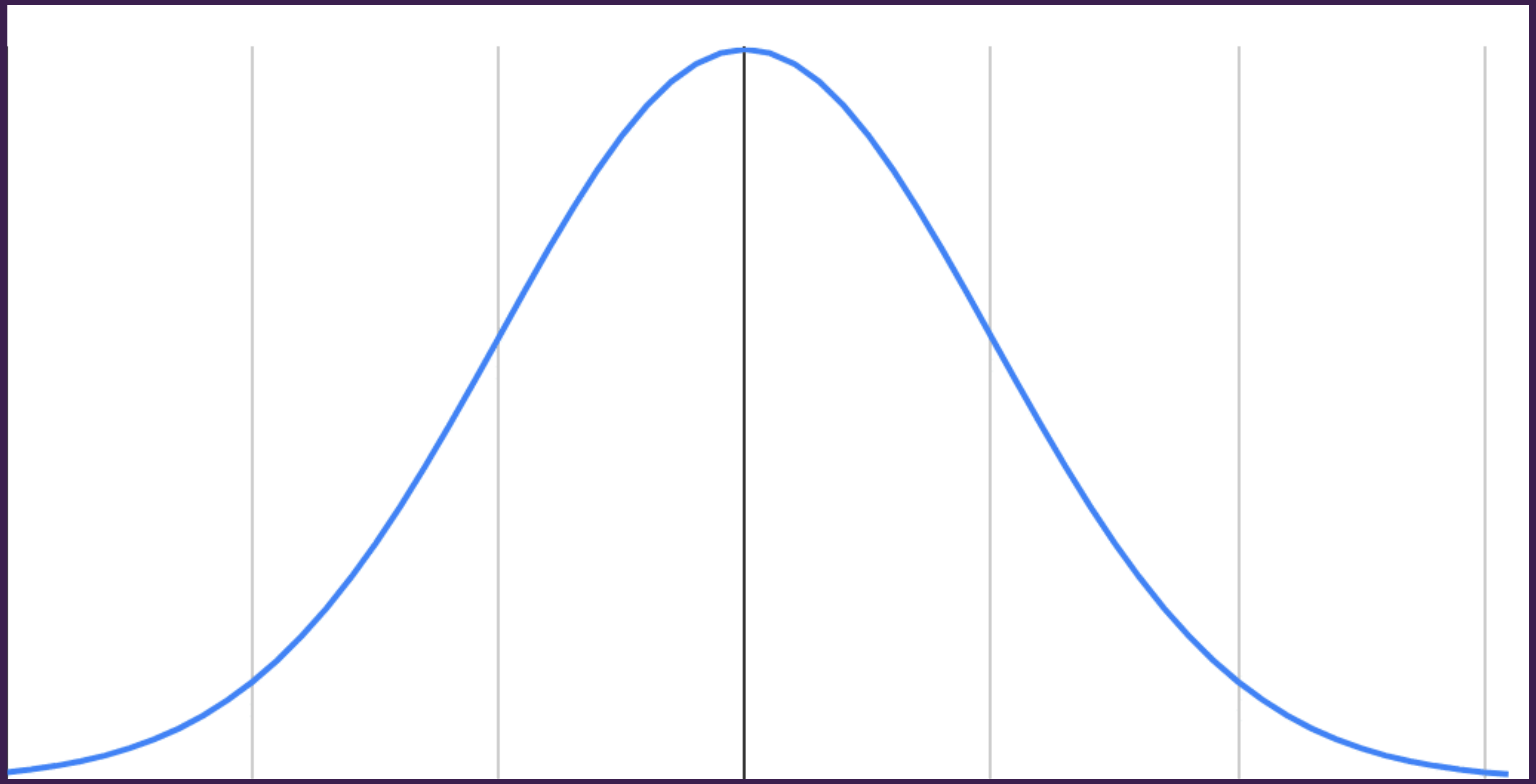
2. Make a habit of generating ideas often (every day)

    Keep a journal of ideas!

“If you want to have a good idea, you must have many ideas.”

– Nobel Prize winning chemist Linus Pauling

“If you want to have a good idea, you must have many ideas.”



$2 \cdot \sigma = 95\%$ of samples

$3 \cdot \sigma = 99.7\%$ of samples

Quantity > Quality Mindset

Famous photography class story — Prof. Jerry Uelsmann

Some Strategies and Stories

Rage-based research

When a pattern or underlying assumption in the field starts to dig at you until you decide to prove that it's wrong.

Flash Organizations: Crowdsourcing Complex Work By Structuring Crowds As Organizations

Melissa A. Valentine, Daniela Retelny,
Alexandra To, Negar Rahmati, Tulsee Doshi, Michael S. Bernstein
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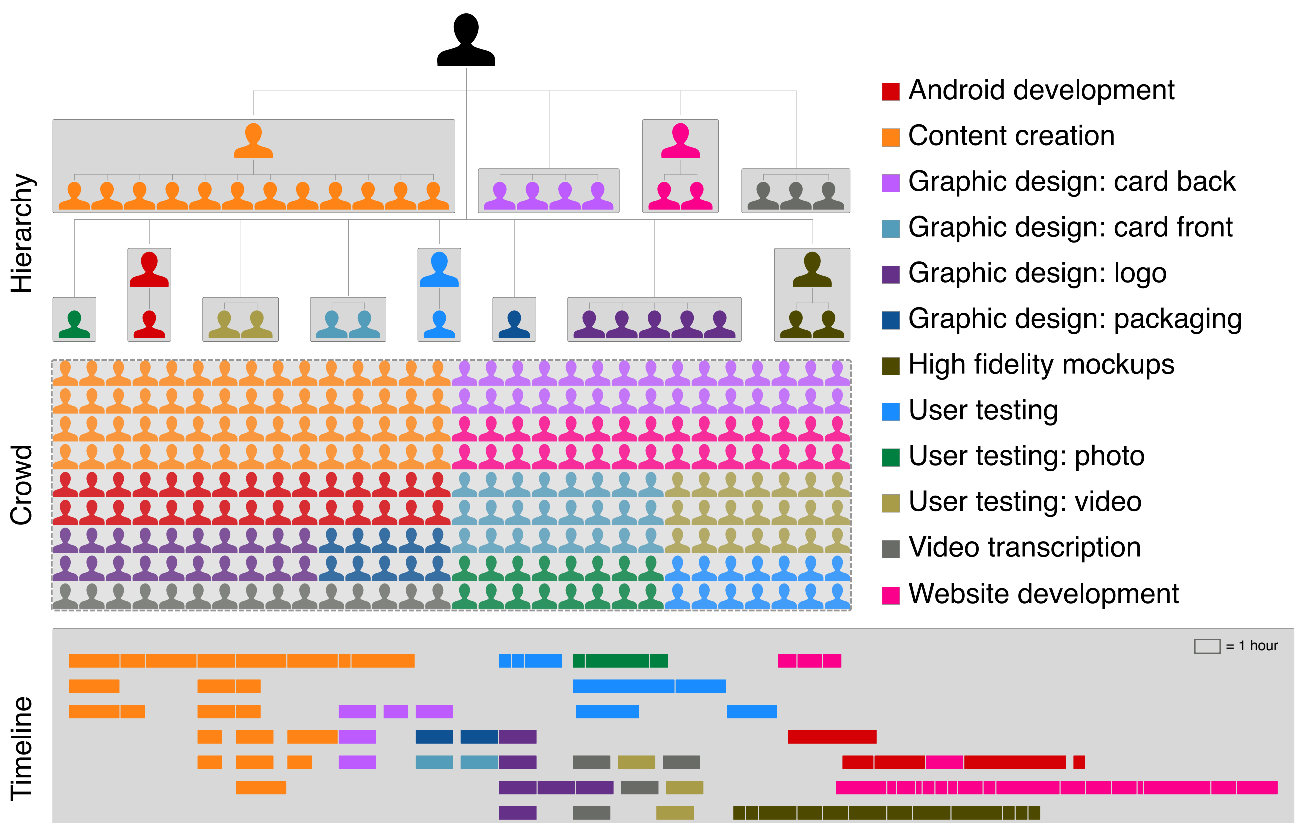
ABSTRACT
This paper introduces *flash organizations:* crowds structured like organizations to achieve complex and open-ended goals. Microtask workflows, the dominant crowdsourcing structures today, only enable goals that are so simple and modular that their path can be entirely pre-defined. We present a system that organizes crowd workers into computationally-represented structures inspired by those used in organizations — roles, teams, and hierarchies — which support emergent and adaptive coordination toward open-ended goals. Our system introduces two technical contributions: 1) encoding the crowd's division of labor into de-individualized roles, much as movie crews or disaster response teams use roles to support coordination between on-demand workers who have not worked



When new tools reopen old problems

Social Simulacra: Creating Populated Prototypes for Social Computing Systems

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ABSTRACT

Social computing prototypes probe the social behaviors that may arise in an envisioned system design. This prototyping practice is currently limited to recruiting small groups of people. Unfortunately, many challenges do not arise until a system is populated at a larger scale. Can a designer understand how a social system might behave when populated, and make adjustments to the design before the system falls prey to such challenges? We introduce *social simulacra*, a prototyping technique that generates a breadth of realistic social interactions that may emerge when a social computing system is populated. Social simulacra take as input the designer's description of a community's design—goal, rules, and

KEYWORDS

social computing, prototyping

ACM Reference Format:
Joon Sung Park, Lindsay Popowski, Carrie J. Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. 2022. Social Simulacra: Creating Populated Prototypes for Social Computing Systems. In *The 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22), October 29-November 2, 2022, Bend, OR, USA.* ACM, New York, NY, USA, 18 pages. https://doi.org/10.1145/3526113.3545616

1 INTRODUCTION

When you see a new north star

Searching for Computer Vision
North Stars

Li Fei-Fei & Ranjay Krishna

Computer vision is one of the most fundamental areas of artificial intelligence research. It has contributed to the tremendous progress in the recent deep learning revolution in AI. In this essay, we provide a perspective of the recent evolution of object recognition in computer vision, a flagship research topic that led to the breakthrough data set of ImageNet and its ensuing algorithm developments. We argue that much of this progress is rooted in the pursuit of research "north stars," wherein researchers focus on critical problems of a scientific discipline that can galvanize major efforts

Which approach do I apply?

This is a skill you develop through mentorship — it's highly contingent, and depends on the problem and solution space that you're navigating.

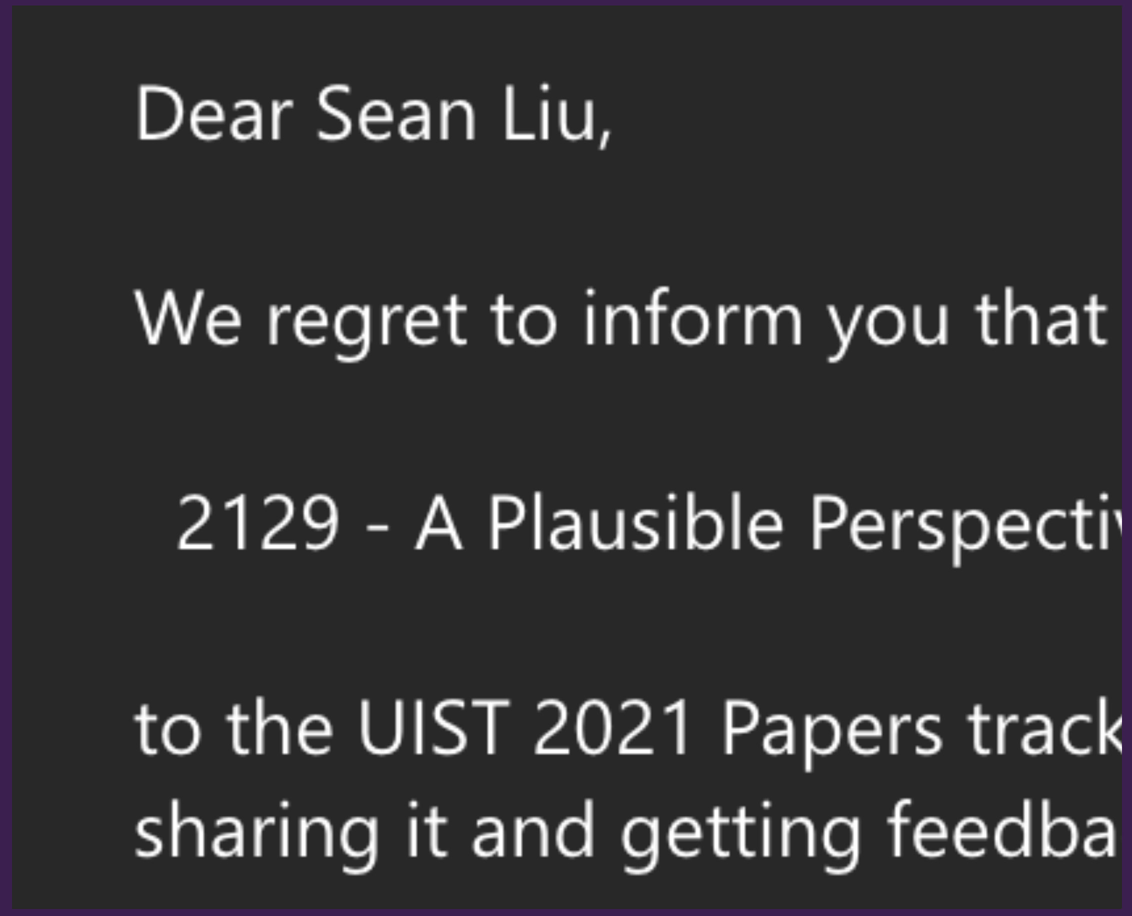
My suggestion: try on different hats around the problems you're interested in, and see what works.

Dealing with rejection

:(

Rejection is a fact of life in research.

I've gotten rejected a lot. It hurts.


Dear Sean Liu,

We regret to inform you that

2129 - A Plausible Perspecti

to the UIST 2021 Papers track
sharing it and getting feedba

JOHANNES HAUSHOFER
CV OF FAILURES

Most of what I try fails, but these failures are often invisible, while the successes are visible. I have noticed that this sometimes gives others the impression that most things work out for me. As a result, they are more likely to attribute their own failures to themselves, rather than the fact that the world is stochastic, applications are crapshoots, and selection committees and referees have bad days. This CV of Failures is an attempt to balance the record and provide some perspective.

This idea is not mine, but due to a wonderful article in *Nature* by **Melanie I. Stefan**, who is a Lecturer in the School of Biomedical Sciences at the University of Edinburgh. You can find her original article here, her website here, her publications here, and follow her on Twitter under *@MelanieIStefan*.

I am also not the first academic to post their CV of failures. Earlier examples are here, here, here, and here.

This CV is unlikely to be complete – it was written from memory and probably omits a lot of stuff. So if it's shorter than yours, it's likely because you have better memory, or because you're better at trying things than me.

Degree programs I did not get into

2008	PhD Program in Economics, Stockholm School of Economics
2003	Graduate Course in Medicine, Cambridge University Graduate Course in Medicine, UCL PhD Program in Psychology, Harvard University PhD Program in Neuroscience and Psychology, Stanford University
1999	BA in International Relations, London School of Economics

Academic positions and fellowships I did not get

We are pleased to inform you that your paper has been accepted

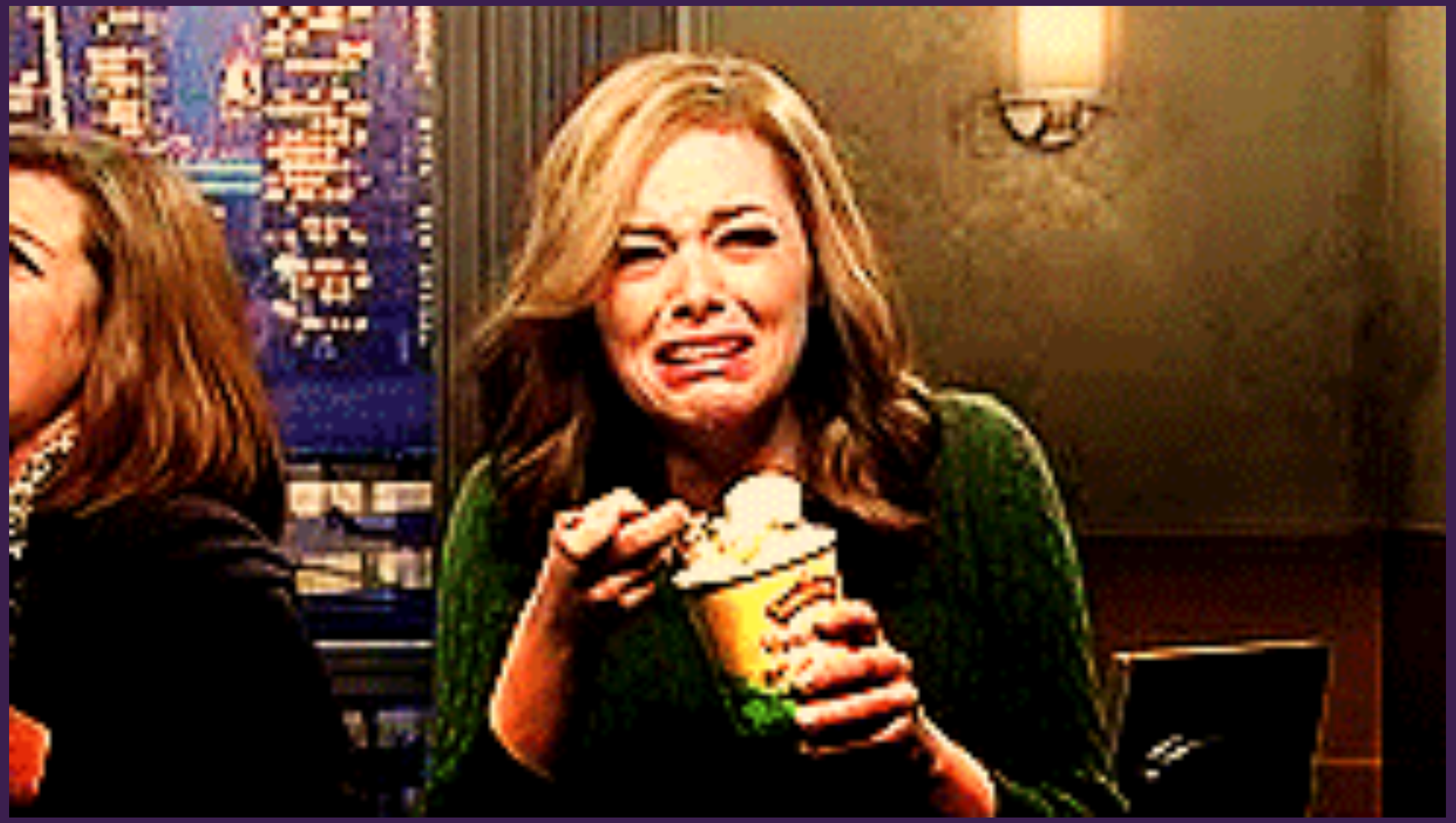
As a grad student

As junior faculty

As tenured faculty

From: https://researchinprogress.tumblr.com/post/33884075941/we-are-pleased-to-inform-you-that-your-paper-has

We regret to inform you that your paper has not been accepted



As a grad student

As junior faculty

As tenured faculty

From: https://researchinprogress.tumblr.com/post/33946389387/we-regret-to-inform-you-that-your-paper-has-not

How to handle bad reviews

First, take the time you need to emotionally process it. My process basically follows the Kübler-Ross model:

1. Denial and isolation
2. Anger
3. Bargaining
4. Depression
5. Acceptance

This is a very natural human reaction, and not one we directly have control over, so just let it happen.

Making the most of it

I see two common clusters of bad reviews:

1) People who don't get the paper. These reviews don't engage with the core idea, or engage with the wrong aspects of the idea, and their critiques come across as surface-level as a result.

2) People who get the paper. These reviews are often really incisive and take down core assumptions or approaches you're taking.

Each of these clusters has something to tell us about our paper.

“They don’t get it”

These reviews suggest one of two things:

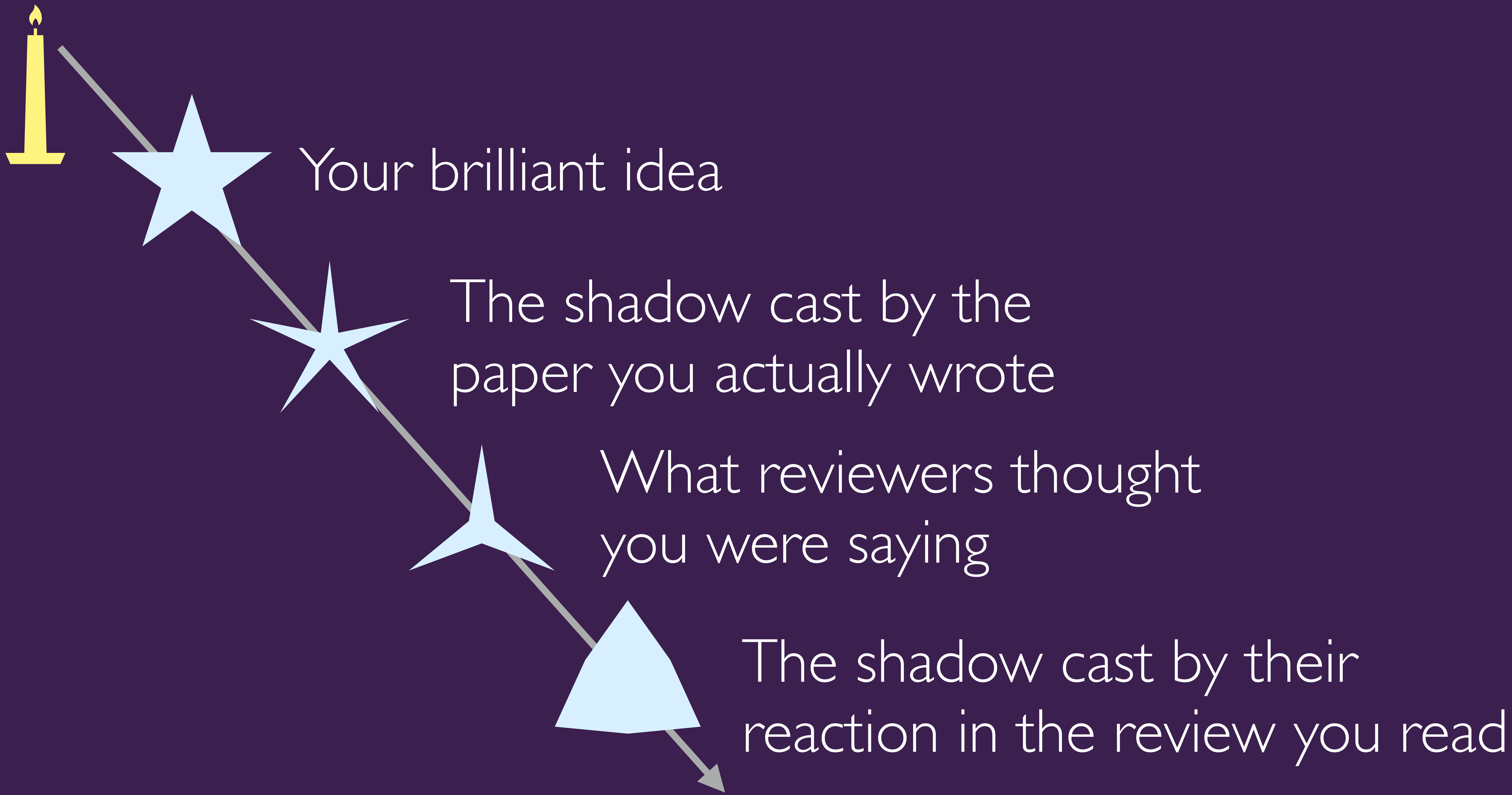
Your paper didn’t get in front of the right kind of reviewer, like it didn’t hit someone who works in the right area.

(Then: what are you signaling in your title or abstract that is attracting the wrong kind of reviewer?)

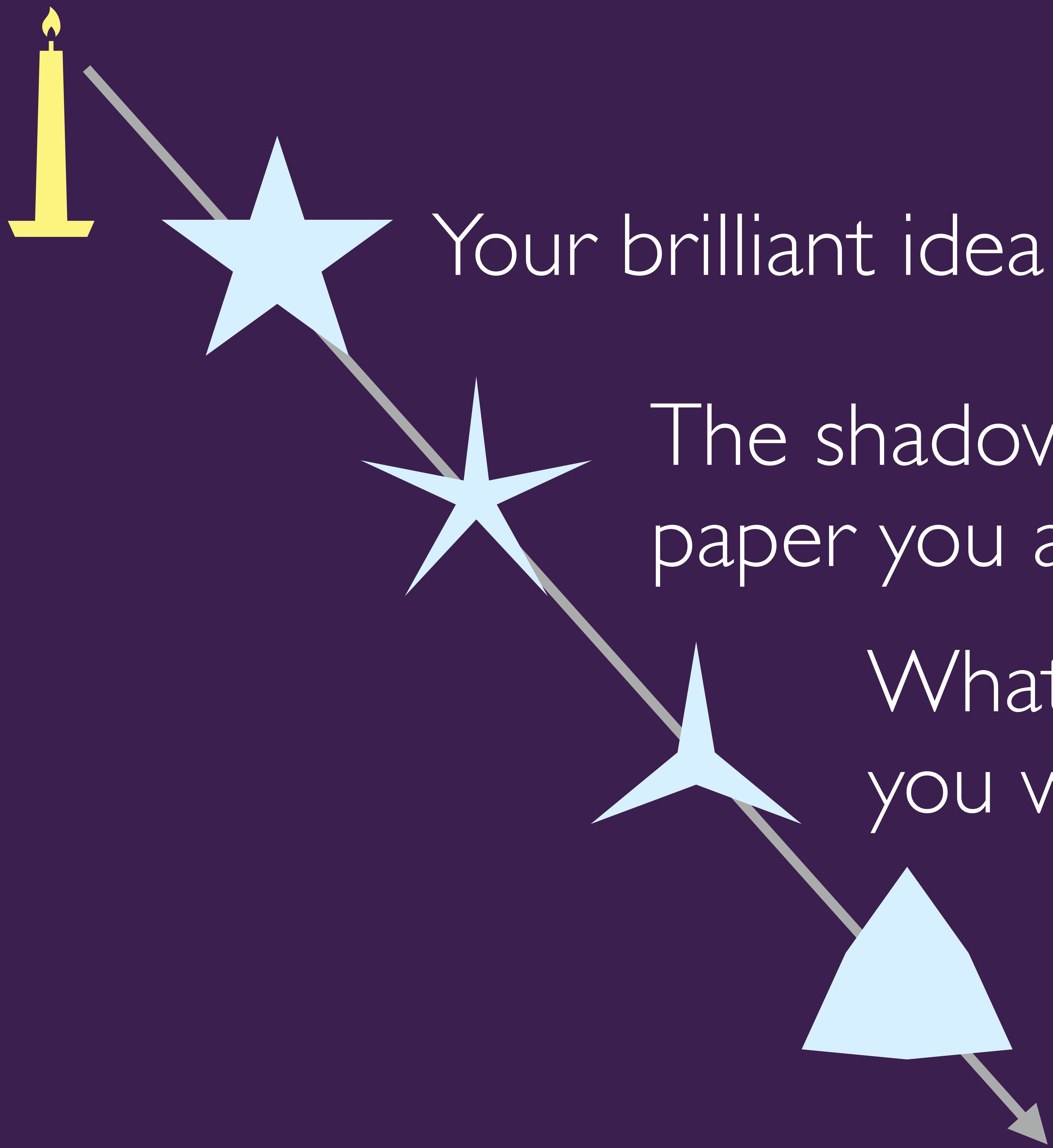
Your paper got in front of the right kind of reviewer, but they didn’t connect with your idea

(Let’s talk about Plato’s Cave…)

Plato’s Cave


Your brilliant idea
The shadow cast by the paper you actually wrote
What reviewers thought you were saying
The shadow cast by their reaction in the review you read

Plato's Cave



Your brilliant idea

The shadow cast by the paper you actually wrote

What reviewers thought you were saying

The shadow cast by their reaction in the review you read

Your goal: invert the transformation to understand what really needs to change about your idea or its presentation.

Corollary: don't take the feedback literally.

“They get it”

These reviews are the really good kind of burn. It hurts because they’re right.

- You can shortcut the Plato’s Cave process here, and take their advice more at face value.

Possible outcomes

Non-exclusive options

- Reframe the paper: reconsider your bit flip (“what is the goal?”)
- Perform additional engineering or evaluation work (“how well did the paper achieve the goal?”)

Revise and resubmit

I have, multiple times, transitioned a paper from a reject to a very successful submission.

Did those papers get in front of more sympathetic reviewers? Maybe.

Did those papers benefit from a more refined vision, execution, and articulation? Absolutely.

In some cases, rejection is actually the best outcome. I'd rather have a paper rejected, iterate, and then make impact, than barely get a paper accepted and never have the impact it could have had.

What questions do you have?

Your journey has just started!

What’s Next?

Continuing CS197 Research

- CAs are happy to continue working with you! Enroll in CS195 units and continue your CS197 project toward a workshop, work in progress, or paper

Work in other labs at Stanford

- We will do outreach to other labs and get PhD student mentors
- We will share the positions and then you can “apply” via email
- CAs will provide a private recommendation to the PhD student mentor you’re applying to

What's Next?

CURIS research

Apply to curis.stanford.edu (Deadline in Dec for summer in 2024)

Feel free to reach out to us if you have any questions about career, academia, etc!

Reminder:

Submit your attendance on Canvas!

Picking Projects