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Achim Koh, Visiting Assistant Professor

Pratt Institute School of Information

144 W. 14th St., 6th Floor

New York, NY 10011-7301

Email: akoh7@pratt.edu

URL: https://scalarvectortensor.net

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INFO 697-03: Machine Learning

Fall 2020

Class Hours: Tuesdays, 6:30p – 9:20p

Office Hours: By appointment

Credits: 3

Prerequisites: INFO 654 Information Technologies, or by permission

Location: PMC 606

Course Description:

Machine learning is a rapidly growing field that develops algorithms for tasks such as data classification and prediction. These algorithms are programmed to operate and adjust themselves independently of human intervention (i.e., to learn), allowing data work to occur quickly and at scale. Machine learning is a key technology behind the automation across many social areas today, often branded AI.

This course offers an introduction to machine learning as a practical tool that we can use, and as a technological field with social implications. We will learn about key concepts in machine learning; survey a few key machine learning techniques, such as supervised methods for machine learning (regression and classification), which attempt to map data onto desired outputs, and unsupervised methods (clustering and association), which attempt to find structure within data itself; use openly available tools to implement these techniques on text and image data; learn how to assess the effectiveness of different techniques on particular datasets; and discuss basic issues that confront all machine learning methods.

Readings, class discussions, and hands-on sessions will be complemented by guest lectures (TBD) from machine learning practitioners. Students will be assessed via a final project developed throughout the course, in addition to the project proposal, presentation, class participation, and lab assignments.

This syllabus is a living document; expect it to evolve over the course of the semester. All changes will be communicated in class and the updated syllabus will be uploaded on LMS. Since this is a new course, your participation and input will be crucial in shaping it to your needs. Feel free to ask questions and give feedback or suggestions, in person or via email, as we move into the semester.

Course Goals:

The goals of this course are to:

* introduce students to key concepts and some common techniques in machine learning, as well as openly available tools
* help students to develop technical and critical thinking skills regarding machine learning
* enable students to conduct a machine learning experiment and communicate the result of their project

**Student Learning Outcomes:**

By the end of the course, students will be able to:

* describe different machine learning methods, including their limitations
* select an appropriate machine learning method for a given use case
* implement machine learning algorithms and assess their performance
* execute a machine learning experiment using openly available tools
* support the design of their experiment by discussing both the technical aspect and the topic’s significance

**Course Schedule and Readings:**

**> Week 1 - 8/27: Introduction – What is Machine Learning?**

Readings:

|  |
| --- |
| * Meredith Broussard, *Artificial Unintelligence*, ch.2-3 (13-39) – via LMS |
| * Gideon Lewis-Kraus, “The Great A.I. Awakening” http://web.archive.org/web/20161215073155/https://www.nytimes.com/2016/12/14/magazine/the- great-ai-awakening.html |
| * Noah Lorang, Data scientists mostly just do arithmetic and that’s a good thing, <https://m.signalvnoise.com/data-scientists-mostly-just-do-arithmetic-and-thats-a-good-thing/> * David Donoho (2017) 50 Years of Data Science, Journal of Computational and Graphical Statistics, 26:4, 745-766, https://www.tandfonline.com/doi/full/10.1080/10618600.2017.1384734 |

Lab: Getting started with Python, Git

Assignment: Data Collection

**> Week 2 - 9/3: Data, Bias, Communication**

Readings:

* Paul Ford, “What is Code?” <https://www.bloomberg.com/graphics/2015-paul-ford-what-is-code/>
* Lisa Gitelman (ed.), “Raw Data” Is an Oxymoron, introduction (1-14) http://raley.english.ucsb.edu/wp-content/Engl800/RawData-excerpts.pdf
* Lessons from the pulse model, <https://thegradient.pub/pulse-lessons/>
* Wickham, H. (2014). Tidy Data. Journal of Statistical Software, 59(10), 1 - 23. doi:http://dx.doi.org/10.18637/jss.v059.i10
* This is how AI bias really happens—and why it’s so hard to fix, https://www.technologyreview.com/2019/02/04/137602/this-is-how-ai-bias-really-happensand-why-its-so-hard-to-fix/
* O'Neil, C. (2016). The Ethical Data Scientist. <https://slate.com/technology/2016/02/how-to-bring-better-ethics-to-data-science.html>
* Wong, D. M. (2010). The Wall Street Journal guide to information graphics: The dos and don'ts of presenting data, facts, and figures. WW Norton.
* Drucker, J. (2011). Humanities approaches to graphical display. Digital Humanities Quarterly, 5(1), 1-21.
* Chun, W. H. K. (2005). On software, or the persistence of visual knowledge. grey room, 26-51. via LMS

Supplemental Material:

* Prabhu, V. U., & Birhane, A. (2020). Large image datasets: A pyrrhic win for computer vision?. arXiv preprint arXiv:2006.16923.
* Konold, C., Finzer, W., & Kreetong, K. (2017). Modeling as a Core Component of Structuring Data. Statistics Education Research Journal, 16(2).
* Galloway, A. (2015). “The Computational Decision” <http://cultureandcommunication.org/galloway/the-computational-decision>
* Podcast: Peter Wang (part 1/2): CEO/founder Anaconda, Creator of PyData https://podcasts.apple.com/us/podcast/peter-wang-part-1-2-ceo-founder-anaconda-creator-of-pydata/id1478016790?i=1000459268650

Lab: Working with data in Python, Visualization

Assignment:

**> Week 3 - 9/10: intro to supervised learning, linear models**

Due: Lab assignment #1 (submit by 9/9)

Readings:

* A visual introduction to machine learningURL
* Daly, L. (2017) “AI Literacy: The basics of machine learning”. https://worldwritable.com/ai-literacy-the-basics-of-machine-learning-2e20f93e34b4
* Gene Kogan and Francis Tseng, “Fundamentals, introduction to machine learning” https://github.com/ml4a/ml4a-guides/blob/master/notebooks/fundamentals.ipynb
* James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). Chapter 2.1 (15-28)
* Müller, A. C., & Guido, S. (2016). Introduction to machine learning with Python: a guide for data scientists. ". Chapter 2.1, 2.2 (27-84)

Supplemental Material:

* Khan Academy, “Least-squares regression equations” (MOOC module, playlist) https://www.khanacademy.org/math/statistics-probability/describing-relationships-quantitative-data/regression-library/v/introduction-to-residuals-and-least-squares-regression

Supplemental Material:

Lab: Introduction to scikit-learn

**> Week 4 - 9/17: Classification continued; regression; gradient descent**

Readings:

* James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). Chapter 8 (303-332)
* Müller, A. C., & Guido, S. (2016). *Introduction to machine learning with Python: a guide for data scientists*. ". Chapter 2.3 (31-121)
* Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press. Chapter 5.1 (96-105)
* [Chris Deotte, “Classifier Playground” http://www.ccom.ucsd.edu/~cdeotte/programs/classify.html](Chris%20Deotte,%20“Classifier%20Playground”%20http://www.ccom.ucsd.edu/~cdeotte/programs/classify.html)
* Kearns, M., & Roth, A. (2019). The ethical algorithm: The science of socially aware algorithm design. Oxford University Press., chapter 1

Lab:

**> Week 5 - 9/24: Unsupervised learning - clustering, mixture models**

Due: Lab assignment #2 (submit by 9/23)

Readings:

* Müller, A. C., & Guido, S. (2016). *Introduction to machine learning with Python: a guide for data scientists*. ". Chapter 3 (133-210)
* James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). Chapter 10 (373-412)
* Kearns, M., & Roth, A. (2019). The ethical algorithm: The science of socially aware algorithm design. Oxford University Press., chapter 2

Supplemental Material:

* Privacy and ML, two unexpected allies http://www.cleverhans.io/privacy/2018/04/29/privacy-and-machine-learning.html
* Ji, Z., Lipton, Z. C., & Elkan, C. (2014). Differential privacy and machine learning: a survey and review. *arXiv preprint arXiv:1412.7584*.

Lab: Features and parameters; model evaluation; data prep

**> Week 6 - 10/1: Project planning**

In the first part of this class, students will share project ideas and give each other feedback.

Readings:

* Patrick Hebron, “Rethinking Design Tools in the Age of Machine Learning” <https://medium.com/artists-and-machine-intelligence/rethinking-design-tools-in-the-age-of-machine-learning-369f3f07ab6c>
* M.C. Elish and Tim Hwang, An AI Pattern Language, <https://datasociety.net/pubs/ia/AI_Pattern_Language.pdf>
* Lovejoy, J. & Holbrook, J. (2017). Human-Centered Machine Learning. https://medium.com/google-design/human-centered-machine-learning-a770d10562cd
* O'neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Broadway Books. ch.1 & conclusion (1-31, 199-218) – via LMS

Supplemental Material:

* [Example projects and resources: https://www.are.na/achim-koh/ml-design-ish](file:///Users/Amiros/GitHub/Machine_Learning_Pratt/Example%20projects%20and%20resources:%20https:/www.are.na/achim-koh/ml-design-ish) (The linked list is a preliminary one and will be updated; also, the examples are meant primarily as inspirations, and do not indicate what the final project should look like)

Lab:

**> Week 7 - 10/8: NO CLASS - Midterm break**

**> Week 8 - 10/15: Model evaluation, tuning, dimensionality reduction, feature processing**

Due: Project proposal (submit by 10/13)

Readings:

* Müller, A. C., & Guido, S. (2016). *Introduction to machine learning with Python: a guide for data scientists*. ". Chapter 5 (253-304)
* James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). cp 2.2 (28-42)
* Limitations of Interpretable Machine Learning, <https://compstat-lmu.github.io/iml_methods_limitations/>

Lab: Introduction to TensorFlow

**> Week 9 - 10/22: Neural networks**

Readings:

* Müller, A. C., & Guido, S. (2016). *Introduction to machine learning with Python: a guide for data scientists*. ". Chapter 2.3.8 (106-121)
* Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press. Chapter 6, 7.8
* The Coding Train, “10: Neural Networks - The Nature of Code” (YouTube playlist) https://www.youtube.com/playlist?list=PLRqwX-V7Uu6aCibgK1PTWWu9by6XFdCfh
* 3Blue1Brown, “Neural Networks” (YouTube playlist) <https://www.youtube.com/playlist?list=PLZHQObOWTQDNU6R1_67000Dx_ZCJB-3pi>
* Daniel Smilkov and Shan Carter, “A Neural Network Playground” https://playground.tensorflow.org/

Lab: TensorFlow continued

Guest Speaker: TBD

**> Week 10 - 10/29: Neural Networks - contd**

Due: Lab assignment #3 (submit by 10/28)

This will be a lab-focused session. We will learn about data pipelines, re-using your models, etc. Then, we will workshop your project with the main goal of verifying that you are on track with the class timeline.

Readings:

* Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press. Chapter 9, 10, 11
* Chris Deotte, “Neural Network Playground” http://www.ccom.ucsd.edu/~cdeotte/programs/neuralnetwork.html
* Daniel Shiffman, The Nature of Code, ch.10 <https://natureofcode.com/book/chapter-10-neural-networks/>
* Andrew Ng. Nuts and Bolts of Applying Deep Learning https://www.youtube.com/watch?v=F1ka6a13S9I

Supplemental Material:

* Machine Learning with Differential Privacy in TF <http://www.cleverhans.io/privacy/2019/03/26/machine-learning-with-differential-privacy-in-tensorflow.html>

**> Week 11 - 11/5: Cloud, pre-trained models, MLOps, ML products – Project workshop**

Readings:

* Shan Carter and Michael Nielsen, “Using Artificial Intelligence to Augment Human Intelligence” <https://distill.pub/2017/aia/>
* MLOps, <https://cloud.google.com/solutions/machine-learning/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning>
* Andrew Ng. Transfer Learning. https://www.youtube.com/watch?v=yofjFQddwHE
* Podcast: Data Science in the Cloud (with Paige Bailey). <https://www.datacamp.com/community/podcast/data-science-in-the-cloud>

Supplemental Material:

* Podcast: Jitendra Malik: Computer Vision. https://lexfridman.com/jitendra-malik/

Guest Speaker: TBD

Lab: Project workshop

**> Week 12 - 11/12: Human-Centric AI, Fairness**

Readings:

* Alex Galloway, “Are Algorithms Biased?” http://cultureandcommunication.org/galloway/are-algorithms-biased
* Blaise Agüera y Arcas, Margaret Mitchell and Alexander Todorov, “Physiognomy’s New Clothes” https://medium.com/@blaisea/physiognomys-new-clothes-f2d4b59fdd6a
* Diana ben-Aaron, “Weizenbaum examines computers and society” http://tech.mit.edu/V105/N16/weisen.16n.html
* Julia Angwin et al., “Machine Bias” https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing
* Shannon Mattern, “The Ethics of Automating Design” https://wordsinspace.net/shannon/2019/02/13/the-ethics-of-automating-design/
* Roelof Pieters and Samim Winiger, “Creative AI: On the Democratisation & Escalation of Creativity” https://medium.com/@creativeai/creativeai-9d4b2346faf3
* Cathy O'Neil. Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy, Ch 1 (15-31)
* coding is for everyone - as long as you speak english, https://www.wired.com/story/coding-is-for-everyoneas-long-as-you-speak-english/
* Patrick Hebron, “Rethinking Design Tools in the Age of Machine Learning” https://medium.com/artists-and-machine-intelligence/rethinking-design-tools-in-the-age-of-machine-learning-369f3f07ab6c
* Wrongfully Accused by an Algorithm https://www.nytimes.com/2020/08/03/podcasts/the-daily/algorithmic-justice-racism.html
* is your algorithm racist? <https://www.politico.com/agenda/story/2018/02/07/algorithmic-bias-software-recommendations-000631/>
* West, S.M., Whittaker, M. and Crawford, K. (2019). Discriminating Systems: Gender, Race and Power in AI. AI Now Institute. https://ainowinstitute.org/discriminatingsystems.pdf

Lab:

**> Week 13 - 11/19: Labor and Machine Learning**

This will be a lab-focused session that introduces unsupervised learning, which is a different ML paradigm than supervised learning (such as classification and regression).

Lab: Clustering algorithms

Readings:

* Siddhartha Mukherjee, “AI Versus MD” http://web.archive.org/web/20170427141526/http://www.newyorker.com/magazine/2017/04/03/ai- versus-md
* where will predictive text take us? <https://www.newyorker.com/magazine/2019/10/14/can-a-machine-learn-to-write-for-the-new-yorker>
* How three French students used borrowed code to put the first AI portrait in Christie’s. https://www.theverge.com/2018/10/23/18013190/ai-art-portrait-auction-christies-belamy-obvious-robbie-barrat-gans https://www.theverge.com/2018/10/23/18013190/ai-art-portrait-auction-christies-belamy-obvious-robbie-barrat-gans
* Cade Metz, “A.I. Is Learning From Humans. Many Humans.” https://www.nytimes.com/2019/08/16/technology/ai-humans.html
* Why Are Good Jobs Disappearing if Robots Aren’t Taking Them? Part I and II, https://points.datasociety.net/why-are-good-jobs-disappearing-if-robots-arent-taking-them-9f8d4845302a
* Algorithmic Management in the workplace, <https://datasociety.net/wp-content/uploads/2019/02/DS_Algorithmic_Management_Explainer.pdf>

Supplemental Material:

* Shannon Mattern, “Maintenance and Care” https://placesjournal.org/article/maintenance-and-care/
* Rosenblat, A. (2018). *Uberland: How algorithms are rewriting the rules of work*. Univ of California Press.
* Kate Crawford and Vladan Joler, Anatomy of an AI System <https://anatomyof.ai/>
* Astra Taylor, “The Automation Charade” https://logicmag.io/failure/the-automation-charade/

**> Week 14 - 11/26: Be a Good Engineer! Software Abstraction, Reproducibility, Open Source**

Due: Lab assignment #4 (submit by 11/25)

This will be a lab-focused session that continues on the theme of unsupervised learning.

Lab: Dimensionality reduction; visualization

Readings:

* Nick Seaver, “Knowing Algorithms” https://digitalsts.net/essays/knowing-algorithms/
* Good enough practices in scientific computing; Greg Wilson, Jennifer Bryan, Karen Cranston, Justin Kitzes, Lex Nederbragt, Tracy K. Teal (2017).
* Causey, Tray. Software development skills for data scientists. http://treycausey.com/software\_dev\_skills.html
* Why Is Open-Source So Important? Part One: Principles And Parity, <https://www.forbes.com/sites/charlestowersclark/2019/09/24/why-is-open-source-so-important-part-one-principles-and-parity/#5882840961f7>
* Production ML systems. https://developers.google.com/machine-learning/crash-course/production-ml-systems

Supplemental Material:

* The Practice of Reproducible Research; Justin Kitzes, Daniel Turek, Fatma Deniz (2018). <https://www.practicereproducibleresearch.org>
* docker for DS <https://www.kdnuggets.com/2018/01/docker-data-science.html>

**> Week 15 - 12/3: ML Industry, Data Science Career**

Readings:

* Shana Lynch, “Andrew Ng: Why AI Is the New Electricity” https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity
* Market your data science like a product, <https://medium.com/indeed-engineering/marketing-for-data-science-a-7-step-go-to-market-plan-for-your-next-data-product-60c034c34d55>
* Imposter syndrome in data science; Caitlin Hudon (2018). https://caitlinhudon.com/2018/01/19/imposter-syndrome-in-data-science/
* Doing data science at Twitter https://medium.com/@rchang/my-two-year-journey-as-a-data-scientist-at-twitter-f0c13298aee6
* Podcast: Getting Your First Data Science Job (with Chris Albon). <https://www.datacamp.com/community/podcast/getting-your-first-data-science-job>

Lab: TBD

**> Week 16 - 12/10: Presentations**

Due: Final project (before class)

**Textbooks, Readings and Materials:**

All reading materials and course slides (if applicable) will be provided as hyperlinks or downloadable files through LMS.

Students will need a Google account for certain lab sessions. I believe the Pratt email address can serve this purpose, giving you access to Google Drive and Colab. In the latter part of the course, students will also need an account for Runway ML; details on how to sign up will be provided as needed.

Additional resources including technical tutorials, example projects and datasets, resources about critical discourse, and more are listed on this webpage, and will be updated as necessary: <https://www.are.na/achim-koh/machine-learning-fall-2019>

**Projects, Papers and Assignments:**

**> Readings and Discussions**

Throughout the semester, we will survey diverse perspectives about machine learning as a socially situated technology. The assigned readings will be complemented by in-class discussions, typically at the beginning of the class.

Each week (except for weeks with no readings assigned; see course schedule), one or two students will act as motivators and write provocations on the readings of the week on the LMS forum. This will allow us to start the conversation in advance of class and carry it on afterwards. Please post your provocations by the end of the day Sunday before class.

A provocation will include a summary of key points in the readings, as well as questions / observations you would like to raise or make. The provocations will serve as starting points of the in-class discussion and some of them will scaffold towards the project proposal and final project.

Students who are not motivators for the week are expected to complete the readings before class, and contribute to the discussion in class and/or online by replying to the forum thread.

**> Lab assignments**

The latter part of each class will be a lab session related to the topic of the week. Sometimes, the lab session will be accompanied by a lecture-style session before it; in other cases, we will move into the lab session right after discussions.

At the end of some lab sessions, I will give you take-home assignments (4 total). The assignments will scaffold towards the final project. For example, you will be asked to explain some machine learning terminology or write code that does a specific task. Details on how to submit the homework will be communicated in class. The homework assignments are due by the end of the day Monday before the next class.

I may also ask you to write down the amount of time you spent working on the assignment. This amount of time does NOT affect gradings in any way; I am asking in order to gauge whether I am giving you too much work or whether you are having trouble with some of the course material.

**> Project proposal**

I will ask you to choose a topic that you would like to explore in your final project, and to submit a proposal by mid-semester.

On October 1, we will have an in-class activity where you will share your idea(s) and give peer feedback. Your 800- to 1200-word proposal is due by the end of the day Sunday, October 13, and should include:

* A description of the data you intend to use
* A description of the machine learning task you intend to perform
* A tentative and brief survey of existing work on the topic
* A discussion of the significance of your topic

We will discuss the proposal in further detail in the coming weeks.

**> Final project + presentation**

Your final project is to run an experiment that applies a machine learning technique (such as classification, regression, clustering, etc) that we learned on a dataset of your choice. You can design the project as a complete piece on its own, or as a component of a larger project.

Projects are due before the final class in the form of a write-up detailing your work process; you also need to submit the resulting model / dataset and code used. We will dedicate our class on December 10 to presentations.

A detailed rubric for the project and presentation will be distributed separately.

**Assessment and Grading**

Lab assignments 20%

Participation (discussions and peer feedback) 20%

Project proposal 20%

Final project 30%

Presentation 10%

Pratt’s grading scale:

Superior work: A 4.0 (96-100) A- 3.7 (90-95)

Very good work: B+ 3.3 (87-89) B 3.0 (83-86) B- 2.7 (80-82)

Marginally satisfactory: C+ 2.3 (77-79) C 2.0 (73-76)

Failed: F 0.0 (0-72)

**Portfolio**

Work completed for this course may be included in your portfolio. For more information on each program’s portfolio requirements, please visit the program’s respective webpage:

* MS Library & Information Science: Portfolio - <http://bit.ly/prattmslisportfolio>
* MS Information Experience Design: Portfolio - <http://bit.ly/prattmsixdportfolio>
* MS Data Analytics and Visualization: Portfolio - <http://bit.ly/prattmsdavportfolio>
* MS Museums and Digital Culture: Portfolio - <http://bit.ly/prattmsmdcportfolio>

You are encouraged to meet with your advisor about including projects in your portfolio.

**Policies**

*This Course’s Attendance Policy*

Students are allowed two individual absences for any reason; no notice or documentation is required. If you miss a session, be sure that you complete the readings, consult your classmates or the professor about the class, and (as always) demonstrate your knowledge of previous topics in later sessions. Upon a third or fourth absence, your grade will be lowered by one mark for each absence. Five absences will result in failure of the course (F). Also, please note that a grade of C- is considered failing at the graduate level.

Students who encounter long-term health issues should provide documentation to the Office of Health and Counseling and discuss their options with the professor.

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| **Absences** | **Penalty** | **Examples** |
| 0-2 | None | N/A |
| 3-4 | One mark per absence | A → A- (3rd absence) → B+ (4th absence)  A- → B+ (3rd absence) → B (4th absence)  B+ → B (3rd absence) → B- (4th absence) |
| 5+ | Failure of the course | N/A |

For more information on Pratt Institute’s Attendance Policy, please visit <http://bit.ly/prattattendance>.

*Academic Integrity Code*

Academic integrity at Pratt means using your own and original ideas in creating academic work. It also means that if you use the ideas or influence of others in your work, you must acknowledge them. For more information on Pratt’s Academic Integrity Standards, please visit <http://bit.ly/prattacademicintegrity>.

*Students with Disabilities and Accessibility*

Pratt Institute is committed to the full inclusion of all students. If you are a student with a disability and require accommodations, please contact the Learning/Access Center (L/AC) at [LAC@pratt.edu](mailto:LAC@pratt.edu) to schedule an appointment to discuss these accommodations. Students with disabilities who have already registered with the L/AC are encouraged to speak to the professor about accommodations they may need to produce an accessible learning environment.

Requests for accommodation should be made as far in advance as reasonably possible to allow sufficient time to make any necessary modifications to ensure the relevant classes, programs, or activities are readily accessible. The Learning/Access Center is available to Pratt students, confidentially, with additional resources and information to facilitate full access to all campus programs and activities and provide support related to any other disability-related matters.

For more information, please visit <http://www.pratt.edu/accessibility/>.

*Human Rights, Equity, BERT, and Title IX*

Pratt Institute seeks to provide an environment that is free of bias, discrimination, and harassment. If you have been the victim of harassment, discrimination, bias, or sexual misconduct, we encourage you to report this.

If you inform me (your professor) of an issue of harassment, discrimination or bias, or sexual misconduct I will keep the information as private as I can, but I am required to bring it to the attention of the institution’s Title IX Coordinator. You can access Title IX services by emailing [titleix@pratt.edu](mailto:titleix@pratt.edu). You can also speak to someone confidentially by contacting our non-mandatory reporters: Health Services at 718-399-4542, Counseling Services 718-687-5356 or Campus Ministries 718-596-4840.

In cases of Bias, this information may go to our Bias Education & Response Taskforce (BERT). You can contact BERT by either reaching out directly via [bert@pratt.edu](mailto:bert@pratt.edu) or by contacting the BERT Co-Chair and Title IX Coordinator, Dr. Esmilda Abreu.

For more information, please refer to the Community Standards webpage: <http://bit.ly/prattcommunitystandards>.

*Revisions to the Syllabus*

All changes will be communicated in class and the updated syllabus will be uploaded on LMS. This version is current as of ~~August 26, 2019~~ September 11, 2019.