PLSC 597: Text as Data
Fall 2019

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Description

This course investigates the use of digitized texts – news articles, speeches, laws, treaties, press releases, party manifestos, campaign ads, interviews, transcripts, open-ended surveys, Tweets, Reddit posts, Youtube comments, Yelp reviews ... – as sources of data for social science research.

We'll begin the semester with overviews of the "text as data" field in political science and more broadly in computational social science, as well as the big picture in overlapping fields like "natural language processing" and "computational linguistics." Here we will discuss what sorts of social scientific questions we can address with text as data, and some of the challenges and opportunities of using text as social science data.

We'll then begin discussing the theory and mechanics of how to convert text into data. This will include topics like preprocessing text and related NLP tasks (e.g., stemming, tokenizing) and representing text as data (e.g., bag-of-words, word embeddings, measures of association), as well as discussion of the downstream consequences. We'll start the semester assuming we're working with "clean" text, but throughout the course of the semester we will have exercises and/or mini-tutorials about some of the more practical data science issues when dealing with real-world "dirty" text (e.g., file encodings, file formats, data that has been poorly transcribed, thumb-typed, or OCRed) and of obtaining or sharing text in the first place (e.g., the mechanics and ethics of web scraping).

We'll then turn to the major approaches to measuring social science concepts with textual data, including rule-based methods, supervised learning from human-coded or known examples, and unsupervised methods from matrix decompositions to generative Bayesian measurement models. As we go, we will discuss particular measurment objectives like classification, scaling, topic modeling, and analysis of sentiment and stance, as well as ways of validating our models. We will in parallel be learning about the neural network / deep learning approach that has come to dominate NLP in recent years. Early in the semester, we will discuss the logic of neural nets and core concepts for NLP like embeddings, language models, and transfer learning. Nearer the end of the semester, we will dive in to this a little deeper, so to speak, and discuss concepts in the rapidly changing state-of-the-art like convolutional neural nets, recurrent neural nets, the attention mechanism, and transformers.

The course will assume students have a base facility with Python, R, or similar, and some graduate level work in statistical inference, quantitative social science methodology, or machine learning.

Assignments and Grades

Grades will be based on the following:

- **Engagement in Seminar - 20%**
  - **Readings and Seminar Discussion** *To this end, I want you each to send me – by MONDAY 7:00am each week, by email – lists of terms / concepts that you encountered in that week's reading in three categories: (1) terms/concepts that were new but you think you now understand, (2) terms/concepts that seem to be used differently than in the context of your home discipline, with a sentence or two of explanation, and (3) terms/concepts you still find confusing, with a sentence or two of explanation.*
  - Full 20 points if you are present every week, have made a good faith effort to provide your lists of confusing terms and concepts on time, have thoughtfully read all of the assignments, are prepared to talk about the week's readings and themes and consistently contribute in ways that are productive to the discussion (good questions, thoughtful responses, etc.), with all of that weighted more heavily. If you don't do any of that, 0 points. Sliding scale in between.

- **Exercises - 20%** It is my intention to have exercises (almost) weekly for the first 8-10 weeks. Generally, you are welcome to speak with each other about the exercises, but code must be your own or its source documented in the code. I will use code plagiarism detection software if it appears necessary. After the fact, I will in some cases share your code, or a modification thereof, as an example solution.

- **Project - 40%** Research paper. This may be an application of interest to your (or some) discipline, which uses text as data, or a methodological contribution relevant to the literature on text as data. (It may not, broadly speaking, be a data collection just for the sake of data collection, full stop.) You'll need to submit a one page description of your proposed paper/project by October 10, but I encourage you to do so, or to discuss it with me, as soon as you formulate your idea.

  Papers must be in a format plausible as a submission (other than anonymization) to an appropriate peer-reviewed outlet, with appropriate supplementary materials available. This might range from a computer science "short paper" format (e.g., four pages plus references in the dense two-column ACL or NeurIPS style file) or social science "letter" format (about 3-4000 words) to a full journal article (8-12000 words). Submissions should indicate what the hypothetical publication target is. Shorter versions should have the "pith" – the density of actual content like results – appropriate to such formats.

  Papers will be submitted a month from the end of the semester. Each of you will receive (and write) two (random, blind) peer reviews within two weeks. At the end of the semester you will submit a revised version of your paper along with a memo to reviewers and the editor (me) discussing how (or why not) reviewer comments have been addressed.

  If your scientific objective requires data collection and cleaning beyond the scale of what is possible in this time frame, modify your objective. Consider, for example, whether you can conduct a pilot study on a smaller sample or on a readily available proxy for the ultimate data of interest.

Papers may not require the violation of copyright or other legal constraints, or violate any appropriate terms of service.

- **Oct 10 (Thu) - Project proposal / description due, but encouraged earlier**
- **Nov 13 (Wed) - Initial submission deadline**
- **Dec 1 (Sun)- Receive peer reviews this day or sooner**
- **Dec 18 (Wed) - Final submission deadline**

- **Project Peer Reviews - 20%**

  You will have two weeks to provide peer reviews of two colleagues' papers, assigned randomly by me single-blind (the author will not know who acted as reviewers). Submit your reviews in plain text so that I can ensure reviewer anonymity. The sole criterion I will use to grade these is "constructiveness." A constructive review offers reasonable suggestions for improvement of the paper, is not unnecessarily snide in any criticism it offers, and is returned on time.

  - **Nov 15 (Fri) - Receive papers to review by this date.**
  - **Nov 30 (Sat) - Deadline to return reviews.** Note: if a paper is received by a reviewer later than Nov 15, that reviewer has two weeks from that date to return the review, but the final submission deadline for the paper is not extended.

Readings - Fall 2019

There is no textbook for the course and most of our readings will be articles. But we will read, or I will refer you to, multiple sections of each of the following free books or reference materials:

- **[SLP]** Daniel Jurafsky and James Martin. 2018. *Speech & Language Processing* 3rd ed., draft. https://web.stanford.edu/~jurafsky/slp3/
- **[NLP]** Jacob Eisenstein. 2018. *Natural Language Processing* Draft. https://github.com/jacobeisenstein/gt-nlp-class/blob/master/notes/eisenstein-nlp-notes.pdf
- **[IIR]** Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze. 2009. *Introduction to Information Retrieval* Cambridge University Press. http://nlp.stanford.edu/IR-book/.

Tutorial Notebooks & Code - Discussed in Class

Examples of notebooks I have (at least partially) prepared and will share via the website and discuss in class.

- "R tools for text-as-data and NLP."
- "Introduction to quanteda." (R)
- "Text manipulation and processing with quanteda." (R)
- "Python tools for text-as-data and NLP."
- "Introduction to NLP with TextBlob, nltk, and pattern." (Python)
- "Introduction to NLP with spaCy." (Python)
- "Cosine similarity and tf-idf weighting." (R)

- "Dictionary-based sentiment analysis with Lexicoder." (R)
- "Supervised learning and text classification." (R / Python)
- "The Latent Dirichlet Allocation (LDA) topic model." (R / Python)
- "The Structural Topic Model (STM)." (R)
- "Feed-forward neural networks with Keras sequential API and Tensorflow." (R/Python)
- "Implementing word2vec with Keras functional API." (Python)
- "Introduction to deep learning with PyTorch on Google Colab." (Python/Colab)
- "Introduction to sense2vec." (Python)

Nitty gritty things like file formats, encodings, messy data (OCR, PDF, misspelled), etc., are tucked into notebooks, exercises, or other topics. For some discussion of such topics see Goist and Monroe (2019) "Taking Data Seriously in the Design of Data Science Projects" in the *SAGE Handbook of Research Methodology for Political Science and International Relations*.

August 27 - Introductions; Syllabus; Administrivia

Sep 3 - Overviews; What we can (try to) do with text

- Grimmer, Justin and Brandon Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Documents." *Political Analysis*. 21(3): 267-297.
- DiMaggio, Paul. 2015. "Adapting computational text analysis to social science (and vice versa)." *Big Data & Society* 2(2).
- John Wilkerson and Andreu Casas. 2017. "Large-Scale Computerized Text Analysis in Political Science: Opportunities and Challenges." *Annual Review of Political Science*
- **[NLP]** Ch. 1, "Introduction," esp. Sect. 1.1, "Natural Language Processing and Its Neighbors."
- (Skim very superficially) "NLP-Overview: Modern Deep Learning Techniques Applied to Natural Language Processing." https://nlpoverview.com/index.html.
- Further reference:
  - Matthew Gentzkow, Bryan T. Kelly, and Matt Taddy. 2017. "Text as Data." https://web.stanford.edu/~gentzkow/research/text-as-data.pdf
  - Brendan O'Connor, David Bamman, and Noah A. Smith. 2011. "Computational Text Analysis for Social Science: Model Assumptions and Complexity." (2011) NIPS Workshop on Computational Social Science and the Wisdom of Crowds.
  - Monroe, Burt and Phil Schrodt. 2008. "Introduction to the Special Issue: The Statistical Analysis of Political Text." Political Analysis 16, 4, 351-355.
  - Margaret E. Roberts. 2016. "Introduction to the Virtual Issue: Recent Innovations in Text Analysis for Social Science." *Political Analysis* https://doi.org/10.1017/S1047198700014418

September 10 - Manipulating and Preprocessing Text; Regular Expressions.

- **[SLP]** Ch. 2, "Regular Expressions, Text Normalization, and Edit Distance."
- Matthew Denny and Arthur Spirling. 2018. "Text Preprocessing For Unsupervised Learning: Why It Matters, When It Misleads, And What To Do About It." *Political Analysis* 26(2): 168-89.
- (We will go over some basic options for text processing in R and Python, as well as regular expressions.)

September 17 & (part) 24 - Representing, Exploring, and Comparing Texts; Vector Space; Embeddings; Parse Trees; Language Models

- **[IIR]** Ch 6, "Scoring, Term Weighting, and the Vector Space Model."
- **[SLP]** Ch. 6, "Vector Semantics."
- Aylin Caliskan, Joanna J. Bryson, and Arvind Narayanan. 2017. "Semantics Derived Automatically from Language Corpora Contain Human Biases." *Science*. https://arxiv.org/abs/1608.07187.
- Burt L. Monroe, Michael Colaresi, and Kevin M. Quinn. 2008. "Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict." *Political Analysis*. 16(4): 372-403. https://doi.org/10.1093/pan/mpn018.
- Further reference:
  - **[IIR]** Ch. 18, "Matrix Decomposition and Latent Semantic Indexing."
  - Jeffrey Pennington, Richard Socher, Christopher Manning. 2014. "GloVe: Global vectors for word representation." *EMNLP* https://nlp.stanford.edu/projects/glove/.
  - Tolga Bolukbasi, Kai-Wei Chang, James Zou, Venkatesh Saligrama, Adam Kalai. 2016. "Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings." https://arxiv.org/abs/1607.06520.
  - Eitan Adam Pechenick, Christopher M. Danforth, and Peter Sheridan Dodds. 2015. "Characterizing the Google Books Corpus: Strong Limits to Inferences of Socio-Cultural and Linguistic Evolution." *PLoS One*. https://doi.org/10.1371/journal.pone.0137041.

September 24 (part) - Dictionaries, Lexicons, & Keywords.

- Lori Young and Stuart Soroka. 2012. "Affective News: The Automated Coding of Sentiment in Political Texts." *Political Communication* 29(2): 205-31. https://doi-org.ezaccess.libraries.psu.edu/10.1080/10584609.2012.671234. (Lexicoder).
- Leah Windsor, Nia Dowell, Alistair Windsor, and John Kaltner. 2018. "Leader Language and Political Survival Strategies." *International Interactions* 44(2): 321-336, https://doi-org.ezaccess.libraries.psu.edu/10.1080/03050629.2017.1345737. (LIWC). (For more on LIWC see: Tausczik, Y. R., and Pennebaker, J. W. 2010. "The psychological meaning of words: LIWC and computerized text analysis methods." *Journal of language and social psychology*, 29(1), 24-54.)
- **[SLP]** Ch. 19 "Lexicons for Sentiment, Affect, and Connotation."
- Further reference:
  - Fridolin Linder. 2017. "Improved Data Collection for Online Research Using Query Expansion and Active Learning." SSRN: https://dx.doi.org/10.2139/ssrn.3026393.
  - See also event data readings.

October 1 & 8 - Supervised Learning & Classification; Introduction to Neural Networks for NLP.

- **[SLP]** Chapters 4 (Naive Bayes and Sentiment Classification) and 5 (Logistic Regression).
- **[NLP]** Chapter 2 - "Linear text classification," (Ch. 3 "Nonlinear classification"), and Ch. 4 "Linguistic applications of classification."
- Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. "Thumbs up? Sentiment classification using machine learning techniques." *Proceedings of EMNLP*, pp. 79–86. http://www.cs.cornell.edu/home/llee/papers/sentiment.pdf.

- D'Orazio, V., Landis, S. T., Palmer, G. and Schrodt, P. 2014. "Separating the Wheat from the Chaff: Applications of Automated Document Classification Using Support Vector Machines," *Political Analysis*, 22(2), pp. 224242. doi: 10.1093/pan/mpt030.
- Benoit, K., Conway, D., Lauderdale, B. E., Laver, M., and Mikhaylov, S. 2016. "Crowd-sourced text analysis: reproducible and agile production of political data." *American Political Science Review*, 110(2), 278-295.
- Theocharis, Y., Barber, P., Fazekas, Z., Popa, S. A. and Parnet, O. 2016. "A Bad Workman Blames His Tweets: The Consequences of Citizens Uncivil Twitter Use When Interacting With Party Candidates." *Journal of Communication*, 66: 10071031.

Background note: If you haven't seen supervised learning / classification before - in say, IST or STAT 557: (a) we're in the same methodological neighborhood as "logistic regression" aka "logit," and modern alternatives, and (b) For a fairly gentle introduction to supervised learning and classification generally (not just in text), with lots of R code and examples, see James et al. 2014 *Introduction to Statistical Learning*. Chapter 4 (Classification), Chapter 8 (Tree-based Methods), Chapter 9 (Support Vector Machines) `http://www-bcf.usc.edu/~gareth/ISL/`.

October 15 & 22 - Unsupervised learning: Clustering, matrix factorization (e.g., LSA, NMF), generative topic modeling (e.g., LDA), topic modeling with structure (e.g., STM), scaling (e.g., WordFish), validation

- David M. Blei . 2012. "Probabilistic Topic Models."
- Roberts, Stewart, Tingley, Airoldi. 2013. "The Structural Topic Model and Applied Social Science." `https://scholar.princeton.edu/files/bstewart/files/stmnips2013.pdf` (I encourage you to seek out more complete treatments here: `https://www.structuraltopicmodel.com`, including R package vignette, and more well known papers Roberts et al 2014 *American Journal of Political Science* and Lucas et al., 2015, *Political Analysis*.) Here's an STM example application: Gilardi, F., Shipan, C. R., and Wueest, B. 2018. "Policy Diffusion: The Issue-Definition Stage." Working paper, University of Zurich. `https://www.fabriziogilardi.org/resources/papers/policy-diffusion-issue-definition.pdf`.
- **[NLP]** Chapter 5 "Learning without supervision."
- Daniel D. Lee and H. Sebastian Seung. 1999. "Learning the parts of objects through non-negative matrix factorization." *Nature*.
- (We will also revisit Quinn et al 2010, and Grimmer and Stewart 2013 for their discussions of validation.)

Scaling (on day 2)

- Slapin and Proksch. 2008. "A scaling model for estimating time-series party positions from texts." *American Journal of Political Science*. (WordFish)
- Benjamin Lauderdale and Alex Herzog. 2016. "Measuring political positions from legislative speech." *Political Analysis*. (WordShoal)
- For further reference:
  - Lowe, Benoit, Mikhalov, and Laver. 2011. "Scaling policy preferences from coded political texts." *Legislative Studies Quarterly*.
  - Lowe, W. 2008. "Understanding Wordscores." *Political Analysis*, 16(4), 356-371.
  - Nicholas Beauchamp. 2017. "Predicting and interpolating state-level polls using Twitter textual data." *American Journal of Political Science*
  - See also Hobbs 2018 (under transfer learning section).

October 29 - Neural networks, deep learning, and embeddings redux; distributed representations; pretraining and transfer learning.

- **[SLP]** Ch 5. "Neural Networks and Neural Language Models."
- Christopher Olah. 2014. "Deep Learning, NLP, and Representations." http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/
- Sebastian Ruder. 2018. "NLP's ImageNet moment has arrived." https://thegradient.pub/nlp-imagenet/
- Jay Allomar. 2018. "A Visual and Interactive Guide to the Basics of Neural Networks." and "A Visual and Interactive Look at Basic Neural Network Math."
- For more on neural nets and classification, see **[NLP]**, Ch.3, "Nonlinear Classification."
- For those who want deeper on word embeddings, I recommend (but am not assigning)
  - **[NLP]** Chapter 14, "Distributional and distributed semantics."
  - Levy and Goldberg. 2014. "Neural Word Embeddings as Implicit Matrix Factorization.." https://levyomer.files.wordpress.com/2014/09/neural-word-embeddings-as-implicit-matrix-factorization.pdf.
  - Pennington, Socher, and Manning. 2014. "GloVe: Global Vectors for Word Representation." https://nlp.stanford.edu/projects/glove/.
  - Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. "Efficient Estimation of Word Representations in Vector Space." *Proceedings of Workshop at ICLR.* (Original word2vec, a tough read.)
  - Quoc Le and Tomas Mikalov. 2014. "Distributed Representations of Sentences and Documents." *JMLR.* (doc2vec).
- For those who want deeper on deep learning generally, I recommend (but am not assigning):
  - Goodfellow, Bengio, and Courville. 2016. Deep Learning. MIT Press. http://www.deeplearningbook.org.
  - Howard, Jeremy. Video series: "Practical Deep Learning for Coders." https://www.youtube.com/playlist?list=PLfYUBJiXbdtSIJb-Qd3pw0cqCbkGeS0xn.

November 5 & 12 - Convolutional neural nets (CNNs); Recurrent Neural Nets (RNNS), specialized RNNs (e.g., LSTMs, bi-LSTMs, GRUs); ELMo, ULMFiT and friends.

- Andrej Karpathy. "The Unreasonable Effectiveness of Recurrent Neural Networks."
- **[SLP]** Chapter 9, "Sequence processing with recurrent neural networks."
- **[NLP]** Chapter 6, "Language modeling," Chapter 7 "Sequence labeling," Chapter 8 "Applications of sequence labeling."
- Noah Smith. 2019. "Contextual Word Representations: A Contextual Introduction."
- For further reference:
  - Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, Luke Zettlemoyer. 2018. "Deep Contextualized Word Representations." https://arxiv.org/abs/1802.05365 (ELMo).
  - Jeremy Howard and Sebastian Ruder. 2018. "Universal Language Model Fine-tuning for Text Classification." (ULMFiT)

November 19 – Attention mechanisms; transformer networks; BERT, OpenAI-GPT and friends

- Jay Allomar. 2018. "The Illustrated Transformer."
- Jay Allomar. 2018. "The Illustrated BERT, ELMo, and co. (How NLP Cracked Transfer Learning.")
- Jay Allomar. 2019. "The Illustrated GPT-2 (Visualizing Transformer Language Models.)"
- For further reference:
  - Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. "Attention is All You Need."
  - Jacob Devlin, Ming-wei Chang, Kenton Lee, and Kristina Toutanova. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding."

November 26 – No class (Thanksgiving Week)

December 3 – Procrustes, CCA and related transfer learning; multilingual text analysis; short texts

- Mitchell Goist and Burt L. Monroe. 2018. "Analysis of Multilingual Political Text." (Presented at New Directions in Text as Data, Seattle).
- Waleed Ammar, George Mulcaire, Yulia Tsvetkov, Guillaume Lample, Chris Dyer, Noah A. Smith. 2016. "Massively multilingual word embeddings." https://arxiv.org/abs/1602.01925
- Will Hobbs. 2018. "Text Scaling for Open-Ended Survey Responses and Social Media Posts."

December 10 - Catchup / recap / grab-bag of possible other topics.

Possible topic: Generating realistic synthetic text / seq2seq models

- Jay Allomar. 2018. "Visualizing a Neural Machine Translation Model (Mechanics of Seq2seq Models with Attention)."
- Neumann and Monroe. 2019.
- Sutskever, et al. 2014.

Information extraction; event data

- **[SLP]** Ch. 17, "Information Extraction."; Ch. 18, "Semantic Role Labelling."; Ch. 20, "Coreference Resolution and Entity Linking."
- **[NLP]** Ch. 17. "Information extraction."
- Beieler, J., Brandt, P. T., Halterman, A., Schrodt, P. A., & Simpson, E. M. 2016. "Generating political event data in near real time," in Alvarez, M. (ed.) *Computational Social Science.* Cambridge: Cambridge University Press.
- Schrodt, Philip. 2019/8. "Stuff I tell people about event data." https://asecondmouse.wordpress.com/2019/03/05/stuff-i-tell-people-about-event-data/; "Seven current challenges in event data." https://asecondmouse.wordpress.com/2019/03/13/seven-current-challenges-in-event-data/; "Should an event coder be more like a baby?" https://asecondmouse.wordpress.com/2018/06/05/should-an-event-coder-be-more-like-a-baby/

- Wei Wang, Ryan Kennedy, David Lazer, Naren Ramakrishnan. 2016. "Growing Pains for Global Monitoring of Societal Events." *Science*. 353:6307, pp. 1502–1503. https://doi.org/10.1126/science.aaf6758
- Universal dependency parsing. http://lindat.mff.cuni.cz/services/udpipe/run.php

Causal inference

- Naoki Egami, Christian J. Fong, Justin Grimmer, Margaret E. Roberts, Brandon M. Stewart. 2018. "How to Make Causal Inferences Using Texts." https://scholar.princeton.edu/sites/default/files/bstewart/files/ais.pdf
- Zach Wood-Doughty, Ilya Shpitser, Mark Dredze. 2018. "Challenges of Using Text Classifiers for Causal Inference." *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 45864598.* https://www.aclweb.org/anthology/D18-1488.

Keeping track of the NLP cutting edge

- "NLP-Overview: Modern Deep Learning Techniques Applied to Natural Language Processing." https://nlpoverview.com/index.html.
- "NLP-Progress: Repository to track the progress in Natural Language Processing (NLP), including the datasets and the current state-of-the-art for the most common NLP tasks." https://nlpprogress.com.
- "Awesome-NLP: A curated list of resources dedicated to Natural Language Processing (NLP)." https://github.com/keon/awesome-nlp

Penn State Policy Statements

Academic Integrity

Academic integrity is the pursuit of scholarly activity in an open, honest and responsible manner. Academic integrity is a basic guiding principle for all academic activity at The Pennsylvania State University, and all members of the University community are expected to act in accordance with this principle. Consistent with this expectation, the Universitys Code of Conduct states that all students should act with personal integrity, respect other students dignity, rights and property, and help create and maintain an environment in which all can succeed through the fruits of their efforts.

Academic integrity includes a commitment by all members of the University community not to engage in or tolerate acts of falsification, misrepresentation or deception. Such acts of dishonesty violate the fundamental ethical principles of the University community and compromise the worth of work completed by others.

Disability Accomodation

Penn State welcomes students with disabilities into the Universitys educational programs. Every Penn State campus has an office for students with disabilities. Student Disability Resources (SDR) website provides contact information for every Penn State campus (http://equity.psu.edu/sdr/disability-coordinator). For further information, please visit the Student Disability Resources website (http://equity.psu.edu/sdr/).

In order to receive consideration for reasonable accommodations, you must contact the appropriate disability services office at the campus where you are officially enrolled, participate in an intake interview, and provide documentation: See documentation guidelines at (http://equity.psu.edu/sdr/guidelines). If the documentation supports your request for reasonable accommodations, your campus disability services office will provide you with an accommodation letter. Please share this letter with your instructors and discuss the accommodations with them as early as possible. You must follow this process for every semester that you request accommodations.

Psychological Services

Many students at Penn State face personal challenges or have psychological needs that may interfere with their academic progress, social development, or emotional wellbeing. The university offers a variety of confidential services to help you through difficult times, including individual and group counseling, crisis intervention, consultations, online chats, and mental health screenings. These services are provided by staff who welcome all students and embrace a philosophy respectful of clients cultural and religious backgrounds, and sensitive to differences in race, ability, gender identity and sexual orientation.

- Counseling and Psychological Services at University Park (CAPS) (http://studentaffairs.psu.edu/counseling/): 814-863-0395
- Penn State Crisis Line (24 hours/7 days/week): 877-229-6400
- Crisis Text Line (24 hours/7 days/week): Text LIONS to 741741

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