10-718: Machine Learning in Practice
Fall 2021
Syllabus

Instructor Information

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Class Information

Lecture Time & Location: Tuesday, Thursday, 4:40-6:00pm, MM A14
Lab Time & Location: Wednesday, 4:40-6:00pm, MM A14
Website: https://github.com/dssg/MLinPractice

Course Description

This is a project-based course designed to provide students training and experience in solving real-world problems using machine learning, exploring the interface between research and practice, with a particular focus on topics in fairness and explainability.

The goal of this course is to give students exposure to the nuance of applying machine learning to the real-world, where common assumptions (like iid and stationarity) break down, and the growing needs for (and limitations of) approaches to improve fairness and explainability of these applications. Through project assignments, lectures, discussions, and readings, students will learn about and experience building machine learning systems for real-world problems and data, as well as applying and evaluating the utility of proposed methods for enhancing the interpretability and fairness of machine learning models. Through the course, students will develop skills in problem formulation, working with messy data, making ML design choices appropriate for the problem at hand, model selection, model interpretability, understanding and mitigating algorithmic bias & disparities, and evaluating the impact of deployed models.

Textbook & Software

Textbook: Unfortunately, there is no good textbook that covers all the topics to give a good understanding of how to do ML in the real world. This course will heavily reply on our experiences working on real-world projects, augmented by selected readings from various sources – each week, we'll have selected readings from a variety of sources, listed below.

Software: For project work, we will provide students with access to AWS machines to run larger models. We will also have a PostgreSQL available to store and analyze data but you are not required to use it. Students will be expected to store project code in a shared github repository, so you should create an account if you do not already have one (github.com).

Phone, Laptop, and Device Policy

Because much of the work in this course involves group discussions and responding thoughtfully to your colleagues' progress reports, mobile devices (including laptops, smartphones, tablets, blackberries, palm pilots, apple newton, and tamagotchi) are not permitted for use during the class. If you have a disability or other reason that necessitates the use of a mobile device, please speak to one of the instructors or teaching assistants.

Grading

Note that this course is pass/fail. Throughout the semester, students will work together in small groups on an applied machine learning project that will illustrate the concepts discussed in class and readings.

Graded components will include:

- Weekly project update assignments (10%)
- Midterm take-home exam (20%)
- Write-up on interpretability findings (15%)
- Write-up on fairness findings (15%)
- Group presentation (5%)
- Future research or project proposal (15%)
- Quizzes on readings and concepts (5%)
- Class attendance and participation (10%)
- Submitting weekly check-in and feedback forms (5%)

Projects and Deliverables

Broadly, the course will be divided into three modules: 1) applied end-to-end machine learning pipelines, 2) model interpretability, and 3) fairness in machine learning. Throughout the course, students will work in groups of 4-5 to use an applied project based on a real-world problem to explore the ideas and methods covered in each module in detail. During the project, students will be responsible for several key deliverables:

- Throughout the first module (covering applied ML pipelines), groups will submit short project update assignments on a weekly basis to get feedback on their approach and initial results.
- At the end of the first module, there will be a take-home midterm exam focused on the concepts and skills emphasized in this portion of the course.
- During the interpretability and fairness modules, each group will be responsible for a 15-minute presentation on one of the methods we will consider in class. This presentation should introduce the method at a high level, provide a general understanding of how it works, discuss preliminary results from implementing the method for their project, and give some thought to strengths and weaknesses. A second group will be assigned for each method as a "discussant" both of these groups will need to implement the method before class.
- Also during these modules, groups will each be responsible for apply three of the methods we discuss in the context of their project (one from each day of discussion; note that you may use either an existing implementation or write your own). At the end of the module, the analysis and results obtained with these methods should be written up in the format of an extended technical abstract 3-4 pages in length, detailing the methods, how they were used in their project, findings, and any recommendations.

Additionally, at the end of the semester, each group will be responsible for developing a proposal for future work that draws on the work they have done throughout the semester to describe an existing gap in current state of knowledge about how to apply machine learning methods in practice and suggests an approach to fill this gap. This proposal should be around 7-10 pages in length and can focus either on academic research or an applied project that might be taken on in an industry or public sector setting, but in either case should draw on the concepts and results from the semester to describe potentially valuable directions for new work.

Tentative Schedule

The course is divided into three modules:

1. Applying ML to Practical Problems
2. Understanding ML Models
3. Fairness in ML

Each week, there are three scheduled sessions: On Tuesday and Thursdays, we will meet together as a class for lectures and class discussion. On Wednesdays, we have a lab/recitation time that will be available for your team to meet and work together – in general, you may do so either in the assigned room on campus where course staff will be available or elsewhere. This is scheduled course time and the expectation is that you will use it to work on the class project. Additionally, we may ask to either meet with specific teams during these sessions to give feedback based on your weekly project updates or potentially require the entire class to meet (if, for instance, there is very common feedback relevant to most or all of the groups). Although we're dedicating some time in class to work with your group, please note that successfully completing the project will require considerable work outside of class time as well and will constitute the majority of the “homework” for the course.

Below is a preliminary schedule of the course, including the readings that will be assigned for that week. Please be sure to have read and be prepared to discuss the readings before the specified class session. Most of these topics can be (and often are) the focus of entire courses and generally we'll only scratch the surface, but hopefully inspire you to delve deeper into areas that interest you (and you'll find plenty of open research questions in each). Optional readings are also listed for most sessions which may be of interest to students who wish to delve deeper in a given area as well as provide additional context for your related project work.

Module I: Applying ML to Practical Problems

- **Tuesday, August 31: Introduction**
  On Tuesday, we'll provide an introduction to the class, its goals, and an overview of the applied project we will be using as a motivating example throughout the semester.

- **Thursday, September 2: Project Scoping**
  DUE TODAY: Project team selections

  On Thursday, we'll talk about scoping, problem definition, and understanding and balancing organizational goals. Well before the outset of technical work, a decision needs to be made about whether a given problem can and should be addressed with machine learning: is the problem significant, feasible to solve with a technical approach, and of sufficient importance to the organization that they will devote resources to implementing the solution? How will success be measured? How will (often competing) goals of efficiency, effectiveness, and equity be balanced? During this lecture, we'll also touch on topics surrounding acquiring data and record linkage across systems.

  Required Reading for Thursday:

  - *Data Science Project Scoping Guide* Available Online

  Optional Readings:

  - *Fine-grained dengue forecasting using telephone triage services* by Rehman, NA, et al. Sci. Adv. 2016. Available Online
  - *Deconstructing Statistical Questions* by Hand, D.J. J. Royal Stat Soc. A 157(3) 1994. Available Online
  - *Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning* by Potash, E, et al. KDD 2015.

- **Tuesday, September 7: Obtaining, Storing, and Linking Data**
  On Tuesday, we will look at some of the nuances of obtaining and using data in real-world projects, including a discussion of the strengths and weaknesses of different options for data storage as well as the practical aspects of dealing with linkage of records from many different sources.

  Optional Reading for Tuesday:

- *Data Matching* by Christen, P. Springer (2012). Chapter 2: The Data Matching Process Available Online
- *Big Data and Social Science* edited by Foster, Ghani, et al. Chapter 4: Databases.
- *Broken Promises of Privacy* by Ohm, P. UCLA Law Review. 2009. Introduction and Section 1. Available Online

• **Thursday, September 9: Analytical Formulation and Baselines**
On Thursday, we'll discuss analytical formulation of applied projects. Distinct from the initial scoping, a true analytical formulation of your problem can only come after you have developed an understanding of the data at hand, which in turn will often result in a greater understanding of the problem itself. Here, you'll ask how specifically your label (if relevant) is defined in the data, what types of information are available as features, and what baseline you'll be measure performance against. Very rarely is the appropriate baseline as simple as "random choice" or the population prevalence. Rather, it should reflect what would be expected to happen otherwise: perhaps a simple decision rule that an expert would come up with or even a pre-existing statistical model that the current effort is seeking to replace.

Required Reading for Thursday:

- TBD?
- *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations* by Obermeyer, Z., Powers, B., et al. Science. 2019. Available Online

Optional Readings for Thursday:

- *Always Start with a Stupid Model, No Exceptions* by Ameisen, E. Medium. Available Online
- *Create a Common-Sense Baseline First* by Ramakrishnan. Medium. Available Online
- *Data Science for Business* by Provost and Fawcett. O'Reilly. 2013. Chapter 2: Business Problems and Data Science Available Online

• **Tuesday, September 14: Feature Engineering and Imputation**
In many real-world contexts, expressing domain expertise through thoughtful feature engineering can dramatically improve model performance by understanding what underlying factors are likely to be predictive and helping the model find these relationships. Likewise, most data sets you'll encounter in practice are littered with outliers, inconsistencies, and missingness. Handling these data issues in a smart way can be critical to a project's success. Class on Tuesday will focus on these aspects of dealing with often messy and inconsistent data encountered in applied projects.

Required Reading/Watching for Tuesday:

- Short Video Lecture and corresponding slides

Optional Readings for Tuesday:

- *Missing Data Conundrum* by Akinfaderin, W. Medium. Available Online
- *Feature Engineering for Machine Learning* by Zhang, A. and Casari, A. O'Reilly. 2018. Chapter 2: Fancy Tricks with Simple Numbers Available Online

- *Missing-data imputation* by Gelman, A. Available Online

- **Thursday, September 16: ML Modeling in Practice**
  Class on Thursday will focus on some of the practical aspects of applying machine learning to real-world problems. In other classes, you have implemented and worked with a wide variety of machine learning methods, but where should you start when dealing with a real problem in practice? What is a "reasonable" hyperparameter grid to consider? What pitfalls might you encounter in these situations and how can you avoid them?

  Required Readings for Thursday:

  - TBD?

- **Tuesday, September 21: Model Evaluation Metrics**
  On Tuesday, we'll introduce topics around choosing performance metrics and evaluating classifiers. In most cases, a vast array of methods — each with a number of tunable hyperparameters — can be brought to bear on your modeling question. How do you decide which models are better than others and how can you be confident this decision will generalize into the future when the model is deployed? How should you balance considerations of performance, explainability, and fairness when making these decisions? Are models that are performing equally well all learning the same patterns and generating the same predictions? How should you select one to deploy if they are not? In this class, we'll begin to answer these questions, focusing on the choice of performance metrics how their relate to your project's goals, scope, and formulation.

  Required Readings for Tuesday:

  - TBD?

- **Thursday, September 23: Model Validation Strategies**
  On Thursday, we'll continue the discussion of model evaluation with a focus on validation strategies. Introductory machine learning classes tend to focus on techniques such as k-fold cross-validation to guard against over-fitting, but is this always the best approach in practice? How does your choice of validation strategy relate to the manner in which you are hoping your model will generalize?

  Required Readings for Thursday:

  - *Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure* by Roberts, DR, Bahn, V, et al. Ecography 40:2017. Available Online

  Optional Readings for Thursday:

  - *Time Series Nested Cross-Validation* by Cochrane, C. Medium. Available Online
  - *The Secrets of Machine Learning* by Rudin, C. and Carlson, D. arXiv preprint: 1906.01998. 2019. Available Online
  - *Big Data and Social Science (2nd edition)* edited by Foster, Ghani, et al. Chapter 7: Machine Learning. Available Online

- **Tuesday, September 28: Model Validation Continued**
  On Tuesday, we'll continue our discussion from the previous week, delving into the details of winnowing down a large number of model specifications to one or a handful that perform "best" for some definition of "best". In particular, we'll focus on the common case of machine learning problems with a strong time series component and the desire to balance performance and stability in model selection.

  Required Readings for Tuesday:

  – *Transductive Optimization of Top k Precision* by Liu, LP, Dietterich, TG, et al. IJCAI 2016. Available Online

  Optional Reading for Tuesday:

  – *Evaluating and Comparing Classifiers* by Stapor, K. CORES 2017. Available Online

- **Thursday, September 30: Module I Review**
  On Thursday, we'll take some time to step back and review the concepts we have covered so far, with the goals of help ensure all the projects are on track for the second and third modules, preparing for next week's concept-focused midterm exam, and highlighting what we see as the most important take-aways from this section of the course.

  Required Readings for Thursday:

  – *Three Pitfalls to Avoid in Machine Learning* by Riley, P. Nature. 527. 2019 (Comment) Available Online

  – *Top 10 ways your Machine Learning models may have leakage* by Ghani, R. et al. DSSG Blog. Available Online

- **Tuesday, October 5: Midterm Exam and Group Work (No Class Meeting)**
  We won't meet together as a class this week to provide some extra time for the take-home midterm and to work together to finalize the modeling portion of your project.

- **DUE WEDNESDAY, OCTOBER 6:** Take-home midterm exam

- **Thursday, October 7: Group Work (No Class Meeting)**
  We won't meet together as a class this week to provide some extra time for the take-home midterm and to work together to finalize the modeling portion of your project.

Module II: Understanding ML Models

- **Tuesday, October 12: Model Interpretability Overview**
  Model interpretability can be thought of at two levels: global (how the model works in aggregate) and local (why an individual prediction came out as it did). On Tuesday, we'll focus on the bigger picture: discussing the landscape of model interpretability and well as different use cases and users.

  Required Readings for Tuesday:

- *Explainable Machine Learning for Public Policy: Use Cases, Gaps, and Research Directions* by Amarasinghe, K., et al. arXiv preprint: arxiv/2010.14374 Available Online
- *Benchmarking and Survey of Explanation Methods for Black Box Models* by Bodria, F., et al. arXiv preprint: arxiv/2102.13076 Available Online

- **Thursday, October 14: NO CLASSES – Mid-Semester Break**

- **Tuesday, October 19: Practical Understanding of ML Models**
  On Tuesday, we'll continue our discussion of model interpretability by introducing some simple and practical analyses to perform after the modeling process and what it means to compare performance across model specifications. These methods can help provide a basic understanding of how your model is distinguishing between predicted classes and play an important role in detecting bugs such as leakage.

  Required Readings for Tuesday:

  - TBD?

- **Thursday, October 21: Inherently-Interpretable Methods**
  On Thursday, we'll start our deeper dives into specific methods by looking at inherently interpretable methods, including GA^2M models, RiskSLIM, and Interpretable Decision Sets . Groups will give a 15 minute presentation on each method and then we will spend the remainder of the class session comparing the methods and discussing the use cases in which they may be most appropriate.

  Required Readings **to Skim** for Thursday:

  - *Intelligible Models for HealthCare: Predicting Pneumonia Risk and Hospital 30-day Readmission* by Caruana, R, et al. KDD 2015. Available Online
  - *Optimized Scoring Systems: Toward Trust in Machine Learning for Healthcare and Criminal Justice* by Rudin, C, and Usutn, B. INFORMS Journal on Applied Analytics. 2018. Available Online
  - *Interpretable Decision Sets: A Joint Framework for Description and Prediction* by Lakkaraju, H, et al. KDD 2016. Available Online

- **Tuesday, October 26: Post-Hoc Local Explanations**
  On Tuesday, we'll continue our discussion model interpretability by looking at three methods that can provide local, feature-based explanations without relying on the details of the underlying model: LIME, SHAP, and MAPLE.

  Required Readings **to Skim** for Thursday:

  - *Why Should I Trust You? Explaining the Predictions of any Classifier* by Ribeiro, MT, Singh, S, and Guestrin, C. KDD 2016. Available Online
  - *A Unified Approach to Interpreting Model Predictions* by Lundberg, SM and Lee, S. NIPS 2017. Available Online
  - TBD?
  - *Model Agnostic Supervised Local Explanations* by Plumb, G, Molitor, D, and Talwalkar, AS. NIPS 2018. Available Online

Optional Readings for Tuesday:

- *Explainable machine-learning predictions for the prevention of hypoxaemia during surgery* by Lundberg, SM, Nair, B, et al. Nature Biomed. Eng. 2018. Available Online
- *Explainable AI for Trees* by Lundberg, SM, Erion, G, et al. arXiv preprint: arxiv/1905.04610. Available Online
- TBD?

- **Thursday, October 28: Other Interpretability Methods**
  On Thursday, we'll take a look at some of the other methods people have explored for model interpretability, such as counterfactual (DiCE), influence functions, and example-based methods

  Required Readings **to Skim** for Thursday:

  - *Explaining Machine Learning Classifiers through Diverse Counterfactual Explanations* by Mothilal, R, et al. FAT* 2020. Available Online
  - *Understanding Black-box Predictions via Influence Functions* by Koh, P.W. and Liang, P. ICML 2017. Available Online
  - *Tree Space Prototypes: Another Look at Making Tree Ensembles Interpretable* by Tan, S., et al. FODS 2020. Available Online

- **Tuesday, November 2: Module II Review**
  On Tuesday, we'll wrap up our discussion of ML interpretability with a brief review of the methods we've covered (and what we haven't had time to discuss)

Module III: Fairness in ML

- **Thursday, November 4: ML Ethics and Fairness Overview**
  On Thursday, we'll shift our focus to ethical issues in machine learning, beginning with a discussion of the broader landscape, including questions around privacy, transparency, and accountability.

  Required Readings for Thursday:

  - *Ethics and Data Science* by Loukides, M., Mason, H., and Patil, D.J. O'Reilly (2018). Entire Book (don't worry – it's short!) Available Online
  - TBD Princeton Ethics Case Study

- **DUE FRIDAY, NOVEMBER 5:** Extended Abstract on Interpretability

- **Tuesday, November 9: Intro to Fairness**
  On Tuesday, we'll introduce topics in ML fairness specifically, where we will focus our methods deep dives for the remainder of the semester: Just as important as assessing whether your model is making accurate predictions is determining whether it is doing so in a fair manner. But, what do we mean by fairness? How can you measure it and what can you do to mitigate any disparities you might find? Where in your pipeline can bias be introduced? (spoiler: everywhere). This class will provide a very brief introduction to the expansive field

of algorithmic fairness.

Required Readings for Tuesday:

- *Fairness Definitions Explained* by Verma, S and Rubin, J. Available Online
- *A Theory of Justice* by Rawls, J. 1971. Chapter 1: Justice as Fairness, pp. 1-19. Available Online
- *Racial Equity in Algorithmic Criminal Justice* by Huq, A. Duke Law Journal. 2018. Available Online [Focus on sections: I.B.2, all of section II, III introduction, III.B, and III.D.3]

Optional Readings for Tuesday:

- *Is Algorithmic Affirmative Action Legal?* by Bent, JR. Georgetown Law Journal. 2019. Available Online
- *Does Mitigating ML's Impact Disparity Require Treatment Disparity?* by Lipton, Z, McAuley, J, and Chouldechova, A. NIPS 2018. Available Online
- *Equality of Opportunity* by Roemer, JE and Trannoy, A. 2013. Available Online

- **Thursday, November 11: Pre-Processing FairML Methods**
On Thursday, we'll start exploring fairness-enhancing methods by specifically looking at pre-processing methods that work upstream of the machine learning models themselves in hopes of reducing downstream biases in the pipeline. In particular, we will focus on three strategies: removing sensitive attributes (and correlated features), re-sampling the training data, or generating synthetic data for model training.

Required Readings **to Skim** for Thursday:

- *Interventional Fairness: Causal Database Repair for Algorithmic Fairness* by Salimi, B., et al. SIGMOD 2019. Available Online
- *Data preprocessing techniques for classification without discrimination* by Kamiran, F. and Calders, T. Knowledge Information Systems (2012). Available Online
- *Tuning Fairness by Balancing Target Labels* by Kehrenberg, T., et al. Frontiers in Artificial Intelligence (2020). Available Online
- TBD?

Optional Readings for Thursday:

- *Fairness Through Awareness* by Dwork, C, Hardt, M, et al. ITCS 2012. Available Online

- **Tuesday, November 16: In-Processing FairML Methods**
On Tuesday, we'll look at in-processing methods for improving fairness by adding constraints (or regularization terms) to the optimization performed during model training, focusing on methods proposed by Zafar, Celis, and Microsoft Research.

Required Readings **to Skim** for Tuesday:

- *Fairness Constraints: Mechanisms for Fair Classification* Zafar, M, Valera I, et al. PMLR 2017. Available Online

  - *Classification with fairness constraints: A meta-algorithm with provable guarantees* by Celis, E, Huang, L, et al. FAT* 2019. Available Online
  - *Fairlearn: A toolkit for assessing and improving fairness in AI* by Bird, S., et al. Microsoft Research Whitepaper (2020). Available Online

  Optional Readings for Tuesday:

  - *Fairness Beyond Disparate Treatment & Disparate Impact: Learning Classification without Disparate Mistreatment* by Zafar, M., et al. WWW 2017. Available Online

- **Thursday, November 18: Post-Process FairML Methods**
  On Thursday, we'll turn to post-processing methods, including fairness-aware model selection, decoupled models, and post-hoc score adjustments.

  Required Readings **to Skim** for Thursday:

  - *Promoting Fairness through Hyperparameter Optimization* by Cruz, A.F., et al. arXiv preprint: arxiv/2103.12715 Available Online
  - *Decoupled Classifiers for Group-Fair and Efficient Machine Learning* by Dwork, C, et al. PMLR 2018. Available Online
  - *Equality of Opportunity in Supervised Learning* by Hardt, M. and Price, E. NIPS 2016. Available Online
  - TBD?

  Optional Readings for Thursday:

  - *Case study: predictive fairness to reduce misdemeanor recidivism through social service interventions* by Rodolfa, K.T., et al. FAT* 2020. Available Online

- **Tuesday, November 23: Module III Review**
  On Tuesday, we'll wrap up our discussion of ML interpretability with a brief review of the methods we've covered (and what we haven't had time to discuss)

- **Wednesday, November 24: NO CLASSES – Thanksgiving**

- **Thursday, November 25: NO CLASSES – Thanksgiving**

- **Tuesday, November 30: Field Trials**
  On Tuesday, we'll briefly discuss field trials and issues of causality, critical for understanding how your model actually generalizes to real-world applications. Even with careful planning and handling of the data, the only way to truly understand how well your model works is by testing it in the field. Generally, you're concerned not only with its predictiveness, but the actual ability of the model to help the program achieve its policy goals, such as improving outcomes among the population it serves. Typically, this involves working closely with policy makers to develop a field trial using either randomization or non-experimental methods depending on the constraints of the setting.

  Required Readings for Tuesday:

  - *The seven tools of causal inference, with reflections on machine learning* by Pearl, J. Comm ACM. 2019 Available Online

Optional Readings for Tuesday:

- *Elements of Causal Inference* by Peters et al. MIT Press. Chapters 1 and 2. Available Online (Open Access Link)

- **DUE WEDNESDAY, DECEMBER 1:** Extended Abstract on Fairness

- **Thursday, December 2: Wrap-Up**
  On Thursday, we'll wrap up the course with a review of the topics we've covered throughout the semester and some comments on the important take-home messages we hope will be useful in your future research and work.

- **DUE DECEMBER 9 (Finals Week): Research/Project Proposal**
  Based on the results of your project work throughout the semester as well as the methods and approaches we have discussed, each group will write a final report (due December 9) proposing a direction for future work as described above.

More Resources

You may find a number of books useful as general background reading on specific topics covered in class, but these are by no means required texts for the course:

- *Big Data and Social Science* edited by Foster, Ghani, et al. Available Online
- *Practical Fairness: Achieving Fair and Secure Data Models* by Nielsen
- *Fairness and Machine Learning* by Barocas, Hardt, and Narayana
- *Weapons of Math Destruction* by O'Neil
- *Exploratory Data Analysis* by Tukey
- *Data Science for Business* by Provost and Fawcett

Additionally, the Global Communication Center (GCC) can provide assistance with the written or oral communication assignments in this class. The GCC is a free service, open to all students, and located in Hunt Library. You can learn more on the GCC website: cmu.edu/gcc.

Your Responsibilities

Attendance: Because much of this course is focused on discussion with your classmates, attending each session is important to both your ability to learn from the course and to contribute to what others get out of it as well. As such, you'll be expected to attend every session and your participation will factor into your grade as described above. Should anything come up will require you to miss a class (illness, conferences, etc), please let one of the course staff know in advance.

Academic Integrity: Violations of class and university academic integrity policies will not be tolerated. Any instances of copying, cheating, plagiarism, or other academic integrity violations will be reported to your advisor and the dean of students in addition to resulting in an immediate failure of the course.

Resources

Students with Disabilities: We value inclusion and will work to ensure that all students have the resources they need to fully participate in our course. Please use the Office of Disability Resource's online system to notify us of any necessary accommodations as early in the semester as possible. If you suspect that you have a disability but are not yet registered with the Office of Disability Resources, you can contact them at access@andrew.cmu.edu

Health and Wellness: As a student, you may experience a range of challenges that can interfere with learning, such as strained relationships, increased anxiety, substance use, feeling down, difficulty concentrating and/or lack of motivation. These mental health concerns or stressful events may diminish your academic performance and/or reduce your ability to participate in daily activities. CMU services are available, and treatment does work.

All of us benefit from support during times of struggle. There are many helpful resources available on campus and an important part of the college experience is learning how to ask for help. Asking for support sooner rather than later is almost always helpful.

If you or anyone you know experiences any academic stress, difficult life events, or feelings like anxiety or depression, we strongly encourage you to seek support. Counseling and Psychological Services (CaPS) is here to help: call 412-268-2922 and visit their website at cmu.edu/counseling/. Consider reaching out to a friend, faculty or family member you trust for help getting connected to the support that can help.

If you or someone you know is feeling suicidal or in danger of self-harm, call someone immediately, day or night:

CaPS: 412-268-2922
Re:solve Crisis Network: 888-796-8226
If the situation is life threatening, call the police
On campus: CMU Police: 412-268-2323
Off campus: 911

Discrimination and Harassment: Everyone has a right to feel safe and respected on campus. If you or someone you know has been impacted by sexual harassment, assault, or discrimination, resources are available to help. You can make a report by contacting the University's Office of Title IX Initiatives by email (tix@andrew.cmu.edu) or phone (412-268-7125).

Confidential reporting services are available through the Counseling and Psychological Services and University Health Center, as well as the Ethics Reporting Hotline at 877-700-7050 or www.reportit.net (user name: tartans; password: plaid).

You can learn more about these options, policies, and resources by visiting the University's Title IX Office webpage at https://www.cmu.edu/title-ix/index.html

In case of an emergency, contact University Police 412-268-2323 on campus or call 911 off campus.

Student Academic Success Center (SASC)

SASC focuses on creating spaces for students to engage in their coursework and approach learning through a variety of group and individual tutoring options. They offer many opportunities for students to deepen their understanding of who they are as learners, communicators, and scholars. Their workshops are free to the CMU community and meet the needs of all disciplines and levels of study. SASC programs to support student learning include the following (program titles link to webpages):

- Academic Coaching – This program provides holistic, one-on-one peer support and group workshops to help undergraduate and graduate students implement habits for success. Academic Coaching assists students with time management, productive learning and study habits, organization, stress management, and other skills. Request an initial consultation here.
- Peer Tutoring – Peer Tutoring is offered in two formats for students seeking support related to their coursework. Drop-In tutoring targets our highest demand courses through regularly scheduled open tutoring sessions during the fall and spring semesters. Tutoring by appointment consists of ongoing individualized and small group sessions.You can utilize tutoring to discuss course related content, clarify and ask questions, and work through practice problems. Visit the webpage to see courses currently being supported by Peer Tutoring.
- Communication Support – Communication Support offers free one-on-one communication consulting as well as group workshops to support strong written, oral, and visual communication in texts including IMRaD and thesis-driven essays, data-driven reports, oral presentations, posters and visual design, advanced research, application materials, grant proposals, business and public policy documents, data visualisation, and team projects. Appointments are available to undergraduate and graduate students from any discipline at CMU. Schedule an appointment on their website (in-person, zoom synchronous, or recorded video), attend a workshop, or consult handouts or videos to strengthen communication skills.
- Language and Cross-Cultural Support – This program supports students seeking help with language and cross-cultural skills for academic and professional success through individual and group sessions. Students can get assistance with writing academic emails, learning expectations and strategies for clear academic writing, pronunciation, grammar, fluency, and more. Make an appointment with a Language Development Specialist to get individualized coaching.
- Supplemental Instruction (SI) – This program offers a non-remedial approach to learning in historically difficult courses at CMU. It utilizes a peer-led collaborative group study approach to help students succeed and is facilitated by an SI leader, a CMU student who has successfully completed the course. SI offers a way to connect with other students studying the same course, a guaranteed weekly study time that reinforces learning and retention of information, as well as a place to learn and integrate study tools and exam techniques specific to a course. Visit the website to see courses with SI available here.