10-718, 94-889: Machine Learning for Public Policy Lab
Spring 2020
Syllabus

Instructor Information

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Class Information

Time & Location: Tuesday and Thursday, 3:00-4:20pm, GHC 4307
Website: https://github.com/dssg/mlforpublicpolicylab

Course Description

This is a project-based course designed to provide students training and experience in solving real-world problems using machine learning, with a focus on problems from public policy and social good.

Through lectures, discussions, readings, and project assignments, students will learn about and experience building end-to-end machine learning systems, starting from project definition and scoping, through modeling, to field validation and turning their analysis into action. Through the course, students will develop skills in problem formulation, working with messy data, communicating about machine learning with non-technical stakeholders, model interpretability, understanding and mitigating algorithmic bias & disparities, and evaluating the impact of deployed models.

Students will be expected to know python, and have prior coursework in machine learning.

Textbook & Software

Textbook: The course will rely on selected readings from various sources and has no required textbook – 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 a shared data and ML infrastructure. Data will be available in a postgreSQL database and SQL and python will be used throughout the course. 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). **More Details to follow.**

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

Throughout the semesters, 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:

- Written scope and proposal for their project work (10%)

- Peer reviews of three peer project proposals (2.5%)

- Technical ML plan for their project (2.5%)

- Detailed feature list for their project (2.5%)

- Two technical deep-dive group presentations on the current progress of their project work (7.5% each)

- Draft of research proposal section for the final project report (5%)

- Draft of field trial design section for the final project report (5%)

- Final group presentation of results targeted towards policy stakeholders (15%)

- Written final project report and code (20%)

- Class participation during discussion of readings and group deep dives (15%)

- Other assignments (10%)

- Submitting weekly check-in and feedback forms (5%)

The data used for the course projects should be considered sensitive and private and must remain in the secure computing environment provided for the course. **Any attempt to download any portion of the project data to a machine outside this environment will result in automatic failure of the class.** Note that you may use tools like SQL clients, jupyter notebooks, etc. to interact with the data on the remote servers, but may not save the dataset (or a portion of it) to disk on a local machine.

Applied ML Project

Beginning in the second week of class, groups of 4 or 5 students will work together on a machine learning project throughout the semester with one of several real-world public policy problems. Each week, every group will be expected to provide a quick (2 minute) check-in on their current status and two groups will provide a 20 minute deep-dive on their progress, with a focus on how the week's topic applies to their problem. In addition to helping connect readings and discussion topics to an applied domain, these deep dive presentations will give you a chance to elicit input and feedback from your classmates about challenges you're facing (and they likely are too!) in your analyses.

Throughout the semester, students will be responsible for several intermediate deliverables as they work on their group projects:

- An initial project proposal, submitted as a group, including the project scope and preliminary descriptive statistics about the entities in their dataset. The proposal should be 4-5 pages in length, not including figures, tables, or references.

- A technical ML plan, submitted as a group, how the scope described in their proposal can be formulated as a machine learning problem and the elements of the pipeline the group will be building.

- A description of specific features to be built for the modeling project, submitted as a group and describing the underlying data, level at which information is available, aggregation strategies (e.g., over time or geography), and plan for handling missing values.

- A draft of the research proposal section of the final report, 2-3 pages in length.

- A draft of the field trial design section of the final report, 2-3 pages in length.

At the end of the semester, each group will be responsible for a final presentation (10 minutes in length plus 3 minutes for questions). While the deep dive presentations should be more technical in nature, the final presentation should be geared towards the relevant decision makers for your project, including an overview of the problem and approach, your results, policy recommendations, and limitations of the work.

Accompanying the final presentation is a written report, approximately 15 pages in length, which should include:

- An executive summary not to exceed 1 page that succinctly describes the project, results, and recommendations.

- An overview of the problem, its significance, and the scope and goals of the current work.

- A description of the methodology and results of the analysis. The report should also provide a link to well-documented code in your group's course github repository.

- Design of a field trial to evaluate the accuracy of the resulting model in practice as well as its ability to help the organization achieve its goals.

- A proposal for future avenues of research beyond the scope of this work, for instance on novel machine learning methods to improve on the current work, new policy interventions to evaluate or explore, or other related research opportunities.

- Concluding lessons and recommendations for the partner organization.

Tentative Schedule

In general, the course will be structured around two sessions each week:

- During the Tuesday sessions, each group will give a 2 minute status update on their project work highlighting progress and stumbling blocks, followed by a discussion of the week's topic and readings.

- During the Thursday sessions (starting in the fourth week of class), two or three groups will give 20 minute deep dive presentations on their projects and how it relates to the week's topic.

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.

- **Week 1 (Jan 13–17): Introduction and Project Scoping**
  On Tuesday, we'll provide an introduction to the class, its goals, and an overview of the project options to help you decide what you're interested in working on for the remainder of the semester.

  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 policy 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 policy makers 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?

  Required Readings for Thursday:

    - *Data Science Project Scoping Guide* Available Online

– *Using Machine Learning to Assess the Risk of and Prevent Water Main Breaks* by Kumar, A, Rizvi, SAA, et al. KDD 2018. Available Online

Optional Reading:

– *Deconstructing Statistical Questions* by Hand, D.J. J. Royal Stat Soc. A 157(3) 1994. Available Online

- **Week 2 (Jan 20–24): Case Studies and Acquiring Data**
  This week, we'll organize groups and begin project work

  Practical examples can provide a great way to gain an understanding of the nuance of applying machine learning to policy problems, so Tuesday will focus on a class discussion of the two case studies of recent applications that have been deployed in the real world.

  Required Readings for Tuesday:

  – *Fine-grained dengue forecasting using telephone triage services* by Rehman, NA, et al. Sci. Adv. 2016. Available Online
  – *Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning* by Potash, E, et al. KDD 2015. Available Online
  – *What Happens When an Algorithm Cuts Your Health Care* by Lecher, C. 2018. (The Verge) Available Online

  On Thursday, we'll delve into some of the details of acquiring data, protecting privacy, and linking records across data sources. Acquiring data from a project partner is often an involved process with a number of legal and technical aspects. Researchers need to understand how the data acquired may and may not be used (typically formalized in a data use agreement as well as underlying law) and ensure that the privacy of individuals in the dataset is protected (potentially both through access restrictions and techniques like anonymization). One data has been acquired, it often needs to be transformed to ingest into the system used for analysis, records from multiple data sources linked, and data structured for further analysis.

  Optional Readings:

  – *Broken Promises of Privacy* by Ohm, P. UCLA Law Review. 2009. Introduction and Section 1. Available Online
  – *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.

- **Week 3 (Jan 27–31): Data Exploration and ML Pipelines Overview**
  Work on your project during this week should include continuing to develop and refine your scope as you begin to explore the data. You'll also need to prepare and load some data into a database in order to make use of it in your modeling.

  Tuesday of this week will provide a crash course in exploratory data analysis. Data exploration is fundamental to developing an understanding of the nuances of the data and how the policy problem you initially scoped can be specifically formulated as a machine learning

problem. This process involves generating and plotting summary statistics, exploring trends over time and understanding rapid changes in distributions, as well as identifying missing data and outliers. Typically, data exploration should involve considerable input from domain experts as you develop an understanding of how the data relates to the underlying generative process, as well as its idiosyncrasies and limitations.

Required Reading for Tuesday:

– TBD reading on data exploration
– *Practical Statistics for Data Scientists* by Bruce, A. and Bruce, P. O'Reilly (2017). Chapter 1: Exploratory Data Analysis Available Online

On Thursday, we'll describe the components of typical machine learning pipelines. End-to-end ML Pipelines can quickly become unwieldy with several moving pieces and well-structured, modular code is often critical to detecting and fixing bugs in the process. This session will provide an overview of the pipeline, each underlying element, and some best practices for building them.

Required Reading for Thursday:

– *Architecting a Machine Learning Pipeline* by Koen, S. (Medium) Available Online

Optional Readings:

– *Data Analysis, Exploratory* by Brillinger. Available Online
– *Meet Michelangelo: Uber's Machine Learning Platform* by Hermann, J and Del Balso, M. Available Online

- **Week 4 (Feb 3–7): Analytical Formulation and the Importance of the Baseline**
  Thursday of this week will include the first set of deep dive presentations. At this point in your project work, you should be developing your initial end-to-end pipeline.

  Due Thursday, Feb. 6: Project proposal with scope and descriptive statistics.

  Distinct from the initial scoping, a true analytical formulation of your policy 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 target variable (if relevant) is defined in the data, what types of information are available as predictors, 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 Readings for Tuesday:

  – *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations* by Obermeyer, Z., Powers, B., et al. Science. 2019. Available Online
  – *Always Start with a Stupid Model, No Exceptions* by Ameisen, E. Medium. Available Online

Optional Readings:

- *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

- **Week 5 (Feb 10–14): Feature Engineering and Imputation**
  Pipeline development should be continuing in your project, with a focus on producing the simplest-possible version of the full system.

  Due Thursday, Feb. 13: Peer reviews of three project proposals.

  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.

  Required Readings for Tuesday:

  - *TBD Case Study on Feature Development* by TBD. Available Online
  - *Missing Data Conundrum* by Akinfaderin, W. Medium. Available Online

  Optional Readings:

  - *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

- **Week 6 (Feb 17–21): Choosing Performance Metrics and Evaluating Classifiers, Part I**
  By this week, your group should have a very simple version of an end-to-end pipeline with preliminary results for a single model specification.

  Due Thursday, Feb. 20: Technical modeling plan

  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 carry forward into the future when the model is deployed? How should you balance considerations of performance and fairness when making these decisions? Are models that are performing similarly well giving similar predictions? What should you do if they are not? In this week, we'll begin to answer these questions, focusing on cross-validation stategies and choosing performance metrics.

  Required Readings for Tuesday:

  - *Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure* by Roberts, DR, Bahn, V, et al. Ecography 40:2017. Available Online
  - *The Secrets of Machine Learning* by Rudin, C. and Carlson, D. arXiv preprint: 1906.01998. 2019. Available Online

Optional Readings:

- *Big Data and Social Science* edited by Foster, Ghani, et al. Chapter 5: Machine Learning.

- **Week 7 (Feb 24–28): Choosing Performance Metrics and Evaluating Classifiers, Part II**
During this week, your pipeline development and refinement should continue with a widening set of model specifications and features to explore.

  This week, 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:

  - *Evaluating and Comparing Classifiers* by Stapor, K. CORES 2017. Available Online
  - *Transductive Optimization of Top k Precision* by Liu, LP, Dietterich, TG, et al. IJCAI 2016. Available Online

- **Week 8 (Mar 2–6): Overfitting, Leakage, and Issues in Deployment**
By this week, your group should have a preliminary set of "correct but crappy" results reflecting a relatively simple model grid and the features you prioritized to build as a first pass.

  So you think you have a great model, you've "validated" it on holdout data, and you're all ready to go... Models can fail to generalize to novel data data in a multitude of ways and this week we'll be exploring some of the reasons that things can go wrong in building models for real-world deployment. Issues like overfitting and leakage can threaten the external validity of your model even in the context of a stable world, but changes in policies and data collection techniques pose considerable challenges as well.

  Required Readings for Tuesday:

  - *Three Pitfalls to Avoid in Machine Learning* by Riley, P. Nature. 527. 2019 (Comment) Available Online
  - *Leakage in Data Mining* by Kaufman, S., Rosset, S., et al. TKDD. 2011. Available Online
  - *Why is Machine Learning Deployment Hard?* by Gonfalonieri, A. Medium. Available Online

  Optional Readings:

  - *Data Science for Business* by Provost and Fawcett. O'Reilly. 2013. Chapter 5: Overfitting and Its Avoidance Available Online
  - *Overview of Different Approaches to Deploying Machine Learning Models in Production* by Kervizic, J. KDnuggets. Available Online

- **Week 9 (Mar 16–20): Model Interpretability, Part I**
At this point, your group should be continuing to refine and expand on your preliminary modeling results.

Due Thursday, Mar. 19: Refined feature list

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). This week, we'll focus on the bigger picture: understanding how a model is performing globally and what it means to compare this performance across model specifications.

Required Readings for Tuesday:

- *Interpretable Classification Models for Recidivism Prediction* by Zeng, J, Ustun, B, and Rudin, C. J. Royal Stat. Soc. A. 2016. Available Online
- *Intelligible Models for HealthCare: Predicting Pneumonia Risk and Hospital 30-day Readmission* by Caruana, R, et al. KDD 2015. Available Online

- **Week 10 (Mar 23-27): Model Interpretability, Part II**
  By this week, project work should be beginning to focus more heavily on evaluation, model selection, and interpretation.

  This week, we'll look at the other side of interpretability, with a focus on several practical applications of local explanations: they can help researchers debug and improve their models, build trust among stakeholders (including a growing legal movement towards a "right to explanation"), help those acting on model predictions understand when they should override the model with their judgement, and importantly help those actors decide not only on whom to intervene but suggest what sort of intervention to take.

  Required Readings for Tuesday:

  - *Why Should I Trust You? Explaining the Predictions of any Classifier* by Ribeiro, MT, Singh, S, and Guestring, C. KDD 2016. Available Online
  - *Model Agnostic Supervised Local Explanations* by Plumb, G, Molitor, D, and Talwalkar, AS. NIPS 2018. Available Online
  - *Explainable machine-learning predictions for the prevention of hypoxaemia during surgery* by Lundberg, SM, Nair, B, et al. Nature Biomed. Eng. 2018. Available Online

  Optional Readings:

  - *A Unified Approach to Interpreting Model Predictions* by Lundberg, SM and Lee, S. NIPS 2017. Available Online
  - *Explainable AI for Trees* by Lundberg, SM, Erion, G, et al. arXiv preprint: arxiv/1905.04610. Available Online

- **Week 11 (Mar 30–Apr 3): Algorithmic Bias and Fairness, Part I**
  By this week, you should be finalizing your modeling results and beginning to look at bias and disparities in your models.

  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 week 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:

- *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

- **Week 12 (Apr 6–10): Algorithmic Bias and Fairness, Part II**
  During this week, your group should be continuing to investigate any disparities in your model results as well as performing any other necessary post-modeling analyses.

  Due Thursday, Apr. 9: Draft research proposal section for your final report.

  This week, we'll continue our discussion of bias and fairness with a very brief survey of practical considerations and open research questions in the rapidly-developing field.

  Required Readings for Tuesday:

  - *A case study of algorithm-assisted decision making in child maltreatment hotline screening decisions* by Chouldechova, A, Putnam-Hornstein, E, et al. PMLR. 2018. Available Online
  - *Equality of Opportunity in Supervised Learning* by Hardt, M. and Price, E. NIPS 2016. Available Online
  - *Classification with fairness constraints: A meta-algorithm with provable guarantees* by Celis, E, Huang, L, et al. FAT* 2019. Available Online

  Optional Readings:

  - *Fairness Through Awareness* by Dwork, C, Hardt, M, et al. ITCS 2012. Available Online
  - *Fairness Constraints: Mechanisms for Fair Classification* Zafar, M, Valera I, et al. PMLR 2017. Available Online
  - *Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments* by Chouldechova, A. Big Data. 2017. Available Online

- **Week 13 (Apr 13–17): Causality and Field Validation**
  Note: No classes on Thursday, April 16, so there will be no deep dive this week. By this week, you should be wrapping up any remaining technical work and beginning to put together results for your group's final report and presentation.

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
- *TBD Case study with field trial (Lead paper?)* by TBD. Available Online

Optional Readings:

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

- **Week 14 (Apr 20–24): From Analysis to Action, Accountability and Transparency**
  This week will be the last week of deep dive presentations. By this week, your group should be well into the process of preparing your final report and presentation.

  Due Thursday, Apr. 23: Draft field trial design for your final report.

  For a machine learning practitioner, developing a model is only one aspect of the job. They must also be able to communicate about what their models can and (importantly) cannot achieve to non-technical stakeholders, as well as develop a strategy for deploying their models in a manner that allows for ongoing monitoring of performance and equity measures along with continual improvement through feedback about errors. Too often overlooked (especially when "black box" models are deployed by third party contractors to agencies with little capacity to maintain them), these considerations are critical to the long-term success of a project.

  Both practitioners and researchers of machine learning and artificial intelligence additionally have a responsibility to act in an ethical way and consider the broader social impact of their work. However, reasonable people can disagree on exactly what constitutes ethical behavior and transparency isn't necessarily a goal in its own right (nor even desirable in all cases, such as where bad actors could game a system).

  Required Readings for Tuesday

  - *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
  - *Communicating Data with Tableau* by Jones, B. O'Reilly (2014). Chapter 1: Communicating Data Available Online
  - *Teaching Statistics: A Bag of Tricks* by Gelman, A and Nolan, D. O'Reilly (2014). Chapter 11: Lying with Statistics Available Online

Optional Readings:

- *Designing Effective Tables* CMU GCC [Available Online](#)
- *Improving Data Displays* by Wainer, H. Chance. 2007 [Available Online](#)
- *Making Data Talk* National Cancer Institute. 2011 [Available Online](#)
- *The Visual Display of Quantitative Information* by Tufte, E. Graphics Press. 2001.

- **Week 15 (Apr 27–May 1): Final Presentations**
  During this final week of classes, each group will give a presentation about their applied ML project as described above.

- **Finals Week (May 4–7): Final Report Due**
  Incorporating the results of your project work throughout the semester as well as feedback from your final presentation, each group will write a final project report (due date TBD) as described above.

More Resources

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

- *Big Data and Social Science* edited by Foster, Ghani, et al.

- *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.

Data Security: As noted above, the data used for the project work in this course should be considered sensitive and care must be taken to protect the privacy of those in the dataset. The data must remain on the computing environment provided for the class and attempts to download it to any other machine will result in failure of the course.

Additionally, care must be taken to avoid accidentally committing any raw data, queries containing identifiable information, or secrets (key files, database passwords, etc) to github. Should this occur, or should you have any reason to believe your personal computer or private key has been compromised, you must immediately notify the course staff of the issue.

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.