# CS 594 Deep Representation Learning (DRL)
# Spring 2023

## Course Modality: In person

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| **Instructor:** | **Prof. Xinhua Zhang** (zhangx@uic.edu) |
| **Lecture time:** | **6 ~ 8:40 PM, Wednesday** |
| **Lecture venue:** | **BSB 385 (note NOT TBH anymore)** |
| **Office hours:** (**Zoom + In-person**) | 12-1 PM, Thursday (North End, Level 3, Daley Library)<br>Starting from week 2. |

**Course links (bookmark whenever appropriate)**:

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| **Piazza** | https://piazza.com/uic/spring2023/2023springcs59434724<br>You can register using your UIC netid with no need of instructor's approval. |
| **Master Schedule** | https://piazza.com/class/lcbn89qvlvh588/post/6<br>First register on Piazza as above. This schedule is pinned on top of the left list. |
| **Gradescope** | https://www.gradescope.com/courses/480022<br>It will be used only for the lab, and an auto-grader will be available there.<br>You can log in with School Credentials or via Blackboard (left banner). |
| **Zoom** | https://uic.zoom.us/j/83380974884?pwd=Tm0zZVhJejQydnRnR1Y2dHB2dTBudz09<br>Password for app or computer: Kb4B0HHj Meeting ID: 833 8097 4884<br>Phone No. for dial-in: 312 626 6799 with passcode 30856275<br>**This is for office hour only**. In addition to in-person visits, you can also join **office hours** by Zoom. First come first served on a joint queue. |
| **Blackboard** | Announcement, Echo 360, course project submission, question for reading units, grades |

## Use of Online Tools (see the URLs on the first page)

| What | Where | Who can access | |
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| | | Week 1 and 2 | Week 3 and onwards |
| Slides and other documents | Piazza | Anyone[1] | Registered + Auditing |
| Technical discussion, Q&A | Piazza [2, 3] | Anyone | Registered + Auditing |
| Announcement, project submission, question for reading units, grade | Blackboard [4] | Registered + Auditing | Registered + Auditing |
| Echo 360 of lecture recordings (also streaming in real time) [5] | Blackboard | Registered + Auditing | Registered + Auditing |
| Office hour (not recorded) | **Zoom + In person** | Anyone | Anyone |
| Lab | Gradescope | Registered + Auditing | N.A. |

| for collaboration within groups (but not for instruction) | | |
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| Teams, Slack | Github, Bitbucket | Box.com, Onedrive, Google drive |

1. Anyone refers to anyone with a UIC netid. Contact the instructor if you do not have it.
2. Piazza is highly catered to getting you help fast and efficiently from classmates and the instructor. Rather than emailing questions to the instructor, you are encouraged to post on Piazza your **technical questions**, general questions about the course content, assignments, grading rubric, etc. If you have any problems or feedback for the Piazza developers, email team@piazza.com.
3. If you have any personal or **non-technical questions** such as medical considerations, please send an email directly to the instructor (zhangx@uic.edu). Re-grading of assignments should be requested on Gradescope (not email).
4. For general announcements and notifications, I will send emails to the whole class via **Blackboard**. Please check your email frequently, especially around deadlines (homework and exam). The message will also be recorded on Blackboard in the announcement section.
5. We strongly recommend attending the lectures in person. The online option is only for those who really cannot make it due to health reasons, etc.

**It is your responsibility to check emails frequently (at least once a day).**

## Software and hardware

1. Python for the lab. You can use any language for the course project or reproduction of experiments in the papers.
2. You are required to use collaborative tools for labs and course project, including
    a. Slack or Teams for messaging. UIC does not have license for slack, but the free version might be sufficient.
    b. Github or Bitbucket for code maintenance (free with their respective education packs).
    c. Box, Onedrive, or Google-cloud for file sharing (all free from UIC).

## Eligibility and Pre-requisites

This class is intended for graduate students who are interested in machine learning research. It focuses on machine learning methodology rather than pure application, meaning that it is **not** intended to apply some *existing* learning methods to new application problems. Instead, it requires **nontrivial** novelty in the method itself, targeting publishable quality at NeurIPS, ICML, COLT, UAI, ICLR, AISTATS conferences, as opposed to ICCV, CVPR, ECCV, ACL, EMNLP, NAACL, KDD, WSDM, SIGIR, CIKM, or WWW.

Students are required to have taken and received an 'A' or 'B' in **all** the following courses: CS 412, MATH 310/320, STAT 401, and CS 251.

To ensure that all students understand the math required in course, a self-evaluation will be posted on Piazza under Resources, along with some background math readings.

**If you would like to audit, please send an email to the instructor (zhangx@uic.edu).**

## Course Description

The recent success of deep learning stems in a large part from the capability of neural networks in synthesizing intrinsic (low-dimensional) representations of data, superseding traditional shallow methods that assumes the representation is given. Representation learning has been shown effective for many types of data (images and natural language) with a variety of prior structures (invariance, equivariance, disentanglement), and under a range of learning scenarios (multi-task, multi-modal, domain adaptation, reinforcement learning). It capitalizes on unlabeled data which is often cheap and abundant and sometimes virtually unlimited. It also facilitates the incorporation of diverse desiderata of learning such as fairness, safety, and explainability. We will cover most of the cutting-edge techniques for scalable representation learning and unsupervised/self-supervised learning, especially in the context of deep neural networks, and apply them to important applications.

## Course Materials

40% of the course will be based on textbooks, and 60% on papers. Please consult the Schedule on Piazza for a tentative list of weekly topics. Each week can be either book discussion or paper discussion. The instructor will lead the first few weeks of discussion, followed by student's presentation of chapters and papers.

### Required Texts (available electronically via UIC library or web)

[Murphy] (Chapter 20-28, 32, 33) Kevin Murphy. *Probabilistic Machine Learning: Advanced Topics*. MIT Press, 2023.

[Alpaydin] (Chapter 6 and 18 only) Ethem Alpaydin. *Introduction to Machine Learning*, **3rd** edition. MIT Press, 2014.

### Reference:

[GBC] Ian Goodfellow, Yoshua Bengio, and Aaron Courville, *Deep Learning*. MIT Press, 2016.

[Murphy] provides a very up-to-date distillation of the vast machine learning literature. Some chapters can be viewed as a summary of many recent papers, which makes them good reading materials for this seminar course.

You will need to use numpy in the lab. Here is a numpy primer: Python Data Science Handbook, covering numpy, Pandas, Matplotlib. You should at least know that y = xMatrix[0] is a shallow copy, where xMatrix is a 2-D numpy array. Understand how to make a deep copy. The book provides many notebooks for learning. You can create your Jupyter notebook to run on Google Cloud, or locally on your own machine via VS Code and Anaconda (as opposed to directly downloading Python from the official site). Anaconda is the choice for data science. Data used in this lab has been processed for your convenience.

## Method of Instruction

This class will consist of **three** components:

- Lectures. Background topics in machine and representation learning pertaining to key problems, methods, and challenges in representation learning presented by the instructor.
- Readings and discussions of previous research. Each week, we will read, analyze, and discuss two **reading units**. Each unit is either 1) **a chapter of [Murphy]**, 2) or **a paper deck**, which consists of one primary paper and at most one secondary paper in representation learning.
- Research project. Students will undertake a research project of their interest, relevant to any of the general themes of the course. The project will consist of original research, and will be in groups of 1-3 students (depending on student enrollment). There will be a proposal, a mid-term status review (for any necessary course correction), a final presentation, and a project report.

## Schedule

Here is a tentative list of weekly topics. See a more updated one at the Schedule on Piazza, which also details the tentative paper decks organized in the following topics. Note

- At the end of week 2, we will randomly assign registered students to the reading units.
- Feel free to (and in fact oftentimes should) delve into some papers cited by the paper deck.
- The first paper in each row is the primary one, followed by a secondary paper if any.

| | Topic | Papers |
|---|---|---|
| 1 | Disentangled DRL | Challenging Common Assumptions in the Unsupervised Learning of Disentangled Representations (ICML 2019)<br>Disentangling by Factorising (ICML 2018) |
| 2 | Invariant DRL | (Implicit)^2: Implicit Layers for Implicit Representations (NeurIPS 2021)<br>Proximal Mapping for Deep Regularization (NeurIPS 2020) |
| 3 | Equivariant DRL | Group Equivariant Convolutional Networks (ICML 2016) |
| 4 | Fair DRL | Flexibly Fair Representation Learning by Disentanglement (ICML 2019) |

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| | | On the Fairness of Disentangled Representations (NeurIPS 2019) |
| 5 | Metric/similarity based learning | FaceNet: A Unified Embedding for Face Recognition and Clustering (CVPR 2015)<br>ArcFace: Additive Angular Margin Loss for Deep Face Recognition (CVPR 2019) |
| 6 | Robust DRL | Learning Adversarially Robust Representations via Worst-Case Mutual Information Maximization (ICML 2020)<br>Robust Representation Learning via Perceptual Similarity Metrics (ICML 2021) |
| 7 | Graph representation learning | Semi-Supervised Classification with Graph Convolutional Networks (ICLR 2017)<br>Metapath2Vec: Scalable Representation Learning for Heterogeneous Networks (KDD 2017) |
| 8 | DRL for sequential data (large language model) | Emergent Abilities of Large Language Models (TMLR, 2022) |
| 9 | DRL for meta-learning and continual learning | Meta-Learning Representations for Continual Learning (NeurIPS 2019)<br>Continual Unsupervised Representation Learning (NeurIPS 2019) |
| 10 | DRL for domain adaptation | Implicit Task-Driven Probability Discrepancy Measure for Unsupervised Domain Adaptation (NeurIPS 2020)<br>Domain-Adversarial Training of Neural Networks (JMLR, 2016) |
| 11 | DRL for multi-task learning | Deep Multi-task Representation Learning: A Tensor Factorisation Approach (ICLR 2017)<br>An Overview of Multi-Task Learning in Deep Neural Networks (arXiv:1706.05098) |
| 12 | DRL for reinforcement learning | Reinforcement Learning with Prototypical Representations (ICML 2021)<br>Data-Efficient Reinforcement Learning with Self-Predictive Representations (ICLR 2021) |
| 13 | DRL for neural architecture search (NAS) | Does Unsupervised Architecture Representation Learning Help Neural Architecture Search? NeurIPS 2020 |

| Week | First half (6 – 7:15 PM) | Presenter | Second half (7:25 – 8:40 PM) | Presenter |
|---|---|---|---|---|
| 1 | Syllabus | Prof | Supervised Rep Learning<br>Ch 16 of [Murphy] + U-Net + Ch 6, 9, 10 of [GBC] | Prof |
| 2 | Unsupervised Rep Learning<br>Ch 6 of [Alpaydin] | Prof | Self-supervised Rep Learning<br>(papers) | Prof |
| 3 | Ch 20-21 of [Murphy] | Prof | Paper (deck) #1 | Prof |

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| 4 | Ch 22 of [Murphy] | Group 1 | Paper (deck) #2 | Group 2 |
| 5 | Ch 23 of [Murphy] | Group 3 | Paper (deck) #3 | Group 4 |
| 6 | Ch 24 of [Murphy] | | Paper (deck) #4 | |
| 7 | Ch 25 of [Murphy] | | Paper (deck) #5 | |
| 8 | Ch 26 of [Murphy] | | Paper (deck) #6 | |
| 9 | Ch 19 of [Murphy] | | Paper (deck) #7 | |
| 10 | Ch 27-28 of [Murphy] | | Paper (deck) #8 | |
| 11 | Ch 32 of [Murphy] | | Paper (deck) #9 | |
| 12 | Ch 18 of [Alpaydin] (reinforcement learning) | Prof | Paper (deck) #10 | |
| 13 | Ch 33 of [Murphy] | | Paper (deck) #11 | |
| 14 | Paper (deck) #12 | | Paper (deck) #13 | |
| 15 | Course Project Presentation | | | |

## Papers and Book Chapters

Reading, analyzing, and discussing academic papers is the primary component of this course. To that end, each student is expected to read, **prior to** the class meeting, every paper and book chapter of interest, and come to class prepared to discuss them.

**Reading papers**

Reading and comprehending a research paper can be a challenging activity. When reading a paper, keep these questions in mind:

1. What problem does this work try to solve? (Note that this isn't a question about what technical problem the paper overcomes.)
2. Is this an important problem?
3. Why is prior work (if any) insufficient to solve the problem?
4. What is the proposed solution?
5. What technical contribution does the proposed solution contain?
6. How is the proposed solution evaluated?
7. Is the evaluation reasonable?
8. How would you continue this line of research? (I.e., what future work would you do if you were working on this topic.)

- **Paper/Chapter presentation**

Each unit will be presented by a group of Y=3 students, and these groups will be different from the group of course project. We will randomly form each group of presentation, and randomly determine their roles which are divided into the following categories following this link:

**Librarian:** Some topics may be new for the majority of students in the class. Prepare a very brief lecture to provide just enough background knowledge to equip others with basics of the subject.

**Reviewer:** Complete a full – critical but not necessarily negative – review of the paper. Follow the guidelines for NeurIPS reviewers (under "Review Content"), taking note of the example reviews included therein. In particular, please answer questions 1 to 10 under "Review Content", including assigning an overall score.  The guideline also provides examples.

**Archaeologist:** Determine where this paper sits in the context of previous and subsequent work. Find and report on one prior paper that substantially influenced the current paper and one newer paper that cites this current paper.

**Researcher:** Propose an imaginary follow-up project -- not just based on the current but only possible due to the existence and success of the current paper.

**Industry practitioner:** Propose a new application for the method in the paper (not already discussed in class), and discuss at least one positive and negative impact of this application.

**Hacker:** Implement a small part of the paper on a small dataset or toy problem. Or alternatively, if an official implementation exists just try to break the model -- showcase examples of successful and not so successful results on novel inputs.

**Private Investigator:** Find out background information on one of the paper authors. Where have they worked? What did they study? What previous projects might have led to working on this one? What do you think motivated them to work on this project?

A group's presentation can also cover, but not limited to, the 8 questions under the heading "**Reading papers**".  Each talk will last 40 minutes, leaving 35 minutes for discussion.  To minimize time spent between context switches, students are encouraged to use a shared Google Slide document to include any slides to complement their presentations. Each student should title their slides using a role emoji (e.g. 🧙: Aykut) and present their views about 8-10 mins. Note that the slides will act as a mnemonic and should help to clarify your points -- also note that your presentation role determines what you should include in your slides. The only exception are the hackers, who can perform demos using Jupyter notebooks.

**A few tips from this link:**

- Keep in mind that the class has (or should have) all already read the assigned unit. It is important to present the unit, but the emphasis should be on providing context and either diving more thoroughly into specific aspects of the unit or present follow-on work. You can also briefly talk about your own ideas of how to build upon the paper for future work.

- When going beyond the assigned unit, here you need to slow-down and provide context for the class. The class likely isn't aware of this work and you can't present it at the same pace as you would present the assigned unit.
- Use lots of illustrations and other visual aids. In particular, don't limit yourself to the figures and illustrations that are found in the assigned unit.
- You do **not** have to finish the presentation before opening up the discussions where other students can pitch in on an important point. Do it any time you like.
- You may consult any online resource to help with the presentation, including other papers, blogs, tutorials, talks, or even emails with the author. Make sure they are cited in your slides though.
- You may want to spend 1 or 2 slides describing the competing methods used in the experiments.
- You can weave the questions received from the instructor on Tuesday into the presentation. Put each question in a single slide and go deep in answering it. Do not implicitly give the answers in the presentation. If the answer is you don't know, then maybe skip that question or alternatively open it up to discussion for the class. Also try to pause a couple of times in between the presentation to take questions / comments.

**Grading**: each student is expected to be involved in presenting **Z=22*Y / #enrol** number of units through the semester. If #enrol = 22, then Z ≈ 3. We will adjust the value of Y (presentation group size) in response to #enrol, so that Z stays close to 3. You can earn up to **W=50** points each time you present in your assigned role.

Send the link of Google Slide or PowerPoint file to the instructor by email by 5:50 PM of the day.

- **Discussion & participation**

As a key component of the course, we will discuss the papers and book chapters read in class. Everybody must participate. **For each reading unit, all *non-presenting* students must submit a question on Blackboard by <u>23:59 of the Monday of the same week</u>**. The professor will send some questions to the presenting group on Tuesday noon so that they can prepare. The remaining questions will be reserved for the class in real time.

The question you raise for each reading unit will earn at most **V=5** points, based on how interesting it is.

Here are some examples of **interesting** questions (5 points):

- How does the solution compare with another algorithm A, which bears marked resemblance in the methodology? And why does such a difference matter?
- I think the paper's aim can be achieved by another algorithm that is much simpler. So what's the real advantage of this paper's method?
- Although the experiment has covered A, B, C, I am still not convinced with the paper's superiority in the aspect of XYZ, because …
- I do not find the empirical comparison fair in the following sense …

Here are some **less interesting** questions (3 points):

- What is the computational cost of the algorithm (if it is not so hard to analyze)?
- I propose extending this algorithm by combining it with another existing method (if such a combination is straightforward).

Here are some **boring** questions (1 points):

- Why does Equation 2 imply Equation 3? (unless it is really nontrivial)
- What does the symbol x mean in Equation 2?
- What is the problem addressed by the paper?
- How large is the dataset?

- **(no) Paper summary**

While many CS 594 courses involve writing a structured paper summary for each week's reading, I decide **not to do so**, because most likely, chatGPT can do an even better job here. So I decided to use questions to help you focus your thoughts about the papers.

## Course research project

The course project is perhaps the most rewarding assignment in CS 594. You may do in any area of machine learning, including those not covered in class. **The project will consist of original research.** Since this course focuses on machine learning methodology rather than pure application, the project is **not** meant to apply some existing learning algorithms to a new application problem. Instead, it requires nontrivial novelty in the method itself, which targets publishable quality at ICML, NeurIPS, COLT, UAI, ICLR conference, instead of ICCV, CVPR, ECCV, ACL, EMNLP, NAACL, KDD, WSDM, SIGIR, or WWW.

Course projects are to be conducted in groups of 1-3 students, and will be proposed and completed throughout the semester. You can find teammates by going to Piazza, and a random grouping will be organized as the last resort. To find the email address (i.e., netid) by first and last name, try https://www.uic.edu/apps/find-people. You can form groups by yourselves (**which is different from reading unit presentation**). The evaluation criteria are invariant to the group size.

The submitted work must be the student's (or the group's) own work. If working in a group, each member of the team will receive the same grade; the group is responsible for making a fair division of work between its members. It is important that you keep the final project in mind throughout the entire semester. Groups that form and research ideas for topics early will have more time to realize their goals (and an easier time, too) than a group that devises their topic on the night before the project proposal is due.

One or multiple members of each group will give a presentation for **10–15** minutes on the last week of class about your project, and submit a short 5–8 page writeup (in NeurIPS format). The goal is to have the resulting writeup to be of sufficient quality and novelty to submit to a workshop or conference in machine learning.

**Deadlines**

- One-page project proposal: Jan 31 at 23:59.
- Two-page project status update: March 3 at 23:59.
- Project presentations will take place in class on Wed, April 26.
- Final report: April 28 at 5 PM. If the project works out especially well, the NeurIPS deadline will be just around the corner by the end of the course.

## Exams

There are no exams.

## Lab

There will be a Jupyter lab on PCA to help you kick start using numpy. It does **not** need to be submitted and an auto-grader will be provided on Gradescope for your self-evaluation.

## Evaluation Criteria

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| Reading unit questions | 5 * **19** = 95 points |
| Reading unit presentations | 50 * **3** = 150 points |
| Project | 250 points |
| Lab 1 | 0 points |

Your letter grade will be an A if you get at least 85% of the total points, B if 70% to 84.99%, C if 55% to 69.99%, and F if below 55%. I reserve the right to raise your letter grade.

## Course Policies

**Academic dishonesty will not be tolerated.** Please see the CS department policy below on the topic; this policy specifies penalties for violations. Academic misconduct will be handled according to UIC's Student Disciplinary Policy: http://dos.uic.edu/conductforstudents.shtml

What is academic dishonesty? To hand in any work which is not 100% the student's creation, unless you are explicitly allowed to do so.

### Collaboration Policy

1. **Presentation of reading units**: Discussion with other students is permitted. However, you must stick with the role that is assigned randomly to you. You must create the slides by yourself, although some figures and illustrations can be brought from elsewhere (but do cite them properly!).

2. **Questions for reading units**: discussion with other students is permitted. However, each student must formulate and organize his or her own questions.

3. **Course project:** all members of each group should make nearly the same amount of contribution to each lab and project. All members should be responsible for the whole submission of the team, not only his/her own contributed part. You are supposed to understand the work of your teammates inside out and be able to answer questions when asked. If one member plagiarized, then **all members** of the team will receive the **same** penalty.

   For computer programs, if we cannot determine which team copied from which, we may, at our discretion, give failing grades to both groups. It is the responsibility of all engineering and computer science professionals to safeguard their company's "trade secrets." An employee who allows trade secrets to be obtained by competitors will almost certainly be fired. So, YOU are responsible for making sure that your directories have permissions set so that only you can read your files, for being sure to log out at the end of working in the computer lab, etc.

**Policy for Missed or Late Evaluation**

1. **Late submissions**: Unless specified otherwise, all deadlines will be Chicago time. Late submissions will not be accepted in any case, unless there is a **documented** personal emergency. Arrangements must be made with the instructor as soon as possible after the emergency arises, preferably well before the homework due date.

   Presentation of reading units cannot be made up. If you have to miss it due to, e.g., medical emergency, discuss with the instructor as early as possible.

   **Advice:** If for whatever reason you don't manage to finish an assignment (finding a super interesting question, preparing a perfect presentation), move forward with what you have. Partial credit will be given.

2. **Statute of limitations**: No grading questions or complaints — no matter how justified — will be listened to **TWO** weeks after the grade in question has been released.

**Religious Holidays**

Students who wish to observe their religious holidays shall notify the faculty member by the tenth day of the semester of the date when they will be absent. The faculty member shall make every reasonable effort to honor the request, not penalize the student for missing the class, and if an examination or assignment is due during the absence, give the student an exam or assignment equivalent to the one completed by those students in attendance. If the student feels aggrieved, he/she may request remedy through the campus grievance procedure. http://oae.uic.edu/docs/ReligiousHolidaysFY20152017.pdf

## CS department policy on academic dishonesty

The CS Department will not tolerate cheating by its students. The MINIMUM penalty for any student found cheating will be to receive an F for the course and to have the event recorded in a department and/or College record. The maximum penalty will be expulsion from the University.
Cheating includes all the following, though this is not a complete list:

- Copying or any other form of getting or giving assistance from another student during any test, quiz, exam, midterm, etc.
- Plagiarism–turning in writing that is copied from some other source.
- Obtaining solutions to homework by posting to the Internet for assistance, purchasing assistance, obtaining copies of solutions manuals for instructors, and obtaining copies of previous year's homework solutions.
- Computer programs: Any time you look at another student's code, it is cheating. (Exception: If you are EXPLICITLY told that you may do so by the instructor.)

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