Due Thurs 5/31, 10am:

**Assignment 9:** Draft Talk

5-min talk (+1 min Q&A)

**Note:** Section on Thurs!
Section on Thurs 6/1

Practice Presentation & Peer Review

Final Project Report & Advising: Thurs 6/1 — Wed 6/7

Due Tues 6/13, 3:30pm:

- Final paper, final talk, project due.
- Final exam slot: (3:30-6:30pm): we will meet in 60-109 for presentations!
Overview From Here: 197C

**Small Group meeting** on Thurs 6/1

Practice Presentation

Research mentor feedback due: Tues 6/6

Get feedback on your draft proposal from your research mentor

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!
Grading Scheme

Encourage mastery learning:

If a section of the final paper improves on the original submission, we will upgrade the original assignment grade to the higher final grade.

For example, Introduction assignment was a √, but the Introduction in the final paper was a √+ —> Update original to √+

Conversely, final submissions that do not address feedback will be penalized in the final talk and final paper grades.

If you do not submit anything for an assignment (or make a low-effort submission), you will not be able to improve your grade later for that assignment.
Anonymous Feedback!

Thank you for the feedback!

197:

**Lecture topics**: Project ideation, exploring topics, keeping up-to-date, etc.

**Team dynamics**: CAs have implemented measures and will check in regularly

**Project** — by now, you should have a clear list of TODOs on what to submit to get an A on your project. Please check w/ your CA!

197C:

**Learning goal**: iterate on your bit flip. Hit the ground running come summer!
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 approach, we define "subtypes" that measure spatial and categorical complexity (Section 5).

Based on our analysis, we propose a semi-supervised approach that leverages image-agnostic features to label missing relationships using as few as 1% labeled instances of each relationship. We learn simple heuristics over these features and assign probabilistic labels to the unlabeled images using a generative model \([\mathcal{G}, \mathcal{B}]\). We evaluate our method's labeling efficacy using the completely labeled VQA dataset \([\mathcal{D}]\) and find that it achieves an F1 score of 57.06, which is 11.84 points higher than other standard semi-supervised methods like label propagation \([\mathcal{L}]\). To demonstrate the utility of our generated labels, we train a state-of-the-art scene graph model \([\mathcal{M}]\) (see Figure 6) and modify its loss function to support probabilistic labels. Our approach achieves 47.53 recall@100 for predicate classification on Visual Genome, improving over the same model trained using only labeled instances by 46.97 points. For scene graph detection, our approach achieves within 0.65 recall@100 of the same model trained on the original Visual Genome dataset with 100% more labeled data. We end by comparing our approach to transfer learning, the de-facto solution for learning from limited labels. We find that our approach improves by 5.56 recall@100 for predicate classification, especially for relationships with high complexity, as it generalizes well to unlabeled subsets.

Our contributions are three-fold. (1) We introduce the first method to complete visual knowledge bases by filling missing visual relationships (Section 2). (2) We show the utility of our generated labels in training existing scene graph prediction models (Section 5). (3) We introduce a metric to characterize the complexity of visual relationships and show that our semi-supervised method improves over transfer learning (Section 5).

2. Related work

Traditional knowledge bases were originally hand-curated by experts from sources \([\mathcal{X}]\). Co-occurrences \([\mathcal{C}]\), language statistics \([\mathcal{S}]\), and within-sentence contexts \([\mathcal{I}]\). Scene graph prediction models have dealt with the difficulty of learning from incomplete knowledge, so recent methods utilize statistical methods \([\mathcal{M}]\) or object-relationship dependencies \([\mathcal{D}]\). Unfortunately, such approaches cannot be directly applied to visual relationships, since 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 \([\mathcal{S}]\), co-occurrences \([\mathcal{C}]\), language statistics \([\mathcal{S}]\), and within-sentence contexts \([\mathcal{I}]\). Scene graph prediction models have dealt with the difficulty of learning from incomplete knowledge, so recent methods utilize statistical methods \([\mathcal{M}]\) or object-relationship dependencies \([\mathcal{D}]\). 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 \([\mathcal{T}]\), 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 \([\mathcal{F}]\), and the target domain is a set of limited labeled 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 \([\mathcal{C}]\), auto-annotated learning \([\mathcal{L}]\), multi-instance learning \([\mathcal{L}]\), and domain va-
Today’s goals

Importance of giving a good talk

Goals of a talk

Tips for giving a clear and convincing talk*

*Adapted from Kayvon Fatahalian's talk: “How to give a clear talk”

Please go to http://graphics.stanford.edu/~kayvonf/misc/cleartalktips.pdf for full slides.
Importance of giving a good talk
Before my PhD

Research Breakdown*

Technical
Method, algorithm, system

90%

Communication
Paper writing, talks, twitter

10%

*Sean's opinion
After my PhD

Research Breakdown*

Technical
Method, algorithm, system

Communication
Paper writing, talks, twitter

50%
50%

*Sean's opinion
Common Misconception

If I do good work, people will automatically know, right?

No. In the real world, everyone is very busy....

Unless they are directly working on a problem related to yours, they most likely will spend little energy in understanding your research.

At best, they will likely just come to your conference talk.
By this point, you’ve made a decision about whether to invest the time & energy to keep listening.
Goal of a Talk

1. Your Research Project
   Importance of the problem
   Why your solution is the right one

2. Introduce a new framing or way of thinking
   What the research community can take away and apply to their own research

3. Show that you are a good researcher — your brand!
   The way you pick problems, think about problems, and approach them
“Content Creators”

Catch people’s attention: Good presentation

Content: Good research

Style / Brand: Your way of picking and thinking about problems
Tips for giving a good talk*

*Abridged version of Kayvon Fatahalian’s talk: “How to give a clear talk”

Please go to [http://graphics.stanford.edu/~kayvonf/misc/cleartalktips.pdf](http://graphics.stanford.edu/~kayvonf/misc/cleartalktips.pdf) for full slides.
Tip 13: Present confidently!

Project your voice. Let the back of the room hear you.

Grab people’s attention

Practice makes perfect :)

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Reminder:
Submit your attendance on Canvas!
Giving Talks

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