CMPT 419

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2025-09-03

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Preface

This website contains the CMPT 419 / 980 Fall 2025 Course Materials. It was produced using "Quarto".

To learn more about Quarto books visit https://quarto.org/docs/books.

Outline

You can find the course outline here. The content will also be pasted at the end of this Introduction Chapter for your convenience.

Syllabus and Course Content

If there's anything you're looking for you can't find in this site, check the Canvas homepage – all internal-facing content is there (lecture recordings, notes, etc.).

The syllabus file describe the overall structure of the course and course policies.

The readings page will be updated weekly.

I will post coding assignments here as the semester goes in (note that assignments from previous offerings are online, as I make these GitHub pages public. Some changes will be made to the assignments). The GitHub will list the requirements and grading scheme. Submission will be via Canvas.

Outline Text

Artificial intelligence (AI) technologies have seen a large surge in interest from researchers, investors, businesses, and everyday end-users. These technologies stand on the shoulders of giants – they rely on a large body of research in computing and other fields, as well as modern feats of engineering from organizations that operate them. However, they also rely heavily on data, and thus, people.

Search engines rely on click data from users and content written by volunteers such as blogs and Wikipedia articles. Recommender systems rely on explicit user feedback (e.g., "star ratings") and behavioral data (e.g., browsing history) that reveal user preferences. Supervised learning relies on crowd workers, volunteers, and sometimes unwitting users (e.g., reCAPTCHA participants) to label images and text. And new generative AI systems rely on the wide swathe of content shared on the web. Without this data generated by the public, technologies that use machine learning and statistical models could not exist. The critical role of data suggests an untapped source of power for data creators, i.e., the broad public. Furthermore, it suggests a number of exciting questions about how a data-centric view can advance both AI research and the development of AI products and other systems.

In this course, we will explore AI technologies with a data-centric, and thus human-centric lens. We will discuss topics such as: - Exposure to foundational reading in interdisciplinary AI - The intersection of humanities scholarship and technical computing aspects of AI - Modern research in data valuation - Relevant work in social computing, including the impact of online platform design choices. - The potential for collective action involving data. How might social movements – ranging from protests that withhold data to movements to collect and share data in the public interest – impact the future of AI? - The economics of data. Students will be introduced to recent work on data markets and unique properties of buying/selling data for AI.

We will read papers on these topics together. Students will work together to synthesize and present knowledge from research papers, and present their own opinions on these topics. The course will centre a structured final project that will enable students to conduct interdisciplinary responsible AI research or bring responsible AI concepts to bear in industry contexts.

Students may benefit from having taken a course in AI, ML, or data science (or have equivalent experience from e.g. an internship, a research project, a personal project).

Example SFU courses: CMPT 310 - Intro Artificial Intelligence CMPT 353 - Computational Data Science CMPT 414 - Computer Vision

Having taken an HCI course or relevant social science course (e.g., sociology, economics) is a plus, but CS students without this experience who want to explore interdisciplinary CS work that is "human-centered" are welcome. Similarly, students in the humanities who have some exposure to data science are also welcome.

We will work through a low-stakes "example assignment" in week 1 so that students can assess their comfort level.

In short, students should ideally be decently comfortable with both (1) working with computational notebooks (Python, R, Julia, etc.), quickly loading and working with quantitative data, training and evaluating machine learning models and (2) reading and critically thinking about new scholarly perspectives and ethical considerations.

This course will include a heavy reading component.

The course will aim to develop the following skills: - students will become more comfortable reading research papers that take an interdisciplinary approach to study AI - students will gain experience presenting information from papers - there will be a project component that incorporates coding - students will be able to articulate some of the ongoing challenges in “human-centric” AI.

Students will gain exposure to the following concepts: - interdisciplinary research in AI - data valuation techniques, and their applications for AI research/practice - social computing

1 Syllabus

CMPT 419 D200, Nicholas Vincent, Spring 2025

1.1 Lectures and Office Hours

See go.sfu.ca for exact location and time.

Office hours TBA (likely after class on Monday + one extra slot + TA office hours to cover more slots for you).

We can have additional office hours by appointment and/or popular demand.

1.2 General structure of our "lecture" time:

- Each Monday (1 hr sessions), we'll briefly discuss the previous week's readings, I'll introduce any readings and assignments for the week, and I'll start the "lecture content" for the week.
- I'll aim to hold at least 5-10 min every Monday to walk through assignments together and take questions. You're welcome to use this time to start working and see if questions arise.
- On Thursday (2 hr sessions), we'll finish lecture content and have a discussion about the lecture/readings for the first hour, and then typically use the second hour for some kind of activity or "lab time". We may use some of this time to work on assignments and projects and to take quizzes or practice quizzes.
- I'll always take questions at the beginning and end of each lecture session. You're always welcome to email me, but I may take 2-3 business days to respond to emails. Asking questions in class will provide a quicker response and your classmates may benefit from your questions as well! Please include "[CMPT 419]" (or CMPT 980) in your email to help me keep track of requests.

This course is designed to have a particularly heavy reading and discussion component. Please be prepared to read quite a bit of material, and to talk about it.

1.3 About course assignments:

Each week has a set of assigned readings:

- There will be a set of mandatory readings.
- There will also be some optional readings. You are encouraged to read the abstracts and/or Introduction sections of the optional readings to see if they align with what you hope to get out of the class. I'll do my best to organize these by theme, and will add more based on the interests you express.
- Each week, you'll submit some relatively brief "reading responses" via Coursys. These will be very lightly graded (there really aren't wrong answers). However, you should be prepared to defend your reading responses live in class (I may cold call students, and you should be able to speak to your reading response in a way that suggests that you did indeed read the required material. You need not agree with the all the arguments presented or understand all the material).
- For reading responses, I strongly recommend against AI assistance. I personally prefer that you submit bullet points rather than bullet points that prompt an LLM to output flowerly text. (I actually read these, and I'm very familiar with all the ChatGPT-isms, and generally don't need to read "This isn't just a great reading suggestion from the professor – it's a groundbreaking article.")

Reading schedule:

- Assigned readings for Week X are considered "finalized" on Monday of the preceding week (Week X-1), and should be completed by Monday of Week X. Each reading response is due immediately before class begins.
  - For example: During class on Monday of Week 2, I'll post and tell you all the required readings for Week 3, which you should finish over the next 7 days.
  - I'll try to provide a solid "look ahead" of course material, but it may be subject to change based on your feedback, course progress, and even current events – so you should check the readings each Monday after class. For instance, in the past, I have extended time to complete readings that students found particularly dense.

1.4 About course organization

The course will be organized roughly in terms of 4 "modules":

- Module 1: Administration and Introduction to Different Frameworks for doing "Human-Centered" or "Data-Centered" Work (Weeks 1-4)
- Module 2: Technical work in data valuation, data scaling, and algorithmic collective action. (Weeks 5-7, 3 in total)
- Module 3: Online platforms, content ecosystems, and data. (Weeks 8-10, 3 in total).

- Module 4: Frontiers in Data Governance: Voting, Markets, and More (Week 11-13, 3 in total).

We will have one assignment per module (coding / data analysis).

1.5 Grading

- 10% reading responses (12 total, drop lowest 2, each worth 1%)
- 20% coding assignments (4 total; 5/5/5/5, drop lowest 1)
- 20% quizzes (2 total; 10/10; may adjust scores for difficulty)
- 50% final project (5% project proposal, 45% actual project; must submit a written document and a presentation for both)

1.6 Course FAQs

Q: Is attendance mandatory?

A: While I won't give you direct marks for attendance, you are highly encouraged to attend class whenever you are able to. I do expect all students to participate in class discussion at some point (i.e. I do want everybody to speak up at least once). I will try to facilitate this "softly" via some cold-calling to discuss reading responses but this will not be strictly enforced (e.g., if circumstances arise, we can meet in office hours to discuss your progress in the course). If a very "loose approach" to soliciting participation isn't working at the mid-point to class, we'll discuss (as a class) alternatives.

I am very supportive of students staying home when sick, and understand a variety of personal situations may arise that prevent you from going to class. You do not need to email me to miss class, but are welcome to ask follow up questions (I may just point you to the class notes and encourage you to talk to your classmates). To earn a high mark in this class, I encourage you to plan to attend all lectures you are able to.

Q: Will this class involve coding?

A: Yes, there will be some coding assignments in the class that are designed to give hands-on experience with certain course concepts. You are free to use a variety of programming languages and tools for these assignments, though will be encouraged to use some "standard" solutions based (primarily: Python for ML and data science related components, Javascript and web-programming for some design components). For coding assignment, LLM assistance will be allowed (with some caveats). I expect available LLM tooling to change quite a bit *during* our semester, so we'll play with tools together as part of the course.

Q: How many assignments will we have?

A: You will complete 4 assignments (involving coding and data analysis) and 1 project.

Q: Can I work in a group?

A: There will be opportunities to do group work, but you must write a contribution statement for everything. You must review all your team's code and writing! Individual assignments that allow group work will have specific details for how this will work.

Q: Are there quizzes, a midterm, and/or a final exam?

A: There will be in-class quizzes, but no "midterm" or "final". They will be announced in advance and some kind of make-up option will be available for sick students. Any "testable" material will be drawn only from in class lecture materials and mandatory readings. The goal of the quizzes is to provide additional incentives to engage with material each week.

Q: What materials do I need?

Reading materials will be provided digitally by the instructor. There will be no single textbook – rather, we will read an assortment of research papers, book chapters, etc. You will be asked to spend some time installing software tools on your own. You will have some flexibility in which tools you choose – there will always be a free option available.

Q: Can I use ChatGPT (etc.)?

A: You may use generative AI tools to assist with your coursework, but must provide complete logs for any outputs you use directly and any artifacts you submit should indicate the provenance of any generative AI outputs.

e.g.

- "This slide was produced by model XYZ"
- "This summary paragraph or code snippet was produced entirely by ChatGPT"
- "This code was generated with the help of ChatGPT, but heavily edited"

Individual assignments may have specific requirements you should pay attention to.

2 Readings

2.1 Week 2

The goal of the week 2 readings is to begin getting some exposure to what different researchers mean when they refer to human and data centered ML/AI. We want to start developing some intuiton for when human-centered practices or data-centred thinking might materially change how we design a system, come up with a research question, or deploy a model.

Reading 2.1: (Chancellor 2023)

First, we'll read "Toward Practices for Human-Centered Machine Learning" by Stevie Chancellor, published in the Communications of the ACM. CACM is a venue in which experts in various fields of computing write broad pieces for the entire computing community.

- How to access: Visit https://cacm.acm.org/magazines/2023/3/270209-toward-practices-for-human-centered-machine-learning/fulltext

Reading 2.2: (Mazumder et al. 2023)

Second, we'll read the Introduction of the DataPerfs paper, published in NeurIPS 2023 Datasets and Benchmarks Track.

- How to access: Visit https://arxiv.org/abs/2207.10062
- Notes: You only need to read the Introduction.

2.1.1 Response Instructions:

1) Please write one to two paragraphs describing why you'd like to work on, or with, ML/AI systems? You can imagine these paragraphs as text you might include in a cover letter. It might be worth expending some serious effort in case you need to use text like this in the future.

2) Please list 1-3 "domains of interest" (e.g., social media, content recommendation, law, health care, mental health, the environment, economics). They can be at any level of granularity (e.g. "AI for health" is OK, as is "AI for oncology"). Similarly to part 1, the purpose of this is to help me identify trends in your interests so I can suggest optional readings that are of interest to you and your classmates!

If you submit any reasonable formatted submission for this reading response, you'll receive full credit. In future response instructions, you might see something along the lines of, "you must quote on of the readings directly to support your point".

For this reading response, you'll submit via Canvas.

3 Assignments

TBA.

4 Project Proposal

4.1 Project Proposal

DEADLINE (Fall 2025): TBA.

We're going to start thinking about our projects relatively early in the term! To scaffold the project ideation, you'll be asked to turn in and present an initial **project proposal** early on in the semester.

You can submit a 1-2 page PDF, text, or Markdown file. Exact length is not critical here: as long as it contains the key ideas, you're good to go.

This proposal is not binding, though you will earn some marks for turning it in and presenting it. You can change your project topic, track, or group after the proposal is submitted (though you're encouraged to stick relatively close to your proposal, just for the sake of your own time).

For the project, you can select from three tracks, described below.

Well before you turn your project in, you will be provided with a much more detailed rubric describing how your project will be graded. For the initial proposal, however, you should just focus on selecting a project that:

- fits your personal interests in the course (including your career goals)
- will give you an opportunity to explore and demonstrate understanding of the key concepts from our readings and lectures.

The two heuristic questions I recommend you ask while brainstorming project ideas:

- Does this project meet the unique individual incentives of all group members (e.g., a chance to work with a particular ML library, a chance to work on a task of interest, a chance to produce a high quality report or prototype to include in my portfolio).
- Does this project offer an opportunity to demonstrate understanding of key concepts from the course? For instance, does it fit into any of the frameworks for human-centered ML and AI that we've seen, or does it relate to any of the calls for data-centric we've seen?

4.1.1 Track 1: Tools and interfaces for human/data-centered AI

Track 1 will be a good fit for front-end focused projects. For this track, you can propose and develop some kind of tool or interface for data-centric AI. This interface might be a web application, mobile application, or even a user-focused CLI prototype.

To fit the project criteria, this tool should help users accomplish some kind of data-related action or some kind of data exploration task. In other words, it should either be targeted at users who want to control the flow of their data, or at data scientists who want to explore data in some way.

Please note that if you're very uncomfortable doing prototyping and frontend development, you may not want to select this track. While I'm happy to support you if you want to learn these topics on the fly, we probably won't have much time to cover core design, frontend, or software engineering concepts in this course, so this project is best suited to students who already have some of those skills and specifically want to use their project work time to advance in this area.

Examples:

- A new interface for interacting with large language models that allows user to save or export conversation data (you might consider forking and contributing to something likehttps://github.com/ollama-webui/ollama-webui)
- A browser extension that helpers user collect and use data generated by their own browsing (e.g. export my YouTube watch history and train a local personalization / recommender system)
- A browser extension that blocks data collection and informs the user how data that's collected might impact AI systems
- A web interface for visually exploring aspects of a dataset, aimed at ML developers

4.1.2 Track 2: ML Project with Data Exploration Component

Track 2 will be the closest to what you might do in a typical project-focused ML course. For this project, you should select a machine learning task of interest and produce a thorough report describing how you might tackle the relevant ML challenges. What will set your project apart from a pure ML focused course is that you will also be asked to conduct a data-centric exploration of the task. This might involve using data valuation techniques we learned in the course, exploring different dataset selection choices, etc.

The DataPerf reading will be particularly useful to projects on this track.

Examples:

- You might select a medical imaging dataset from a research lab or research challenge and show how selecting or deselecting certain training observations impact performance on a carefully chosen held out test set
- You might fine-tune an open language model with a variety of different fine-tuning sets and explore the impact on benchmark performance or quality as perceived by humans

4.1.3 Track 3: Dataset Documentation and AI Auditing

Later in the course, we will discuss some research on dataset documentation and AI auditing. To summarize, this work involves carefully scrutinizing existing datasets and/or the outputs of AI systems to check for potential biases, performance gaps, unusual behavior, etc.

As your project, you might pick a famous dataset or AI system and conduct a systematic documentation effort or "audit".

Examples:

- You might select a popular dataset that's been used to train LLMs like ChatGPT and use a mix of manual inspection and ML-powered investigation to try and understand the demographics of dataset contributors, or biases in the underlying the content.
- A fun example of this might involve a question like, "How much do various fandom communities discussing their favorite movie, book, anime, etc." contribute to the success of ChatGPT?

If you wish to pursue this option, please consult with the instructor first to discuss properly scoping this kind of project (obviously, investigating every single piece of training data underlying ChatGPT will not be possible with the time we have).

References:

- BookCorpus datasheet:https://datasets-benchmarks-proceedings.neurips.cc/paper/2021/file/54229abfcfa5 Paper-round1.pd
- Mozilla's Common Crawl data investigation:https://foundation.mozilla.org/en/blog/Mozilla-Report-How-Common-Crawl-Data-Infrastructure-Shaped-the-Battle-Royale-over-Generative-AI/

4.1.4 Mixing the tracks

If you have an idea for a project that involves mixing multiple tracks, that is totally great! Please let us know via the initial proposal draft.

In particular, mixing tracks might make sense if you have a larger group of students who want to work on multiple parts of a particular problem. For instance, if you want to build a prototype system that hooks up with a ML model and reports the results of a dataset documentation effort, you can definitely do so.

5 Project Rubric

TBA.

References

Chancellor, Stevie. 2023. "Toward Practices for Human-Centered Machine Learning." *Communications of the ACM* 66 (3): 78–85.

Mazumder, Mark, Colby Banbury, Xiaozhe Yao, Bojan Karlaš, William Gaviria Rojas, Sudnya Diamos, Greg Diamos, et al. 2023. "Dataperf: Benchmarks for Data-Centric Ai Development." *Advances in Neural Information Processing Systems* 36: 5320–47.